USE OF HYPERSONTRAL IMAGERY TO DISTINGUISH CORN PHENOLOGY

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ABSTRACT

During the 2005 growing season, a study was conducted at the Iowa State University Entomology Research Farm in Ames, Iowa to evaluate the ability of hyperspectral imagery to discriminate different growth stages of corn. The experiment consisted of three different hybrids (two transgenic, one non-transgenic) each planted at three different times (approximately two week intervals) during the spring of 2005. Hyperspectral imagery was acquired six times throughout the growing season using the Institute for Technology Development’s (ITD) RDACS-H4 airborne hyperspectral camera system. Imagery was collected in the 393-nm to 1000-nm range of the electromagnetic spectrum at a spatial resolution of 0.5 meters. The primary analysis for growth stage delineation was conducted with the MIXED procedure in SAS. The MIXED procedure is able to model the correlation and covariance structures encountered in a repeated measures analysis setting and compensate for spatial variability. In addition to the statistical analysis, supervised classification was performed on the individual image dates using Maximum Likelihood Classification. In general, mixed model predictions of crop growth corresponded well with ground observations. Repeated measures analysis revealed the greatest differences between planting dates occurred in the near-infrared (NIR) portion of the spectrum. However, differences were also observed in the visible portion of the spectrum. Supervised classification accuracies tended to improve later in the growing season – particularly in late August. Overall classification accuracies ranged from 80%-98% for classifying the different planting dates for each of the hybrids.

INTRODUCTION

Crop phenology (growth stage) information is an important component of many research projects, yield prediction models, and application of production inputs. However, determination of crop phenology over large geographic areas is often difficult, especially considering the time required to collect ground data. Remotely sensed imagery, particularly hyperspectral imagery, may be useful for distinguishing the growth stages of agricultural crops.

Remote sensing has been utilized in many situations to determine vegetation phenology and/or crop type. Collins (1978) utilized an airborne spectroradiometer to detect the red spectral shift in the chlorophyll absorption edge and thus discriminate crop type and maturity. The study found that the position of the red edge shifts toward longer wavelengths during the crop growth cycle. Additionally, significant relationships between spectral response
and agronomic variables (i.e., leaf area index, biomass, plant height, plant water content) have been observed in a number of studies (Kimes et al., 1981; Gilabert et al., 1996). Similarly, Zhang et al. (2002) studied the relationship between the spatial variability in climate and vegetation phenology using the Moderate Resolution Imaging Spectroradiometer (MODIS). They were able to identify phonological transition dates over the North American continent by combining temporal vegetation indices derived from MODIS with climatic data.

The goal of this study was to utilize hyperspectral imagery to identify different growth stages in corn (*Zea mays* L.). Specific objectives were to: 1) identify portions of the spectrum where the greatest separability existed for various planting dates and the resulting differences in crop phenology; and 2) utilize remotely sensed data to classify phonological stages observed in ground-truth data.

**METHODOLOGY**

**Experiment Design**

The experiment was conducted near Ames, IA and consisted of a randomized complete block (RCB) design with six replications (Figure 1). The experiment utilized three different corn hybrids (two transgenic, one non-transgenic) each planted at three different dates during the spring of 2005. The planting dates utilized and growing degree days (GDD) between plantings are shown in Table 1.

| Table 1. Planting dates and difference in growing degree days (GDD) between planting dates. |
|----------------------------------------|-----------------|-----------------|-----------------|
| 1  | 04 May 2005  | 124  | 0‡  |
| 2  | 23 May 2005  | 143  | 130  |
| 3  | 06 Jun. 2005 | 157  | 251  |

† Difference in growing degrees from the first planting on 04 May 2005
‡ Based on 10 deg. C.
Remotely Sensed Imagery

Hyperspectral imagery was acquired at 0.5 meter resolution on six different occasions during the growing season (Table 2) with the ITD RDACS-H4 airborne camera system (Mao, 2000). The RDACS-H4 uses a single Cooke camera fitted with a prism-grating filter and collects 240 bands of spectral information.

**Table 2. Image acquisition dates.**

<table>
<thead>
<tr>
<th>Acquisition</th>
<th>Date</th>
<th>Planting 1</th>
<th>Planting 2</th>
<th>Planting 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11 Jul. 2006</td>
<td>303</td>
<td>173</td>
<td>52</td>
</tr>
<tr>
<td>2</td>
<td>01 Aug. 2006</td>
<td>697</td>
<td>567</td>
<td>446</td>
</tr>
<tr>
<td>3</td>
<td>17 Aug. 2006</td>
<td>1007</td>
<td>877</td>
<td>756</td>
</tr>
<tr>
<td>4</td>
<td>30 Aug. 2006</td>
<td>1167</td>
<td>1037</td>
<td>916</td>
</tr>
<tr>
<td>5</td>
<td>10 Sep. 2006</td>
<td>1322</td>
<td>1192</td>
<td>1071</td>
</tr>
<tr>
<td>6</td>
<td>21 Sep. 2006</td>
<td>1571</td>
<td>1441</td>
<td>1320</td>
</tr>
</tbody>
</table>
The first step in the pre-processing of the RDACS-H4 imagery was the removal of electronic noise via a Minimum Noise Fraction (MNF) rotation (Green et al., 1998). The MNF rotation is essentially two cascaded principal component transformations performed on the image data to isolate the noise from the signal. The noise removal process uses both the raw hyperspectral imagery as well as a dark current image.

After noise removal, the RDACS-H4 imagery was calibrated to relative reflectance. Calibration was accomplished using the empirical line method (Smith and Milton, 1999). The empirical line algorithm develops an equation between the digital numbers for the calibration tarps in the imagery and the “true” reflectance values for each tarp based on spectroradiometer scans collected on the same day as the imagery.

Finally, steps were taken to straighten and register the imagery to geo-referenced coordinates. Compensation for image distortion caused by the roll, pitch, and yaw of the aircraft is provided by a Zeiss gyro-stabilized mount. None-the-less, the imagery still contains some distortion and is especially apparent when caused by the roll of the aircraft. Subtle changes in the look angle of the airplane will result in major distortion of the imagery. The first rectification processing step performed on the imagery was a simple program that allows the user to draw a line along the image over an area which should be a linear feature perpendicular to the roll distortion of the image (i.e., a road). This information is then used to shift pixels either left or right in the X direction to remove much of the distortion. The imagery was then geo-referenced using sixteen 0.25 meter square wooden panels painted white placed at the corners and between plots and then ground referenced with a centimeter accuracy GPS developed 1st order polynomial geo-correction equations with less than 0.5 pixel accuracy results when used to geo-reference 0.5 meter resolution hyperspectral imagery.

Finally, to further reduce the noise in the datasets and reduce the dimensionality of the data, the calibrated imagery was spectrally resampled to 80 bands. The spectral range remained the same (393-1100 nm), however the band width (centers) was increased from 2.96 nm to 8.88 nm. Reflectance values were then extracted from the geo-referenced, calibrated airborne imagery from pixels placed completely within the plots. This information was saved to ASCII files and tied to ground truth information for statistical analysis. Pixels within each plot were then averaged for a plot mean value.

Statistical Analysis

Once the pixels residing in the individual plots were extracted and a plot average computed, the data were subjected to a number of statistical analyses. To identify portions of the spectrum where separability existed between treatments, the MIXED procedure in The SAS System (SAS Institute, Cary, North Carolina) was used to fit a random effects analysis of variance (ANOVA) model (Littell et al., 1996). A random effects model was utilized because it was felt that inferences should not be limited to only the three hybrids and three planting dates used in the study. But rather that these hybrids and planting dates were selected from a population of hybrids and planting dates.

To examine how the spectral reflectance changed over time with respect to growth stage, further analysis was performed using a random coefficient model (Laird and Ware, 1982; Wolfinger, 1996). The random coefficient model builds upon analysis of covariance by modeling slopes as outcomes for the subjects (i.e., hybrid × planting date combinations) in the experiment. For this particular study, reflectance was modeled as a quadratic function of growth stage for each hybrid × planting date combination thus providing an estimate of reflectance change for different stages of crop growth. For all statistical tests, a significance level of 0.05 was used.

Image Analysis

In addition to statistical analysis discussed above, image analysis was performed using the Maximum Likelihood Classification algorithm (Reference) in ENVI (Research Systems Inc., Boulder, Colorado) to perform two different classifications: 1) to identify the different planting treatments; and 2) to identify specific growth stages observed in the crop. Pixels were randomly selected from all of the plots and divided into two groups: one for training the classifier and one for computing classification accuracies. By setting aside a portion of the selected pixels to use for the accuracy assessment, an unbiased estimate of classification accuracy was calculated. For all classifications, the entire spectrum (i.e., 80 bands) was used in the analysis.

RESULTS AND DISCUSSION

Statistical Analysis

The graphs in Figure 2 show the differences (in percent reflectance) as determined by the random effects ANOVA model. For each date, comparisons were made between the three planting dates for separability using
ESTIMATE statements in the MIXED procedure. On 11 Jul. 2005, the greatest differences were observed beginning near the red edge and extending into the near-infrared (NIR), with small or no differences observed in the visible portion of the spectrum. Little separability was observed on 01 Aug. 2005 and 17 Aug. 2005. On these particular dates, the separability that did exist was confined to relatively narrow portions of the spectrum and was not observed between all combinations of planting dates.

The greatest overall separability was observed in the 30 Aug. 2005 imagery as well as the two September dates. On 30 Aug. 2005, differences were primarily in the visible portion of the spectrum as well as the red edge. As expected, the greatest difference was observed between the first and third plantings. This trend was also observed on the September dates. The differences observed between the first and second plantings as well as the second and third planting were not nearly as large in magnitude as those observed between the first and third plantings.

Results of the random coefficient model (RCM) analysis are shown in Figures 3-5. The RCM analysis can be thought of as a “slopes as outcome” analysis as the output of interest are the intercepts and slopes of the regression model for each hybrid × planting date combination (i.e., subject) in the experiment. In this case, reflectance was modeled as a quadratic function of growth stage. Although this analysis was performed for every band in the dataset, the results presented were selected from the green (548-nm; Figure 3), red (646-nm; Figure 4), and NIR (841-nm, Figure 5) bands.

For the three wavelengths shown, the three different hybrids from a given planting date tend to be clustered and follow a similar trend. Hybrids from first planting typically exhibit a substantially different trend than do those from the second and third plantings. Typically, the second planting group exhibits a pattern similar to that observed with the population regression line (shown in red). The greatest differences were always observed between the first and third planting groups. It is interesting to note that for each planting group, the two transgenic hybrids (P34N42 and P34N44) closely track each other, but differ significantly from the non-transgenic (P34N43) hybrid.
Figure 3. Random coefficient regression lines for each of the hybrid x planting date combinations (i.e., subjects) for the selected green band (548-nm).

Figure 4. Random coefficient regression lines for each of the hybrid x planting date combinations (i.e., subjects) for the selected red band (646-nm).
Figure 5. Random coefficient regression lines for each of the hybrid x planting date combinations (i.e., subjects) for the selected near-infrared band (841-nm).

Image Analysis

Classification accuracies for the supervised maximum likelihood classifications identifying the different planting dates are shown in Table 3. In general, classification accuracies were excellent with the lowest overall accuracy observed being 80%. Accuracies greater than 90% were observed on 11 Jul. 2005, 30 Aug. 2005, 10 Sep. 2005, and 21 Sep. 2005. The highest overall accuracy, 98%, was observed on 30 Aug. 2005. Accuracies for the individual classes (i.e., planting groups) were typically highest for Planting three (3), followed by Planting two (2).

Table 3. Classification accuracies for identifying the different planting treatments

<table>
<thead>
<tr>
<th>Acquisition Date</th>
<th>Planting 1</th>
<th>Planting 2</th>
<th>Planting 3</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 Jul. 2005</td>
<td>89</td>
<td>94</td>
<td>94</td>
<td>93</td>
</tr>
<tr>
<td>01 Aug. 2005</td>
<td>61</td>
<td>83</td>
<td>94</td>
<td>80</td>
</tr>
<tr>
<td>17 Aug. 2005</td>
<td>80</td>
<td>73</td>
<td>100</td>
<td>85</td>
</tr>
<tr>
<td>30 Aug. 2005</td>
<td>94</td>
<td>100</td>
<td>100</td>
<td>98</td>
</tr>
<tr>
<td>10 Sep. 2005</td>
<td>89</td>
<td>94</td>
<td>89</td>
<td>91</td>
</tr>
<tr>
<td>21 Sep. 2005</td>
<td>94</td>
<td>94</td>
<td>100</td>
<td>96</td>
</tr>
</tbody>
</table>

Classification accuracies for identifying the ground-observed growth stages with hyperspectral imagery are shown in Table 4. This analysis was not performed for imagery acquired on 10 Sep. 2005 as ground data was not available for that particular date. Classification accuracies for 11 Jul. 2005 and 17 Aug. 2005 were very poor as overall accuracies were 52% and 30%, respectively. The highest overall accuracies were observed on 30 Aug. 2005 (Figure 6) followed by 21 Sep. 2005. Given the results of the ANOVA, this was somewhat expected as the greatest separability was observed in the visible portion of the spectrum on 30 Aug. 2005.
Table 4. Classification accuracies for growth stage identification.

<table>
<thead>
<tr>
<th>Acquisition Date</th>
<th>Number of Stages</th>
<th>Overall Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 Jul. 2005</td>
<td>10</td>
<td>52</td>
</tr>
<tr>
<td>01 Aug. 2005</td>
<td>3</td>
<td>80</td>
</tr>
<tr>
<td>17 Aug. 2005</td>
<td>3</td>
<td>30</td>
</tr>
<tr>
<td>30 Aug. 2005</td>
<td>3</td>
<td>98</td>
</tr>
<tr>
<td>21 Sep. 2005</td>
<td>2</td>
<td>85</td>
</tr>
</tbody>
</table>

Figure 6. Plot map (left) showing the three planting groups and classification map (right) showing the three growth stages classified using Maximum Likelihood Classification. The classification map was derived from imagery collected on 30 Aug. 2005.
CONCLUSIONS

In a study located in central Iowa, hyperspectral imagery was evaluated for its ability to distinguish between different physiological stages of corn. Six dates of imagery were acquired, processed to relative reflectance, and subjected to statistical and image analysis algorithms. Of the six dates of imagery analyzed, the greatest statistical separability (as determined by ANOVA) was found to occur in late August and early- to mid-September. The greatest separation tended to occur when the crop was in the mid- to late-reproductive growth stages (R3-R5).

Classification accuracies for identifying the three planting treatments and specific growth stages ranged from 52% to 98%. The highest overall accuracies for both types of classifications were found to occur on 30 Aug. 2005. However, acceptable accuracies for identifying the different planting treatments were observed on multiple acquisition dates.

Although this study was only conducted during a single growing season, the results indicate hyperspectral imagery is useful for identifying specific phonological stages of corn. Successful identification of corn growth stages has many practical applications, and would be very useful from a crop monitoring and/or yield prediction standpoint.

REFERENCES


