AGRICULTURAL APPLICATIONS OF AIRBORNE HYPERSPECTRAL DATA:

WEED DETECTION•

J.C. Deguise, K. Staenz
Canada Centre for Remote Sensing
Natural Resources Canada
Ottawa, Ont., Canada

J. Lefebvre
MacDonald Dettwiler and Associates
Richmond, B.C., Canada

ABSTRACT

Weed infestation in commercial crops in Canada is a major problem to producers. To help the reduction of the amount of herbicides used for the control of weeds, the potential of high spatial resolution airborne hyperspectral data was exploited for the detection of weeds in a crop of canola. Both manual and automatic endmember selection approaches were used to extract the weed endmember spectrum from the image cube. Results obtained from constrained linear spectral unmixing using this endmember are discussed.

1.0 INTRODUCTION

For most commercial crops in Canada, weed infestation is a major problem that has to be addressed at an early stage of growth. Often the producer decides to apply a uniformly strong dose of herbicide throughout the field to be certain that weeds are eradicated. For financial and environmental reasons, various methods have been proposed to apply these herbicides in a more targeted fashion, with the goal of decreasing the overall amount being used. Numerous systems are installed on commercial sprayers, controlling individual nozzles in real time where weed patches are detected by sensors mounted ahead of the sprayer. As an alternative method, high spatial resolution hyperspectral data could be used for the purpose of early within-field weed detection. Early detection of weeds from remotely sensed hyperspectral data could serve as an additional source of information to be used in programmable commercial sprayers.

The Canada Centre for Remote Sensing, in collaboration with Agriculture and Agri-Food Canada and the private sector, is leading a study on the applications of remote sensing for precision agriculture in Canada. An important component of this program is the use of high spectral and high spatial resolution remote sensing data for agricultural information extraction. Encouraging results have been obtained previously by applying linear spectral unmixing techniques to agricultural remote sensing imagery (Staenz et al., 1997; Deguise et al., 1998). The purpose of this study is to

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investigate the application of constrained linear spectral unmixing of airborne hyperspectral data for the early detection of common weeds in young crops.

2.0 DATA DESCRIPTION

The particular field under study in this paper is near the town of Altona, Manitoba, Canada and was planted with canola in early May 1996. The field dimensions are approximately 400m by 850m. In late June, *in situ* observation confirmed the presence of large patches of Canada Thistle in the field, visually distinct from the crop.

Hyperspectral imagery was acquired over this field with the Compact Airborne Spectrographic Imager (*casi*) on the 30 June 1996. The aircraft was flying at an altitude of 2500 m above the ground resulting in a pixel size of 4m by 4m. Data were collected over the wavelength range from 464 nm to 1004 nm in 96 contiguous, 6.8 nm wide, spectral bands sampled at 5.8 nm intervals (Anger et al., 1996). The lack of aircraft attitude data precluded any attempt of geometric correction to remove distortion caused by the irregular motion of the plane.

3.0 METHODS

Figure 1 illustrates the general data processing steps which were carried out using the Imaging Spectrometer Data Analysis System (ISDAS) (Staenz *et al*., 1998) to generate fraction images from the data cube. The first step was to find the spectrum of each target component (e.g. crop type, weed, soil, shadow, etc.) in the calibrated hyperspectral radiance cube. This was achieved using two component (endmember) spectra selection procedures: a manual approach using scatter plots in a principal component (PC) space and an automatic technique based on the “Iterative Error Analysis” (IEA) method (Szeredi et al., 1999).

The manual retrieval of the image-based endmember spectra involved viewing several two-dimensional projections of the scatterplot of pixels in PC space. The endmember spectra were extracted from averages of the pixels located at the extremities of the scatterplot. These pixels are often referred to as the “purest pixels” (Boardman, 1993).

As for the manual endmember extraction process, the automatic IEA technique depends on the existence of relatively pure pixels within the scene since the endmembers are formed from one or an average of several image pixels. Briefly, the algorithm begins with an initial vector representing the mean spectrum of the data. A constrained unmixing in terms of this vector is performed and the group of vectors (pixel spectra) with the largest resulting unmixing error are averaged together to form the first endmember. Another constrained unmixing is then performed with the first endmember and the group of vectors with the largest unmixing error are averaged together to form the second endmember. This process of unmixing is iterated until either the unmixing error is below some threshold or a predetermined number of endmembers is reached. The endmembers are then visually inspected to avoid the inclusion of spurious endmembers (no physical meaning) in the analysis.

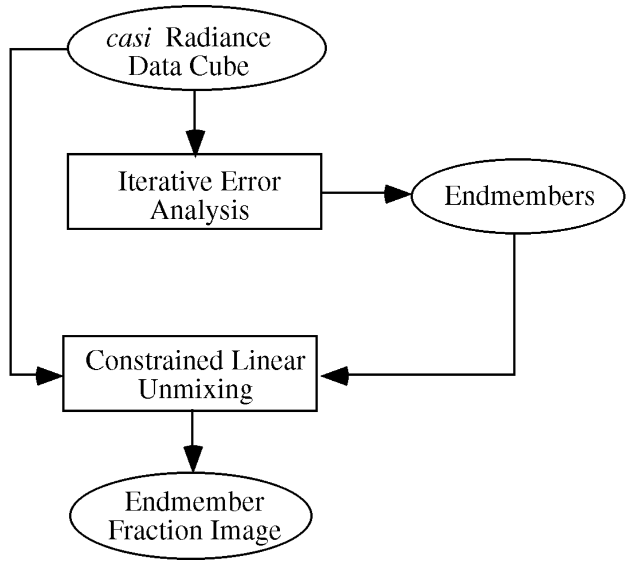

Figure 1: Data processing flow chart of spectral unmixing of casi hyperspectral data

Finally, each set of endmembers was then used in a constrained, linear unmixing process wherein the radiance spectrum of an image pixel is expressed as a linear sum of N endmember spectra (Boardman, 1995; Shimabukuru and Smith, 1991) with the additional constraints that the fractions of each pixel be positive and their sum be equal to one.

4.0 RESULTS

A critical step in spectral unmixing is the extraction of the endmembers. Selecting endmembers from vegetative imagery is often difficult since the spectral behaviour of vegetation types is very similar and lacks the diagnostic absorption features such as those present in minerals. Accordingly, a specific vegetation spectrum is often a linear combination of spectra of other vegetation types and, therefore, cannot be identified via spectral unmixing. Figure 2 displays the spectra of the two major vegetation components in the field: Canola and Canada Thistle (weed). These spectra were measured in the field with a hand-held GER3700 spectroradiometer. Note that in the spectral *casi* range (464 nm to 1004 nm), these two spectral signatures are different in amplitude but similar in shape.

The weed endmember could not be found in any PC plane using the manual endmember selection procedure. Endmembers obtained by this method did not yield fraction images delineating the known weed patches in the field. However, the automatic IEA approach was successful in extracting a weed endmember. The pixel spectra forming the IEA weed endmember are highlighted in the scatterplot of Figure 3. In this and all the other projections visualized, these three purest weed pixels never appeared near the extremities of the scatterplots. This explains why the manual endmember selection approach to the imagery was unsuccessful. Both endmember selection procedures retrieved additional endmembers which could not be related to various vigor stages of canola, and soil.

However, it is beyond the scope of this study to discuss these endmembers and associated fraction images.

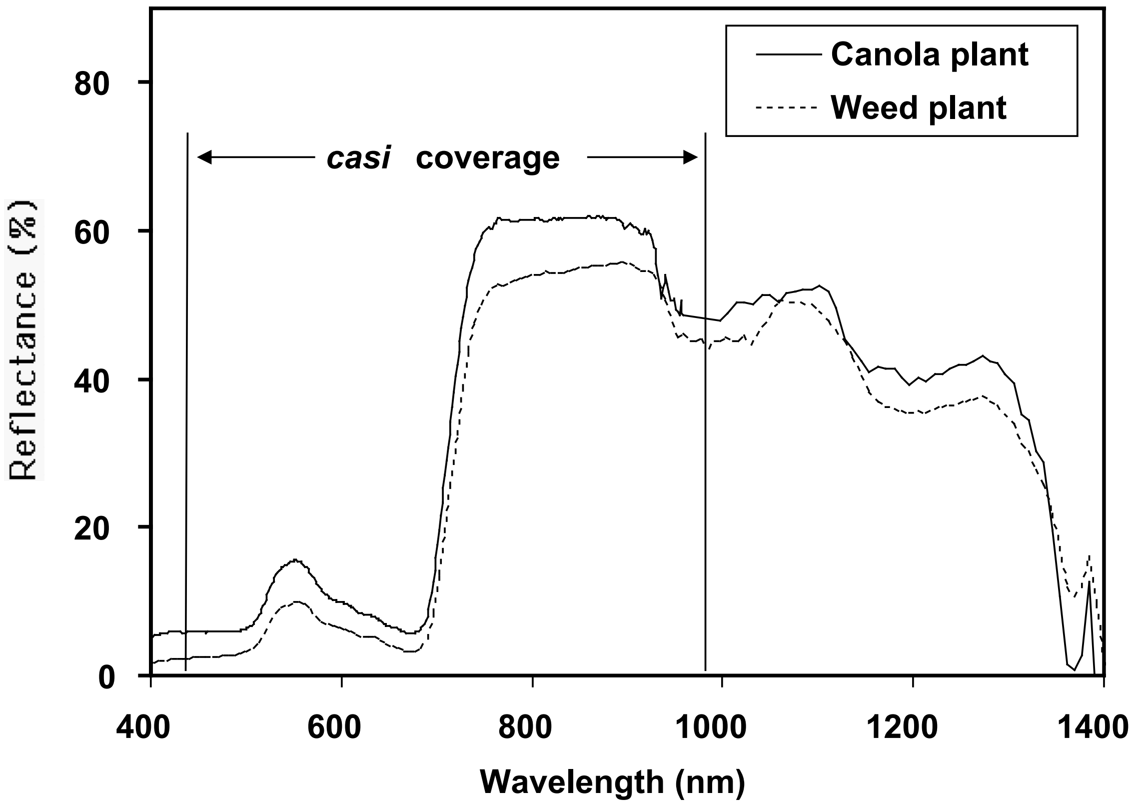

Figure 2: Comparison of canola and weed reflectance spectra acquired with a GER370 spectroradiometer.

Figure 4a shows the resulting weed fraction image using constrained linear unmixing in combination with the endmembers retrieved with the IEA approach. A visual comparison of the fraction image with the *casi* image (band 24:587.2 nm) in Figure 4b shows a good correspondence of the dark weed patches. Ground observations confirmed our interpretation that the dark patches in Figure 4b correspond to weeds. In addition, the sub-pixel information from the spectral unmixing results reveals the presence of weeds in neighboring pixels. These are much harder to separate from the crop in the radiance image when the weeds are not the main contributors to the overall signal of the pixel.

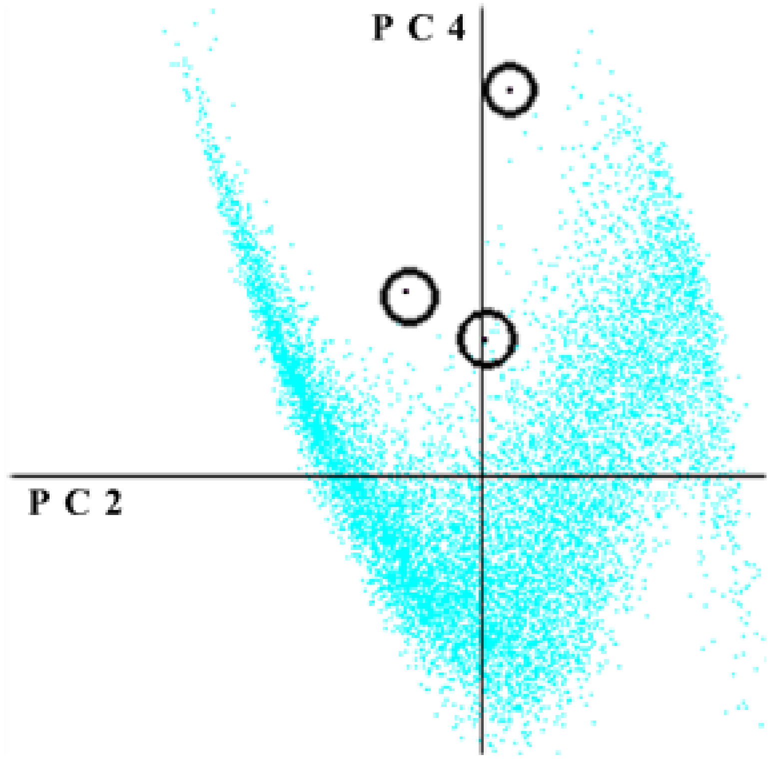

Figure 3: Scatterplot of principal components PC2 and PC4 showing the location of the weed pixels extracted with the automatic IEA approach.

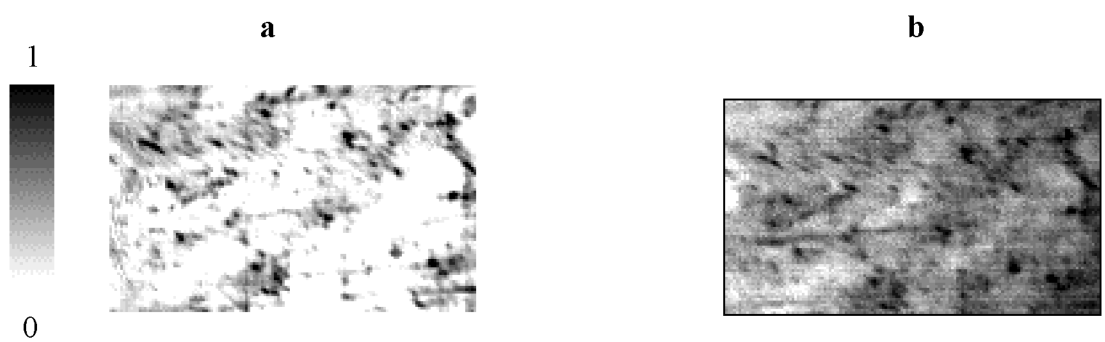

Figure 4: a) The fraction image of weeds within the canola field (white colour tones indicate a low fraction while black represents a high fraction). b) The casi image of band 24 (587.2 nm) showing the weed patches in black in the canola field.

The same data analysis procedure was also applied to surface reflectance retrieved from the radiance data cube (Staenz and Williams, 1997). Using this data set, the results did not match the weed patterns in Figure 4. One possible explanation could be that the small spectral feature differences between weeds and canola, used by the spectral unmixing algorithm, might be reduced due to uncertainties of the atmospheric modeling. Further investigations have to be carried out in order to fully understand the reasons why the weed patches could not be identified using the reflectance data.

5.0 CONCLUSION

This paper demonstrates the potential of hyperspectral *casi* radiance data for the detection of weeds within a canola field. Results indicate a good match between visually identified weed patches in an image of *casi* band 24 (587.2 nm) and those derived with constrained linear unmixing using the iterative error analysis (IEA) approach to extract automatically the weed endmember from the scene. The advantage of spectral unmixing is that the resulting fraction map identifies pixels with lower weed concentrations than can be detected with any *casi* single-band image or a combination of bands. The performance of the automatic endmember selection, the IEA, was superior to the standard procedure, a manual approach selecting the endmembers from the extremities of scatterplots in principal component space. It was not possible to identify the weed endmember using the latter approach. Investigations using the surface reflectance instead of the radiance data revealed that neither the automatic nor the manual endmember selection procedure could find the weed endmember. Therefore, further investigations will be directed towards the endmember selection process involving the surface reflectance data cube.

6.0 REFERENCES

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