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Extraction of Forest Plantation Extents Using Majority Voting Classification Fusion Algorithm

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Satellite Phased Array L-band Synthetic Aperture Radar-2 has great advantages in extracting natural and industrial forest plantation in tropical areas, but it suffer from presence of speckle that create problem to identify the forest body. Optimal fusion of Landsat-8 operational land imager bands with ALOS PALSAR-2 can provide the ideal complementary information for an accurate forest extraction while suppressing unwanted information. The goal of this study is to analyze the potential ability of Landsat-8 OLI and ALOS PALSAR-2 as complementary data resources in order to extract land cover especially forest types. Comprehensive preprocessing analysis (e.g. geometric correction, filtering enhancement and polarization combination) were conducted on ALOS PALSAR-2 dataset in order to make the imagery ready for processing. Principal component index method as one of the most effective Pan-Sharpening fusion approaches was used to synthesize Landsat and ALOS PALSAR-2 images. Three different classifiers methods (support vector machine, k-nearest neighborhood, and random forest) were employed and then fused by majority voting algorithm to generate more robust and precise classification result. Accuracy of the final fused result was assessed on the basis of ground truth points by using confusion matrices and kappa coefficient. This study proves that the accurate and reliable majority voting fusion method can be used to extract large-scale land cover with emphasis on natural and industrial forest plantation from synthetic aperture radar and optical datasets.

Keywords: ALOS PALSAR-2, Landsat-8 OLI, Majority Voting, Remote sensing.

1. INTRODUCTION

Precise extraction of land cover particularly forest feature is of important for natural resources management, and forest assessment. Using traditional ground survey systems, this mission can be time-consuming, difficult, and often impossible for a large scale regions (Bagli and Soille, 2003). In recent decades due to the advance growth of remote sensing knowledge, many remotely sensed datasets at a countless variety of resolutions and scales have become accessible for most earth observation applications, which significantly simplifies and facilitates observers' task (Brack, 2006). Nevertheless, how to assess particular data to increase our knowledge of target application and how to explore the value of data from remote sources to offer enhanced classifications of land information becomes a key issue in image processing (Lehmann, E et al 2012). Recently, many researches have been studied on image fusion techniques and their benefits in refining information context, whether spatially or spectrally (L. Stowe *et al.*, 1991) and (Almeida-Filho et al, 2005). Furthermore, numerous works have been taken the place on the potential of fusing multisource images for the sake of land cover improvement (Lardeux et al, 2009*)*. However, less attention has been paid to particular ground object delineation like industrial forest plantations (Miettinen et al, 2010). There are several challenges on types of matching information that is expected to be combined from different datasets as well as kinds of fusion method that must be applied for the improvement of the result. Data fusion basically discusses the way that information should be combined from several sources in order to advance the quality of the original single source. This can be accomplished at three different levels of the image fusion processing namely, pixel level, feature level and classifier level (Yitayew, 2012).

Numerous researches have been published on combination of synthetic aperture radar (SAR) and optical data (Amarsaikhan, 2007; Venkataraman, 2004; Hong, 2014). Yet, most of them focused on image fusion techniques rather than classifier fusion methods. Few studies have been implemented on retrieving and merging the SAR features with optical sensors in forest applications. The major motive for mining or merging class labels from different classifiers is that particular labels might be sustained in fusion procedure which can be valuable for refining the fusion results. By using just single classification method, which one aspect of data is highlighted, can results in uncertainty. Consequently, these methods shrink the requirement of the results to a particular classification method, once diversity and independence are considered in selection of classification method (Fard et al, 2014).

In order to successfully separate industrial forest plantations from natural forest extents, and extract forest types as accurate and complete as possible, reliable features derived from both Landsat-8 Operational Land Imager (OLI) and Satellite Phased Array L-band Synthetic Aperture Radar-2 (ALOS PALSAR-2) should be highlighted. As it is known, optical data contains information on the reflective and emissive characteristics of the Earth surface features, while the SAR data contains information on the surface roughness, texture and dielectric properties of natural and man-made objects (Xiao et al, 2014).

The goal of this study is to analyze the potential ability of Landsat-8 OLI and ALOS PALSAR-2 as complementary information resources in order to extracting land cover types especially forest features. To do that, we apply a comprehensive preprocessing on Landsat and ALOS PALSAR-2 data is the first and fundamental step of this study. Principal component index (PCI) method as one of the most effective Pan-Sharpening fusion approach is used to synthesis Landsat and ALOS PALSAR-2 Images. Subsequently, different classifiers including, support vector machine (SVM), k-nearest neighborhood (KNN), and random forest (RF) are employed for supervise classifications. Finally, land cover classes from mentioned classifiers were combined by using majority voting (MV) fusion method to generate a robust and precise land cover map. By the end, the classification accuracy was tested based on 105 training site acquired from Google Earth using confusion matrices and kappa coefficient.

2. STUDY AREA AND DATA

The study area is located in Peretak district of Selangor Province, Peninsular Malaysia (3°33' 43"N, 101°34'55"E) with a total land area of 10796 hectares. The study site is characterized by such classes as built-up area, suburban area, farmland area, and water area. Peretak has a sub-tropical humid monsoon climate, with high annual rainfall up to 2500 mm/year and two distinct seasons, namely, a wet season from March to September, and a dry season from October to February of next year. Figure 1 shows the location of study area.

In this research, we used three different satellite imagery including, optical, active radar and Altimeter sensors. The Landsat-8 OLI and ALOS PALSAR-2 images were captured on March 2016. In addition to the Shuttle Radar Topography Mission (SRTM) satellite images that utilized for height and topology extraction. The SAR data over the study area was acquired by the ALOS-2 PALSAR-2 sensor at L-band (~24cm wavelength) with 6.25m spatial resolution in fine-beam dual-polarization mode (HH and HV), in an ascending orbit with off-nadir angle of 28.6°.

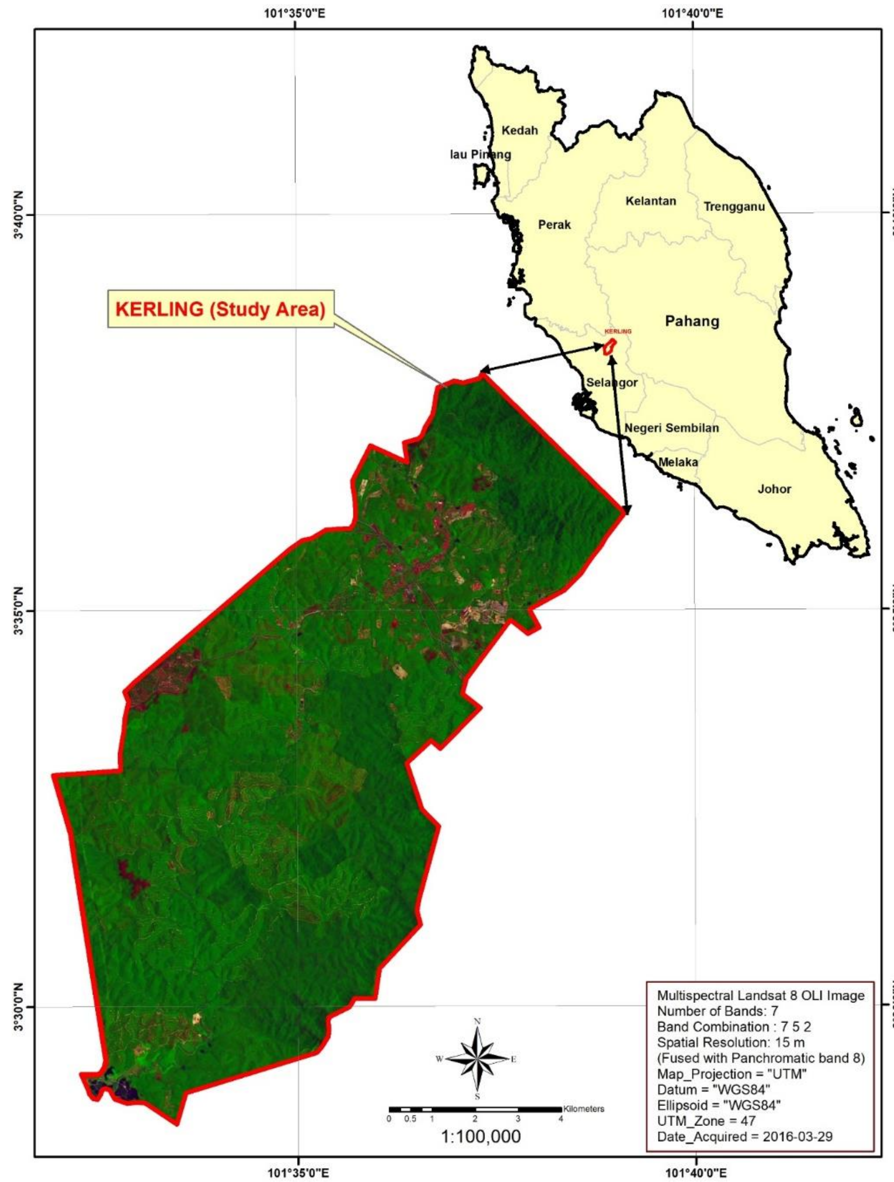

Figure 1: location of the study area which is a part of Selangor, Malaysia

3. METHODOLOGY

This research divided by two parts, first part is to conduct preprocessing for Landsat and ALOS PALSAR-2 level 1.5 data. Second part is classification of ALOS PALSAR-2 L-band Image and Landsat multispectral data individually as well as their combination through image fusion techniques. The accuracy test of these results is from ground truth data comparing with the image classification data. In order to extract forest and industrial plantation map from satellite imagery, we conducted several stages namely, image pre-processing, classification, fusion techniques and accuracy assessment (Figure 2).

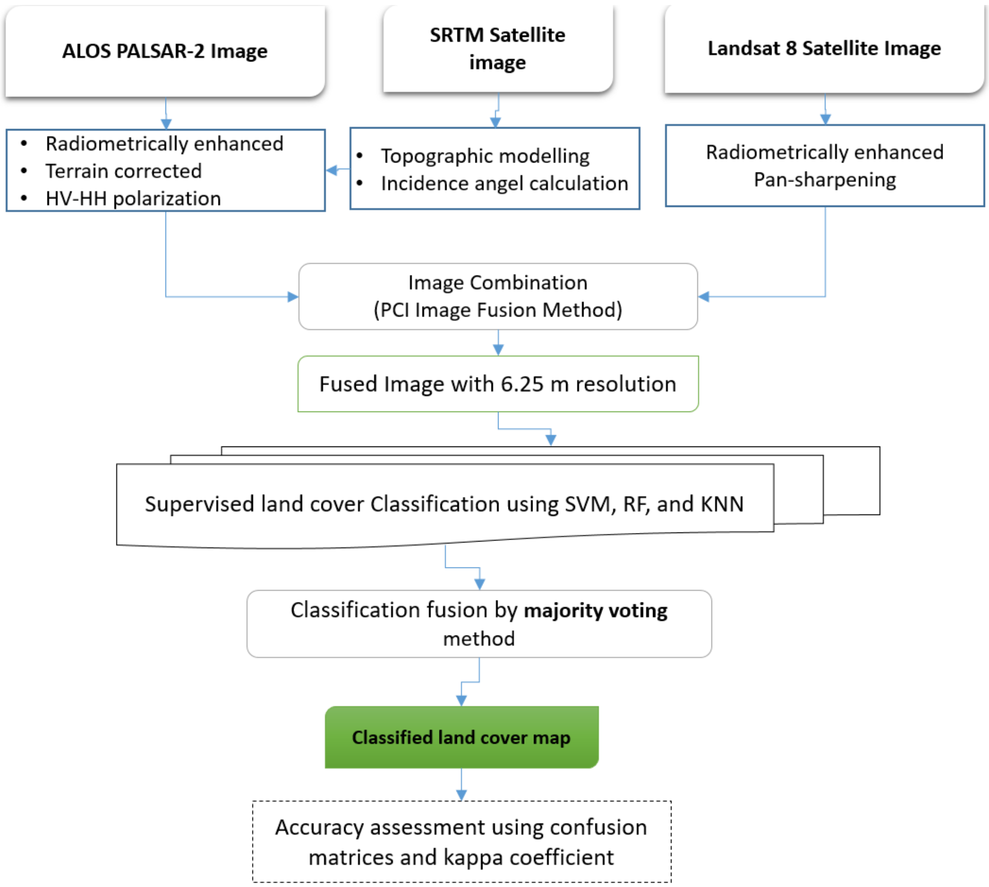

Figure 2. Framework of classification, fusion techniques and accuracy assessment

3.1 Preprocessing of ALOS PALSAR-2

The SAR data over the study area was acquired by the ALOS-2 PALSAR-2 sensor at L-band (~24cm wavelength) with 6.25m spatial resolution in fine-beam dual-polarization mode (HH and HV), in an ascending orbit with off-nadir angle of 28.6°. The data was pre-processed according to the following steps:
1) Removing antenna gain variation effects, 2) Speckle filtering by means of adaptive Lee-Sigma, Frost and Gamma-MAP filters, 3) Orthorectification and Re-projection to UTM project to match the SRTM DEM and Landsat projection, 4) Radiometric calibration through converting (DN) values into Backscatter Intensity in decibel format (dB), 5) Slope or terrain illumination correction using resampled 6.25 m DEM, 6) Calculation of difference band and ratio Layers and ultimately 7) Layer Stacking and spatial subset for creation of final calibrated, orthorectified, terrain corrected and normalized RGB Stacked Image.

3.2 Supervised Image Classification

In order to separate land cover classes with maximum margin we applied three well-known classifiers. Supervised image classification was processed via three different classifier methods including SVM, KNN and RF to map natural forest and industrial forest plantations in the study area.

3.3 Fusion of Classified maps

To acquire a robust classification result it is possible to fuse the classified maps coming from dissimilar classification methods. This approach can maximize the strength of each classified pixel by assigning the optimal label to target pixel that was estimated from confusion matrix.

3.4 Fusion processing

For each input pixel, the MV method consists in choosing the more frequent class label among all classification maps to fuse. In case of not unique more frequent class labels, the undecided value is set for such pixels in the fused output image.

4. RESULTS AND DISCUSSIONS

The co-Registration and Orthorectification were implemented on ALOS PALSAR-2 image from 25 GCPs points using Landsat (resampled band 5) and SRTM image. Digital elevation model (DEM) was extracted from SRTM with a resolution of 30 meters and then resampled to 6.25 m for registration with ALOS PALSAR-2 bands in order to process the terrain correction. All datasets were projected to “UTM, WGS84, and Zone 47 N”. Antenna Pattern Correction plots for HH, HV polarized bands as well as eliminated antenna gain variations band of HV and HH respectively. Radiometric enhancement, normalized and terrain correction were applied on Dual polarized ALOS PALSAR-2 bands of HH and HV accordingly (Fig 3).

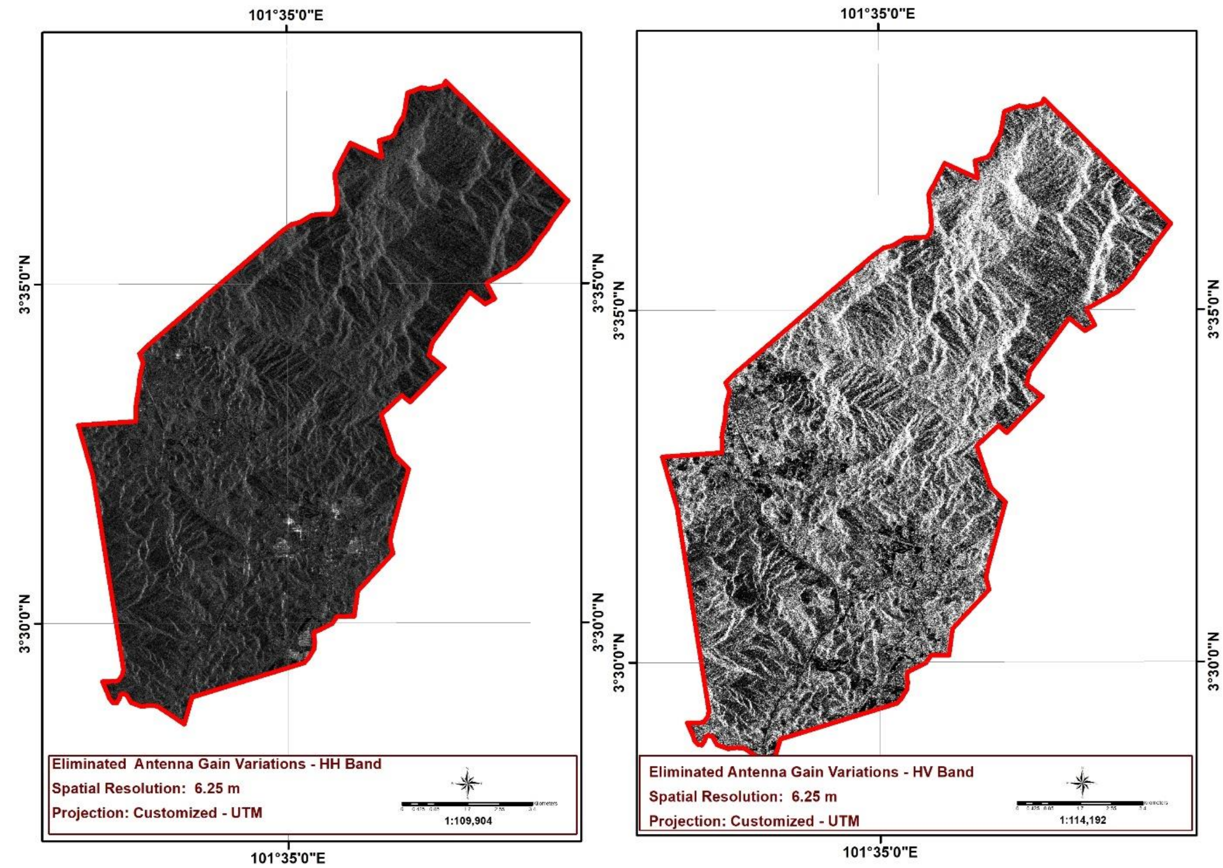

Figure 3. Pre-processing steps on ALOS PALSAR-2

Subsequently, calibrated Landsat and ALOS PALSAR-2 images were fused using pan-sharpening algorithm. Three pixel based classifiers then implemented on (Fig 4).

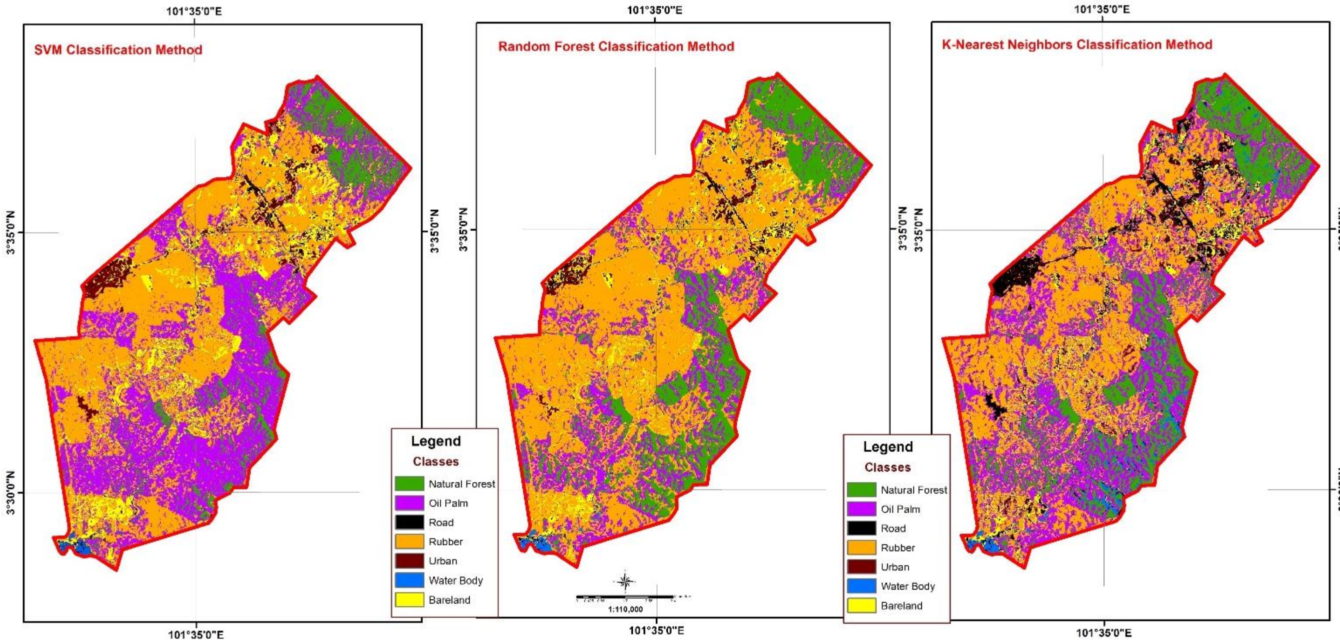

Figure 4. Land cover classification maps using pixel based SVM (left) RF (center) K-NN (right) methods.

Comparison and analysis of different classification maps from indicate that no single pixel based classifier provided comprehensive and thorough separation of all the broad classes or the plantations and forest classes. Furthermore results showed the combination of multispectral Landsat-8 OLI with ALOS PALSAR-2 difference HH-HV band having the most separation between plantation and forested pixels compare to each sensors individually. Landsat-8 image have multiple bands, and different band combinations show different aspects of land cover features, which are helpful in identifying a particular land cover type; but as different objects have same spectral signature and different signatures may correspond to same objects, natural forest areas tend to be confused with other land cover types specially Oil palm and rubber area.

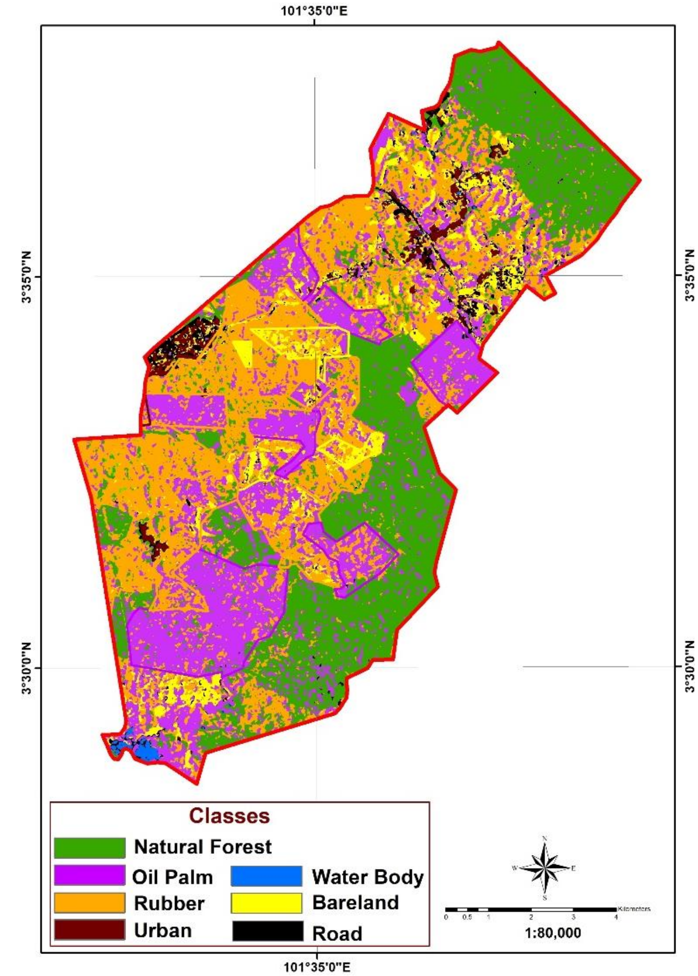

Figure 4. Fusion of Classified maps by MV method

Through calculation of confusion matrix and kappa coefficient the accuracy was assessed using an independent set of 105 training region of interests. Table 1 shows the accuracy of each class as well as overall accuracy. Validation of the classification results was performed by randomly selecting a total of 74 ROI polygons, and visually comparing the assigned class with actual land. Considering the phenology and object size, we used 74 ROI polygons, including 9 Oil Palm ROIs, 11 Rubber, 11 Natural Forest, 18 Urban, 9 Water, and 16 Agriculture ROIs (Table 2). Both datasets (Training and Validation) were obtained from Google Earth in 2016.

Table 2: Distribution of the number of ROI areas among the classes for the training and validation sets

Land cover Class	Training Set	Validation Set
Natural Forest	28	11
Oil Palm	17	9
Rubber	12	11
Urban	18	18
Agriculture	17	16
Water Body	13	9
Total	105	74

Many factors can negatively affect the accuracy of classification including classification method, datasets, and training sample selection. In this study however, most of the class perfectly matched to real boundary on the ground due to several detailed fusion processes that improved the quality of datasets and methods.

Table 3: Confusion matrix and classification accuracies for accuracy assessment of fused final land cover map

Lan cover class	Agriculture	Natural Forest	Oil Palm	Rubber	Urban	Water Body
Agriculture	93439	2649	27981	44000	4916	323
Natural Forest	1959	697020	131575	126171	1032	70
Oil Palm	495	29807	413879	101561	1150	31
Rubber	1199	65784	146593	531864	5830	103
Urban	10364	3089	36374	31183	70774	1694
Water Body	65	15	1	0	0	88626
			Precision of the different classes			
	% 75	% 97	% 87	% 85	% 95	% 97
		Kappa index:		0.663		
		Overall accuracy index:		91.3 %		

The Final fused land cover map using MV fusion method indicated accuracy of 91.3% compare to 80.4%, 75.1% and 71.2 achieved from SVM, RF and KNN, respectively. This study proves that reliable, large-scale maps of land cover with emphasis on discrimination of industrial forest plantation from natural forest can be derived using confusion of SAR and Optic data via new confusion of classification approach. This method can be applied to other tropical regions.

5. CONCLUSION

Classification Fusion Algorithms are generally used to offer a flexible approach to combine multiple sources into an integrated one. ALOS-2 PALSAR-2 dataset has a great advantage in extracting natural forest extents from industrial forest plantation, but they generally have some speckles which destroy the integrity of forest body extracted. Appropriate combination of Landsat-8 OLI bands with ALOS HV and HH-HV will best fuse the complementary information of both for the purpose of accurate forest type extraction while suppressing unwanted information.

In this study, by different level of fusion techniques, we proposed an appropriate combination method to accurately extract (91.3%) the forest types as well as other land cover features. In overall, most of the land cover class perfectly matched with real boundary on the ground due to several detailed fusion processes that substantially improved the quality of datasets and methods. This method also, can be applied to other tropical regions where forest discrimination is a concern.

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