Multi-level Adaptive Support Vector Machine Classification for Tropical Tree Species

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Abstract
High diversity of tree species in tropical forest is a constraint to achieve satisfactory accuracy in tree species classification, as accuracy reduces with the increasing of target tree species. A new multi-level adaptive classification procedure is introduced in the present study employing Support Vector Machine (SVM). The experiment handled 20 tropical tree species classification using in-situ hyperspectral data. Three levels of classification were carried out and the final overall classification accuracy was improved to 74.56% from the beginning accuracy produced by SVM itself. Result of SVM also has proven its better capability than Maximum Likelihood Classification (MLC) in tropical tree species classification.

1. Introduction

Classification is a process which divides entities or events into groups based on their distinguishable characteristics. In remote sensing classification, distinguishable characteristics of objects are presented by spatial or spectral information extracted from remote sensing data. In this context, remote sensing data with fine spatial resolution or high spectral resolution in large number of spectral bands have widely been used in various classification tasks as well as tree species classification. Hyperspectral remote sensing data in narrow spectral bands across visible, near infrared and short-wave infrared bands could describe the chemical and physical properties of vegetation that can distinguish among different tree species. Thus, in recent years, hyperspectral remote sensing has become important to classify different tree species. Airborne hyperspectral data from various sensors such as Carnegie Airborne Observatory-Alpha system (CAO), Hyperspectral Digital Imagery Collection Experiment (HYDICE) and Airborne Imaging Spectrometer for Applications (AISA) and also *in-situ* hyperspectral data which is collected using portable ground based spectroscopy sensors have been used for tree species classification at different tropical forests. However, research on tree species classification using hyperspectral remote sensing for the tropical environment is not so widespread. Clark et al., (2005) have applied reflectance of narrow bands of hyperspectral data to classify seven tropical tree species at leaf, pixel, and tree crown levels respectively. Their results showed a 100% classification accuracy at leaf scale using *in-situ* hyperspectral data.

Meanwhile, the overall accuracy was reduced at pixel and tree crown levels when airborne hyperspectral imagery was used. Later, research team of Clark et al., (2005) studied the potential of vegetation indices, absorption based metrics, and spectral derivative metrics in improving classification accuracy of their previous study (Clark and Roberts, 2012). Other studies in tropical forests were spectral variability analysis and species classification using *in-situ* hyperspectral data (Féret and Asner, 2011) and tree species classification with different classifiers using airborne hyperspectral and resulted overall accuracy of all classifiers were reducing gradually from a low to higher number of tree species in classification (Féret and Asner, 2013). Also, airborne hyperspectral data has been tested on tree species classification of tropical forest in Panama using binary SVM and biased SVM (Baldeck et al., 2015). In the study, biased SVM outperformed binary SVM in tree species classification. The recent tree species classification studies in Malaysia also focused on the usage of hyperspectral remote sensing data where AISA airborne hyperspectral data has been applied to different tropical rainforests in this nation. However, there is still big gap in understanding hyperspectral remote sensing capabilities and its potentials to cope with different challenges in Malaysia tropical rainforest tree species classification. Interestingly, conclusions from those studies agreed that high diversity of tree species has posed a great challenge to species classification of forests in Malaysia (Jusoff, 2007, Hasmadi et al., 2010 and Shafri et al., 2007).

Previous studies has shown that the classification accuracy of tropical tree species decreased when the number of species were high (Féret and Asner, 2013). The situation could be explained as a high number of tree species shortened the distance of data clusters among tree species (due to reduced data separability among species) in a n-dimensional data space and eventually increased the classification errors (Féret and Asner, 2011). In regular tree species classification procedure, single classification level was carried out by a classifier with input spectral bands that are selected by a rigorous spectral feature selection method. The selection of input spectral bands was expected to produce an optimal overall accuracy in the classification where no any further improvement on that accuracy should be needed. However, some previous studies have shown that selected spectral bands or spectral metrics might not always have optimum discriminatory power to successfully classify all the targeted tree species (Jones et al., 2010 and Wang and Sousa, 2009). Thus, we need an effective classification procedure with the aid of spectral feature selection method to cope with the issue of high diversity of tropical forest tree species. A spectrum with hundreds or thousands of continuous narrow spectral bands in hyperspectral remote sensing data has high correlated adjacent bands which provided redundant spectral information in tree species classification. In order to input informative bands, studies have applied feature selection methods such as Stepwise Discriminant Analysis (SDA) (Vyas et al., 2011), sequential forward floating selection (SFFS) (Dalponte et al., 2013), and ANOVA analysis (Pu, 2009, Adam and Mutanga, 2009 and Prospere et al., 2014) to choose important spectral bands in species classification). Feature selection searches on spectral bands that could describe distribution of data clusters at maximum distances among tree species in an n-dimensional data space during classification process (Wang and Sousa, 2009). By adopting this procedure, redundancy of spectral information among input bands could be minimized and less training samples are required to achieve a satisfactory classification result (Vyas et al., 2011). To our best knowledge, there is no tree species classification procedure which improves the output accuracy in a hierarchical structure. Multi-level adaptive classification procedure was newly introduced in this study to handle tropical tree species classification. In contrast to regular tree species classification, the multi-level adaptive classification procedure allows the overall accuracy of tree species classification to be improved after several times of continuous classification processes.

The objective of this study was to examine the effectiveness of this classification procedure in tropical environment of Malaysia where high diversity of tree species could be a constraint to achieve a satisfactory classification result. Support Vector Machine has been shown to outperform other classification techniques in some tree species classification studies (Dalponte et al., 2013 and Féret and Asner, 2013). Thus, in this study we tested the use of SVM with the multi-level adaptive classification procedure to classify various tropical tree species and compared the results of SVM with that of Maximum Likelihood Classifier.

2. Methodology

2.1 Data Collection

The study area is a well-managed urban forest (Hutan Bandar Mutiara Rini) which is located at Skudai, Johor Bahru, Malaysia. There are more than thirty tree species planted in this patch of forest and 20 dominant species were selected in this study to be discriminated using hyperspectral remote sensing data. In July of 2014, field data collection process was conducted where ***in-situ*** hyperspectral data of the selected 20 tree species were collected. During samples collection, random selection of 6-9 trees in the forest was chosen for each target tree species. From each selected tree, three branches were cut-off from different parts of the tree crown and all leaves samples were sent to laboratory for ***in-situ*** hyperspectral data measuring. ***In-situ*** hyperspectral data was suggested to be used in testing and evaluating new methods for tree species classification. Its ground-based acquired data has higher quality compared to that of airborne hyperspectral data (Jones et al., 2010). In laboratory, in-situ hyperspectral data of leaves samples were measured by setting up a full range spectroradiometer (350 nm until 2500 nm in spectral range with 3nm VNIR and 8nm SWIR spectral resolution) with a pair of tungsten lamps as artificial light source. Calibration was done on dark current to minimize the instrument's internal noise, and white reference (a perfect light source reflector) reading was taken by the spectroradiometer before spectral measurements. Throughout the process, white reference reading was checked frequently to ensure an accurate spectral measurement has been made. In this study, three sets of spectral measurements were taken for each leaves sample, i.e. measurements of 1) tree branch, 2) all leaves with upper side faced towards spectroradiometer, and 3) mixed of leaves with upper side and down side faced towards spectroradiometer. A total of 1203 tree species samples spectra were collected for tree species classification in this study (Table 1).

Table 1: Collected spectra samples from 20 tree species in the study

	Species Name	Code	No. of tree	No. of spectral sample			Total
				Branch (B)	Front (F)	Mixture (M)	
1	Alstonia Angostiloba	AA	7	21	21	21	63
2	Aquilaria Malaccensis	AM	7	20	20	20	60
3	Bucida Molineti	BM	6	18	-	18	36
4	Calophyllum Spp.	CA	6	17	17	17	51
5	Cinnamomum Iners	CI	8	23	23	22	68
6	Dyera Costulata	DC	6	17	17	17	51
7	Drybalanops Oblongifolia	DO	8	14	14	14	42
8	Eugenia Oleina	EO	7	21	21	21	63
9	Palouium Gutta	FF	8	24	23	24	71
10	Hopea Odorata	HO	9	27	27	27	81
11	Kayea Ferrea	KF	8	24	24	23	71
12	Maniltoa Browneoides	MB	8	23	23	23	69
13	Pterygota Alata	PA	6	12	12	12	36
14	Palouium Gutta	PG	8	24	24	24	72
15	Peltophorum Pterocarpum	PP	8	24	24	24	72
16	Syzygium Grande	SG	7	21	21	21	63
17	Shorea spp.	SH	6	16	16	16	48
18	Shorea Roxburghii	SR	9	27	27	27	81
19	Samanea Saman	SS	7	21	-	21	42
20	Shorea Singkawang	SSI	8	21	21	21	63
			147				1203

2.2 Spectral Features

In this study, vegetation indices and absorption-based metrics were used as two different groups of input spectral features in the species classification. Vegetation indices are derivative information from optical remote sensing data which involves reflectance of two or more bands in a simple mathematical calculation. Commonly, vegetation indices are applied to describe the vegetation status such as water content, chlorophyll, nitrogen and other chemical pigment level of leaves, and also physical structure of leaves or canopy. Pu et al., (2003) introduced absorption-based metric to assess the water content of oak trees. Absorption based metric extracts spectral information from spectral absorption curves along hyperspectral spectrum such as red, near infrared and shortwave infrared wavelengths. The extracted information were the width, depth, area size and asymmetry of absorption curve. Previous study believed that these metrics could describe chlorophyll and water content of a vegetation (Pu et al., 2003). In order to magnify spectral absorption curve, continuum removal technique was applied on hyperspectral data before metric extraction (Manevski et al., 2011). A total of 20 vegetation indices and 12 absorption-based metrics were used in this study as shown in Tables 2a and 2b respectively. Out of all data samples, one-third of the samples were randomly selected from each tree species for spectral features selection procedure and also for classification (training) process. On the other hand, the remaining samples were reserved for accuracy assessment of tree species classification.

2.3 Spectral Features Selection

Stepwise Discriminant Analysis (SDA) was applied to choose the most useful spectral features from the 20 vegetation indices and 12 absorption based metrics as input in classification. This stepwise analysis was commented as an effective spectral feature selection method (Vyas et al., 2011). In the discriminant analysis, multivariate significant test was carried out by Wilk's lambda to assess discriminatory power of the 32 spectral features in tropical tree species classification of the current study. As a stepwise process, spectral feature with the highest discriminatory power was the first to be selected and followed by the second highest one. The procedure stopped when there was no more significant decrease in the resultant value of Wilk's lambda. All the selected spectral features were used as input parameters in the classification procedure.

2.4 Multi-level Adaptive Classification

Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC) were adopted in this study as multi-level adaptive classification procedure for tropical tree species classification (Figure 1).

Table 2a: List of vegetation indices used in the tree species classification

Vegetation Indices			
Normalized Difference Vegetation Indices (NDVI)	(R798 - R679) / (R798 + R679)	Structural Independent Pigment Index (SIPI)	(R445 - R800) / (R680 + R800)
Red Edge NDVI (RE NDVI)	(R750 - R705) / (R750 + R705)	Leaf Chlorophyll Index (LCI)	(R850 - R710) / (R850 + R680)
Soil-Adjusted Vegetation Indices (SAVI)	1.5 * (R798 - R679) / (R798 + R679 + R0.5)	Normalized Difference Water Index (NDWI)	(R862 - R1239) / (R862 + R1239)
Atmospherically Resistant Vegetation Index (ARVI)	[R798 - 2 (R679) + R482] / [R798 + 2 (R679) + R482]	Water Band Index (WBI)	R902 / R972
Anthocyanin Reflectance Index 2 (ARI 2)	R798 * [(1 / R550) - (1 / R699)]	3-Band Ratio at 975nm (RATIO975)	(2 * R960 - 990) / (R920 – 940 + R1090 - 1110)
Carotenoid Reflectance Index (CRI)	R800 * [(1 / R520) - (1 / R550)]	3-Band Ratio at 1200nm (RATIO1200)	(2 * R1180 -1220) / (R1090 - 1110 + R1265 - 1285)
Carotenoid Reflectance Index 1 (CRI 1)	(1 / R511) - (1 / R550)	Photochemical Reflectance Index (PRI)	(R532 - R568) / (R532 + R568)
Carotenoid Reflectance Index 2 (CRI 2)	(1 / R511) - (1 / R699)	Red-Edge Vegetation Stress Index (RVSI)	(R719 + R752) / (2 - R733)
Normalized Difference Lignin Index (NDLI)	[Log (1 / R1748) - Log (1 / R1675)] / [Log (1 / R1748) + Log (1 / R1675)]	Normalized Total Pigment to Chlorophyll Index (NPCI)	(R680 - R430) / (R680 + R430)
Normalized Difference Nitrogen Index (NDNI)	[Log (1 / R1507) - Log (1 / R1675)] / [Log (1 / R1507) + Log (1 / R1675)]	Normalized Phaeophytinization Index (NPQI)	(R415 - R435) / (R415 + R435)
** Ri refers to reflectance value at band i of a tree species spectrum.			

Table 2b: List of absorption based metrics used in the tree species classification

Absorption Based Metrics		
Red Absorption (500nm-750nm)	Near Infrared Absorption (1145nm-1270nm)	Short-wave Infrared Absorption (1376-1600nm)
RED_D	NIR_D	SWIR_D
RED_W	NIR_W	SWIR_W
RED_A	NIR_A	SWIR_A
RED_AS	NIR_AS	SWIR_AS
** Absorption Depth (D) = The lowest continuum removed value within a spectral absorption region.		
** Absorption Width (W) = The length of straight line across half of the absorption depth within a spectral absorption region.		
** Absorption Area (A) = The absorption depth times absorption width (D x W) of a spectral absorption region.		
** Asymmetry (As) = The ratio of left area (A) to the right area (B) from the absorption center within a spectral absorption region.		

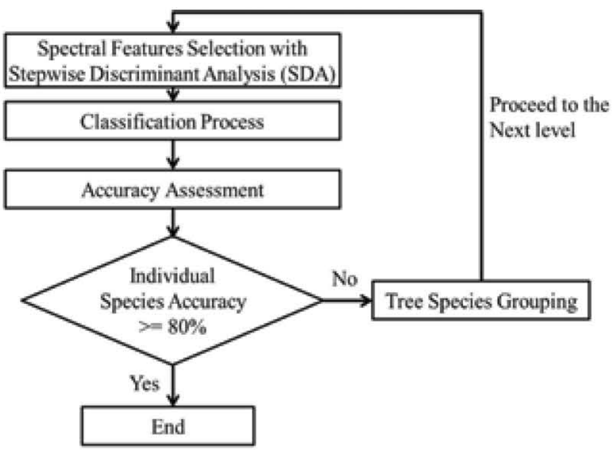

Figure 1: Work flow of multi-level adaptive classification procedure

At the beginning of the process, selected spectral features using Stepwise Discriminant Analysis (SDA) were used as input in running the classification with both SVM and MLC for 20 tree species. Accuracy assessment was carried out on both SVM and MLC classification results. Any tree species with individual accuracy greater or equal to 80% was considered as satisfactory classification and was excluded from further classification process. The remaining species were grouped into several smaller tree species groups based on the confusion matrix. In this context, any two or more species which have significant classification errors (commission and omission) among each other were assigned into a group. Prior to the second level classification, adaptive features selection procedure using SDA searched on discriminative spectral features from all vegetation indices and absorption-based metrics for each smaller species group. Since species and number of species were different among smaller tree species groups, selection of spectral features given by SDA were not identical. It is called adaptive features selection where searching is based on spectral information needs of individual species group in classification. Then, classification at the second level was carried out for each tree species group with their dedicated spectral features selection. Merging the classification results for all species groups as well as the outperformed tree species at the previous level was done with both SVM and MLC. Overall accuracy assessment was performed for all tree species at this level of classification. The process was repeated as shown in Figure 1 to further improvement of tree species classification at the next classification level. Any tree species with ~80% individual accuracy at the first and second classification levels were excluded from further classification and its satisfactory accuracy remained.

3. Results and Discussions

Multi-level adaptive classification procedure adopted Support Vector Machine (SVM) and then Maximum Likelihood Classifier (MLC) to classify 20 tropical tree species. The comparison of two results is as shown in Tables 3a and 3b. SVM improved the accuracy of classification from 69.41% to 74.56% at the third level of classification. Meanwhile, MLC produced classification accuracy of 64.98% and 69.53% at the first and third levels of classification, respectively. In the current study, SVM and MLC have proven that multi-level adaptive classification could improve tree species classification accuracy although the improvement was recorded about 5% for both classifiers. The improvement of overall accuracy could be noticed after each level classification. In the present study, SVM was found to perform better than MLC in classifying all the 20 tropical tree species with selected vegetation indices and absorption-based metrics. The overall accuracy at the third level classification was recorded as 74.56% and 69.53% for SVM and MLC, respectively. Besides, performance of SVM also better than MLC at all levels of classification. In this multi-level adaptive classification study, any tree species has individual classification accuracy more than or equal to 80% was considered as satisfactory result and was excluded from further classification.

Table 3a: The classification result of Support Vector Machine (SVM)

SVM Classification	Tree Species Group	Spectral Metrics Selection	Overall Accuracy (%)	Kappa Statistic
First Level	20 species	ARVI, NDLI, LCI, WBI, RATIO975, RATIO1200, NPQI, RED_W, RED_AS, NIR_A, NIR_AS, SWIR_D, SWIR_A	**69.41**	**0.68**
	Excluded tree species in the next classification were AM, CA, MB, SS			
Second Level	7 species (BM, EO, FF, HO, PP, SG, SR)	ARI2, CRI, NDLI, NDNI, RATIO975, RATIO1200, PRI, NPCI, NPQI, RED_AS, NIR_D, NIR_W, SWIR_A		
	7 species (AA, DO, KF, PA, PG, SH, SSI)	ARVI, ARI2, NDLI, SIPI, NDWI, RATIO1200, RVSI, NPCI, NPQI, RED_W, RED_A, NIR_W, SWIR_D, SWIR_A		
	2 species (CI, DC)	WBI, NPQI, NIR_A		
	20 species		**74.18**	**0.73**
	Excluded tree species in the next classification were AM, CA, CI, DC, EO, HO, KF, MB, PG, SR, SS			
Third Level	4 species (BM, FF, PP, SG)	RE_NDVI, CRI, ARVI, NDLI, RATIO975, RATIO1200, NPQI, RED_W, RED_AS, NIR_W, NIR_AS, SWIR_D, SWIR_A		
	5 species (AA, DO, PA, SH, SSI)	ARVI, ARI2, NDLI, NDNI, RATIO975, RVSI, NPQI, RED_D, RED_W, NIR_W, SWIR_D, SWIR_A, SWIR_AS		
	20 species		**74.56**	**0.73**

Table 3b: The classification result of Maximum Likelihood Classifier (MLC)

MLC Classification	Tree Species Group	Spectral Metrics Selection	Overall Accuracy (%)	Kappa Statistic
First Level	20 species	ARVI, NDLI, LCI, WBI, RATIO975, RATIO1200, NPQI, RED_W, RED_AS, NIR_A, NIR_AS, SWIR_D, SWIR_A	**64.98**	**0.63**
	Excluded tree species in the next classification were AM, CA			
Second Level	4 species (BM, CI, DC, SR)	ARI2, RVSI, NPQI, NIR_AS, SWIR_AS,		
	14 species (AA, DO, EO, FF, HO, KF, MB, PA, PG, PP, SG, SH, SS, SSI)	ARVI, NDLI, LCI, RATIO975, RATIO1200, NPCI, NPQI, RED_W, RED_AS, NIR_A, SWIR_D, SWIR_A, SWIR_AS		
	20 species		**66.12**	**0.64**
	Excluded tree species in the next classification were AM, CA, EO, HO			
Third Level	9 species (DO, FF, KF, MB, PA, PP, SG, SH, SS)	RE_NDVI, ARVI, NDLI, RATIO975, RATIO1200, NPQI, RED_A, NIR_D, NIR_A, NIR_AS, SWIR_D, SWIR_W, SWIR_AS		
	3 species (AA, PG, SSI)	NDLI, RVSI, RED_W, NIR_W, SWIR_AS		
	2 species (CI, DC)	WBI, NPQI, NIR_A		
	2 species (BM, SR)	RE_NDVI, NDLI, NIR_W, NIR_A, SWIR_W		
	20 species		**69.53**	**0.68**

As shown in tables 3a and 3b, SVM has successfully discriminated four tree species (AM, CA, MB, SS) but only two species (AM, CA) were classified by MLC although both classifiers used the same selection of spectral features at the first level of classification. After the second level classification, SVM produced another seven tree species; CI, DC, EO, HO, KF, PG and SR (refer to tree species scientific name in Table 1) while only other two species have high individual accuracy in MLC classification. In other words, SVM successfully discriminate three times better than that of MLC in terms of number of species at second level classification. The finding coincides with a boreal forest species classification study where SVM performed better than MLC to classify pine, spruce, birch, and other tree species using hyperspectral data (Dalponte et al., 2013). Another study in tropical tree species classification also commented that SVM is an outperformed classifier (Féret and Asner, 2013). Table 4 shows the effectiveness of SVM in multi-level adaptive classification procedure via presenting the difference in commission and omission errors between the first and third levels of classification for 20 tree species. The highlighted species (i.e. AM, CA, MB and SS) have no difference in errors as these species have achieved 80% individual accuracy in the first level and were excluded in the next classification level. In general, the classification result shows a good improvement in the third level classification where most of the tree species reduced commission and omission errors and some species have reduced between 20% to 50% of errors (in bold). The discriminatory power of the 32 spectral features (vegetation indices and absorption based metrics) in species classification was tree species oriented.

Table 4: Commission and omission errors produced by SVM for the first and third levels of classification

Tree Species	Commission Error (%)			Omission Error (%)		
	1st Level		3rd Level	1st Level		3rd Level
AA	36.0	⟶	23.7	23.8	⟵	31.0
AM	10.3	⟷	10.3	10.3	⟷	10.3
BM	**46.2**	⟶	**20.0**	**68.2**	⟶	**45.5**
CA	3.1	⟷	3.1	6.1	⟷	6.1
CI	24.4	⟶	21.1	29.6	⟵	31.8
DC	28.1	⟵	34.3	30.3	⟷	30.3
DO	50.0	⟵	56.3	**88.9**	⟶	**48.2**
EO	**30.0**	⟶	**14.6**	**33.3**	⟶	**16.7**
FF	13.6	⟵	29.3	19.2	⟶	12.8
HO	**43.2**	⟶	**20.7**	22.2	⟶	14.8
KF	22.5	⟶	17.4	19.2	⟷	19.2
MB	15.6	⟷	15.6	15.6	⟷	15.6
PA	33.3	⟵	44.4	42.9	⟶	28.6
PG	27.3	⟶	18.6	16.7	⟵	27.1
PP	35.4	⟶	25.5	35.4	⟶	27.1
SG	31.0	⟶	29.3	31.0	⟷	31.0
SH	45.5	⟶	42.1	81.8	⟶	66.7
SR	51.6	⟶	34.4	**42.6**	⟶	**22.2**
SS	7.7	⟷	7.7	14.3	⟷	14.3
SSI	51.6	⟶	43.5	28.6	⟵	36.6

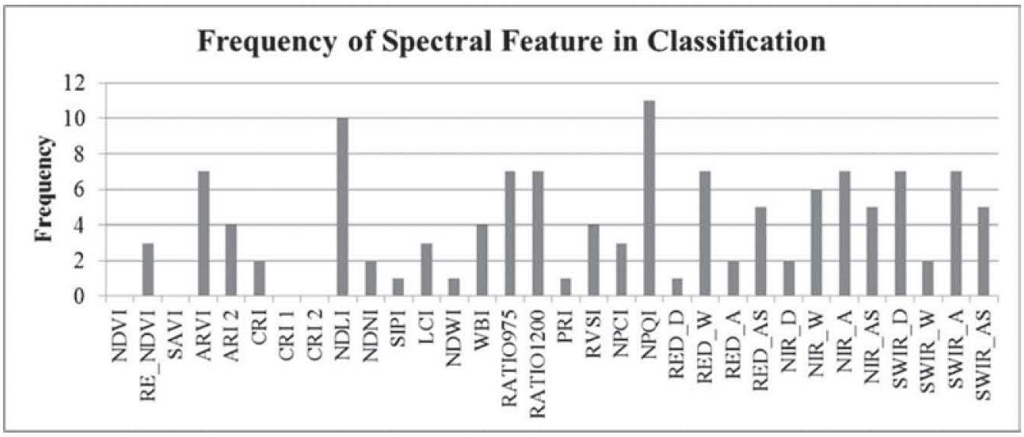

Figure 2: Frequency of spectral feature selected by Stepwise Discriminant Analysis (SDA)

Since the spectral features in selection depend on members of tree species group, there was no identical set of spectral features given by Stepwise Discriminant Analysis (SDA) in this study (Tables 3a and 3b). This situation indicated that spectral features selection was highly correlated with tree species. Some previous studies have commented that a selection of spectral metrics or spectral reflectance bands might not sensitive towards all tree species (Jones et al., 2010 and Wang and Sousa, 2009). In this study, both vegetation indices and absorption-based metrics were equally important as input spectral features in tropical tree species classification. Frequency of each spectral feature selected by SDA in the SVM and MLC classifications has been counted and shown in Figure 2. As both classifiers have a total of 13 spectral features selections (tables 3a and 3b) in multi-level adaptive classification, the highest frequency of a spectral feature should not be more than 13. Five vegetation indices and five spectral-based metrics were selected by SDA for at least six times. Normalized Phaeophytinization Index (NPQI) was the most important spectral feature in current study and followed by Normalized Difference Lignin Index (NDLI). Both are vegetation indices that describe chemical properties of leaves at blue and shortwave infrared wavelengths, respectively. Pu (2009) also found NPQI as one of the important spectral features in tree species classification study. Among absorption-based metrics, RED_W, NIR_A, SWIR_D and SWIR_A have the highest frequencies. Previous studies identified that NIR_A extracted from absorption wavelengths at around 1200nm was an important metric in tree species classification (Pu, 2009; Clark and Roberts, 2012). NIR_A could be useful to describe water content of leaves while SWIR_D and SWIR_A are indicators for chemical pigments of leaves at shortwave infrared region. In-situ hyperspectral remote sensing data was found very useful in current tree species classification as the ten most important spectral features (in Figure 2) were extracted from different spectral regions along the hyperspectral spectrum.

4. Conclusion

Tree species classification is always a challenging task in the tropical environment due to high species diversity. The present study has deployed multi-level adaptive classification procedure with Support Vector Machine (SVM) and Maximum Likelihood Classifier (MLC) in classifying 20 tropical tree species using in-situ hyperspectral data. The results of the study have proven the potential of multi-level adaptive SVM classification for tropical tree species classification where the final overall accuracy was recorded as 74.56%. Moreover, the study also proved that discriminatory power of the 32 spectral features (vegetation indices and absorption based metrics) were tree species oriented where spectral features selections produced by Stepwise Discriminant Analysis (SDA) depends on members of tree species group. Both vegetation indices and absorption-based metrics extracted from different spectral regions along hyperspectral spectrum were equally important in tropical tree species classification. Five vegetation indices and five absorption-based metrics have been identified as important spectral features in this study. Multi-level adaptive classification procedure has an advantage in its hierarchical structure where classifications of species groups are independent to each other after the first classification level in process. Pervious study commented that the number of input spectral bands and spectral differences among tree species were highly correlated to performance of classifiers due to intrinsic properties and complexity of classifier itself (Dalponte et al., 2009). In future works, different classifiers could be applied to a multi-level adaptive classification procedure expecting more significant improvement of overall accuracy in tropical tree species classification. Classifiers could be used in different tree species group classifications which were parallel at any level of the multi-level adaptive classification procedure. Besides, other spectral information extracted from hyperspectral remote sensing data like derivative based metrics (Pu, 2009, Jones et al., 2010, Clark and Roberts, 2012 and Ghiyamat et al., 2013) and discrete wavelet transform (Ghiyamat et al., 2015 and Banskota et al., 2011) used in other tree species classification studies could be tested as new input spectral bands in multi-level adaptive classification procedure. Input of new spectral information are expected to enhance the spectral differences among tree species so that the classification result will be improved noticeably compared to that given by the current study.

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