Use of Multispectral Ikonos Imagery for Discriminating between Conventional and Conservation Agricultural Tillage Practices

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Abstract
There is a global concern about the increase in atmospheric concentrations of greenhouse gases. One method being discussed to encourage greenhouse gas mitigation efforts is based on a trading system whereby carbon emitters can buy effective mitigation efforts from farmers implementing conservation tillage practices. These practices sequester carbon from the atmosphere, and such a trading system would require a low-cost and accurate method of verification. Remote sensing technology can offer such a verification technique. This paper is focused on the use of standard image processing procedures applied to a multispectral Ikonos image, to determine whether it is possible to validate that farmers have complied with agreements to implement conservation tillage practices. A principal component analysis (PCA) was performed in order to isolate image variance in cropped fields. Analyses of variance (ANOVA) statistical procedures were used to evaluate the capability of each Ikonos band and each principal component to discriminate between conventional and conservation tillage, in order to produce a map of the probability of conventional tillage. The Ikonos imagery, in combination with ground-reference information, proved to be a useful tool for verification of conservation tillage practices.

Introduction
The long-term conversion of grass and forest lands to crop and grazing land has resulted not only in historic losses of soil carbon worldwide but has also added additional carbon dioxide to the atmosphere. Atmospheric concentrations of CO₂ can be lowered by reducing emissions or by sequestering it from the atmosphere and storing it as soil carbon. A potentially important way of increasing soil carbon is through the restoration of degraded soils and the widespread adoption of soil conservation practices, including the use of conservation tillage (Falloon et al., 1998; Uri et al., 1999; Schlesinger, 2000). Conventional tillage practices aerate the soil and increase microbial activity responsible for oxidizing plant residue. In contrast, conservation tillage practices limit microbial oxygen supply, and reduce microbial activity, which lowers soil carbon consumption. If continued on an annual basis, these practices allow the amount of soil carbon, in the form of plant residue, to increase over time. Thus, conservation tillage practices result in sequestration of carbon dioxide in the soil as organic carbon. Residue also acts as a mechanical barrier to the effects of wind and rain, which reduces soil erosion and improves plant germination (Uri et al., 1999). Plant residue also modifies soil temperature by intercepting solar radiation and insulating the soil, thus reducing thermal variation (Evans and Young, 1970). Changes in soil temperature produced by plant residue may directly influence plant growth, but also may enhance the rate of mineralization, and therefore nutrient availability (Knapp and Seastedt, 1986). Also, plant residue reduces maximum soil temperatures and creates a barrier to water vapor diffusion (Holland and Coleman, 1987), thereby reducing evaporation from the soil and increasing water availability in the root zone.

One way that could efficiently and economically encourage greenhouse gas mitigation efforts is to provide a trading system whereby carbon emitters can buy effective mitigation credits from others who can either avoid emissions or sequester carbon from the atmosphere, such as farmers implementing conservation tillage practices. As an example, CQuest Ltd. of West Des Moines, Iowa, specializes in documenting greenhouse gas mitigation efforts by agricultural producers and landowners and adding services that turn these efforts into tradable Carbon Emission Reduction Credits (CERC). CERCs are standardized greenhouse gas mitigation products measured in terms of the natural warming effect of one metric ton of carbon dioxide (CO₂) in the atmosphere. CERCs are defined by describing various agricultural tillage practices, resource uses that avoid or sequester greenhouse gases and the measurement protocol for quantifying the amount of CO₂ equivalent removed from the atmosphere versus what would have been emitted.

Such a trading system requires a low-cost and accurate technique for guaranteeing compliance. Verification of such a trading system would require low-cost methods to implement, and remote sensing technology offers a means of keeping costs low. Several remote sensing techniques for distinguishing residue type and amount using the middle infrared portion of the spectrum have been documented in the literature (e.g., McNairn and Protz, 1993; van Deventer et al., 1997; Nagler et al., 2000). However, the only operational
This paper is focused on testing the feasibility of using remote sensing technology for discriminating between conventional and conservation tillage practices. Our goal was to use standard image processing procedures to determine whether it is possible to validate that farmers have complied with agreements to implement conservation tillage practices. For this purpose, the visible and near-infrared bands of an Ikonos scene (28 March 2000) were used. Specific project objectives were (1) to assess the usefulness of the Ikonos satellite image to distinguish tillage practices in corn and soybeans, and (2) to investigate image-processing algorithms that can enhance the capability of remotely sensed images to discriminate between tillage practices.

Methods
The project was conducted on farms in Deep Well Township located near the western edge of Hamilton County, Nebraska, approximately 2 miles south and east of the Platte River (Plate 1). A variety of tillage practices are used in the region, but for simplicity, they were categorized in a binary form as either conventional or conservation tillage as defined by the farmers in the study area. The simplest decision rule is adequate to verify compliance with a tillage contract.

An Ikonos multispectral image with 4-m pixels and four broad spectral bands (blue 0.45 to 0.52 μm, green 0.52 to 0.60 μm, red 0.63 to 0.69 μm and near infrared 0.76 to 0.90 μm; Plate 1) was acquired before crop planting on 28 March 2000. At this time of the year, the residue and tillage practices from the previous season are still noticeable. The timing for imagery collection between late March and early April is important for a tillage verification system in this area, because images acquired earlier could be influenced by snow cover. Planting activity could also affect the imagery because of soil disturbance, if acquired later. An initial inspection of the image was performed to determine what visual differences among the fields and tillage practices were discernible in corn and soybean residue. Ground data on tillage practices and type of residue cover (corn or soybeans) from 51 separate fields in the Ikonos image were acquired through interviews with farmers and local inspections.

Initial image processing included the removal of pixels dominated by photosynthetically active vegetation. To accomplish this, a Normalized Difference Vegetation Index (NDVI = [NIR - Red]/[NIR + Red]) image was calculated, and used as a mask to separate green vegetation from bare soil (Plate 1). After living vegetation was masked out from the image, a principal component analysis (PCA) was performed to isolate scene variance in the remaining
cropped fields. Four principal component (PC) images were obtained.

An analysis of variance (ANOVA) was computed to evaluate the capability of each Ikonos band, as well as each PC, to discriminate between corn or soybean residue and both conventional and conservation tillage practices. For these calculations the mean value of each PC from each of the 51 fields within the study area was used. The linear model for the two-way factorial design is given by

\[ Y_{ijk} = \mu + A_i + B_j + (AB)_{ij} + \gamma_{ijk} \]  

where \( Y_{ijk} \) is the digital number (DN), \( \mu \) is the overall mean, \( A_i \) is the effect of residue type \( i \), \( B_j \) is the effect of tillage practice \( j \), \( (AB)_{ij} \) is the interaction between residue type \( i \) and tillage practice \( j \), and \( \gamma_{ijk} \) is the random error term. Tests of null hypotheses that there is no interaction effect, no effect of residue type, and no effect of tillage practice were conducted based on the ANOVA. The ANOVA was performed for the blue, green, red, and near-infrared bands and the four PCs.

After determining which PC(s) could discriminate between residue types and/or tillage practice, a logistic regression [GENMOD procedure (SAS, 1996)] was applied to the average PC values per field. Logistic regression can be used as a predictive tool when the response variables have only two possible outcomes and a binomial distribution, such as conventional versus conservation till, or corn versus soybean residue. The logistic regression model is shown in Equation 2: i.e.,

\[ \ln \left[ \frac{\pi}{1 - \pi} \right] = \alpha + \beta x \]  

where \( \pi \) is the predicted probability of conventional till, or corn residue type, \( x \) is the principal component selected, and \( \alpha \) and \( \beta \) are parameters estimated by the logistic regression (Agresti, 1996). With \( \alpha \) and \( \beta \) from Equation 2, the probability of conventional till and corn residue can be obtained through Equation 3: i.e.,

\[ \pi = \exp (\alpha + \beta x) / [1 + \exp (\alpha + \beta x)] \].  

Figure 1. Principal components obtained from the multispectral Ikonos image of the study area; taken on 28 March 2000. Green vegetation has been removed with the binary mask shown in Plate 1. The first component explains 99.5 percent of scene variance.
To check the goodness-of-fit of the logistic regression model, the Hosmer-Lemeshow test (Hosmer and Lemeshow, 1989) was used.

**Results and Discussion**

The principal component images obtained from the Ikonos scene are shown in Figure 1. PC 1 explains more than 99 percent of total scene variance (excluding green vegetation). PC 1 is primarily a soil brightness component and is highly correlated with each of the original input bands. The remaining three PCs (PCs 2, 3, and 4) explain the remaining scene variance.

The least-squares means of digital numbers (DNs) for each band and PC can be seen in Figure 2. Results of the ANOVA are shown in Tables 1 and 2. All three visible bands of the Ikonos image showed a statistically significant interaction between tillage practice and residue type (Table 1, Figure 2). This interaction means that these bands cannot be used for discriminating residue type and tillage practice independently of each other. The near-
infrared band had no interaction effect, and was sensitive only to residue type, but not to tillage practice. Thus, the original Ikonos bands cannot discriminate tillage practices.

As with the visible bands, PCs 1 and 3 have a significant statistical interaction effect \((p < 0.05)\) between crop residue type and tillage practices (Table 2, Figure 2). This interaction means that, in the case of PC 1, differences between tillage practices could be detected for soybean, but not for corn residue. In the case of PC 3, discrimination between corn and soybean residue could not be obtained for conservation tillage. Therefore, as with the visible bands, PC 1 and PC 3 could not be used for discriminating residue type and tillage practices independently of each other.

PC 3, which explains only 0.09 percent of the original scene variance, is likely related to soil properties such as soil color, organic matter, and clay content (percentage of soil less than 2 \(\mu\)m in size; Figure 3). Soils with less than 30 percent clay content appear darker in the PC 3 image (Figure 1).

On the contrary, PCs 2 and 4 showed no significant interaction \((p > 0.05)\) between crop residue and tillage practices (Table 2, Figure 2). A significant difference between corn and soybean residue was obtained from PC 2 (Table 2); thus, in this Ikonos image, PC 2 is related to residue type, and can be used to discriminate between corn and soybean residue independently of the tillage practice. In other words, PC 2 successfully isolates the spectral influence of residue type. In addition, a significant difference between tillage practices was obtained with PC 4 (Table 2), because conventionally tilled fields have positive values and fields with conservation tillage have negative values within this component. Thus, PC 4 isolates the spectral influence of tillage practices even though it only contains 0.01 percent of scene variance. Logistic regression was applied to PCs 2 and 4 to test whether the presence of conventionally tilled fields and of corn residue could be predicted from the Ikonos imagery (Table 3 and Figure 4). The probability of conventionally tilled fields and of corn residue rise as PCs 2 and 4 increase in magnitude (Figure 4). Both models have a significant goodness-of-fit \((\chi^2 = 14.13, p = 0.078\) for corn residue, and \(\chi^2 = 6.92, p = 0.545\) for conventional corn tillage).

Probability maps of corn residue and conventional tillage (Plates 2a and 2d) were obtained by applying Equation 3 and parameters estimated from the logistic regression (Table 3) to the images of PC 2 and 4. To produce binary maps of residue and tillage practices, respectively (Plates 2b and 2e), a probability threshold of 0.6 was ap-

### Table 2. Results from the ANOVA of Each Principal Component Obtained from the Ikonos Multispectral Image from 28 March 2000

<table>
<thead>
<tr>
<th>Source</th>
<th>NDF*</th>
<th>DDF*</th>
<th>F-value</th>
<th>p-value</th>
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<td>Blue Band</td>
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<td>47</td>
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<td>Green Band</td>
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<td></td>
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<tr>
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<td>47</td>
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<td>0.0032</td>
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</tr>
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</table>

*NDF — Numerator Degrees of Freedom; DDF — Denominator Degrees of Freedom; RT — Residue Type; TP — Tillage practice.
through consecutive years. The ability to discriminate tillage practices is not as strong as that to distinguish between types of crop residue (Plate 2), because there is more scene variance in PC 2 than in PC 4. This analysis shows that valuable information on residue management practices is contained in the broadband Ikonos satellite imagery.

Conclusions
A number of well-known image processing strategies, including unsupervised and supervised classification (results not shown), were tested and it was concluded that principal components analysis (PCA) provides a good method for determining the type of crop residue and tillage practices in agricultural fields. The study area provided substantial variability in soil brightness, which reinforced the usefulness of this technique, because it performed well over both dark and bright soils.

Remote sensing proved to be a useful tool for verification of conservation tillage practices. In order to improve the likelihood of successful image-based verification, remote-sensing techniques should be used in conjunction with ground data collection, in order to build a predictive model, such as the logistic regression technique demonstrated in this paper. Additional research is needed in order to determine the potential effects of off-nadir viewing angles and variable illumination angles (including topographic relief) on the ability to discriminate between crop residue types and tillage practices with Ikonos imagery using the procedures described in this paper.

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References
Plate 2. (a) Probability of corn residue obtained from PC 2. (b) Corn/soybean residue obtained from Plate 2a after spatial smoothing with a 7 by 7 majority filter. (c) Corn/soybean residue map obtained from information provided by farmers. (d) Probability of conventional tillage, obtained from PC 4. (e) Conventional till/conservation till map obtained from Plate 2d after applying a 7 by 7 majority filter. (f) Conventional till/conservation till map obtained from information provided by farmers.


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