# DISCRIMINATING SPECIES USING HYPERSPECTRAL INDICES AT LEAF AND CANOPY SCALES

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# **ABSTRACT:**

Developments in hyperspectral remote sensing have provided new indices or indicators of biochemical and biophysical properties. Most of the studies involving the novel spectral indices have been conducted at the leaf scale and have been rarely investigated for species discrimination. The objectives of the study were to determine hyperspectral indices that (i) are likely to be influenced by change in spectral measurement from the leaf to the canopy scale and (ii) can discriminate species at both scales. Leaf and canopy reflectance measurements were made from six species (3 shrubs, 3 trees) using an ASD spectroradiometer. The two-sample t test was used to evaluate whether significant differences exist between leaf and canopy indices, while differences between species pairs (15 pairs) were evaluated with ANOVA and pair-wise Bonferroni adjusted t tests. The hyperspectral indices evaluated in this study were, in general, sensitive to the change in spectral measurement scale from the leaf to the canopy. However, among the indices studied, red-edge positions (REP) extracted by the linear extrapolation I method were least sensitive to the change in measurement scale as three out of the six species showed no significant differences between the leaf and canopy indices. With respect to species discrimination, the canopy indices were better discriminators than the leaf indices. This is essential for air- or spaceborne remote sensing of species assemblages. The photochemical reflectance index (PRI) showed the highest potential to discriminate species at the canopy scale (all 15 pairs), while the linear extrapolation REPs showed the highest potential to discriminate the same species pairs (10 pairs) at both scales. Hyperspectral indices might provide new possibilities of differentiating plant species.

# 1. INTRODUCTION

Developments in hyperspectral remote sensing have provided more accurate information on structural, biochemical and physiological properties of vegetation (Blackburn, 1998). Most of the work on hyperspectral remote sensing of biophysical and biochemical parameters has been achieved through the development of new hyperspectral indices (Chappelle et al., 1992; Vogelmann et al., 1993; Carter, 1994; Gitelson and Merzlyak, 1997). Spectral indices are mathematical transformations of spectral reflectance to enhance vegetation signal (Huete and Jackson, 1988; Qi et al., 1995). Hyperspectral indices might provide new possibilities for differentiating plant species or communities that differ in canopy structure and/or biochemical compositions (Nagendra, 2001).

The normalised difference vegetation index (NDVI) is the most commonly used multi-spectral index of canopy greenness, a correlate of structural aspects such as canopy cover and leaf area index. NDVI calculation is based on the difference in canopy reflectance at red (670-680 nm) and near-infrared (750– 850 nm) wavelengths (Rouse et al., 1974; Tucker, 1979). NDVI has been used to differentiate communities consisting of structurally distinct formations e.g. savannah, shrubland and dense forest (Achard and Blasco, 1990; Saney and Elliott, 2002) or phenological distinct formations e.g. deciduous versus evergreen forests (Achard and Estreguil, 1995; Van Wagtendonk and Root, 2003). However, attempts to differentiate plant species have been unsuccessful because they tend to produce overlapping canopy NDVI values (Nagendra, 2001; Pettorelli et al., 2005).

New hyperspectral indices that provide closer correlation with the biochemical and physiological properties of intact leaves or canopies have been developed. Several studies show that narrowband vegetation indices involving visible reflectance near 550 and 700 nm can precisely estimate leaf pigments such as chlorophyll a and b (Carter, 1994; Chappelle et al., 1992; Vogelmann et al., 1993; Gitelson and Merzlyak, 1997) and carotenoids (Gamon et al., 1992; Gamon and Surfus, 1999: Gitelson et al., 2002). These pigments have different roles within the process of photosynthesis and their concentrations can depend on factors such as phenology, degree of canopy development and type of environmental stress (Blackburn and Pitman, 1999). Another hyperspectral index of interest is the wavelength of maximum slope in the red-edge (670-780 nm) (Curran et al., 1995; Jago et al., 1999). This point is termed the red-edge position (REP). Changes in leaf chlorophyll content cause shifts in the REP to shorter and longer wavelengths for low and high chlorophyll contents, respectively (Horler et al., 1980; Horler et al., 1983; Miller et al., 1990; Clevers et al., 2002). By using data simulated with radiative transfer models (PROSPECT-SAILH), Cho et al. (2006) showed that REPs located by a novel approach, the linear extrapolation method are more sensitive to leaf chlorophyll content than REPs derived by alternative algorithms, including the linear interpolation (Guyot and Baret, 1988), and inverted Gaussian (Bonham-Carter, 1988) and higher order polynomial fitting (Pu et al., 2003) methods.

Most of the studies involving the novel spectral indices have been conducted at the leaf scale and have not been tested for species discrimination. Fewer studies have been carried out at the canopy scale, for example, using plants grown under controlled conditions (Yoder and Pettigrew-Crosby, 1995), natural canopies (Blackburn, 1998) and simulated data (Barton and North, 2001; Cho et al., 2006). It is questionable whether spectral information acquired at the leaf level can be linearly scaled up to understanding the spectral characteristics at the whole plant or community scale. Several experimental and modelling studies show that vegetation reflectance at the latter scale is not only a function of leaf optical properties but also canopy biophysical attributes (foliage clumping, leaf orientation, leaf area, bark, twigs, flowers), soil reflectance, illumination conditions, viewing geometry and atmospheric conditions (Verhoef, 1984; Kuusk, 1991; Jacquemoud et al., 1995; Yoder and Pettigrew-Crosby, 1995; Asner, 1998). Thus, the main objectives of the study were to determine hyperspectral indices that:

- i are likely to be influenced by change in spectral measurement from the leaf to the canopy scale and
- ii can discriminate species at both scales.

To achieve the above objectives, leaf and top-of-canopy reflectance measurements were made *in situ* from three species of shrubs and three species of trees. Statistical differences between the leaf and canopy indices and between species pairs were examined using the two-sample student t-test.

#### 2. MATERIAL AND METHODS

Plant species	Structural characteristics of the plant		
Hedera helix	Evergreen climbing plant, the adult		
	plants consist of self-supporting erect		
	stem		
Rhododendron sp.	Dense shrub, ~1.5 m, evergreen		
Prunus spinosa	Dense prickly shrub, ~ 3 m, deciduous		
Corylus avellana.	Tree, ~ 4 m, deciduous		
Malus domestica	Tree, $\sim 4$ m, deciduous		
Aesculus hippocastanum	Tree, ~ 3 m, deciduous		

Table 1 Shrub and tree species used in the study.

#### 2.1 Spectral measurements

Leaf and canopy reflectance spectra of three shrub and three tree species (Table 1) were collected on clear sky days (30 August and 2 September 2005) using an ASD spectroradiometer (FieldSpec Pro FR, Analytical Spectral Device, Inc, USA.). The ASD covers the spectral range between 350 to 2500 nm. The sampling interval over the 350-1050 nm range is 1.4 nm with a resolution of 3 nm (bandwidth at half maximum). Over the 1050-2500 nm range, the sampling interval is about 2 nm and the spectral resolution is between 10 and 12 nm. The results are then interpolated by the ASD software to produce readings at every 1nm. A 1.2 m long fibre optic cable with a 25° field of view was used for the measurements. Leaf reflectance measurements were made at about 5 cm above sunlit sides of 20 to 30 leaves on the shrub or tree crowns. A crane was used to attain the crowns of tall trees. With respect to the canopy spectra, 20 to 30 measurements were made at different points above the crown at a distance of 1 m to 1.5 m. Measurements were taken on clear sunny days near solar noon (11 am to 2 pm). The radiance data was converted to reflectance using scans of a white spectralon reference panel. At most two target measurements were made after measuring the reference panel.

#### 2.2 Spectral indices

Only the leaf and canopy spectra in visible-NIR (VNIR, 400-900 nm) range were considered in this study because the SWIR region showed high noise levels, particularly in the major water absorption bands. The VNIR spectra for each species were smoothed using a Savitzky-Golay (Savitzky and Golay, 1964) second order polynomial least-squares function with a five-band window. Vegetation indices and REPs were then computed from the leaf and canopy spectra.

#### 2.2.1 Vegetation indices

Apart from the traditional NDVI, narrowband indices that are sensitive to chlorophyll and carotenoids were adopted in this study. See Table 2 for the full description of the vegetation indices.

# 2.2.2 Red-edge position (REP)

REPs were derived by the linear four-point interpolation approach (Guyot and Baret, 1988), inverted Gaussian modelling (Bonham-Carter, 1988), polynomial fitting technique (Pu et al., 2003) and the linear extrapolation method (Cho and Skidmore, 2006). A full description of these methods can be found in Cho et al. (2006).

Vegetation	Formula	Biophysical	Reference
index		significance	
Normalised	$(R_{830} -$	Canopy greenness,	Rouse et al.,
difference	R670)/(R830	LAI, fraction of	1974;
vegetation index	$+ R_{670}$ )	photosynthetically	Tucker,
(NDVI)		active radiation	1979
Carter index	$R_{760}/R_{695}$	Chlorophyll content	Carter, 1994
(CI)			
Gitelson and	$R_{750}/R_{700}$	Chlorophyll content	Gitelson and
Merzylak index			Merzlyak,
(GMI)			1997
Vogelman index	$R_{740}/R_{720}$	Chlorophyll content	Vogelmann
(VOG)			et al., 1993
Photochemical	$(R_{531} -$	Conversion of	Gamon et
reflectance	$R_{570})/(R_{531})$	xanthophylls-cycle	al., 1992;
index (PRI)	$+ R_{570})$	pigments,	Peñuelas et
		photosynthetic light-	al., 1995
		use efficiency, LAI	
Carotenoid	$R_{800}(1/R_{520} -$	Carotenoids (alpha-	Getilson et
reflectance	$1/R_{550}$ )	and beta-	al., 2002
index (CRI)		xanthophylls),	
		indicator of plant	
		stress	

Table 2. Vegetation indices selected in the study. Note: R = reflectance

#### 2.3 Data analysis

The two-sample t-test for testing whether differences exist between two population means was adopted in this study to determine spectral indices that are likely to be influenced by the canopy effect. Numerous studies have shown that the two-sample t test is robust to considerable departures from its theoretical assumptions (that both samples come at random from normal populations with equal variances), especially if the sample sizes are equal or nearly equal (Boneau, 1960; Cochran, 1947; Posten et al., 1982; Zar, 1996). We tested the research hypothesis that the means of the leaf and canopy indices for each species were different, i.e., Ho:  $\mu_1 = \mu_2$  versus the alternative hypothesis,  $H_1$ :  $\mu_1 \neq \mu_2$ , where  $\mu_1$  and  $\mu_2$  are the means of leaf and canopy indices. The tvalues were calculated using Eq. 1.

$$t = \frac{\bar{X}_{1} - \bar{X}_{2}}{\sqrt{\frac{sd_{1}^{2}}{n_{1}} + \frac{sd_{2}^{2}}{n_{2}}}}$$

(1)

where,  $\bar{X}_1$  and  $\bar{X}_1$ , sd<sub>1</sub> and sd<sub>2</sub>, and n<sub>1</sub> and n<sub>2</sub> represent the means, standard deviations and sample sizes of the leaf and canopy data, respectively.

A two-step procedure was adopted in order to evaluate the potential of the various indices to discriminate between species. First, single factor analysis of variance (ANOVA) was used to test whether differences exist between the species means: the null hypothesis,  $H_0$ :  $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6$  versus the alternative hypothesis,  $H_1$ :  $\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4 \neq \mu_5 \neq \mu_6$ . Secondly, a multiple comparisons test using Bonferroni adjusted t test was carried out in order to determine which pairs of species means differ. Bonferroni adjusted test reduces the chance of committing Type I error (Zar, 1996). We applied the Bonferroni multiple comparisons procedure with  $\alpha = 0.05$  to the data. The alpha level was adjusted downwards by dividing 0.05 by 15 (number of species pairs) i.e. 0.05/15 = 0.003. The critical t for this value is 3.26 for a sample size of n = 20 to 30.

#### 3. **RESULTS**

#### 3.1 Differences between leaf and canopy indices



Figure 1. Mean leaf and canopy reflectance for six plant species. Spectral measurements were carried out *in situ*, on sunlit sides of the leaves and 1-1.5 m above the canopy for leaf and canopy measurements, respectively.

The leaf VNIR reflectances were higher than canopy reflectances for all six species (Fig.1). The question as to whether the differences were significant for each band was tackled using the two-sample t test. The differences were statistically significant (p < 0.05) in all the VNIR bands for all six species, but for *Malus* in the wavelength region between 703-718 nm (Fig.2).

The descriptive statistics of the spectral indices have not been presented, but it can be inferred from the negative t values (Tables 3 and 4) calculated using Eq. 1 that the canopy means were higher than the leaf means. These results contradict those of the reflectance data. There were a few exceptions e.g. for most cases of *Malus* where the leaf means were higher that the canopy means. It is unclear why *Malus* showed the odd behaviour. The leaf-scale data showed higher variability compared to the canopy-scale data for each species as illustrated with NDVI and linear extrapolation I REP using *Rhododendron* (Figure. 3).

The results of the two-sample t test showed that the differences between leaf and canopy means were significant (p < 0.05) in 81% and 74% of the cases for vegetation indices and REPs, respectively. However, when the individual indices were compared, the linear extrapolation I REP showed the highest number cases where the differences were not significant (3 species) followed by the linear extrapolation II REP, Carter index, and Getilson and Merzylak index with two cases each.



Figure.2. Results of two-sample t test for differences between leaf and canopy reflectance for all visible and NIR bands. The wavelength axis cuts the t-values axis at t = 2. Above this critical t value, the difference between the leaf and canopy means is significant (p < 0.05).

Species	NDVI	CI	GMI	VOG	PRI	CRI
Hedera	-2.22*	-0.90 <sup>ns</sup>	-1.24 <sup>ns</sup>	-3.38**	-4.95**	-0.44 <sup>ns</sup>
Rhodo-	-7.43**	-8.73**	-7.40**	-5.66**	7.44**	-
dendron						$10.98^{**}$
Prunus	-4.11**	-4.00**	-4.45**	-7.94**	-5.26**	-3.39**
Corylus	-8.03**	-8.45**	-4.86**	-3.41**	$2.22^{*}$	-9.11**
Malus	-2.02*	-0.5 <sup>ns</sup>	$0.88^{ns}$	$2.33^{*}$	6.47**	-3.94**
Aesculus	-4.78**	-4.2**	-3.49**	-5.08**	1.34 <sup>ns</sup>	-5.23**
nesemms	1.70	1.2	5.17	5.00	1.51	5.25

Table 3 Two-sample t-test for differences between leaf and canopy vegetation indices. \*=p<0.05, \*\*=p<0.01, ns = not significant (p>0.05)

species	Linear interpola tion	Linear extrapola tion I	Linear extrapola tion II	Inverted Gaussian model	Polynomial model
Hedera	-6.28**	-2.76*	-3.65**	-6.24**	-4.94**
Rhodode	-6.98**	-1.48 <sup>ns</sup>	-2.17*	-5.64**	-4.46**
ndron					
Prunus	-11.83**	-4.60**	-5.99**	-11.26**	-10.25**
Corylus	-9.45**	0.73 <sup>ns</sup>	-0.21 <sup>ns</sup>	-7.57**	-7.62**
Malus	1.22 <sup>ns</sup>	6.16**	5.88**	1.64 <sup>ns</sup>	1.83 <sup>ns</sup>
Aesculus	-9.75**	-0.56 <sup>ns</sup>	-1.92 <sup>ns</sup>	-8.56**	-6.84**

Table 4 Two sample t-test for differences between leaf and canopy red-edge position calculated by various methods. \* = p < 0.05, \*\* = p < 0.01, ns = not significant (p>0.05)

#### 3.2 Discriminating species

The results of the one-way analysis of variance (ANOVA) showed significant differences between the species means for all the spectral indices using the leaf and canopy-scale data, i.e. the null hypothesis,  $H_0$ :  $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6$  was rejected for all the indices. P-values less than 0.0001 were obtained for all the tests except for the NDVI using leaf-scale data, which showed a p-value of 0.0139. The results of the multiple comparison test using Bonferroni adjusted t test subsequently showed which pairs of means differ (Fig. 4 and 5).



Figure 3. Comparing the leaf and canopy distributions for (A) NDVI and (B) red-edge positions derived by the linear extrapolation II method for *Rhododendron*.



Figure.4. Results of two-sample t tests for differences between species (15 pairs) at leaf and canopy scale using NDVI, Carter index (CI), Gitelson and Meryzlak index (GMI), Vogelman index (VOG), photochemical reflectance index (PRI) and carotenoid reflectance index (CRI). Broken lines denote critical t value (t = 3.26) after Bonferroni adjustment above which differences were significant. Hedera (He), Rhododendron (Rh), Prunus (Pr), Corylus (Co), Malus (Ma) and Aesculus (Ae).



Figure 5. Results of two-sample t tests for differences between species (15 pairs) at leaf and canopy scale using red-edge positions extracted using linear interpolation, linear extrapolation I, linear extrapolation II, inverted Gaussian modelling and polynomial fitting methods. Broken lines denote critical t value (t = 3.26) after Bonferroni adjustment above which differences were significant. Hedera (He), Rhododendron (Rh), Prunus (Pr), Corylus (Co), Malus (Ma) and Aesculus (Ae).

More species pairs were differentiated using canopy-scale data than the leaf-scale data (Table 5). The potential for NDVI, PRI or CRI to discriminate species was highly biased towards the canopy-scale. The above indices showed the highest differences between the number of separable pairs at the leaf and canopy scales. For example, all 15 species pairs could be differentiated at the canopy level using PRI as against 5 pairs at the leaf scale. The histograms of leaf and canopy PRI in Fig. 6(A) provide a visual appreciation of its species discrimination capability at both levels. The NDVI showed the lowest potential to discriminate species at the leaf level, being able to differentiate only a single pair. GMI and VOG were the best vegetation indices at both leaf and canopy scales.

	Number of significant cases			
Spectral index	Total	at Total at	Same species	
	leaf scal	e canopy	pairs at both	
		scale	scales	
Vegetation indices				
NDVI	1	10	0	
CI	4	10	2	
GMI	8	9	5	
VOG	10	11	7	
PRI	5	15	5	
CRI	3	13	2	
Red-edge position				
Linear interpolation	11	13	9	
Linear extrapolation I	11	13	10	
Linear extrapolation	10	13	10	
II				
Inverted Gaussian	11	12	8	
modelling				
Polynomial fitting	11	12	8	

Table 5. Table 4.5 Summary of two-sample t tests for differences between species (15 pairs in total), showing number of pairs of species significantly discriminated (t > 3.26, p < 0.003) at the leaf, canopy, and at both scales.

In general, REPs performed better than vegetation indices in discriminating species at both scales. When all indices are compared, REPs extracted by the linear extrapolation I and II showed the highest potential in discriminating the same species pairs at both scales (10 pairs). This is further illustrated with the histograms of the linear extrapolation I REPs in Fig 6(B).



Figure.6. Histograms of leaf and canopy indices, namely (A) Photochemical reflectance index (PRI) and (B) linear extrapolation I REP for six species of plants. The histograms illustrate the ability of the indices to differentiate species at the leaf and canopy scales.

A general species separability pattern based on the phenological characteristics appears to emerge at the canopy scale for VOG and REPs. There were lower canopy t values for pairs consisting of species of the same phenology i.e. evergreen vs. evergreen (*Hedera-Rhododendron*) or deciduous vs. deciduous (*Prunus-Corylus, Prunus-Malus, Prunus-Aesculus* and *Corylus-Malus*) in contrast to species of opposing phenology i.e. evergreen vs. deciduous (*Hedera* or *Rhododendron* – *Prunus, Corylus, Malus* or *Aesculus*). See Fig 7. for an illustration of the above phenomenon. There were some few exceptions where species of opposing phenology were weakly discriminated at the canopy scale e.g. *Hedera-Prunus* and *Rhododendron-Prunus*.



Figure.7. Results of two-sample t tests for differences between species (15 pairs) at leaf and canopy scales using red-edge positions extracted using linear interpolation method. Species of opposing phenology (evergreen-deciduous) are better discriminated than species of the same phenology. Hedera (He), Rhododendron (Rh), Prunus (Pr), Corylus (Co), Malus (Ma) and Aesculus (Ae).

# 4. DISCUSSION

#### 4.1 Differences between leaf and canopy indices

The results of this study revealed systematically higher VNIR reflectances at the leaf scale than at the top-of the canopy. The higher leaf VNIR reflectance may be explained by the effect of multiple scattering caused by leaf stacking since the leaf reflectance were measured *in situ*. Blackburn (1999) showed that the NIR and to a lesser degree, the visible reflectance increases with leaf stacking. He equally argues that the spectral reflectance properties of background materials and areas of shadow can have large influence upon that of the whole canopy even when there is complete canopy. For example, Fig. 4.9 shows canopy pictures of *Hedera* and *Rhododendron* with dark areas, which may be due to shadow cast by the uppermost leaves.

The results of this study equally showed significant differences between leaf and canopy indices in 81% and 74% of the cases for vegetation indices and REPs, respectively. Thus, the information contents at both levels are largely different. The change in the spectral information content from the leaf to the canopy scale could be due to differences introduced by the complexity of the canopy, e.g. LAI, foliage clumping and the presence of twigs, flowers and shadow. However, the linear extrapolation I REP appears to be the least sensitive index to these canopy properties followed by the linear extrapolation II REP, Carter index, and Getilson/Merzylak index. These indices are all chlorophyll content indices. The results of this study support growing evidence that REP extracted by the linear extrapolation method might be less sensitive to canopy structural. For example, by using data simulated with radiative transfer models (PROSPECT-SAILH), Cho et al. (2006) showed that REPs located by the linear extrapolation method are more sensitive to leaf chlorophyll content with minimal effect of LAI and leaf mass compared to REPs located by various alternative algorithms. Cho and Skidmore (2006) in an experimental study using leaf stacks showed that REPs located by the linear extrapolation approach were more sensitive to leaf nitrogen concentration than the various REP alternatives.

Other factors that might have affected the canopy spectra include atmospheric conditions and the bidirectional reflectance (BRDF) effect caused by varying view and solar zenith angles. The ratio or vegetation indices are designed to minimise these effects and to enhance the spectral signal of leaf and canopy biochemical and biophysical properties. The impact of the above perturbing factors on NDVI has long been established (Huete and Jackson, 1988; Kaufman and Tanré, 1992; Qi et al., 1995). Only recently was the impact of the BRDF effect on PRI apparent. Barton and North (2001) using simulated data showed that LAI has a high impact on PRI values followed by changing solar and view zeniths. On the other hand, Clevers et al. (2001) demonstrated that REP are less sensitive to atmospheric conditions and Cho et al. (2006) showed that REPs are not sensitive to varying solar zenith angles.

# 4.2 Discriminating species

In this study, we have shown that species were more easily discriminated at the canopy than at the leaf scale. This conclusion held across a variety of hyperspectral indices. This is essential for air-spaceborne remote sensing of species assemblages. It is possible that the optimum spectral information required to discriminate species at the leaf level was not captured in the leaf samples. This could be explained by the high variability in the leaf indices. Hence, the poorer species separability results at the leaf scale. On the other hand, in addition to the possibility of covering the total spectral information among the leaves, canopy reflectance might provide extra information on the canopy structure (leaf orientation, leaf clumping, and colour of twigs and flowers), which might enhance the ability of the indices to discriminate between species.

The impact of the canopy characteristics seems to be highest on NDVI, PRI and CRI, which showed the highest differences between the number of separable species pairs at the leaf and canopy scales. Though Gamon et al (1992) proposed the PRI as a sensitive index to xanthophyll cycle pigment contents; Barton and North (2001) showed that it is highly sensitive to canopy structural properties (LAI and leaf angle distribution). This double property of the PRI might have accounted for the high species separability potential at the canopy scale. A drawback of the PRI is that it is strongly influenced by soil background (Barton and North, 2001). However, soil background was not an important factor in this study. Finally, the results of this study show that the REP largely preserves leaf information for discriminating species when the reflectance measurement is scaled up the canopy, with the linear extrapolation REPs having a slight urge over alternative REP algorithms. However, care should be taken when applying the linear extrapolation method because Cho et al. (2006) showed that it is sensitive to spectral noise. We recommend smoothing of the spectrum when noise is a problem.

# **4.3** Implications for upscaling leaf level information to the canopy scale

The results of this study support experimental and modelling studies, which demonstrate poor signal propagation from the leaf to canopy scale (Verhoef, 1984; Kuusk, 1991; Jacquemoud et al., 1995; Yoder and Pettigrew-Crosby, 1995; Asner, 1998). But the significant finding in this study is that canopy indices have a far superior discriminating power than leaf level indices, which is essential for remote sensing of species at the ecosystem level. Moreover, the study shows that the REP provides the best chance for upscaling leaf level information on species discrimination to the canopy scale. Since leaf chlorophyll content was not measured in this study, it remains to be explained why the REP showed a higher ability to discriminate species at both scales than ratio-based vegetation indices.

#### 5. CONCLUSIONS

This study, although limited in data set, allowed an evaluation of the effects of upscaling reflectance measurements from individual leaves to the top-of-canopy on hyperspectral indices. The conclusion from this study is that spectral indices are generally sensitive to the change in scale of spectral measurement from the leaf to the canopy. However, among the spectral indices studied, the linear extrapolation I REP is least sensitive to the change in measurement scale.

Differences between leaf and canopy indices appear to affect the ability of the spectral indices to differentiate species at both levels. The canopy indices were better discriminators of species than the leaf indices. This is essential for air- or spaceborne remote sensing of species assemblages. The PRI showed the highest potential to discriminate species at the canopy scale. But the REP in general showed the highest potential to discriminate the same species pairs at both scales. Hyperspectral indices might provide new possibilities of differentiating plant species or communities.

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