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Variability of seasonal CASI image data products and potential application for management zone delineation for precision agriculture

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Abstract. The delineation of management zones is an important step to implementing site-specific crop management practices. Remote sensing is a cost-effective way to acquire information needed for delineating management zones, since it has been successfully used for mapping soil properties and monitoring crop growth conditions. Remotely sensed hyperspectral data are particularly effective in deriving crop biophysical parameters in agricultural fields; therefore, the potential of hyperspectral data to contribute to management zone delineation needs to be assessed. In this study, the spatial variability of soil and crops in two agricultural fields was studied using seasonal compact airborne spectrographic imager (CASI) hyperspectral images. Different spectral features including soil brightness and colouration indices, principal components of soil reflectance data, and crop descriptors (leaf area index (LAI) and leaf chlorophyll content) were derived from CASI data and used to partition the fields into homogeneous zones using the fuzzy *k* means unsupervised classification method. The reduction of variances of soil electrical conductivity, LAI, leaf chlorophyll content, and yield was inspected to determine the appropriate number of zones for each field. The zones obtained were interpreted according to the soil survey map and field practices. Analysis of variance (ANOVA) was conducted to examine the effectiveness of the delineation. The study shows that the spatial patterns of the resulting soil zones faithfully represent the soil classes described by the soil survey maps, and the spatial patterns of the resulting crop classes discriminated the different crop growth conditions well. These results show that hyperspectral data provide important information on field variability for management zone delineation in precision agriculture.

Résumé. La délimitation des zones de gestion homogènes est une étape importante dans la mise en place des procédures de gestion localisée des ressources agricoles. La télédétection peut s'avérer éonomiquement viable pour l'acquisition des données requises à la délimitation de ces zones. En effet, elle a déjà permis de cartographier des propriétés de sols et de suivre la croissance des cultures. Les données hyperspectrales sont très utiles pour dériver des descripteurs biophysiques des champs en cultures; il faut donc évaluer le potentiel de la télédétection hyperspectrale à définir adéquatement la délimitation des zones de gestion homogènes. À l'aide d'une série temporelle d'mages hyperspectrales du capteur aéroporté CASI (« compact airborne spectrographic imager »), la variabilité spatiale des propriétés du sol et des cultures dans deux champs agricoles ont été étudiés. Divers indicateurs spectraux, dont les indices de brillance et de coloration du sol, des composantes principales de réflectance du sol et des descripteurs du couvert végétal agricole (l'indice de surface foliaire (LAI) et la teneur en chlorophylle) ont été extraits des données CASI et utilisés pour segmenter les champs en zones homogènes à l'aide d'une classification non dirigée utilisant la méthode de groupement flou à *k* moyens. L'observation de la réduction de la variance de la conductivité électrique du sol, du LAI, de la teneur en chlorophylle des feuilles, et du rendement agricole a permis de déterminer le nombre approprié de zones homogènes dans chaque champ. Les résultats ainsi obtenus ont été évalués et interprétès grâce à l'utilisation de la carte pédologique et des informations sur les pratiques agricoles. Une analyse de variance (ANOVA) a été réalisée pour évaluer la précision de la segmentation retenue. Les vérifications ont confirmé que les zones homogènes déterminées à partir des propriétés spectrales du sol représentaient bien les classes décrites sur la carte pédologique, et que les zones homogènes établies à partir des descripteurs biophysiques du couvert agricole décrivaient bien les diverses conditions de croissance des cultures étudiées. Cela montre bien que la télédétection hyperspectrale est une source d'information importante pour la détection de la variabilité spatiale des champs agricoles ainsi que pour la délimitation des zones de gestion homogènes en agriculture de précision.

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Introduction

One of the important inputs to site-specific management practices in agriculture is the delineation of management zones. A management zone is defined as a portion of a field that expresses a homogeneous combination of yield-limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1998). The delineation of management zones relies on the exploitation of spatial variability of the agriculture field. Zhang et al. (2002) classified the variability into six groups: yield variability, field variability, soil variability, crop variability, variability in anomalous factors, and management variability. Information on the variability can be ascribed as follows: (*i*) seasonally stable conditions, such as yield-based or soil-based management units, which need to be determined only once every season; and (*ii*) seasonally variable conditions, such as soil moisture, weeds, and crop disease, which need to be monitored continuously during the season (Moran et al., 1997).

Remote sensing offers a quick and cost-effective way to obtain information on the variability of agricultural fields, such as soil properties, crop vigour, crop stress, and relative crop yield (Moran et al., 1997). Remotely sensed hyperspectral data have been successfully used in crop studies for estimation of biophysical descriptors (Haboudane et al., 2002; 2004; Thenkabail et al., 2000), prediction of crop vigour and yield (Tomer et al., 1995; Shibayama and Akiyama, 1991), and monitoring of environmental impact (Strachan et al., 2002; Pattey et al., 2001; Leone and Escadafal, 2001; Lelong et al., 1998). These studies demonstrated that hyperspectral remote sensing provides a powerful tool for precision agriculture applications.

The objective of this study was to explore the potential and ability of hyperspectral remote sensing data for management zone delineation in precision agriculture. Crop fields were delineated into homogeneous zones using soil and crop properties extracted from multitemporal compact airborne spectrographic imager (CASI) hyperspectral data, and the acquired zones were interpreted according to the soil survey maps and the treatments applied in the fields.

Study site and hyperspectral data

The study site is located in the former greenbelt farm of Agriculture and Agri-Food Canada, Ottawa, Ontario, Canada (45°18′N, 75°45′W). The two neighbouring fields investigated in the present study are referred to as fields 25 and 23. Field 25 is primarily composed of two soil associations (D3, Brandon series; M3–NG2, Montain, Allendale, and North Gower series) that share similar drainage conditions (poorly drained) and taxonomic classification (orthic humic gleysol). They are differentiated by the subsurface texture, which is finer in D3 (silty clay loam to clay loam) than in M3–NG2 (sandy clay loam to fine sandy loam). Field 23 is composed of seven soil landscape units with variable drainage classes, profile textures, and genetic evolution (Perron et al., 2002). **Figure 1** shows the detailed soil survey map of the two fields, and **Table 1** gives the soil classification legend.

A survey was made in the two fields in November 2002 (Perron et al., 2003) to obtain soil electrical conductivity at two depths, namely 0–30 cm (EC30) and 0–100 cm (EC100). In the year 2001, uniform nitrogen (N) was applied in field 23, and a specific N application pattern was imposed on field 25 (see **Figure 5d** later in the paper). Yield data were acquired during

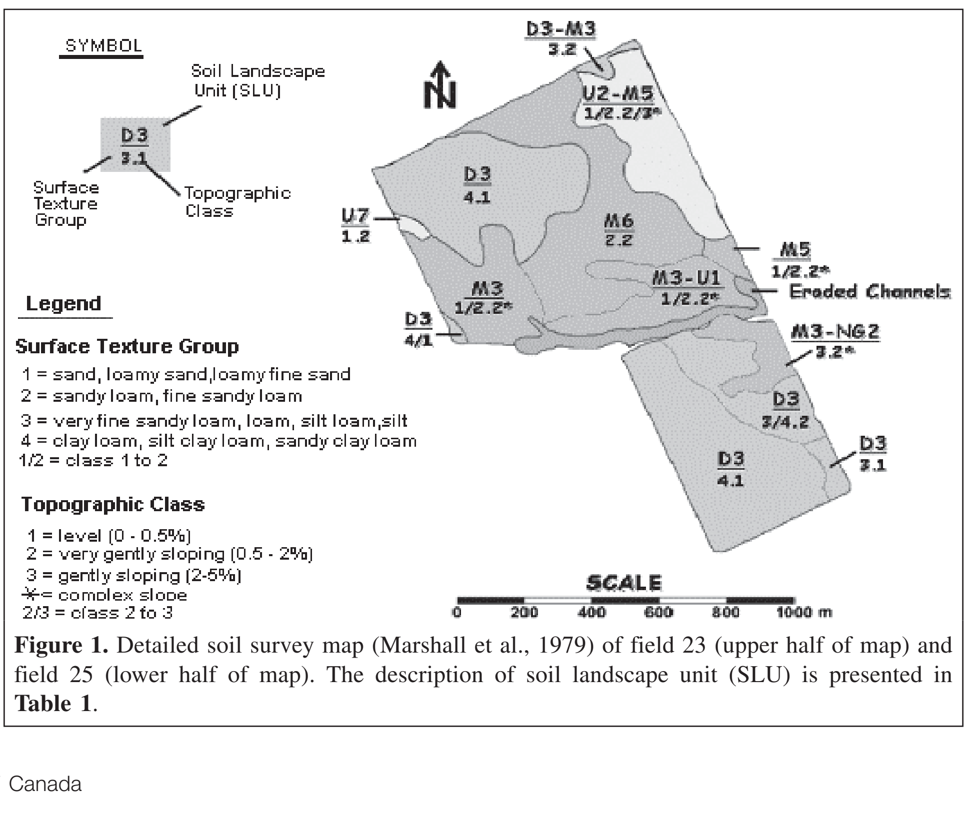

Figure 1. Detailed soil survey map (Marshall et al., 1979) of field 23 (upper half of map) and field 25 (lower half of map). The description of soil landscape unit (SLU) is presented in **Table 1**.

Table 1. Soil classification legend for the two studied fields (see **Figure 1**).

Parent material	SLU[a]	Slope (%)	Soil series	Soil taxonomy	Drainage
Fine-textured marine material (40%–60% clay)	D3	2–5	Brandon	Orthic humic gleysol	Poorly drained
Strongly acid, sandy veneer (25–100 cm) over clayey material	M3	1–3	Mountain	Gleyed sombric brunisol	Imperfectly drained
			Allendale	Orthic humic gleysol	Poorly drained
	M5	0.5–2.0	Allendale	Orthic humic gleysol	Poorly drained
			Montain	Gleyed sombric brunisol	Imperfectly drained
	M6	0–2	Allendale	Orthic humic gleysol	Poorly drained
Moderately fine textured marine material (25%–40% clay)	NG2	0–2	North Gower	Orthic humic gleysol	Poorly drained
Medium- to fine-grained deep sandy material (>100 cm)	U1	2–7	Carlsbad	Orthic sombric brunisol	Well drained
	U2	2–5	Carlsbad	Orthic sombric brunisol	Well drained
			Ramsayville	Gleyed sombric brunisol	Imperfectly drained
	U7	1–2	Ramsayville	Gleyed sombric brunisol	Imperfectly drained
			St. Samuel	Orthic humic gleysol	Poorly drained

[a]Soil landscape unit.

harvest using a combine equipped with a yield monitor for both fields. CASI hyperspectral data were collected four times in 2000 and three times in 2001, spanning crop growing conditions, by intensive field campaigns (IFCs). CASI was operated in the hyperspectral mode with 2 m spatial resolution and 7.5 nm bandwidth. The 72 spectral channels acquired by the sensor covered the visible and near-infrared portions of the solar spectrum, ranging from 408 to 947 nm. The data acquired on 20 June 2000 were chosen for soil partitioning, as the two fields were almost bare of vegetation at that time. In 2001, corn and spring wheat were planted in fields 23 and 25, respectively. Acquisition dates in 2001 were planned to coincide with different phenological development stages, providing image data covering the early, active growth and reproductive crop growth stages. The data from the three IFCs in 2001, acquired on 14 June (IFC1), 26 June (IFC2), and 19 July (IFC3), were used for crop field partitioning to study the spatial and temporal variability of the two crop fields. CASI data were processed to absolute ground reflectance by an operational processing procedure, which includes radiance calibration, atmospheric correction using the CAM5S model, and flat field correction, as described by Haboudane et al. (2004).

Methods

Feature extraction

Feature extraction and selection is a necessary step in hyperspectral data processing due to the large number of spectral channels available. Effective methods for feature extraction are objective oriented. This can be demonstrated by recently developed vegetation indices. The modified triangular vegetation index (MTVI2) is presented as an excellent estimator of leaf area index (LAI) that minimizes leaf chlorophyll content variation (Haboudane et al., 2004), whereas the combined use of the transformed chlorophyll absorption in reflectance index (TCARI) and the optimized soil-adjusted vegetation index (OSAVI) provides a good estimation of leaf chlorophyll content while minimizing LAI variation (Haboudane et al., 2002). Nevertheless, feature selection and extraction inevitably results in information loss; therefore, special care should be taken when implementing any procedure of feature extraction.

Soil reflectance has direct relationships with soil optical properties (colour and brightness) and other soil properties such as texture, soil moisture, and organic matter content (Mattikalli, 1997). Soil brightness and colour are important in differentiating between soil types (Leone and Escadafal, 2001). They are believed to be determined by the amount and state of iron and the content of soil organic matter, carbonate, moisture, etc. Indeed, Huete and Escadafal (1991) concluded that reflectance intensity (or brightness) represents the dominant or principal source of spectral variance among soils, whereas the difference of spectral curve shape (chromatic) is secondary. A common practice to obtain brightness and chromatic information is to convert from a red, green, and blue (RGB) colour composite constructed with multispectral bands to a hue, saturation, and intensity (HSI) colour representation system. In the HSI system, the intensity (I) component represents brightness information, and the hue (H) and saturation (S) components represent chromatic information. In this study, the I and S components are extracted from CASI soil reflectance data of 2000 and are referred to as brightness index (BI) and colouration index (CI). The formulae, presented by Liu and Moore (1990) and modified by Escadafal et al. (1994), are as follows:

$$\mathrm{BI} = (R_{800} + R_{670} + R_{550})/\sqrt{3} \tag{1}$$

$$\mathrm{CI} = (R_{800} - R_{550})/R_{800} \tag{2}$$

where R is the reflectance of the channel, with the central wavelength (in nm) indicated by the subscript. BI is equivalent to the average reflectance of the three channels and is a measure of the brightness of the soil. CI is equivalent to a measure of the slope of the soil spectrum and therefore soil colour (Escadafal et al., 1994). Thus, BI and CI calculated using these two formulae are the first features to be used for soil-based partitioning.

Principal component (PC) analysis is an effective way of feature extraction. It compresses information into a few components and is a powerful tool for feature reduction in hyperspectral data processing. Principal component transformation based on the covariance matrix of soil reflectance data of 2000 was applied to images of fields 23 and 25. The first three components (PC1, PC2, PC3) made up 99.5% of the spectral information in field 23 (82.5%, 16.2%, and 0.9% for the first, second, and third principal components, respectively) and 99.7% in field 25 (91.7%, 7.8%, and 0.2% for the first, second, and third principal components, respectively). They accounted for almost the total variability of soil reflectance data, and thus they were used as another feature set for soil-based partitioning for comparison with the soil BI and CI measures.

LAI and leaf chlorophyll content are two important crop descriptors. They are critical to understanding biophysical processes and for predicting growth and productivity (Tucker et al., 1980; Moran et al., 1997). Therefore, CASI multitemporal products of LAI and leaf chlorophyll content were used for crop-based partitioning. The formulae for LAI estimation are as follows (Haboudane et al., 2004):

$$\mathrm{MTVI2} = \frac{1.5\,[1.2\,(R_{800} - R_{550}) - 2.5\,(R_{670} - R_{550})]}{\sqrt{(2R_{800} + 1)^2 - (6R_{800} - 5\sqrt{R_{670}}) - 0.5}} \tag{3}$$

$$\mathrm{LAI} = 0.2227\,\exp(3.6566 \times \mathrm{MTVI2}) \tag{4}$$

The formulae for leaf chlorophyll content estimation are as follows (Haboudane et al., 2002):

$$\mathrm{OSAVI} = 1.16(R_{800} - R_{670})/(R_{800} + R_{670} + 0.16) \tag{5}$$

$$\mathrm{TCARI} = 3[R_{700} - R_{670} - 0.2(R_{700} - R_{550})R_{700}/R_{670}] \tag{6}$$

$$\mathrm{Chl} = -33.3\,\ln(\mathrm{TCARI}/\mathrm{OSAVI}) - 19.7 \tag{7}$$

where Chl represents leaf chlorophyll content ($\mu g \cdot cm^{-2}$). The data from the three IFCs were clustered in an attempt to reveal the crop spatial patterns and their temporal variation.

Overall, five sets of features were derived from CASI reflectance data and used for field partitioning: soil features BI and CI, soil features PCs (PC1, PC2, and PC3) from soil reflectance data of 2000, and crop features LAI and leaf chlorophyll content derived from CASI crop reflectance data for the three IFCs in 2001. The soil features represent the relatively stable properties of the field, whereas crop features of the three IFCs reveal the seasonally variable conditions in the fields.

Feature preprocessing

More than one feature is used in this study for field partitioning to integrate different aspects of information. Although all the features were extracted from the same source of data, their typical dynamic ranges are quite different. The values of the features within the range relative to 1%–99% of the cumulative histogram were scaled to [0, 1] through a linear stretch. One of the reasons for this processing is that the relative importance of the features to the delineation is unknown, and therefore they were given the same weight via data stretching. This processing also eliminates the outliers from the typical distribution range.

Clustering method

Because the number of management zones and their spatial distribution are unknown, unsupervised methods were used to cluster the field into homogeneous regions by dividing the feature space. The features from the sites are then extracted and related to the measured variables at the same sites to define the class map of the variable of interest. Since the proposition by Bezdek (1981), fuzzy *k* means has become one of the most widely used unsupervised classification methods. It is the most accurate among the unsupervised methods to reproduce the ground data in a complex landscape (Duda and Canty, 2002) and has been used by many researchers to classify remotely sensed image data. The FUZCLUS module provided in the PCI software (PCI Geomatics Enterprises Inc. 2001) was used in our study to partition the selected features.

Determination of the number of zones

The number of management zones is determined by the size of the field, the natural variability within the field, and certain management factors (Zhang et al., 2002). The choice of an appropriate number of classes is a prerequisite before performing unsupervised classification. We determine the optimum number of zones using the method used by Fridgen et al. (2000), which is based on the inspection of the relative total within-class variance (RTWCV) reduction of selected field variables:

$$\mathrm{RTWCV} = \sum_{i=1}^{C} \sum_{j \in \mathrm{class}C} [x_{ij} - \mu_i]^2 / \sum_{j \in \mathrm{field}} [x_j - \mu]^2 \tag{8}$$

where C is the number of zones, x_{ij} is an observation of the variable from zone i, x_j is an observation of the variable in the whole field, μ_i is the average of the variable in zone i, and μ is the average in the whole field. As the number of zones increases, RTWCV will decrease and then level off. The value at which RTWCV levels off, or stops decreasing significantly, is a reasonable estimate of the number of zones that can be used to partition the field.

In this study, to determine the appropriate number of zones, fields 25 and 23 were partitioned into 2–7 zones using the derived soil and crop feature sets. For each of the partitioned results, RTWCV was calculated for the selected variables. The selected variables included (*i*) yield, which is often considered as the ultimate dependent variable; (*ii*) LAI and leaf chlorophyll content, which are the most important crop descriptors; and (*iii*) soil electrical conductivity. Electrical conductivity was measured at depths of 0–0.3 and 0–1.0 m (Perron et al., 2003). The RTWCV values of these selected variables are plotted against the number of zones, and the appropriate number of zones was determined from the plots.

Another factor that should be taken into consideration is the spatial distribution of the samples in a given zone. Pixel-based image classification usually divides the feature space. Thus, pixels in a zone are continuous in feature space but are not necessarily so in the spatial domain. From the point of view of the agricultural producer, management zones should encompass significant areas with continuous spatial distribution. Postclassification spatial filtering improves the delineation by removing the isolated small clusters. In this study, the isolated clusters with fewer than the given number of pixels (i.e., 16 in this study) were detected and marked. For each pixel in the marked clusters, its class attribute was determined by inspecting its neighbour pixels: it was assigned to the class that appeared most in this neighbourhood.

Analysis of variance

Analysis of variance (ANOVA) was conducted to test the difference among the delineated zones for the selected soil and crop properties. The technique is a single-factor ANOVA, with the zone identification as the independent variable and the field descriptors, such as yield, electrical conductivity, LAI, and leaf chlorophyll content, as dependent variables. Rafter et al. (2002) concluded that Tukey's test is the most useful for all pairwise comparisons, and the actual family-wise error rate (FWER) exactly equals the specified value. Therefore, Tukey's multiple comparison method (MCM) was applied to test the difference between the means for the dependent variables in the delineated zones.

Results and discussion

Determination of appropriate number of zones

Figures 2 and **3** show the variance reduction of the selected variables in fields 25 and 23, respectively. Results from five delineations are given: two soil delineations using BI, CI, and principal components (PCs) and three crop delineations using LAI and leaf chlorophyll content at IFC1, IFC2, and IFC3. Variance reduction of all the variables is given for the soil

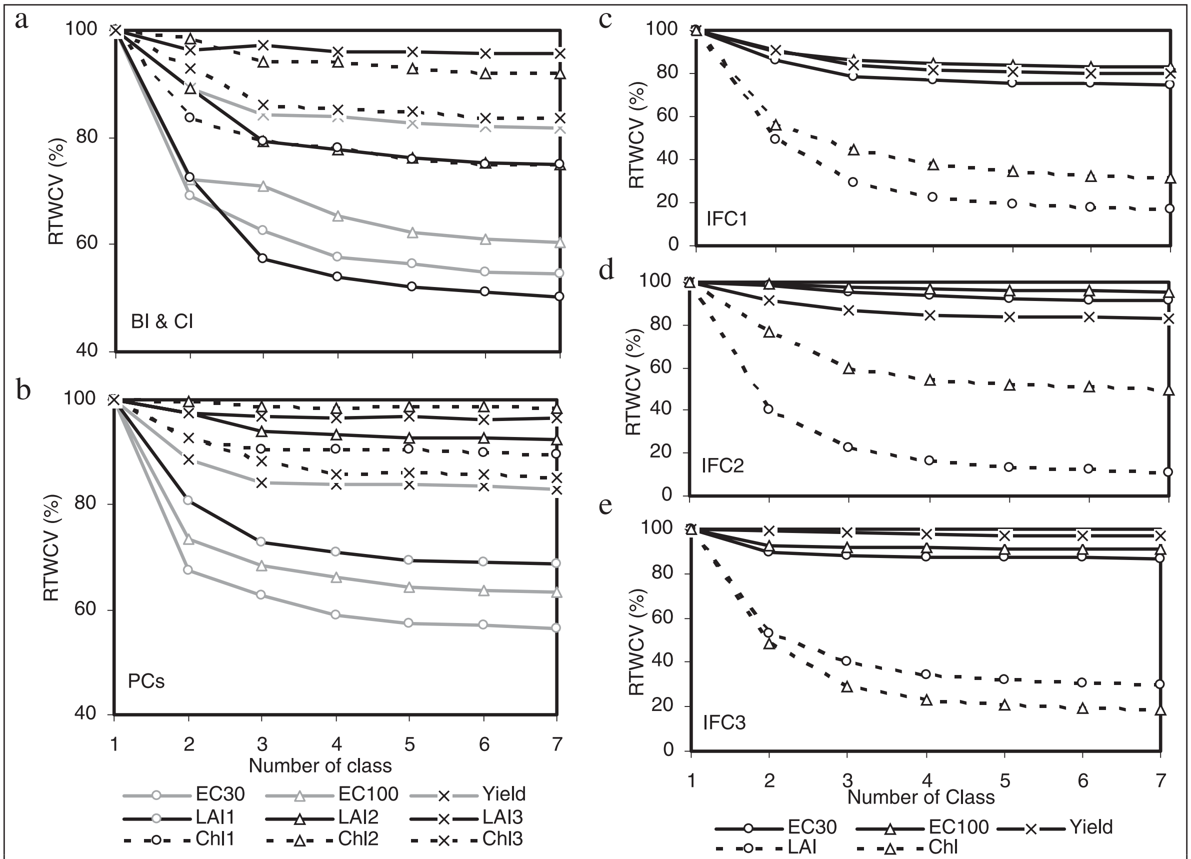

Figure 2. Variance reduction by partitioning field 25 into 2–7 classes using (a) soil brightness and colouration indices (BI and CI, respectively), (b) the first three principal components (PCs) of soil reflectance, and (c–e) leaf area index (LAI) and chlorophyll (Chl) content from IFC1, IFC2, and IFC3, respectively. RTWCV, relative total within-class variance.

delineations, and variance reduction of yield, electrical conductivity, and LAI and leaf chlorophyll content at the specific IFC is given for the crop delineations. In **Figures 2** and **3**, EC30 and EC100 refer to electrical conductivity between 0 and 0.3 m and 0 and 1.0 m depth; LAI1, LAI2, and LAI3 and Chl1, Chl2, and Chl3 represent LAI and leaf chlorophyll content at IFC1, IFC2, and IFC3, respectively.

Three to four zones were recommended for field 25 from an inspection of **Figure 2**. Based on BI and CI, classification of field 25 into four soil zones reduces the variances of EC30, EC100, LAI1, LAI2, and Chl1 to 58%, 65%, 54%, 78%, and 78%, respectively. The results using principal components were almost the same for the first three descriptors, with the variances of the variables specified previously reduced to 59%, 66%, and 71%, and with a limited reduced variance of LAI2 and Chl1 to 93% and 91%, respectively. The soil features as identified by hyperspectral reflectance seem to appropriately reveal the soil properties, as indicated by variance reduction of soil electrical conductivity. Inherent soil fertility indicators like soil texture components (sand, silt, and clay content) and exchangeable cations (Ca and Mg) are closely related to soil electrical conductivity (Nolin et al., 2002; Perron et al., 2002). Soil properties highly influenced by soil fertility management like soil pH and soil tests (available P and K), however, are less closely related to soil electrical conductivity (Perron et al., 2002; 2003). BI–CI and principal components classifications significantly reduced the variances of yield and Chl3 to about 85%, which tends to indicate that the detected soil properties had a restricted impact on growth conditions toward the end of the growing season in this field. In this field, soil properties seemed to explain mainly the variability related to the emergence of the spring wheat. With the progression of the growing season, soil properties captured by soil features did not significantly impact the variability of LAI and leaf chlorophyll content, indicating that there was no detection of N limitation.

Based on LAI and leaf chlorophyll content, classification of field 25 into four crop zones reduces the variances of LAI to about 23%, 16%, and 34% and those of leaf chlorophyll content to 37%, 54%, and 24% at IFC1, IFC2, and IFC3 stages, respectively. The crop zones delineated at IFC1 reduced the variances of EC30 and EC100 to 77% and 82%, respectively. This also indicates that the crop growth condition revealed by LAI and leaf chlorophyll content at IFC1 stage is more affected by the soil properties than those at IFC2 and IFC3. Another observation is that the crop zones delineated at IFC1 and IFC2 reduced the variance of yield to about 82% and 85%, respectively. Thus crop descriptors LAI and leaf chlorophyll content at the earlier development stages have more impact on wheat yield in field 25 than later on.

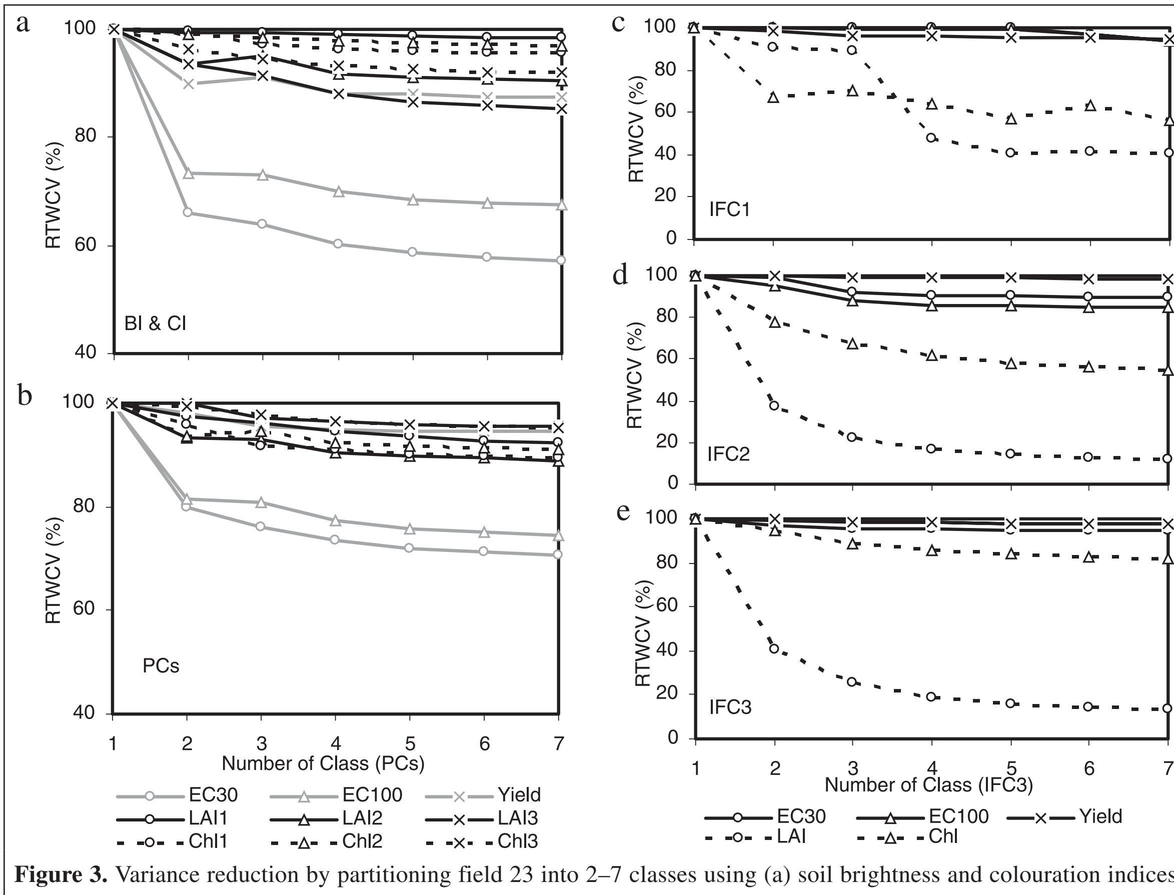

Figure 3. Variance reduction by partitioning field 23 into 2–7 classes using (a) soil brightness and colouration indices (BI and CI, respectively), (b) the first three principal components (PCs) of soil reflectance, and (c–e) LAI and chlorophyll.

Figure 3 suggests that two to three zones are recommended for field 23. When the field was partitioned into three soil zones, the variances of EC30 and EC100 were reduced to about 64% and 73% when BI and CI were used and to about 76% and 81% when PCs were used. Again, the soil features extracted from hyperspectral data seemed to capture the variability of some soil properties in the field. The variances of LAI and leaf chlorophyll content had a limited reduction, however, and the variance of yield was only reduced to 91%. When the field was partitioned using LAI and leaf chlorophyll content, the variances of LAI and leaf chlorophyll at a specific IFC had significant reductions, whereas the variances of yield and electrical conductivity had very limited reductions. The variance reduction of LAI and leaf chlorophyll is not very stable at IFC1. This is because the fraction of crop cover (corn) was very low at that time and therefore the estimated LAI has a very small dynamic range and the estimated leaf chlorophyll content is somewhat uncertain (Haboudane et al., 2002; 2004). For the crop-based delineation, the variances of LAI and leaf chlorophyll content were reduced to about 22% and 67% at IFC2 and 26% and 89% at IFC3, respectively. Compared with field 25, the variance of corn yield in field 23 is less accounted for by soil features and crop descriptors.

Spatial patterns in field 25

Figure 4 shows the results of soil zone delineations in field 25 using the two soil feature sets, e.g., BI and CI and PCs. The results of crop zone delineation using LAI and leaf chlorophyll content for IFC1, IFC2, and IFC3 are given in **Figure 5**. For convenience, the partitioned zones from the two soil feature sets are referred to as soil-based zones, and those from LAI and leaf chlorophyll content as crop-based zones. Soil-based zones and crop-based zones are indicated by the subscripts s and v, which refer to soil and vegetation, respectively.

The soil zones delineated from BI and CI and PCs show some similarities. The spatial patterns of the soil-based zones generally match the soil type distribution as revealed by the soil survey map (**Figure 1**). $C1_s$ and $C2_s$ mostly represent D3 soil series, and $C4_s$ mostly represents M3–NG2 soil series. $C3_s$ distributed in between these two regions may be the transition of these two soil associations. The patterns of $C1_s$ and $C2_s$ delineated using BI and CI are not consistent with the delineation using soil PCs. The soil properties may not be very different between these two delineated zones. $C1_s$ delineated using BI and CI at the upper boundary of the field represents the slope area with low organic matter, low sand content, and high clay content, which indicates soil erosion due to the slope heading toward the creek flowing between the wheat (field 25) and corn (field 23) fields. This pattern is also well defined in the crop zones at IFC1 and IFC2 stages and is typical of low LAI and yield. Soil leveling and stabilization might be required in this area.

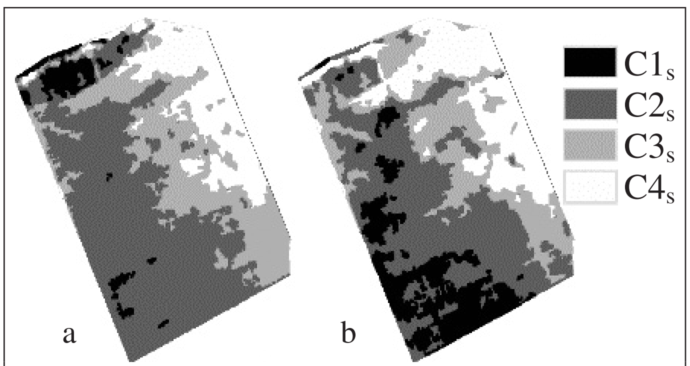

Figure 4. Soil delineation of field 25 into four classes using (a) soil brightness and colouration indices, and (b) principal components. $C1_s$–$C4_s$, soil-based zones 1–4, respectively.

Different levels of N were applied with a specific pattern in the wheat field (**Figure 5d**). The applied N was 0, 41, or 68 kg N ha^{-1} (referred to as 0N, 41N, and 68N, respectively). The crop-based zones derived from the partitioning of LAI and leaf chlorophyll content show the combined effects of soil properties and N application. The 0N application area at the southwestern corner is clearly delineated as $C1_v$ throughout the season. Statistics show that this region has lower final yield, lower LAI, and lower leaf chlorophyll content at all the three IFCs compared with the other zones. N deficiency is the major critical concern. Although recommended amounts of nitrogen (68N) were applied to the slope area, LAI in this region was significantly lower at IFC1 and IFC2 stages. This region, being clearly delineated as $C1_v$ at IFC1 and IFC2 stages, is not favourable for crop growth and led to a lower yield, which was presumably caused by the lack of organic matter as a result of soil erosion toward the creek. Class $C4_v$ defined in IFC1 (upper right corner) overlaps with regions of the M3–NG2 soil series. In this zone, LAI and leaf chlorophyll content of the first two IFCs and final yield have higher values, indicating that the soil type in this area is favourable for crop growth. The crop developed faster in this area than in the other areas, which makes wheat reaching its senescence stage earlier. The decrease of leaf chlorophyll content and green LAI in this region accounted for it being classified as $C1_v$ and $C2_v$ at the IFC3 stage.

Spatial patterns in field 23

Figure 6 shows the results of soil-based zone delineation in field 23 using the two soil feature sets. Results of crop-based zone delineations for IFC1, IFC2, and IFC3 are given in **Figure 7**.

The similarity is weaker between the soil-based zones resulting from BI and CI and PCs in field 23. $C1_s$ mostly represents the poorly drained, fine-textured Brandon series (D3), $C2_s$ is mostly associated with poorly drained and imperfectly drained soils of Allendale and Montain series associations (M6 and M3), and $C3_s$ represents a well-drained to imperfectly drained sandy soil association (U2–M5) regrouping deep (>100 cm) sandy soils (Carlsbad and Ramsayville series) and shallow (25–100 cm) sandy soils over clay material (Allendale and Montain series).

Corn planted in field 23 received a uniform recommended N application. The spatial patterns of the crop classes are therefore mostly caused by the interaction between soil and weather conditions. Crop-based delineation is difficult at IFC1 because corn was at the early emergence stage in the field. Differentiation of $C1_v$, $C2_v$, and $C3_v$ at the IFC1 stage is mainly due to the amount of vegetation cover and the soil properties. At IFC1, LAI in $C3_v$ generally ranges from 0.3 to 0.6, whereas in $C1_v$ and $C2_v$ it is less than 0.3. $C3_v$ delineated at the IFC1 stage also has higher LAI values at IFC2 (from 2.5 to 4.0) and IFC3 (>4.0) than the other delineated zones. The crop-based zones are best delineated at the IFC2 stage, in that the variances of both LAI and leaf chlorophyll content are significantly reduced (**Figure 3**).

Statistical analysis

Relationship between the two soil feature sets

Soil brightness dominates the spectral variance among soils. The first principal component of soil data accounts for the

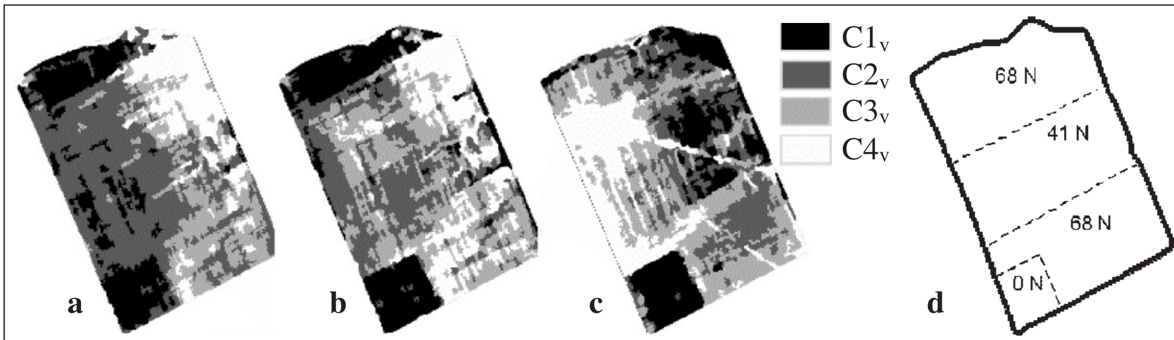

Figure 5. (a–c) Crop delineation of field 25 into four classes using LAI and leaf chlorophyll content at IFC1, IFC2, and IFC3, respectively. $C1_v$–$C4_v$, vegetation (crop) based zones 1–4, respectively. (d) Nitrogen application pattern (0N, 41N, and 68N denote applications of 0, 41, and 68 kg N ha^{-1}, respectively).

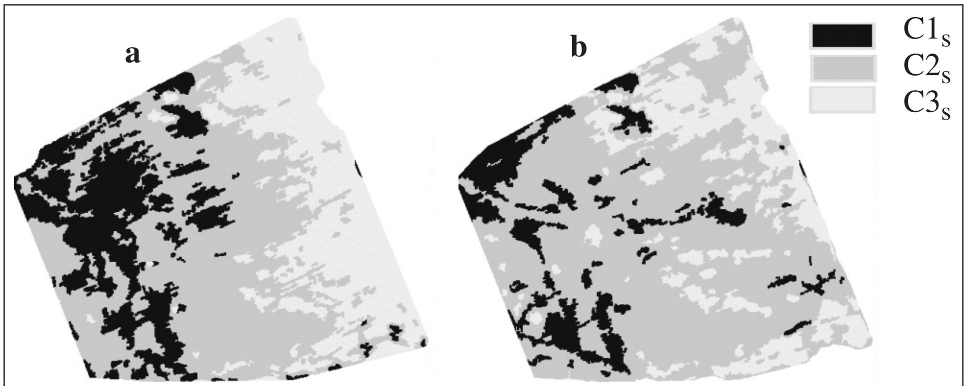

Figure 6. Soil delineation of field 23 into three classes using (a) soil brightness and colouration indices and (b) principal components.

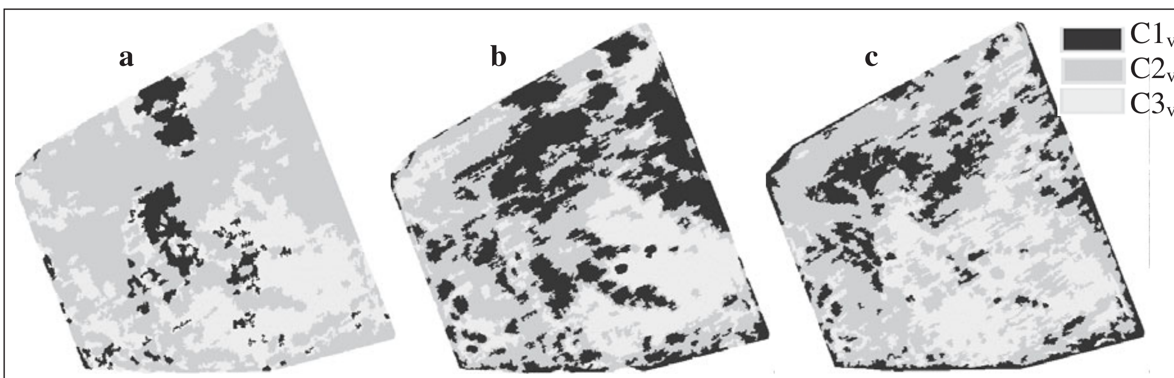

Figure 7. Crop delineation of field 23 into three classes using LAI and leaf chlorophyll content at (a) IFC1, (b) IFC2, and (c) IFC3.

majority of the variability and represents approximately the average value of the spectrum, and therefore it is a measure of soil brightness. The first principal component and soil brightness calculated using Equation (1) are highly linearly correlated, with determination coefficients (R^2) of 0.998 and 0.970 in fields 25 and 23, respectively. This explains the similar results of delineations using PCs and BI and CI (**Figures 2**, **3**, **4**, and **6**). The different information content between the higher order principal components (the second and third) and the chromatic component CI mainly accounts for the difference of the delineations.

Correlation between crop descriptors and yield

The correlation between crop descriptors and yield was analyzed, and the results are given in **Table 2**. In field 25, the correlations between LAI and wheat yield and between leaf chlorophyll content and wheat yield are significant at IFC1 and IFC2 but not significant at IFC3. In field 23, yield is not significantly correlated with LAI or leaf chlorophyll content. This is consistent with the results shown in **Figures 2** and **3**: the variance of yield in field 25 was reduced to 82% and 85% for the crop-based delineation at IFC1 and IFC2, respectively, but there was no significant reduction for the crop-based delineation at IFC3, and there was very limited variance reduction of corn yield in field 23 for the crop-based delineation at any of the three IFCs. The possible reason for the poor correlation in field 23 is that LAI and leaf chlorophyll content did not capture a high productivity spatial feature across the field, which decreased the overall correlation. If this high productivity feature is masked out, then a significant correlation is observed between corn yield and leaf chlorophyll content at IFC2 and IFC3 (**Table 2**, field 23A). The highest correlations were obtained with leaf chlorophyll content.

Zone means and analysis of variance

Figures 8 and **9** show the zone means and standard deviations of the variables in the delineated zones of fields 25 and 23, respectively. For variables EC30, EC100, and yield, the figures show zone means and deviations of the five delineations: crop-based delineations at the three IFCs, and soil-based delineations using BI and CI and PCs. For LAI and leaf chlorophyll content, zone means and deviations of crop delineations at the three IFCs were illustrated. Tukey's test was applied to test the difference of zone means of the variables to evaluate the uniqueness of the delineated zones. The results are also shown in **Figures 8** and **9**. Zones in which the mean values do not differ significantly at the 95% confidence interval are marked with a box above the data bars. For instance, in field 25, the means of soil zones C1 and C2 delineated by BI and CI do not differ significantly at the 95% confidence interval. In this case, a box is shown above the data bar spanning C1 and C2 (see **Figure 8a**).

Table 2. Correlation coefficients between yield and crop descriptors in the two fields.

Field	LAI1	LAI2	LAI3	Chl1	Chl2	Chl3
25	0.57**	0.51**	0.23	0.54**	0.43*	0.15
23	–0.09	–0.10	–0.08	–0.19	–0.13	0.22
23A	0.04	0.15	0.22	–0.13	0.54**	0.68**

Note: The suffixes 1–3 to LAI and Chl represent IFC1–IFC3, respectively. *, significant at $p < 0.01$; **, significant at $p < 0.001$. For field 23A, the high productivity feature was masked out.

In field 25, EC30, EC100, and yield differ significantly between soil-based zones except between C1 and C2. This means that soil features extracted from hyperspectral data revealed some of the soil properties, and the detected soil properties had an important impact on the final yield. It can be observed that yield in this field is negatively related to electrical conductivity. Yield is highest in the soil-based zone C4 and lowest in zones C1 and C2, and EC30 and EC100 are lowest in zone C4 and highest in zones C1 and C2. The high electrical conductivity corresponds to heavier soil texture, and these soils tend to stay saturated for longer periods of time, which is negative for yield. For the crop-based zones, LAI and leaf chlorophyll content differ significantly among the zones, whereas EC30 and EC100 do not differ significantly between some of the crop-based zone pairs. The crop-based zones at IFC3 do not effectively differentiate wheat yield, whereas they are indicative of yield at IFC1 and IFC2. This means that the effective time for delineation of the wheat crop should be earlier than that at IFC3.

In field 23, soil electrical conductivity differs significantly between all pairs of soil-based zones, whereas there is no significant difference in electrical conductivity between the crop-based zones (**Figure 9**). Yield does not differ significantly among the soil-based zones as well as it does among the crop-based zones in this field. Except for LAI at IFC1 and leaf chlorophyll content at IFC3, crop descriptors differ significantly between all pairs of crop-based zones. Zone C1 delineated at IFC1 has a high yield compared with that in the other zones because it is completely within a high-production region in the field. From IFC1 to IFC3, LAI in field 23 increased steadily. For corn in field 23, the effective time for delineation of crop-based zones should be later than that for IFC1.

Conclusions

In this study, multitemporal CASI hyperspectral data were used for zone delineation of two agricultural fields. Different features extracted from hyperspectral data related well to some of the field variables and revealed the variability of seasonally stable and variable information useful for management zone delineation for precision agriculture.

The variability in soil electrical conductivity can be accounted for to a significant extent by the features extracted from hyperspectral soil reflectance data. Several inherent soil fertility indicators like soil texture components (sand, silt, and clay content) and exchangeable cations (Ca and Mg) and soil drainage and related soil moisture conditions could be related to soil electrical conductivity. This is rarely the case, however, for the organic matter content of the surface layer, which is

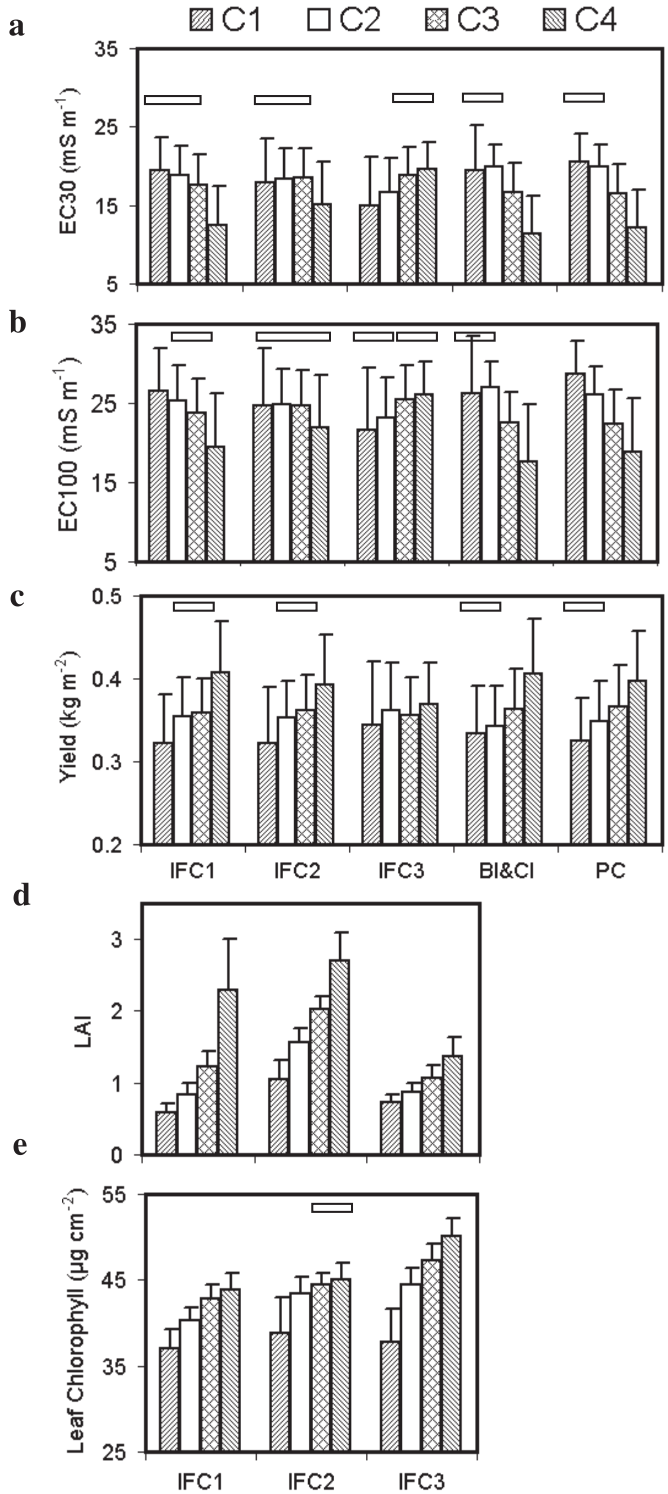

Figure 8. Zone statistics and multiple comparisons for field 25. Variables include electrical conductivity at 0–30 cm (EC30) and 0–100 cm (EC100), yield, LAI, and leaf chlorophyll content; delineations include crop-based delineation at IFC1, IFC2, and IFC3 and soil-based delineations using BI and CI and PCs. The boxes above the data bars indicate the classes that do not differ significantly at the 95% confidence interval. The vertical bars denote standard deviation.

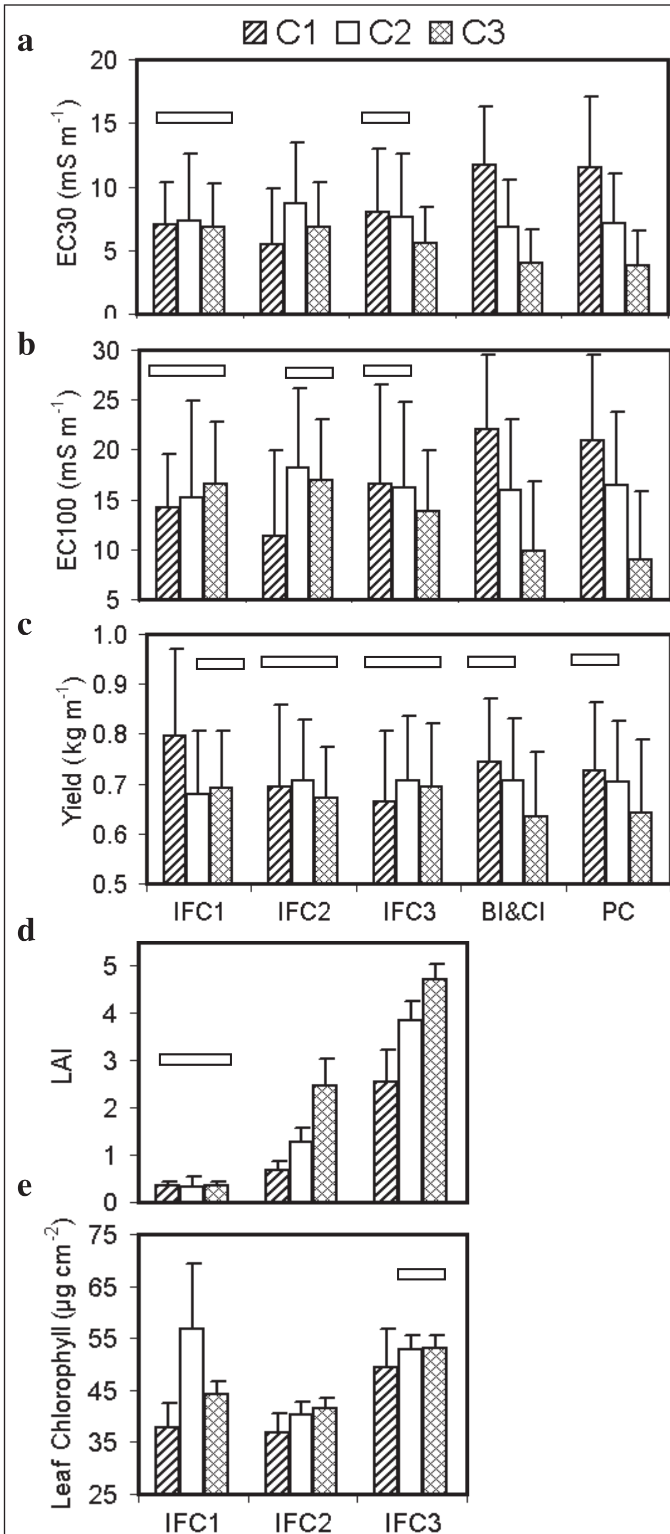

Figure 9. Zone statistics and multiple comparisons for field 23. Variables include electrical conductivity at 0–30 cm (EC30) and 0–100 cm (EC100), yield, LAI, and chlorophyll content; delineations include crop-based delineation at IFC1, IFC2, and IFC3 and soil-based delineations using BI and CI and PCs. The boxes above the data bars indicate the classes that do not differ significantly at the 95% confidence interval. The vertical bars denote standard deviation.

most directly associated with soil reflectance. Therefore, remote sensing data have been shown to play a strong role in soil delineation and could be viewed, under given conditions, as an efficient alternative to soil conductivity mapping for defining within-field homogeneous management zones.

The crop descriptors derived from hyperspectral data are very useful for monitoring crop growth conditions. They revealed the effects of soil properties under natural growth conditions and the effects of special nitrogen application under controlled conditions. The appropriate time to delineate wheat in field 25 was at IFC1 and IFC2 (prior to senescence), and the appropriate time to delineate corn in field 23 was after IFC1 (after complete emergence). Crops can be monitored frequently using LAI and leaf chlorophyll content to monitor seasonally variable information to guide the real-time field practices.

Zone delineation was evaluated by the variance reduction of yield. From this perspective, field 25 is better delineated because the variance of yield was reduced significantly for soil and crop delineations. The soil properties in this field have an important impact on final yield, and crop descriptors LAI and leaf chlorophyll content at the earlier stages (IFC1 and IFC2) are indicative of final yield. Field 23 is not well delineated in terms of variance reduction of yield.

In this study, delineation of management zones of the fields is based solely on the classification of the features extracted from hyperspectral data. Soils and crops were delineated independently using multitemporal hyperspectral data. The combination of soil features and crop descriptors before delineation, or the combination of the delineated results, could give better results for delineation of management zones. The integration of other sources of information, such as soil properties, environmental conditions, and field management factors, may also greatly improve the quality and usefulness (i.e., interpretability) of management zone delineation. In addition to the acquisition of the information on field variability, a more complete understanding of the causes of crop production variability is of great importance, since it will improve the efficiency of the information integration for management zone delineation and its usefulness for development of management strategy. This can be achieved by performing field delineation over several growing seasons to capture the effects of several weather pattern incidences on crop growth.

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References

Bezdek, J. (Editor). 1981. *Pattern recognition with fuzzy objective function algorithm*. Plenum Press, New York.

Doerge, T. 1998. Defining management zones for precision farming. *Crop Insights*, Vol. 8, No. 21. Pioneer Hi-Bred International, Inc., Johnston, Iowa.

Duda, T., and Canty, M. 2002. Unsupervised classification of satellite imagery: choosing a good algorithm. *International Journal of Remote Sensing,* Vol. 23, No. 11, pp. 2193–2212.

Escadafal, R., Belghith, A., and Ben Moussa, H. 1994. Indices spectraux pour la télédétection de la dégradation des milieux naturels en Tunisie aride. In *Proceedings of the 6th International Symposium on Physical Measurements and Signatures in Remote Sensing*, 17–21 January 1994, Val d'Isère, France. CNES. pp. 253–259.

Fridgen, J.J., Kitchen, N.R., and Sudduth, K.A. 2000. Variability of soil and landscape attributes within sub-field management zones. In *Proceedings of the 5th International Conference on Precision Agriculture*, 16–19 July 2000, Bloomington, Minn. CD-ROM. Edited by P.C. Robert, R.H. Rust, and W.E. Larson. ASA–CSSA–SSSA, Madison, Wis.

Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., and Dextraze, L. 2002. Integrated narrow-band vegetation indices for a prediction of crop chlorophyll content for application to precision agriculture. *Remote Sensing of Environment*, Vol. 81, pp. 416–426.

Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J., and Strachan, I. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modeling and validation in the context of precision agriculture. *Remote Sensing of Environment*, Vol. 90, pp. 337–352.

Huete, A.R., and Escadafal, R. 1991. Assessment of biophysical soil properties through spectral decomposition techniques. *Remote Sensing of Environment*, Vol. 35, pp. 149–159.

Lelong, C.C.D., Pinet, P.C., and Poilve, H. 1998. Hyperspectral imaging and stress mapping in agriculture: a case study on wheat in Beauce (France). *Remote Sensing of Environment*, Vol. 66, pp. 179–191.

Leone, A.P., and Escadafal, R. 2001. Statistical analysis of soil colour and spectroradiometer data for hyperspectral remote sensing of soil properties (example in a southern Italy Mediterranean ecosystem). *International Journal of Remote Sensing*, Vol. 22, No. 12, pp. 2311–2328.

Liu, J.G., and Moore, J.Mcm. 1990. Hue image RGB colour composition: a simple technique to suppress shadow and enhance spectral signature. *International Journal of Remote Sensing*, Vol. 11, No. 8, pp. 1521–1530.

Marshall, I.B., Dumanski, J., Huffman, E.C., and Lajoie, P. 1979. *Soils capability and land use in the Ottawa urban fringe*. Land Resource Research Institute, Agriculture Canada, Ottawa, Ont. 59 pp.

Mattikalli, N.M. 1997. Soil colour modelling for the visible and near infrared bands of Landsat sensors using laboratory spectral measurements. *Remote Sensing of Environment*, Vol. 59, pp. 14–28.

Moran, M.S., Inoue, Y., and Barnes, E.M. 1997. Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment*, Vol. 61, pp. 319–346.

Nolin, M.C., Gagnon, B., Leclerc, M.-L., Cambouris, A.N., Belanger, G., and Simard, R.R. 2002. Influence of pedodiversity and land uses on the within-field spatial variability of selected soil and forage quality indicators. In *Proceedings of the 6th International Conference on Precision Agriculture*, 14–17 July 2002, Minneapolis, Minn. CD-ROM. Edited by P.C. Robert et al. ASA–CSSA–SSSA, Madison, Wis.

Pattey, E., Strachan, I.B., Boisvert, J.B., Desjardins, R.L., and McLaughlin, N.B. 2001. Detecting effects of nitrogen rate and weather on corn growth using micrometeorological and hyperspectral reflectance measurements. *Agriculture and Forest Meteorology*, Vol. 108, pp. 85–99.

PCI Geomatics Enterprises Inc. 2001. *EASI/PACE software, version 8.2.3*. PCI Geomatics Enterprises Inc., Richmond Hill, Ont.

Perron, I., Cluis, D.A., Nolin, M.C., and Leclerc, M.-L. 2002. Influence of microtopography and soil electrical conductivity on soil quality and crop yields. In *Proceedings of the 6th International Conference on Precision Agriculture*, 14–17 July 2002, Minneapolis, Minn. CD-ROM. Edited by P.C. Robert et al. ASA–CSSA–SSSA, Madison, Wis.

Perron, I., Nolin, M.C., Pattey, E., Bugden, J.L., and Smith, A. 2003. Comparaison de l'utilisation de la conductivite électrique apparente (CEa) des sols et des donnees polarimetriques RSO pour delimeter des unites d'amenagement agricole. In *25th Canadian Symposium on Remote Sensing – 11e Congrès de l'Association québécoise de télédétection*, 14–16 October 2003, Montréal, Que. CD-ROM.

Rafter, J.A., Abell, M.L., and Braselton, J.P. 2002. Multiple comparison methods for means. *SIAM Review*, Vol. 44, No. 2, pp. 259–278.

Shibayama, M., and Akiyama, T. 1991. Estimating grain yield of maturing rice canopies using high spectral resolution reflectance measurements. *Remote Sensing of Environment*, Vol. 36, pp. 45–53.

Strachan, I.B., Pattey, E., and Boisvert, J.B. 2002. Impact of nitrogen and environmental conditions on corn as detected by hyperspectral reflectance. *Remote Sensing of Environment*, Vol. 80, pp. 213–224.

Thenkabail, P.S., Smith, R.B., and De Pauw, E. 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. *Remote Sensing of Environment*, Vol. 71, pp. 158–182.

Tomer, M.D., Anderson, J.L., and Lamb, J.A. 1995. Landscape analysis of soil and crop data using regression. In *Proceedings of Site-specific Management for Agriculture Systems*, 27–30 March 1994, Minneapolis, Minn. Edited by P.C. Robert, R.H. Rust, and W.E. Larson. ASA–CSSA–SSSA, Madison, Wis. pp. 273–284.

Tucker, C.J., Holben, B.N., Elgin, J.H., Jr., and McMurtrey, J.E. 1980. Relationship of spectral data to grain yield variations. *Photogrammetric Engineering and Remote Sensing*, Vol. 46, pp. 657–666.

Zhang, N., Wang, M., and Wang, N. 2002. Precision agriculture — a worldwide overview. *Computers and Electronics in Agriculture*, Vol. 36, pp. 113–132.

