AN EVALUATION OF HJ-CCD BROADBAND VEGTATION INDICES FOR LEAF CHLOROPHYLL CONTENT ESTIMATION

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ABSTRACT

Leaf chlorophyll content is one of the most important biochemical variables for crop physiological status assessment, crop biomass estimation and crop yield prediction in precision agriculture. Vegetation indices were considered effective for chlorophyll content estimation. Although hyperspectral reflectance is proven to be better than multispectral reflectance for leaf chlorophyll content retrieval, the scarcity of available data from satellite hyperspectral sensors limited its application. It is highly desirable to develop methods for leaf chlorophyll content estimation based on broadband satellite data. In this study, nine broad band vegetation indices were tested for their potential for leaf chlorophyll content estimation. The PROSAIL model was used for sensitivity analysis of the selected vegetation indices. The results of the sensitivity analysis showed that both the chlorophyll vegetation index (CVI) and the triangular greenness index (TGI) had better performance in leaf chlorophyll content estimation. Both CVI and TGI were less sensitive to leaf area index (LAI) and more sensitive to leaf chlorophyll content than the other vegetation indices. Validation based on field measurements showed that CVI (R^2=0.50, P<0.001) and TGI (R^2=0.46, P<0.001) were the most appropriate indices for leaf chlorophyll content estimation. These results demonstrate the possibilities for retrieving leaf chlorophyll content using broadband satellite data in precision agriculture. The preliminary results of this study also shed light on future improvement of vegetation indices for leaf chlorophyll content estimation.

Keywords: leaf chlorophyll content, broadband vegetation indices, sensitive analysis, precision agriculture

INTRODUCTION

Leaf chlorophyll content is a key biochemical variables for crop physiological status assessment(Daughtry, Walthall, et al., 2000), crop biomass estimation and crop yield prediction(Peng and Gitelson, 2012, Peng, Gitelson, et al., 2011) in precision agriculture. Compared with traditional ground method, the method based on satellite data is more suitable for obtaining leaf chlorophyll content over a large area and in real-time. Over the past few years, two categories of methods have been developed and validated for assessing chlorophyll content. One is the inversion of canopy reflectance models, such as the PROSAIL(Botha, Leblon, et al., 2007, Jacquemoud, Verhoef, et al., 2009), ACRM model(Houborg, Anderson, et al., 2009, Houborg and Boegh, 2008), 5scale model(Zhang, Chen, et al., 2008). The other one is the empirical model based on spectral indices derived from ground-based or space-based canopy reflectance (Clevers and Gitelson, 2013, Daughtry, Walthall, et al., 2000, Gitelson, Vina, et al., 2005, Hunt, Daughtry, et al., 2011, Vincini, Frazzi, et al., 2008, Zarco-Tejada, Miller, et al., 2004). The methods based on vegetation indices are proven to be effective due to their convenience in implementation.

A suitable vegetation index should be sensitive to leaf chlorophyll content while resistant to variability of LAI and canopy background reflectance (Daughtry, Walthall, et al., 2000, Haboudane, Miller, et al., 2002). Since reflectance in the green region is proven to be more sensitive to leaf chlorophyll content and useful in detecting greenness information and crop stress(Gitelson, Kaufman, et al., 1996, Gitelson, Vina, et al., 2005), several broadband vegetation indices had been proposed using the green band reflectance. Gitelson and Merzlyak (2003) showed that the ratio vegetation indices integrated with green region could significant increase the accuracy of leaf chlorophyll estimation at higher plant leaves. Daughtry, Walthall, et al. (2000) also found that both MCRVI and NIR/GREEN were more responsive to leaf chlorophyll content compared to NDVI and other broadband vegetation indices. Recently, two other vegetation indices, the chlorophyll vegetation index (CVI)(Vincini, Frazzi, et al., 2008) and the triangular greenness index (TGI)(Hunt, Daughtry, et al., 2011)derived from broadband satellite datasets, have been developed and validated. With recent development in remote sensing, a great number of studies demonstrated the importance and advantages of vegetation indices using narrow bands, especially in the red edge region, provided by hyperspectral reflectance data for assessing leaf chlorophyll content(Gitelson and Merzlyak, 2003, Gitelson, Vina, et al., 2005, Schlemmer, Gitelson, et al., 2013, Wu, Niu, et al., 2008).This is because narrow band reflectance captures more detailed spectral information and subtle changes of a canopy than the broadband reflectance. An integrated narrow-band vegetation index, the combination of the transformed Chlorophyll Absorption in Reflectance Index and the Optimized Soil-Adjusted Vegetation Index (TCARI/OSAVI), developed by Haboudane, Miller, et al. (2002) was proven to be more effective than most other narrow band vegetation indices. The study of Zarco-Tejada, Miller, et al. (2004) showed that MCRVI/OSAVI could be less influenced by canopy background effect than TCARI/OSAVI when for dense canopy. Another important vegetation index, the MERIS terrestrial chlorophyll index (MTCI) based on the red edge band of MERIS, can be directly used for regional chlorophyll content estimation(Dash and Curran, 2004). Other hyperspectral vegetation indices, such as the Normalized Area Over Reflectance Curve (NAOC) (Delegido, Alonso, et al., 2010), were also developed and validated for leaf chlorophyll content estimation.

However, two main factors limited the applications of narrow band vegetation indices. Firstly, satellite hyperspectral sensors usually operate with a narrower swath and a longer revisit cycle than a broadband sensor, hence reduce their timeliness. Secondly, fewer satellite hyperspectral sensors are currently in operation or will become available in the near future. While, most broadband sensors without providing red edge information, such as the Landsat and MODIS, offer large swath coverage, frequent revisit and long time series of dataset. They are very useful for detecting crop status in time in precision agriculture. Thus, there is an urgent need to develop methods for leaf chlorophyll content estimation using broadband reflectance data. In this study, a set of broadband vegetation indices derived from one of China's broadband satellites HuanJing (HJ)-CCD sensor, were tested for their potential in leaf chlorophyll content estimation.

MATERIALS AND METHODS

Study area and field data collection

The study was carried out in the Hongxing Farm, located in the northeast part of China, Heilongjiang Provinces (127° 01′ 30″E, 48° 09′ 30″N). It lies within the Cold-Temperate Zone characterized with a mean annual rainfall of 555 mm and an annual accumulative temperature of 2250 °C from July to September. Soil depth ranges from 30 cm to 50 cm and soil organic matter content ranges from 5% to 7%. Soybean, spring corn and spring wheat are the three major crops.

Field measurements were conducted over different crops in late July and late August, 2011. There were a total of 57 large field plots each having a size approximately of 60m × 60m. For representativeness, measurements were taken at 5 smaller plots along the diagonal of each larger plot and then averaged. In each smaller plot, leaf chlorophyll content and leaf area index (LAI) were measured. LAI was measured using the SUNSCAN canopy analysis system (Delta-T Devices, Cambridge, UK). Leaf chlorophyll content was measured non-destructively using a portable SPAD-502 plus chlorophyll meter (Spectrum Technologies, Inc.) on ten randomly selected leaves in each smaller plot. For each leaf, five independent measurements were taken from the root to the tip. Thus, a total of 50 × 5 SPAD readings were averaged for a larger plot. To obtain the true value of leaf chlorophyll content, SPAD measurements were transformed using the equation developed by Markwell, Osterman, et al. (1995) (Eq.(1)):

$$Chl_{ab} = 0.0893 \times 10^{\left(SPAD^{0.265}\right)}$$

(1)

The Huan Jing (HJ) satellite data

Environmental Protection & Disaster Monitoring Constellation consists of two small satellites, HJ-1-A and HJ-1-B, and was launched on September 6, 2008. The spatial resolution of the CCD sensor is 30 m and the spectral range is 0.43-0.9 um, which includes blue, green, red, and near-infrared bands. Two images were acquired over the study region on July 27 and August 26, 2011 by the satellites. Preprocessing of the HJ image included radiometric calibration, atmospheric correction, and geometric correction using the Environment for Visualizing Images (ENVI) software and the ERDAS software.

Table 1 Vegetation indices selected in this study

Index	formula	Reference
NDVI	$\left(\rho_{nir} - \rho_{red}\right) / \left(\rho_{nir} + \rho_{red}\right)$	(Asrar, Fuchs, et al., 1984)
GNDVI	$\left(\rho_{nir} - \rho_{green}\right) / \left(\rho_{nir} + \rho_{green}\right)$	(Gitelson, Kaufman, et al., 1996)
CI_{green}	$\rho_{nir} / \rho_{green} - 1$	(Gitelson, Vina, et al., 2005)
VARI	$\left(\rho_{nir} - \rho_{red}\right) / \left(\rho_{nir} + \rho_{red} - \rho_{green}\right)$	(Stow, Niphadkar, et al., 2005)
MTVI2	$\frac{1.5\left[1.2\left(\rho_{nir} - \rho_{green}\right) - 2.5\left(\rho_{red} - \rho_{green}\right)\right]}{\sqrt{(2\rho_{nir}+1)^2 - (6\rho_{nir} - 5\sqrt{\rho_{red}}) - 0.5}}$	(Haboudane, Miller, et al., 2004)
EVI	$\left(\rho_{nir} - \rho_{red}\right) / \left(\rho_{nir} + 6\rho_{red} - 7.5\rho_{blue} + 1\right)$	(Huete, Didan, et al., 2002)
TVI	$0.5\left[120\left(R_{nir} - R_{green}\right) - 200\left(R_{red} - R_{green}\right)\right]$	(Broge and Leblanc, 2001)
CVI	$\left(\rho_{nir} / \rho_{green}\right) \cdot \left(\rho_{red} / \rho_{green}\right)$	(Vincini, Frazzi, et al., 2008)
TGI	$-0.5\left[190\left(R_{red} - R_{green}\right) - 220\left(R_{red} - R_{blue}\right)\right]$	(Hunt, Daughtry, et al., 2011)

Selected vegetation indices

For assessing and comparing their use for leaf chlorophyll content estimation, nine broadband vegetation indices were selected in this study. They are the normalized difference vegetation index (NDVI) (Asrar, Fuchs, et al., 1984),the green normalized difference vegetation index (GNDVI)(Gitelson, Kaufman, et al., 1996), the green chlorophyll index (CIgreen)(Gitelson, Vina, et al., 2005), the visible atmospherically resistant index (VARI)(Stow, Niphadkar, et al., 2005), the modified transformed vegetation index (MTVI2)(Haboudane, Miller, et al., 2004), the enhanced vegetation index (EVI) (Huete, Didan, et al., 2002), the triangular vegetation index (TVI)(Broge and Leblanc, 2001), the chlorophyll vegetation index (CVI)(Vincini, Frazzi, et al., 2008) and the triangular greenness index (TGI)(Hunt, Daughtry, et al., 2011). The formulas of the selected vegetation indices are given in the Table 1.

Canopy reflectance simulation and sensitivity analysis

For identifying the drivers of vegetation indices, the PROSAIL model, an integrated PROSPECT leaf (leaf optical PROpertySPECTra model) and SAIL canopy (Scattering from Arbitrarily Inclined Leaves) bidirectional reflectance model (Jacquemoud, Verhoef, et al., 2009), was used in this study for reflectance spectra simulation. A total of14 inputs are needed in the model. All the parameters can be divided into several categories including leaf pigment content, leaf water content, canopy architecture, soil background reflectance, hot spot size, fraction of direction solar irradiance and geometry(Liu, Pattey, et al., 2012, Thorp, Wang, et al., 2012). The detail description of PROSAIL can be found in Jacquemoud, Verhoef, et al. (2009). Using these inputs, canopy reflectance spectra simulated by the PROSAIL model were used to simulate the band reflectance of the HJ satellite and to calculate the selected vegetation indices.

Table 2 Parameters and varables for PROSAIL model

Parameters	range
Leaf chlorophyll a and b content (Cab, ug cm^{-2})	20~80
Leaf carotenoid content (Car, ug cm-2)	5.0~18.0
leaf brown pigment content	0.0
Leaf water content (Cw, g cm-2)	0.0035~0.018
Leaf structure parameter(N)	1.0~2.0
Leaf dry matter content (Cm, g cm-2)	0.0015~0.008
Leaf Area Index (LAI)	0.5~6.0
Average leaf inclination angle	40º ~ 60º
soil	0.0~1.5

Fraction of directional solar irradiance	0.9
solar zenith angle(tts)	45
observer zenith angle(tto)	0
relative azimuth angle (phi)	0

To assess the sensitivity of the selected indices to canopy and leaf parameters, especially LAI and leaf chlorophyll content, a global sensitivity analysis was performed in this study before establishing the relationship between the selected vegetation indices and leaf chlorophyll content. Here, we used the Extended Fourier Amplitude Sensitivity Test (EFAST) method, a global sensitivity analysis (GSA) approach developed by Saltelli(Saltelli and Bolado, 1998). Both the first order index and the total effect index were calculated, but only the total effect index was used for the assessment. We did not consider the effect of acquisition geometry, thus the related inputs were set to constant values and the other 8 inputs were set to free value in random (Table 1).

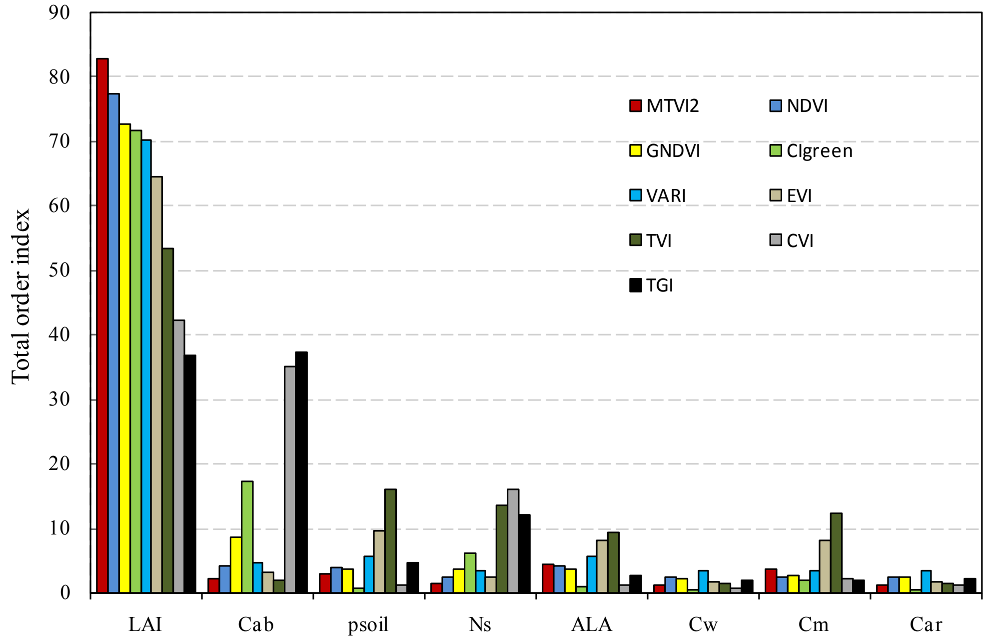

Fig. 1 The total order index of the input parameters assessed using the PROSAIL simulated data

RESULTS AND DISCUSSION

Sensitivity analysis of vegetation indices

The total order index of all the selected vegetation indices responded to each inputs of the PROSAIL model was showed in Fig. 1. The results showed that, LAI was the major driving factor in all the assessed indices, as the total order index of LAI was the largest in every index although with different extent. The total effect index of MTVI2 was the largest while that of CVI and TGI was the lowest. This indicated that both CVI and TGI were less affected by LAI variation. In previous studies, indices such as MTVI2, VARI and EVI had better abilities in reducing background effects and improving the linearity relationship with LAI (Liu, Pattey, et al., 2012, Zhang, Xiao, et al., 2005).

For leaf chlorophyll content, the indices with the green band involved, including GNDVI, CI_{green}, CVI and TGI, had a higher total effect index than MTVI2, NDVI, VARI, EVI and TVI, indicating that they would have a better performance if used for leaf chlorophyll content estimation. This is due to the sensitivity of green band reflectance to chlorophyll content(Gitelson, Kaufman, et al., 1996, Gitelson and Merzlyak, 1998). GNDVI was more sensitive to leaf chlorophyll content than NDVI, but less sensitive than CI_{green}. The advantage of CI_{green} compared with GNDVI was explained by the study of Gitelson, Vina, et al. (2005). Both CVI and TGI were the most sensitive to leaf chlorophyll content as they had the largest total effect index. Both CVI and TGI were less sensitive to canopy background reflectance but more sensitive to leaf mesophyll structure parameter. Since variability of LAI is the strongest contributing factor among all the indices, the ones that are less sensitive to LAI would be more suitable for leaf chlorophyll content estimation. Thus, it could be expected that both CVI and TGI will have a better performance in leaf chlorophyll content retrieval.

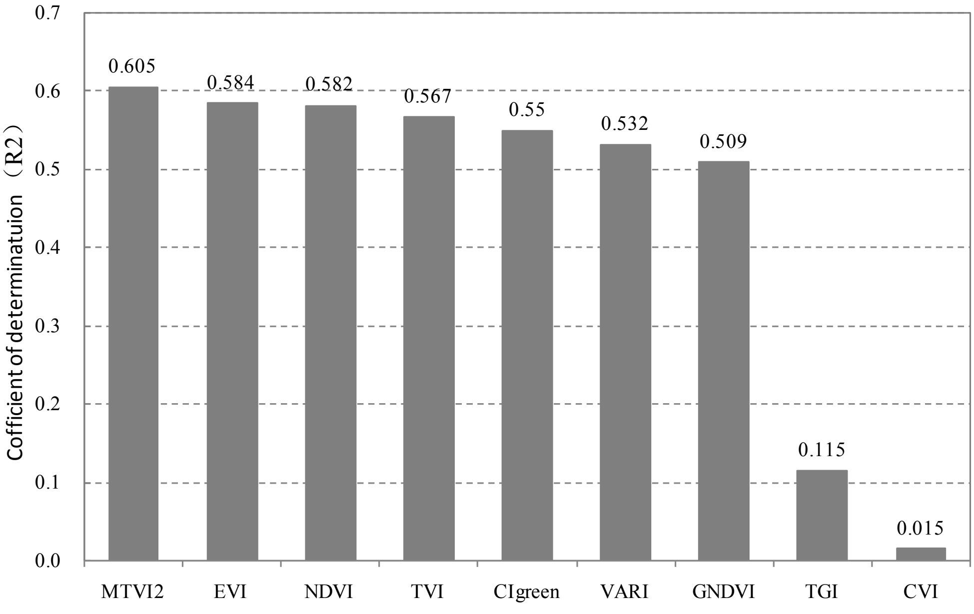

Fig. 2 Correlation between Vegetation indices and LAI

Relationships between LAI and vegetation indices

In the linear relationship between the selected vegetation indices and LAI, MTVI2 achieved the best result with a highest coefficient of determination (R^2=0.61, p<0.001). The other indices were also strongly linearly correlated with LAI (R^2>0.50), except for CVI and TGI, which had the lowest value of

R^2 (<0.12). This means that both CVI and TGI have better ability to reduce the effect of LAI variation. At the same time, there were some differences compared with the results of the sensitivity analysis. The order of selected vegetation indices response to LAI variation was different, such as TGI showed more effected by LAI than CVI in the validation, EVI showed more linear with LAI than GNDVI. The possible reason was the limitation of the PROSAIL for simulating canopy reflectance in ideal conditions(Jacquemoud, Verhoef, et al., 2009).

Table 3 Linear regression between chlorophyll content and vegetation indices (, p<0.001)**

Index	Equation	R^2	RMSE(ug cm^{-2})
NDVI	Y=-0.000x+0.883	0.01	9.03
GNDVI	Y=0.001x+0.730	0.20	8.61
CI_{green}	Y=0.091x+4.413	0.23	8.44
VARI	Y=-0.001x+1.028	0.14	8.57
MTVI2	Y=-0.002x+0.814	0.05	9.06
EVI	Y=-0.000x+0.293	0.00	9.09
TVI	Y=-0.098x+31.81	0.03	9.11
TGI	Y=-0.077x+6.109	0.46**	6.79
CVI	Y=0.166x-0.761	0.50**	6.22

Relationships between chlorophyll content and vegetation indices

To validate the result from the sensitivity analysis, a linear regression analysis was conducted to study the dependency of the selected vegetation indices on leaf chlorophyll content. The results are given in Table 3. The value of R^2 varied from <0.01 to 0.50 and the RMSE varied from 9.11 to 6.22 μgcm^{-2}. Of all the selected vegetation indices, CVI (R^2=0.50, P<0.001) and TGI (R^2=0.46, P<0.001) achieved the best linearity with leaf chlorophyll content, followed by GNDVI and CI_{green}. The result further confirmed that both TGI and CVI were most appropriate indices for leaf chlorophyll content estimation. CVI had a slight higher value of R^2 than TGI, possibly because CVI was less affected by the crop types than TGI, and the blue band reflectance used in TGI was prone to aerosol disturbance, these will be done in the further study.

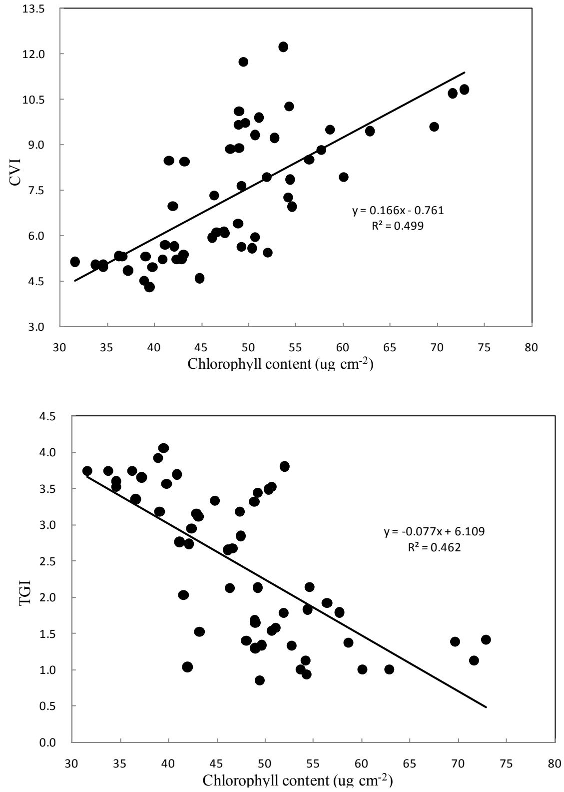

Fig. 3 Relationships between CVI, TGI and leaf chlorophyll content

CONCLUCION

There are two challenges for retrieval of leaf chlorophyll content from canopy reflectance using the broadband satellite data. Canopy reflectance is a function of canopy structure, leaf pigments, background and environment, thus it is much more difficult to obtain leaf chlorophyll content compared with the retrieval of canopy chlorophyll content. In addition, the variation of leaf chlorophyll content is more difficulty to be detected by the broadband remote sensing data than the hyperspectral data. However, hyperspectral satellites data are difficult to obtain over a large region under current situation. In this study, results from the sensitivity analysis and field data validation showed that, both CVI and TGI were more sensitive to leaf chlorophyll content and less sensitive to leaf area index (LAI) and canopy background noise. This indicated that they could be good candidate for leaf chlorophyll content estimation, and had a strong application potential in precision agriculture using broadband satellite data. The preliminary results of this study also shed light on future improvement of vegetation indices for leaf chlorophyll content estimation, especially exploiting spectral information in the green region. Other constraint factors should also be considered in future studies, such as the bi-directional and the mixed pixel effects, and the impact from different vegetation types.

REFERENCE

Asrar, G., M. Fuchs, E. Kanemasu and J. Hatfield. 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agronomy journal 76: 300-306.

Botha, E.J., B. Leblon, B. Zebarth and J. Watmough. 2007. Non-destructive estimation of potato leaf chlorophyll from canopy hyperspectral reflectance using the inverted PROSAIL model. International Journal of Applied Earth Observation and Geoinformation 9: 360-374.

Broge, N.H. and E. Leblanc. 2001. Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Remote sensing of environment 76: 156-172.

Clevers, J.G.P.W. and A.A. Gitelson. 2013. Remote estimation of crop and grass chlorophyll and nitrogen content using red-edge bands on Sentinel-2 and -3. International Journal of Applied Earth Observation and Geoinformation 23: 344-351. doi:http://dx.doi.org/10.1016/j.jag.2012.10.008.

Dash, J. and P. Curran. 2004. The MERIS terrestrial chlorophyll index.

Daughtry, C., C. Walthall, M. Kim, E.B. De Colstoun and J. McMurtrey Iii. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote sensing of Environment 74: 229-239.

Delegido, J., L. Alonso, G. González and J. Moreno. 2010. Estimating chlorophyll content of crops from hyperspectral data using a normalized area over reflectance curve (NAOC). International Journal of Applied Earth Observation and Geoinformation 12: 165-174.

Gitelson, A.A., Y.J. Kaufman and M.N. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment 58: 289-298.

Gitelson, A.A. and M.N. Merzlyak. 1998. Remote sensing of chlorophyll concentration in higher plant leaves. Advances in Space Research 22: 689-692.

Gitelson, A.A. and M.N. Merzlyak. 2003. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of plant physiology 160: 271-282.

Gitelson, A.A., A. Vina, V. Ciganda, D.C. Rundquist and T.J. Arkebauer. 2005. Remote estimation of canopy chlorophyll content in crops. Geophysical Research Letters 32.

Haboudane, D., J.R. Miller, E. Pattey, P.J. Zarco-Tejada and I.B. Strachan. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote sensing of environment 90: 337-352.

Haboudane, D., J.R. Miller, N. Tremblay, P.J. Zarco-Tejada and L. Dextraze. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote sensing of environment 81: 416-426.

Houborg, R., M. Anderson and C. Daughtry. 2009. Utility of an image-based canopy reflectance modeling tool for remote estimation of LAI and leaf chlorophyll content at the field scale. Remote sensing of environment

113: 259-274.
Houborg, R. and E. Boegh. 2008. Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data. Remote sensing of environment 112: 186-202.
Huete, A., K. Didan, T. Miura, E.P. Rodriguez, X. Gao and L.G. Ferreira. 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote sensing of environment 83: 195-213.
Hunt, E.R., C. Daughtry, J.U. Eitel and D.S. Long. 2011. Remote sensing leaf chlorophyll content using a visible band index. Agronomy Journal 103: 1090-1099.
Jacquemoud, S., W. Verhoef, F. Baret, C. Bacour, P.J. Zarco-Tejada, G.P. Asner, et al. 2009. PROSPECT+ SAIL models: A review of use for vegetation characterization. Remote Sensing of Environment 113: S56-S66.
Liu, J., E. Pattey and G. Jégo. 2012. Assessment of vegetation indices for regional crop green LAI estimation from Landsat images over multiple growing seasons. Remote Sensing of Environment 123: 347-358. doi:http://dx.doi.org/10.1016/j.rse.2012.04.002.
Markwell, J., J.C. Osterman and J.L. Mitchell. 1995. Calibration of the Minolta SPAD-502 leaf chlorophyll meter. Photosynthesis Research 46: 467-472.
Peng, Y. and A.A. Gitelson. 2012. Remote estimation of gross primary productivity in soybean and maize based on total crop chlorophyll content. Remote Sensing of Environment 117: 440-448.
Peng, Y., A.A. Gitelson, G. Keydan, D.C. Rundquist and W. Moses. 2011. Remote estimation of gross primary production in maize and support for a new paradigm based on total crop chlorophyll content. Remote Sensing of Environment 115: 978-989.
Saltelli, A. and R. Bolado. 1998. An alternative way to compute Fourier amplitude sensitivity test (FAST). Computational Statistics & Data Analysis 26: 445-460. doi:http://dx.doi.org/10.1016/S0167-9473(97)00043-1.
Schlemmer, M., A. Gitelson, J. Schepers, R. Ferguson, Y. Peng, J. Shanahan, et al. 2013. Remote estimation of nitrogen and chlorophyll contents in maize at leaf and canopy levels. International Journal of Applied Earth Observation and Geoinformation 25: 47-54.
Stow, D., M. Niphadkar and J. Kaiser. 2005. MODIS - derived visible atmospherically resistant index for monitoring chaparral moisture content. International Journal of Remote Sensing 26: 3867-3873.
Thorp, K., G. Wang, A. West, M. Moran, K. Bronson, J. White, et al. 2012. Estimating crop biophysical properties from remote sensing data by inverting linked radiative transfer and ecophysiological models. Remote Sensing of Environment 124: 224-233.
Vincini, M., E. Frazzi and P. D'Alessio. 2008. A broad-band leaf chlorophyll vegetation index at the canopy scale. Precision Agriculture 9: 303-319.
Wu, C., Z. Niu, Q. Tang and W. Huang. 2008. Estimating chlorophyll

content from hyperspectral vegetation indices: Modeling and validation. agricultural and forest meteorology 148: 1230-1241.

Zarco-Tejada, P.J., J. Miller, A. Morales, A. Berjón and J. Agüera. 2004. Hyperspectral indices and model simulation for chlorophyll estimation in open-canopy tree crops. Remote sensing of environment 90: 463-476.

Zhang, Q., X. Xiao, B. Braswell, E. Linder, F. Baret and B. Moore III. 2005. Estimating light absorption by chlorophyll, leaf and canopy in a deciduous broadleaf forest using MODIS data and a radiative transfer model. Remote Sensing of Environment 99: 357-371.

Zhang, Y., J.M. Chen, J.R. Miller and T.L. Noland. 2008. Leaf chlorophyll content retrieval from airborne hyperspectral remote sensing imagery. Remote Sensing of Environment 112: 3234-3247. doi:http://dx.doi.org/10.1016/j.rse.2008.04.005.