THE ROLE OF HYPERSPECTRAL DATA IN UNDERSTANDING THE GLOBAL CARBON CYCLE

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1. Introduction

A major challenge in predicting the consequences of global climate change is to accurately estimate carbon stocks and to predict future CO_2 sequestration and dynamics (NRC, 1999). Climate dynamics and human activities drive changes in land cover and land use, creating unpredictable patterns of disturbance and environmental stresses in natural and managed ecosystems. These changes affect carbon storage, the distribution of carbon in above and below ground compartments, ecosystem productivity, and biogeochemical cycles. A wide range of information is needed to monitor the carbon cycle from properties that regulate fluxes of CO_2, to estimates of standing biomass, land cover types, and land use history. Satellite observations provide the only practical means to obtain a synoptic view of the Earth's ecosystems, their spatial distribution, extent, and temporal dynamics.

Four priority areas have been identified where improved satellite observations of terrestrial landscapes could contribute to greatly reducing the uncertainties in the global carbon budget. These are: (1) land cover characterization at improved spatial resolution, (2) above-ground biomass estimates, (3) areal estimates of disturbance, disturbance type, and time period since the last disturbance, and (4) improved estimates of productivity and controls on productivity. While these categories do not exclusively require hyperspectral data, it can contribute to significant improvements in reducing uncertainties in each area.

Among most important information that satellite observations can contribute is the distribution of land cover types, in particular vegetation, and their spatial variability. For terrestrial biomes, information is needed on the growth form, the cover fraction, canopy density, seasonality and duration of the growing season, the leaf type (conifer, broadleaf) and the photosynthetic pathway (producing four-carbon (C4) or three carbon (C3) carbohydrate products) associated with specific carbon uptake characteristics (DeFries *et al.* 1995; 1999). To understand the consequences of land cover and land use change on the carbon budget, both the biophysical and the human factors that drive land cover and land use changes must be addressed. Natural disturbances (such as wildfire, floods, insect infestations), and human-induced disturbances (e.g., agriculture, urbanization, and logging) may change large areas of the Earth's surface, but more subtle changes may also result in habitat degradation and fragmentation (e.g., selective logging, soil erosion, and pollution). The introduction of non-native species can lead to significant changes at the ecosystem scale in carbon storage and fluxes, redistribution of species, and/or losses of biodiversity. Current satellite observations are inadequate to characterize and verify land cover at the spatial scales needed to assess their impacts on the carbon budget.

Land cover characteristics influence many of the mass and energy exchange processes at the land-atmosphere interface (Cihlar *et al.*, 1997) with a functional dependency on the land cover type. Land use changes play an important additional role because these cause uncertainty in the net flux of CO_2 and the required size of a terrestrial sink (Schimel, 1995). Therefore accurate spatial distribution and percent aerial coverage of the major cover types is essential for correct process modeling. However, current land cover maps derived from AVHRR are coarse at the global scale (e.g., 0.5° - 1°), and primarily rely only on NDVI or a monthly time series to differentiate land cover characteristics (DeFries *et al.*, 1999; Potter *et al.*, 1998; Veroustraete *et al.*, 1996). These NDVI maps are used to generate estimates of multiple model parameters including carbon fluxes, carbon stores, carbon turnover rates, and other land cover properties that impact the carbon budget. Furthermore, NDVI is also used to estimate carbon assimilation processes using fraction of absorbed photosynthetically active radiation (fPAR), net primary productivity (NPP) and net ecosystem productivity (NEP).

Hyperspectral data, having many more spectral bands, provide more independent measures of land surface characteristics. Boardman and Green (2000) explored the intrinsic dimensionality of 510 AVIRIS scenes having a

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range of land cover characteristics and found at least 60-70 above a conservative noise floor, with many individual scenes exceeding 50 spectral dimensions. Because of the scale of variability in ecosystem properties, high spatial resolution (10-100m) is considered critical to developing land cover characterizations, at least for developing appropriate and testable scaling methods to understand the non-linearities in aggregating land cover properties to 1° grids. Green and Boardman (2000) investigated data dimensionality in AVIRIS data and found that the increased signal-to-noise obtained in larger pixels (in this case from 4m to 32m) enhanced the dimensionality despite loss of spatial resolution. This suggests that hyperspectral instruments would not require hyperspatial pixel resolutions. This paper discusses the approaches and variables used for estimating the carbon budget on terrestrial surfaces and the improvements that a hyperspectral satellite sensor could make to reducing the overall uncertainty in the carbon budget.

2. The role of hyperspectral sensors for carbon estimates by improving land cover classification

Key variables are mapping land cover, land use, and land cover conversions, either occurring naturally or due to human disturbances. In all cases where instruments have been compared, HSI instruments provide more detailed information about land cover. For example, predicting whether a boreal forest will become a carbon sink or source demands an accurate knowledge of the distribution of the cover classes in this ecosystem (Steyaert *et al.*, 1997). Ustin and Xiao (2001) compared boreal forest classifications from SPOT and AVIRIS and showed much greater delineation of types and fidelity to a pre-existing field-based map despite similar spatial resolution.

Obtaining baseline maps of the composition of the boreal landscape is of high priority due to predictions for large increases in temperature in this century (IPCC, 1996), the relative inaccessibility of the region, and the potential for feedbacks with other trace gases, e.g., CH_4 production. Landscape heterogeneity (e.g. deciduous and evergreen forests, fens, bogs and small lakes) in boreal ecosystems call into question coarse spatial resolutions between 1 km and 1° x 1°, land cover classification provided by multi-temporal AVHRR data, and persist even with higher spatial resolution Landsat TM data (Steyaert *et al.,* 1997). These issues have been continuously addressed within the BOReal Ecosystem-Atmosphere Study (BOREAS) since a critical contribution to remote sensing science in BOREAS was the development of accurate land cover information at local and regional scales (*BOREAS Experiment Plan,* 1994; Sellers *et al.* 1995). Land cover was mapped at 30m with Landsat TM utilizing a physically-based classification algorithm that employed geometric canopy reflectance models (Hall *et al.,* 1995; 1997). Nevertheless, classification accuracies using such an approach remained low for fens (a major source of methane) and upland conifers. Improvements in land cover mapping were identified as a priority and enhancements were attempted using physical-modeling approaches (Hall *et al.,* 1997; Peddle *et al.,* 1997), and neural networks (Benediktsson *et al.,* 1990; Duguay and Peddle*,* 1996). Zarco-Tejada and Miller (1999), and by Fuentes *et al.* (in press), exploited systematic species differences using hyperspectral instruments and exploiting wavelength regions sensitive to foliar chemistry to obtain significant improvements in land cover characterization of the BOREAS region. Zarco-Tejada and Miller (1999) improved land cover classification (Figure 1) using 16 CASI bands at the TM spatial resolution (originally 3m resampled to 30m) based on three red-edge spectral parameters: the red-edge inflection point (λ_p), the wavelength at the reflectance minimum (λ_o), and a shape parameter (σ), as defined by the inverted-gaussian red-edge curve-fit model (e.g. Hare *et al.*, 1984), and discussed by Miller *et al.* (1990; 1991).

Their approach was based on the separation of land cover types using variables known to affect red edge spectral parameters: vegetation chlorophyll content, canopy structure and canopy cover. An extension of this work by Fuentes *et al.* (in press) (Figure 2) 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, Peñuelas *et al.*, 1997), and the normalized difference water band index (NDWI, Gao, 1996) have been shown to be good indicators of leaf and canopy water content, which vary with vegetation type, LAI, and physiological state *(*Ustin *et al., 1998;* Gamon and Qiu, 199*9;* Serrano *et al.*, 2000). Accuracy assessment of the resulting land cover map, when compared to forest inventory classifications, showed significantly improved classification accuracy with red-edge indices, which exceeded 68% for all classes (Zarco-Tejada and Miller, 1999) and improved to 66.6-80.1% (Fuentes *et al.,* in press) by including water-based indices.

Therefore, hyperspectral sensors enable the use of individual spectral features related to pigment composition (Gitelson and Merzylak, 1996, 1997; Gamon and Surfus, 1999), canopy water content *(*Peñuelas *et al*.,

1997; Ustin *et al*., 1998; Serrano *et al*., 2000), canopy dry plant litter and/or wood (Roberts *et al*., 1993; Ustin *et al*., 1993, 1996, 1998, Asner *et al*., 1998), and forest composition as function of foliar chemistry (Martin *et al.,* 1998; Zarco-Tejada and Miller, 1999; Fuentes *et al.,* in press) achieving better discrimination of vegetation classes than possible from broadband sensors.

LEGEND

- Mixed (yellow)
- Wet Coniferous (dark green)
- Dry Coniferous (green)
- Fen (red)
- Disturbed (blue)
- Water (cyan)
- Deciduous (magenta)

(top left and right)

LEGEND

- Class 1 (yellow)
- Class 2 (green)
- Class 3 (red)
- Class 4 (blue)
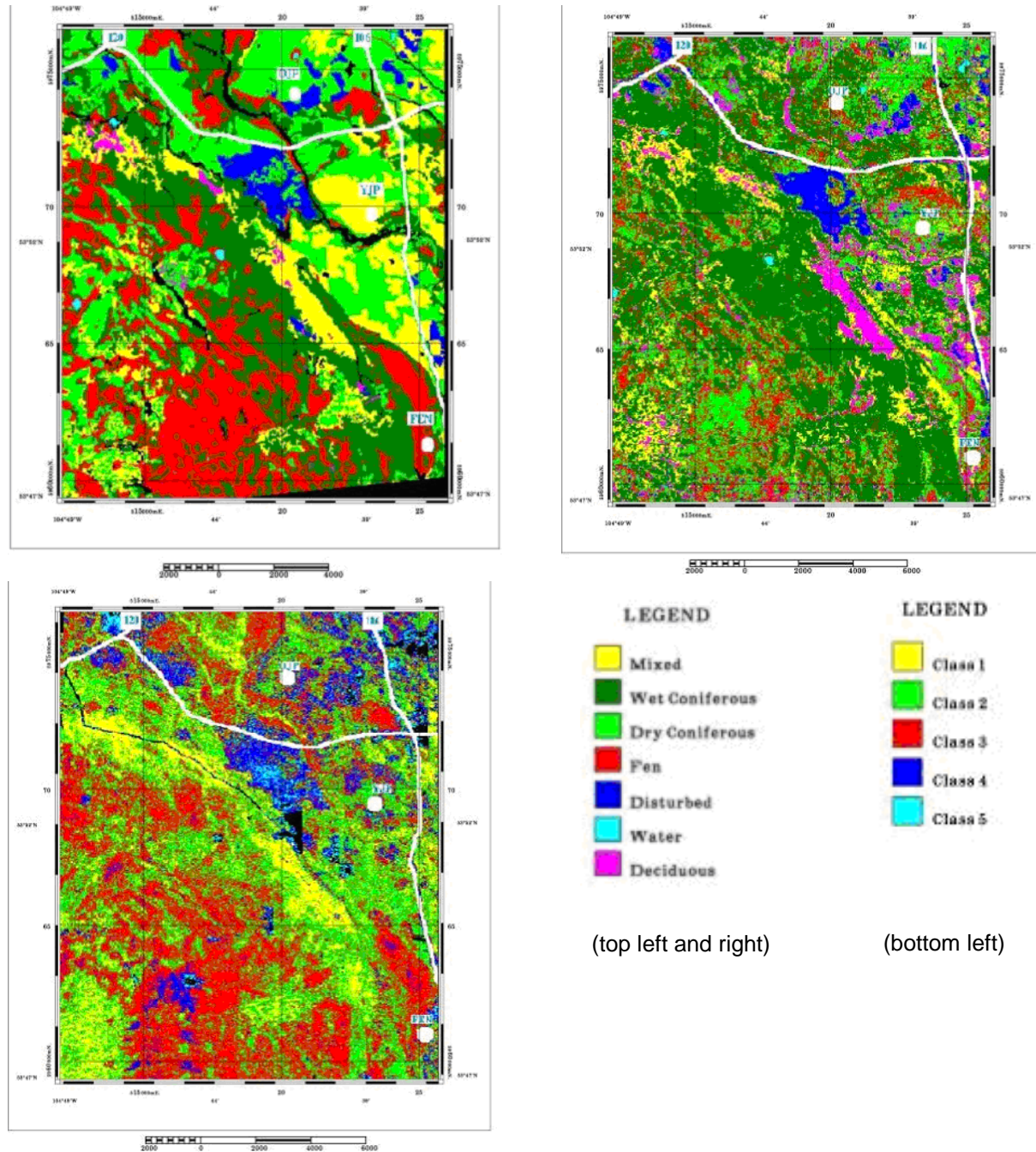- Class 5 (cyan)

(bottom left)

Figure 1. Land cover classes (aggregated into the 7 functionally-dominant landscape units) for the BOREAS Southern Study Area, based on polygon data from *Saskatchewan Environment and Resource Management* used as ground truth (top-left), land cover classification based on Landsat TM data and the physical modeling approach of Hall *et al.* (1995, 1997) (top-right), and classification using the red edge spectral parameters λ_p, λ_o, and σ based on CASI hyperspectral mosaic of the BOREAS SSA modeling grid, re-sampled to 30 m spatial resolution (Zarco-Tejada and Miller, 1999).
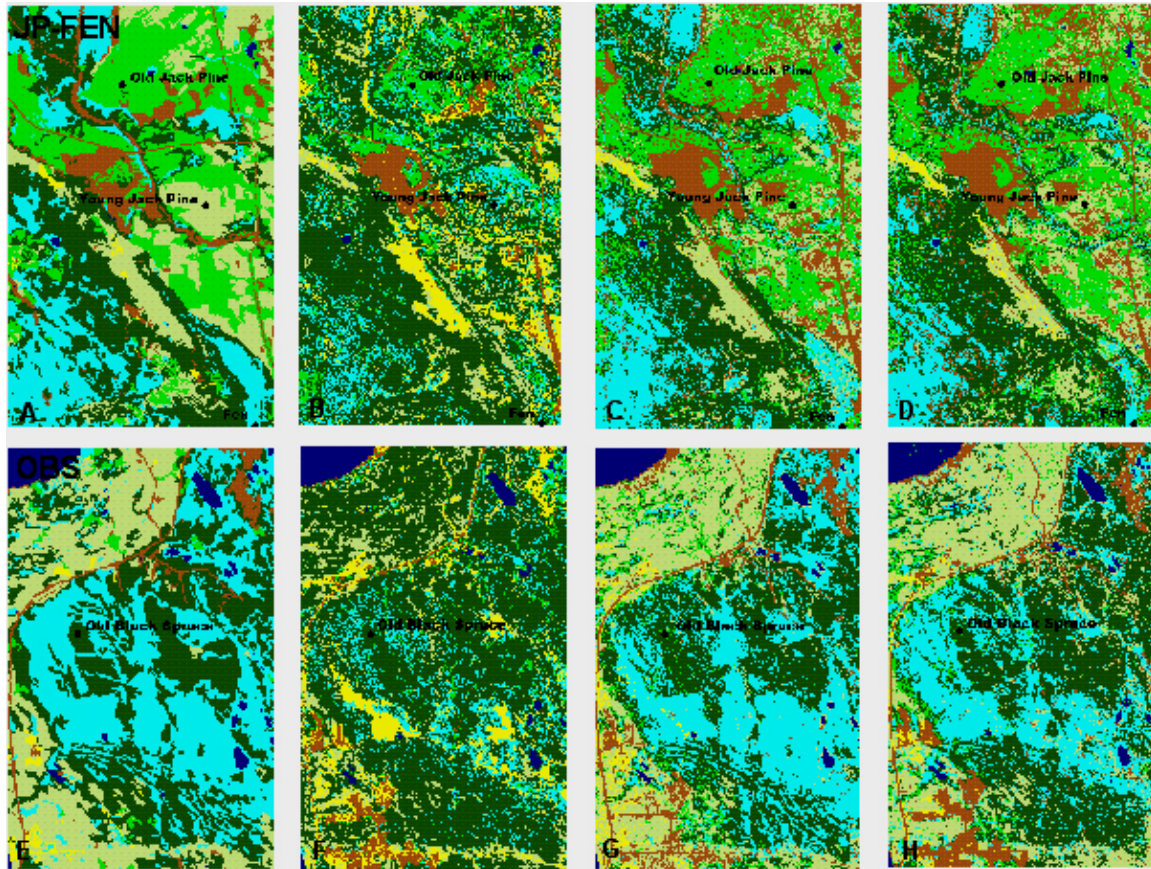
Figure 2. Jack pine-fen (JP-FEN) site (top panels) and Old black spruce (OBS) site (bottom panels). For the evaluation of classification accuracy, the SERM-FBIU (Gruszka, 1998; Panels A & E), obtained from the BOREAS Information System (BORIS), was assumed to be true. The Landsat TM physical classification (Hall, 1999; Panels B & F). The, AVIRIS leaf-based (Panels C & G) and index-based (Panels D & H) maximum likelihood classifications were derived from the July 21, 1994 overflight. (Fuentes *et al.,* in press).

3. Carbon estimates with multispectral coarse resolution remote sensing data

Global estimates of CO_2 dynamics using ecosystem models such as Simple Biosphere Model, SiB2 (Sellers *et al*., 1986, 1996a,b) and CASA (Potter *et al*., 1993; Field *et al*., 1995; Randerson *et al*., 1997) obtain input data from AVHRR-derived NDVI data to capture biophysical and ecological properties used in the models. NDVI is affected by both pigment absorption (blue and red) and the scattering of the medium (NIR), a function of the arrangement of elements of the canopy (structure). Moreover, it is well documented that NDVI saturates at leaf area index (LAI) values substantially below LAI in high productivity sites. Limitations of current methods for deriving canopy biophysical (LAI, structure) and leaf biochemical constituents (chlorophyll (chl_{a+b}), nitrogen (N), and water content (H_2O)) limits accuracy when estimating the significance of photosynthetic processes in regulating some components of the carbon cycle. Moreover, no current remote sensing approaches provide reliable estimates of other critically important ecosystem-level properties such as senescent vegetation (e.g., dry carbon loading) or canopy structural changes. Observations of these factors, which have been demonstrated from hyperspectral imaging systems, would provide a major step toward an improved understanding of the carbon cycle.

Widely used ecosystem models (Sellers *et al*., 1986, 1996a,b) and CASA (Potter *et al*., 1993; Field *et al*., 1995; Randerson *et al*., 1997) use remotely sensed data products for estimating carbon allocation, including new model advances such as a 6-layer soil submodel (Bonan, 1996, 1998). Explicit litter layer (Denning *et al*., 1996),

new parameterizations of carbon and nitrogen allocation, growth and maintenance respiration and decomposition are obtained using new hybrid ecosystem models, e.g., incorporating SYLVAN (Kaduk 1996; Kaduk and Heimann 1996a,b). However remote sensing paramaterizations have not advanced and NDVI is used to simultaneously estimate LAI, evapotranspiration, photosynthesis, primary productivity and carbon cycling.

A number of studies have shown that the NDVI saturates at LAI of 3-4 (Sellers, 1986), while LAI exceeds this for most closed-crown crops and forests. NDVI saturation under-estimates the fluxes of CO_2 and H_2O, and this error feeds back into other physiological processes. One of the key driving variables used by CASA and SiB-2 models is the flux of absorbed PAR, with gross CO_2 uptake, NPP, and canopy conductance all scaled to NDVI. In theory, absorptance of PAR is proportional to NDVI but because both saturate most of the variability occurs at LAI values < 3. Canopies with large variations in LAI also exhibit large differences in total photosynthetic capacity and the quantity of nitrogen and other nutrients in the canopy are incorrectly inferred from an NDVI parameter. NDVI failed to track variation in pigment content, such as might occur under environmentally induced plant stress at study sites with high LAI values (Zarco-Tejada, 2000). Furthermore, maximum site LAI, governed by climate and site conditions is often reached at an early stage of growth while non-photosynthetic components of biomass (stems, roots) continue accumulation throughout the growing season. This biomass estimate saturates at relatively low levels of biomass, and causes NDVI to markedly under-estimate biomass in woody vegetation. Fluxes of CO_2 and H_2O, feed back into other physiological processes that are also under estimated. Figure 3 shows NDVI, red-edge spectral parameter λ_p, and estimated canopy water content, calculated from cotton fields using hyperspectral AVIRIS data. It can be seen that NDVI does not correspond to λ_p, which is highly correlated with pigment content, and functionally with canopy water content.

The accuracy of carbon model predictions in vegetation at higher spatial scales will improve estimates of biophysical parameters through more effective linkage between leaf and canopy radiative transfer models (RT) from hyperspectral data. Estimates of leaf chl_{a+b} and its relationship to N content, LAI, and canopy H_2O, are biophysical parameters that can be retrieved from hyperspectral canopy reflectance data by inversion of coupled leaf and canopy models.
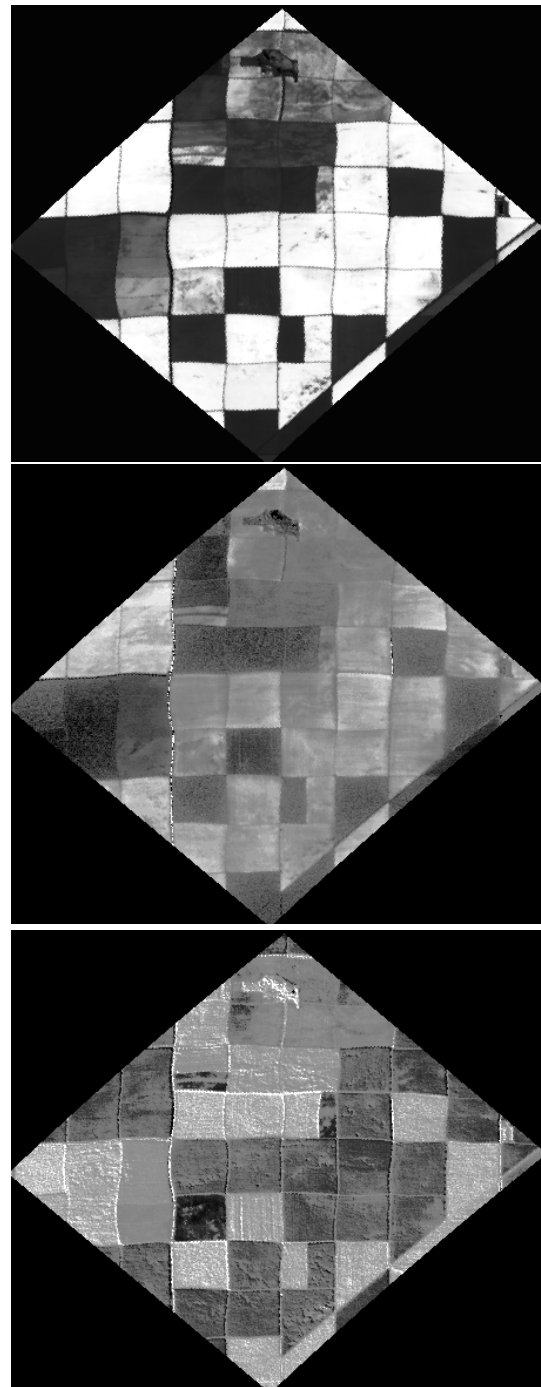

Figure 3. NDVI (top), red edge spectral parameter λ_p (middle), and canopy water content (bottom), calculated from the same cotton fields from AVIRIS data.

3.1. Estimation of other physiological variables using hyperspectral remote sensing

The carbon system is closely linked to the water and energy cycles through regulation of photosynthesis (Sellers *et al.*, 1992; Sellers and Schimel, 1993; Collatz *et al.*, 1991), and to the nitrogen cycle through metabolism (Schimel, 1995). Correctly predicting the linkages between the carbon, water, and nitrogen cycles is crucial to

predicting the changing Earth system and feedback to atmospheric concentrations of greenhouse gases and primary productivity of the biosphere (Schimel, 1995).

The global carbon cycle (i.e., through CO_2 uptake) is affected by alteration of the global N cycle through fertilizer use and air pollution (Schimel, 1995; Vitousek *et al*. 1997). Fertilization of agricultural crops and N deposition affect carbon storage, generate vegetation injury with prolonged N additions (Schultze *et al*., 1989) and increase N losses by gaseous and solute pathways to the soil. Spatial estimation of N in forest and agricultural canopies is important to quantify interactions between the carbon and nitrogen cycles. Estimating leaf nitrogen content is obtained through total chlorophyll concentration, because the majority of leaf N is contained in the carbon-fixing enzyme, RUBP-carboxylase (Daughtry *et al*., 2000; Yoder and Pettigrew-Crosby, 1995). Estimating chlorophyll content from canopies with different structural characteristics requires hyperspectral data to couple specific radiative transfer models with leaf models using red-edge indices in the merit function while minimizing the effects of canopy shadows, understory, and large variations of LAI (Zarco-Tejada *et al*., in press; Zarco-Tejada, 2000). Therefore, accurate estimates of leaf chl_{a+b} at canopy levels with high spatial resolution hyperspectral reflectance data is

Figure 4. Estimation of leaf chl_{a+b} from canopy airborne hyperspectral data by inversion of SAILH+PROSPECT models using R_{750}/R_{710} optical index in the merit function. Using red edge optical indices in the merit function for model inversion avoids effects due to canopy structure and shadows (using all pixels from a study plot, labeled as *all pixels*), obtaining the same pigment estimates when targeting crowns (labeled as *upper 25%*) from 30x30 m study sites (Zarco-Tejada *et al.,* in press).

critical for obtaining estimates of leaf N. Estimation of canopy concentrations of chl_{a+b} have been demonstrated by model inversion using hyperspectral remote sensing data (Jaquemoud, 1993; Jacquemoud *et al.,* 1995; Kuusk, 1998; Demarez and Gastellu-Etchegorry, 2000; Jacquemoud *et al.,* 2000; Zarco-Tejada, 2000; Zarco-Tejada *et al.,* in press). Specific results by Jaquemoud (2000) and Zarco-Tejada *et al*. (in press) using airborne hyperspectral data showed errors of RMSE = 3-8 $\mu g/cm^2$ for chl_{a+b} estimated by linking leaf radiative transfer model (PROSPECT) to infinite reflectance (Hapke, 1993; Yamada and Fujimura, 1991) and canopy reflectance models (SAILH, Kuusk, SPRINT) (Figure 4). These results show accurate estimates of leaf biochemical constituents from hyperspectral reflectance data for both crop and forest canopies (Figure 5).

Many studies have demonstrated a direct relationship between the photosynthetic rate, light absorbance, leaf N, and dry matter production (Alt *et al*., 2000). There appears to be a linear dependence of maximum photosynthetic capacity on leaf N to the point of species-specific optimality. The increases in photosynthetic capacity are strongly correlated with the distribution of Chl_{a+b} and N within crop canopies (Fontes *et al*. 1997). Canopy N distribution exhibits a phenological shift in the LAI (Yin *et al*. 2000). In addition, leaf N exhibits a linear relationship with increases in specific leaf mass (Garnier *et al*. 1999), which are associated with high N.
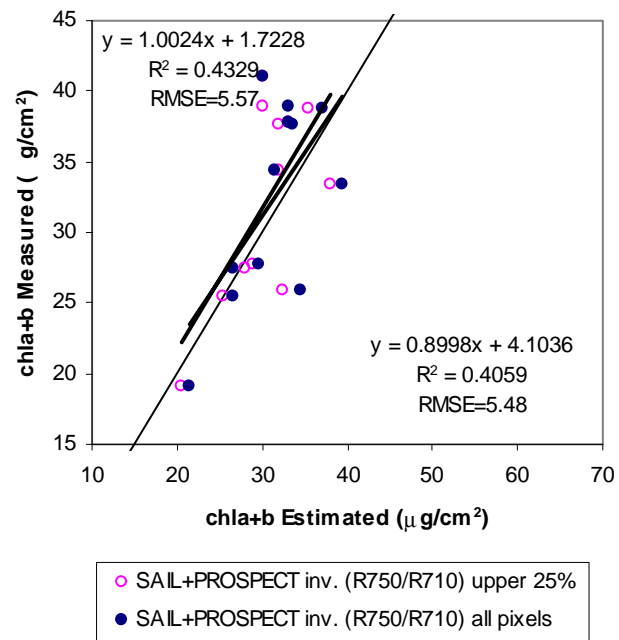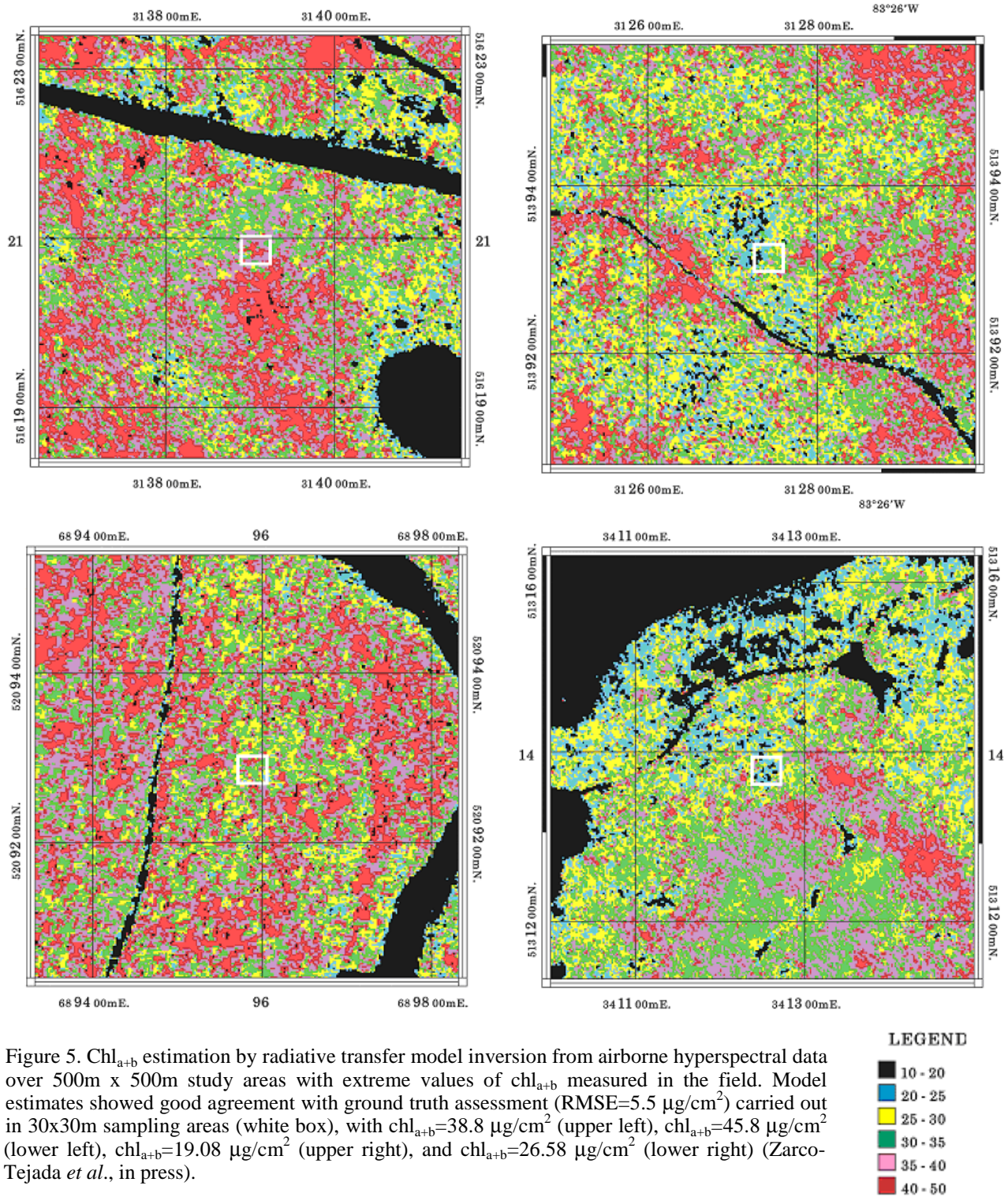
Figure 5. Chl$_{a+b}$ estimation by radiative transfer model inversion from airborne hyperspectral data over 500m x 500m study areas with extreme values of chl$_{a+b}$ measured in the field. Model estimates showed good agreement with ground truth assessment (RMSE=5.5 µg/cm^2) carried out in 30x30m sampling areas (white box), with chl$_{a+b}$=38.8 µg/cm^2 (upper left), chl$_{a+b}$=45.8 µg/cm^2 (lower left), chl$_{a+b}$=19.08 µg/cm^2 (upper right), and chl$_{a+b}$=26.58 µg/cm^2 (lower right) (Zarco-Tejada *et al.*, in press).

LEGEND

- 10 - 20
- 20 - 25
- 25 - 30
- 30 - 35
- 35 - 40
- 40 - 50

Leaf-level optical indices and ratios centered at the water absorption bands at 940nm and 1200nm show good correlations with ground-based measures of leaf water thickness (Ustin *et al.*, 1998; Gao and Goetz, 1995; Serano *et al.*, 2000) and therefore such indices can be used to map canopy water content. In contrast to NDVI, LAI estimated from canopy water content, remains linear to LAI $\geq$ 10 (Roberts *et al.*, 1998). Estimates of canopy water

content contribute information about carbon sequestration at low values and by extending the range of LAI estimates.

Dry carbon (C) stores, including woody stems and roots, and plant litter (i.e., dry leaves and stems) may indicate different ecosystem processes or conditions depending upon the specific setting (Ustin *et al.*, 1993; Asner 1998). In dense forest systems, an increase in plant litter follows disturbance or stresses and has been used in tropical forests to assess stress (Asner *et al.* in review). In drier forests, lower canopy cover allows detection of more plant litter on the ground and provides a spectral estimate of disturbance, physiological and biogeochemical processes. In sparsely vegetated shrublands and savannas dry plant litter and wood indicates fire fuel loading (Asner *et al.* 1998, Roberts *et al.* 1998), and thus becomes a critical observation for predicting wildfires and subsequent CO_2 emissions. Spatial and temporal variability of dry carbon in shrub and grassland ecosystems also indicates variations in climate forcing, such as in precipitation patterns. Asner *et al.* (2000) and Asner and Heidebrecht (in press) showed that dry carbon cover and content cannot be accurately estimated using multispectral observations such as from Landsat or MODIS.

Hyperspectral observations in the shortwave infrared (SWIR) are needed to measure dry C (Asner and Lobell 2000, Asner *et al.* 1998, 1999). The observed variation (Figure 6) in LAI (both chl_{a+b} and H_2O) and litter are highly non-linear mixing processes (Jacquemoud 1993, Jacquemoud *et al.* 1995, Asner *et al.* 1998). In nature, many factors co-vary, creating a highly complex volume mixing problem that is best understood using hyperspectral observations. For instance, while changes in LAI have the most pronounced effect on the VNIR between 0.4 – 1.3µm, dry C has its most pronounced effect in the SWIR from 2.0 -2.4 µm. Observation of the entire reflected solar spectrum (0.4 - 2.5 um) provides the best chance to estimate both the cover and volumetric content of leaf and dry plant litter in many vegetation types.
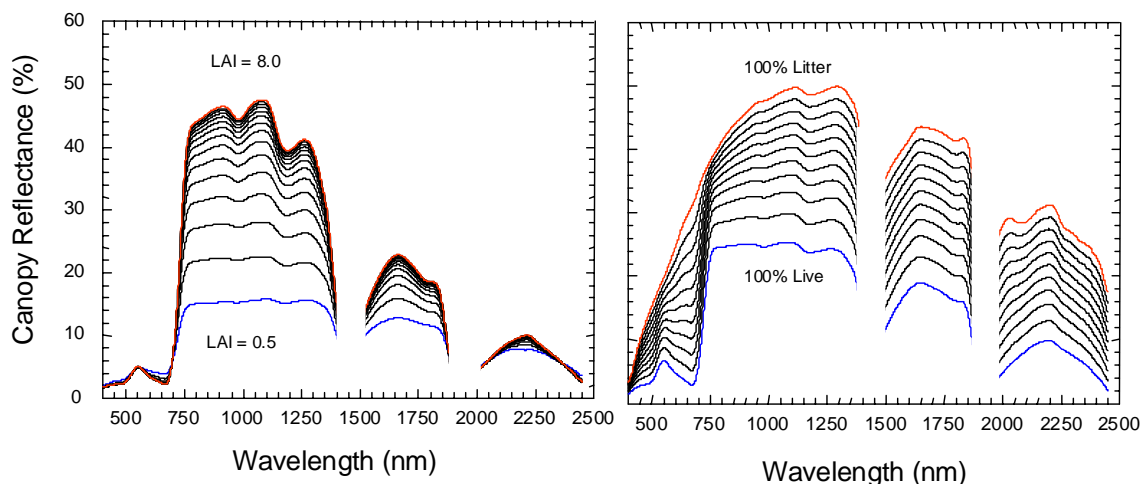

Figure 6. The non-linear effect of changing LAI (left panel) and dry C (right panel) on canopy or pixel-scale reflectance (Asner, 1998).

For example, in savannas, shrublands and woodlands, observed variations in AVIRIS hyperspectral signatures were highly indicative of the 3-dimensional variation in LAI and dry C (Figure 7). Simultaneous observation of both LAI and dry carbon area index (NPVAI) produced highly accurate maps of structural and functional vegetation types and of fire fuel load (Asner *et al.* 1998). Similarly, Asner *et al.* (1999) quantified live and senescent aboveground biomass in the central Amazon basin using hyperspectral observations. In most humid tropical ecosystems, the combination of LAI and NPVAI indicates nutrient limitations for both NPP and C storage (Asner *et al.* 1999). Observed hyperspectral variation in these parameters contributes to regional carbon fluxes and stocks.

Knowledge of soil properties and below ground C stores is limited. While optical sensors do not penetrate into the soil, some surface properties can be estimated. Ahn *et al.* (1999) used AVIRIS data to map soil surface properties, demonstrating the potential to map heterogeneity and identify localized characteristics, e.g., soil organic

carbon (SOC) and soil inorganic carbon (SIC). Palacios-Orueta and Ustin (1996) spectrally separated closely related agricultural soils and showed differences in SOC using AVIRIS and field data. In the Santa Monica Mountains AVIRIS methodologies were extended to mapping SOC and iron content (Palacios-Orueta and Ustin 1998; Palacios-Orueta *et al.*, 1999). Schreier *et al.* (1988) quantified the relationship of SOC to moisture, exchangeable Calcium and Magnesium cation exchange capacity, and soil color, with established procedures and reference reflectance libraries been developed from soil samples (Krishnan *et al.*, 1980; Henderson *et al.*, 1989; Henderson *et al.*, 1992; Kimes *et al.*, 1993; Wilcox *et al.*, 1994).
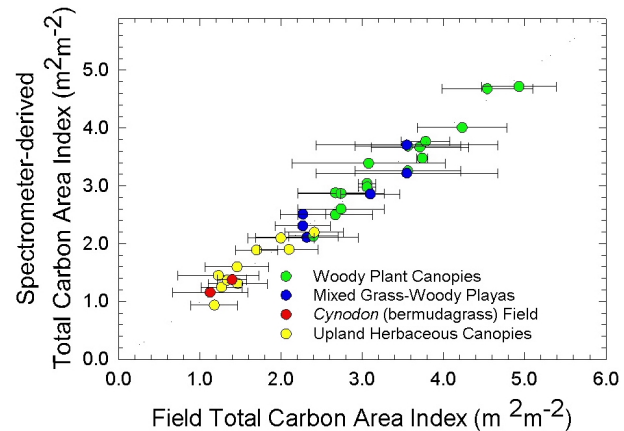

Figure 7. Comparison of field and AVIRIS-derived total carbon content of savanna woody and herbaceous vegetation canopies on the Rio Grande Plains of South Texas. Horizontal bars indicate uncertainty in field measurement techniques (Asner *et al.*, 1998).

4. Conclusions

Years of modeling and experimental research have shown that vegetation canopies are strongly under-determined remote sensing problems. Multiple combinations of vegetation structural and functional characteristics produce similar reflectance signatures, as have been observed in multi-spectral remote sensing instruments. Hyperspectral observations provide additional degrees of freedom that allow improved resolution of vegetation land cover maps and estimates of physiological properties e.g., LAI, fPAR, Chl_{a+b} and H_2O. Imaging spectroscopy opens the door to measurements that are directly indicative of ecosystem structure and functioning, such as chlorophyll concentration and dry C loading.

Hyperspectral data from a satellite platform can provide the best information, with current technology, on how the global carbon budget is changing. The design of a sampling instrument with pointing capability and Landat-type spatial resolution (30 m) and nadir repeat frequency (16 day), a 40-60 km swath (e.g., SPOT), and 200 spectral bands at AVIRIS quality signal-to-noise (e.g., 1000:1 in VNIR and 500:1 SWIR) would provide the information needed to significantly reduce uncertainties in the global carbon budget.

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