REMOTE SENSING OF VEGETATION BIOPHYSICAL PARAMETERS FOR DETECTING STRESS CONDITION AND LAND COVER CHANGES

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ABSTRACT. New remote sensing methods based on narrow-band hyperspectral instruments enable the estimation of vegetation biophysical parameters and leaf biochemicals used to detect nutritional and water stress condition. This paper summarizes new advances in hyperspectral and thermal remote sensing for vegetation monitoring through biochemical and biophysical parameter estimation, discussing the potential for detecting water stress using high-resolution thermal instruments onboard airborne platforms.

RESUMEN. Nuevos métodos de teledetección basados en sensores hiperespectrales de banda estrecha permiten potencialmente la estimación de parámetros biofísicos de la vegetación y la detección de la concentración de constituyentes bioquímicos foliares asociados a niveles de estrés nutricional e hídrico. Este artículo resume avances en la detección de estrés nutricional mediante la estimación de parámetros bioquímicos, así como la viabilidad de la detección de estrés hídrico mediante sensores térmicos de alta resolución espacial instalados en vehículos aerotransportados.

1.- Introduction

In the 30 years since the launch of the first Earth Resources Technology Satellite (ERTS) on 23 July 1972, remote sensing data has become integral to environmental monitoring and assessment throughout the world. During this time, we have seen analysis of the data advance from simple visual observations to sophisticated interpretations based on first principles of spectroscopy and electromagnetic radiation. From the beginning of satellite data, starting with NASA's Multispectral Scanner (MSS, launched in 1972) and Thematic Mapper (TM, launched in 1984) and NOAA's Advanced Very High Resolution Radiometer (AVHRR, launched in 1978), satellites have demonstrated that measurement of land cover advanced our understanding of the spatial and temporal variability of many ecosystems and environmental conditions. In doing this, remote sensing observations have brought a new awareness of the spatial context in which ecological processes occur, while emphasizing the inter-connection of ecosystems. The advent of digital multispectral satellite and airborne sensors stimulated the development of new computerized analytical tools and visualization methods, initiated thinking about detecting biogeochemical processes that are measurable in different regions of the electromagnetic spectrum (EM), including measuring the fluxes and storage of materials between the air, land, sea components of biogeochemical (BGC) cycles. This paper summarizes the progress made on land cover mapping, and vegetation biophysical parameter and biochemical estimation using hyperspectral and thermal sensors.

2.- Land cover mapping

Land cover characteristics influence mass and energy exchanges at the land-atmosphere boundary (Cihlar et al. 1997). Land cover maps are derived from coarse AVHRR data at the global scale (e.g., 0.5° - 1°), and rely on the Normalized Difference Vegetation Index (NDVI) or a monthly time series of NDVI to differentiate land cover into regionally specific vegetation types (DeFries et al. 1994, 1999; Verstraete et al. 1996; Potter and Brooks, 1998). The global extent of land-use conversions increase uncertainty in the net flux of CO_2 (Schimel, 1995). More accurate spatial distribution and percent cover of the major ecosystem types is essential to improve BGC process models as is the variance within classes. NDVI data are used as inputs for many model parameters in Global Circulation Models (GCMs) and BGC models including properties for estimating carbon fluxes, stores, and turnover rates, as well as other land cover characteristics impacting the carbon budget. NDVI is also used to estimate carbon assimilation processes using the fraction of absorbed Photosynthetically Active Radiation (fPAR), net primary productivity (NPP) and net ecosystem productivity (NEP).

The most widely used ecosystem models (Foley et al. 1998) only use vegetation index (NDVI) data products to aid in estimating carbon uptake and allocation in vegetation. However, remote sensing paramaterizations have not advanced along with the model advances and do not take advantage of the new data resources. Only one variable—NDVI—is used to estimate multiple plant properties including LAI, evapotranspiration, photosynthesis, primary productivity and carbon cycling (e.g., Running et al. 1999).

A major research effort to reduce carbon cycle uncertainties over the last decade has improved estimates of CO_2 fluxes between the biosphere and atmosphere. Process modeling has received the most attention, which as produced more realistic mechanistic models (e.g., ; Field et al. 1995; Asner et al. 2001). The greatest contribution of remote sensing to BGC models has been in making spatially distributed land cover maps (e.g., DeFries and Townshend, 1994; Los et al. 2000) and measurement of absorption of photosynthetically active radiation (PAR) (Field et al. 1995). There is widespread agreement among carbon cycle researchers that additional constraints on land-surface processes are essential for new advances in prognostic capability. Imaging spectrometers (hyperspectral imaging instruments), multi-band, multi-polarization radar, and multi-band lidar could provide some of the needed information.

Lasers promise to provide improved estimates of canopy biomass, canopy height and roughness, which are used in estimating productivity, biogeochemical fluxes and biometeorological modeling and to address issues like fuel load for wildfire hazard. Airborne systems can produce maps with horizontal resolutions of submeters to meters and height resolutions of a few centimeters. With new multiband satellites capable of global mapping e.g., MODIS, SPOT Vegetation, SeaWIFS, MERIS, which in some cases have multiple viewing capabilities (e.g., POLDER, SPOT-5, MISR), there are opportunities to measure new features related to the canopy structure and to assess the non-photosynthetic components of the plant canopy, like the aboveground water content, woody tissues and plant litter. These instruments could provide more information on the 3-dimensional structure of the canopy and provide independent information on soil and geologic conditions, all of which could improve land cover mapping. In all cases where optical instruments have been compared, hyperspectral imaging (HSI) instruments provide more detailed information about land cover than multiband instruments. Ustin and Xiao (2001) compared classifications from SPOT and NASA's airborne Advanced Visible Infrared Imaging Spectrometer (AVIRIS) both with 20 m spatial resolution and showed much greater delineation of cover types compared to pre-existing field-based vegetation maps. AVIRIS measures 224 spectral bands at ~10 nm bandwidth over the 400-2500 nm wavelength region. Fine-scale landscape heterogeneity in boreal ecosystems (e.g. deciduous and evergreen forests, fens, bogs and small lakes) call into question the use of coarse spatial resolution data (between 1 km and 1º) obtained from the NOAA Advanced Very High Resolution Radiometer (AVHRR). Many of these problems persist even with high spatial resolution Landsat TM data (Steyaert et al. 1997). As an example, a critical contribution to the BOREAS program was the development of accurate land cover information at local and regional scales (Sellers et al. 1995) for which Landsat Thematic Mapper (TM) data was analyzed utilizing a physically-based classification algorithm that employed geometric canopy reflectance models (Hall et al. 1999). Their approach exploited systematic species differences by focusing on wavelength regions sensitive to foliar chemistry (Fig. 1). Spectral parameters used were the red-edge inflection point (λ_p), the wavelength at the reflectance minimum (λ_o), and a shape parameter (σ), as defined by an inverted-Gaussian red-edge curve-fit model (e.g., Hare et al. 1984). In contrast to multiband sensors, hyperspectral instruments can measure individual spectral features related to pigment composition (Peñuelas et al. 1995), canopy water content (Serrano et al. 2000), canopy dry plant litter and/or wood, or other aspects of foliar chemistry (Martin et al. 1998; Serrano et al. 2002). An extension of this work used pigment classes in a spectral unmixing procedure to map the relative abundance of pigments, and seven indices of vegetation structure and physiological function related to the pigment content and calculated from water absorption features. Indices such as the water band index (WBI), and the normalized difference water band index (NDWI, Gao, 1996) vary with vegetation type, LAI, and physiological state. Accuracy of the resulting land cover map, when compared to forest inventory classifications, were significantly improved using red-edge indices, which exceeded 68% for all classes (Zarco-Tejada et al. 1999). This result improved to 66.6%-80.1% by including water-based indices (Fuentes et al. 2001), demonstrating the superior results obtained with hyperspectral instruments.

3.- Vegetation stress detection

Because of the importance of photosynthetic function, leaf optical properties have been the subject of hundreds of studies since the middle of the last century. Most papers focused on the spectral properties of leaves (hemispherical reflectance and transmittance) which were used to estimate their biochemical content (chlorophyll, water, dry matter, etc.) and their anatomical structure. When foliage changes through phenological aging or when plants undergo environmental stresses, leaf chlorophyll content is observed to decline. This results in an increase in the reflectance and transmittance over the visible spectrum. These relationships were usually established empirically or directly estimated, using a physical model. Consequently, the bidirectional properties of leaves have received little investigation in contrast to plant canopies, where this has stimulated more study.

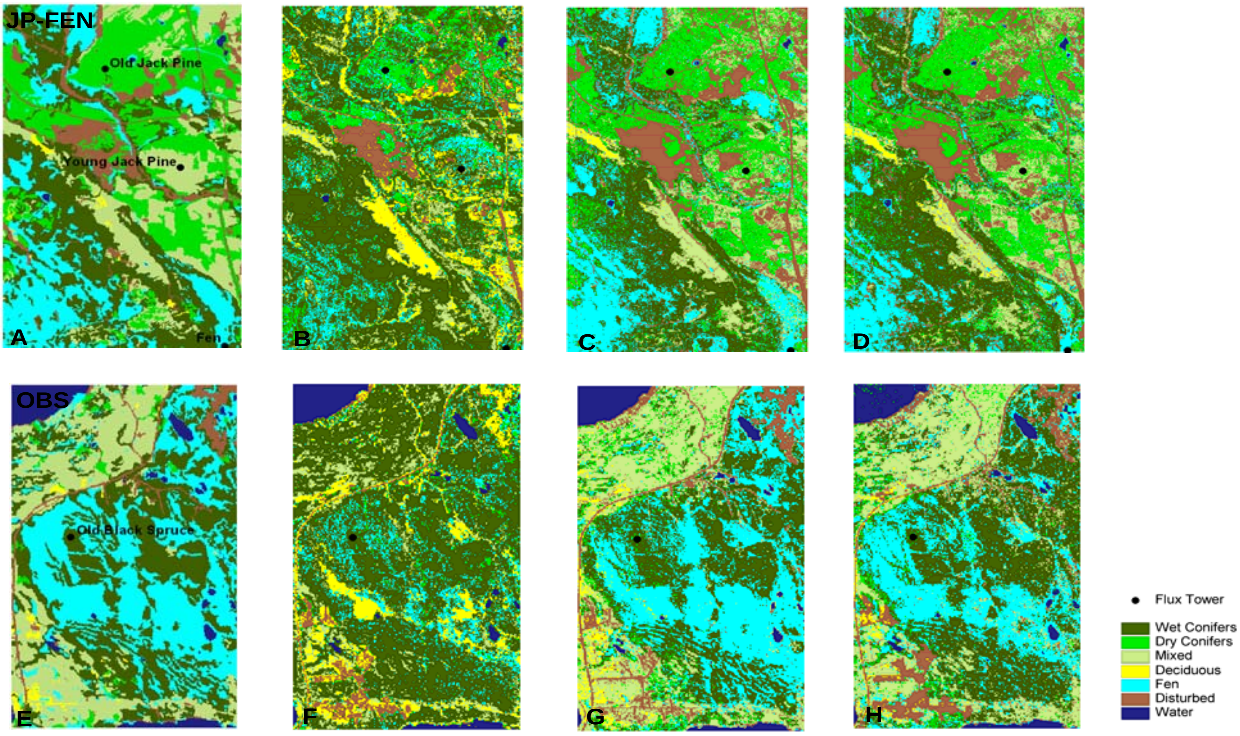

Fig 1. Vegetation map of the JP-FEN (jack pine fen) site (top) and OBS (old black spruce) site (bottom). Evaluation of classification accuracy of different methods, where panels a and e are the SERM FBIU map obtained from the BOREAS Information System (BORIS), and assumed to be true. Panels b and f are the Landsat TM physical classification from BORIS (Hall, 1999). Panels c and g are the AVIRIS leaf-based and Panels d and h are the index-based classifications, derived from the 21 July 1994 overflight.

Although the leaf surface characteristics are intuitively understood to be the primary factor involved in BRDF properties, the impact of these leaf surface properties on airborne and satellite data has not been determined. The current generation of spaceborne sensors (e.g., MISR and POLDER) measure the radiance of targets at several viewing angles that provide an opportunity to investigate this aspect of leaf optical properties as discussed in recent workshops on multiangular remote sensing (Verstraete and Pinty 2001). The sizes of the scattering objects on leaf surfaces (e.g., waxes and hairs) will produce wavelength dependent scattering that is independent of the canopy structure and independent of leaf biochemistry. Hundreds of papers have detailed variation in spectral properties in relation to leaf biochemical composition and structure, which themselves depend on many factors including the species, developmental or microclimate position of the leaf on the plant, and whether it is stressed or not. The domain of optical observations is divided from 400 nm to 2500 nm in three parts: the visible (400 nm - 700 nm) characterized by a strong absorption of light by photosynthetic pigments in a green leaf (Fig. 2); the near-infrared plateau (700 nm - 1100 nm) where absorption is limited to dry leaf matter but where multiple scattering within the leaf, related to the fraction of air spaces, i.e., to the internal structure, drives the reflectance and transmittance levels; and the middle-infrared and shortwave-infared (SWIR, 1100 nm - 2500 nm) which is also a zone of strong absorption, primarily by water in fresh leaves and secondarily, by dry matter (dry carbon compounds like cellulose and lignin, nitrogen, sugars, and other plant compounds) when the leaf wilts and dries. All of these observations and experimental measurements are a prerequisite to extracting biophysical information.

3.1. Biochemistry estimation for nutrient stress detection

Quantitative estimation of leaf biochemical and canopy biophysical variables is a key element to the successful application of remote sensing in vegetation monitoring, a major goal in terrestrial ecology and a long-term research objective given the complexity of the vegetation canopies and phenomena (Goetz et al., 1992). Accurate estimates of leaf pigments, nitrogen, dry matter, water content, and leaf area index (LAI) from remote sensing can assist in determining vegetation physiological status (Carter, 1994), the study of species and seasonal dependence, and may serve as bioindicators of vegetation stress (e.g. Zarco-Tejada et al., 2001).

The estimation of leaf biochemistry in field crops and orchard tree crops have important potential implications for agricultural field management, crop stress and chlorosis detection, and especially for precision agriculture practices. Chlorophyll concentration (C_{ab}) and other leaf biochemical constituents, such as dry matter (C_m) and water content (C_w) may be used as indicators of crop stress through their potential influence on nutritional deficiencies. Such deficiencies may be related to crop chlorosis that can be successfully treated thereby improving yields and the final crop quality. On the other hand, over-fertilization of crops affects carbon storage, generates vegetation injury for prolonged N additions and increases N losses by gaseous and solute pathways to the soil. The total chlorophyll content in leaves decreases in stressed vegetation, changing the proportion of light-absorbing pigments and leading to less overall absorption due to lower chlorophyll *a* and *b* concentrations at the leaf level. Differences in reflectance between healthy and stressed vegetation due to changes in pigment content have been detected in the reflectance *green peak* and along the *red edge*, providing remote detection methods to map vegetation stress through the influence of chlorophyll content variation.

Several narrow-band leaf-level optical indices have been suggested for C_{ab} estimation from hyperspectral reflectance data (see Zarco-Tejada et al., 2001). Red Edge Reflectance Indices such as Vogelmann (R_{740}/R_{720}) and (R_{734}-R_{747})/(R_{715}+R_{726}); Gitelson & Merzlyak (R_{750}/R_{700}); Carter (R_{695}/R_{760}); Zarco-Tejada & Miller (R_{750}/R_{710}), and Spectral and Derivative Indices such as the red edge parameters λ_p, λ_o, σ (Miller et al. 1990), and derivative indices (D_{715}/D_{705}) and DP21 ($D\lambda_p/D_{703}$) have been shown to yield the best results for C_{ab} estimation at both leaf and canopy levels. Recently, combinations of indices based on TCARI, MCARI, and OSAVI, such as TCARI/OSAVI and MCARI/OSAVI (Haboudane et al., 2002), have been demonstrated to successfully minimize the effects of soil background variation and LAI canopy changes, resulting in prediction relationships for easy use for precision agriculture with *Compact Airborne Spectrographic Imager* (CASI) hyperspectral imagery.

The successful estimation of leaf biochemical constituents from hyperspectral data in homogeneous crops (Haboudane et al., 2002) and closed forest canopies (Zarco-Tejada et al., 2001) has demonstrated the utility of *scaled-up* indices through radiative transfer simulation. Moreover, model inversion techniques, based on linked leaf-canopy radiative transfer models, have been shown to be a feasible method for biochemical estimation from canopy-level reflectance in closed canopies and through simulation studies modelling 3D forest canopies (Demarez and Gastellu-Etchegorry, 2000).

Several indices have been proposed in the literature to track chlorophyll concentration, although such indices do not show the same performance at the leaf and at the canopy levels, due to the effects of scene components, soil and shadows, on canopy-level indices. Generally good

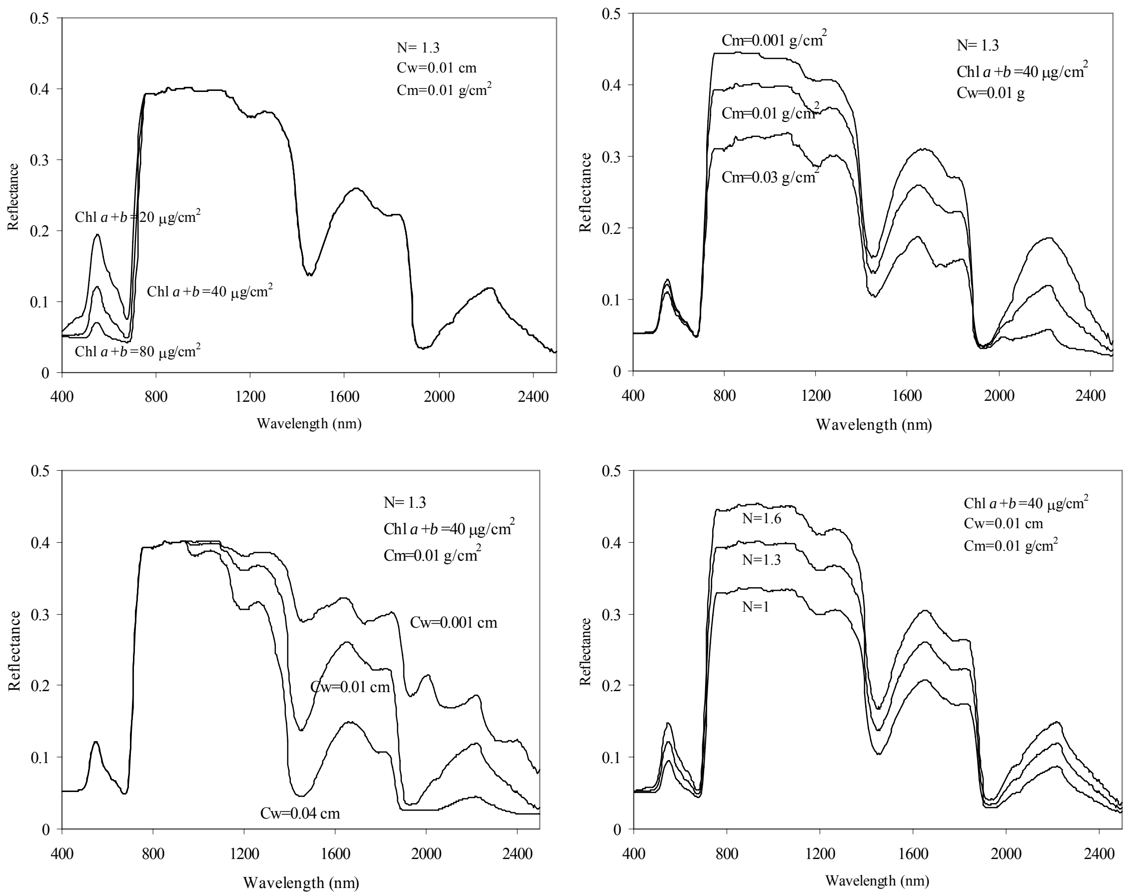

Fig. 2. Effects of leaf biochemical constituents such as chlorophyll Ca+b (upper left), dry matter Cm (upper right), equivalent water thickness Cw (lower left), and leaf structural parameter N (lower right) on leaf reflectance, simulated using the PROSPECT model.

results are found for C_{ab} estimation at the leaf level with *red edge* and spectral and derivative indices such as R_{750}/R_{710}, R_{740}/R_{720}, $(R_{734}-R_{747})/(R_{715}+R_{726})$, $(R_{734}-R_{747})/(R_{715}+R_{720})$, D_{715}/D_{705}, R_{750}/R_{550}, R_{750}/R_{700}, R_{695}/R_{760}, λ_p, $D_{\lambda p}/D_{703}$, and $D_{\lambda p}/D_{720}$ (Zarco-Tejada et al., 2001). In agricultural canopies, with large effects of soil background and LAI variation at different growth stages, combined indices have been proposed to minimize such background soil effects while maximizing the sensitivity to C_{ab}. CARI *(Chlorophyll Absorption in Reflectance Index)* was shown to reduce the variability of photosynthetically active radiation due to non-photosynthetic materials. MCARI *(Modified Chlorophyll Absorption in Reflectance Index)* was a modification of CARI to minimize the combined effects of the soil reflectance and the non-photosynthetic materials. SAVI *(Soil-Adjusted Vegetation Index)* and OSAVI *(Optimized Soil-Adjusted Vegetation Index)* were proposed as soil-line vegetation indices that could be combined with MCARI to reduce background reflectance contributions. Successful C_{ab} estimation on corn agricultural canopies at different growing stages was achieved with the TCARI/OSAVI combined index, proving its robustness in the presence of variations in canopy LAI and background exposure (Haboudane et al., 2002), and olive orchards (Fig. 3).

relationships between leaf reflectance and leaf water content, and *scaling-up* methods to canopy level through radiative transfer simulation.

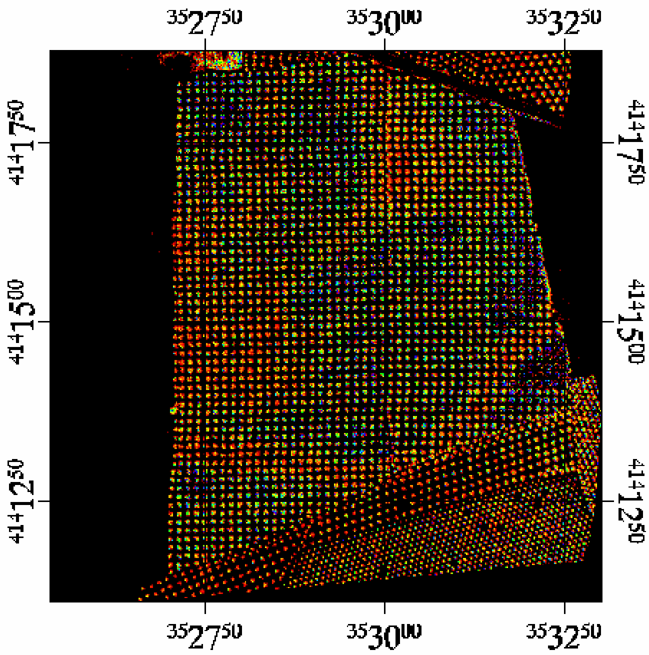

Fig. 3. Mapping chlorophyll concentration at the crown level by scaling up MCARI/OSAVI through PROSPECT-SAILH from 1-m ROSIS image.

3.2. Water content estimation

The remote determination of one of these biochemical constituents, vegetation water content, has important implications in agriculture and forestry, it is essential for drought assessment in natural vegetation, and it is a major driver in predicting the susceptibility to fire. Several studies demonstrate the existing link between leaf-level reflectance in the 400-2500 nm spectral region and the amount of water in the leaf through optical indices, regression analysis and radiative transfer modeling (Gausman et al., 1970). The primary and secondary effects of water content on leaf reflectance showed that sensitivity of leaf reflectance to water content was greatest in spectral bands centered at 1450, 1940, and 2500 nm. Indirect effects of water content on reflectance were also found at 400 nm, in the red edge at 700 nm and on vegetation indices such as NDVI. The effects of leaf structure on the water absorption bands showed that derivative reflectance calculated in the water absorption features minimized the effects due to leaf structure, therefore maximizing the sensitivity to leaf water content. Lately, the broad use of leaf radiative transfer models such as PROSPECT (Jacquemoud and Baret, 1990) for broadleaf species, enable the simulation of the leaf optical properties as a function of leaf structural and biochemical constituents such as chlorophyll *a*+*b* (C_{a+b}), dry matter (C_m), and leaf equivalent water thickness (C_w). Several research efforts focus on the application of leaf-level indices calculated from water-absorption bands, statistical

As an example, airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery was used to derive equivalent water thickness in vegetation using nonlinear and linear least squares spectral matching techniques, achieving good agreements with ground measured leaf fuel moisture content (Gao and Goetz, 1995). Other ratios, such as the Plant Water Index (PWI, R970/R900) was used to map vegetation water content with AVIRIS imagery, but found to be affected not only by water content, but also by canopy structure and viewing geometry therefore highly dependent on bi-directional and geometrical effects of the vegetation canopy. The Normalized Difference Water Index (NDWI) calculated as (R860-R1240)/(R860+R1240) was suggested by Gao (1996) in a theoretical study, demonstrating its potential applicability for canopy-level water content estimation based on the liquid water absorption band centered at 1240 nm enhanced by canopy scattering.

MODIS reflectance data were processed from the same period for equivalent water thickness estimation by model inversion linking the PROSPECT leaf model and SAILH canopy reflectance model. MODIS reflectance data, viewing geometry values, and LAI were used as inputs in the model inversion for estimation of leaf equivalent water thickness, dry matter, and leaf structure. Results showed good correlation between the time series of MODIS-estimated equivalent water thickness and ground measured leaf fuel moisture content (r^2=0.7), demonstrating that these inversion

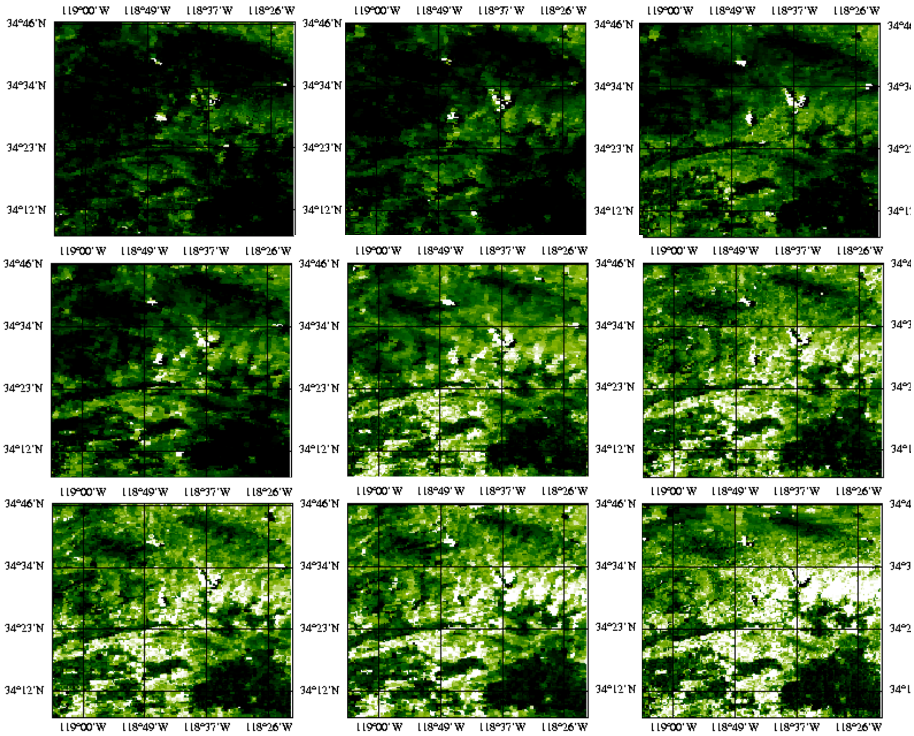

Fig. 4. Time series of MODIS-estimated leaf water content in vegetation for the period June-September 2000. Reflectance and viewing geometry (ts, tv, ps) from MOD09A1, and LAI from MOD15A2 MODIS products were used as input parameters in the iteration method, with N, Cw and Cm leaf parameters subject to inversion. Darker green color corresponds to higher Cw.

methods could potentially be used for global monitoring of leaf water content in vegetation (Fig. 4).

3.2.1. Thermal remote sensing for stress detection

Water stress develops in crops when the evaporative demand exceeds the supply of water from the soil. As a result, plant water status declines and that affects physiological processes, such as leaf expansion and other growth processes. Most crops are very sensitive to water deficits, and their yield is negatively affected even by short-term water deficits. Although water content in vegetation canopies can be assessed by remote sensing, leaf water potential is a more precise indicator of the plant water status for predicting effects of water deficits on crop yields because small changes in the relative water content of leaf tissues corresponds to large changes in leaf water potential. Changes in leaf water content that may be easily detectable normally occur at advanced stages of dehydration, being therefore a parameter of limited interest for predicting crop water status for situations where high crop productivity levels are sought. Even though there is interest in obtaining leaf water potential information, it is often suggested that pre-dawn measurements of leaf water potential are the most accurate to estimate soil moisture status but the inconvenience and narrowness of time window makes this measurement impractical. The dynamics of the daily course of leaf water potential (LWP) makes it difficult to determine the appropriate time of measurement; however, LWP in sunny days is relatively constant for several hours around solar noon, the time when it reaches its minimum value. When the plant is stressed and transpiration decreases, the crop canopy temperature tends to rise appreciably because of the reduction in evaporative cooling. This is the basis for the approach of sensing crop stress by monitoring canopy temperature with thermal infrared radiation (Jackson et al., 1977). This technique has been widely studied and developed mainly using hand-held thermal infrared thermometers. Despite the potential usefulness of remote sensing for thermal detection in vegetation canopies, studies where satellite or airborne thermal remote sensing is used for water stress detection are uncommon, in particular for open canopies such as tree crops. This is probably due to the lack of sensors onboard satellites with optimal spatial resolution to monitor orchard crops at the tree scale (i.e. ideally 0.5 to 2 m resolution in the thermal region), with current available sensors varying from 90 m (ASTER) to 1000 m (MODIS) pixel size. In addition, there are the current and future severe limitations with Landsat. Even in the case of high-spatial resolution imagery collected from airborne sensors, shadows and direct soil influences involve problems in the canopy temperature retrieval due to the canopy heterogeneity characteristic in orchard canopies.

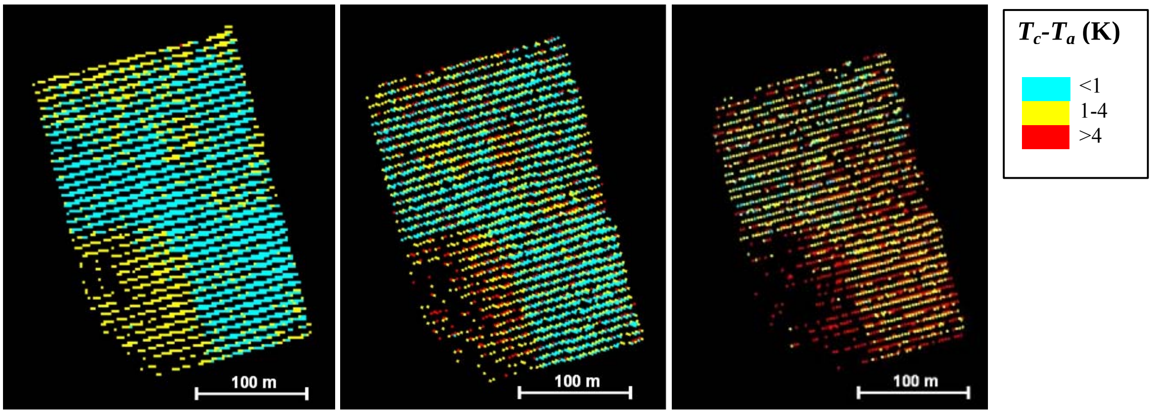

Fig. 5. Canopy temperature (Tc) minus air temperature (Ta) images obtained from the AHS sensor on 25 July 2004 at three over fight times: (d) at 7:30, (e) at 9:30 and (f) at 12:30 GMT.

Nevertheless, recent studies on surface temperature estimation with high spatial resolution remote sensing imagery have proved that this technology is available for obtaining accurate measurement of surface temperature. Different methods can be used to retrieve land surface temperature from thermal infrared data provided by only one or two thermal bands, as for example the single-channel methods or the split-window technique. Land surface temperature and emissivity can be also obtained from multispectral thermal data using the Temperature and Emissivity Separation (TES) algorithm. A detailed review of methods can be found in Sobrino et al (2002). The feasibility of these methods for retrieving land surface temperature from ten thermal-infrared bands of the *Airborne Hyperspectral Scanner* (AHS) is assessed in Sobrino et al. (2006).

Recent results by Sepulcre-Cantó et al. (2006) demonstrate i) that the remote sensing detection of mild water stress in a commercial peach orchard is feasible over treatments under deficit irrigation; and ii) that there is potential for the application of thermal remote sensing as an indicator of some fruit quality parameters in open-canopy orchards at the tree scale. Results of the 2004 and 2005 field campaigns showed that canopy temperature, stem water potential and stomatal conductance varied with the irrigation treatments applied to olive and peach trees. Infrared thermal sensors and thermal cameras were able to detect the temperature differences due to water stress even under the conditions in the peach orchard where limited irrigation deficits were applied to sustain maximum productivity. However, in the olive, Tc-Ta yielded up to 6 K for trees under deficit irrigation during the period of maximum stress, while Tc-Ta yielded 5 K for trees under well irrigated treatment. The peach tree crowns were warmer than the olives, with Tc-Ta of up to 7 K for trees under deficit irrigation and 6 K for well irrigated trees. Field measurements with the thermal camera showed a greater thermal homogeneity for the crown temperature in well-watered trees, obtaining a determination coefficient of r^2=0.48 between standard deviation of the imagery and the stem water potential. Results obtained from the AHS imagery showed at midday on 16 July 2005 differences in Tc-Ta between fully irrigated and stressed of 2 K in both cases (olive and peach trees). These results show that AHS sensor was able to detect thermal differences between olive and peach trees under different deficit irrigation treatments. Determination coefficients between crown Tc-Ta obtained with the airborne AHS thermal imagery and olive tree stomatal conductance yielded r^2=0.60 (12:30 GMT) for individual trees, and r^2=0.87 (7:30 GMT) for plots of 12 trees under the same irrigation treatment. Determination coefficients between olive stem water potential and Tc-Ta for individual trees r^2=0.49 (12:30 GMT), and r^2=0.52 (12:30 GMT) for plots of 12 trees under the same treatment. These results confirm that temperature differences observed in trees under different irrigation treatments were due to water stress. Results on the peach orchard also showed successful detection of water stress as a function of mild water deficits imposed by different irrigation levels that aimed at maintaining full commercial productivity. Maps of Tc-Ta could be used to assess the level of water deficits over orchards and to predict its impact on yield and fruit quality.

4.- Conclusions

In this chapter we have attempted to highlight recent advances in image processing and data analysis for understanding the function and structure of the plant canopy. We have pointed out areas where ecosystem and global change models need improved data products to reduce their current levels of uncertainty. Clearly this is a shifting baseline since instruments and models are improving at a rapid pace. Nonetheless, there remains a wide range of problems that need to be solved to extend our understanding. Many of these issues will be improved quickly while others may take a decade or more, depending on how rapidly new instrument technologies and computational/mathematical tools become widely available to the research community. The importance of addressing environmental problems and issues using remote sensing data will continue to apply pressure for developing improved measurement and monitoring methods. For the first time ever, it is possible to observe the Earth from space using data spanning the spatial resolutions of sub-meter Quickbird to km scale AVHRR, SeaWIFS, MERIS, and others and at time intervals from multiple times daily to bimonthly. The abundance of data sources makes it possible to monitor the earth at virtually any scale appropriate to the analysis. Progress is shown on the application of hyperspectral and thermal remote sensing methods for nutrient and water stress detection in crops, obtaining temperature estimates of individual tree crowns from airborne imagery. These methods have potential applications in water stress detection and irrigation scheduling in orchard canopies in the context of precision agriculture.

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