

Normalization of uncalibrated late-season digital aerial imagery for evaluating corn nitrogen status

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Abstract Using uncalibrated digital aerial imagery (DAI) for diagnosing in-season nitrogen (N) status of corn (*Zea mays* L.) is challenging because of the dynamic nature of corn growth and the difficulty of obtaining timely imagery. Late-season DAI is more accurate for identifying areas deficient in N than early-season imagery. Even so, the quantitative use of the imagery across many fields is still limited because DAI is often not radiometrically calibrated. This study tested whether spectral characteristics of corn canopy derived from normalized uncalibrated late-season DAI could predict final corn N status. Color and near-infrared (NIR) imagery was collected in late August or early September across Iowa from 683 corn fields in 2006, 824 in 2007, and 828 fields in 2007. Four sampling areas (one within a target-deficient area) were selected within each field for conducting the end-of-season corn stalk nitrate test (CSNT). Each image was enhanced to increase the dynamic range within each field and to normalize reflectance values across all fields within a 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 CSNT categories) using a binary logistic regression (BLR). The green reflectance had the highest prediction rate, which was 70, 64, and 60% in 2006, 2007, and 2008, respectively. The results suggest that the normalized (enhanced) late-season uncalibrated DAI can be used to predict final corn N status in large-scale on-farm evaluation studies.

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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 farmers because of their need to increase N fertilizer use efficiency. Diagnostic tools, such as soil and plant tissue testing, chlorophyll meters, canopy sensors, and aerial imagery, are being tested for their ability to improve N management. However, the reliability of these and other N diagnostic tools depends largely, at least, on three factors: (i) the amount and quality of data used in the test calibration; (ii) the experience of farmers and agronomists when adopting, using, and evaluating 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 difficult (Blackmer and White 1998; Zhang et al. 2008, 2010). To reduce this uncertainty, new tools and strategies are needed that can provide reliable feedback about N management at the end of the growing season and objectively evaluate the performance of various N fertilizer recommendation systems and management practices. The overall 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).

The possible tools for end-of-season N assessments are the corn stalk nitrate test (CSNT) and digital aerial imagery (DAI) of the corn canopy. The end-of-season CSNT was developed to diagnose the final N status of corn fields. It is based on measuring stalk $\text{NO}_3\text{-N}$ 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 US 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 an individual field. Many Iowa corn fields show large spatial variability in canopy color and yields, which can be due to variable N losses, variability in soil properties, non-uniformity of N fertilizer and manure applications or fertilizer application errors.

Late-season DAI of the corn canopy can be useful for characterizing within-field variability in corn canopy color and for guiding the stalk nitrate sample selection within fields. Use of DAI is becoming more common. Agronomists and farmers can buy DAI from many commercial sources or rent planes 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, provided through the National Agriculture Imagery Program (Farm Service Agency, USDA). However, unlike CSNT, which is reliable for diagnosing near-optimum and excessive N status, DAI works only in the deficient and near-optimum ranges. 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 (Blackmer and White 1998; Blackmer et al. 1996). Combining CSNT and DAI, would be a reasonable way to assess corn N status on a large scale (Blackmer and Kyveryga 2008).

A recent 2-year evaluation study that involved sampling about 700 corn fields across Iowa each year showed that CSNT and late-season DAI can be used to identify significant differences in corn N status between major N management practices having various timing of application, N forms, previous crops, tillage practices, and soil drainage classes (Kyveryga et al. 2010). However, a quantitative assessment of the extent to which DAI helped to guide the stalk nitrate sampling within the fields studied was not done. In addition, the major drawback of DAI is that, unlike satellite imagery, it is not radiometrically calibrated or corrected. This, however, limits the use of canopy reflectance values across many corn fields because uncalibrated DAI is often taken by different cameras, at different times, and from fields having different corn hybrids and planting dates. In addition, several errors of geometric and radiometric origin are possible due to effects of the cloud haze, shadow, sun angle, sensing geometry (some parts of the imagery have different reflectance values) and other (Morgan et al. 2010).

Radiometric calibration and equalization of uncalibrated aerial imagery is a very complex process. Several methods are available; some of them are based on using calibrated satellite-born imagery as a reference, using complex mathematical (empirical) formulas or using additional referenced points with known reflectance values (Haest et al. 2009; Pan et al. 2010). All these methods are not very feasible for large-scale on-farm evaluations because of a large number of fields required for sampling and the potential high costs for purchasing additional satellite imagery and for reprocessing DAI. Therefore, the objective of this study was to utilize a relatively simple method for normalizing (enhancing) uncalibrated DAI to quantify the ability of spectral characteristics of the corn canopy to predict the final N status of many corn fields across Iowa.

Materials and methods

Late-season DAI of the corn canopy was collected from 683 fields in 2006, 824 fields in 2007, and 828 fields in 2008. The fields were selected for guided corn stalk nitrate evaluations conducted across Iowa. The original objective of the evaluations was to identify relative differences in N status between different management practices commonly used by farmers. Detailed information about crop rotation, timing and forms of N fertilizer and manure applications, and tillage practices 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 farmers with their normal N fertilizer and manure management practices.

Imagery characteristics and image normalization (enhancement) method

Field boundaries for collecting DAI 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 farmers' descriptions. The 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 2-to-3 weeks in each year. The time of imagery acquisition ranged from late morning to early afternoon during a given day.

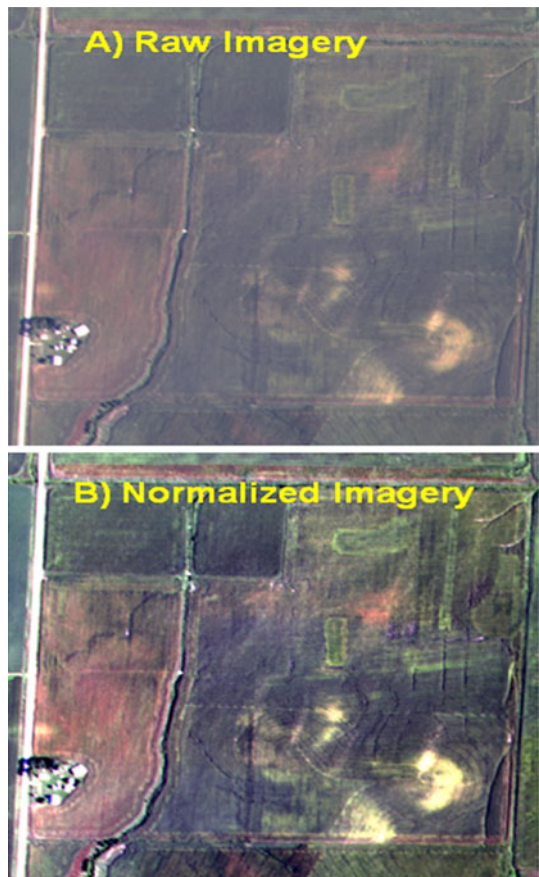
The imagery was collected in late August or early September. Images from fields in southern tiers of Iowa counties were taken earlier than from those in northern tiers. Four 12-bit digital cameras with CCD (charge coupled display) array of 1 600 × 1 200 were used to collect the imagery. During cloud free days, the imagery was taken from a height of about 2 400 m above the ground surface. 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, georeferenced, and tonally balanced with a spatial resolution of about 1 m. The composed 12-bit images were converted to 8-bit data.

The images were ortho-rectified using the US Geological Survey 7.5 min digital elevation models. Each image was visually checked for the presence of more than one corn hybrid, extensive areas damaged by wind or hail, and for large areas damaged by a flood, weeds, pests or diseases. Images that had above-mentioned features and had other visible problems not related to N management were not used in this analysis.

Each composed, uncalibrated raw 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 standard deviations 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 (Fig. 1). Also, the enhanced imagery

Fig. 1 Raw and normalized (enhanced) color DAI of the corn canopy. The raw DAI was enhanced by increasing the image dynamic range, which is a range in digital reflectance values between the darkest and the lightest parts of the imagery within a field. The normalized imagery had about 80% of digital counts between plus and minus two standard deviations from the mean reflectance for each band in each field



partially decreased the overwhelming effects of light scattering from nearby roads, buildings, waterways, and other features on the imagery.

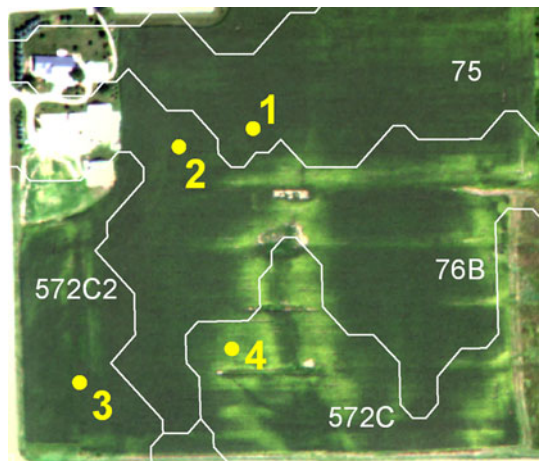
Corn stalk nitrate sampling

Four sampling areas were selected within each corn field by overlaying a digital color (red, green, and blue bands) image with a digital soil map of the field (Fig. 2). The digital soil map (1:12 000 the mapping scale) for each county was downloaded from the Iowa Cooperating Soil Survey (2003). One sampling area was selected within each of the three predominant soil types within the field. These three sampling areas were selected within relatively uniform areas 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 3 samples from the predominant soil types are referred to as Sample 1, 2, and 3 to represent the average N status of corn fields and the fourth, target N deficient sample is referred to as Sample 4.

X and Y coordinates for the sampling areas were uploaded to handheld GPS units, which were used to find the sampling areas within fields. Another set of coordinates were recorded after samples were collected to verify the exact sampling locations.

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 and composed into one sample representing each sampling area. Twenty centimeter stalk segments were cut by a custom-made cutter that controlled the exact sample length and the height of the cut (15 cm) 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 Midwest Laboratories (Omaha, Nebraska, USA) for analyses on the same day of the sampling, or the samples were put in a refrigerator and sent to the laboratory on the next day. Once in the laboratory, the composite samples were dried at 65C and ground to pass through a 1-mm mesh. The samples were extracted with 2 M KCl,

Fig. 2 Four sampling areas selected using late-season normalized (enhanced) DAI and digital soil maps for conducting the end-of-season CSNT. Sample 1, 2, and 3 were selected within three predominant soil types (75, 76B, and 572C) to characterize the field-average N status of corn, and Sample 4 was selected within a target deficient area to confirm that the yellow or lighter color on the imagery was attributed to N stress



and the solutions were filtered and analyzed for stalk $\text{NO}_3\text{-N}$ values with a Lachat flow-injection analyzer (Lachat Instruments, Milwaukee, WI). All corn stalk samples were processed and analyzed in the same way in each year, and the laboratory analyzes were completed within a month after the sample collection.

The CSNT categories indicate corn N sufficiency: the plant N demand relative to the N supply. The sufficiency categories are deficient, marginal, optimal, and excessive, based on the original studies for calibrating the test in Iowa (Binford et al. 1992). The deficient category ($<250 \text{ mg kg}^{-1}$) suggests the high probability of yield and economic losses from the reduced N supply during the season. The marginal category ($250\text{--}700 \text{ mg kg}^{-1}$) suggests that only a portion of the samples had N deficiencies that significantly reduced yields and returns to N fertilizer. The optimal category ($700\text{--}2\,000 \text{ mg kg}^{-1}$) suggests that the yields were maximized with the N supply available during the growing season. The excessive category ($>2\,000 \text{ mg kg}^{-1}$) suggests that the N supply exceeded corn N needs during the growing season.

Image analysis

Reflectance values from each of the 4 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 into one dataset using the Append tool of Data Management. Only mean reflectance values were used in the analyses.

In addition to reflectance values for individual bands, 3 vegetative indices were calculated. The Normalized Difference Vegetation Index (NDVI) was calculated as $\text{NIR} - \text{Red} / \text{NIR} + \text{Red}$ (Deering 1978). The Green Normalized Difference Vegetative Index (GNDVI) was calculated $\text{NIR} - \text{Green} / \text{NIR} + \text{Green}$ (Buschmann and Nagel 1993). The Chlorophyll Index (Green) was calculated as $\text{NIR} / \text{Green} - 1$ (Gitelson et al. 2005). The vegetation indices were used to standardize reflectance values from individual bands of uncalibrated imagery and quantify relationships between spectral characteristics of the imagery and stalk test outcomes across all fields.

To estimate the effect of image enhancement method on reflectance value distributions for each field, pixel counts were calculated using the Tabulate Area and Table Select tools of Spatial Analysis in ArcGIS software. Pixel count distributions were compared for the raw (without normalization) and enhanced DAI.

Statistical analysis

Empirical frequency distributions of stalk $\text{NO}_3\text{-N}$ 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 versus Sufficient (a combination of marginal, optimal, and excessive CSNT test 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 Inst 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 a total number of stalk samples sampled in all fields in each 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. The kappa index is 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

Kernel density plots show distributions of stalk $\text{NO}_3\text{-N}$ values for four stalk samples collected during 3 years (Fig. 3). 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 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 differences between Samples 1, 2, 3 and 4 suggest that visual observations on the imagery were helpful in separating deficient from N sufficient areas.

The stalk $\text{NO}_3\text{-N}$ 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. 3). Stalk nitrate median values for Sample 4 were in one stalk test category lower than those values calculated for Sample 1, 2, and 3 across all fields. For example, the stalk nitrate median value for Sample 4 was in the marginal category in 2006 and in the deficient category in 2007 and 2008.

The height of the density curves suggests that a larger number of samples tested deficient in 2007 and 2008 than in 2006. This difference could be attributed to the amount of spring rainfall received each year. For example, the fields sampled in 2007 received, on average, about 70 mm more rainfall in Spring than those sampled in 2006. Fields sampled in 2008 received about 40 mm more spring rainfall (data from 4-km grids received from Iowa Environmental Mesonet, Agronomy Department, Iowa State University) than in 2007. Also, rainfall in June of 2008 was twice the normal June rainfall (about 100 mm)

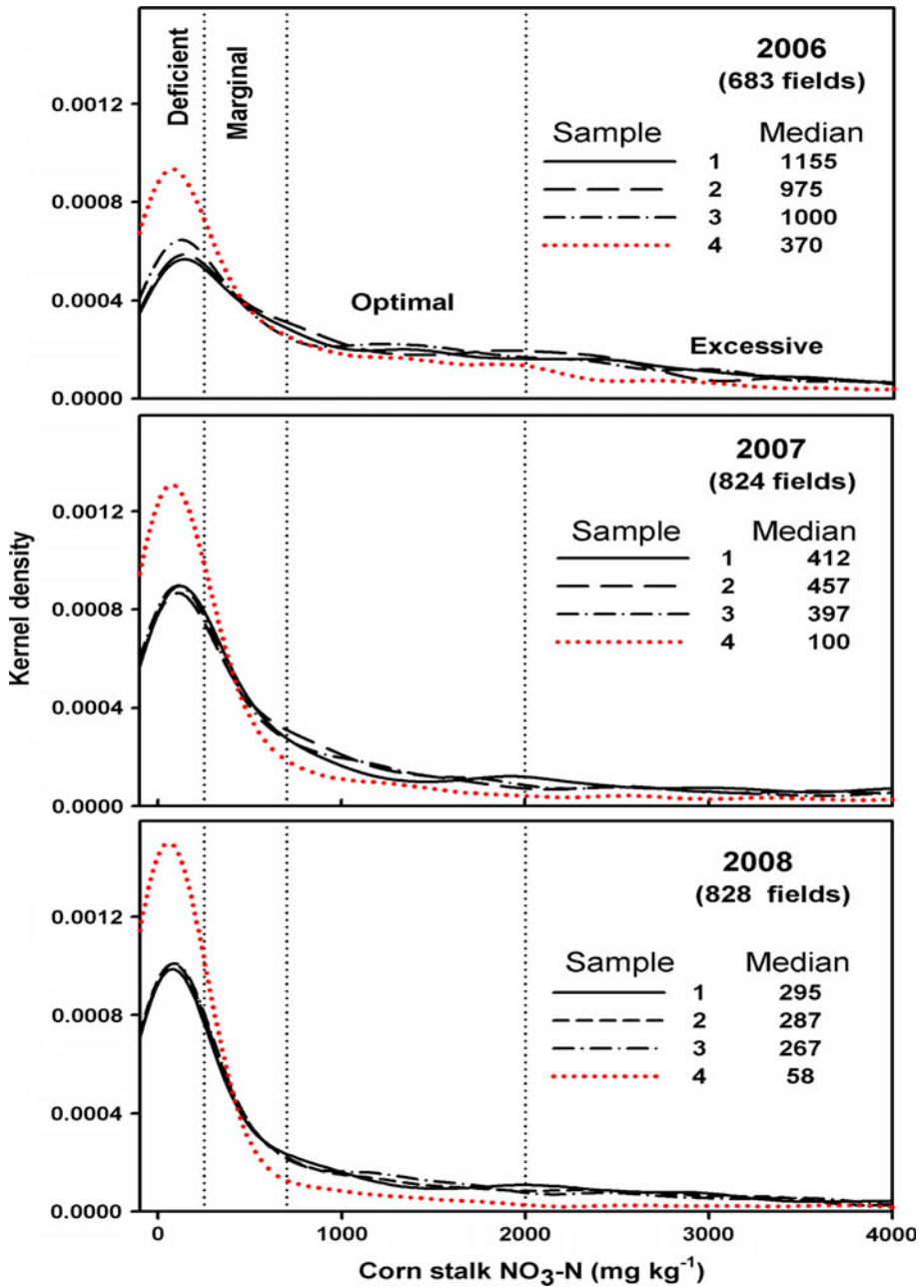


Fig. 3 Distribution densities for stalk nitrate values for Sample 1, 2, and 3 collected to identify the average field N status and for a target deficient Sample 4 collected from 683 corn fields in 2006, 824 in 2007, and 827 fields in 2008

across the state. The large amount of spring rainfall in 2006 and 2007 increased the likelihood of N losses from the soil and applied commercial N fertilizers and animal manure and increased the likelihood for detecting N-deficient areas within corn fields (Kyveryga et al. 2010).

Figure 4 shows the percentage of stalk samples that tested in different stalk test categories for the 4 samples collected within each field during 3 years. The yellow color of the mosaic stack plots 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, 45% in 2007, and 50% in 2008. For Sample 4, which was collected in areas that appeared deficient on the imagery, about 45% of samples tested deficient in 2006, 60% in 2007, and 75% in 2008. Similarly for Sample 4, the percentage of samples that tested in the excessive category decreased from about 20% in 2006 to 15% in 2007 and to 10% in 2008.

The observations from Sample 4 indicated a relative 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 and to 75% in 2008 (Fig. 4), which was partially confounded by the rainfall



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

patterns and N losses within the fields. It was difficult to find areas with lighter canopy color within some fields in 2006 because of below average rainfall received in June and July (data not shown). However, a decrease in chlorophyll concentration and increase in canopy reflectance values can be observed when corn plants experience soil moisture stress during a growing season or when the plants start senescence (Samborski et al. 2009).

Reflectance value distributions

Red, green, blue, and NIR reflectance values extracted from each sampling area within fields in 2006 are shown in Fig. 5. The 2007 and 2008 data are not shown because the kernel density curves showed the same patterns. The general patterns in reflectance distributions among the four samples during 3 years matched those produced by the stalk $\text{NO}_3\text{-N}$ distributions shown in Fig. 3. The target deficient, Sample 4, had the largest

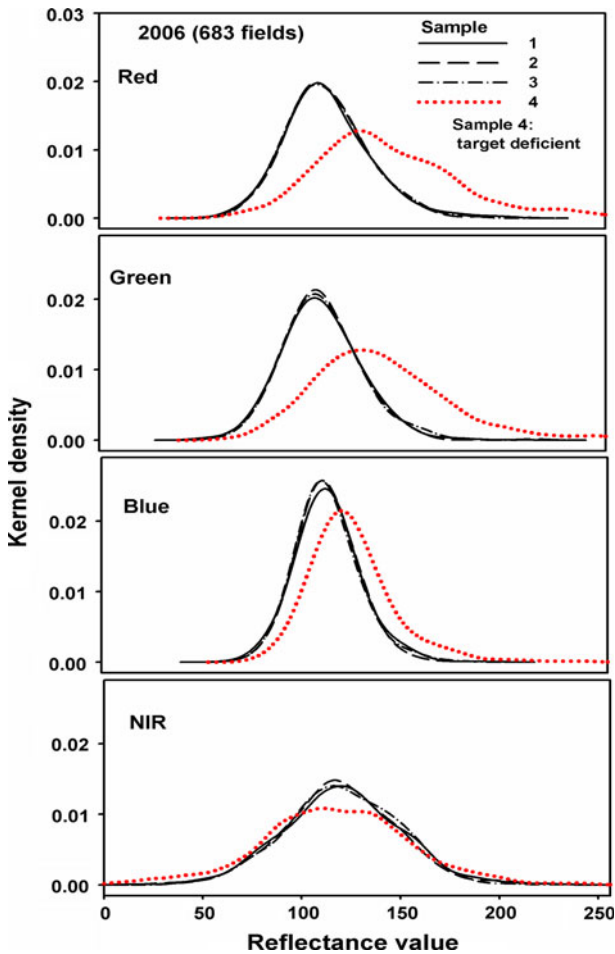


Fig. 5 Distribution densities of reflectance values for different bands for Sample 1, 2, and 3 representing the average field N status and for a target deficient Sample 4 collected within 683 corn fields evaluated in 2006

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 NIR reflectance did not show a clear separation among the reflectance distributions, probably because NIR band is only sensitive for the changes in plant biomass and canopy structure (Hatfield et al. 2008). Unlike the kernel densities for stalk $\text{NO}_3\text{-N}$ values (Fig. 3), 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 of Sample 4 collected in 2006 (Fig. 5).

Predicting late-season corn N status

Table 1 shows the relationship between reflectance values or vegetation indices derived from the normalized imagery and binary corn N status and predictive efficiencies of BLR for data collected in each year. The Deficient category was selected as the reference category. The odds ratios (used here instead of slopes of regression models) for the red and green reflectance were >1 , indicating that with the increase in reflectance values, the

Table 1 Predictive efficiencies of BLR for relating reflectance values of individual bands and three calculated vegetative indices of enhanced (normalized) uncalibrated DAI to a binary corn N status expressed as Deficient and Sufficient (a combination of marginal, optimal, and excessive stalk nitrate test categories) for 686 corn fields evaluated in 2006, 834 in 2007, and 828 fields evaluated in 2008

Band or Vegetation Index	Intercept	Odds ratio ^a	95% Confidence interval for odds ratio	Correct classification rate (%)	Kappa index
2006					
Red	-2.26	1.012	1.009–1.015	69	0.05
Green	-2.75	1.017	1.010–1.020	70	0.11
NDVI ^b	-0.78	0.34	0.22–0.52	67	0.01
GNDVI ^c	-0.79	0.21	0.13–0.34	68	0.02
Chlorophyll Index (Green)	-0.74	0.42	0.32–0.55	68	0.01
2007					
Red	-1.60	1.013	1.010–1.016	60	0.19
Green	-2.07	1.019	1.015–1.020	64	0.24
NDVI	-0.17	0.21	0.13–0.32	60	0.18
GNDVI	-0.22	0.079	0.046–0.14	61	0.19
Chlorophyll Index (Green)	-0.17	0.27	0.20–0.36	61	0.20
2008					
Red	-1.26	1.017	1.017–1.023	57	0.15
Green	-1.43	1.014	1.012–1.016	60	0.20
NDVI	1.03	0.069	0.026–0.18	58	0.07
GNDVI	1.38	0.060	0.027–0.13	59	0.12
Chlorophyll Index (Green)	1.06	0.58	0.49–0.70	58	0.14

^a An odds ratio of 1 is an equivalent to a probability of 0.5, suggesting that both Deficient and Sufficient categories are equally likely. Deficient category was the reference category in BLR analysis

^b Normalized Difference Vegetation Index

^c Green Normalized Difference Vegetation Index

probability of testing in the Deficient stalk test category increased. The odds ratios for the vegetative indices such as NDVI, GNDVI, Chlorophyll Index (Green) were <1 , indicating that with the increase in the indices values the probability of testing Deficient decreased. An odds ratio of 1 is an equivalent to a probability of 0.5, suggesting that both Deficient and Sufficient categories are equally likely. The regression models were statistically significant for each independent variable because 95% confidence intervals did not cross a value of 1 for data in each year.

For the 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. 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.

The BLR model predictive efficiencies for the 2007 and 2008 data were in agreement with those for the 2006 data (Table 1). The green band had the largest correct classification rates and kappa index values. Although the correct classification rates were about 10% lower for the 2007 and 2008 imagery compared with those for 2006 imagery, kappa index increased from 0.10 to 0.19. Surprisingly, the use of 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 additionally normalize the reflectance values and improve the predictability when using the uncalibrated DAI.

Distributions of pixel counts of the green band for the enhanced (normalized) and raw DAI for each field showed that the enhancement method tended to normalize the reflectance distributions in each field and it produced a pseudocalibration effect on the imagery (Fig. 6, only four fields evaluated in 2007 are shown). This, in turn, suggests that the imagery not only helped to select sampling areas within fields but also reflectance characteristics of the corn canopy could be used, with some degree of uncertainty, to predict the final N status across many corn fields that may have different corn hybrids or different dates of taking the imagery.

Caution should be exercised when trying to use green reflectance to predict N status from fields that were not evaluated 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/>.

Conclusion

Late-season normalized (enhanced) uncalibrated DAI helped to select sampling areas for CSNT conducted within >2 000 corn fields evaluated across Iowa during 3 years. Areas with lighter color or higher visible waveband reflectance values on the imagery indicated deficient corn N status in about 46% of samples collected within target deficient areas in the relatively dry 2006, about 66% of samples in the relatively wet 2007, and in about 75%

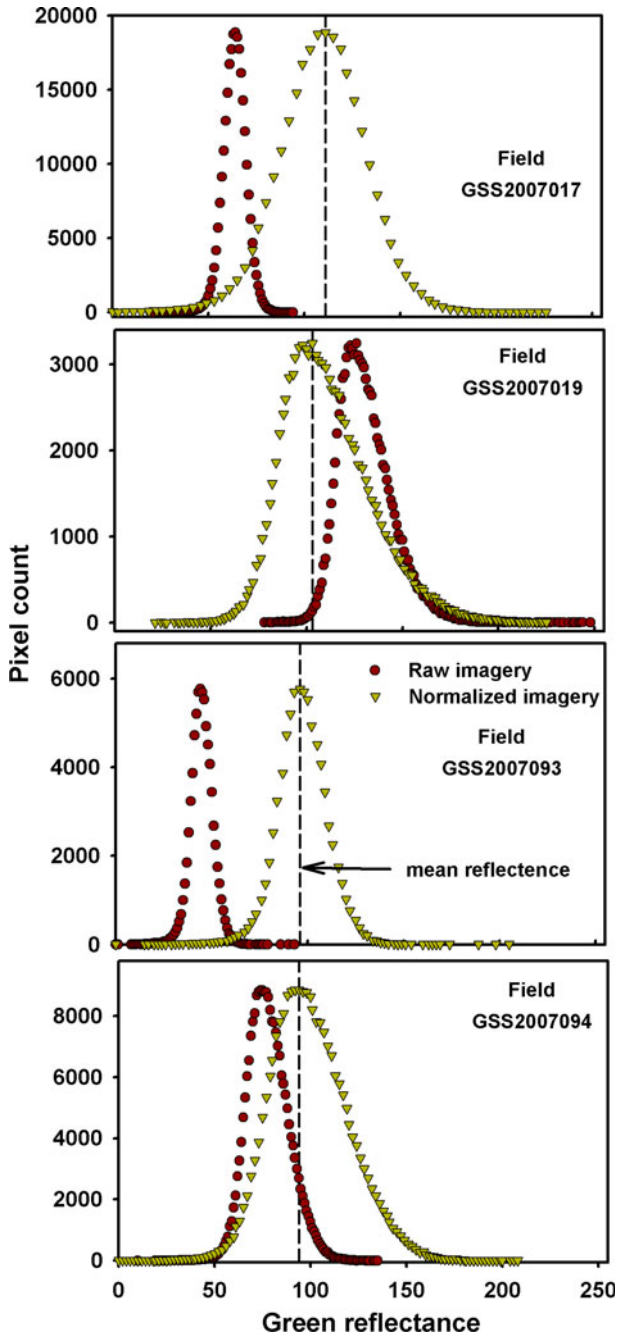


Fig. 6 Distribution of pixels counts for green reflectance values for the raw and enhanced (normalized) uncalibrated DAI for selected four 30 or 40-ha corn fields evaluated in 2007

of samples in the excessively wet 2008. Green reflectance was the best predictor (60–70% correct prediction rates) for identifying Deficient versus Sufficient corn N status among reflectance values of individual bands and three calculated vegetation indices such NDVI, GNDVI, and Chlorophyll Index (Green).

With the proposed image enhancement (normalization) method, uncalibrated DAI can be potentially used to predict late-season corn N status across many fields. This approach partially allows reducing potential problems associated with the use of uncalibrated (not radiometrically corrected) imagery and reducing effects of different corn hybrids on reflectance values the corn canopy as well as reducing effects of different timing of taking the imagery.

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