MAPPING HIGH RESOLUTION FOREST CHEMISTRY WITH AISA

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ABSTRACT:

In the current study, 2002 AVIRIS and 2006 AISA high resolution imagery were applied to the spectroscopic investigation of spatio-temporal variations in forest chemistry. Focused primarily on the foliar biochemistry of Douglas-fir (Pseudotsuga menziesii) stands within the Greater Victoria Watershed, Victoria, BC, Canada, samples were collected and relationships between chemistry and reflectance were established. Partial least-squares regression (PLS) was employed to estimate chemistry from canopy reflectance spectra. Data were stratified through the use of hyperspectral/LIDAR forest products, transformed to second order derivative imagery and chemistry maps generated from the PLS coefficients. Chemistry estimation achieved R^2 values $\geq$ 0.93 for both datasets. The PLS models applied to the hyperspectral imagery yielded two temporally discrete chemistry maps. Temporal and spatial differences were investigated. Conditions, anticipated to significantly impact forest chemistry, exhibited correspondence with spatial variations in the new forest information chemistry product.

INTRODUCTION:

Through research focused on the objective of spectral determination of target chemical attributes, certain technologies and methods are developed. The increased spectral resolving power of modern airborne instruments and partial least-squares regression (PLS) are two such innovations (Smith, Martin et al. 2003). Traditional foliar chemistry sampling methods have been extremely limited in density and spatial extent, due to the expense of ground resources (Ustin, Roberts et al. 2004). The primary motivation for the present study is the development and application of forest chemistry monitoring tools in the assessment of the sustainability of forest management practices.

Foliar biochemistry can provide information on biogeochemical cycling, ecosystem fitness (Asner, Martin et al. 2009) and photosynthetic proficiency (Gamon, Penuelas et al. 1992). Photosynthetic pigments have long been recognized as sensitive indicators of physiologic status (Lichtenthaler 1987). Recent leaf level stress studies concede, through chlorophyll florescence and CO_2 assimilation rates, changes in photosynthetic function occur prior to changes in pigment content and composition. Although ESA's 2002 SIFLEX program and similar research have made progress, these technologies are not yet operational for large-scale terrestrial studies (Naumann, Young et al. 2007). Currently, the application of PLS regression to hyperspectral remotely sensed data holds the most promise in forest chemistry mapping (Schlerf, Atzberger et al. 2003; Asner, Martin et al. 2009).

SITE AND INSTRUMENTATION:

The Greater Victoria Watershed District (GVWD) study site (Victoria, BC, Canada) has been the subject of scientific research by regional and federal agencies for more than 30 years (Goodenough, Bhogal et al. 2001). The site experiences a moist temperate climate with dry summers. The mean elevation of the GVWD is roughly 400 meters above sea level and ranges from 30 to 800m. Surface slopes within the study site are generally 15 degrees and as steep as 32°. The forest species occurring within the GVWD are typical of the Coastal Western Hemlock Biogeoclimatic zone. Douglas-fir (*Pseudotsuga menziesii*) is the most abundant, while Western Red Cedar (*Thuja plicata*) and Western Hemlock (*Tsuga heterophylla*) are present. Throughout dry regions of the study site, no single understory vegetation type prevails. Salal (*Gaultheria shallon*) is dominant in areas with sufficient soil moisture.

A 4m AVIRIS (Advanced Visible/Infrared Imaging Spectrometer) dataset was acquired on August 12, 2002, from a Twin Otter platform. The AVIRIS spectral traits include; a spectral range of 400-2500nm, sampled every ~9.7nm, roughly 10nm bandwidths, and 224 bands. Orthorectification was performed by a rational function model and a 25m DEM generated from TRIM (Terrain Resource Inventory Mapping) data. Atmospheric correction was performed with FLAASH software. AVIRIS data were further corrected to surface reflectance using an empirical line calibration (ELC) method with ASD spectra acquired simultaneously with airborne data.

Four years and one month following the AVIRIS acquisition, the University of Victoria's Dual AISA (Airborne Imaging Spectrometer for Applications) hyperspectral sensor was flown over the GVWD. The 2m AISA data has 492 spectrally contiguous bands, sampled every 2.37nm (VNIR) and 6.30nm (SWIR) from 395 to 2503nm. The AISA data were radiometrically corrected using a combination of ATCOR-4 and ELC. The AISA data were orthorectified to a 2m LIDAR digital surface model. LIDAR and AISA data were acquired simultaneously from the Navajo platform.

The AVIRIS sensor is a high quality research instrument which, in relation to the applications based AISA sensor, translates to a significantly increased operational cost. Through the application of temporally invariant ground targets an ELC was executed to calibrate the AISA data to the AVIRIS. In order to perform the ELC, it was first necessary to spatially and spectrally resample the AISA. Spatial resizing was performed through a 2x2 low pass filter, while the spectral resampling used a spectral response weighted function to approximate AVIRIS data. Atmospheric water absorption regions (1350-1435nm and 1805-1960nm) were excluded from both datasets. The procedure yielded a linear expression for each band that would translate AISA data to AVIRIS (Goodenough, Niemann et al. 2008)

METHODS:

Wet Lab Chemistry

Current and non-current foliar samples were collected by helicopter from the upper canopies of ten trees at each of the 54 study plots. The 30m diameter plots were registered by DGPS measurements and occurred at a variety of slopes, aspects and elevations. Plots were selected to capture a variety of stand ages, ranging from immature to old growth.

Organic chemistry analysis was conducted at the Pacific Forestry Centre through Dimethyl Sulfoxide pigment extractions of intact needle samples. Chemical contents of supernatants were determined spectrophotometrically (Goodenough, Bhogal et al. 2001).

Reflectance

Niemann and Goodenough (2003) demonstrated that understory vegetation had a significant impact on biochemistry estimates, especially in stands with low canopy closure. In addition, there was expected to be a significant species effect on reflectance. To mitigate these issues, masks were generated to stratify the hyperspectral data.

A canopy height model (CHM) was generated from LIDAR data, which was used to omit pixels below a threshold of 4m. The LIDAR mask ensured that only pixels with a large canopy fraction would be used in estimating forest chemistry. A forest cover classification study was conducted on the AVIRIS dataset (Goodenough, Niemann et al. 2008). The classification achieved an overall accuracy of 91.6%. The classification product was used in generating a mask to omit all non-target reflectors.

PLS Regression

The masked hyperspectral datasets were inserted into the processing stream developed for estimating canopy chemistry. To achieve a plot representative spectral response the data were filtered to yield ~30m responses. Plot level spectra were extracted and biochemistry values were generated as the mean of ten samples. It has been recognized that plot reflectance is significantly affected by sensing geometry, slope and aspect (Teillet, Guindon et al. 1982). However, spectral shape remains generally unaffected (Wang, Okin et al. 2007). To investigate whether plot spectral shape or magnitude is more closely related to chemistry, derivative spectra were processed alongside reflectance responses. The estimation performance of the plot curves was determined through regression analysis.

PLS was implemented with plot spectra as the independent, and biochemistry the dependent variables (Bennett and Embrechts 2003). The PLS regression method is closely tied with principal component regression (PCR). PCR defines latent variables that maximize variance within the spectral domain, while PLS defines optimized latent variables that maximize covariance between the spectral and chemistry data (Schlerf, Atzberger et al. 2003). Ultimately, the final PLS model was produced through an iterative process where a randomly selected third of the data were omitted and the model estimated. The average R^2 and standard deviations (n=10,000) were used to assess model performance. The PLS model is composed of a regression coefficient for each wavelength band. Therefore, a final estimated chemical value from a given reflectance (or derivative) spectra is given by the dot product of the coefficient vector with the spectral vector.

Contextual Filter

Given that the PLS model was generated through species specific samples, extrapolating estimates to different species was expected to inflate errors. Chemistry estimates were limited to only the species from which the model was derived. A customized low pass filter was developed that accepted a mask layer. The filter omitted from calculations, any pixel values occurring within the mask. LIDAR derived height masks and hyperspectral derived species masks were used in the contextual filter algorithm. The product of the contextual filter was imagery representative of mature Douglas-fir canopies (~30m).

Transformations converted reflectance and pseudo-absorbance data to first and second derivatives by the methods of (Goodenough, Dyk et al. 2007). Chemistry maps were generated once the coefficient vector was applied to the imagery.

Analysis

The analysis conducted to validate the new forest chemistry products investigated basic assumptions of growth and foliar biochemistry. It is recognized that, relative to new needle growth, non-current foliage has higher chlorophyll but lower nitrogen content in Douglas-fir trees (Thomson, Goodenough et al. 1996). Additionally, the spatial distribution of new foliage is not temporally static. New foliage grows at terminal branches and these occur in higher concentrations at the tops of canopies (Bond and Franklin 2002). The canopy proportion of new to old foliage decreases as trees age. Thus, it was expected that young and mature tree stands would be separable in the image chemistry data.

Foliar nitrogen is linked with nitrogen availability, but is moderated by translocation during times of low availability (Hawkins and Henry 1999). Nitrogen availability is dependent on mineralization and nitrification rates which

Table 1: PLS Regression Results			
	Nitrogen	Chlorophyll-a	Chlorophyll-b
AVIRIS	0.89±0.06	0.92±0.05	0.85±0.08
AISA	0.91±0.04	0.87±0.05	0.80±0.11

Mean R^2 ± standard deviation, n=10,000

fluctuate temporally and spatially with soil moisture content and temperature (Warren, Livingston et al. 2004). As a result, foliar nitrogen varies with weather and topography, such that, wet lower elevations with shallow slopes are more likely to experience canopies with higher nitrogen levels. These assumptions were tested through a LIDAR BEM and the new forest chemistry products.

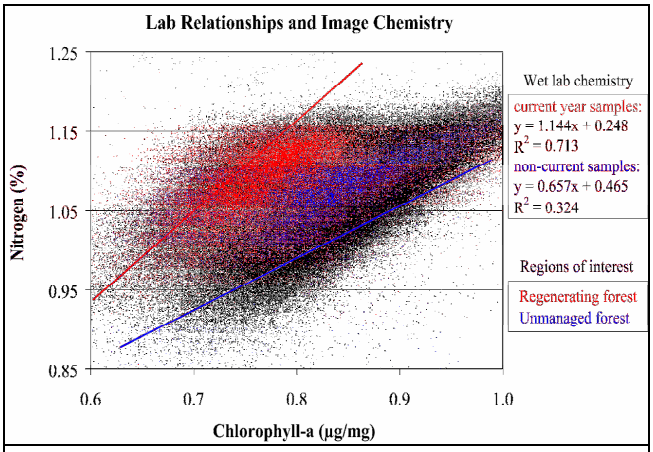

Figure 1: The two distinct clusters represent regenerating (red) and unmanaged (blue) forest regions. Lab data are represented by lines.

RESULTS AND DISCUSSION:

PLS regression analysis demonstrated that derivative spectra produced more accurate models for predicting chemistry than reflectance spectra. Chemistry was best estimated through second derivative spectra. These results support claims that spectral shape is more closely related to chemical composition than reflectance magnitude.

Given the relative abundance of pigments and the resulting signal strength, it was anticipated and confirmed that chlorophyll-a was more accurately estimated than chlorophyll-b (table 1). The higher R^2 achieved by AISA in estimating nitrogen may be attributed to the finer spectral resolution of the sensor. The AVIRIS regression likely benefited from more coarse nitrogen spectral features and the correlated chlorophyll signal in estimating nitrogen. Predictions between the two hyperspectral datasets were in near perfect agreement (CHLa: y= 0.99x + 0.01, R^2: 0.97).

General assumptions were assessed to validate the chemistry dataset. Topographic effects were expected to have significant impacts on foliar biochemistry. Elevation was expected to control chemistry through its effect on moisture and thus nutrient availability. Regions of interest were generated that suggested higher foliar nitrogen, chlorophyll-a, chlorophyll-b and a higher chlorophyll-a/b at lower elevations. Aspect was also assessed for an impact on chemistry as aspect directly relates to the light environment. South facing slopes generally receive more irradiance than northern aspects. This condition translates to lower moisture availability on south facing slopes. Aspect classes supported these assumptions through higher foliar nitrogen occurring on north facing slopes. Additionally, given northern aspects experience less incident radiation, chlorophyll a/b was expected to be lower on north facing aspects (Major, Mosseler et al. 2009). This relationship was confirmed in the aspect class statistics. The general assumptions concerning topographic control over foliar chemistry were confirmed (figure 1).

Mapping regenerating and unmanaged plots into biochemical feature space revealed clusters located in the proximity of current needle growth, observed in the wet laboratory data (figure 2). The change in this biochemical relationship with needle age was observed through the scatter plots of AISA (2006) and AVIRIS (2002) chemistry maps.

It was predicted that as managed stands matured, chlorophyll content would increase. As canopy closure increased with age, more sun exposed foliage would be present and therefore would exhibit increased chlorophyll a/b. The mapped biochemistry however, implied that mean chlorophyll-a had decreased since the AVIRIS acquisition. These results imply that the forest management practices applied at the harvest sites have affected forest

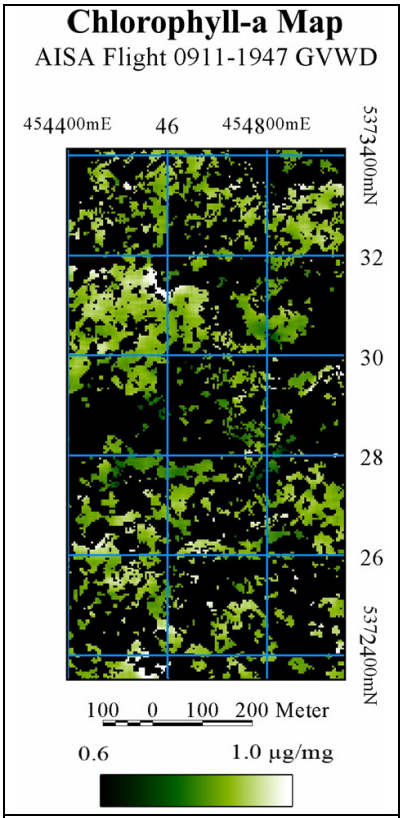

Figure 2: AISA chemistry map

health. Alternatively, it is plausible that the stand has reached a developmental age that experienced larger variations in terminal growth and as a result contributed to surface roughness and mutual canopy shading. As the proportion of shadows increased, changes within the pigment pool occurred as accessory pigment content increased to optimize photon capture in low light (Major, Mosseler et al. 2009).

CONCLUSIONS:

This study successfully applied partial least squares regression to two temporally discrete hyperspectral datasets to estimate foliar chemistry. Coefficients of determination greater than 0.8 mean sufficient accuracy was achieved in estimating nitrogen and foliar pigments. Chemistry maps derived from AVIRIS and AISA were in near perfect agreement, the implications of which, suggest that the more affordable AISA data are sufficient in quality to map chemistry. Through biochemical feature space, forest management methods were contrasted and regenerating young stands were discriminated from unmanaged plots. The current research suggests that these management practices are impacting forest health in a way that is detectable from airborne hyperspectral sensors. More research is required to determine the specific causes of these changes in managed forest plots. This project is contributing to the development of a new forest management tool. The newly developed procedure has exhibited unprecedented sampling densities and extent, and demonstrated the potential for large scale forest chemistry research; an area of study previously considered inaccessible.

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