USING LATE-SEASON UNCALIBRATED DIGITAL AERIAL IMAGERY FOR PREDICTING CORN NITROGEN STATUS WITHIN FIELDS

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ABSTRACT

Using uncalibrated digital aerial imagery (DAI) for diagnosing in-season nitrogen (N) deficiencies of corn (*Zea mays* L.) is challenging because of the dynamic nature of corn growth and the difficulty of obtaining timely imagery. Digital aerial imagery taken later during the growing season is more accurate in identifying areas deficient in N. Even so, the quantitative use of late-season DAI across many fields is still limited because the imagery is not truly calibrated. This study tested whether spectral characteristics of corn canopy derived from uncalibrated late-season DAI could predict corn N status within and across fields. Color and near-infrared (NIR) imagery was collected in late August or early September across Iowa from 602 corn fields in 2006 and from 690 in 2007. Four sampling areas (one within a target-deficient area as seen in the imagery) were selected within each field for conducting the late-season corn stalk nitrate test (CSNT). The imagery was enhanced to increase the dynamic range and to normalize reflectance values across all fields within a given year. The reflectance values of individual bands and three vegetation indices were used to predict corn N status expressed as Deficient and Sufficient (a combination of marginal, optimal, and excessive stalk test categories) using a binary logistic regression (BLR). The green reflectance had the largest potential to separate the target-deficient samples from non-deficient samples, and the highest prediction rate in BLR, ranging from 70% for 2006 and 64% for 2007 data. The results confirmed that with the appropriate enhancement method late-season uncalibrated DAI can be used to accurately predict N-deficient and sufficient areas within corn fields.

Keywords: uncalibrated digital aerial imagery, the late-season corn stalk nitrate test, and nitrogen fertilizer management.

INTRODUCTION

Nitrogen (N) fertilizer management in corn (*Zea mays* L.) production is being scrutinized intensively by the general public because of mounting environmental concerns for nitrate pollution of water and by growers because of their need to increase N fertilizer use efficiency. Several diagnostic tools, such as soil and tissue testing, chlorophyll meters, canopy sensors, and aerial imagery, are currently available to estimate in-season N fertilizer needs. However, the reliability of these and other N diagnostic tools depends largely on three factors: (i) the amount and quality of data used in the test calibration; (ii) the experience of growers and agronomists when adopting and using these tools, and; (iii) the degree of spatial and temporal variability in corn N status found within corn fields.

Because of the dynamic nature of N transformation in the soil, which along with unpredictable soil temperatures and rainfall patterns make N losses highly variable, diagnosing in-season N deficiencies is extremely difficult in Iowa (Zhang et al., 2008; Zhang et al., 2010). To reduce this uncertainty, we need tools that can provide reliable feedback about N management at the end of the growing season. Growers need a strategy that allows them to objectively evaluate the performance of the various N fertilizer recommendation systems and practices. This strategy should be focused on systematic collection of the feedback information about corn N status over time to improve and refine N management (Blackmer and Kyveryga, 2008).

In this study, we described two late-season evaluation tools: the corn stalk nitrate test (CSNT) and digital aerial imagery (DAI) of the corn canopy. The end-of-season corn stalk nitrate test was developed to diagnose the N status of corn fields. It is based on measuring stalk NO_3-N concentrations in the lower portions of plants after corn has reached physiological maturity (Binford et al., 1992). The test was found to be reliable in several studies across the U.S. Midwest, specifically for identifying near-optimum and excessive N supply (Brouder et al., 2000; Wilhelm et al., 2005). A large study in the Iowa River basin showed that CSNT can be used as a reliable evaluation tool on a large scale (Balkcom et al., 2003). The stalk nitrate test is relatively inexpensive, but it provides only a point estimate in N status within a field.

Many Iowa fields show a large degree of spatial variability, which can be due to N losses, non-uniformity of N fertilizer and manure applications, and fertilizer application errors. Late-season DAI of corn canopy can be useful for characterizing spatial variability in corn canopy color due to non-uniformity of fertilizer applications and for guiding the stalk nitrate sample selection within fields.

Use of DAI is becoming more common. Growers can buy DAI from many commercial sources or rent a plane and take their own DAI for a relatively low cost. In Iowa, most of fields are flown and imagery is available for free on the internet. However, unlike CSNT, which is reliable for diagnosing near-optimum and excessive N status, DAI works only in the deficient range. Therefore, using DAI requires reference or rich strips having a sufficient amount of N in order to calibrate the imagery for above-optimal N supply. Combining these two diagnostic tools (CSNT and DAI), which work in different ranges of N sufficiency, would be a reasonable way to develop a strategy that can be used to conduct reliable evaluations of N status on a large scale (Blackmer and Kyveryga, 2008).

A recent two-year study that involved sampling about 700 corn fields across Iowa each year showed that CSNT and late-season DAI can be used to identify differences in corn N status between different N management practices having various time of application and N form, previous crop, tillage, and soil drainage class (Kyveryga et al., 2010). However, a quantitative assessment of the extent to which DAI helped to guide the stalk nitrate sampling within fields was not done. In addition, the major drawback of DAI is that it is not truly calibrated. This limits the use of canopy reflectance values across many corn fields because the imagery is often taken by different cameras, at different times, and from fields having different corn hybrids and planting dates.

The objective of this study was to demonstrate the value of the late-season color and near-infrared DAI of corn canopy for guiding CSNT sampling in a large number of corn fields managed by growers across Iowa. Specifically, we attempted to quantify the predictive power of spectral characteristics of corn canopy derived from the DAI to predict N status within fields.

MATERIALS AND METHODS

Late-season DAI of corn canopy was collected from 683 fields in 2006 and 824 fields in 2007, which were selected for a guided corn stalk nitrate survey conducted across Iowa. The original objective of the survey was to identify the relative differences in N status between different management practices commonly used by growers.Detailed information about crop rotation, timing and form of N fertilizer and manure applications, and tillage was described elsewhere (Kyveryga et al., 2010). At least two fields were located in every county in each year. The sampled fields were managed by growers with their normal N management practices.

Field boundaries were created using Google Earth (Google Inc, Mountain View, CA) or Arc View GIS 3.3 software (Environ. Syst. Res. Inst., Redlands, CA) based on growers' descriptions. Field boundaries were used to develop flight plans for aircrafts when taking images in different parts of the state. All images were taken within a period of two to three weeks in both years. The time of image acquisition ranged from late morning to late afternoon during a given day.

The imagery was produced in late August or early September. Images from fields in southern tiers of Iowa counties were taken earlier than from those in northern tiers. The imagery was taken from a height of about 2400 m above the ground surface with four band digital cameras. The blue band captured a spectral range from 410 to 490 nm, the green band from 510 to 590 nm, the red band from 610 to 690 nm, and the near-infrared (NIR) captured from 800 to 900 nm. Twenty to 30 individual images were taken within each field. These individual images were then ortho-mosaiced into one composed digital image of the entire field. The final composed digital images were GIS ready, georeferencesed, and tonally balanced with a resolution about 1m. The images were ortho-rectified by using the USGS 7.5 minute digital elevation models. The digital cameras used were 12 bit, but the images were converted to 8 bit data.

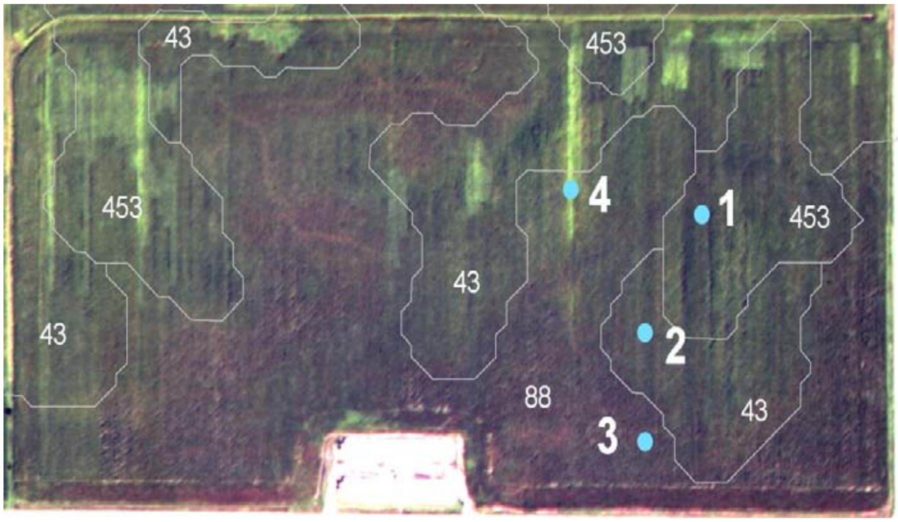

Figure 1. Selecting sampling areas for corn stalk nitrate testing using the late season digital color aerial imagery and digital soil maps. Sample 1, 2, and 3 were selected within three predominate soil map units, and Sample 4 was selected within a target deficient area within each field.

Each composed image was enhanced by extending the dynamic range (i.e, a range in digital reflectance values between the darkest and the lightest parts of the imagery within a field) for each band in ERDAS Imagine Software (ERDAS, Norcross, GA). The enhanced imagery had about 80% of digital counts between plus and minus two SD from the mean reflectance for each band. The average dynamic range was from about 50 to 80 digital counts for each field. The enhanced imagery provided more distinct visual differences in corn canopy reflectance. Also, the enhanced imagery partially decreased the overwhelming effects of light scattering from nearby roads, buildings, waterways, and other features.

Each image was visually checked for the presence of more than one corn hybrid, areas damaged by wind or hail, and for flood, weed, pest or disease damaged areas within the field. Images that had above-mentioned features and had other visible problems were not used in this analysis. The final number of fields used in the analysis was 602 for 2006 and 690 for 2007 data.

Corn Stalk Nitrate Sampling

Four sampling areas were selected within each field by overlaying the digital color (red, green, and blue bands) image with a digital soil map of the field (Fig. 1). The digital soil map for each county was downloaded from the Iowa Cooperating Soil Survey (2003).

For the corn stalk nitrate rest, one sampling area was selected within each of the three predominant soil types within the field. Each sampling area was selected in a relatively uniform area in corn color and plant stand. A fourth sample was collected within the area of the field that looked to be the most N deficient or lighter, more yellow or less green than the rest of the field. The fourth, potentially

N deficient sample was collected to confirm that the areas with relatively higher reflectance values were due to N deficiency rather than due to other stresses such as moisture, poor drainage, herbicide injuries or early plant senescence. In further discussions, the three samples from the predominant soil types are referred as Sample 1, 2, and 3 and the fourth, target N deficient sample is referred as Sample 4.

The stalk samples were collected about 3 weeks after corn grain reached the black layer stage (physiological maturity) or just before the harvest. Ten individual stalk segments were collected from each of the four sampling areas within the field. Six-inch stalk segments were cut by a custom-made cutter that controlled the exact sample length and the height of the cut about the ground. Two corn rows were sampled for a length of 6-8 m, avoiding plants that were irregularly spaced, damaged or barren. The stalk samples were placed into cloth bags and sent to the laboratory for the analysis. Once in the laboratory, the samples were dried at 65C and ground to pass through a 1-mm mesh. The samples were extracted with 2M KCl, and the solutions were filtered and analyzed for stalk NO_3-N values with a Lachat flow-injection analyzer (Lachat Instruments, Milwaukee, WI).

The CSNT categories indicate corn N sufficiency: the plant N demand relative to the supply. The sufficiency categories are deficient, marginal, optimal, and excessive , based on the original studies for calibrating the test (Binford et al., 1992). The deficient category (<250 mg kg^{-1}) suggests a high probability of yield and economic losses from the reduced N supply during the season. The marginal category (250-700 mg kg^{-1}) suggests that only a portion of the samples had N deficiencies that significantly reduced yields and returns to N fertilizer. The optimal category (700-2000 mg kg^{-1}) suggests that the yields were maximized with the N supply available during the growing season. The excessive category (>2000 mg kg^{-1}) suggests that the N supply exceeded corn N needs during the growing season.

Image Analysis

The reflectance values from each of the four bands were extracted using ArcGIS Desktop 9.3.1 software (Environ. Syst. Re. Inst., Redlands, CA). First, a 2.5 m radius buffer was drawn around each sampling point. Then, the Model Builder was used to build a model that extracted reflectance values from each band and from many images simultaneously using the Zonal Statistics Tool of Spatial Analysis. The extracted reflectance values (mean, median, range, and a number of counts) from four sampling areas from each band were combined in one dataset using the Append Tool. Only mean reflectance values were used in the analyses.

In addition to reflectance values for individual bands, three vegetative indices were calculated. The Normalized Difference Vegetation Index (NDVI) was calculated as NIR-Red/NIR+Red (Deering, 1978). The Green Normalized Difference Vegetative Index (GNDVI) was calculated NIR-Green/NIR+Green (Buschmann and Nagel, 1993). The Chlorophyll Index (Green) was calculated as NIR/Green-1 (Gitelson et al., 2005). The vegetation indices were used to standardize reflectance values from individual bands and to determine more predictable relationships between spectral characteristics and stalk test outcomes across all fields.

Statistical Analysis

The empirical frequency distributions of stalk NO_3-N values for the four samples and their corresponding reflectance values for each band were expressed as kernel densities. The kernel densities were calculated in R (R Development Core Team, 2004) using mean reflectance values for each sampling area. The kernel density is a nonparametric way for estimating the probability density function for a given variable. Unlike histograms, kernel densities do not group data into bins; instead, they use small bumps estimated by the kernel function.

Binary logistic regressions (BLR) were used to predict stalk nitrate test outcomes by using reflectance values from individual bands and the calculated vegetation indices. The stalk test outcomes were grouped into Deficient vs Sufficient (a combination of marginal, optimal, and excessive categories). The reference response category was Deficient in BLR analysis. The data were pooled across all fields within a year.

Proc Logistic Procedure of the SAS software (SAS Institute, 2005) was used for estimating parameters for BLR. Predictive accuracies of the BLR were calculated by using the correct classification/prediction rate and the kappa statistics. The correct classification rate indicates the percentage of correctly predicted Deficient and Sufficient samples relative to the total number of stalk samples across all fields within a year. The predictive accuracies were calculated for a range of cutoff probabilities, from 0.3 to 0.7, by 0.05 increments. Because for the majority of independent variables, the correct classification rates were maximized at the probability level 0.5, 0.51 was used as the cutoff probability to separate Deficient from Sufficient samples. The kappa index corrects for the chance in agreement between the predicted and observed response categories. The index compares the agreement against that, which might be expected by a random chance. It is assumed to be more indicative if the percentage of samples in one of the two categories is very low or very high. To test whether possible correlations between stalk test outcomes within fields would affect predictive accuracies of BLR, statistical models with mixed effects were fit, where fields were selected as a random factor. The mixed regression models did not improve predictabilities; thus, the stalk test outcomes within each field were assumed to be independent.

RESULTS AND DISCUSSION

Corn Stalk Nitrate Distributions

The kernel density plots show the distributions of stalk NO_3-N values for four stalk samples collected within 602 fields in 2006 and within 690 fields in 2007 across Iowa (Fig 2). Samples 1, 2, and 3 were collected from the three predominant soil types within each field, while Sample 4 was collected within the target N deficient area as seen on the DAI. A striking feature from the plots depicting each sample in each year is that Sample 4 had higher densities within a range where stalk samples tested deficient and marginal and smaller densities within a range where stalk samples tested optimal and excessive. The distinct difference between Sample 1, 2, 3, and Sample 4 suggests that visual observations on the imagery were helpful in separating N-deficient and sufficient areas.

The stalk NO_3-N values were not normally distributed, but they were positively (right) skewed because of a relatively small number of samples that tested in the excessive test category compared with those that tested in the deficient category (Fig. 2). The median values for Sample 4 calculated across all fields were in one stalk test category lower than the median values calculated for Sample 1, 2, and 3. For example, the median value for Sample 4 was in the marginal category in 2006 and in the deficient category in 2007.

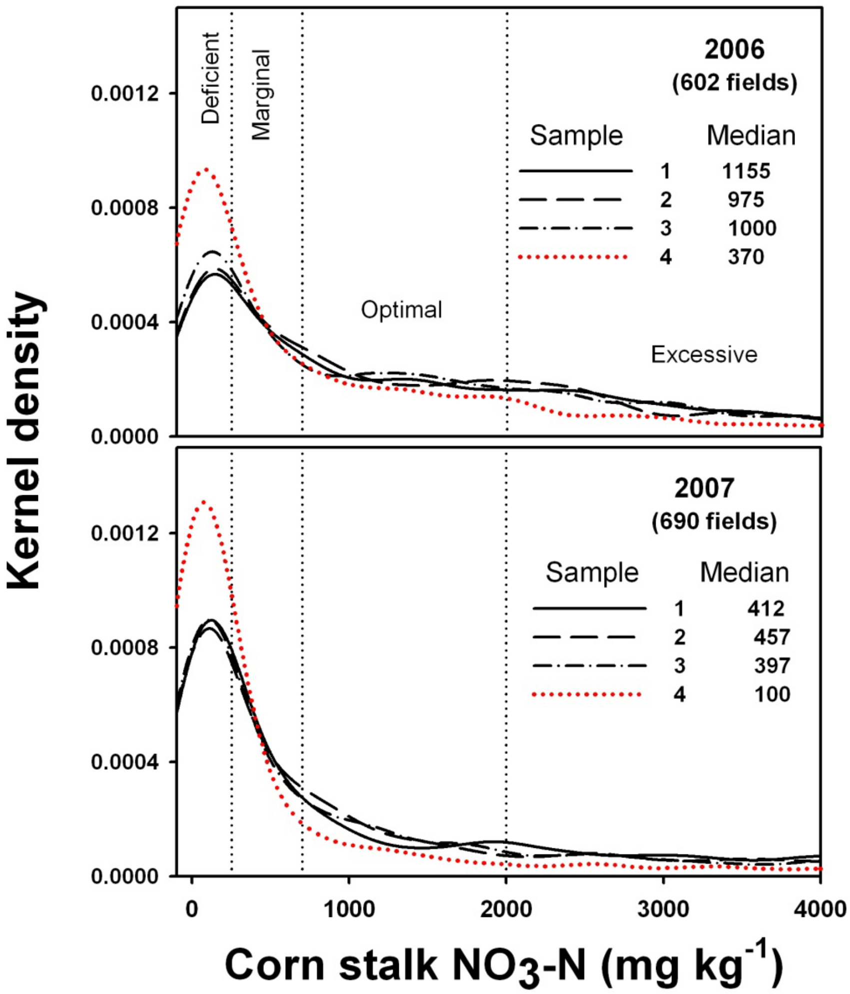

Figure 2. Distribution densities for stalk nitrate values for Sample 1, 2, and 3 collected to represent the average field N status and for a target deficient Sample 4 collected from 602 fields in 2006 and 690 fields in 2007.

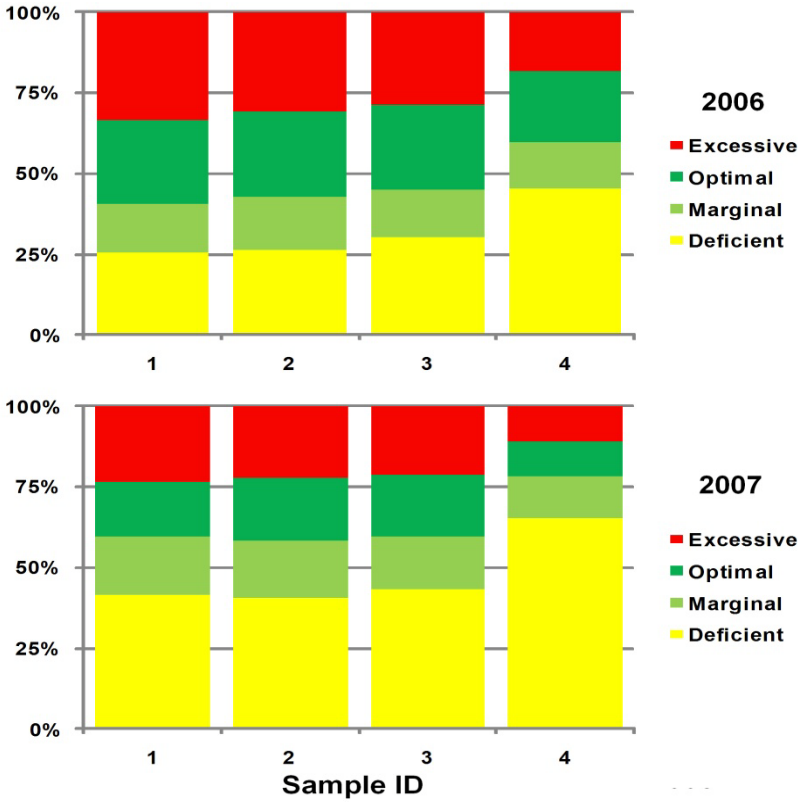

Figure 3. Percentage of samples tested in different stalk nitrate test categories. Samples 1, 2, and 3 were collected to identify the average field N status and Sample 4 was collected within the target deficient area within each field.

The height of the density curves suggests that a larger number of samples were tested deficient in 2007 than in 2006. This difference could be attributed to the amount of spring rainfall received during each year. For example, the fields sampled in 2007 received on average about 70 mm or 2.8 inches more spring rainfall than those sampled in 2006. The larger amount of spring rainfall in 2007 increased the likelihood of N losses from the soil and applied N fertilizer, and increased the chance for detecting N-deficient areas within corn fields (Kyveryga et al., 2010).

Figure 3 shows the percentage of stalk samples that tested in different stalk test categories for the four samples collected within each field during two years. The yellow color indicates the deficient category; the light green, the marginal; the dark green, the optimal, and the red color, the excessive category. For Samples 1, 2, 3, about 25% of observations were in the deficient stalk nitrate test category in 2006, and about 45% in 2007. For Sample 4, which was collected in areas that appeared deficient on the imagery, about 45% of samples were deficient in 2006 and 60% in 2007. Similarly for Sample 4, the percentage of samples that tested in the excessive category decreased from about 20% in 2006 to about 10% in 2007.

The observations from Sample 4 indicate the success rate in visually identifying areas deficient in N on the color DAI. The success rate increased from 46 % in 2006 to 66% in 2007 (Fig. 3), which was partially confounded by the rainfall patterns and N losses within the fields. Within some fields in 2006, it was difficult to find areas with lighter canopy color because of below average rainfall received during the second half of the growing season in 2006. A decrease in chlorophyll concentration and increase in canopy reflectance are common during soil moisture stress and plant senescence.

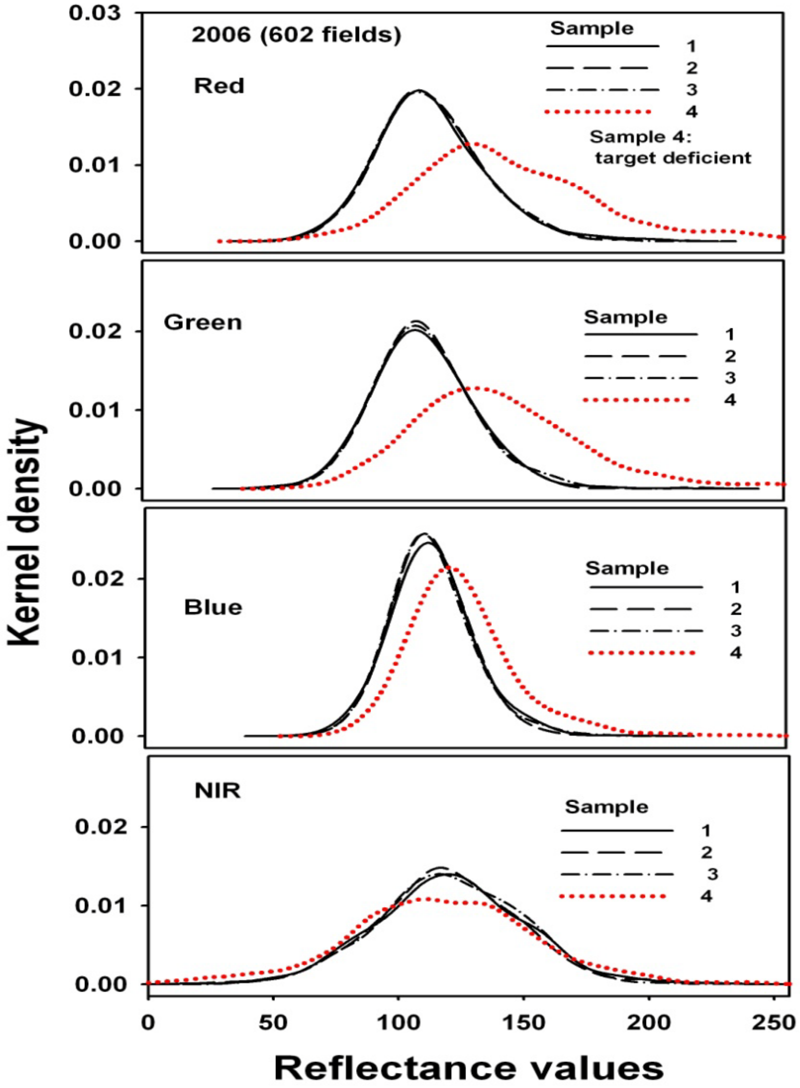

Figure 4. Distribution densities of reflectance values for different bands for Sample 1, 2, and 3 representing the average field N status and for the target deficient Sample 4 for 602 corn fields sampled in 2006.

Reflectance Value Distributions

Red, green, blue, and near-infrared (NIR) reflectance values extracted from each sampling area within fields in 2006 are shown in Figure 4. The 2007 data are not shown because the kernel density curves showed the same patterns. The patterns in reflectance distributions among the four samples in both years matched those produced by the stalk NO_3-N distributions shown in Figure. 2. The target deficient, Sample 4 had the largest reflectance values, and kernel densities were shifted to the right for three visible spectra compared with those for Sample 1, 2, and 3. The most distinct differences among the reflectance distributions were for the red and green bands, which are sensitive to the changes in chlorophyll and pigment concentrations in plant leaves. The near-infrared reflectance did not show a clear separation among the reflectance distributions, probably because NIR is only sensitive to the changes in plant biomass and canopy structure (Hatfield et al., 2008). Unlike the kernel densities for stalk NO_3-N values (Fig. 2), the densities for reflectance values for all individual bands were almost normally distributed with a slight evidence for a bimodal distribution for the red band in 2006 (Fig.4).

Predicting Late-Season Corn N Status

Table 1 shows the relationship between reflectance values or vegetation indices and stalk test outcomes, and predictive efficiencies of binary logistic regressions (BLR) for data collected in each year. The Deficient category was selected as the reference category. The regression models were highly significant for each independent variable. The slopes (odds ratios) for the red and green reflectance were >1, indicating that with the increase in reflectance values, the probability of testing in the Deficient stalk test category significantly increased.

For 2006 data, the green reflectance had the largest correct classification or prediction rate and the kappa index (Table 1). Seventy percent of samples were classified correctly using green reflectance, 69% using red, 68% using GNDVI and Chlorophyll Index (Green), and 67% of samples using NDVI. These predictability values were relatively good, considering that a correct classification rate below 50% would be attributed to a random chance. It is always possible that some of the stalk test outcomes are predicted by the random chance, especially if the percentage of samples in one of the test categories is relatively small. The kappa statistics makes adjustment for the randomness by using the observed probabilities to calculate the expected probabilities. Kappa index ranged from 0.01 to 0.1, with the highest values for green reflectance. Kappa values close to 1 indicate a perfect prediction, and those values between 0.1 and 0.2 indicate a fair prediction.

Table 1. Predictive efficiencies of binary logistic regressions (BLR) for relating reflectance values of individual bands and three calculated vegetative indices to corn stalk nitrate categories expressed as Deficient and Sufficient (combined Marginal, Optimal, and Excessive categories) for the survey data of 602 corn fields sampled in 2006 and 690 fields in 2007.

Band or Vegetation Index	Odds ratio #	Correct classification rate (%)	Kappa index
Red	1.012 (1.013)‡	69 (60)	0.05 (0.19)
Green	1.017 (1.019)	70 (64)	0.10 (0.24)
NDVI¶	0.341 (0.205)	67 (60)	0.01 (0.18)
GNDVI§	0.211 (0.079)	68 (61)	0.02 (0.19)
Chlorophyll Index (Green)	0.423 (0.271)	68 (61)	0.01 (0.20)

Deficient category was the reference category in BLR analysis.

‡ Data in parenthesis were collected in 2007.

¶ Normalized Difference Vegetation Index.

§ Green Normalized Difference Vegetation Index.

The model predictive efficiencies for the 2007 data were in agreement with those for the 2006 data (Table 1). The green band had the largest correct classification rate and the kappa index. Although the correct classification rate was 10% lower for the 2007 imagery compared with that for 2006 imagery, the kappa index increased from 0.10 to 0.19. Surprisingly, the use of the vegetative indices such as NDVI, GNDVI, and Chlorophyll Index (Green) did not improve predictability compared with the use of green or red reflectance alone. Originally, we speculated that these vegetation indices would help normalize the reflectance data and help improve the predictability when using the uncalibrated DAI.

Caution should be exercised when using green reflectance to predict N status from fields that were not sampled or used in the categorical regression analysis described in Table 1. However, this possibility can be tested in future studies. Currently, many states are offering free color DAI through the National Agriculture Imagery Program (Farm Service Agency, USDA). The imagery for Iowa is available at http://ortho.gis.iastate.edu/.

CONCLUSIONS

Late-season DAI was helpful for selecting sampling areas for CSNT conducted within >1300 corn fields sampled across Iowa during two years. The lighter color or higher reflectance as seen on the imagery indicated deficient corn N status in 46% of samples collected within target deficient areas in the relatively dry, 2006 and 66% of samples in the relatively wet, 2007. Green reflectance was the best predictor, from 60 to 70%, for identifying Deficient vs Sufficient corn N status among reflectance values of other individual bands and three calculated vegetation indices. With the appropriate image enhancement method, uncalibrated DAI can be potentially used to predict late-season corn N status within fields.

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