Influence of tree species complexity on discrimination performance of vegetation Indices

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Abstract
Performance of different vegetation indices (VIs) in combination with single- and multiple-endmember (SEM and MEM) for discriminating Corsican and Scots pines with different ages and Broadleaves tree species is demonstrated by using an airborne hyperspectral data. The analysis is performed in three different complexity levels. The results show by increasing tree species complexity, overall accuracy significantly reduced. An overall accuracy up to 90% is obtained from the first category with the least complexity; however, it is reduced to 55% in the third category with the highest complexity. By employing MEM, performance of normalized difference vegetation index (NDVI) is increased by 10%.

Keywords: Tree species discrimination, different age covers, airborne hyperspectral data, vegetation indices, multiple-endmember, remote sensing.

Introduction
Forests cover classification plays a key role in biodiversity assessment, forest resource management, and sustainable conservation planning, especially with increasing threats and pressure on forest resources. Remote sensing offers an effective and practical solution for monitoring forest cover by species discrimination and floristic mapping over wide geographic area by overcoming the limitations on data acquisition and analysis of field survey. On the other hand, remote sensing derived vegetation index, with assessing some of biochemical and biophysical parameters of vegetation offered a practical and economical means to estimate the bio parameters of the species and it has been used for individual tree species discrimination and identification [Cho et al., 2008; Hashemi et al., 2013]. Vegetation indices (VIs) are mathematical combinations of various bands [Jensen, 1983] that were first developed in the 1970s for satellite sensors based applications such as assessing vegetation condition, foliage, cover, phenology, and etc, which have been highly successful [Kerr and
Multispectral imaging have commonly been employed since 1960s in different fields such as forestry, agriculture, geology, urban and others for discriminating different types of vegetation, rocks, soils, water, and other man-made material covers. Multispectral sensors consists few number of bands, three to six spectral bands, with very broad spectral bands that ranges from the visible to near infrared and in some cases with one or more thermal infrared bands. However, the spectral information provided by such wide band is the mixture or overlapping of wide range of wavelengths.

Hyperspectral sensors on the other hand, consists of hundreds of bands closely packed with high spectral resolution, usually 10-20 nm, covering from visible to mid-infrared and thermal infrared. Hyperspectral remote sensing data with ability to resolve the reflectance responses of image features with fine spectral detail provides significant information for forest tree species identification and classification based on detecting vegetation stress and it has proven useful in mapping tree species at the pixel level based on variability in spectral reflectance at leaf to crown scales [Clark et al., 2005; Youngentob et al., 2011].

Although, both multispectral and hyperspectral data can be used in VIs, however, the former one provides a less accurate output as each of its spectral band consists mixture of information from wide range of wavelengths, whereas in the later one, due to very narrow and many number of spectral bands, the spectral data allows for in-depth observation of earth surface features, what would be lost within the coarse bandwidths in multispectral imaging. This is demonstrated by Lee et al. [2004] in a comparison study between broadband multispectral and hyperspectral data in estimating vegetation leaf area index.

However, due to the high spectral resolution, the cost of airborne hyperspectral images is significantly high, especially for wide band data. VIs are combination of object reflectance at two or more specific wavelengths that reveal specific characteristics of vegetation. This would be significantly useful for reducing the costs of remote sensing based applications. Over the years, various VIs have been developed to improve vegetation identification based on their different spectral properties. They can decrease the effects of irradiance and exposure while maintaining sensitivity to vegetation and increase contrast between different features on image. So far, there are several reports that are used VIs for discriminating tree species using airborne hyperspectral or spectrometer data, however, they are often developed and implemented on broadleaf species [Croft et al., 2014b]. Relatively, there are little study examined VIs for discriminating needle leaves tree species that represent a large component of boreal forests and significant global ecosystems [Croft et al., 2014b]. Pu [2009] used different spectral variables and VIs to discriminate 11 different broadleaf species with the aid of two supervised classification algorithms, i.e., artificial neural network (ANN) and linear discriminant analysis (LDA) with in situ hyperspectral data. Lee and Yeh [2009] presented monitoring of shifting wetland vegetation (mangrove communities) by using NDVI and maximum likelihood classification (MLC) over SPOT, Landsat, and QuickBird imagery. Stagakis et al. [2012] demonstrated monitoring of water stress and fruit quality in an orange orchard using narrow-band structural and physiological VIs extracted from a multispectral data. Jensen et al. [2012] studied the potential of classifying individual urban tree species employing VIs with airborne hyperspectral data. Alonzo et al. [2014] demonstrated urban tree species mapping employing NDVI and LDA classifier by combining Lidar data with hyperspectral data to improve the classification accuracy. Qi et al. [2014] investigated the
impact of understory on overstorey leaf area index (LAI) estimation for five forest types (a mixed broadleaved-Korean pine forest, a spruce-fir valley forest, a secondary birch forest, a Korean pine plantation and a Dahurian larch plantation), utilizing VIs extracted from a Landsat 5 TM satellite image. Heiskanen et al. [2013] examined sensitivity of narrowband VIs for estimating LAI in southern boreal forest including coniferous and broadleaved, using three Hyperion images and compared with broadband VIs. Croft et al. [2014b] employed different VIs for estimating foliar chlorophyll content from different leaf and canopy structures including broad- and needle-leaves using medium-spectral resolution imaging spectrometer data acquired by satellite. Further on tree species discrimination, there is very limited study reported on discriminating tree species with different ages using airborne hyperspectral data particularly employing VIs. In fact, the work of Croft et al. [2014a] is the only work reported on analyzing the effect of tree species age on chlorophyll content and leaf area index (LAI).

On the other hand, due to high spectral variability within species, multiple-endmember [Roberts et al., 1998] is proposed to mitigate within class spectral variability by testing multiple combinations of endmembers. Multiple-endmember spectral mixture analysis (MESMA) has been applied in a wide range of fields such as plant species mapping [Dennison and Roberts, 2003; Yougentob et al., 2011], landform mapping [Ballantine et al., 2005] urban remote sensing [Powell et al., 2007; Franke et al., 2009] and discriminating tree species with different ages [Ghiyamat et al., 2013]. However, very limited study examined performance of VIs with multiple-endmember to see how this technique can influence on performance of VIs. Thorp et al. [2013] utilized MESMA and VIs (i.e., NDVI and cellulose absorption index) for mapping semi-arid rangeland vegetation using hyperspectral image. They have shown that MESMA is insensitive to image spatial resolution, and thereby, a useful tool for airborne imagery application that lack optimum image spatial resolution.

The purpose of this study is to evaluate performance of different VIs in discriminating tree species with different age covers and different complexities considering traditional single-endmember and multiple-endmember analysis. This work is continuing our previous works in discriminating tree species with different ages using original reflectance and derivative spectra [Ghiyamat et al., 2013] and discrete wavelet transform (DWT) [Ghiyamat et al., 2015]. The same data set used in those previous works is used in this study too. However, all discrimination methods utilized in our previous reports have required the full hyperspectral bands for tree species discrimination. In this study, VIs are employed where required only 2-3 bands out of the full hyperspectral bands. In particular, the main objectives of this study are:

1) To check out how performance of VIs (by utilizing only 2-3 bands) is comparable with other discrimination techniques that utilize full hyperspectral bands;
2) To investigate the influence of tree species complexity on discrimination performance of VIs;
3) To understand the impact of single- and multiple-endmembers on improving performance of VIs;
4) To compare performance of different VIs on discriminating tree species with different ages and different complexity levels.
Materials and methods

Study area and hyperspectral imagery

This study is conducted at the Thetford forest in East Anglia (0° 41’ 40.89” to 0° 43’ 50.96” N and 52° 26’ 40.43” to 52° 25’ 14.72” E). Thetford is the largest man-made pine forest in Britain, which covered an area of about 22,000 ha and it consists mainly of planted and managed Corsican and Scots pine of different age classes. The hyperspectral data (Fig. 1 - left) has a spatial resolution of 5 meters and an average spectral resolution of 15 nm. The spectral data contains 126 spectral bands from 0.45 μm to 2.48 μm, as the other detail spectral characteristics of the HyMap data are shown in Table 1. The HyMap sensor provides an excellent signal to noise ratio of >500:1. For the Thetford hyperspectral data, a ground reference vector data generated from the UK Forestry Commission’s GIS is available as shown in Figure 1 (right). The ground reference is labeled with six tree covers including Broadleaves (BLs), old Corsican pine (OCP), mature Corsican pine (MCP), young Corsican pine (YCP), old Scots pine (OSP), and young Scots pine (YSP), where the young, mature, and old trees had around 16, 34, and 70 years old, respectively in the data acquiring time.

![Figure 1 - Hyperspectral image (left) and ground reference data (right).](image)

| Table 1 - Spectral characteristics of the HyMap sensor. |
|---------------------------------------------------------|
| Spectral configuration | VIS: Visible; NIR: Near infrared; SWIR: Shortwave infrared |
| Module | VIS | 0.45 – 0.89 μm | Bandwidth across module | 15 – 16 nm | Average spectral sampling interval | 15 nm |
| NIR | 0.89 – 1.35 μm | 15 – 16 nm | 15 nm |
| SWIR1 | 1.40 – 1.80 μm | 15 – 16 nm | 13 nm |
| SWIR2 | 1.95 – 2.48 μm | 18 – 20 nm | 17 nm |

| Table 2 - The number of ROIs and total pixels per tree species selected from hyperspectral data. |
|-------------------------------------------------------------|
| Species | BLs | MCP | OCP | YCP | OSP | YSP |
| No. of ROIs | 6 | 6 | 6 | 6 | 6 | 4 |
| Total No. of pixels | 321 | 308 | 306 | 318 | 328 | 216 |
| No. of training pixels | 90 | 90 | 90 | 90 | 90 | 60 |
| No. of testing pixels | 231 | 218 | 216 | 228 | 238 | 126 |
Tree species discrimination in this study is performed in three different complexity levels, which are: discrimination between BLs and pines tree species (considering as least complex level); discrimination between BLs, Corsican pines (CP), and Scots Pines (SP) (as medium complexity); and discrimination between all the six tree covers including Old, Mature, and Young Corsican Pine, Old and Young Scots Pines, and BLs (as the most complex category). For this purpose, several groups of pixels in the form of region of interest (ROI) are selected randomly and manually from different location for each tree cover. ROIs are selected arbitrary from different locations per vegetation cover by plotting a polygon on the image (as the polygons/ROIs are shown in Fig. 1 - right). The ROIs per vegetation cover are selected in reference to the ground truth data. Thus, the spectral data of those pixels under the developed polygons/ROIs are extracted and are used for discrimination analysis. All process of ROI selection is performed in ENVI (Environment for Visualizing Images) software. The ROI is used since the individual tree crowns from the hyperspectral image is not distinguishable due to the low spatial resolution (5 m), therefore, each ROI might contains pixels from one, two or more trees from the same tree cover. The number of ROIs and the total number of pixels per tree cover that are selected in this study are shown in Table 2. Each ROI in this study contains approximately about 50 pixels.

**Vegetation indices**

Seven vegetation indices with the detail presented in Table 3 are used in this study. The closest spectral bands available in the hyperspectral data used for each VI are also presented in this table.

NDVI [Rouse et al., 1973] is the most popular vegetation index used in remote sensing for monitoring plant growth, canopy greenness, vegetation cover, LAI, and biomass. However, the traditional NDVI, which was based on the difference in canopy reflectance at red (670-680 nm) and near-infrared (750-850 nm) has been shown that it was unsuccessful in differentiating plant species [Nagendra, 2001; Pettorelli et al., 2005]. Narrow band NDVI developed by Mutanga and Skidmore [2004], which provides closer correlation with biochemical and physiological properties of leaves or canopies, shows better performance in discriminating plant species [Cho et al., 2008]. PRI is widely used in evaluating carotenoid/chlorophyll ratio in green leaves. Also, it compares the reflectance of red and blue region of the spectrum as it measures the reflectance on either side of the green hump around 550 nm [Gamon et al., 1992; Gamon et al., 1997; Sims and Gamon, 2002]. CRI is shown to be sensitive in expressing the carotenoids such as alpha- and beta-carotene in plant foliage [Gitelson et al., 2002]. Cho et al. [2008] demonstrated that both PRI and CRI has high potential in differentiating species at the canopy scale. Also, they have observed that GMI, VOG and linear extrapolation REP techniques can perform very well in discriminating plants at both leaf and canopy scales.

Three REP techniques based on the four-point Linear, Lagrangian technique, and linear extrapolation techniques are used in this study as well. The linear interpolation as described by Guyot and Baret [1988] assumes that the reflectance curve at the red-edge can be simplified to a straight line centered around a midpoint between the reflectance in the NIR at about 780 nm and the reflectance of chlorophyll absorption feature about 670 nm. The reflectance and wavelength of REP at the inflection point is estimated based on a linear interpolation with the aid of reflectance values at 700 and 740 nm as the detail reported in [Guyot et al., 1992; Carter, 1994; Clevers et al., 2001; Pu et al., 2003].
**Table 3 - The list of VIs used in this study, their characteristics, equations and the wavelengths and band number available in the study area close to the bands in VIs equation.**

| Vegetation indices | Characteristic of the plant related with the variable/index | Equation | Reference wavelength (nm) | Thatford image | Wavelength (nm) | Band No. |
|--------------------|-------------------------------------------------------------|----------|--------------------------|----------------|----------------|----------|
| Narrow band NDVI: Normalized difference vegetation index | Biochemical and physiological properties of leaves [Mutanga and Skidmore, 2004] | NDVI = \( \frac{(R_{833} - R_{680})}{(R_{833} + R_{680})} \) | 833 | 829.2 | 27 |
| | | | 680 | 676.9 | 17 |
| NDWI: Normalized difference water index | Liquid content [Gao, 1996] | NDWI = \( \frac{(R_{864} - R_{1245})}{(R_{864} + R_{1245})} \) | 864 | 859.8 | 29 |
| | | | 1245 | (1238.7+1253.2) /2=1245.95 | (55&56) |
| MSI: Moisture stress index | Leaf water content [Hunt Jr and Rock, 1989] | MSI = \( \frac{R_{500}}{R_{820}} \) | 1600 | 1596.5 | 77 |
| | | | 820 | (814.1+829.2)/2=821.65 | (26&27) |
| PRI: Photochemical/physiological reflectance index | Water stress [Pu, 2009] Carotenoid/ chlorophyll ratio [Gamon et al., 1992] | PRI = \( \frac{(R_{531} - R_{570})}{(R_{531} + R_{570})} \) | 531 | 531.1 | (7&8) |
| | | | 570 | 569.5 | 10 |
| CRI: Carotenoid reflectance index | Carotenoids content [Gitelson et al., 2002] | CRI = \( \frac{1}{\left(\frac{R_{510}}{R_{550}}\right)} - \frac{1}{\left(\frac{R_{450}}{R_{500}}\right)} \) | 510 | 507.4 | 6 |
| | | | 550 | 554.2 | 9 |
| GMI: Gitelson and Merzylak index | Chlorophyll content [Gitelson and Merzlyak, 1997] | GMI = \( \frac{R_{550}}{R_{700}} \) | 750 | 753.4 | 22 |
| | | | 700 | (692.4+707.8)/2=700.1 | (18&19) |
| VOG: Voglmam index | Chlorophyll content [Vogelmann et al., 1993] | VOG = \( \frac{R_{740}}{R_{720}} \) | 740 | 738.1 | 21 |
| | | | 720 | 722.9 | 20 |
| Linear REP | Chlorophyll content [Guyot and Baret, 1988] | Refer to section “Endmember selection” | 670 | (661.7+676.9)/2 = 669.3 | (16&17) |
| | | | 700 | (694.4+707.8)/2=700.1 | (18&19) |
| | | | 740 | 738.1 | 21 |
| | | | 780 | 783.5 | 24 |
| Linear Extrapolation REP (bands are based on 1st derivative) | Biochemical and biophysical parameters [Cho and Skidmore, 2006; Cho, 2007] | Refer to section “Endmember selection” | 680 | 684.65 | 17 |
| | | | 694 | 700.1 | 18 |
| | | | 724 or 732 | 730.5 | 20 |
| | | | 760 | 760.95 | 22 |

In Lagrangian REP technique, Dawson and Curran [1998] presented a technique based upon a three-point interpolation (Lagrangian technique) based on second order curve fitting technique for locating the REP. The technique fits a second-order polynomial curve to the three first-derivative bands, centered near the maximum slope position, where the maximum peak in the fitted curve is referred as the Lagrangian REP as the detail can be found in Dawson and Curran [1998] and Pu et al. [2003].

The REP based on linear extrapolation technique [Cho and Skidmore, 2006] is calculated as the wavelength at the intersection of two straight lines extrapolated through two points on
the far-red flank and two points on NIR flank of the red-edge (680-760 nm) first derivative reflectance spectrum. Four coordinate points or wavebands are required to calculate the REP by the linear extrapolation technique. Cho and Skidmore [2006] identified two combinations of wavebands for calculating leaf nitrogen-sensitive REPs called linear extrapolation I involving far-red 680 and 694 nm in combination with NIR 724 and 760 nm, and linear extrapolation II involving far-red 680 and 694 nm in combination with NIR 732 and 760 nm. Where in this study, the extrapolation II is used due to the availability of hyperspectral band more close to the 732 nm.

**Endmember selection**

Usually, endmember or reference spectra can be obtained in two ways; one by scanning the fresh leaves of the trees using spectrometer and the other is from the hyperspectral image. Multiple-endmember (MEM) refers to the case that more than one reference spectra per species are considered in discrimination process. In contrast, the conventional method refers to the case that all the reference spectra per species are averaged out to form a single-endmember (SEM).

![Figure 2 - Reference spectra for SEM (top) and MEM (bottom) for three complexity levels with (a) simplest complexity including BLs and Pines; (b) medium complexity including BLs, CP, and SP; and (c) the highest complexity including BLs, YCP, MCP, OCP, YSP, and OSP.](image)

In this study, both single- and multiple-endmember techniques are used where they are collected directly from the hyperspectral image. From the total pixels per ROI that are extracted from the hyperspectral image, about one third of them are randomly selected as the training samples (or endmember) and the other two thirds are used as the target (or testing) samples. This is performed by an algorithm in Matlab software to select the training samples per ROI randomly (without any supervision). For the case of MEM, all the training pixels are used as MEM, while for SEM, they are averaged out. Figure 2 show the SEM (top) and MEM (bottom) for the three complexity categories.
**Classification accuracy evaluation**

Figure 3 shows the schematic diagram of the tree species discrimination process and the classification accuracy evaluation used in this study. The figure shows discrimination of the classification with three species, i.e., BLs, CP, and SP. First, several ROIs per vegetation cover are selected from the hyperspectral image. The training samples are then randomly selected and separated from the testing spectra. Every testing spectrum is compared with the reference spectra/endmember to evaluate their separability/similarity. Euclidean distance is used to calculate the distance between every testing pixel and the reference spectra. As presented in Figure 3, every testing spectrum is compared with all reference spectra. Here in Figure 3, three reference spectra are considered which are related to species BLs, CP, and SP. The testing pixel would be similar to the species that provides the smallest distance or highest similarity with the reference spectra.

![Figure 3 - Schematic diagram of tree species discrimination accuracy evaluation.](image)

In the case of MEM, multiple distances will be calculated for each testing sample. The minimum distance will be then considered per species. The target pixel would be similar to the species that it provides the smallest distance with the corresponding endmember.
Discrimination producer accuracy (acc.) is calculated by considering the number of classified target pixels over the total number of tested pixels. The overall/mean accuracy is then calculated considering the user and producer accuracy.

Evaluation of each VI is performed based on its overall accuracy and the minimum (Min) and maximum (Max) accuracy obtained from different tree species within user and producer accuracy. For simplicity in comparing performance of different VIs considering these three parameters, a fourth parameter is introduced in this study to weight the value of overall accuracy, minimum and maximum accuracy as Weight (%) = a% (Overall acc.) + b% (Min acc.) + c% (Max acc.). This weight calculation provides additional information that includes all the three accuracy values instead of considering only the overall accuracy. The coefficients $a$ and $b$ should be considered within a range of 40-50%, while coefficient $c$ should be within 5-15%. The highest weight is given to overall accuracy because it reflects more information including the accuracy of all individual tree species in the user and producer accuracy. The weight of Min accuracy is selected near to the overall accuracy because the Min accuracy shows that there is no any individual tree discriminated with lower that that value. The lowest weight is given to the Max accuracy because it is not very useful if a technique can classify an individual tree with very high accuracy but the accuracy of the other trees are low. Variation of the coefficients within the mentioned range does not influence much on the output result. For clarity, few examples are presented in Table 4. In these examples, five techniques (A to E) are shown with almost similar overall accuracy, however, different Min and Max accuracy. As the results of nine different sets of coefficients shown in this table, the output results are relatively comparable, where in all cases, the techniques C and E with the highest Min accuracy are amongst the best techniques. In this study, the coefficients $a$, $b$, and $c$ are defined for 50%, 40% and 10%, respectively.

**Table 4 - Influence of nine different sets of weights’ coefficients applied on five different techniques, where showing almost comparable results out of the nine different coefficients. The coefficients in row 6 are the set used in this study.**

| No. | Weight Percentage | A  | B  | C  | D  | E  |
|-----|-------------------|----|----|----|----|----|
| 1   | $a = b = 45\%$; $c = 10\%$ | 33.0 | 35.6 | 38.1 | 32.4 | 37.9 |
| 2   | $a = 40\%$; $b = 45\%$; $c = 15\%$ | 35.3 | 36.6 | 39.3 | 33.5 | 39.6 |
| 3   | $a = 45\%$; $b = 40\%$; $c = 15\%$ | 37.4 | 38.0 | 40.4 | 34.9 | 40.8 |
| 4   | $a = 40\%$; $b = 40\%$; $c = 20\%$ | 19.9 | 22.0 | 22.8 | 20.2 | 22.4 |
| 5   | $a = 40\%$; $b = 50\%$; $c = 10\%$ | 17.9 | 18.8 | 19.7 | 17.3 | 19.7 |
| 6   | $a = 50\%$; $b = 40\%$; $c = 10\%$ | **30.9** | **32.6** | **34.9** | **29.7** | **34.9** |
| 7   | $a = 50\%$; $b = 45\%$; $c = 5\%$ | 36.3 | 37.3 | 39.8 | 34.2 | 40.1 |
| 8   | $a = 45\%$; $b = 50\%$; $c = 5\%$ | 29.4 | 30.8 | 32.4 | 28.2 | 32.5 |
| 9   | $a = b = 47.5\%$; $c = 5\%$ | 19.8 | 21.3 | 22.2 | 19.5 | 22.1 |
The variability/separability within/between tree species is also visualized in the form of scatter plot. Figure 4 shows an exemplary results visualizing the within/between species variation/separability based on the example shown in Figure 3. The results labeled BLs-BLs shown in Figure 4 (a) represent the within BLs species variation obtained when 50 testing samples from BLs species are compared with three reference spectra of BLs, CP, and SP. The distance/variation between BLs-BLs to BLs-CP and BLs-SP shows the between species variation or how separable is BLs from the CP and SP species. Similarly, the results presented in Figure 4b and 4c show the within/between species variation for 30 and 40 testing samples selected from SP and CP, respectively.

![Figure 4 - Exemplary results for showing the within/between species variation/separation for (a) BLs, (b) SP, and (c) CP species.](image)

**Results**

Discrimination of tree species with different ages is performed using VIs. Influence of multiple-endmember on performance of VIs is evaluated. The study is performed in three complexity levels namely First, Second, and Third Complexity levels with the least to the most complexity, respectively, as their performance are described in the following sections.

**First complexity category**

Figure 5 shows the result of tree species discrimination for the first category with the simplest complexity by using single- and multiple-endmembers. As the results imply, up to 90% overall discrimination accuracy is obtained in this category using NDVI and GMI for both SEM and MEM. Considering the weight value (data bar), MEM provided almost similar performance compared to SEM with slightly lower accuracy, except for NDVI, where MEM shows about 10% higher accuracy for the case of Min accuracy. Table 5 shows example of the error matrix for the GMI using SEM and MEM. In this table, the Max and Min accuracy are highlighted in *Italic* and *Bold* and the producer, user and overall accuracies are highlighted with *Underline*, **Bold-Underline**, and ***Bold-Italic-Underline***, respectively.
Figure 5 - Discrimination accuracy comparison between different VIs for the first complexity category using SEM and MEM

Table 5 - Example of error matrix for GMI using SEM and MEM based on the first complexity category. The Max and Min accuracy are highlighted in *Italic* and Bold and the producer, user and overall accuracy are highlighted with *Underline*, *Bold-Underline*, and *Bold-Italic-Underline*, respectively.

| GMI-SEM | BLs | Pines | Total | Producer acc. | GMI-MEM | BLs | Pines | Total | Producer acc. |
|---------|-----|-------|-------|---------------|---------|-----|-------|-------|---------------|
| BLs     | 215 | 16    | 231   | 93.07         | BLs     | 180 | 51    | 231   | 77.92         |
| Pines   | 62  | 994   | 1056  | 94.13         | Pines   | 37  | 1019  | 1056  | 96.50         |
| Total   | 277 | 1010  | 1287  | 93.60         | Total   | 217 | 1070  | 1287  | 87.21         |
| User acc. | 77.62 | 98.42 | **88.02** | **90.81** | User acc. | 82.95 | 95.23 | **89.09** | **88.15** |

Figure 6 - Visualization of tree species separation provided by GMI for SEM (top) and MEM (bottom). (a and c) within (BLs-BLs) and between (BLs-Pines) species variation when the sample pixels selected from BLs species. (b and d) within (Pines-Pines) and between (Pines-BLs) species variation when the sample pixels selected from Pines species.
Figure 6 shows the spectral variation within- and between-tree species for BLs and Pines; where BLs-BLs shows the variation within-Broadleaves trees and Pines-Pines shows the variation within-Pine trees. On the other hand, BLs-Pines shows the spectral variation between-BLs and Pines trees when the testing samples were selected from BLs species, while Pine-BLs is for the case when the testing samples were selected from Pines trees. As the graph implies, in both SEM and MEM, the mixing between BLs and Pines species occurred around the same ROIs; for example, the sample numbers within 662 to 900. Although performance of MEM and SEM are almost similar, the within species variation provided by MEM is significantly lower compared to SEM. This provides a better spectral separation between BLs and Pines. For example, the variation value provided by Pines-Pines and Pines-BLs are 0.22 and 0.77 in SEM and 7.6E-6 and 1.45E-3 in MEM, respectively. This provides a larger between-to-within ratio of 190 for MEM compared to 3.5 in SEM.

Second complexity category

Figure 7 shows the discrimination accuracy comparison between different VIs considering the second complexity category using both SEM and MEM. Although, there is no significant difference between performance of SEM and MEM in terms of overall accuracy, the Min accuracy provided by MEM has slightly higher accuracy in most VIs and vice versa for Max accuracy. Overall, the highest discrimination accuracy is obtained using NDVI and GMI with 66 and 64% overall accuracy using MEM, respectively, which are about 3% higher than SEM.

Table 6 shows the detail of error matrix for GMI using SEM and MEM. The Min accuracy provided by MEM is about 10% higher compared to the Min accuracy provided by SEM. The highest discrimination accuracy in all cases is related to BLs tree species. Another observation is the large similarity between the Corsican and Scots pines. For example, out of 662 testing samples pixels selected from CP; 301 of them are correctly classified, while 347 and 17 of them are misclassified as SP and BLs using SEM, respectively. A
better insight on these similarities/dissimilarities can be seen from Figure 8. In this figure, the spectral variations within and between tree species for SEM and MEM using GMI are presented. The high similarities between CP and SP, and dissimilarity between BLs and Pine trees are very obvious.

Table 6 - Example of error matrix for GMI using SEM and MEM based on the second complexity category. The Max and Min accuracy are highlighted in *Italic* and Bold and the producer, user and overall accuracy are highlighted with *Underline*, *Bold-Underline*, and *Bold-Italic-Underline*, respectively.

|                | GMI-SEM |        |        |        |        | GMI-MEM |        |        |        |        |
|----------------|---------|--------|--------|--------|--------|---------|--------|--------|--------|--------|
|                | BLs     | CP     | SP     | Total  | Producer acc. | BLs     | CP     | SP     | Total  | Producer acc. |
| BLs            | 205     | 0      | 26     | 231    | 88.74  | 180     | 24     | 27     | 231    | 77.92  |
| CP             | 14      | 301    | 347    | 662    | 45.47  | 17      | 423    | 222    | 662    | 63.90  |
| SP             | 33      | 162    | 199    | 394    | 50.51  | 20      | 178    | 196    | 394    | 49.75  |
| Total          | 252     | 463    | 572    | 1287   | 61.57  | 217     | 625    | 445    | 1287   | 63.86  |
| User acc.      | 81.35   | 65.01  | 34.79  | **60.38** |         | 82.95   | 67.68  | 44.04  | **64.89** | **64.37** |

Figure 8 - Visualization of tree species separation provided by GMI for SEM (top) and MEM (bottom). (a and d) within (BLs-BLs) and between (BLs-CP and BLs-SP) species variation when the sample pixels selected from BLs species. (b and e) within (CP-CP) and between (CP-BLs and CP-SP) species variation when the sample pixels selected from CP. (c and f) within (SP-SP) and between (SP-BLs and SP-CP) species variation when the sample pixels selected from SP.

**Third complexity category**

Figure 9 shows the performance comparison between different VIs in discriminating tree species for the third complexity category using SEM and MEM. Again the performance difference between SEM and MEM is not significant. However almost in all VIs, MEM offered higher accuracy for Min accuracy and vice versa for Max accuracy compared to SEM. Amongst different VIs, the highest discrimination accuracy obtained in SEM are GMI, VOG, and REP-Lextra with overall accuracy of 55, 51 and 49%, respectively. In MEM, the highest overall accuracies are obtained from GMI, VOG, and NDVI with 52.6, 50, and 48%, respectively.
The detail of error matrix for GMI is presented in Table 7 for both SEM and MEM. The highest discrimination accuracy in all cases is related to BLs tree species. A high similarity is observed between mature pine (MCP) with the old pines (OCP and OSP) especially OSP; between young pines (YCP and YSP); and between BLs with MCP and OSP. These similarities can be well presented by showing the spectral variation between and within tree species (Fig. 10). The high similarity between MCP with OSP can be seen from Figures 10, 11b, and 11e; between YCP and YSP can be found from Figures 10, 11d and 11f.

Table 7 - Example of error matrix for GMI using SEM and MEM based on the third complexity category. The Max and Min accuracy are highlighted in *Italic* and Bold and the producer, user and overall accuracy are highlighted with Underline, Bold-Underline, and **Bold-Italic-Underline**, respectively.

|        | GMI-SEM |     |     |     | Total | Producer acc. | GMI-MEM |     |     |     | Total | Producer acc. |
|--------|---------|-----|-----|-----|-------|--------------|---------|-----|-----|-----|-------|--------------|
|        | BLs     | MCP | OCP | YCP | YSP   | Total        | BLs     | MCP | OCP | YCP | YSP   | Total        |
|        | 172     | 1   | 0   | 0   | 58    | 231          | 180     | 23  | 1   | 0   | 27    | 231          |
|        | MCP     | 0   | 65  | 40  | 0     | 113          | 218     | 70  | 38  | 0   | 89    | 218          |
|        | OCP     | 0   | 26  | 164 | 20    | 2            | 4       | 216 | 75.93| 75.93| 75.93| 75.93|
|        | YCP     | 0   | 0   | 17  | 101   | 0            | 110     | 228 | 44.30| 44.30| 44.30| 44.30|
|        | OSP     | 8   | 95  | 46  | 1     | 88           | 0       | 238 | 36.97| 36.97| 36.97| 36.97|
|        | YSP     | 0   | 0   | 24  | 30    | 0            | 102     | 156 | 65.38| 65.38| 65.38| 65.38|
| Total  | 180     | 187 | 291 | 152 | 261   | 216          | 1287    | 54.48|      |      |      | 54.48|
| User acc. | 95.56 | 34.76| 56.36| 66.45| 33.72| 47.22 | 55.68 | 55.08|      |      |      | 55.08|
|        | BLs     | 180 | 23  | 1   | 0     | 27           | 0       | 231 | 77.92| 77.92| 77.92| 77.92|
|        | MCP     | 17  | 70  | 38  | 0     | 89           | 4       | 218 | 32.11| 32.11| 32.11| 32.11|
|        | OCP     | 0   | 23  | 116 | 19    | 31           | 27      | 216 | 53.70| 53.70| 53.70| 53.70|
|        | YCP     | 0   | 0   | 37  | 120   | 4            | 67      | 228 | 52.63| 52.63| 52.63| 52.63|
|        | OSP     | 20  | 77  | 42  | 0     | 92           | 7       | 238 | 38.66| 38.66| 38.66| 38.66|
|        | YSP     | 0   | 0   | 14  | 45    | 3            | 94      | 156 | 60.26| 60.26| 60.26| 60.26|
| Total  | 217     | 193 | 248 | 184 | 246   | 199          | 1287    | 52.55|      |      |      | 52.55|
| User acc. | 82.95 | 36.27| 46.77| 65.22| 37.40| 47.24 | 52.64 | 52.59|      |      |      | 52.59|
Figure 10 - Visualization of tree species separation provided by GMI for SEM, (a) within (BLs-BLs) and between (BLs-MCP, BLs-OCP, BLs-YCP, BLs-OSP, and BLs-YSP) species variation when the sample pixels selected from BLs species; (b) within (MCP-MCP) and between (MCP-BLs, MCP-OCP, MCP-YCP, MCP-OSP, and MCP-YSP) species variation when the sample pixels selected from MCP; (c) within (OCP-OCP) and between (OCP-BLs, OCP-MCP, OCP-YCP, OCP-OSP, and OCP-YSP) species variation when the sample pixels selected from OCP; (d) within (YCP-YCP) and between (YCP-BLs, YCP-MCP, YCP-OCP, YCP-OSP, and YCP-YSP) species variation when the sample pixels selected from YCP species; (e) within (OSP-OSP) and between (OSP-BLs, OSP-MCP, OSP-OCP, OSP-YCP, and OSP-YSP) species variation when the sample pixels selected from OSP; (f) within (YSP-YSP) and between (YSP-BLs, YSP-MCP, YSP-OCP, YSP-YCP, and YSP-OSP) species variation when the sample pixels selected from YSP.
Figure 11 - Visualization of tree species separation provided by GMI for MEM, (a) within (BLs-BLs) and between (BLs-MCP, BLs-OCP, BLs-YCP, BLs-OSP, and BLs-YSP) species variation when the sample pixels selected from BLs species; (b) within (MCP-MCP) and between (MCP-BLs, MCP-OCP, MCP-YCP, MCP-OSP, and MCP-YSP) species variation when the sample pixels selected from MCP; (c) within (OCP-OCP) and between (OCP-BLs, OCP-MCP, OCP-YCP, OCP-OSP, and OCP-YSP) species variation when the sample pixels selected from OCP; (d) within (YCP-YCP) and between (YCP-BLs, YCP-MCP, YCP-OCP, YCP-OSP, and YCP-YSP) species variation when the sample pixels selected from YCP species; (e) within (OSP-OSP) and between (OSP-BLs, OSP-MCP, OSP-OCP, OSP-YCP, and OSP-YSP) species variation when the sample pixels selected from OSP; (f) within (YSP-YSP) and between (YSP-BLs, YSP-MCP, YSP-OCP, YSP-YCP, and YSP-OSP) species variation when the sample pixels selected from YSP.

Discussion

Figure 12 shows the summary comparison of all VIs in the three complexity categories using SEM and MEM. As the results imply, overall accuracy is significantly reduced from the first to the third complexity category. This result shows the direct effect of tree species complexity on the discrimination performance of VIs.

The main difficulty in discriminating tree species with different ages (Third Complexity Category) was the high similarity between the tree species in the same age category such as young tree species (YCP and YSP) or between old species and mature. The high similarity between the species in the same age would be due to the similarity in chlorophyll content of the species [Croft et al., 2014a]. Croft et al. [2014a] have shown that there is a strong temporal correlation between leaf chlorophyll with stand age up to around 40 years, meaning that no further increase in leaf chlorophyll after 40 years. This high similarity between-tree species caused the discrimination of tree species with different ages very challenging.

On the other hand, in all complexity categories, BLs species were discriminated with the highest accuracy. This is observed in almost all VIs. This is due to the leave structure with
larger leave area and higher reflectance (Fig. 2) in BLs species compared to the Pine species [Heiskanen et al., 2013]. This is in agreement with observation by Croft et al. [2014b] where broadleaf samples exhibit extremely strong relationships between spectral indices and leaf chlorophyll content and presented strong results at leaf and canopy scales. Amongst different VIs, GMI, NDVI, and VOG followed by REP techniques have shown the highest potential for discriminating tree species with different ages. These VIs show about the same range of discrimination accuracies with less than 10% differences. GMI and VOG are associated with very close spectral bands between 700 to 750 nm, where is located in the edge of NIR, where the plant spectrum has the transition from the chlorophyll absorption in the red band (around 650 nm) and immediately increase the reflectance around 700 to 750 nm. On the other hand, the narrow band NDVI is associated with the chlorophyll absorption in the red band at 680 nm and the top of the NIR around 833 nm band. The VIs associated in these bands seem to be more useful for discriminating tree species with different ages. Heiskanen et al. [2013] observed that narrow band VIs based on NIR bands, and NIR and SWIR bands shows the strongest linear relationships with LAI over its typical range of variation and independent on tree species type. The comparison between SEM and MEM shows that there is not much improvements from MEM compared to SEM in discriminating tree species with different ages using VIs, unless for NDVI. This is relatively agreed with the finding of Thorp et al. [2013] in which MESMA could not distinguish between different shrub species (i.e., mesquite, creosote bush, and tarbush), while it was supportive in distinguishing between green shrub vegetation and nonphotosyntetic grass vegetation. Table 8 shows a comparison between the performance of SEM and MEM using VIs (i.e., GMI) performed in this study with the previously reported works using the same hyperspectral data; i.e., the original reflectance, first and second derivative spectra reported in [Ghiyamat et al., 2013] and discrete wavelet transform (DWT) [Ghiyamat et al., 2015].

Figure 12 - Overall accuracy comparison between the three complexity categories using SEM and MEM.
Table 8 - Overall accuracy comparison between VIs and original reflectance, 1st, and 2nd derivative spectra (discriminated using Euclidean distance) using SEM and MEM for the three complexity categories and DWT using three different spectral measure techniques (i.e., Spectral angle mapper (SAM), Spectral information divergence (SID), and Tangent based combination of SAM with SID (SID(TAN))) applied only on the third complexity level.

| Complexity Category | VIs (the highest overall accuracy, i.e., GMI) | Original reflectance with Euclidean distance [Ghiyamat et al., 2013] | First derivative with Euclidean distance [Ghiyamat et al., 2013] | Second derivative with Euclidean distance [Ghiyamat et al., 2013] | Discrete wavelet transform and SEM [Ghiyamat et al., 2015] |
|---------------------|------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
|                     | SEM                              | MEM                              | SEM                              | MEM                              | SEM                              | MEM                              | SAM                 | SID                 | SID(TAN)            |
| First Category with least complexity | 90.8                            | 89.5                            | 78.1                            | 92.4                            | 90.0                            | 87.5                            | 92.1                | 86.1                | -                   |
| Second Category with medium complexity | 63.1                            | 66.2                            | 59.8                            | 76.8                            | 66.9                            | 65.0                            | 62.0                | 60.2                | -                   |
| Third Category with most complexity   | 55.1                            | 52.6                            | 63.2                            | 71.5                            | 43.3                            | 50.8                            | 39.3                | 41.4                | 65                  |
|                                    |                                  |                                 |                                 |                                 |                                 |                                 | 71.4                | 68.6                |

Considering SEM, the results in Table 8 shows that VIs was more successful in discriminating tree species with the low complexity compared to the original reflectance, first derivative and second derivative spectra. VIs shows about 12.7% and 3.3% higher discrimination accuracy compared to the original reflectance in the first and the second complexity categories, respectively. However, in the higher complexity category, the original reflectance shows 8.1% higher accuracy compared to VIs. Compared to derivative spectra, VIs outperformed both 1st and 2nd derivative spectra in all the three complexity categories, especially in the most complex category.

For the case of MEM, while it was very effective for the original reflectance to improve the discrimination accuracy, it could not provide further improvement for all VIs. For instant, for GMI presented in Table 8, performance of GMI with MEM is almost comparable with GMI in SEM, except for the case of second complexity category. However, for the case of NDVI, MEM could gain the discrimination accuracy by about 3%, 2% and 10% in the first, second and the third complexity level, respectively, showing more suitability of MEM for NDVI compared to GMI. As presented in Figure 5, 7, and 9, performance of GMI and NDVI in discriminating tree species with different ages in all the three complexity categories was very similar. One of the interesting properties of MEM observed in this study is that; although, overall accuracy of MEM and SEM are almost the same, by using MEM, the lowest or minimum discrimination accuracy in SEM can be improved. This was very significant in the second and third complexity levels as shown in Figure 7 and 9, respectively. For example, in NDVI (Fig. 9), the minimum discrimination accuracy amongst the 6 three species was 6% using SEM, however, this is improved to 35% by using MEM. The results in Figure 7 and 9 show that the minimum discrimination accuracy in
almost all VIs is improved up to more closer to the overall SEM [Ghiyamat et al., 2015] to classify the forested area into broadleaf trees, coniferous trees, mixed forest or clear-cut with an accuracy of about 90% by using multispectral and LiDAR data.

Conclusion
Discrimination of tree species with different age covers are demonstrated using different VIs based on an airborne hyperspectral data. The influence of multiple-endmember on performance of tree species discrimination with different ages is investigated. The study is designed to analyze performance of these techniques in three complexity categories, i.e., 1) discrimination between broadleaves and pine tree species; 2) discrimination between broadleaves, Corsican pines and Scots pines; and 3) discrimination between old, mature, and young Corsican pines, and old and young Scots pines, and broadleaves. VIs are shown to be very useful for discriminating tree species with lower complexity. A discrimination accuracy of more than 90% is obtained for distinguishing between pines with broadleaves tree species. However, their performance is significantly reduced to around 66% and 55% as the tree species complexity is increased, i.e., second and third complexity levels, respectively. Although, the overall accuracy using VIs was not higher compared to the other techniques, it should be noted that in VI method, there are only two bands involved compared to hundreds of bands used in other techniques. Even by using two bands, performance of VIs was comparable with other techniques particularly in the lower complexity level. This suggests suitability of VIs for tree species discrimination with less complexity. Amongst different VIs, GMI, NDVI, and VOG, have shown the highest potential for discriminating tree species with different ages in all the three complexity levels. While MEM is shown to be very useful in improving discrimination accuracy of original reflectance spectra; it could not help to improve performance of VIs further, unless for NDVI that its performance is improved by about 2-10% from the first to the third tree species complexity category. On the other hand, MEM has shown to be very useful in discriminating tree species with high similarity or complexity mainly due to using multiple reference spectra. The worst discrimination accuracies offered by MEM technique have shown to be relatively closer to the overall accuracy value compared to what observed in SEM approach. Overall, the study reveals the weakness of tree species discrimination techniques particularly for complex tree covers including different ages.

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