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VALIDATION OF A HYPERSPECTRAL CURVE-FITTING TECHNIQUE FOR MAPPING CROP WATER STATUS

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Abstract

The estimation of plant water status is an essential component of precision crop management, and is directly related to plant physiological processes and ultimately crop yield. Hyperspectral models developed to estimate plant water content have met with limited success and have not been rigorously validated. A spectrum matching technique was applied to the hyperspectral data to directly calculate the canopy equivalent water thickness (EWT) using a look-up table approach. The objective of this study was to test the validity of this algorithm using crop water status information collected on the ground. Data were acquired over an experimental test site near Indian Head, Saskatchewan using the Probe-1 airborne hyperspectral sensor. Plant biomass samples were collected simultaneously from 96 plots spanning eight fields of various crop types (wheat, canola, and peas). The model was validated against EWT estimated from biomass samples as well as more conventional measures of crop water status. Results indicate that the liquid water retrieval technique can be used to estimate crop water status for broad-leafed crops such as peas and canola, but is not a reliable estimator of wheat this early stage of vegetative growth. This may be related to the low level of water in the crop and the contribution of soil to the reflectance signal.

Introduction

The quantification of plant water status, along with other parameters related to plant growth and development are crucial components of precision crop management (Moran *et al*., 1997). The accurate estimation of crop water content has potential for use in variable rate irrigation scheduling, early yield prediction and as input into crop ecophysiological models. Traditional methods of quantifying plant water status require destructive point sampling which is costly and provides limited spatial coverage. Extrapolation of point samples to areal coverages through geostatistical techniques such as kriging is often inaccurate (Pacheptsky and Acock, 1997). Remote sensing offers the potential to rapidly quantify plant characteristics over a large spatial scale, if suitable models can be developed to extract biophysical parameters.

The objective of this study is to test a model developed by Staenz *et al*. (1997) for the estimation of canopy water status using hyperspectral sensors. The model provides high spatial resolution information on canopy water content, at an appropriate scale for agricultural studies. Application of this and similar models has been limited to AVIRIS sensors over naturally vegetated landscapes in drought-prone areas.

Models of Plant Water Status

The development of high resolution, hyperspectral airborne sensors permits the opportunity to quantify microscale plant processes, such as plant water stress, over field scales. Liquid water absorbs solar radiation strongly in a series of absorption bands in the near infrared (NIR) and short-wave infrared (SWIR) regions (Curacio and Petty, 1951). Changes in plant liquid water content impact the optical properties of leaves in two ways. Changes in the amount of liquid water effect the reflectance spectra directly by the absorption by water, which is apparent in the "depth" of the absorption features. Secondly, as leaves lose turgor pressure, changes in the arrangement of the interfaces between cell walls, intercellular air pockets, chloroplasts and protoplasm occur. This impacts the internal scattering processes within the leaves that influence the overall shape of the reflectance spectra (Carter, 1991). This complexity has inhibited the development of useful models.

Several methods have been used for the quantification of plant water concentration using hyperspectral remote sensing. Empirical relationships between reflectance in the NIR and SWIR and water content have largely proved unsuccessful, with sensitivity limited to plants with less than 70 percent of full saturation, (Bowman, 1989; Riggs and Running, 1991). Derivative spectroscopy can remove some of the confounding variables that may influence infrared reflectance that are not related to plant water content (Danson *et al.,* 1992; Shibayama *et al*., 1993), but these models are highly influenced by the degree of spectral smoothing (Rollin and Milton, 1998). Both of these approaches have met with limited success in the estimation of water content at canopy level under field conditions.

Semi-empirical models have more recently been used to quantify water status in field situations. Indices based on the relative depth of the absorption features have been developed to minimize the variability resulting from spectral smoothing and the confounding effects of multiple internal scattering. These are generally based on a ratio of reflectance at an absorption maximum and a reference wavelength. The water index (WI), is the most commonly used and is the ratio of reflectance at 900 nm and 970 nm (Peñuelas *et al*., 1993). The WI has been found to be related to gravimetric or volumetric measures of canopy water status (Gamon *et al*., 1999; Champagne *et al*., 2001). This can be attributed to the strong relationship between WI and canopy biomass. As the biomass in the sensor field of view increases, the volume of water also increases due to the relationship between dry matter accumulation and plant water. Optical indices have had only limited testing using airborne sensors. Moreover, simple band ratios represent empirical estimations of plant water status, making the development of widely applicable relationships difficult (Datt, 1999).

To overcome the limitations of indices, a semi-empirical approach to the estimation of canopy water status was developed to directly derive the equivalent water thickness The depth of the water absorption features is related to the overlapping absorption of atmospheric water vapour and plant liquid water. The absorption peak of liquid water is offset to longer wavelengths by approximately 20 nm, making it possible to separate the absorption effects of each phase. According to the Beer-Lambert law, the transmission of radiation in these overlapping absorption bands is directly related to the total amount of water in each phase in a given pixel. Using the Malkmus (1967) atmospheric transmission model, a curve fitting procedure was developed to estimate column atmospheric water vapour and separate this amount from liquid water in the target vegetation, based on the offset in the absorption minima (Gao and Goetz, 1990). Combining a non-linear least squares curve-fitting technique with a radiative transfer code, a selection of spectral bands in the 850 to 1250 nm range (including both the 940 nm and 1140 nm atmospheric water vapour absorption and the 970 nm and 1180 nm liquid water absorption minima), can be used to calculate the canopy equivalent water thickness (EWT) (Green *et al*., 1991). Using airborne sensors, the absorption maxima at 1300 nm, and

1880 nm 2500 nm are not usable since there is near total atmospheric absorption of water and, as a result, near zero reflectance (Bull, 1991). The EWT is the hypothetical thickness of a sheet of liquid water in the target. This is functionally equivalent to the volume of water in the canopy and is a measure of plant water status. This algorithm and similar curve-fitting techniques have been applied using AVIRIS data over vegetated landscapes (Gao and Goetz, 1994; Roberts *et al*., 1997; Ustin *et al.*, 1998). Staenz *et al*. (1997) modified this algorithm to apply it to data sets from various sensors and incorporated a look-up table (LUT) approach to the calculation of at-sensor radiance to decrease the computation time. This approach has not been rigorously tested using ground information on plant water content.

Materials and Methods

The study was conducted over a precision test farm near Indian Head, Saskatchewan (50° N, 104° W). The site included eight fields, four seeded with wheat (*Triticum.)*, two with canola (*Brassica kaber*) and two with peas (*Lathyrus.*). All fields were in the vegetative stages of growth at the time of sampling.

Image Data Collection and Processing

Image data were acquired using the airborne Probe-1 hyperspectral sensor (Earth Search Sciences Inc., 2001). The Probe-1 is a "whiskbroom style" instrument that collects data in a cross-track direction by mechanical scanning and in an along-track direction by movement of the airborne platform. This sensor collects upwelling radiance in 128 spectral bands in the visible, NIR and SWIR between 440 nm and 2500 nm. The bandwidth is between 11 and 18 nm at full width half maximum (FWHM). Probe-1 is mounted on a three-axis gyrostabilizer to minimize geometric distortion from the aircraft movement. The flying altitude was 2500 m for a swath width of 3 km and a spatial resolution of 5 m.

Image processing was carried out using the Imaging Spectrometer Data Analysis System (ISDAS), a software package, developed at the Canada Centre for Remote Sensing, for processing and analysing hyperspectral data (Staenz *et al*., 1998). A vicarious calibration of the sensor was required to correct for errors in the calibration coefficients supplied with the data (Secker *et al*., 2001). A radiometric re-calibration of the sensor radiance was made using ground spectra obtained simultaneous to aircraft data acquisition over a section of pavement, using a portable spectroradiometer (GER Corporation).

Liquid Water Derived from Probe Data

Image data were used to calculate canopy equivalent water thickness (EWT) using a spectral curve fitting procedure described by Staenz *et al*. (1997) and implemented in the IDSAS atmospheric correction tool. The model calculates canopy EWT by fitting a water absorption coefficient spectrum based on the Beer-Lambert law. An initial set of surface reflectances was selected over the 940 nm atmospheric water absorption region and adjusted for liquid water transmittance. The adjusted surface reflectance was converted to an at-sensor radiance using look-up table parameters derived using the MODTRAN 3 radiative transfer code (Berk *et al*., 1989). The predicted at-sensor radiance is compared to the measured radiance using a non-linear least-squares fitting technique (Press, 1992). The model retrieves both the atmospheric water vapour content and the canopy liquid water on a pixel-by pixel-basis.

The water index was calculated from image reflectance values to test the usefulness of this method of liquid water retrieval against other remote sensing techniques.

Field Vegetation Data

Biomass samples were collected at 96 sampling locations, distributed over the eight fields, on the day of the image acquisition. At each location, three replicates were taken within 2-3 m of the centre of the sampling site. For each replicate, all of the aboveground crop biomass samples were harvested within a 0.5 m by 0.5 m area. Samples were weighed within one hour of harvest to obtain fresh weight. Samples were then oven dried at

105°C for 48-72 hours or until no changes in weight were observed by further drying. Sites were located using a GPS receiver with ±1m accuracy.

Several measures of plant water status were used to compare ground measurements to the EWT derived from the image data. This was done to isolate the indicator that the image data best detects and to resolve this to indicators that are of greater use for the physiological assessment of crop health. These are described in Table 1. The gravimetric water content (GWC) is indicative of the level of plant water stress and varies under ambient environmental conditions. Water content expressed as a percentage of fresh mass (GWC_F)is generally used, but can be misleading when water content is high since large variations of water amount result in only small changes in GWC_F. Water content expressed as a percentage of dry mass (GWC_D) is a suitable measure, except under conditions of extreme water stress, where depletion of dry matter will occur as a result of changes in physiological productivity of the plant when changes in actual water amount have not occurred. The EWT is the hypothetical depth of water in the canopy layer and is functionally the same as the EWT calculated from the image.

Plant Water Measure	Formulation
Gravimetric Water Content (% of Fresh Mass)	$GWC_F = \frac{(FM - DM)}{FM}$
Gravimetric Water Content (% Dry Mass)	$GWC_D = \frac{(FM - DM)}{DM}$
Equivalent Water Thickness (cm)	$EWT = \frac{(FM - DM)}{\rho_w \times A}$

Table 1. Plant water content measures calculated from biomass samples. FM is the fresh mass, DM is the dry mass, ρ_w is a physical constant representing the density of water (1 g cm^{-3}) and A is the ground area from which the vegetation was sampled (0.25 m^2).

In addition to biomass, plant height was recorded at each sampling location. Vegetation, soil and residue fractions were estimated using vertical photographs collected over each site using a digital camera mounted on a tripod. These were digitized in three channels (blue, green and red) and processed with PCI ImageWorks (PCI Geomatics, 1997). Unsupervised classification was carried out and classes were aggregated into leaf cover, residue, and soil components.

Image Registration

Ground sampling locations were located in the Probe-1 image using an image to image registration with a georeferenced IKONOS panchromatic image of 1 m resolution. The georeferenced image was warped to fit the Probe data using a 2nd order polynomial in the GCPworks module of PCI software . Due to the high root mean squared error (RMSE = 3) of the image registration, data were extracted from both a single pixel and a 5x5 pixel window surrounding the georeferenced location. This was done to determine if errors in the image registration would produce significant differences in the results.

Results

The values of EWT extracted from the image for a single pixel and for a 5x5 pixel window were compared. On average, the values extracted from the 5 pixel window were 5% higher than the single pixel values. The average variation of EWT within each window was 17% of the measured value, suggesting there was significant variation in water content in a relatively small area. For this reason, the 5 pixel window values were retained for analysis to minimize the errors resulting from the image-to-image registration. Further work must be done to improve the accuracy of the registration process.

Model Validation

The relationship between EWT measured from the image and from the biomass samples is given in Figure 1. A direct relationship between the EWT from the image and the EWT from the biomass could not be established since the ranges of the two data sets were not of the same magnitude. The values extracted from the image ranged from 0.05 cm to 0.22 cm while the calculated values from the biomass range from 0.9 cm to 26.9 cm. This suggests that the sensor is only detecting a fraction of the canopy liquid water. The crop height for all fields averaged 30 cm, and was higher for peas and lowest for wheat. Further studies are needed to assess the penetration depth of NIR reflectance.

The relationship between measured and image derived water content is relatively strong for the pea and canola crops, and non-existent for the wheat crop. This could be a result of the sampling procedure used. The water content of the biomass is derived from all of the above ground plant matter, including leaves and stems. The accumulation of water in the plant at this early growth stage might not be apparent at the sensor level if it is primarily in the stems. Further investigation must be done to examine the reasons for these results. The liquid water in plants with broader leaves, canola and peas, was more easily detectable than grass species like wheat for the less advanced stage of growth observed here.

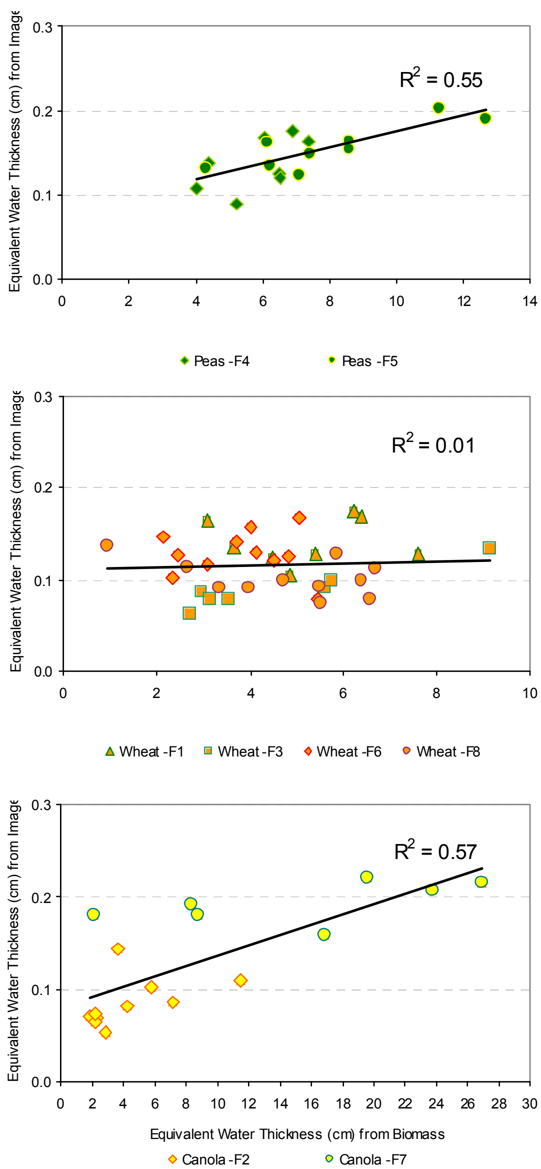

Figure 1. Relationship between image derived EWT and EWT calculated from biomass sampling for each crop type.

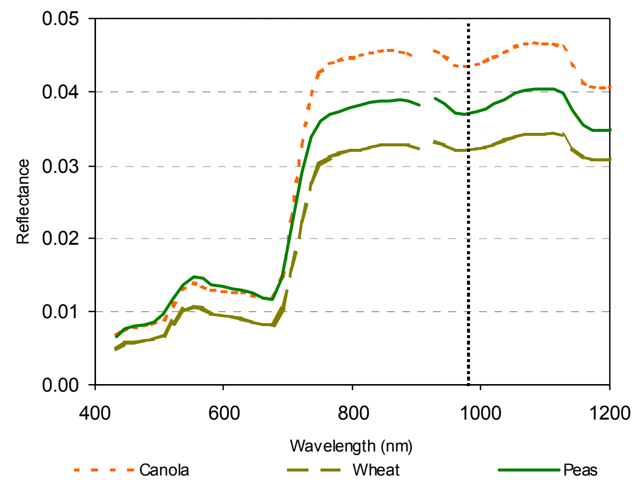

Figure 2. Average reflectance curves for each crop type. The dotted line indicates 970 nm.

Both the image derived and the biomass water contents have the lowest range for wheat. For all crop types, there was a larger scatter of points at biomass EWT's of less than 8 cm suggests that at lower water contents, the image derived EWT is not a good estimator of total canopy water. This is consistent with results that found the absorption feature to be dominated by noise at low levels of water absorption (Gamon *et al.*, 1999). This is also dependent on the noise inherent to the sensor The reflectance curves in the visible and NIR is given in Figure 2. The 970 nm absorption feature is shallowest for wheat and deeper for canola and peas. The relatively low level of water in the wheat crop at this early growth stage results in minimal absorption, making the estimation of plant water content unreliable. The combination of the low level of plant liquid water and the physical nature of wheat plants contributed to the lack of sensitivity of the model. The model should

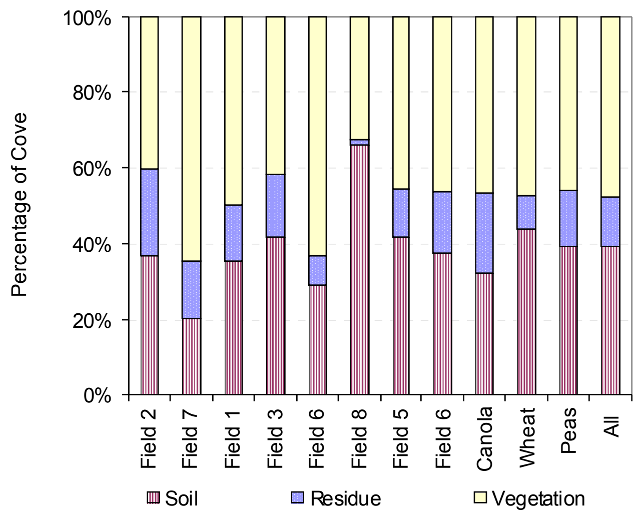

Figure 3. Land-cover fractions from vertical photographs.

be validated using data from more phenologically advanced crops to confirm these observations.

The cover fractions for each field and for each crop type are given in Figure 3. Soil was a significant portion of most of the fields, averaging 40% over all fields. Wheat had a slightly higher proportion of soil through all four fields, as high as 66% in Field 8. The fraction of green vegetation was similar for all crop types, averaging 46 % for peas and canola and 47 % for wheat. Overall, the image equivalent water thickness was positively correlated with the amount of green vegetation cover (r = 0.71 for canola, r = 0.73 for peas and r = 0.61 for wheat). The percentage vegetation cover for the wheat fields was comparable with the pea and canola fields, meaning that the green vegetation cover was evident in the photographs but was not detected by the estimation of water content. This could be again related to the prominence of stems in the measured water content. The high amount of exposed soil in the wheat fields could also have the effect of saturating the reflectance signal.

	GWC_F	GWC_D	EWT
Canola	0.75	0.73	0.72
Wheat	0.05	0.10	0.09
Peas	0.76	0.72	0.74
All	0.50	0.54	0.54

Table 2. Correlation coefficients between image derived EWT and various expressions of water content, averaged for each crop type.

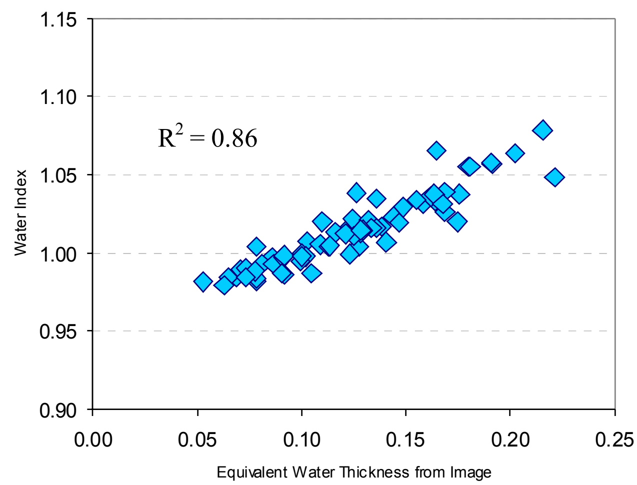

Figure 4. Relationship between Water Index and model derived EWT.

Equivalent Water Thickness and Water Index

The image derived EWT was highly correlated with the Water Index calculated from the image reflectance (Figure 3). This is consistent with results found for natural vegetation (Gamon *et al.*, 1999). This suggests that the model currently being tested is as good as what is currently available for remotely sensed estimates of plant water content using optical sensors. Deriving the EWT directly has the advantage over WI in that it is calculated directly from the image radiance and does not require conversion to reflectance.

Expression of Plant Water Content

The correlation coefficients for image-derived EWT and expressions of water content from biomass sampling are given in Table 2. There is little difference between the correlations for all three measures, suggesting the image derived EWT is a consistent estimator of all three measures. While EWT is a term largely confined to remote sensing studies, the consistency of the relationship between image derived EWT and other more conventional measures of water status, justifies the use of EWT in agricultural studies.

CONCLUSION

Preliminary results indicate that the curve-fitting model is a reasonably good estimator of crop water status in both canola and peas, but a poor estimator for wheat crops at this stage of crop growth. Equivalent water thickness, as estimated by the model, was found to be correlated with EWT calculated from the biomass, as well as more conventional measures of plant water content, making it a suitable measure of crop physiological status. The model offers a potential improvement over conventional vegetation indices, which must be empirically calibrated to each scene. Further research is needed to examine the incongruity between biomass EWT and sensor derived EWT.

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