Object-based Classification of High Resolution SAR Images for Within Field Homogeneous Zone Delineation

Jiangui Liu, Elizabeth Pattey, and Michel C. Nolin

Abstract
Delineating management zones is important in agriculture for implementing site-specific practices. We delineated within-field homogeneous zones over a corn and a wheat field using high spatial resolution multi-temporal airborne C-band synthetic aperture radar (SAR) imagery with an object-based fuzzy k-means classification approach. Image objects were generated by a segmentation procedure implemented in eCognition® software, and were classified as basic processing units using SAR data. Results were evaluated using analysis of variance and variance reduction of soil electrical conductivity (EC), leaf area index (LAI), and crop yield. The object-based approach provided better results than a pixel-based approach. The variance reduction in LAI, and soil EC varied with SAR acquisition time and incidence angle. Although the variance reduction of yield was not as significant as that of LAI and EC, average yield among the delineated zones were different in most cases. The SAR data classification produced interpretable patterns of soil and crop spatial variability, which can be used to infer within-field management zones.

Introduction
There is a growing interest in delineating management zones for implementing site-specific practices in agriculture. Management zones are delineated by classifying the within-field spatial variability of yield limiting factors (Doerge, 1999). Different inputs, such as nutrient, seed rate, water, tillage, and soil management, can then be applied accordingly for optimal profitability and environmental sustainability. To avoid the uncertainty related with interpolation procedures and achieve robust zone delineation, data should be densely sampled within a field. This is an expensive practice using conventional survey methods. High-resolution satellite remote sensing potentially provides a cost-effective and non-invasive way to obtain crop field information continuously over space and frequently through a season.

As reviewed by Moran et al. (1997), the variability of many field descriptors could be mapped with remote sensing techniques by measuring short-wave (0.4 to 2.6 μm) reflected radiance, long-wave (3 to 16 μm) emitted radiance, or synthetic aperture radar (SAR; 0.9 to 25 cm) backscatter. While single remote sensing observation at an optimal time is useful in mapping seasonally-stable field descriptors, e.g., soil-based management units, multi-temporal observations are especially important to capture unexpected environmental impacts, map temporal variation, and obtain seasonal profiles of crop descriptors that could be used as inputs to crop models (Wiegand et al., 1986). Furthermore, since the crop canopy integrates the effects of the weather, soil properties, and other stresses (e.g., disease or nutrient deficiencies) (Wiegand and Richardson, 1984), stable and dynamic soil properties could also be mapped by multi-temporal observations when the crop is present. Thus, classification of high spatial resolution remote sensing images could provide useful information for within field management zone delineation. The all-weather acquisition capability of radar makes it advantageous over optical remote sensing, since obtaining multi-temporal optical data can be challenging due to cloud cover. The availability of data from RADARSAT-2, with its multi-polarization or fully polarimetric modes, and higher spatial resolution (Fox et al., 2004), could boost the application of SAR data in agriculture (McNairn and Brisco, 2004). The objective of this study was to exploit the variability in multi-temporal, multi-polarized high spatial resolution SAR imagery for within field homogeneous zone delineation for site-specific agriculture using a classification approach.

Classification of land-cover using SAR data was mainly based on the sensitivity of radar backscatter to target structural information (Dobson et al., 1995). A few general land-cover types can thus be differentiated. A widely used method for unsupervised classification of polarimetric SAR data through target decomposition was devised by Cloude and Pottier (1997), in which pixels were divided into eight feasible zones in the entropy (H) and anisotropy (a) plane according to different scattering mechanisms. By using this method for an initial unsupervised classification to derive training sets, Lee et al. (1999 and 2004) developed a supervised classifier based on a complex Wishart distribution. These kinds of methods require spatial averaging to obtain a robust estimation of a coherency matrix; hence, they tend to degrade the spatial resolution. Furthermore, it could be difficult to segment an agricultural field according to the

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scattering mechanisms, since a single mechanism usually dominates within a field. In this study the three linearly polarized backscatter coefficients, HH, HV, and VV, were synthesized and used for classification.

An intrinsic shortcoming of a conventional pixel-based classifier is that it is based on global behavior of the feature set without considering the spatial information. It ensures optimal segmentation in the feature domain, but not necessarily in the spatial domain. This leads to fragmentation within field spatial patterns and fractal boundaries that cannot be managed by farmers. Moreover, in order to derive meaningful spatial patterns, coherent speckle noise in SAR data has to be reduced by speckle filters, which reduces the effective spatial resolution. Baring these factors in mind, an object based classification scheme was proposed in this study to classify the synthesized polarized data. The field was first segmented into small homogeneous areas, referred to as image objects or image primitives, using eCognition® software (Baatz et al., 2002). Both spectral and spatial information were utilized at this preliminary stage. Average values of SAR data in these image objects were then extracted and classified using an unsupervised Fuzzy k-means algorithm implemented in FuzMe 3.0 (Minasny and McBratney, 2002). The classification was evaluated using three field descriptors: (a) soil electrical conductivity (EC), which was related to a few important soil properties, (b) green LAI, an important indicator for crop development status, and (c) the crop yield. This provided an assessment of SAR data classification for potential management zone delineation.

**Materials**

**The Study Site**

The study site was located in the former Greenbelt Farm in Ottawa, Ontario, Canada (45°18’ N, 75°45’ W). Two neighboring fields, one planted with corn and another with wheat in the 2001 growing season were considered in the study. The field planted with corn (72 ha) is characterized with a high pedodiversity level, with six soil series combinations and moderately to poorly drained conditions. The field planted with wheat (52 ha) is characterized with a lower pedodiversity level, with two soil series combinations and mainly a poorly drained condition (Marshall et al., 1977). Three intensive field campaigns (IFC) were carried out to monitor crop growth conditions. Remote sensing data were acquired on 13 June, 26 June, and 19 July 2001 for the three campaigns. Airborne C-Band (5.3 GHz) polarimetric SAR data were acquired with the Environment Canada Convair-580 SAR system (CV-580). Airborne hyperspectral data were acquired with the CRESTech Compact Airborne Spectrographic Imager (CASI), with 2 m resolution and 72 bands in the visible-near infrared range. Crop biophysical descriptors, including phenological stage, height, biomass, leaf area index (LAI), and crop fraction, were also collected during the three campaigns. During the first campaign (IFC1), wheat was in the tillering phase with a few areas at the stem elongation stage. The crop fraction of cover ranged from 40 percent to 80 percent in response to different soil conditions and nitrogen treatments. Three to six leaves were expanded for the corn plants, and the crop fraction was approximately 10 percent. During the second campaign (IFC2), wheat was in between the stem elongation and heading phases. For corn, six to nine leaves were expanded and the fraction of coverage ranged between 30 percent and 70 percent. The height of the corn canopy exceeded 1 m in the productive areas. During the third field campaign (IFC3), portions of the wheat field were already senescing, while the corn reached full coverage with eight to thirteen expanded leaves and emerging tassels in the productive areas.

**CV-580 SAR Data**

CV-580 polarimetric SAR data were acquired at two nominal incidence angles, about 35° and 55° at field center. Radiometric calibration was accomplished at the Canada Center for Remote Sensing (CCRS). A radiometric accuracy of 0.8 dB and phase accuracy of 10° were achieved. Geocoded products were also processed at CCRS, with a 4 m pixel size.

Speckle noise was reduced using Kuan filter with a minimum window size, i.e., 3 pixels by 3 pixels. The three linearly polarized backscatter coefficients HH, VV, and HV were synthesized using the software package Polinmetric Workstation (PWS) (Touzi and Charbonneau, 2004). Due to difficulties during the acquisition, SAR data were not acquired on 26 June with the 35° incidence angle. Consequently, five radar data sets were available for analysis: three acquisitions with a 55° incidence angle for each of the field campaigns, and two acquisitions with a 35° incidence angle for the first and the third field campaigns.

**Biophysical Measurements**

Maps of soil EC, yield, and multi-temporal green LAI were generated for the two fields. The spatial variability of soil EC is dominated by static factors and exhibits relatively constant patterns, while its magnitude is affected by the dynamic soil properties (Corwin and Lesch, 2005). Therefore, spatial and temporal measurements of soil EC are powerful tools in precision agriculture studies (Corwin and Lesch, 2003; Corwin et al., 2003). Soil EC was measured in November 2002 using the VERIS-3100 at 0 to 30 cm (EC30) and 0 to 100 cm (EC100) depths, with a sampling rate of approximately 150 points ha⁻¹. Soil EC data measured in these two fields was correlated with soil texture, drainage property, and some soil quality indicators (Perron et al., 2003). Maps of multi-temporal green LAI were generated from CASI hyperspectral data for the three field campaigns using vegetation index MTVI2 (Haboudane et al., 2004). The LAI maps revealed the within-field crop growth condition variability (Haboudane et al., 2004; Liu et al., 2005).

Yield in 2001 was measured when the wheat was harvested on 22 August and the corn on 10 October. Data from a yield monitor (GreenStar Combine Yield Systems, Deere and Co., Moline, Illinois) and a global positioning system (GPS) were recorded with a 1 Hz rate. The final yield was processed as dry grain mass in kg/m². The measured point data of soil EC and crop yield were interpolated to a 4 by 4 m raster format. The estimated green LAI was mutually co-registered with the SAR data for further analysis.

**Methods**

**Image Segmentation**

Figure 1 shows an object-based unsupervised fuzzy k-means classification procedure for within field homogeneous zone delineation. The fields were first segmented into image objects or image primitives using eCognition® software (Baatz et al., 2002). Because it is strongly correlated with a few soil properties, and its spatial patterns are relatively stable over time (Corwin et al., 2003; Perron et al., 2003), soil EC was used for the first level segmentation to obtain meaningful image objects. In the second level, the obtained image objects were further segmented in three consecutive steps using the linear polarization data acquired for the three campaigns.

Segmentation in eCognition® is a bottom up region-merging procedure. As pairs of image objects merge, the
results in an inhomogeneous, and the heterogeneity increases. Starting from single pixels, smaller regions are iteratively merged into bigger ones, until the increase of heterogeneity of any merger does not exceed a given threshold. Heterogeneity of an image object defined in eCognition® is split into spectral heterogeneity, which is related with the variance of data within the object, and spatial heterogeneity, which is related with the shape of the object. The spatial heterogeneity consists of “smoothness” and “compactness.” Weighting factors control the relative contributions between spectral and spatial heterogeneity, and between smoothness and compactness to the overall heterogeneity (Benz et al., 2004). Thus, both the spectral and spatial information contained in the feature sets are utilized in the segmentation stage. The heterogeneity threshold is referred to as the scale factor, and is an important parameter for segmentation in eCognition®. A bigger scale factor results in larger objects. Determination of an optimal scale factor is affected by scene characteristics, data dynamic range, and the objectives. Preprocessing such as calibration, scaling and mathematical conversion (e.g., conversion of digital numbers to dB) that changes the data dynamic range may influence the value of an optimal scale factor.

In this study, the weighting factors for spectral and shape heterogeneity were set to 0.7 and 0.3, respectively, and that for compactness and smoothness were set to 0.8 and 0.2, respectively. These parameters were approximate to the default settings. The scale factors for the first and the second level segmentations were set to 10 and 4, respectively, so that the image objects are not too big to keep the important scene details. The averages of the backscattering in the HH, VV, and HV polarizations were calculated for the objects derived from the above segmentation procedure, and were exported from eCognition® to an ASCII format file for classification.

**Fuzzy k-means Classification**

Fuzzy k-means classifier implemented in FuzMe (Minasny and McBratney, 2002) was used to classify the derived image objects using SAR data. Mahalanobis distance was chosen as the measure of difference between objects, since it standardizes data and accounts for the correlation between the features. The fuzzy exponential was set to 1.25 to allow adequate fuzziness while achieving convergence of classification. Image objects were classified into 2 to 10 classes. The fuzziness Performance Index (FPI) and Modified Partition Entropy (MPE) were reported as functions of the number of classes. The optimal number of classes into which the image objects can be grouped was determined by the minimum FPI and MPE values (Roubens, 1982). For comparison purpose, classification was also applied on a pixel basis.

**Evaluation of the Classification**

To evaluate the potential of classification as a tool for within field homogeneous zone delineation, a method proposed by Fridgen et al. (2000) and used by Liu et al. (2005) was adopted here. This method is effective to evaluate the delineation of field descriptors with non-categorical variability. Basically, for the classification of an agricultural field and a selected field descriptor, the sum of within class variances of this descriptor can be calculated. Compared with the total within field variance, the percent variance reduction is an evaluation criterion. The more variance reduction, the better this descriptor is delineated by the classification. Four spatially continuous field descriptors, green LAI, EC30, and EC100, and the final crop yield, were selected as evaluation variables. The percent variance reduction is the Analysis of Variance (ANOVA). It assesses whether the average field descriptors between different classes are significantly different. This was done using Statistica software (StatSoft, Inc., 2005).

**Results and Discussion**

**Statistics of Field Descriptors and SAR Backscattering Coefficients**

Average, standard deviation (STDEV), and coefficient of variation (CV) for the selected field descriptors were reported in Table 1. Here CV refers to the ratio between the standard deviation and the average value. CV of soil EC in the cornfield was much higher than that in the wheat field. This was

![Diagram](image_url)

**Figure 1.** The study procedure. (LAI: leaf area index derived from the Compact Airborne Spectral Imager; PWS: Polarimetry Work Station).
in conformity with the fact that the cornfield had a higher pedodiversity than the wheat field (Marshall et al., 1979). From IF1 to IF3, average LAI of the corn increased steadily, while CV reached maximum at IF2. Crop growth conditions in the wheat field were quite different due to the differences in soil conditions and nitrogen treatments (Liu et al., 2005). Average LAI reached maximum at IF2, whereas the CV value was largest at IF1, and dropped significantly at the last campaign. CV of the yield was smaller than the other descriptors in these two fields.

Field averages and standard deviations of HH, VV, and HV polarizations and the green LAI for the three campaigns were shown in Figure 2. Relative to the wavelength of C-Band radar, corn and wheat are typical of broad and narrow leaf crops, respectively. The temporal variation in backscatter demonstrated the differences in radar responses to these two kinds of crops. For the corn, radar backscatter was the lowest while its variance was the most significant during the first campaign. The variance in backscattering was mainly due to the variability of soil surface conditions, e.g., moisture and roughness. As the crop developed in the following two campaigns, the backscattering approached a saturation level while the variance decreased significantly. This is a typical phenomenon for wide leaf crops (Ferrazzoli et al., 1997). Backscatter from the crop became the dominant factor in the radar response, whereas soil surface information was increasingly attenuated. For instance, the standard deviations of backscattered HH polarization over the corn canopy at 55° incidence angle were 2.1, 1.4, and 1.2 dB, with within field averages of −14.5, −9.6, and −10.8 dB for the three campaigns, respectively. Similar trends can be observed for the other two polarizations and at both incidence angles. The backscatter recorded at a 35° incidence angle was always stronger than that at a 55° incidence angle.

For the wheat, the magnitude and the variance of radar backscatter did not change as much as that observed for the corn canopy. For instance, the average HH polarized backscatter at a 55° incidence angle were −12.9, −11.2, and −11.0 dB, and the standard deviations were 1.2, 1.2, and 1.1 dB for the three campaigns, respectively. A variation of angular dependency of VV polarization was observed in the wheat field at IF3. A stronger VV backscatter was observed at a 55° incident angle than at a 35° incidence angle, which was consistent with the observation by Mattia et al. (2003). For the 55° SAR acquisitions, HH and VV polarizations had the greatest difference in the wheat field at IF2, when green LAI was the greatest. Whereas in the cornfield, the difference between HH and VV polarizations was almost unchanged when green LAI increased from the lowest level at IF1 to the highest level at IF3.

Image Segmentation
The first level segmentation using soil EC produced 264 image objects in the cornfield and 86 objects in the wheat field. In the second level, the sequential segmentation of the linear polarization data generated 841 image objects in the cornfield, and 248 in the wheat field. These image objects were supposed to have captured the field variability revealed by the spectral and spatial information contained in

![Figure 2](image-url)

Figure 2. Average and standard deviation of multi-temporal SAR backscattering coefficients and green LAI for corn (a) and (b), and wheat (c) and (d). There was no 35° incidence angle SAR data acquisition on 26 June 2001, i.e., Calendar day 177. (Ave.: Average; STDEV: Standard deviation).
the soil EC data and the multi-temporal SAR data, and will be further grouped in the next step. Figure 3 shows the polygons derived for the two segmentation levels overlain on EC100 map.

The Number of Classes
FPI and MPE as functions of the number of classes were plotted in Figure 4 for the 55° incidence angle data. FPI and MPE decreased significantly when the fields were classified into three classes. When the number of classes increased, a decreasing trend could be observed without a well-defined minimum value. Similar results were observed for the 35° acquisitions (data not shown). Therefore, both of the fields were classified into three classes for all the three campaigns. However, this is determined on the synthesized linear polarization data only. It does not mean that three classes are best for all the field descriptors. The effectiveness for delineating those field descriptors requires independent evaluation.

Variance Reduction
Percent variance reduction of green LAI, yield, and soil EC due to the classifications was calculated to assess the performance of the delineations. The results were reported in Table 2. To serve as a comparison, the results from the pixel-based approach were also included. For classification of the corn at IFC1 with the 55° SAR data, although a higher variance reduction of green LAI was achieved with the pixel-based approach (21.9 percent) than the object-based approach (10.5 percent), this was probably related to the significantly lower variability in LAI (standard deviation 0.09). However, generally a greater variance reduction was achieved with the object-based approach than with the pixel-based approach, which supported the use of the object-based method in this study. The following sections only present the results from the object-based approach.

In the cornfield, variance reduction of soil EC and green LAI due to classification decreased considerably from IFC1 to IFC3. The fully developed corn canopy during IFC3 caused two effects. First, direct backscattering from the soil was reduced by the significant interaction between the incident microwaves and the corn canopy. Second, radar backscatter from the mature canopy saturated so that the signal was not sensitive to the variability of crop biomass. At IFC1, classification of SAR data with the steeper incidence angle (35°) was more effective than the shallower incidence angle (55°) with respect to the reduction in the variance of soil EC. The percent variance reductions of EC30 and EC100 were 22.9 percent and 25.1 percent for the 35° acquisition, and 18.2 percent and 20.6 percent for the 55° acquisition, respectively.

In the wheat field, the variance reduction of soil EC due to classification did not show a decreasing trend from IFC1 to IFC3. The canopy development was likely responding to the soil variability. In addition, particularly as the wheat canopy senesces, the microwaves can penetrate the canopy.

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Figure 3. Segmentation results of (a) the corn and (b) the wheat fields. The upper and the lower rows show the polygons of the first and the second level segmentation, respectively.
Table 2. Variance Reduction of the Selected Field Descriptors Due to Classification of SAR Data. Results of Object-based and Pixel-based classifications were reported as a comparison; the values in the table represented percent of variance reduction relative to the total within field variance.

<table>
<thead>
<tr>
<th>Field</th>
<th>IFC1</th>
<th>IFC1</th>
<th>IFC2/IFC3</th>
<th>IFC1</th>
<th>IFC1</th>
<th>IFC2/IFC3</th>
</tr>
</thead>
<tbody>
<tr>
<td>IFC1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IFC2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IFC3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EC30 (mS m⁻¹)</td>
<td>18.2</td>
<td>22.9</td>
<td>13.2</td>
<td>7.1</td>
<td>1.1</td>
<td>17.2</td>
</tr>
<tr>
<td>EC100(mSm⁻¹)</td>
<td>20.6</td>
<td>25.1</td>
<td>17.4</td>
<td>7.3</td>
<td>1.3</td>
<td>20.9</td>
</tr>
<tr>
<td>Corn LAI (m² m⁻²)</td>
<td>10.5</td>
<td>15.2</td>
<td>15.1</td>
<td>3.3</td>
<td>4.8</td>
<td>21.9</td>
</tr>
<tr>
<td>Yield (kgm⁻²)</td>
<td>4.6</td>
<td>6.6</td>
<td>6.9</td>
<td>1.6</td>
<td>1.4</td>
<td>3.3</td>
</tr>
<tr>
<td>EC30 (mS m⁻¹)</td>
<td>11.1</td>
<td>15.4</td>
<td>21.8</td>
<td>16.2</td>
<td>10.0</td>
<td>10.3</td>
</tr>
<tr>
<td>EC100(mSm⁻¹)</td>
<td>7.9</td>
<td>12.0</td>
<td>15.3</td>
<td>12.7</td>
<td>7.0</td>
<td>8.1</td>
</tr>
<tr>
<td>Wheat LAI (m² m⁻²)</td>
<td>19.3</td>
<td>23.7</td>
<td>17.8</td>
<td>8.5</td>
<td>1.6</td>
<td>17.1</td>
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<tr>
<td>Yield (kgm⁻²)</td>
<td>5.9</td>
<td>7.2</td>
<td>8.4</td>
<td>7.0</td>
<td>6.3</td>
<td>4.1</td>
</tr>
</tbody>
</table>

The northeastern corner of the wheat field was characterized with sandy clay loam to fine sandy loam, whereas least two months before harvesting, leaving a large interval within which the crop growth conditions were not monitored by remote sensing.

Evaluation of the Classifications

The potential of classification as a tool for homogeneous zone delineation was evaluated using the selected field descriptors. The classification maps of the two fields were shown in Figures 5 and 6, respectively. The average values of the field descriptors and radar backscatter for each class were reported in Tables 3 and 4. Analysis of Variance (ANOVA) was performed using Statistica, and the results were also included in the two tables in order to evaluate if the average values were different between the classes. Values that do not differ at a 95 percent significance level were shaded.

In the corn field, spatial patterns were well delineated from the classifications for the first two campaigns. Visual comparison between Figures 5a and 5d showed that SAR incidence angle had a slight influence on the spatial patterns during IFC1. Spatial patterns derived at IFC2 (Figure 5b) were also similar to that derived at IFC1 (Figure 5a), although some small areas were dissolved from Class 1 into Classes 2 and 3, and some others altered class attributes between classes 2 and 3. The areas of Class 1 are well to imperfectly drained sandy soil associations of deep and shallow sandy soils over clay materials. Class 2 represented an imperfectly drained to poorly drained conditions of sandy loam to fine sandy loam soil, and Class 3 represented poorly drained fine textured clay loam to silty clay loam soil. The field descriptors were significantly different in these three classes. Both EC30 and EC100 were significantly lower in Class 1 than the other two classes. Either because of a drier soil condition, or a slower canopy development (i.e., lower LAI) in response to this dry condition, the HH and VV backscatter were the weakest in this class, with more than 2 dB lower at IFC1 and 1.4 dB lower at IFC2 when compared with the other two classes. At the first two IFCs, HV polarization was positively related with LAI in that, both LAI and HV backscatter increased in the order of classes 1, 3, 2. This was because HV polarization mostly represented a volumetric scattering component of canopy, which increased with the increasing of canopy biomass. The spatial patterns of the different classes obtained at IFC3 (Figure 5c and 5e) were spatially fragmented. Due to the reduced variability of SAR data at this stage, the discriminant ability was limited, leading to decreased differences between classes (Table 3).

The northeastern corner of the wheat field was characterized with sandy clay loam to fine sandy loam, whereas...
the other portions were characterized by silty clay loam to clay loam. At IFC1, all the field descriptors were significantly different among the delineated classes with the 55° incidence angle data (Figure 6a). LAI was highest in Class 2 (to the eastern portion of the field) and lowest in Class 1 (to the western portion of the field). For the 35° incidence angle, LAI in Class 2 was distinctively higher than the other two classes (Figure 6d). At IFC2, LAI among the three classes were significantly different (Figure 6b). Class 2 delineated at this time was in conformity with the sandy soil distribution area. Soil electrical conductivity was significantly lower, and the wheat canopy developed faster in this region than the other regions. Among the three classes obtained at IFC3, soil electrical conductivity was lower in Class 2 than the other two classes, but LAI was not well differentiated. Due to a larger portion of vertical structure of wheat canopy, the VV polarization was the most distinctive among the delineated classes in all the cases.

### Table 3. Averages of the Selected Field Descriptors and Radar Polarizations in Each Delineated Homogeneous Zone in the Cornfield. "C" Represents Classes. For a Given Classification, the Shaded Values were Not Different at 0.05 Significance Level as Determined by Analysis of Variance (ANOVA)

<table>
<thead>
<tr>
<th>Field Descriptors</th>
<th>SAR Polarizations (dB)</th>
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<tbody>
<tr>
<td><strong>Corn</strong> C</td>
<td><strong>Yield (kg m⁻²)</strong></td>
</tr>
<tr>
<td>1</td>
<td>0.65</td>
</tr>
<tr>
<td>IFC1 2</td>
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</tr>
<tr>
<td>55°</td>
<td>0.73</td>
</tr>
<tr>
<td>1</td>
<td>0.64</td>
</tr>
<tr>
<td>IFC1 2</td>
<td>0.69</td>
</tr>
<tr>
<td>35°</td>
<td>0.74</td>
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<tr>
<td>1</td>
<td>0.63</td>
</tr>
<tr>
<td>IFC2 2</td>
<td>0.69</td>
</tr>
<tr>
<td>55°</td>
<td>0.73</td>
</tr>
<tr>
<td>1</td>
<td>0.68</td>
</tr>
<tr>
<td>IFC3 2</td>
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</tr>
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<td>55°</td>
<td>0.72</td>
</tr>
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<td>0.67</td>
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<tr>
<td>IFC3 2</td>
<td>0.70</td>
</tr>
<tr>
<td>35°</td>
<td>0.72</td>
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</table>

### Table 4. Averages of the Selected Field Descriptors and Radar Polarizations in Each Delineated Homogeneous Zone in the Wheat Field. "C" Represents Classes. For a Given Classification, the Shaded Values were Not Different at 0.05 Significance Level as Determined by Analysis of Variance (ANOVA)

<table>
<thead>
<tr>
<th>Field Descriptors</th>
<th>SAR Polarizations (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wheat</strong> C</td>
<td><strong>Yield (kg m⁻²)</strong></td>
</tr>
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<td>0.33</td>
</tr>
<tr>
<td>IFC1 2</td>
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</tr>
<tr>
<td>55°</td>
<td>0.35</td>
</tr>
<tr>
<td>1</td>
<td>0.32</td>
</tr>
<tr>
<td>IFC1 2</td>
<td>0.38</td>
</tr>
<tr>
<td>35°</td>
<td>0.36</td>
</tr>
<tr>
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<td>0.35</td>
</tr>
<tr>
<td>IFC2 2</td>
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</tr>
<tr>
<td>55°</td>
<td>0.34</td>
</tr>
<tr>
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<td>0.34</td>
</tr>
<tr>
<td>IFC3 2</td>
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<td>1</td>
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</tr>
<tr>
<td>IFC3 2</td>
<td>0.38</td>
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</tbody>
</table>
The yield of both corn and wheat was significantly different among the delineated classes for most of the cases. As observed from the class statistics, the two crops responded differently to the sandy soil. In the cornfield, there was a slower canopy development and a lower yield in the sandy soil areas, whereas in the wheat field, the crop developed faster and the final yield was the highest in the sandy soil area.

**Conclusions**

An object-based Fuzzy k-means unsupervised classification approach was proposed in this study for within field homogenous zone delineation using C-band multi-polarization SAR data. Multi-temporal linear polarization data over a cornfield and a wheat field were synthesized from CV-580 C-Band polarimetric SAR data and were classified using the proposed approach. Classification was evaluated by inspecting the variance reduction and analysis of variance (ANOVA) of the selected field descriptors, green LAI, yield, and soil electrical conductivity.

In most of the cases, the object-based classification achieved better results than the pixel-based classification for the selected field descriptors, as evaluated by variance reduction of field descriptors. Although *a priori* knowledge, such as soil properties represented by the electrical conductivity measurements, can be helpful to define meaningful image objects, the advantages of the algorithm implemented in eCognition® reside in the integration of spatial heterogeneity with spectral heterogeneity in the segmentation stage. Thus, information in both the spatial and spectral domain of remote sensing data could be exploited for better image analysis.

Classification of multi-temporal multi-polarization SAR data produced spatial patterns that were interpretable using crop and soil information. SAR is capable of delineating...
within field spatial patterns of relatively stable soil properties
when crop fraction is low. With the crop development, the
classification can map the crop growth conditions as repre-
sented by green LAI. Different behaviors in seasonal variation
of backscatter and its variability were observed for wheat and
corn canopies. Although yield could be discriminated among
different classes, the achieved variance reduction is limited.

It should be noted that SAR backscatter is an integration
of scattering and attenuation within a tightly coupled soil-
crop system. Further studies are expected to explore the
polarimetric information to decouple this system for quanti-
tative retrieval of field descriptors.

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