LAND COVER CLASSIFICATION OF ALOS PALSAR DATA USING SUPPORT VECTOR MACHINE

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Abstract. Land cover classification is one of the extensive used applications in the field of remote sensing. Recently, Synthetic Aperture Radar (SAR) data has become an increasing popular data source because its capability to penetrate through clouds, haze, and smoke. This study showed on an alternative method for land cover classification of ALOS-PALSAR data using Support Vector Machine (SVM) classifier. SVM discriminates two classes by fitting an optimal separating hyperplane to the training data in a multidimensional feature space, by using only the closest training samples. In order to minimize the presence of outliers in the training samples and to increase inter-class separabilities, prior to classification, a training sample selection and evaluation technique by identifying its position in a horizontal vertical–vertical horizontal polarization (HV-HH) feature space was applied. The effectiveness of our method was demonstrated using ALOS PALSAR data (25 m mosaic, dual polarization) acquired in Jambi and South Sumatra, Indonesia. There were nine different classes discriminated: forest, rubber plantation, mangrove & shrubs with trees, oilpalm & coconut, shrubs, cropland, bare soil, settlement, and water. Overall accuracy of 87.79% was obtained, with producer's accuracies for forest, rubber plantation, mangrove & shrubs with trees, cropland, and water class were greater than 92%.

Keywords: *Land cover, ALOS-PALSAR, support vector machine (SVM), classification, Jambi, South Sumatra.*

1 INTRODUCTION

One of the main applications of wide-area land cover maps was the use of land cover type to parameterize global-, continental-, and regional- scale models for land use such as vegetation and non-vegetation coverage, climate, and carbon model (Hoekman *et al.*, 2010). Recently, Synthetic Aperture Radar (SAR) satellite imaging has become an increasing popular data source because its capability to penetrate through clouds, haze, and smoke since they can produce serious problems for optical satellite sensor observations (JAXA, 2010; Hoekman *et al.*, 2010).

To effectively derive reliable information from SAR data, appropriate classification techniques are essential. Numerous classification methods, such as statistics classifiers and Neural Network classifier, have been used in the application. However, the former needed the statistics information in the training samples, and the latter usually converged slowly and tended to converge to a local optimization (Tso and Mather, 2001; Sambodo *et al.*, 2007).

Support Vector Machine (SVM) has become an increasing tool for machine learning tasks involving classification, recognition, or detection (Zhang *et al.*, 2010). SVMs aim to discriminate two classes by fitting an optimal separating hyperplane to the training data within a multidimensional feature space, by using only the closest training samples (Vapnik, 1998; Waske and Benediktsson, 2007). Thus, the approach only considered samples close to class boundary and work well with small training sets, even high dimensional data sets were classified (Melgani and Bruzzone, 2004; Waske and Benediktsson, 2007). Similar to Neural Networks, they were not constrained to assumptions concerning the distribution of the input data and can handle different scaled data (Waske and Benediktsson, 2007).

Literatures showed that SVMs were not relatively sensitive to training sample size and many researchers have improved SVMs to successfully work with limited quantity and quality of training samples (Mountrakis *et al.*, 2011). For example, Waske and Benediktsson (2007) showed that the classification of multisensor datasets (SAR and optical imagery) with only a small training sample size using single SVM as well as an approach based on fusion of SVMs outperformed all other parametric and nonparametric classification techniques (maximum likelihood classifier, decision tree classifier, boosted decision tree classifier) with more than 3% accuracy improvement. Zhang *et al.* (2010) proposed a Polarimetric SAR image classification by combining multiple component scattering model, image texture, and SVM that produced 84,7 % accuracy with five land cover classes.

In this paper, we investigated the use of the SVMs approach for land cover mapping in the tropical areas using ALOS-PALSAR 25m mosaic data covering the part of Jambi and South Sumatra Province, Indonesia for the year of 2010. Our ground truth dataset was sparse and sometimes ambiguous mainly due to: 1) the large variation in landscapes as well as seasonal variation; 2) the large time difference between SAR data acquisition (year 2010) and ground data collection (year 2013). Thus, an SVM based classification was considered suitable here due to its ability to successfully work with limited training samples. However, the presence of outliers and inter-class confusion in the training samples for each land cover class should be handled carefully in order to achieve a satisfactory classification result. For these reasons, we applied a training samples selection and evaluation technique by identifying its position in HV-HH (horizontal vertical – vertical horizontal polarization) feature space as a precursor step of classification process. This technique allows us to minimize the presence of outliers in the training samples and to perform the class aggregation if their separabilities in HV-HH feature space were too low.

2 MATERIAL AND METHODS

2.1 Data

The SAR data used in this study were ALOS-PALSAR data, L-band, 25 m resolution, dual polarization (HH+HV) mosaic covering the part of Jambi and South Sumatra Province, Indonesia (Figure 1). These data were acquired in several acquisition dates during the year of 2010 by ALOS (Advanced Land Observing Satellite) and pre-processed (orthorectification, slope correction, and mosaicked) by JAXA-EORC (Japan Aerospace Exploration Agency – Earth Observation Research Center).

The scene under study contains different type of land covers: forest, swamp forest, acacia, rubber plantation, mangrove, shrubs, oil palm, coconut, cropland, bare soil, settlement, and water area. For the generation of training and testing data sets, we conducted a ground survey activity in March 2013 and the result was summarized in Figure 1.

2.2 Data Analyses

The flowchart of the ALOS-PALSAR classification used in this study is shown in Figure 2. It starts with the conversion of Digital Number (DN) of ALOS-PALSAR data to Gamma Naught $¥^{0}$ in decibel unit, which is defined as radar backscatter per unit area of the incident wavefront (perpendicular to slant range) (Motohka, 2012):

$$¥^{0} = 10 * \log_{10}\left\langle DN^{2}\right\rangle + CF \quad [\mathrm{dB}] \qquad (1)$$

Where the Calibration Factor $CF = -83.0\,[\mathrm{dB}]$, and $\langle ... \rangle$ represent averaging over 3x3 window size.

Region of Interest (ROIs) for each land cover class was then identified mainly based on ground survey information. For each class, at least ten ROIs were selected and their statistics (mean and variance-covariance) were then calculated and plotted in the HV-HH feature space. The center of the ellipses coincided with the mean backscatter values. The variance-covariance defined the direction and length of the ellipse axes. Ideally, each ROI had relatively small ellipse shape (indicating the selected samples were quite homogeneous or small variance-covariance). Ellipse centers for ROIs with same class were also close to each other but relatively separated for ROIs with different classes. To achieve these, selection and evaluation using HV-HH feature space plot should be done iteratively. At the end of this step, when two or more classes were highly overlapping, these classes were then aggregated into a single class. It was better to obtain high classification accuracy with less number of classes, rather than use the entire class information but with low accuracy. The whole ROI dataset then divided into two datasets, around 60% for training and around 40% for testing the SVM classifier.

Once the training samples for each class had been generated, the SVM classification was then performed. In this study, we used library LIBSVM (Chang and Lin, 2011). The SVM classification method is explained briefly in the following sub-section.

Finally, the accuracy of classification result was estimated using confusion matrix (using testing samples).

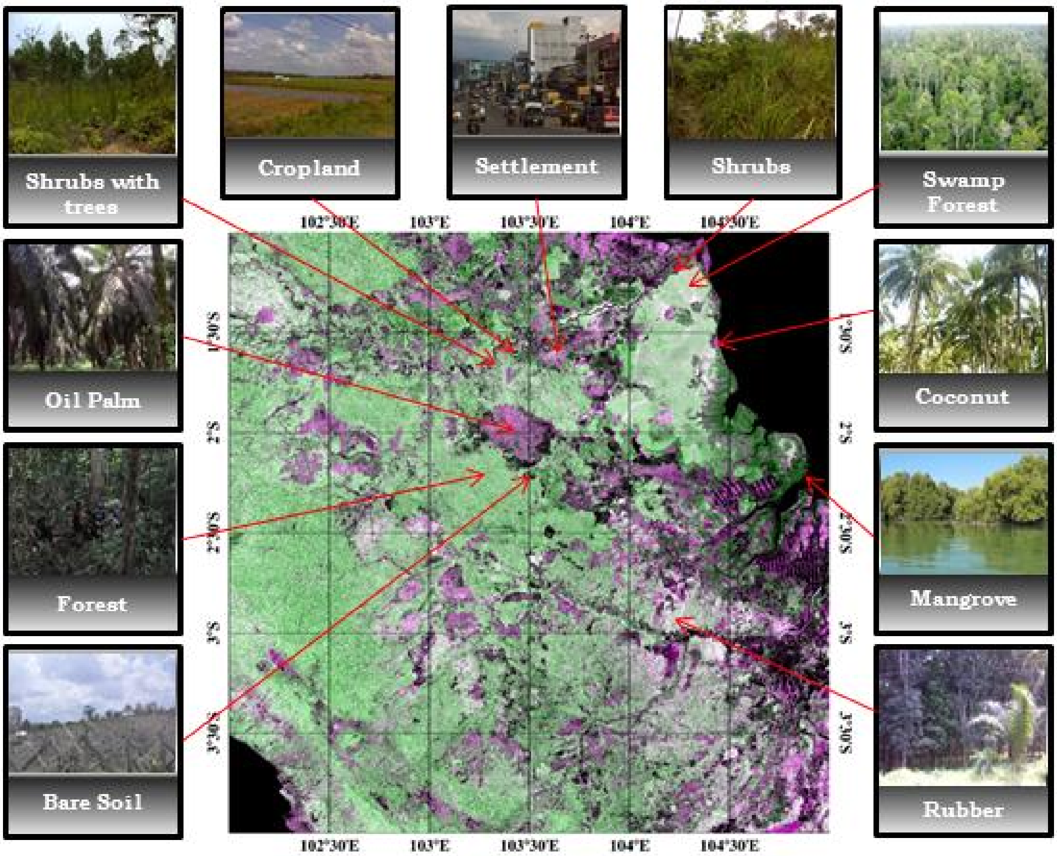


Figure 1. ALOS PALSAR 25m mosaic data the part of Jambi and South Sumatra Province and ground survey information.

2.3 Support vector machine (SVM) classification

Support vector machines were a general class of learning architecture inspired from statistical learning theory that performs structural risk minimization on a nested set structure of separating hyperplanes (Vapnik, 1998). SVM showed good performance in solving small samples, nonlinear, high dimensional pattern classification problems

(Vapnik, 1998; Fletcher, 2009; Chang and Lin, 2011).

In a two-class case (i.e., class 1 and class 2 in Figure 3), a support vector classifier attempted to find a hyperplane that maximizes the distance from the members of each class to the optimal hyperplane.

Suppose we have L number of training samples represented by:

$$\{\mathbf{x}_i, y_i\} \quad i = 1, \ldots \mathrm{L}, \quad \mathbf{x} \in \Re^n \qquad (2)$$

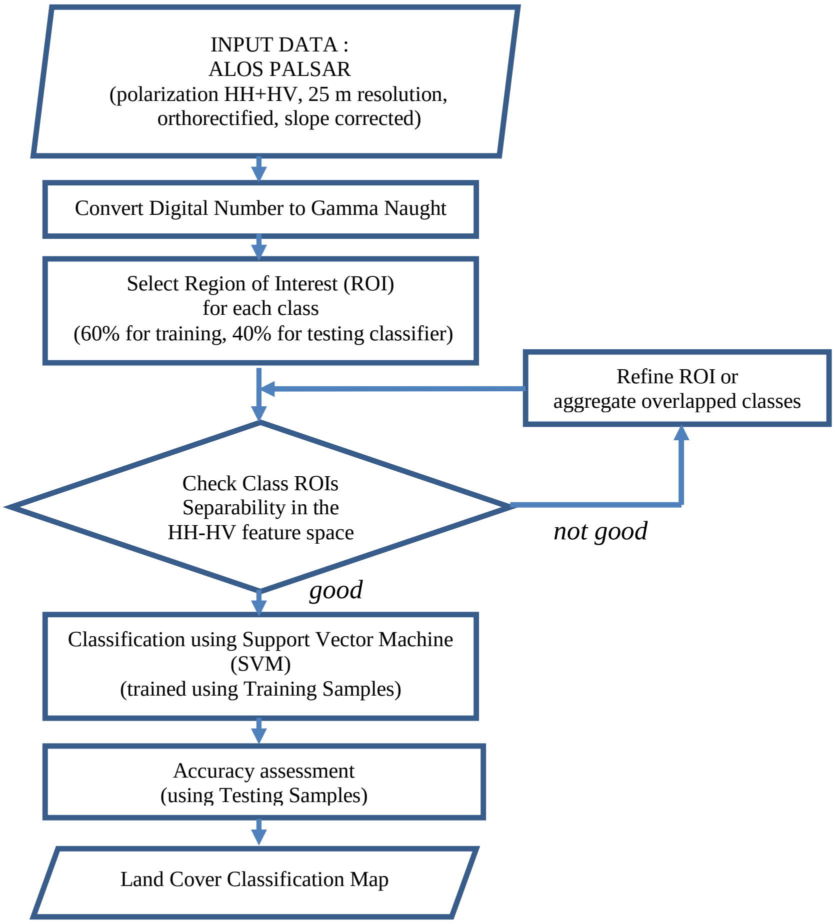


Figure 2. Flowchart of the ALOS-PALSAR classification method.

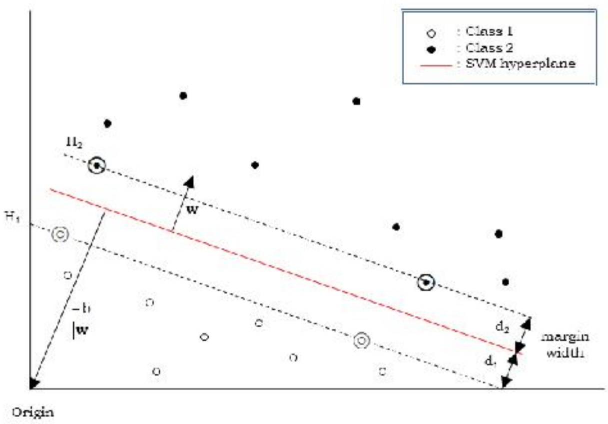


Figure 3. Hyperplane through two linearly separable classes (Adapted from Fletcher, 2009)

where $\mathbf{x}_i$ is an n-dimensional input vector and $y_i \in \{-1, 1\}$ is the corresponding class label of $\mathbf{x}_i$. The feature space of two classes of samples can be separated by hyperplane $\mathbf{w}.\mathbf{x} + b = 0$, where vector $\mathbf{w}$ is normal to the hyperplane, and $\frac{b}{\|\mathbf{w}\|}$ is the perpendicular distance from the hyperplane to the origin. Figure 3 depicts an example of geometry in two-dimensional feature space. The sample data on H_1 and H_2 are called support vectors, which satisfy $\mathbf{w}.\mathbf{x}_i + b = 1$ for H_1 and satisfy $\mathbf{w}.\mathbf{x}_i + b = -1$ for H_2. The distance between separating hyperplane is called margin. Simple vector geometry shows that the margin is equal to $\frac{1}{\|\mathbf{w}\|}$ and maximizing it is equivalent to finding:

$\min\|\mathbf{w}\|$ such that

$$y_i(\mathbf{x}_i \cdot \mathbf{w} + b) - 1 \geq 0 \qquad \forall_i \tag{3}$$

Minimizing $\|\mathbf{w}\|$ is equivalent to minimizing $\frac{1}{2}\|\mathbf{w}\|^2$ and the use of this term makes it possible to perform Quadratic Programming (QP) optimization.

This concept can be extended to the case when the classes are not fully linearly separable (Figure 4). A positive slack variable, $\P_i$, $i = 1,...L$ can be introduced such that the condition in equation (2) can be written as:

$$y_i(\mathbf{x}_i . \mathbf{w} + b) - 1 + \P_i \geq 0 \qquad \forall_i$$

where $\P_i \geq 0 \qquad \forall_i$ (4)

In this *soft margin* SVM, samples on the incorrect side of the margin boundary have a penalty that increases with the distance from it. The support vector approach for minimizing the number of misclassifications is then to find: $\min \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{L}\xi_i$ such that $y_i(\mathbf{x}_i \cdot \mathbf{w} + b) - 1 + \xi_i \geq 0 \quad \forall_i$ (5)

where the parameter C controls the trade-off between the slack variable penalty and the size of the margin. Using Lagrangian and QP method, we need to minimize with respect to $\mathbf{w}, b$ and ξ_i, and maximize with respect to Lagrange multipliers $\boldsymbol{\alpha}$ (where $\alpha_i \geq 0$, $\mu_i \geq 0$ $\forall_i$). Finally each new point $\mathbf{x}'$ is classified by evaluating:

$$y' = \operatorname{sgn}(\mathbf{w} \cdot \mathbf{x}' + b)$$

where $\mathbf{w} = \sum_{i=1}^{L} \sim_i y_i \mathbf{x}_i$ (6)

SVM has originally been developed for two-class problem (binary classification problem). However, land cover classification in this study is a multi-class problem. In the literature, several approaches have been introduced to extend the SVM algorithm to solve multi-class problems. In this study, multi-class SVM is implemented using the one-versus-one (OAO) strategy, in which $k(k-1)/2$ binary classifiers are trained (k is number of class); the final class is found by a voting scheme.

3 RESULT AND DISCUSSION

We perform the evaluation of training samples before the classification process. In the initial stage, based on ground survey information, actually there are 12 land cover classes which potentially can be distinguished: forest, swamp forest, acacia, rubber plantation, mangrove, shrubs, oil palm, coconut, cropland, bare soil, settlement, and water area. The HV-HH feature space plot of the class sample ROIs (Region of Interest) is shown in Figure 5a (all water class samples are below -20 dB, and not plotted in this figure). This plot was

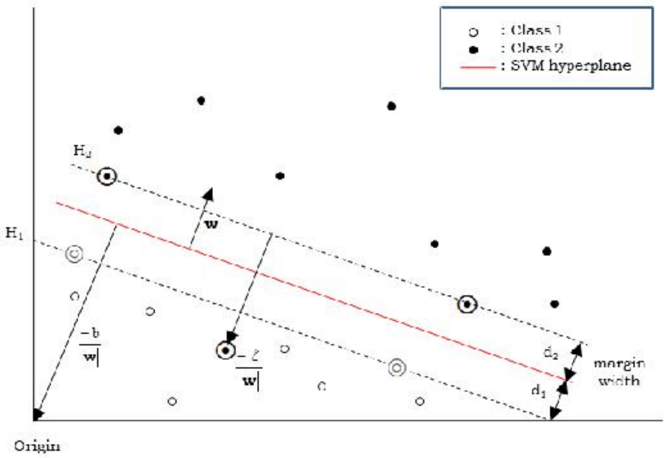
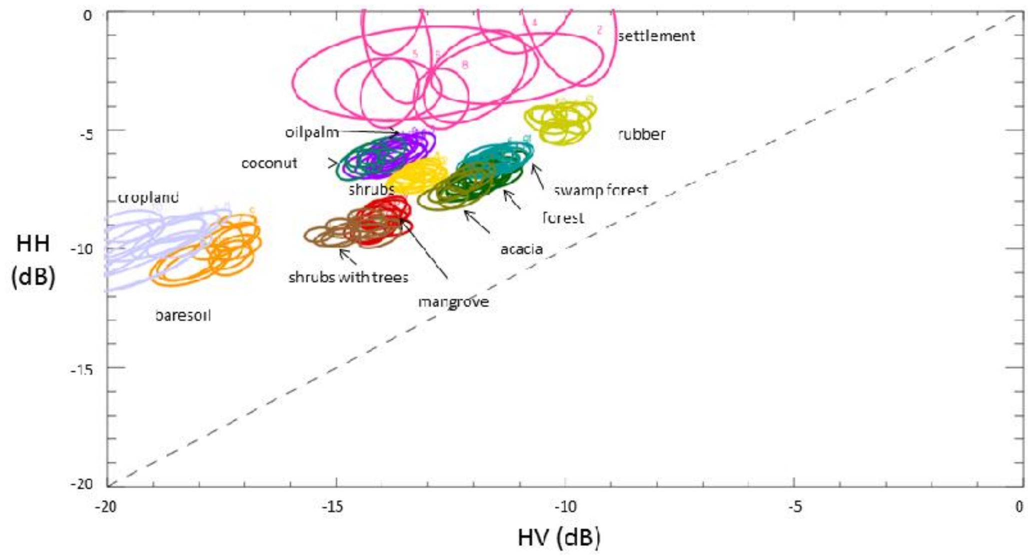
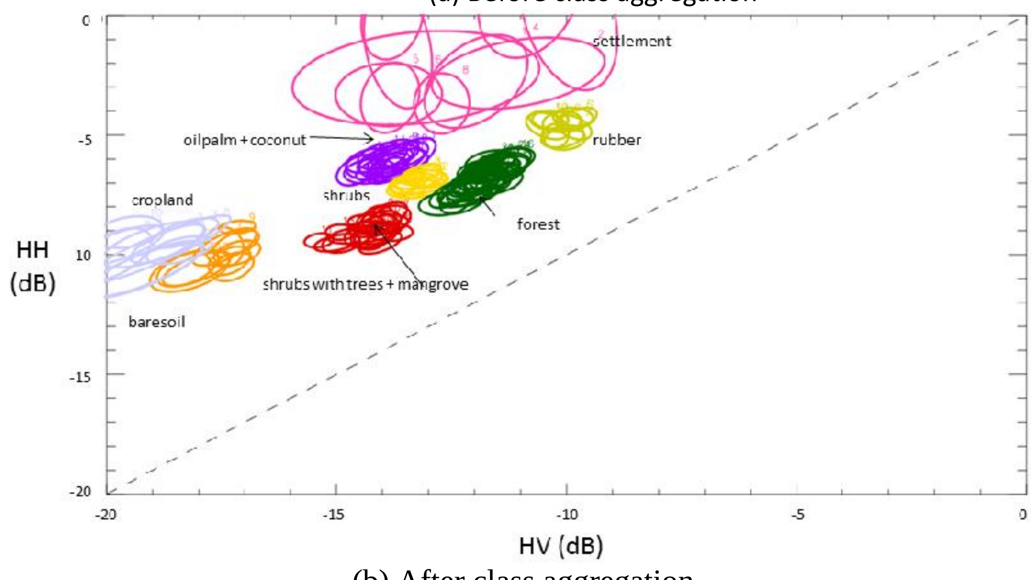


Figure 4. Hyperplane through two non-linearly separable classes (Adapted from Fletcher, 2009).



(a) Before class aggregation



(b) After class aggregation

Figure 5. The HV-HH feature space plot of the class sample ROIs (Region of Interest).

obtained iteratively, which at each iteration we try to get ellipse shapes as small as possible indicating that the selected training samples are quite homogeneous (or small variance-covariance).

From this plot, it can be seen that a lot of class overlap occurred, probably due to the limited channels of the SAR data. For example, the forest class is overlapped with acacia and swamp forest class. The oil palm plantation class is overlapped with coconut plantation class. The mangrove class is overlapped with "shrubs with trees" class. These class overlaps would complicate the classifier in determining the optimum class boundaries and consequently will decrease the classification accuracy. Therefore, we aggregate the overlapped classes into one class. Forest, swamp forest, and acacia are aggregated into "forest" class. Similarly, mangrove and shrubs with trees are aggregated into "mangrove + shrubs with trees" class. Oil palm and coconut are also aggregated into "oil palm + coconut" class. After class aggregation, totally we obtain optimum training samples for nine classes (forest, rubber plantation, mangrove+shrubs with trees, oil palm+coconut, shrubs, cropland, bare soil, settlement, and water class), and resulting HV-HH feature space plot is shown in Figure 5b.

The classification result using SVM classifier is presented in Figure 6, and the corresponding confusion matrix is presented in Table 1. Overall accuracy 87.79% (with Kappa value 0.858) is obtained. The water, rubber plantation, cropland, and mangrove & shrubs with trees can be well discriminated from each other. The forest can be distinguished with other classes, however some misclassification between forest, rubber plantation, mangrove & shrubs with trees are also occurred, mainly due to their similar radar backscattering characteristics. The shrubs cannot be clearly identified by SVM classifier. This may be due the position of shrub samples in the feature space are closely surrounded by other classes so that the resulting class boundary is less optimum.

As comparison, the classification result using Maximum Likelihood classifier is also presented in Figure 7, and the corresponding confusion matrix is presented in Table 2. From the confusion matrix, it can be found that the accuracy exhibited by the SVM classifier is higher (3.47%) than by Maximum Likelihood classifier. This result can also be confirmed in Figure 7, which some misclassification between forest, mangrove & shrubs with trees, oil palm & coconut, and settlement are occurred evidently, and especially bare soil areas cannot be accurately identified by Maximum Likelihood classifier.

The finding of this study suggest that SVM can perform adequately as land cover classification tool using SAR data. Although SVM did not produce significantly better result than the Maximum Likelihood classifier, it provided less omission error (or higher producer's accuracy) in classifying forest, mangrove & shrubs with trees, oil palm & coconut than Maximum Likelihood classifier. This distinction may be important for future studies especially in monitoring forest and non-forest area and its change in Indonesia, for example due to area extension of oil palm plantation.

4 CONCLUSION

Support Vector Machine (SVM) classifier is very promising in generating a land cover classification map from ALOS-PALSAR 25m mosaic data used in this study. In our experiment, we combined SVM with a training samples selection and evaluation technique by identifying its position in a HV-HH feature space in order to minimize the presence of outliers in the training samples and to increase inter-class separabilities. There were nine different classes discriminated: forest, rubber plantation, mangrove & shrubs with trees, oilpalm & coconut, shrubs, cropland, bare soil, settlement, and water. Overall accuracy of 87.79% was obtained, with producer's accuracies for forest, rubber plantation, mangrove & shrubs with trees, cropland, and water class were greater than 92%.

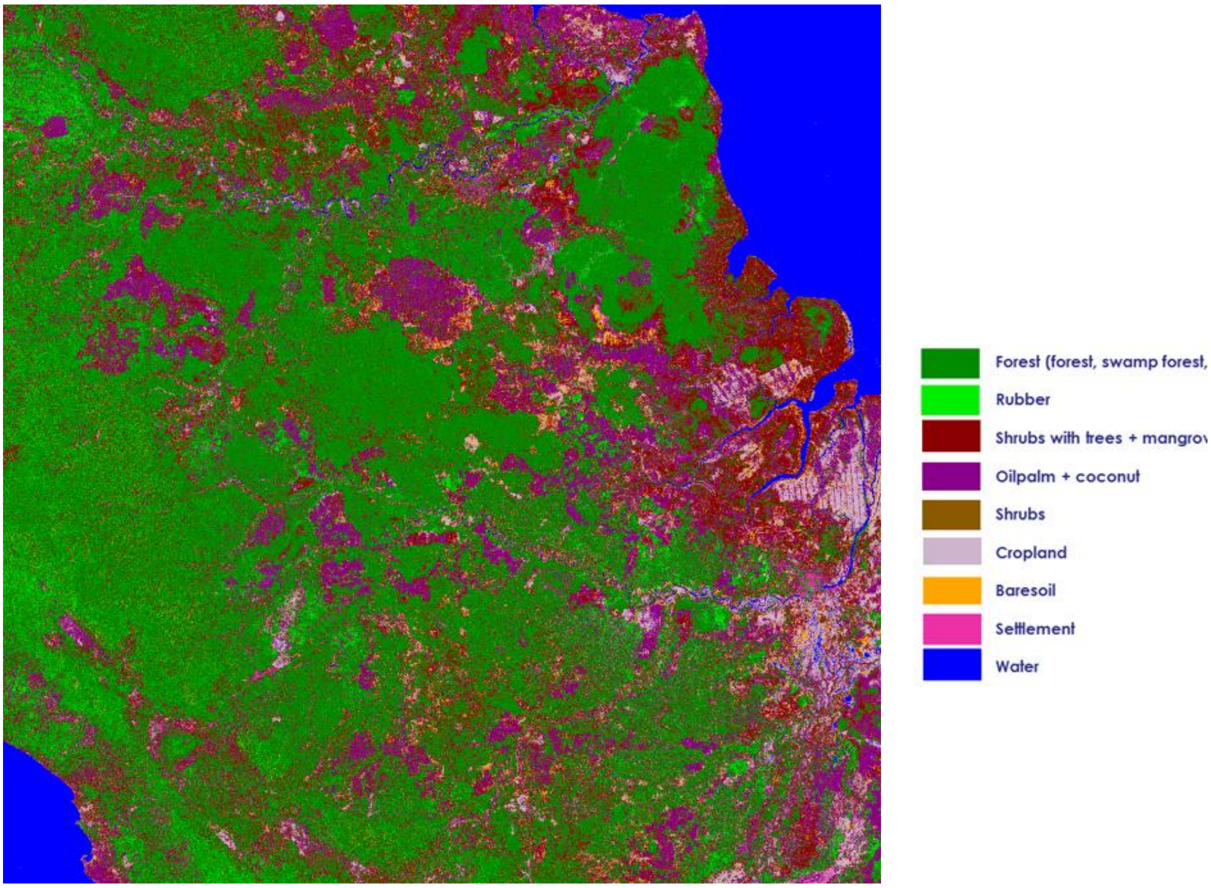


Figure 6. Classification result using Support Vector Machine classifier.

Table 1. Confusion matrix of Support Vector Machine classifier.

Reference Data / Classified Data	Forest	Rubber plantation	Mangrove + shrubs with trees	Oilpalm + coconut	Shrubs	Cropland	Baresoil	Settlement	Water	User's accuracy
Forest	4452	61	73	28	338	0	0	38	0	89.22
Rubber plantation	106	1326	0	2	0	0	0	109	0	85.94
Mangrove + shrubs with trees	113	0	2278	24	41	2	5	0	0	92.49
Oilpalm + coconut	15	0	19	1951	228	11	1	182	0	81.06
Shrubs	118	0	50	155	580	0	0	0	0	64.23
Cropland	0	0	0	1	0	1239	221	0	0	84.80
Baresoil	0	0	1	0	0	59	291	0	0	82.91
Settlement	0	2	0	25	0	0	0	880	0	97.02
Water	0	0	0	0	0	0	0	0	1583	100.00
Producer's accuracy	92.67	95.46	94.09	89.25	48.86	94.51	56.18	72.79	100.00	
				Overall accuracy: 87.79%				Kappa Coefficient: 0.855		

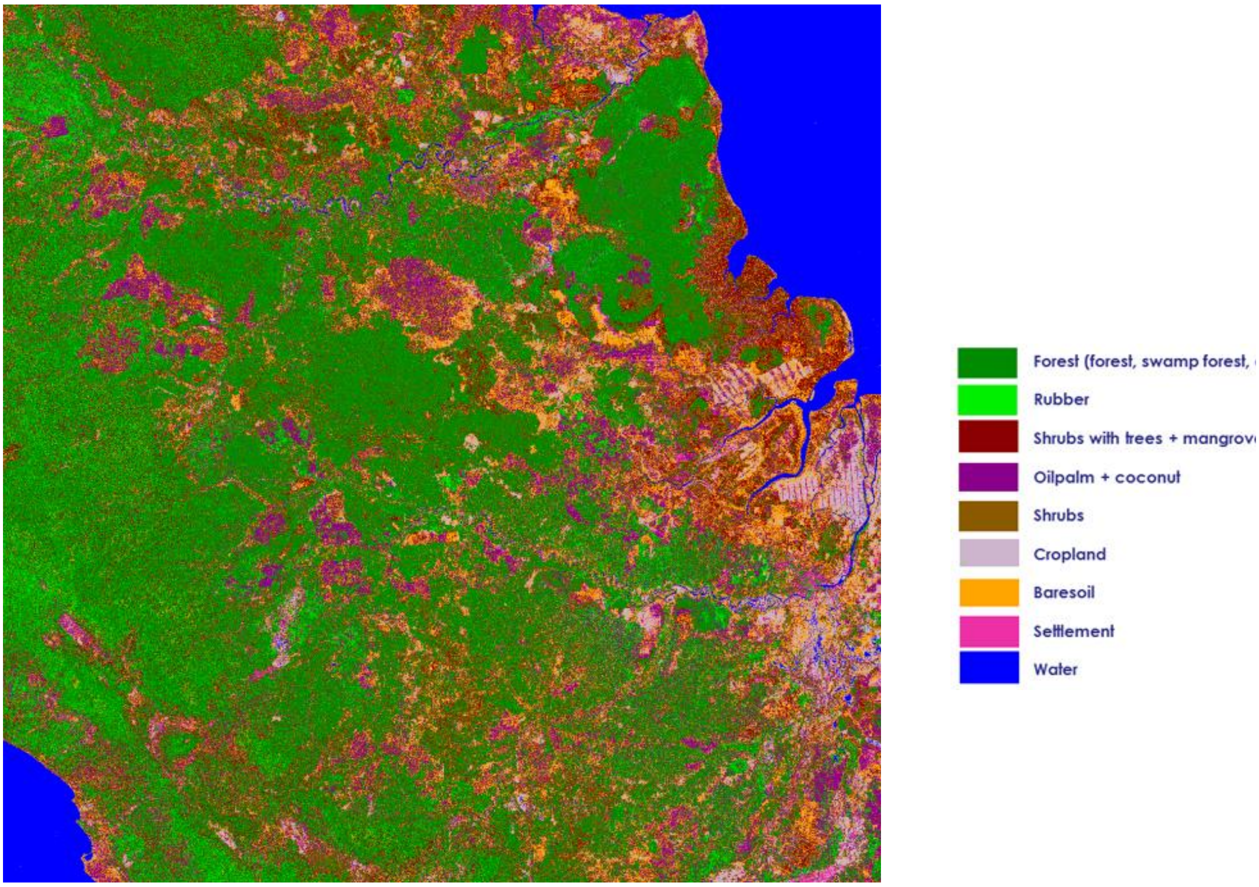


Figure 7. Classification result using Maximum Likelihood classifier.

Table 2. Confusion matrix of Maximum Likelihood classifier.

Reference Data Classified Data	Forest	Rubber plantation	Mangrove + shrubs with trees	Oilpalm + coconut	Shrubs	Cropland	Baresoil	Settlement	Water	User's accuracy
Forest	4083	62	25	17	145	0	0	41	0	93.97
Rubber plantation	138	1322	0	0	0	0	0	124	0	83.46
Mangrove + shrubs with trees	161	0	2079	1	16	0	0	0	0	92.11
Oilpalm + coconut	15	5	6	1727	124	1	0	181	0	83.88
Shrubs	403	0	71	287	860	0	0	3	0	52.96
Cropland	0	0	0	1	0	1232	237	0	0	83.81
Baresoil	4	0	240	79	42	78	281	23	0	37.62
Settlement	0	0	0	74	0	0	0	837	0	91.88
Water	0	0	0	0	0	0	0	0	1583	100.00
Producer's accuracy	84.99	95.18	85.87	79.00	72.45	93.97	54.25	69.23	100.00	
				Overall accuracy: 84.32%				Kappa Coefficient: 0.816		

Furthermore, it has been shown that SVM classifier gave better results compared with maximum likelihood classifier (about 3.47%). Our future work will focus on using other additional input features such as image texture. This can overcome the limitation of the current method to discriminate swamp forest, acacia, shrubs, and mangrove with natural forest and can help to further improve the classification performance.

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