Stress Detection in Crops with Hyperspectral Remote Sensing and Physical Simulation Models

P.J. Zarco-Tejada[a], A. Berjón[b], and J.R. Miller[c]

[a] Institute for Sustainable Agriculture (IAS-CSIC), Córdoba (Spain), pzarco@ias.csic.es
[b] GOA-UVA, Universidad de Valladolid, Spain
[c] Dept. Earth and Space Science & Engineering, York University, Toronto, Canada

ABSTRACT

Progress made on the detection of stress in heterogeneous crop canopies with hyperspectral remote sensing imagery is presented. High-spatial resolution multispectral remote sensing imagery was collected in 2002, 2003 and 2004 over vineyard and olive orchards in Spain. Imagery acquired with the *Compact Airborne Spectrographic Imager* (CASI) and the *Reflective Optics System Imaging Spectrometer* (ROSIS) in the visible and near infrared wavelength regions 400-950 nm at 1 m resolution, and with the *Airborne Hyperspectral Scanner* (AHS) in the reflective and thermal regions at 2 m resolution enabled the study of narrow-band vegetation indices and model simulation for estimation of chlorophyll content for chlorosis detection at the tree and vine level, as well as deriving thermal information function of the stress status. Ground data collection consisted of measurements of crown transmittance with a PCA LAI-2000 and geometrical measurements of crown projected area, height, crown cross-section, and biochemical constituents such as chlorophyll *a+b* and carotenoids, enabling the estimation of crown leaf area index, crown leaf density, biophysical variables related to the crown intercepted radiation, such as crop yield and canopy fractional cover, as well as crop functioning through chlorophyll content estimation. Leaf and canopy simulation models, such as PROSPECT, SAILH, FLIM, and rowMCRM were used and the *scaling up* methodology presented.

Keywords: crop stress, water stress, hyperspectral remote sensing, vegetation indices, scaling up

1 INTRODUCTION

Leaf chlorophyll *a+b* (C_{a+b}) and leaf area index (LAI) are indicators of stress and growth that may be estimated by radiative transfer modelling from hyperspectral data in the 400-2500 nm spectral region. Estimation of such leaf biochemical and canopy biophysical variables from remote sensing data requires appropriate modelling strategies for *Olea europaea* L. and *Vitis vinifera* L. canopies, accounting for structure through its dominant effect on the bi-directional reflectance (BRDF) signature. Successful estimation of leaf biochemistry from remote sensing methods in open canopies of *Olea europaea* L. and *Vitis vinifera* L. has remained an elusive goal to date, presumably due to the difficulties to access data from hyperspectral sensors and to the complexity of the physical approaches required for modeling such canopies. C_{a+b} and other leaf biochemical constituents such as dry matter content (C_m) and water content (C_w) are indicators of plant stress and nutritional deficiencies associated with relative availability of elements N, P, K, Fe, Ca, Mn, Zn and Mg, among others [1-6]. Chlorosis in olive trees caused by such deficiencies can be successfully treated thereby improving yields and the final quality of the fruit [7-9]. Specifically, Fe and N deficiencies resulting in chlorosis symptoms in vineyards cause a decrease of fruit yield and quality in the current and the subsequent year as fruit buds develop poorly [6].

2 HYPERSPECTRAL INDICES AND MODEL SIMULATION

Several hyperspectral indices, proposed in the literature track and quantify chlorophyll concentration [10-13], allowing remote detection methods to identify and map vegetation stress through the influence of chlorophyll content variation. These physiologically-based vegetation indices are shown in Table 1 (see [13] for a full review). In agricultural canopies with large spectral contributions by the soil background and LAI variation in different growth stages, combined indices have been proposed to minimize background soil effects while maximizing the sensitivity to C_{a+b} [14-15]. CARI *(Chlorophyll Absorption in Reflectance Index)* [16], MCARI *(Modified Chlorophyll Absorption in Reflectance Index)* [17], SAVI *(Soil-Adjusted Vegetation Index)* [18] and OSAVI *(Optimized Soil-Adjusted Vegetation Index)* [19] were proposed as soil-line vegetation indices to be combined with MCARI to reduce background contributions [17] such as in the form TCARI/OSAVI or MCARI/OSAVI. Nevertheless, and despite the successful relationships obtained between specific optical indices and leaf biochemistry, estimation of such biochemical components at canopy level from remote sensing requires appropriate modelling strategies for these heterogeneous canopies, accounting for structure through its dominant effect on the bi-directional reflectance (BRDF) signature. Methods for *scaling-up* of indices such as MCARI, TCARI and OSAVI have been successfully studied to investigate the effects of scene components on indices calculated from pure crown pixels and from aggregated soil, shadow and crown reflectance in olive tree orchards [20]. Relationships between optical indices and ground-measured C_{ab} yielded reasonable results with 1-m ROSIS imagery when targeting crowns, with the best results obtained for MCARI/OSAVI, MCARI, and TCARI indices. However, results indicated that these combined indices were highly affected by soil background and shadow components in open canopies, requiring the use of open-canopy radiative transfer methods since canopy reflectance is then function of the three components: crown, soil and shadows. The linked models PROSPECT-SAILH-FLIM improved the estimates of chlorophyll concentration from open tree canopies with significant effects of soil and shadow scene components on the aggregated pixels. Similar methods were applied for chlorosis detection in vineyards with 1 m CASI imagery (Figure 1); in this case PROSPECT linked to the rowMCRM model, which refers to the *Markov-Chain Canopy Reflectance Model* (MCRM) [21-22] with additions to simulate the row crop structure (developed within the frame of the *Crop Reflectance Operational Models for Agriculture* project (CROMA)) was used to simulate different scene component proportions, row orientations, and vineyard dimensions (Figure 2). Field sampling campaigns were conducted in July 2002 and July 2003 for biochemical analysis of leaf C_{ab} in study areas of *Vitis vinifera* L. in *Ribera del Duero* D.O. in Northern Spain. A total of 1467 leaves were used for determination of C_{ab} on 88 study sites comprising the campaigns conducted in 2002 and 2003, which generated a database of optical properties of 605 leaves collected.

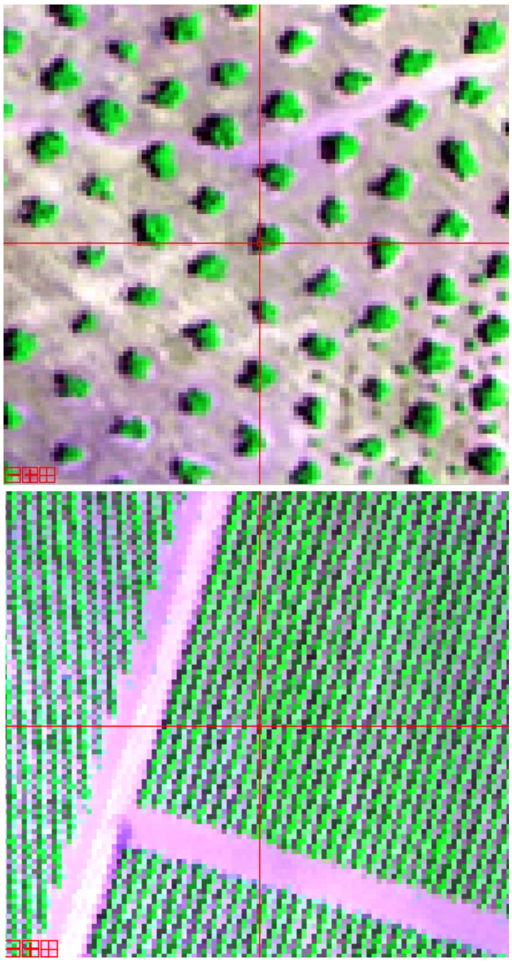
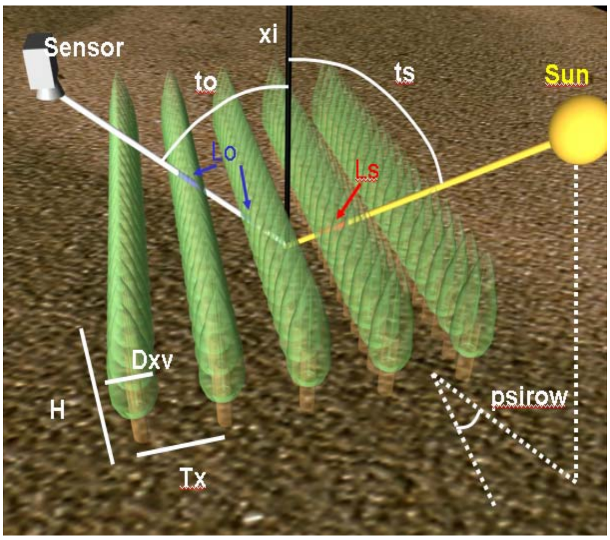


Figure 1. CASI images collected at 1m spatial resolution from olive and vineyard study fields.



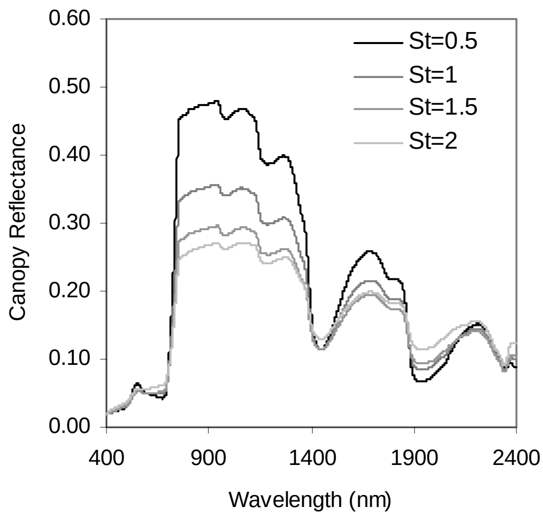


Figure 2. Model simulation of row-structured discontinuous canopies with rowMCRM radiative transfer model (left). Vineyard canopy reflectance simulation as function of the visible strip length in the row crop (St=0.5, 1m, 1.5m and 2m) (right).

Table 1. Vegetation indices for biochemical and LAI estimation calculated from multispectral and hyperspectral imagery

Vegetation Index	Equation	Reference
Structural Indices		
Normalized Difference Vegetation Index (NDVI)	$NDVI = (R_{NIR} - R_{red})/(R_{NIR} + R_{red})$	Rouse *et al.* (1974)
Modified Triangular Vegetation Index (MTVI1)	$MTVI1 = 1.2 * [1.2 * (R_{800} - R_{550}) - 2.5 * (R_{670} - R_{550})]$	Haboudane *et al.* (2004)
Modified Triangular Vegetation Index (MTVI2)	$MTVI2 = \frac{1.5 * [1.2 * (R_{800} - R_{550}) - 2.5 * (R_{670} - R_{550})]}{\sqrt{(2 * R_{800} + 1)^2 - (6 * R_{800} - 5 * \sqrt{R_{670}}) - 0.5}}$	Haboudane *et al.* (2004)
Renormalized Difference Vegetation Index (RDVI)	$RDVI = (R_{800} - R_{670}) / \sqrt{(R_{800} + R_{670})}$	Rougean and Breon, (1995)
Simple Ratio Index (SR)	$SR = R_{NIR}/R_{red}$	Jordan (1969); Rouse *et al.* (1974)
Modified Chlorophyll Absorption in Reflectance Index ($MCARI_1$)	$MCARI1 = 1.2 * [2.5 * (R_{800} - R_{670}) - 1.3 * (R_{800} - R_{550})]$	Haboudane *et al.* (2004)
Modified Chlorophyll Absorption in Reflectance Index ($MCARI_2$)	$MCARI2 = \frac{1.5 * [2.5 * (R_{800} - R_{670}) - 1.3 * (R_{800} - R_{550})]}{\sqrt{(2 * R_{800} + 1)^2 - (6 * R_{800} - 5 * \sqrt{R_{670}}) - 0.5}}$	Haboudane *et al.* (2004)
Soil Adjusted Vegetation Index (SAVI)	$SAVI = (1 + L) * (R_{800} - R_{670}) / (R_{800} + R_{670} + L)$ $[\, L\ \varepsilon\ (0,1) \,]$	Huete (1988) Qi *et al.* (1994)
Improved SAVI with self-adjustment factor L (MSAVI)	$MSAVI = \frac{1}{2}\left[2 * R_{800} + 1 - \sqrt{(2 * R_{800} + 1)^2 - 8 * (R_{800} - R_{670})}\right]$	Qi *et al.* (1994)
Optimized Soil-Adjusted Vegetation Index (OSAVI)	$OSAVI = (1 + 0.16) * (R_{800} - R_{670}) / (R_{800} + R_{670} + 0.16)$	Rondeaux *et al.* (1996)
Chlorophyll Indices		
Greenness Index (G)	$G = (R_{554})/(R_{677})$	-
Modified Chlorophyll Absorption in Reflectance Index (MCARI)	$MCARI = [(R_{700} - R_{670}) - 0.2 * (R_{700} - R_{550})] * (R_{700} / R_{670})$	Daughtry *et al.* (2000)
Transformed CARI (TCARI)	$TCARI = 3 * [(R_{700} - R_{670}) - 0.2 * (R_{700} - R_{550}) * (R_{700} / R_{670})]$	Haboudane *et al* (2002)
Triangular Vegetation Index (TVI)	$TVI = 0.5 * [120 * (R_{750} - R_{550}) - 200 * (R_{670} - R_{550})]$	Broge and Leblanc (2000)
Zarco-Tejada & Miller	$ZM = (R_{750})/(R_{710})$	Zarco-Tejada *et al.* (2001)
Simple R. Pigment Ind. (SRPI)	$SRPI = (R_{430})/(R_{680})$	Peñuelas et al. (1995)
Normalized Phaeophytinization Index (NPQI)	$NPQI = (R_{415} - R_{435})/ (R_{415} + R_{435})$	Barnes et al. (1992)
Photochemical Reflectance Index (PRI)	$PRI1 = (R_{528} - R_{567})/(R_{528} + R_{567})$ $PRI2 = (R_{531} - R_{570})/(R_{531} + R_{570})$	Gamon et al. (1992)
Normalized Pigment Chlorophyll Index (NPCI)	$NPCI = (R_{680} - R_{430})/ (R_{680} + R_{430})$	Peñuelas et al. (1994)
Carter Indices	$Ctr1 = (R_{695})/(R_{420})$ $Ctr2 = (R_{695})/(R_{760})$	Carter (1994) Carter et al. (1996)
Lichtenthaler indices	$Lic1 = (R_{800} - R_{680})/ (R_{800} + R_{680})$ $Lic2 = (R_{440})/(R_{690})$	Lichtenthaler et al. (1996)
Structure Intensive Pigment Index (SIPI)	$SIPI = (R_{800} - R_{450})/ (R_{800} + R_{650})$	Peñuelas et al. (1995)
Vogelmann indices	$Vog1 = (R_{740})/(R_{720})$ $Vog2 = (R_{734} - R_{747})/(R_{715} + R_{726})$ $Vog3 = (R_{734} - R_{747})/(R_{715} + R_{720})$	Vogelmann et al. (1993); Zarco-Tejada et al. (1999)
Gitelson and Merzlyak	$GM1=R_{750}/R_{550}$ $GM2=R_{750}/R_{700}$	Gitelson & Merzlyak (1997)

3 RESULTS

The application of optical indices in discontinuous crop canopies such as *Olea europaea* L. and *Vitis vinifera* L., where canopy structure plays an important role, and the effects of LAI, shadows and soil in the modelled reflectance have demonstrated the requirement for radiative transfer simulation methods for accurate estimates of biochemical constituents. Relationships between optical indices and ground measured C_{ab} yielded reasonable results with 1-m ROSIS imagery when targeting crowns, obtaining the best results for MCARI/OSAVI, MCARI, and TCARI indices. Relationships between optical indices and ground measured C_{ab} when using 1-m ROSIS imagery targeting olive crowns yielded r^2=0.6 with TCARI, r^2=0.64 with MCARI, r^2=0.48 with TCARI/OSAVI combined index, and r^2=0.69 with MCARI/OSAVI. The predictive relationship calculated for the MCARI/OSAVI index through PROSPECT-SAILH using a gradient of soil backgrounds from bright to dark soil reflectance yielded r^2=0.67 and RMSE=10.9 μg/cm^2 when applied to ROSIS pure-crown spectra. In the case of aggregated scene components, when lower spatial resolution imagery is available, a relationship between MCARI/OSAVI and C_{ab} developed using PROSPECT-SAILH-FLIM to account for the scene components that were missing in the PROSPECT-SAILH simulation, significantly improved the estimation of C_{ab} than when using only SAILH for aggregated pixels.

In *Vitis vinifera* L. canopies, leaf reflectance and transmittance measurements enabled the validation of optical indices for this crop. Results show that the best optical indices for chlorophyll estimation in vine leaves were the indices ZM, VOG_1, VOG_2, VOG_3, GM_1, GM_2, MCARI, TCARI, MCARI/OSAVI, and TCARI/OSAVI (Table 1 and Figure 3, top). Chlorophyll *a & b* estimation by inversion of the PROSPECT leaf model using a database of 605 leaf reflectance and transmittance vine spectra yielded a determination coefficient of r^2=0.95, with an RMSE=5.3 μg/cm^2 (Figure 3, centre). The *scaling up* of TCARI/OSAVI index through PROSPECT linked to rowMCRM radiative transfer model yielded a determination coefficient of r^2=0.71 and RMSE=10.5 μg/cm^2 (Figure 3, bottom). These results indicate the validity of the mentioned narrow-band vegetation indices for chlorophyll estimation in open tree and vine crops, and the successful estimation of chlorophyll *a & b* by PROSPECT model inversion linked to SAILH+FLIM in orchard trees, and rowMCRM in row-structured canopies such as vineyards.

4 CONCLUSIONS

Progress made on the estimation of chlorophyll *a&b* for stress and chlorosis detection in open tree crops and row-structured crop canopies demonstrate the validity of combined indices such as TCARI/OSAVI, both at the leaf and canopy levels. Correct estimation of C_{ab} at the canopy level was successful using appropriate radiative transfer simulation with PROSPECT linked to SAILH-FLIM (orchard crops) and rowMCRM (row-structured crops such as vineyards).

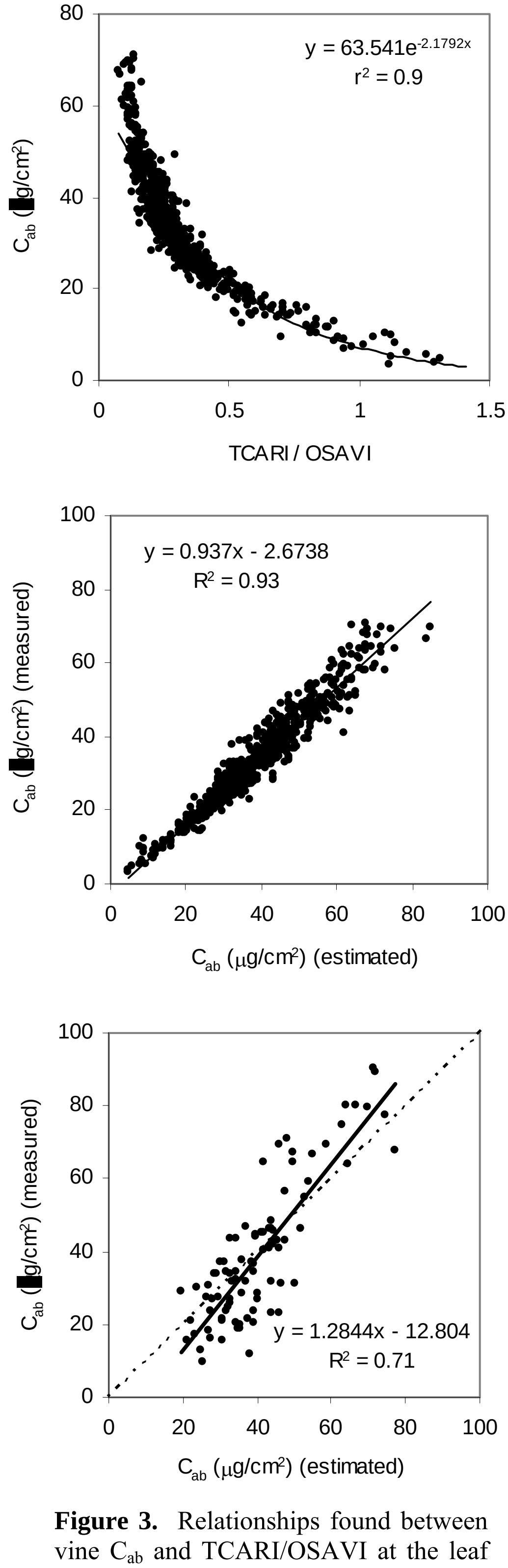


Figure 3. Relationships found between vine C_{ab} and TCARI/OSAVI at the leaf level (top), by model inversion (centre), and at the canopy level by scaling up TCARI/OSAVI through PROSPECT linked to rowMCRM model (bottom).

ACKNOWLEDGMENTS

The authors gratefully acknowledge the HySens project support provided through the *Access to Research Infrastructures* EU Program. Financial support from the Spanish Ministry of Science and Technology (MCyT) for the project AGL2002-04407-C03, and financial support to P.J. Zarco-Tejada under the *Ramón y Cajal* and *Averroes* Programs are also acknowledged. We thank L. Gray, York University (Canada), and S. Holzwarth and A. Müeller from DLR (Germany) for efficient airborne field campaigns with CASI, ROSIS, and DAIS sensors, providing coordination with field data collection. J. Praks and A. Kuusk are acknowledged for providing the rowMCRM code. Support provided by R. López-Lozano on the graphic simulations is also appreciated.

REFERENCES

[1] MARSCHNER, H., ROMHELD, V., KISSEL, M., 1986: Different strategies in higher plants in mobilization and uptake of iron, *J. Plant Nutr*. 9, 695-713.

[2] FERNANDEZ-ESCOBAR, R., MORENO, R., AND GARCIA-CREUS, M., 1999: Seasonal changes of mineral nutrients in olive leaves during the alternate-bearing cycle, *Scientia Horticulturae* 82, 24-45.

[3] JOLLEY, V.D., AND BROWN, J.C., 1994: Genetically controlled uptake and use of iron by plants, In: Manthey, J.A., Crowley, D.E., Luster, D.G. (Eds.), Biochemistry of metal micronutrients in the rhizosphere, Lewis Publishers, Boca Raton, pp. 251-266.

[4] CHEN, Y., AND BARAK, P., 1982: Iron nutrition of plants in calcareous soils, *Adv. Agron*. 35, 217-240.

[5] WALLACE, A., 1991: Rational approaches to control of iron deficiency other than plant breeding and choice of resistant cultivars, *Plant Soil* 130, 281-288.

[6] TAGLIAVINI, M., ROMBOLA, A.D., 2001: Iron deficiency and chlorosis in orchard and vineyard ecosystems, *European Journal of Agronomy* 15, 71-92.

[7] CHOVA, M.M., PEÑA, F., DEL CAMPILLO, M., DELGADO, A., DIAZ, M.A., 2000: Efecto de la corrección de la clorosis férrica en olivar con fosfato de hierro en los parámetros de calidad del aceite de oliva, *Edafología* 7-2.

[8] CORDEIRO, A.M., ALCANTARA, E., AND BARRANCO, D., 1995: Differences in tolerance to iron deficiency among olive cultivar. In: Iron nutrition in soils and plants, 197-200, Ed. J. Abadia, Kluwer, Netherlands.

[9] GUTIERREZ-ROSALES, G., GARRIDO-FERNANDEZ, F.J., GALLIARDO-GUERRERO, L., AND GANDUL-ROJAS, B., 1992: Action of chlorophylls on the stability of virgin olive oil, *J. Am. Oil Chem. Soc*., 69.

[10] VOGELMANN, J. E., ROCK, B. N. AND MOSS, D. M., 1993: Red edge spectral measurements from sugar maple leaves, *International Journal of Remote Sensing,* 14:1563-1575.

[11] GITELSON, A. A. AND MERZLYAK, M. N., 1996: Signature Analysis of Leaf Reflectance Spectra: Algorithm Development for Remote Sensing of Chlorophyll, *Journal of Plant Physiology,* 148:494-500.

[12] CARTER, G. A., 1994: Ratios of leaf reflectances in narrow wavebands as indicators of plant stress, *International Journal of Remote Sensing,* 15:697-704.

[13] ZARCO-TEJADA, P.J., MILLER, J.R., MOHAMMED, G.H., NOLAND, T.L., AND SAMPSON, P.H., 2001: *Scaling-up* and model inversion methods with narrow-band optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data, *IEEE Trans. on Geoscience and Remote Sensing*, 39(7), 1491-1507.

[14] HABOUDANE, D., MILLER, J.R., TREMBLAY, N, ZARCO-TEJADA, P.J., AND DEXTRAZE, L., 2002: Integration of Hyperspectral Vegetation Indices for Prediction of Crop Chlorophyll Content for Application to Precision Agriculture, *Remote Sens. of Environ.*, 81(2-3), 416-426.

[15] HABOUDANE, D., MILLER, J.R., PATTEY, E., ZARCO-TEJADA, P.J., AND STRACHAN, I., 2004: Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modelling and validation in the context of precision agriculture, *Remote Sens. of Environ.,* 90(3), 337-352.

[16] KIM, M. S., DAUGHTRY, C. S. T., CHAPPELLE, E. W., MCMURTREY III, J. E., AND WALTHALL, C. L., 1994: The use of high spectral resolution bands for estimating absorbed photosynthetically active radiation, *6^{th} Symp. On Phys. Meas. and Signatures in Rem. Sens. Jan. 17-21, 1994, Val D'Isere, France*, pp. 299-306.

[17] DAUGHTRY, C. S. T., WALTHALL, C. L., KIM, M.S., BROWN DE COLSTOUN, E., 2000: Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance, *Remote Sens. of Environ.* , 74: 229-239.

[18] HUETE, A.R., 1988: A soil-adjusted vegetation index (SAVI), *Remote Sens. of Environ.*, 25: 295-309.

[19] RONDEAUX, G., STEVEN, M., AND BARET, F., 1996: Optimization of soil-adjusted vegetation indices, *Remote Sens. of Environ*, 55: 95-107.

[20] ZARCO-TEJADA, P.J., J.R. MILLER, A. MORALES, A. BERJÓN, AND J. AGÜERA, 2004: Hyperspectral Indices and Model Simulation for Chlorophyll Estimation in Open-Canopy Tree Crops, RSE, 90(4), 463-476.

[21] KUUSK, A., 1995: A Markov chain model of canopy reflectance, *Agr. and Forest Meteorology.* 76:221-236.

[22] KUUSK, A., 1995: A fast, invertible canopy reflectance model, *Remote Sens. of Environ.*, 51:342-350.