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Towards estimation of canopy foliar biomass with spectral reflectance measurements

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ABSTRACT

Canopy foliar biomass, defined as the product of leaf dry matter content and leaf area index, is an important measurement for global biogeochemical cycles. This study explores the potential for retrieving foliar biomass in green canopies using a spectral index, the Normalized Dry Matter Index (NDMI). This narrow-band index is based on absorption at the C–H bond stretch overtone and is correlated with leaf dry matter content in fresh green leaves. PROSPECT and SAIL model simulations suggest that the NDMI at the canopy scale is able to minimize the effects of leaf thickness and leaf water content and to maximize sensitivity to variation in canopy foliar biomass. The simulation outputs were analyzed with an ANOVA, and 87% of the variation in the NDMI is explained by leaf dry matter content. The NDMI was linearly related to foliar biomass (g cm^{-2}) from model simulations ($R^2 = 0.97$). The NDMI calculated from spectral reflectances for one to four stacked leaves was also correlated with total leaf biomass ($R^2 = 0.59$). These results suggest that it may be possible to determine foliar biomass from airborne and satellite-borne imaging spectrometers, such as NASA's HyspIRI mission.

1. Introduction

Current methods for estimating leaf dry matter content (C_m, g cm^{-2}) from remotely sensed data are based on inversion of leaf and canopy radiative transfer simulation models (Jacquemoud et al., 2009). Canopy dry matter content, also known as foliar biomass (FB, g cm^{-2}), is the quantity of dry matter per unit area of ground surface:

$$FB = LAI \bullet C_m \tag{1}$$

where LAI is the leaf area index. With imaging spectrometer data, small absorption features may be quantified with spectral indices in order to extract canopy information, which may be obscured by liquid water in fresh leaves (Gao & Goetz, 1994).

Differentiation between foliar biomass and leaf area index is important because within the canopy of a single tree, there are differences in C_m (Cavaleri et al., 2010; Sack et al., 2006; Tobin et al., 2006), which affect photosynthetic rates, respiration rates and nutrient contents (Reich et al., 1999). In addition, foliar biomass is an important parameter in the estimation of fuel moisture content, the amount of water per unit of dry matter, which is critical to both fire ignition and propagation, and thus may be used to predict the occurrence and spread of wildfire (Burgan & Rothermel, 1984; Riaño et al., 2005; Roberts et al., 2006; Yebra et al., 2008). Therefore, efficient and accurate detection of the temporal dynamics and spatial variations of foliar biomass would help monitor key properties and processes in different ecosystems.

Most recently, the Normalized Dry Matter Index (NDMI) was proposed by Wang et al. (in press) for the remote sensing of C_m for fresh green leaves. By examining the relationship between the spectral reflectance and dry matter content of fresh leaves across a wide range of species, a narrow-band, normalized index combining two distinct wavebands centered at 1649 nm and 1722 nm was found to best estimate the dry matter content in green leaves. The NDMI is defined as:

$$NDMI = (R_{1649} - R_{1722}) / (R_{1649} + R_{1722}) \tag{2}$$

where R is the spectral reflectance at wavelengths of 1649 and 1722 nm, respectively (Wang et al., in press). This narrow-band index is based on absorption at the C–H bond stretch overtone at 1722 nm; C–H bonds are found in practically all leaf biochemical constituents. Using the LOPEX data set (Hosgood et al., 1995), the NDMI is more highly correlated with C_m than with either leaf lignin or cellulose contents (Wang et al., 2011).

The ability of the NDMI to estimate foliar C_m in fresh green leaves is enhanced using the residuals between the measured leaf reflectance and the predicted reflectance based on leaf water content (Wang et al., 2011). The 1649 and 1722 nm wavebands used in the NDMI have been found to correspond closely with the highest and lowest residuals, respectively. At the canopy scale, there may be sufficient total dry matter content to detect differences in reflectance

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at 1649 and 1722 nm, without making corrections for canopy water content.

In this study, we extend our previous work by using the NDMI to estimate foliar dry matter content at the canopy level. Sensitivity analyses of the changes in leaf dry matter content and other canopy parameters on the NDMI were conducted using PROSPECT and SAIL model simulations. Spectral reflectances of stacked leaves from laboratory measurements were used to test predictions from the PROSPECT and SAIL model simulations.

2. Data and methods

2.1. Leaf measurements

We assume that spectral reflectances from stacked leaves could be used to simulate the reflectance from leaves in a canopy (Blackburn, 1999; Miller et al., 1992; Stone et al., 2001). The laboratory datasets were obtained in the summers of 2003 and 2010, consisting of 20 leaf samples from small-leaf linden (*Tilia cordata*), 20 from black oak (*Quercus velutina*), 18 from corn (*Zea mays*) and 21 from soybean (*Glycine max*). Leaf samples were collected from the field, placed in plastic bags, stored in a cooler, and transported to the laboratory for measurement. First, spectral reflectances and transmittances of single leaves were measured using a LiCor Inc. (Lincoln, Nebraska, United States) LI1800-12 integrating sphere and an ASD (Analytical Spectral Devices, Inc., Boulder, Colorado, United States) FieldSpec Pro FR spectroradiometer. Then, 2 to 4 leaves were stacked, one on top of the other, and the stack was placed at the sample port of the integrating sphere with the adaxial side of the leaves in front. The LAI was simply taken to be equal to the number of layers of leaves in the stack. Leaf fresh weight, dry weight area, and area were measured for each leaf to calculate leaf C_m, which was then summed for a leaf stack.

2.2. PROSPECT and SAIL model simulations

As in Wang et al. (in press), we used PROSPECT version 4 (Feret et al., 2008; Jacquemoud & Baret, 1990; Jacquemoud et al., 2009) to calculate leaf reflectance and transmittance from 400 to 2500 nm with a 1-nm step as a function of a leaf structure parameter (N), total leaf chlorophyll a and b content (C_{ab}), leaf water content (C_w), and leaf dry matter content (C_m). C_m values ranged from 0.005 to 0.030 g cm^{-2} with an increment of 0.005 g cm^{-2}, C_w values ranged from 0.004 to 0.034 g cm^{-2} with an increment of 0.01 g cm^{-2}, and the leaf parameter N (number of parallel plates) ranged from 1 to 4 with an increment of 1 (Table 1). Because the influence of chlorophylls a and b is limited to visible wavelengths, C_{ab} was set at 40 μg cm^{-2} for all PROSPECT simulations.

Table 1
Input parameters for PROSPECT and SAIL model simulations.

Model	Parameters	Values
PROSPECT	Leaf structure parameter (N)	1, 2, 3, and 4
	Chlorophyll content (C_{ab}, μg cm^{-2})	40
	Water content (C_w, g cm^{-2})	0.004–0.034
	Dry matter content (C_m, g cm^{-2})	0.005–0.030
SAIL	Leaf area index (LAI)	1, 1.5, 2, and 3
	Leaf angle distribution (LAD)	Erectophile, planophile, and spherical
	Fraction of direct solar irradiance	0.8
	Solar declination	0°
	Latitude	36°
	View zenith angle	Nadir
	View azimuth angle	Not applicable
	Time of day (hour)	10:00

The Scattering by Arbitrarily Inclined Leaves (SAIL) model (Verhoef, 1984) was used to simulate canopy spectral reflectance as a function of leaf reflectance and transmittance, soil background reflectance, leaf area index (LAI), and leaf angle distribution (LAD). Three different soils: Barnes, Codorus and Othello (Fig. 1A) were selected in order to span the range of reflectance expected in most agricultural fields (Daughtry et al., 1997). The soil reflectance spectra show differences in brightness, but no absorption features from 1600 to 1800 nm wavelength (Fig. 1B).

Four LAI levels (1.0, 1.5, 2.0, and 3.0) and three LAD (erectophile, plannophile and spherical) were used. The other SAIL model parameters are summarized in Table 1.

2.3. Description of approaches

In order to quantify the relative influence of each leaf variable on the leaf reflectance, the difference of spectra reflectance is obtained using the PROSPECT simulations by varying each variable separately from the lowest to highest values listed in Table 1, while keeping other parameters fixed at median values. Median values of $C_m = 0.01$ g cm^{-2}, and $C_w = 0.014$ g cm^{-2}, and $N = 2$ were used as the basis for comparisons. The effect of dry matter content on leaf reflectance between 1600 and 1800 nm is then calculated using simulations with C_m from 0.005 to 0.030 g cm^{-2} and with fixed values of other parameters ($C_{ab} = 40$ μg cm^{-2}, $C_w = 0.014$ g cm^{-2}, and $N = 2$).

At the canopy level, SAIL model simulations and laboratory measurements of stacked leaves were used to examine potential LAI effects on the canopy NDMI. The multi-way Analysis of Variance

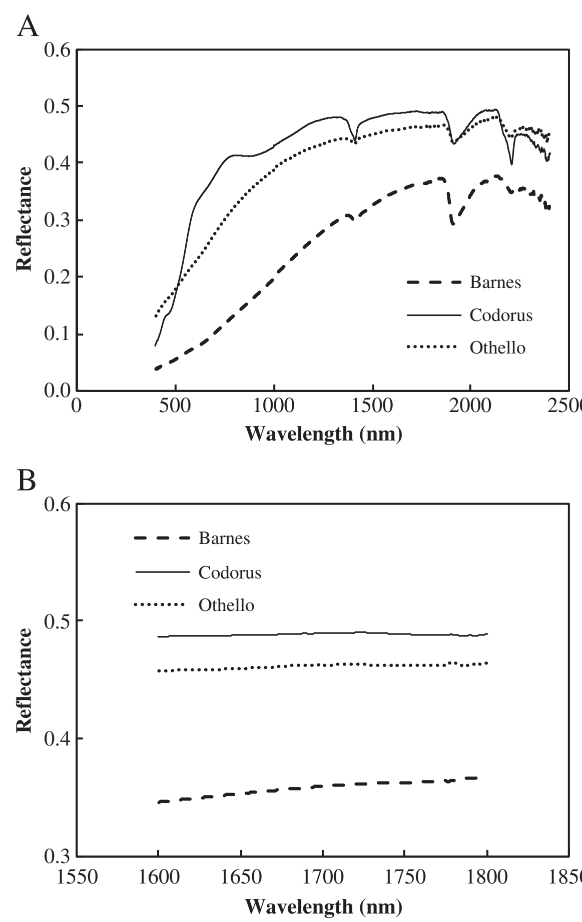

Fig. 1. (A) Reflectance spectra of three different dry soils, and (B) Expansion of panel (A) for 1600 and 1800 nm wavelength.

(ANOVA) using the "anovan" function in Matlab (The Mathworks, Natick, MA, USA) was then conducted to quantify the effect of each variable on the simulated NDMI at the canopy level derived from PROSPECT-SAIL model simulations. The NDMI was calculated using Eq. (2). Total foliar biomass was estimated as the product of LAI and leaf C_m according to Eq. (1).

3. Results

3.1. Sensitivity analysis of leaf reflectance

Fig. 2 displays the variations of the reflectance spectrum over 1600–1800 nm due to changes of C_m and the combined effects of N and C_w. The effects of C_m and the combination of N and C_w factors were obtained as the reflectance difference by varying each variable separately from the lowest to highest values listed in Table 1 at a given time, while the other parameters were fixed at median values. The dashed lines denote the location of the 1649 nm and 1722 nm wavelengths used in the NDMI. It is observed that 1722 nm is the wavelength which had the strongest sensitivity to C_m and the least sensitivity to the combination of N and C_w, while the 1649 nm wavelength exhibited lower C_m effects and greater effects of the other parameters.

Both the model simulations and laboratory measurements revealed the same characteristics regarding the leaf spectra over 1600–1800 nm. For a given set of input parameters, the model simulations showed that leaves with the lowest dry matter content had the highest reflectance. An increase of dry matter content decreased the reflectance (Fig. 3A). The reflectance difference between 1649 and 1722 nm ranged from 0.02 to 0.04 for the lowest to highest dry matter contents. The NDMI values ranged from 0.02 to 0.09.

The soybean leaf had lower dry matter content and had higher reflectance compared to the linden and oak leaves (Fig. 3B), while the corn leaf, which had the median value of C_m, had lowest reflectance in this case. The reflectance difference between 1649 and 1722 nm ranged from 0.009 to 0.03, and the NDMI values ranged from 0.01 to 0.04 from soybean to linden.

3.2. Sensitivity analysis of canopy reflectance

Canopy reflectance spectra of PROSPECT-SAIL simulations with different levels of LAI, and of laboratory measurements of linden spectra for 1 to 4 stacked leaves are shown in Fig. 4A and B, respectively.

Typically, the SAIL model simulations indicated that reflectances in the shortwave infrared decreased with greater LAI (Fig. 4A). The reflectance difference between 1649 and 1722 nm was 0.007 for an LAI = 1 and 0.01 for an LAI = 3. For the laboratory measurements however, the background reflectance behind the stacked leaves was about zero, so the shortwave reflectances increased with the number of leaf layers (Fig. 4B). The reflectance differences between 1649 and 1722 nm were 0.02 and 0.05 for one and four leaves, respectively.

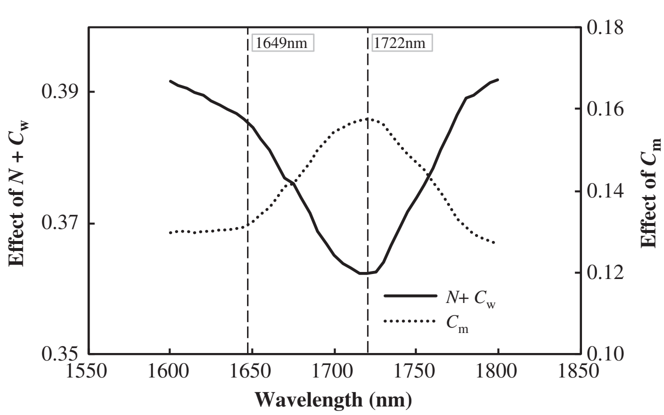

Fig. 2. Effects of dry matter content (C_m) and the combination of the leaf structural parameter (N) and the leaf water content (C_w) on simulated leaf reflectance by using lowest and highest values of each parameter separately (Table 1).

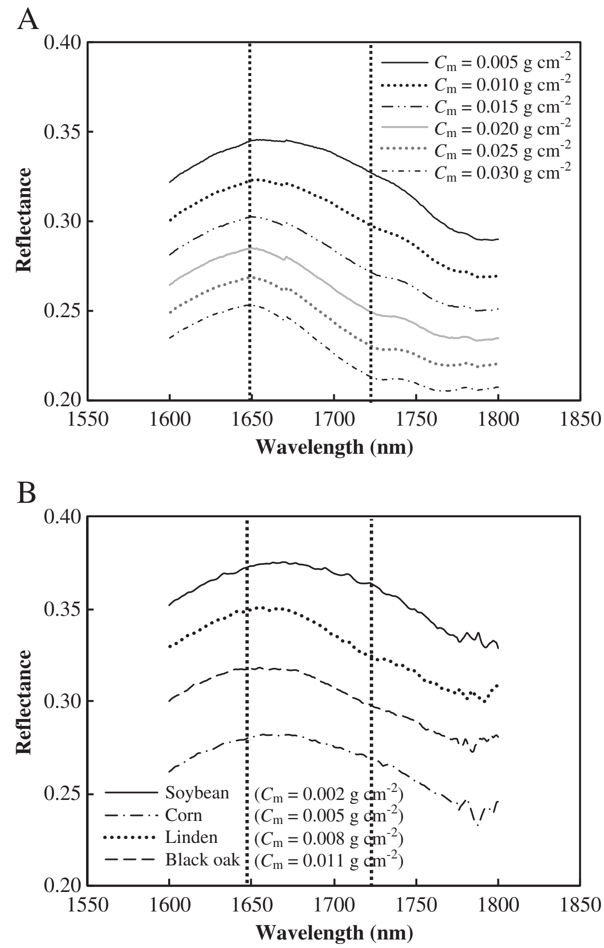

Fig. 3. (A) PROSPECT simulations of leaf reflectance spectra with C_m from 0.005 to 0.030 g cm^{-2}, $N = 2$, $C_{ab} = 40.0$ μg cm^{-2}, and $C_w = 0.014$ g cm^{-2}, and (B) soybean, corn, linden, and black oak leaf reflectance spectra with measured C_m values of 0.002, 0.005, 0.008, and 0.011 g cm^{-2}, respectively.

3.3. Sensitivity analysis of the canopy NDMI

The results of the ANOVA analysis showed that, at the canopy level, C_m explained a significant proportion (57.4%) of the NDMI variance, followed by LAI, which accounted for 26.3% of the NDMI variance (Table 2). The NDMI was more strongly influenced by canopy FB, defined as the product of LAI and leaf C_m, which explained 86.7% of the NDMI variance (Table 3). The contribution by LAD was significant and accounted for about 2% of the NDMI variation (Tables 2 and 3). N and C_w were also significant sources of variation, but had little influence on the NDMI. The small effect of different soil backgrounds on the NDMI could have been caused by: (1) the SAIL model assumption of a continuous canopy, or (2) the small spectral variation from 1500 to 1800 nm in the three soils. These simulations suggested that the NDMI at the canopy level was able to minimize the effects of some canopy variables, and was able to maximize sensitivity to variation in foliar biomass. However, vegetation canopies are often discontinuous, creating shadows and exposing soil (Huemmrich, 2001), so more research is required using airborne imaging spectrometers to test the NDMI at the canopy scale.

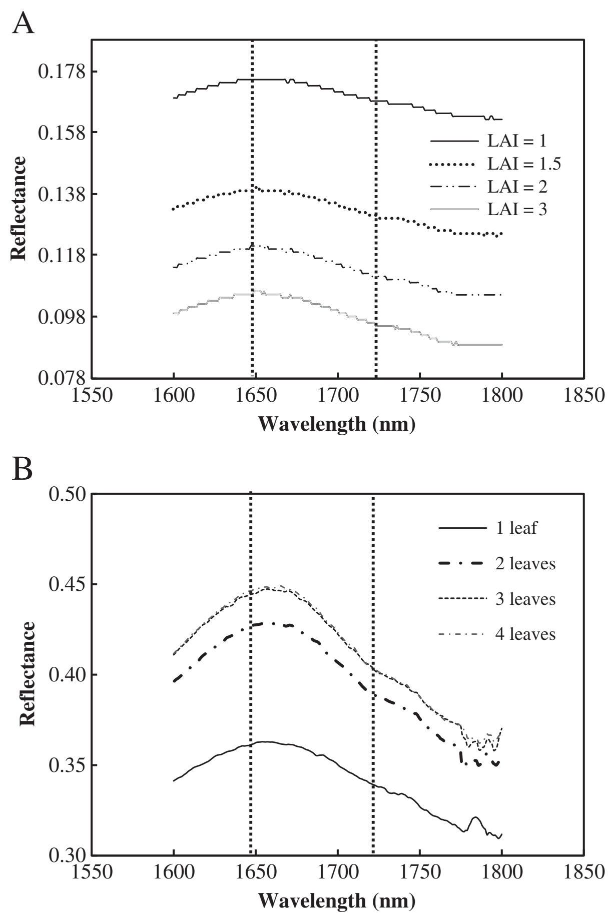

Fig. 4. (A) SAIL model simulations for various LAI with C_m of 0.015 g cm^{-2} and a spherical LAD, and (B) Reflectance spectra for stacked leaves of linden.

3.4. NDMI and foliar biomass

For each level of LAI, linear relationships were observed between NDMI and leaf C_m (Fig. 5). From these simulations, foliar biomass and NDMI were also linearly related (Fig. 6).

For the laboratory experiments, the slope of the regression line between FB and NDMI was 0.64 (Fig. 7), which was considerably below the slope from the SAIL model simulations (Fig. 6). It was found that the differences between the data and regression line increased with foliar biomass for linden and oak samples, which have higher dry matter content compared to corn and soybean. Furthermore, correction for foliar water content, as developed by Wang et al. (2011), did not improve the R^2 between NDMI and foliar biomass (data not shown), which indicated that the correction for water content may be only required to distinguish very small differences at the canopy scale. The fact that the PROSPECT-SAIL simulated dataset performed better than laboratory measurements might be a result that models always represent a reasonable simplification of complex phenomena.

Table 2
Percent of variation in the simulated Normalized Dry Matter Index (NDMI) associated with C_m, N, C_w, LAI, LAD and soil background.

	C_m	N	C_w	LAI	LAD	Soil	Error	Total
Source of variation (%)	57.4	0.8	0.6	26.3	2.1	0.01	7.1	94.3
Degrees of freedom	5	4	4	3	2	3	154	
P-value	<0.001	<0.001	<0.001	<0.001	<0.001	0.97		

Table 3
Percent of variation in simulated NDMI associated with foliar biomass (FB, g cm^{-2})[a], N, C_w, LAD and soil background.

	FB	N	C_w	LAD	Soil	Error	Total
Source of variation (%)	86.7	0.8	0.6	2.1	0.01	4.1	94.3
Degrees of freedom	14	4	4	2	3	148	
P-value	<0.001	<0.001	<0.001	<0.001	0.97		

[a]FB = LAI • leaf C_m.

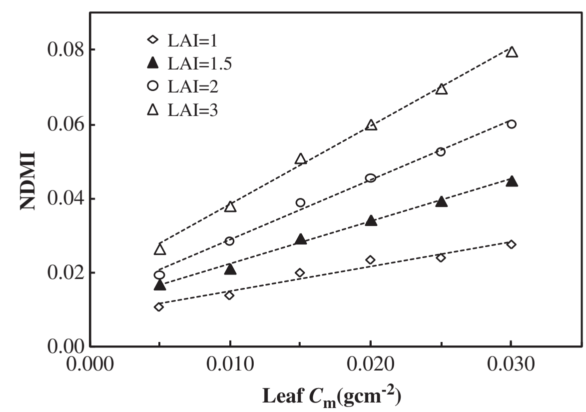

Fig. 5. Normalized Dry Matter Index (NDMI) versus leaf C_m for various LAI from SAIL model simulations.

Table 4 summarizes the statistical analyses of the regressions between NDMI and foliar biomass, including the coefficient of determination (R^2), probability that the regression slope is zero (P-value), and the standard error of the estimate. The results demonstrated that there was good correlation between NDMI and foliar biomass, with R^2 values of 0.99 and 0.59 for simulations and data, respectively. Although the ability of the NDMI to estimate foliar biomass from laboratory experiments was low compared with model simulations, the NDMI was still sensitive to foliar biomass.

4. Conclusions

This study explored potential for retrieving foliar biomass for a range of species by using the newly proposed index, the Normalized Dry Matter Index (NDMI). Earlier studies using reflectance spectra from data and PROSPECT model simulations (Wang et al., in press, 2011) showed that foliar water did not completely obscure the absorption feature of the C–H bond stretch overtone at 1722 nm, and that the NDMI was strongly correlated with leaf dry matter content in fresh green leaves. The stacked-leaf data and PROSPECT-SAIL model

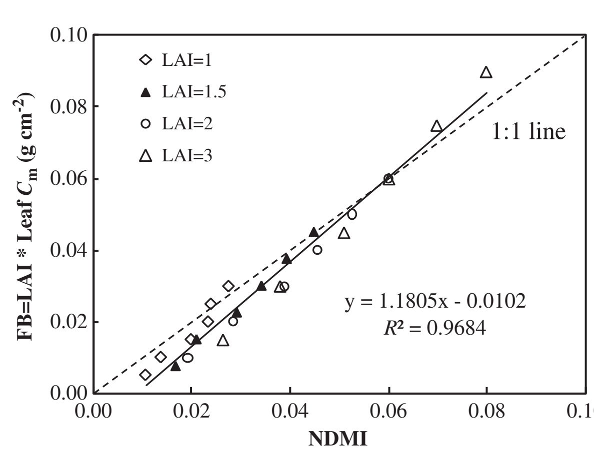

Fig. 6. NDMI versus foliar biomass from SAIL model simulations.

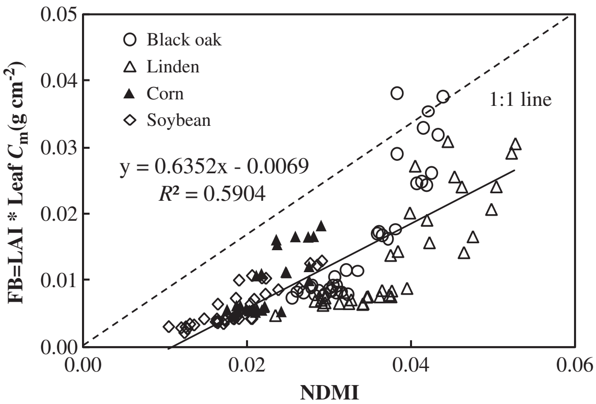

Fig. 7. NDMI versus foliar biomass from reflectance spectra of stacked leaves.

Table 4
Statistics from regressions between foliar biomass and NDMI.

	Slope	R^2	*P*-value	Standard error of estimate g cm^{-2})
PROSPECT-SAIL	1.18	0.97	<0.001	0.0033
Laboratory data	0.64	0.59	<0.001	0.0051

simulations in this study showed that, as expected, LAI had a significant influence on the NDMI at the canopy level. Though some other canopy variables had an influence on the NDMI, the ANOVA analyses showed that the foliar biomass (calculated as the product of C_m and LAI) explained most of the variation in the NDMI. However, these results need to be tested with imaging spectrometer data acquired over a variety of land cover types and with more-realistic canopy simulation models.

These results suggest that the NDMI determined from future NASA missions, such as HyspIRI, could be used to estimate foliar biomass over large areas, and then combined with LAI data products from other sensors to estimate average leaf properties for that area.

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