SPATIAL HIGH RESOLUTION CROP MEASUREMENTS WITH AIRBORNE HYPERSPECTRAL REMOTE SENSING

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ABSTRACT

With the future launch of high spectral and spatial resolution satellites, we foresee that that it will be possible to use the information from these satellites in a timely fashion for the detection of stress, the prediction of yield and as a diagnostic tool for recurring low productivity areas for numerous crops. Preliminary results indicate a correlation between the vegetation fraction of airborne hyperspectral pixels and ground truth validation measurements. The advantages of the pixel unmixing algorithm for within-field crop properties mapping will be demonstrated.

INTRODUCTION

The important role of remote sensing in precision agriculture was well summarized in a recent paper by Moran *et al.* (1997). With the long list of environmental satellites announced for launch in the coming years, and the increasing use of digital databases for farm management, the role of remote sensing cannot be ignored. In particular many authors have demonstrated relationships between plant reflectance and agricultural parameters of crops (Hinzman *et al*., 1986; McMurtrey *et al*., 1994; Blackmer *et al*., 1995). Previous studies were based mostly on hand held spectro-radiometer reflectance measurements above individual plants or small portions of a field. In particular, Ma *et al.* (1996) suggested that remotely sensed reflectance is a more efficient way of determining plant nitrogen status over large areas than taking costly and time consuming field measurements. This paper will report on preliminary results obtained from visible and near infrared airborne hyperspectral imagery.

The Canada Centre for Remote Sensing, in collaboration with Agriculture Canada and the private sector, is leading a study on the applications of remote sensing to precision agriculture in Canada. An important component of this program is the use of high spectral and spatial resolution remote sensing data for agricultural information extraction. In the context of this multi-year precision agriculture program, agricultural biophysical and hyperspectral airborne data were collected in July 1997 in the region of Carman, Manitoba (Canada).

DATA ACQUISITION AND PROCESSING

The field of interest for this report was planted with potatoes in regular rows oriented perpendicular to the direction of the image acquisition flight. The plants in this field were at the early flowering stage.

Location of a regular grid of 24 sites in this field was pre-determined. A real time differential GPS was used to locate these sites in the field. Each site consisted of a 0.5 m by 0.5 m area. On July 13, 1997 the mean height of the plants was measured, photographs were taken and personal observations/comments were recorded at each site. The total mass of vegetation contained within each site was then cut and bagged for immediate total weight determination (wet biomass). The sealed bags were sent to a laboratory, the content was oven dried and re-weighed (dry biomass) to determine the water content and the total leaf area of the samples.

On July 15, 1997, this potato field was imaged with a Compact Airborne Spectrographic Imager (*casi*). The hyperspectral data set was acquired at an altitude of 2600 m above ground. At this altitude and with the selected data acquisition configuration of the sensor, each pixel of the image covered a ground area of 4m by 4m and measured radiance in 96 narrow spectral bands (6.6 nm full width at half-maximum) ranging from 413 nm to 956 nm.

Processing of the *casi* hyperspectral radiance data has been carried out with the "Imaging Spectrometer Data Analysis System" (ISDAS) developed at the Canada Centre for Remote Sensing in collaboration with industry (Staenz *et al*., 1996). To avoid pixel re-sampling, only a line shift correction was applied to the imagery to remove the aircraft roll effects. The pixel shift of each line was calculated using the roll data recorded during the flight with a precise inertial aircraft attitude measurement system. Atmospheric correction using the MODTRAN3 radiative transfer model was then applied to the imagery converting the at-sensor radiance into surface reflectance (Staenz and Williams, 1997a). A post-processing module of ISDAS was finally used to remove remaining atmospheric and calibration effects from the reflectance (Staenz and Williams, 1997).

A constrained linear unmixing procedure was applied to the reflectance data. This spectral analysis method expresses the reflectance spectrum of an image pixel as a linear sum of individual spectra from "pure pixels" (Shimabukuru and Smith, 1991; Boardman, 1995). These pure pixels were selected by performing a principal component (PC) analysis on the reflectance data set. Scatter plots of a pair of PCs were generated. Three endmembers were selected from averages of those pure pixels located in the extremities of the scatter plot: high and low density vegetation and bare soil. For each pixel of the image, the spectral unmixing procedure calculates “fraction” of the total reflectance spectra contributed by each endmember.

In order to demonstrate the use of remotely sensed crop reflectance for within-field variability measurements, the location of the ground sampling sites had to be established in the roll-corrected image. As mentioned previously, in order to preserve the radiometric integrity of the data, a full image-to-map registration was not considered. Our experience also showed that polynomial fit tools currently available in commercial image analysis packages do not lead to a satisfactory registration accuracy for non-orthoganal data from airborne line scanner and push-broom type scanners.

A specialized software system for correcting airborne imagery developed at the Canada Centre for Remote Sensing called GEOCOR (Gibson, 1994) has been used to correct and georeference another similar *casi* image of this field with sufficient accuracy. However, this system does not permit the usage of the transformation equations backward to transpose the geolocation of our sampling sites into the non-geometrically corrected image.

Given this major constraint, the twenty-four sites were located using their geographic coordinates in the *casi* image corrected with GEOCOR. Based on the location of these sites in the geometrically corrected image, the sampling points were visually located in the non-corrected image using relative distance to natural features visible in both images. To account for the location uncertainty, analysis results were computed and averaged over a 3 by 3 pixel matrix centered on these estimated locations.

RESULTS

Table 1 shows the Pearson correlation coefficients of the wet biomass of the plants with the other biophysical parameters (crop height, dry biomass and leaf area) measured at all the sites.

Table 1. Correlation of biophysical parameters.

	Wet Biomass
Crop Height	0.65
Dry Biomass	0.88
Leaf Area	0.91

Because of the strength of the correlation between the biophysical parameters in Table 1, only the wet biomass was used for further investigation purposes.

Figure 1 shows the high-density vegetation endmember fraction compared to the wet biomass data collected at each site of the potato field. The high-density vegetation endmember fraction for each of the nine reflectance pixels surrounding the estimated location, their mean and the wet biomass are plotted for each site.

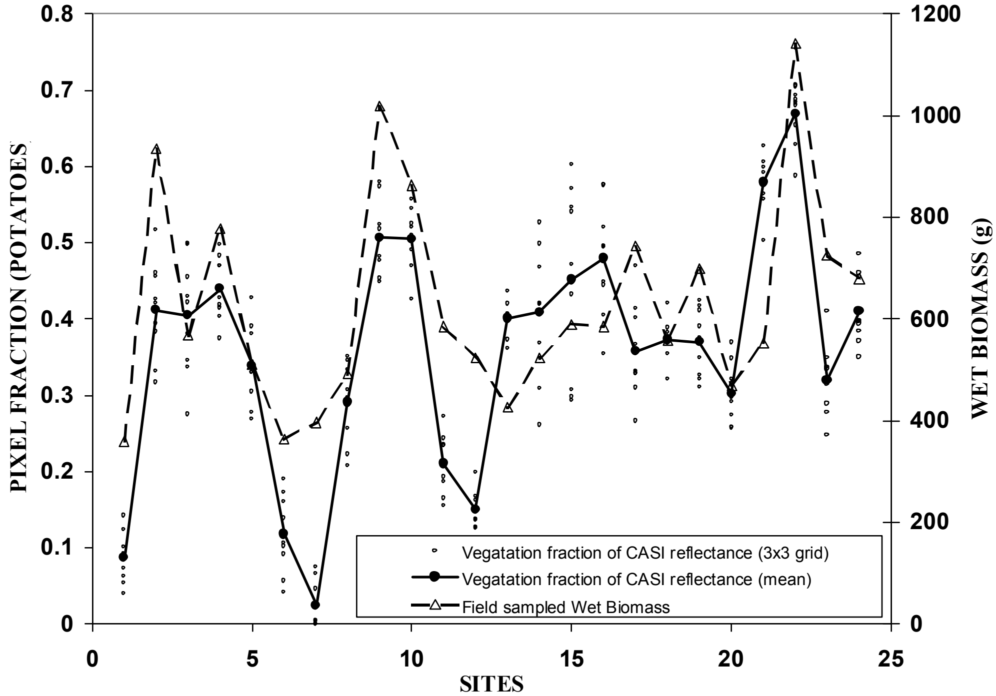

Figure 1. Endmember fraction (potato) from pixel unmixing and wet biomass of ground samples at each site.

Figure 2 is a scatter plot of these two quantities showing a linear regression with a coefficient of determination (R^2) of 0.476.

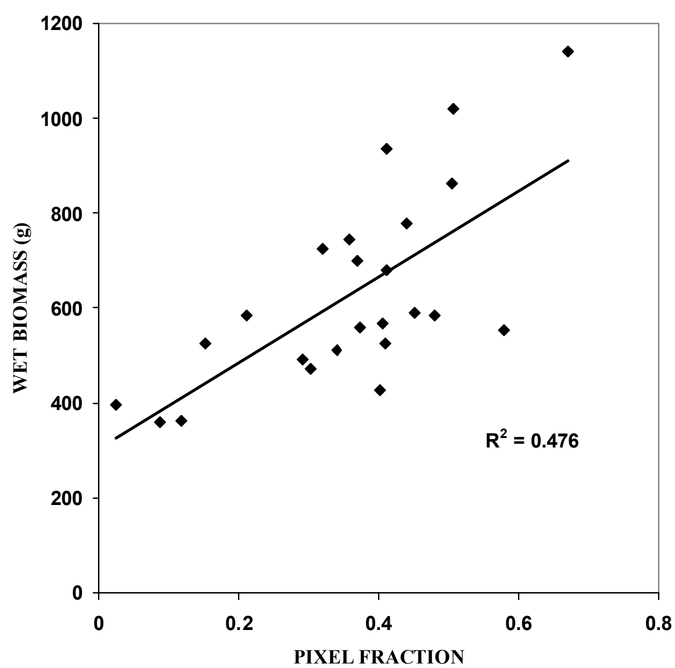

Figure 2. Relationship between crop wet biomass and endmember fraction (potato) from pixel unmixing.

DISCUSSION

Figure 1 shows an evident relationship between the image pixel vegetation fraction retrieved from hyperspectral data and the measured biomass. For most of the sites, the upward and downward trends are the same for both data sets. However, at many sites, the amplitude of the change in these two curves is quite different which partially explains the lower R^2 of the linear relation in Figure 2. At this stage of our analysis we showed that hyperspectral pixel unmixing procedures can map relative within-field variability of potato biomass. However, we cannot make a quantitative estimate of agricultural parameters with only this method. Further empirical or physical modeling, or a combination of both is required for this purpose (Staenz et al., 1998; Staenz et al., 1997b). The main reasons for this are the location uncertainty of the field samples in the image, the uncertainty of the representation of these field measurements taken from a small site relative to the pixel size of the image, and the heterogeneity of the crop reflectance in the area selected for sampling.

This method would gain enormously if the location of the ground sampling sites in the geometrically non-corrected image could be improved. Future studies should be done in more homogeneous areas with well-marked sampling sites that can be easily identified in the imagery. Field sampling of biophysical parameters should be done on a larger area to better match the image pixel size.

The potential for pixel fractions to map within-field biophysical variability cannot be denied. The advantage of this method, compared to other techniques such as vegetation indices, is its capability to estimate the contribution of each component to the total reflectance of a pixel. This feature is most advantageous in the case of row crop where an important proportion of the pixel reflectance is due to soil or where weed infestation is important. This method also takes full advantage of the spectral information in the image compared to empirical methods establishing a relationship between biophysical data and a limited number (combination) of spectral bands. Contrary to empirical methods, pixel unmixing does not require ground reference data to create a mapping function involving the sensor signal.

CONCLUSION

Preliminary validation tests indicate that the use of linear spectral unmixing to extract endmember fractions has the potential to permit within-field mapping of potato crop properties and eventually some other similar row crops. This method can provide data over an entire field that can easily be compared to other biophysical data in a GIS database. The use of hyperspectral data may not be cost-effective now, but should become a valuable tool for precision agriculture when satellite-based hyperspectral data are available in the near future.

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