Vegetation Index to estimate chlorophyll content from multispectral remote sensing data

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Abstract
Normalized Area Vegetation Index (NAVI) is proposed for estimating chlorophyll content (Chl) from remote sensing data. NAVI is obtained using only two bands on red and near infrared regions of the spectrum. It is derived from the hyperspectral NAOC index, which was initially developed for the Chl mapping. For determining the relationship between NAOC and NAVI we used 257 spectra obtained with the Proba/CHRIS sensor during the SPARC-2003/2004 campaigns in Barrax, Spain. NAVI was estimated with different pairs of bands and a correlation matrix with NAOC index was obtained. Results show very good linear correlation coefficients, with values ≥ 0.97. NAVI allows to estimate leaf Chl from satellite data with medium spectral resolution.

Keywords: Chlorophyll, remote sensing, Vegetation Index, NAOC index, leaf reflectance.

Introduction
Vegetation monitoring is a relevant topic in the science and applications of remote sensing. Several satellite missions have been launched with the specific objective of monitoring changes in the vegetation cover over the Earth surface [Delegido et al., 2011]. In this sense, recently much attention has been paid to the development of methods to derive spatially distributed maps of Chlorophyll content (Chl) in vegetation using remote sensing techniques [Delegido et al., 2010]. Leaf Chl is one of the most important vegetation parameters. It is of great interest in several fields of study such as precision agriculture, since leaf Chl is an indicator of photosynthetic activity [Lichtenthaler, 1987], and also can be used to indirectly estimate soil nitrogen content or to define optimum fertilization [Blackmer et al., 1996; Ustin et al., 2004]. In addition, knowledge of Chl on a regional and global scale are important in ecology [Cramer et al., 1999], in studies on climate change, and in the study of plant stress [Flexas et al., 2000], amongst others applications. The study of leaf reflectance provides information about Chl and other agronomic variables.
such as leaf area, crop cover, biomass, crop type, nutrient status, and yield [Jordan, 1969; Pearson and Miller, 1972]. Thus, the use of spectral data from satellites allows the study of these biophysical variables on a regional-scale. Several multispectral vegetation indices have been proposed for the general study of vegetation status, as the Ratio Vegetation Index (RVI) [Hatfield et al., 2008] and the Normalized Difference Vegetation Index (NDVI) [Rouse et al., 1974], which have proved their predictive power in assessing Chl and other leaf pigments. In addition, some specific indices have been developed for the study of Chl based on leaf reflectance [Daughtry et al., 2000; Sims, 2002; Dash and Curran, 2004; Gitelson et al., 2005; Haboudane et al., 2008].

Due to the recent development of hyperspectral sensors, which acquire a quasi-continuous reflectance spectrum, new and more robust Chl detection methods and indices have been, and are being, developed. One such example is the NAOC (Normalized Area Over reflectance Curve) index, which is a spectral index based on the normalized integral of many spectral bands initially developed for the Chl mapping of heterogeneous cropping areas [Delegido et al., 2010]. The NAOC index was validated with experimental Chl data from a wide variety of vegetation types including grass, crops and fruit trees [Delegido et al., 2010, 2011]. According to Delegido et al. [2011], the experimental relationship between NAOC and Chl is given by:

\[
Chl = 97.87 \times NAOC - 2.77 \quad [1]
\]

where Chl is in μg/cm². A recent study comparing the predictive power of the NAOC against 32 established indices sensitive to Chl found that the NAOC was one of the most accurate [Verrelst et al., 2012].

While the hyperspectral indices have a greater sensibility that multispectral indices for estimating biophysical variables, such as leaf Chl, these last can be applied with the main satellite sensors. Then, although the NAOC index has a good accuracy for estimating Chl, its use with satellite images is not always possible. Therefore, in this work we propose a new multispectral vegetation index, derived of NAOC index, for estimating Leaf Chl from different satellite missions. The objective focuses on consider the great sensitivity of NAOC index for estimating leaf Chl and obtain a simplified expression without need using hyperspectral sensors. Here, the relationship between the proposed vegetation index and the NAOC formulation is discussed.

**Model**

The NAOC index is defined as:

\[
NAOC = 1 - \frac{\int_a^b \rho_{\lambda} d\lambda}{\rho_b(b-a)} \quad [2]
\]

where \( \rho \) is the reflectance, \( \lambda \) is the effective wavelength, and ‘\( a \)’ and ‘\( b \)’ are the integration limits. The best results from \( NAOC \) were obtained by setting the integration limits to \( a = 643 \text{ nm} \) and \( b = 795 \text{ nm} \) (\( r = 0.91 \)) [Delegido et al., 2010]. For hyperspectral data, the
integral of quasi-continuous reflectance spectrum is obtained by sum of rectangles under reflectance curve, using the trapezoidal rule. Thus, $NAOC$ index is calculated as:

$$NAOC = \frac{\rho_b(b-a) - \left[ \rho_a \frac{\Delta \lambda_a}{2} + \sum_{i=a+1}^{b-1} \rho_i \Delta \lambda_i + \rho_b \frac{\Delta \lambda_b}{2} \right]}{\rho_b(b-a)}$$ \[3\]

where $\Delta \lambda_i$ is the band spacing for the band $i = a, a+1, ..., b-1, b$. The numerator represents the Area Over reflectance Curve ($AOC$) and $\rho_b(b-a)$ corresponds to area of the rectangle between the integration limits (Fig. 1).

If just the two spectral bands on the integration limits are considered, $AOC$ can be approximated as:

$$AOC \approx \frac{\rho_b - \rho_a}{2} (b - a)$$ \[4\]

and thus, $NAOC$ index is estimated as:

$$NAOC \approx \frac{1}{2} \left( 1 - \frac{\rho_a}{\rho_b} \right)$$ \[5\]

Figure 1 shows the typical reflectance curves of a green crop and a bare soil. The dark blue area corresponds to the $AOC$, while which the area of dotted triangle corresponds to its approximation given by Equation 4.

Considering only the term between parentheses defined in Equation 5, here we propose a new vegetation index called $NAVI$ (Normalized Area Vegetation Index), and it is expressed as:
where $\lambda_1$ and $\lambda_2$ are the center wavelengths of the red and infrared bands considered, respectively. Also $NAVI$ can be expressed as $(1 - RVI)$, where the $RVI$ has been widely used for estimating Leaf Chl and other biophysical variables. The proposed index represents the area of the rectangle $(\rho_{\lambda_2} - \rho_{\lambda_1})(\lambda_2 - \lambda_1)$ divided by the area of the rectangle between the integration limits $\rho_{\lambda_2} (\lambda_2 - \lambda_1)$, to obtain area values normalized to 1 (Fig. 2). Thus, the $NAVI$ varies between 0 and 1, increasing with higher Chl.

Figure 2 - Scheme for estimating $NAVI$ using the red and infrared bands of a typical multispectral satellite sensor.

**Materials and methods**

In this study, we used spectra of different crop plots obtained with the CHRIS (Compact High Resolution Imaging Spectrometer) sensor during the SPARC-2003 and SPARC-2004 campaigns in Barrax, La Mancha, Spain [Delegido et al., 2010].

CHRIS is a sensor onboard Proba platform which provides high spatial resolution hyperspectral/multiangular data, acquiring five consecutive images from five different view zenith angles in one single satellite overpass. CHRIS measures over the visible/near-infrared (V/NIR) spectra from 400 to 1050 nm. It can operate in different modes, balancing the number of spectral bands, size of the covered area, and spatial resolution. CHRIS was operated in Mode 1 for the campaign days (62 bands with bandwidth from 5.6 to 33 nm depending on the wavelength and a spatial resolution of 34 m at nadir) [Delegido et al., 2010; Verrelst et al., 2012]. The images were geometrically corrected [Alonso and Moreno, 2005], followed by atmospheric correction according to the method proposed in Guanter et al. [2005].

We selected all Proba/CHRIS spectra obtained at nadir (0°) from the crop plots (these same data were used in the development of $NAOC$ index). In total, the present study included 257 spectra of alfalfa, corn, garlic, onion, papaver, potato, sugar beet, sunflower, vine and wheat. We calculated the area under the curve between bands located on $a = 643$ nm and $b = 795$ nm for each Proba/CHRIS spectrum, followed by calculation of the $NAOC$ values.
Leaf Chl was measured for crop sites at the time of the satellite overpass. However, Chl measurements were not used in this study. Since the relationship between leaf Chl measurements and NAOC index was previously validated for a wide variety of vegetation types, in this work we focus on the study of the relationship between the NAOC and NAVI values. The present study has two aims: 1) to evaluate the relationship between NAOC and NAVI values, considering \( \lambda_1 = a = 643 \) nm and \( \lambda_2 = b = 795 \) nm; 2) to evaluate the same relationship but varying the pair of bands used to calculate the NAVI, according with scheme showed in Figure 2.

**Results and discussion**

NAOC is graphically represented versus NAVI in Figure 3, where \( \lambda_1 = a = 643 \) nm and \( \lambda_2 = b = 795 \) nm are considered. Results show a linear distribution, with a very good correlation coefficient \((r = 0.992)\). It proves that is possible to calculate NAOC index with only two spectral bands, with similar results to those obtained with the Proba/CHRIS spectra. Furthermore, the relationship found is consistent with the approximation defined in Equation 5.

![Figure 3 - NAOC index versus NAVI values obtained between 643 and 795 nm.](image)

However, most common satellites used not have bands in the integration limits “a” and “b”. Thus, we obtained a correlation matrix (Tab. 1) between NAOC index and NAVI depending of the \( \lambda_1 \) and \( \lambda_2 \) bands, where \( \lambda_1 \) varies between band 18 (605 nm) and band 32 (718 nm) and \( \lambda_2 \) between band 33 (725 nm) and band 51 (880 nm) of the Proba/CHRIS sensor. Table 1 shows very good correlation coefficients in all cases, being \( r \geq 0.97 \) for the \( \lambda_1 \) and \( \lambda_2 \) bands on red and near infrared regions, respectively. These results are very important, confirm that NAOC index can be calculated with good accuracy using two spectral bands for obtaining Chl from multispectral satellite data.

Table 2 shows the relationships between NAOC and NAVI considering \( \lambda_1 \) and \( \lambda_2 \) in the center wavelengths of red and infrared bands for different satellite missions, where \( \alpha \) and \( \beta \) are the intercept and slope of the linear regression and \( r \) is the correlation coefficient. From these results, we observed that \( \alpha \) varies between -0.01 and -0.05 and \( \beta \) varies between 0.55 and 0.59 respectively, and their values show relation with the wavelengths considered \((\lambda_1 \) and \( \lambda_2 \)).
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Table 1 - Linear correlation coefficients, $r$, between NAOC index (considering integration limits proposed by Delegido et al., 2010) and NAVI depending of the $\lambda_1$ and $\lambda_2$ bands (in nm).

| $\lambda_1$ (nm) | $\lambda_2$ (nm) | $r$ |
|------------------|------------------|-----|
| 725              | 731              | 0.977 |
| 738              | 745              | 0.984 |
| 751              | 758              | 0.991 |
| 765              | 773              | 0.993 |
| 780              | 788              | 0.993 |
| 795              | 803              | 0.993 |
| 811              | 831              | 0.993 |
| 844              | 853              | 0.993 |
| 862              | 870              | 0.993 |
| 880              |                  | 0.993 |

Therefore, considering $\lambda_1$ between 634 and 683 nm and $\lambda_2$ between 810 and 880 nm, we propose obtain $\alpha$ and $\beta$ values by means the following equations:

$$
\alpha = \alpha_0 + \alpha_1 \lambda_1 + \alpha_2 \lambda_2 \quad [7]
$$

$$
\beta = \beta_0 + \beta_1 \lambda_1 + \beta_2 \lambda_2 \quad [8]
$$

where $\alpha_0 = (-0.58 \pm 0.04)$, $\alpha_1 = (0.00126 \pm 0.00004)$ nm$^{-1}$, $\alpha_2 = (-0.00034 \pm 0.00003)$ nm$^{-1}$, $\beta_0 = (1.27 \pm 0.04)$, $\beta_1 = (-0.00152 \pm 0.00005)$ nm$^{-1}$ and $\beta_2 = (0.00036 \pm 0.00004)$ nm$^{-1}$, with $r = 0.983$ in both multiple linear regressions. In this sense, from Eqs. 7 and 8 can be obtain the relationship between NAVI and NAOC index for any satellite (in addition to those described in Tab. 2). Thus, is possible combine these kind of relationships with Equation 1 to estimate Chl from satellite data. For example, leaf Chl can be obtained from Landsat 8 data as:

Table 2 - Relationships between NAOC index and NAVI for different widely used satellite missions.

| Satellite/Sensor | $\lambda_1$ (nm) | $\lambda_2$ (nm) | Linear regression |
|------------------|------------------|------------------|------------------|
|                  |                  |                  | $\alpha$ | $\beta$ | $r$ |
| TERRA-AQUA/MODIS | 646              | 856              | -0.046 | 0.589 | 0.991 |
| Landsat 7/ETM+   | 662              | 835              | -0.019 | 0.555 | 0.990 |
| Landsat 8/OLI    | 655              | 865              | -0.047 | 0.588 | 0.990 |
| TERRA/ASTER      | 660              | 810              | -0.011 | 0.548 | 0.990 |
| SPOT 4/HRVIR     | 655              | 830              | -0.030 | 0.570 | 0.991 |
| SPOT 5/HRG       | 645              | 835              | -0.043 | 0.588 | 0.992 |

Therefore, considering $\lambda_1$ between 634 and 683 nm and $\lambda_2$ between 810 and 880 nm, we propose obtain $\alpha$ and $\beta$ values by means the following equations:

$$
\alpha = \alpha_0 + \alpha_1 \lambda_1 + \alpha_2 \lambda_2 \quad [7]
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where $\alpha_0 = (-0.58 \pm 0.04)$, $\alpha_1 = (0.00126 \pm 0.00004)$ nm$^{-1}$, $\alpha_2 = (-0.00034 \pm 0.00003)$ nm$^{-1}$, $\beta_0 = (1.27 \pm 0.04)$, $\beta_1 = (-0.00152 \pm 0.00005)$ nm$^{-1}$ and $\beta_2 = (0.00036 \pm 0.00004)$ nm$^{-1}$, with $r = 0.983$ in both multiple linear regressions. In this sense, from Eqs. 7 and 8 can be obtain the relationship between NAVI and NAOC index for any satellite (in addition to those described in Tab. 2). Thus, is possible combine these kind of relationships with Equation 1 to estimate Chl from satellite data. For example, leaf Chl can be obtained from Landsat 8 data as:
\[ Chl = 57.55 \text{NAVI} - 7.37 \] [9]

where the red and near infrared bands of Landsat 8/OLI sensor are used for estimating NAVI. In summary, in this work we proved that NAOC index can be calculated with good accuracy using only two bands, when hyperspectral data are not available. Then, from the NAOC formulation, a new index called NAVI was proposed. The relationship between NAOC and NAVI was proved, considering different pairs of bands, which justifies the simplification proposed for estimating leaf Chl using only two spectral bands.

In future studies we will studying the relationship between NAVI and Chl measurements using spectroradiometers, multispectral satellite data (e.g. Landsat 8/OLI data) and handheld optical chlorophyll meters.

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