Late-season digital aerial imagery and stalk nitrate testing to estimate the percentage of areas with different nitrogen status within fields

P.M. Kyveryga, T.M. Blackmer, R. Pearson, and T.F. Morris

Abstract: Precision agriculture technologies offer potential economic and environmental benefits from site-specific management of nitrogen (N) fertilizer and animal manure sources for corn (*Zea mays* L.). However, lack of knowledge and reliable methodology for developing and evaluating site-specific N fertilizer recommendations are the major obstacles for realizing these potential benefits. The objective of this study was to evaluate corn N status at the field scale and across many fields using late-season digital aerial imagery and the end-of-season corn stalk nitrate test in large-scale on-farm evaluation studies. About 30 groups of farmers, lead by agronomists and crop consultants, were formed across Iowa to evaluate different N management practices. Late-season color digital aerial imagery and digital soil maps were used to guide the collection of the corn stalk nitrate test samples within 683 cornfields in 2006, 824 fields in 2007, and 828 fields in 2008. Four areas—one from each of the three predominant soil types and one within a target-deficient area—were sampled in each field. Multilevel binary logistic regressions were used to quantify the relationship between green reflectance of the corn canopy and corn N status, expressed as deficient and sufficient (a combination of marginal, optimal, and excessive categories of the corn stalk nitrate test), within and across the fields. Percentages of areas within fields with deficient and sufficient N status were estimated using distributions of pixel counts of green reflectance of the corn canopy. Multiple regression analysis was used to identify factors affecting percentage-deficient area within the fields. Results showed that N management category (a combination of N form and timing of application) and early season rainfall (May, June, or cumulative from March through June) had the largest effects on percentage-deficient area. Fields with liquid swine manure applied in the fall or urea-ammonium nitrate solution applied in the spring (before planting) or urea-ammonium nitrate solution applied at sidedress had larger areas of N deficiency than fields with anhydrous ammonia applied in the spring. Larger early season rainfalls also increased percentage-deficient area during each year. The results of large-scale evaluations can be used to develop more accurate site-specific N recommendations based on knowledge of differences between management practices and effects of soil properties and rainfall on N status within fields. Future evaluations can identify areas that persistently have excessive N status and quantify potential N fertilizer reductions within those areas or fields.

Key words: adaptive management—corn stalk nitrate test—digital aerial imagery—nitrogen management—precision agriculture technologies—spatial variability

Farmers are rapidly adopting various precision agriculture technologies (PAT), such as yield monitoring, variable-rate fertilizer applications, and remote sensing tools (Griffin et al. 2008). Spatial and temporal variability in soil properties, plant characteristics, and crop yields can be used to guide applications of commercial fertilizers, lime, and animal manure sources tailored to individual fields or areas within fields. However, a great expectation that the use of PAT would substantially increase profitability and rapidly minimize the offsite impact of corn (*Zea mays* L.) production under rainfed conditions of the US Midwest has not been completely realized.

The limited success of adopting and using PAT for nitrogen (N) fertilizer management for corn occurs for several reasons (Blackmer and White 1998; Hansen et al. 2004; Hatfield 2000; Kyveryga et al. 2011a; Massey et al. 2008; Sawyer et al. 2006; Scharf et al. 2005; Schepers et al. 2004): (1) the general nitrogen fertilizer recommendations (GNFR) or best management practices based on field averages are not adequate for making site-specific (e.g., variable) N fertilizer prescriptions; (2) the majority of GNFR have a limited amount of calibration and support data, which is mostly collected in controlled small-plot experiments that often do not represent farmers' common management practices (e.g., types and width of fertilizer application equipment, forms of commercial fertilizer and animal manure); (3) the majority of GNFR are based on estimating field-average economically optimal N fertilizer rates without considering possible differences between timing, forms, and methods of fertilizer and animal manure applications; (4) the majority of GNFR ignore the large uncertainty when predicting the amount of N potentially available to the plants from the soil, fertilizer, and animal manure sources; (5) the majority of GNFR do not consider large temporal variability in amount of rainfall and large spatial variability in observed N losses within fields; and (6) there is growing evidence that researchers need a reliable and practical methodology for developing and evaluating various site-specific N fertilizer recommendations using on-farm studies.

Faced with these challenges and possible environmental regulations when using animal manure and commercial fertilizer sources, farmers across Iowa began forming groups to evaluate N management practices on their farms utilizing PAT (Blackmer and Kyveryga 2010; Ostermeier 2007; Van De Woestyne 2005). The primary focus of these

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on-farm evaluations was to assess the economic effect of reducing farmers' normal N fertilizer rates by about one-third in field-scale on-farm replicated strip trials. Farmers used global positioning systems (GPSs) and guidance systems to record locations of the N fertilizer treatments within fields and to combine yield-monitoring systems with GPS to record harvested yields. Also, late-season digital aerial imagery (DAI) was used to verify treatment locations, to identify possible application and other management errors within fields, and to visually assess the magnitude of yield differences between the two N rates studied. The secondary focus of these on-farm evaluations was to enable individual growers to evaluate the current N management practices and the performance of any GNFR developed by land-grant universities or private industry. Such evaluations would allow researchers from public and private institutions to use, pool, and analyze the data from many groups of farmers and to identify management and environmental factors that are important for developing and fine-tuning site-specific N recommendations for different geographic areas.

On-farm evaluations with two N fertilizer treatments conducted in Iowa fall under the general umbrella that is called adaptive management. The adaptive management concept is based on evaluations of biological systems or processes that are characterized by large variability, uncertainty, and complex management (Holling 1978; Lee 1993; Walters and Hilborn 1978). In general, adaptive management can be described as a cycle of at least six repeated steps: (1) identifying a critical management problem; (2) designing a simple, practical, and efficient experiment or policy to study the problem; (3) conducting the experiment or implementing the policy; (4) evaluating the outcomes; (5) learning from the outcomes; and 6) adjusting management based on the observed outcomes.

The fundamental difference between adaptive management studies at the field scale in agriculture and controlled small-plot experiments is that the former are based on farmers' participatory learning. This means that group members conducting on-farm evaluations—farmers, consultants, along with scientists and other stakeholders—identify the most critical management problems and agree that the problems are legitimate problems (Pahl-Wostl et al. 2007) that can be solved by conducting on-farm evaluations.
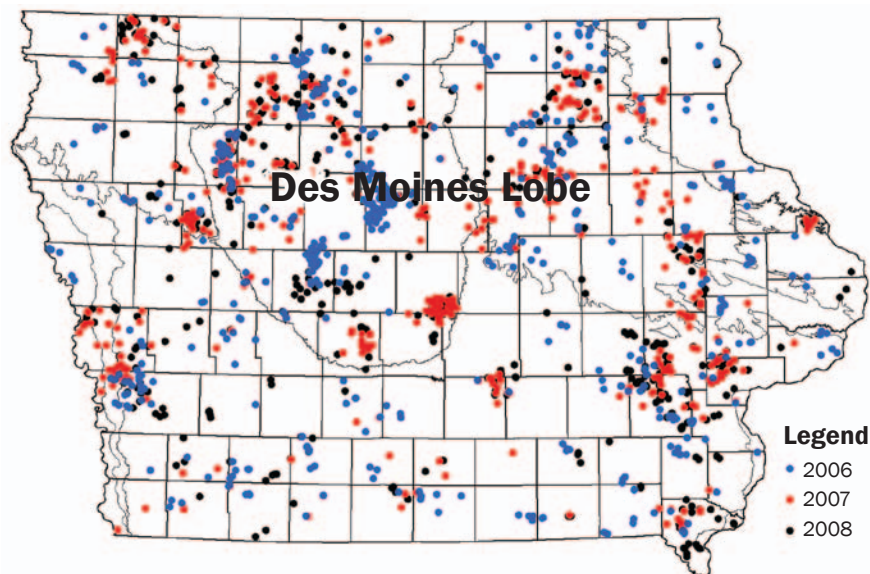
Also, farmers and local agronomists working in an adaptive management framework are solely responsible for conducting on-farm experiments by applying treatments within their fields, harvesting the crop, making crop phenological observations, following quality control protocol, and collecting the essential management information, whereas farmers involved in small-plot studies are not involved in applying treatments or making observations about the treatments. Farmers in adaptive management studies also use their normal management practices, corn hybrids, and application equipment. They own the data, but summaries of individual evaluations not identifiable by farmer are publicly available (ISA 2010). The analysis of data and the decision support system for adaptive management evaluations also differ from that of controlled small-plot experiments as adaptive management studies offer more practical and management-oriented decision support systems that can be used for better predictions of management outcomes under uncertainty (Neyberg et al. 2006).

While yield monitoring and GPS technology can be effectively used in on-farm evaluations, a large percentage of farmers across the Midwest use yield monitoring technology without analyzing the observed data (Griffin et al. 2008). To engage farmers in on-farm evaluations, a special program was developed to collect feedback informa-

tion about the N status from many cornfields across Iowa (Kyveryga et al. 2010). The program was based on using late-season DAI of corn canopy and digital soil maps to guide the collection of corn stalk nitrate test (CSNT) samples within fields. The CSNT is based on measuring late-season N sufficiency (the supply relative to the demand) or corn N status before the harvest. The test provides feedback in N status that can be used for assessing whether N management (i.e., N rate, timing, form, or method of application) was optimized or not in a given year. The high accuracy of the CSNT for diagnosing the N status of corn in the near-optimal and excessive categories has been confirmed in several studies conducted across the Midwest (Balkcom et al. 2003; Brouder et al. 2000; Wilhelm et al. 2005; Yang 2000). The DAI has a high sensitivity for diagnosing the deficient or below-optimal N status of corn (Blackmer et al. 1996; Hatfield et al. 2008).

Two years of on-farm evaluations using DAI and CSNT across Iowa identified significant differences in the field-average N status between five management practices based on forms and timing of fertilizer N and manure applications, the previous crop, and tillage practices (Kyveryga et al. 2010). A follow-up analysis showed how DAI used in the evaluation studies was processed, enhanced, and normalized to predict the field-average N status across many corn-

fields (Kyveryga et al. 2011b). In addition to knowing the field-average N status of corn, growers, agronomists, technical providers, and conservation specialists are often interested in evaluating corn N status spatially within individual fields. After observing large spatial variability in DAI, participants of on-farm evaluations often request estimates of the size of the area that is deficient, sufficient, or excessive within cornfields; and identify the major factors (including form and timing of N application, rainfall amount, and others) that affect spatial variability of the N status within cornfields.

The objective of this study was to demonstrate the combined use of late-season DAI and CSNT for evaluating corn N status within fields and across many fields in on-farm evaluation studies conducted across Iowa during three years. Specifically, we attempted to develop a method for calibrating corn canopy characteristics to CSNT outcomes to estimate the percentage area with a different N status within cornfields.

Materials and Methods

The study included collecting late-season DAI and CSNT samples from 683 cornfields across Iowa in 2006, 824 fields in 2007, and 828 fields in 2008 (figure 1). At least two fields were sampled in each county during the study. About 30 groups (see clusters on the map) were formed across the state. Each group had 10 to 25 farmers and was led by a local commercial agronomist or independent crop consultant. The group leader was partially responsible for identifying potential fields for evaluations, delineating field boundaries, collecting management information from farmers, sampling the fields, and organizing group meetings to discuss DAI imagery and CSNT results. More specific information about management practices, total N rates applied with manure and commercial fertilizers, and differences between field average corn N status for different N management categories (N forms and timing of N application) were discussed elsewhere (Kyveryga et al. 2010)

Imagery Collection and Processing. The late-season DAI was collected in late August or early September. This time of imagery collection in Iowa coincides with the time when N stress in corn is the most pronounced as plants deplete the soil and fertilizer N supplies. Four 12-bit digital cameras with a charge coupled display array of 1,600 ×

Figure 2

An example of late-season digital color (red, green, and blue bands) aerial imagery of the corn canopy used in on-farm evaluations of nitrogen status across Iowa. Corn stalk samples 1, 2, and 3 were collected within three predominant soil types to characterize the average field nitrogen status. Corn stalk sample 4 was collected within an area that looked deficient or yellow. Sample 1 for this field tested optimal, sample 2 deficient, sample 3 optimal, and sample 4 deficient. Soil type map labels are as follows: Clarion (138B and 138C2), Nicollet (55), and Webster (107).
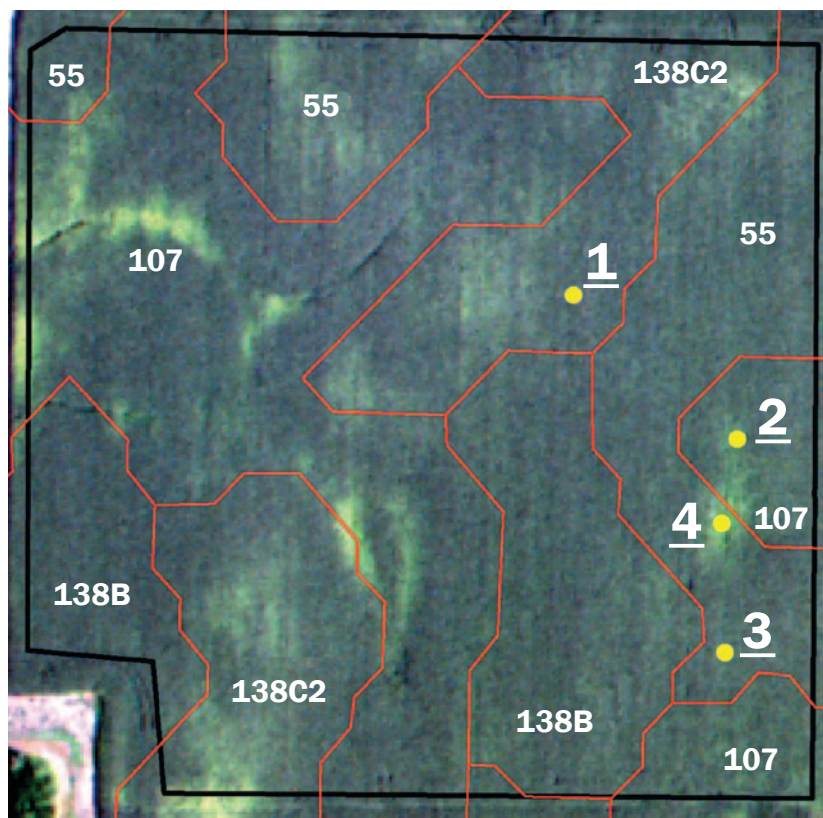
1,200 were used to collect the imagery. The imagery was taken from a height of about 2,400 m (7,920 ft) above the ground. During a flight, about twenty individual images were taken from each field. Then these individual images were composed or mosaiced into one 8-bit, georeferenced, tonally balanced image with a spatial resolution of about 1 m (3.3 ft). The raw mosaiced imagery had four spectral bands: blue (410 to 490 nm), green (510 to 590 nm), red (610 to 690 nm), and near infrared (800 to 900 nm). Each image was orthorectified by using the US Geological Survey 7.5 minute digital elevation models.

The imagery was not radiometrically corrected to absolute reflectance values, meaning that the reflectance values across the fields were not normalized. Therefore, this made it difficult to compare the absolute canopy reflectance values across many fields. To partially normalize reflectance values across the fields and remove the overwhelming effects

of light scattering from nearby roads and buildings, the imagery was enhanced by extending the dynamic range of each spectral band using ERDAS Imagine Software (ERDAS, Norcross, Georgia). The image enhancement increased the range in reflectance between the darkest and the lightest part of the imagery and allowed identification of more distinct visual differences of the corn canopy. Kyveryga et al. (2011b) described the effects of the imagery enhancement on the ability of the image spectral characteristics to predict the field-average N status across many fields within a year.

Corn Stalk Nitrate Sample Collection. Color (red, green, and blue bands) DAI was overlaid with a digital soil map to select four sampling locations for CSNT within each field (figure 2). Three corn stalk samples were collected within three predominant soil types (based on their area within the fields) to characterize the field-average N status.

The fourth sample was collected within the area that appeared to be the most N deficient, with lighter or less green or more yellow color of corn canopy. This target-deficient sample was collected to confirm that the more yellow color (less plant chlorophyll concentration) of corn canopy was associated with N deficiency but not with other plant stresses, such as lack or excessive soil moisture, herbicide injury, or early corn senescence. Coordinates for the selected sample locations were uploaded to a hand-held GPS that was used to navigate within fields. To verify exact sampling locations, coordinates were recorded after the samples were collected within a field.

Stalk samples were collected from two to five weeks after corn grain reached physiological maturity or black layer stage. Ten 20 cm (8 in) stalk segments (15 cm [6 in] above the ground) were cut within each sampling area (Blackmer and Mallarino 1996) that included two corn rows extending for about 10 to 12 m (33 to 40 ft). The collected samples were analyzed for stalk nitrate nitrogen concentrations with a Lachat flow-injection analyzer (Lachat Instruments, Milwaukee, Wisconsin).

The late-season CSNT was developed to diagnose N sufficiency (N supply relative to N demand) or corn N status (Binford et al. 1990; Binford et al. 1992). The test results are reported as four nitrate nitrogen sufficiency categories: deficient (<250 mg kg^{-1}), marginal (250 to 700 mg kg^{-1}), optimal (700 to 2,000 mg kg^{-1}), and excessive (>2,000 mg kg^{-1}). The deficient category suggests low N availability from the soil and fertilizer sources, resulting in a high probability of economic yield loss from the N deficiency. The marginal category suggests that economic yield responses from additional N applications would be equally likely. The optimal category indicates that the N supply matched the corn N demand and the relatively low probability of yield response to additional N. The excessive category suggests that the N supply exceeded the plant N demand.

Stalk nitrate concentrations were expressed as N sufficiency categories in statistical analyses because the nitrate concentrations were not normally distributed (Kyveryga et al. 2011b) and because CSNT was developed as a qualitative categorical diagnostic tool (Binford et al. 1990; Binford et al. 1992).

Digital Aerial Image and Statistical Analyses. To calibrate image characteristics to the observed CSNT outcomes within each field, canopy reflectance values were extracted for blue, green, red, and near-infrared bands of the corn canopy reflectance for each sampling area (figure 2) using ArcGIS Desktop 9.3.1 (Environmental Systems Research Institute, Redlands, California). First, a buffer of 5 m (16.5 ft) in a diameter was created around each sampling point. Then, we used the Zonal Statistics tool of Spatial Analysis to build a geographical information system model that extracted image reflectance values from many images at a time. Mean reflectance values for each band from each sampling location were combined into one dataset using the Append Tool of ArcGIS.

A unique challenge when trying to calibrate the imagery to CSNT outcomes was that some fields were flown on different dates, and corn hybrids were not the same across all fields. The different hybrids often have different spectral characteristics of the corn canopy. Although the image enhancement procedure had partially normalized the reflectance values within and across fields sampled within each year (Kyveryga et al. 2011b), complete pooling of the data across all fields would not be sufficient for accurately predicting corn N status spatially within cornfields. Another challenge was that establishing a reliable relationship between image reflectance characteristics and stalk test outcomes would be difficult because only four calibration points (four values for reflectance and four categorical values for CSNT) could be used within each field. We used a multilevel binary logistic regression approach (BLR) to avoid complete pooling of the data and ignoring within-field variation or using a limited number of observations within each field.

Multilevel (hierarchical or random effects) models are effective for modeling relationships between variables that are structured or nested in many groups or observed at different levels or scales (Gelman and Hill 2007; McMahon and Diez 2007). This type of analysis deals with various sources of variation at different scales. For multilevel regressions, model parameters (i.e., intercepts and slopes) can vary within each group for the lower level, and these regression parameters are modeled simultaneously with the model parameters for the higher level or hierarchy. The upper level model parameters, known as hyperparameters, are assigned a probability distribution or a probability model with some parameters (e.g., mean and standard deviation) that are directly related or connected to the parameters of regressions within groups of the lower level. Simply, the hyperparameters for the upper level regression are being modeled using the data at the lower level, and the hyperparameters control the parameters for the lower level regressions. The multilevel regression analysis is sometimes called partial pooling regression because it provides a compromise between complete pooling and no-pooling data analyses (Gelman and Hill 2007).

The general multilevel BLR in our analysis had two levels: within-field regression that modeled within-field variation, that is variation among individual sampling areas within a field; and field-level regression that modeled variation across all fields sampled in the state within a year. Parameters for the field-level model were estimated as averages of the parameters from the within-field models. Within-field variation was taken into account at the same time when estimating field-level (the average across all fields) regression coefficients, whereas the between-field variation was accounted for when estimating regression coefficients for within-field level models.

Because corn hybrids were not the same across all fields and some fields were flown on different dates, intercepts and slopes for within-field level models were set as random factors, which means that the intercepts and slopes varied by fields (figure 3). The two response categories used in the BLR were deficient and sufficient (a combination of marginal, optimal, and excessive categories of CSNT). The sufficient category was used as a reference category in BLR, meaning that the vertical axis indicated the probability to test in the sufficient category of N status.

Reflectance of individual bands and several vegetative indices (data not shown) were used as predictor variables in multilevel BLR. We used the Akaike Information Criteria to identify the best predictor variable in multilevel regressions, with smaller values for the statistics indicating the better predictors. A preliminary analysis showed that BLR with green reflectance as a predictor had a larger predictability of binary N status than regressions with red, blue, near-infrared reflectance, or other commonly used vegetation indices (data not shown). Thus, further results and discussions were focused on green reflectance of the corn canopy. Multilevel model parameters were estimated using the lme4 package (Bates and Maechler 2010) for the

Figure 3

An example of using multilevel binary logistic regressions (BLR) to calibrate green reflectance values of late-season digital aerial imagery (DAI) of the corn canopy to observed nitrogen (N) status, expressed as deficient and sufficient, within four of 683 cornfields evaluated in 2006. The field IDs of the four fields are (a) 2006AGRI01, (b) 2006BAND04, (c) 2006AGRI05, and (d) 2006NC069. The within-field level model, shown as solid lines, had intercepts and slopes that varied within fields because different corn hybrids were planted across the fields and some fields were flown on different dates. The field-level (statewide) model, shown as dash lines, indicates the average relationship across all fields within a year. The within-field level model predicted the relationship even as four observations within a field were tested in the same binary response category of corn N status because intercepts and slopes were random, meaning that the intercept and slope for each field represented a sample from a larger population of all potential reflectance values.
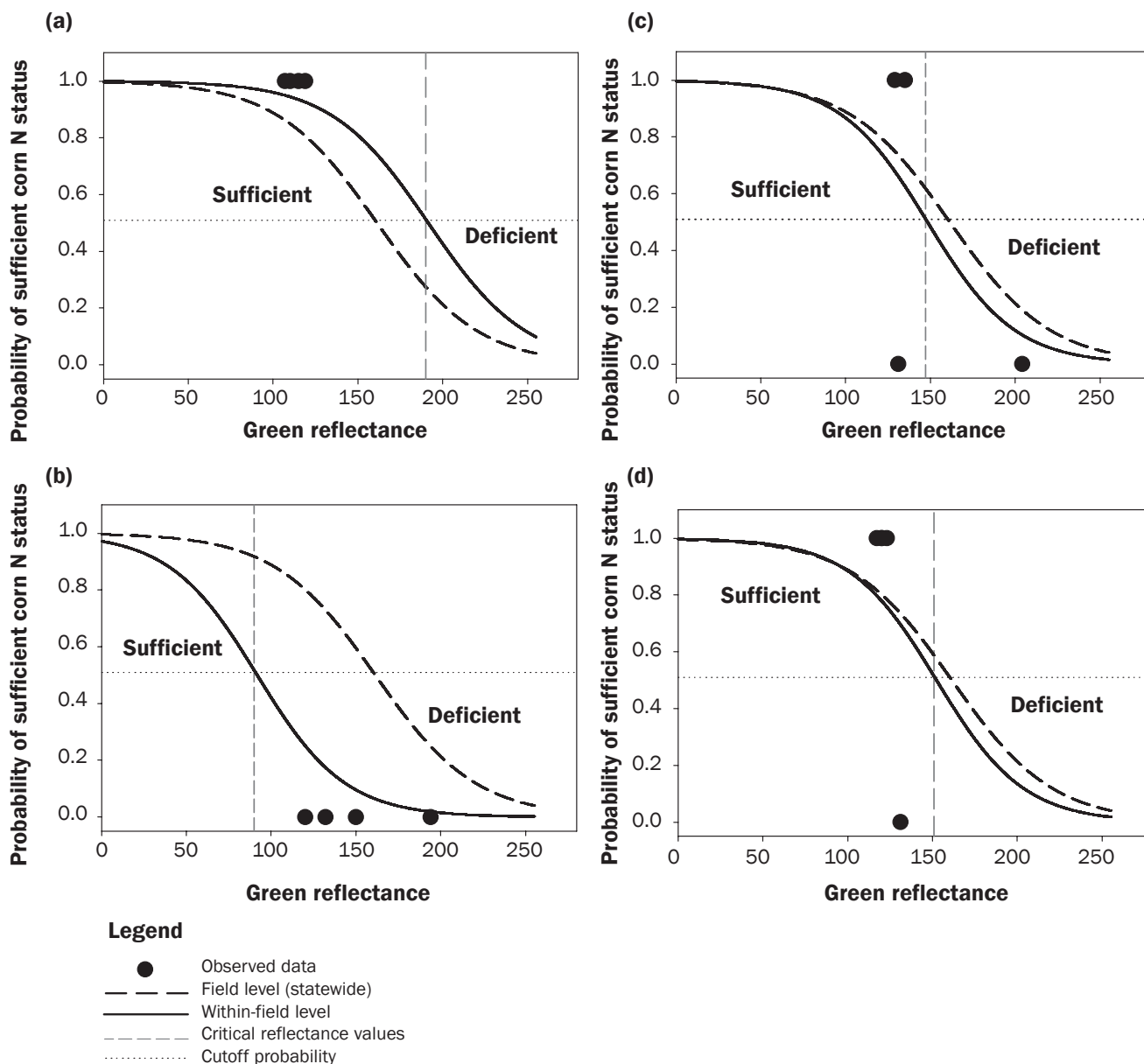
R Statistical Program (R Development Core Team 2004).

To correctly separate deficient samples from sufficient, we estimated critical green reflectance values by using the estimated intercept and slope values calculated for each field. A cutoff probability was set as 0.51.

Thus, stalk samples were predicted as deficient if the probability to test sufficient was <0.51 and as sufficient if the corresponding probability was >0.51 (figure 3). The agreement between the predicted and observed categories in the binary N status of corn was tested by calculating the percentage of cor-

rect prediction and the Cohen Kappa Index (Cohen 1960). The Cohen Kappa Index makes adjustments for randomness when checking the agreement between predicted and observed categories. We used the "concord" package of the R statistical software to

estimate Cohen Kappa Index values (Lemon and Fellows 2009).

To calculate percentage area that was predicted deficient or sufficient within each field, distributions of pixel count values for green reflectance were derived in ArcGIS software using the Tabulate Area and Table Select tools of Spatial Analysis. The critical green reflectance values estimated by multilevel BLR were used to classify the distributions of pixel count values into deficient and sufficient categories (figure 4). Fields were not used if they had more than one corn hybrid or other visual problems not related to N management or if they had several waterways, buffer strips or terraces that we could not mask in ArcGIS because of their complex spatial patterns within the fields. The same criteria were applied to fields that had several flooded or replanted areas. The percentage of fields not used was 17% in 2006, 43% in 2007, and 31% in 2008.

Multiple regression analysis was used to estimate the effect of several predictor variables on the percentage of deficient area within fields in each year. The predictor variables studied include N management category (a combination of the form and timing of fertilizer and manure applications), monthly average rainfall, cumulative spring or summer rainfall, total N rate applied, previous crop, field size (ha), and date of taking the DAI. Predictors that were not statistically significant at $p < 0.1$ level were dropped from the final regression model, except for the total N rate.

To determine whether the size of deficient area varied among major soil types within fields, pixel count distributions for the green band were extracted for each soil type in all fields sampled within the Des Moines Lobe Landform Area (figure 1). Critical reflectance values derived for each field (figure 3) were used to estimate the percentage of deficient and sufficient areas for each soil type within each field. Two hundred seventeen fields were analyzed for the 2006 data, 126 fields were analyzed for the 2007 data, and 185 fields were analyzed for the 2008 data. Only mean percent deficient areas for Clarion, Nicollet, Canisteo, Webster, and Okoboji soil types were summarized. These soil types were selected because they covered the majority of the area within the selected fields and because they represent the two most common soil associations (Clarion-Nicollet-Webster and Canisteo-Nicollet-Webster) for the central

Figure 4

An example of estimating the critical reflectance value for separating deficient and sufficient areas in corn nitrogen status. Percent deficient and percent sufficient areas were estimated based on the distribution of pixel counts of green reflectance of the corn canopy in each field. This is the same field as the one shown in figure 2.
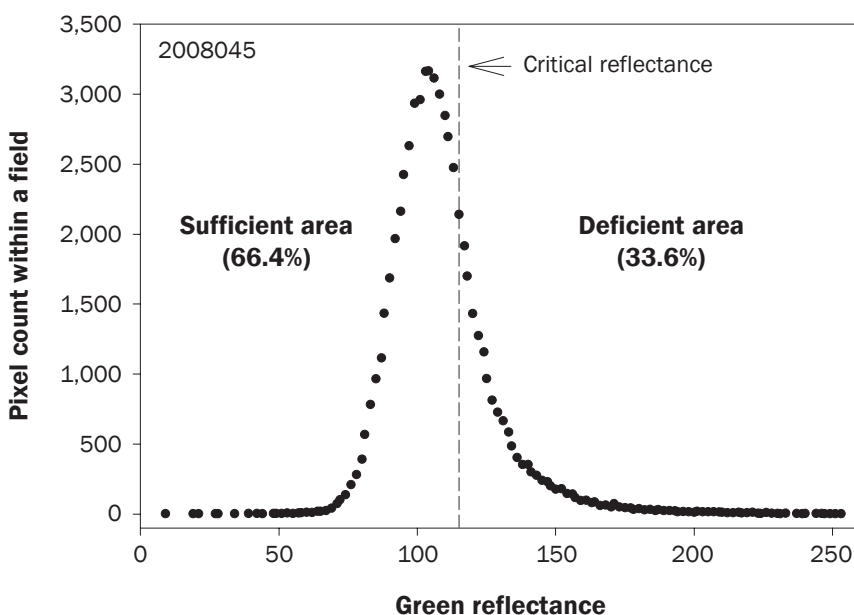
Iowa. An analysis of variance was performed to estimate the effect of the major soil types, the previous crop, and their interactions with the percent-deficient area in each year.

Spatially interpolated monthly average rainfall data (4 km [13,200 ft] grids) were downloaded from the Iowa Environmental Mesonet, Agronomy Department, Iowa State University (ISU 2009). Each field was assigned a rainfall value from the rainfall grid located nearest the field sampled. Digital soil maps (1:12000 the mapping scale) for each county were downloaded from the Iowa Cooperating Soil Survey (Iowa Cooperating Soil Survey 2003).

Results and Discussion

Relating Imagery to Corn Nitrogen Status. Figure 3 illustrates how multilevel BLRs were used to calibrate green reflectance of the corn canopy to observed deficient (shown as 0) and sufficient (shown as 1) categories of corn N status. Based on within-field model predictions, the solid lines show the probability of having sufficient N status as the green reflectance increased or as the corn canopy became more yellow or lighter in color on the imagery. The dashed line shows the field-level model, which predicts the weighted-average probability to test sufficient in N status across all fields within a year.

The intercept and slope for the field-level model were estimated as averages of intercept and slope values of the multilevel model applied for a sample of 683 fields evaluated in 2006. For the within-field level model, the intercept and slopes varied by fields to make adjustments for different hybrids planted and different dates and timing of taking DAI.

Only four fields of 565 are shown in figure 3 to illustrate two different situations when the observed N status was both deficient and sufficient (figures 3c and 3d) or either deficient or sufficient (figures 3a and 3b) within a field. Because multilevel regressions are based on partial pooling of data and because intercepts and slopes were set as random effects (i.e., they represented a sample from a larger population of all potential reflectance values of the corn canopy within fields), model parameters were estimated even if all four stalk samples collected within a field (figure 2) were tested in one of the two binary categories of N status (figure 3a and 3b).

The probability of being measured as sufficient decreased as green reflectance values increased (figure 3), suggesting that the lighter color on the imagery indicated corn N deficiency. The average slope values across all fields (the field-level model) within a year are shown in table 1. The average slopes were negative and were almost the same magni-

Table 1

Summaries of field-level (statewide) multilevel binary logistic regression (BLR) (averages across all fields within a year) predicting percentage area with deficient and sufficient corn N status using green canopy reflectance of late-season digital aerial imagery (DAI). The sufficient category was used as a reference in BLR, meaning that negative slopes indicate the lower probability of testing sufficient with an increase in the canopy reflectance or increase in yellow or lighter color on the imagery.

Year	Number of fields	Intercept (standard error)	Slope (standard error)	Total correct prediction (%)	Correct prediction of deficient N status (%)	Cohen Kappa Index
2006	683	5.43 (0.40)	−0.0340 (0.0032)	89	71	0.57
2007	824	5.95 (0.46)	−0.0591 (0.0039)	86	93	0.65
2008	828	3.74 (0.27)	−0.0372 (0.0023)	89	90	0.76

tude among all the years. For example, with one unit increase in green reflectance, the probability of being measured as sufficient decreased by 3% in 2006 and in 2008 and decreased by 6% in 2007. Estimated standard errors for the average slope values for the field-level models were about 10 to 15 times smaller than their corresponding slope estimates, indicating that the slopes had relatively narrow confidence intervals (data not shown), despite the fact that the fields varied greatly in the observed N status and corn canopy characteristics.

The multilevel BLR correctly predicted 89% of observations in 2006 and 2008 and predicted 86% of observations in 2007 (table 1). These estimates were about 20% to 25% higher than similar predictions using an ordinal BLR fit to the complete pooled data (i.e., ignoring differences within the fields) within a year (data not shown). This suggests that the multilevel BLR analysis had an advantage compared with the analysis based on complete pooling of data across all fields within a year. The relatively high predictability (>86% correct predictions) of the multilevel BLR (table 1) was confirmed also by the high Cohen Kappa Index values, which make adjustments for random chance in the agreement between the predicted and observed categories of binary corn N status.

Deficient and Sufficient Areas within Fields. The critical reflectance values that separated sufficient and deficient samples are shown as dashed lines in figure 3. Based on the within-field model, samples that had the predicted probability <0.51 were classified as deficient; those with the probability >0.51 were classified as sufficient. Because fields had stalk samples with different observed N statuses and different corn hybrids planted, the estimated critical reflectance ranges also varied greatly among fields and years. For example, a mean critical range for green reflectance for all fields was 155 with a coefficient of variation of 32% in 2006, 100 with a

coefficient of variation of 21% in 2007, and 109 with a coefficient of variation of 54% in 2008.

The estimated critical ranges were used to estimate the size (%) of predicted deficient and sufficient areas within fields using pixel counts of green reflectance of corn canopy. Pixel count distributions were derived for each field (figure 4). Some fields were not used in the analysis because they had more than one corn hybrid, had many waterways, buffer strips, or flooded areas, or had visually identified management problems that were not related to N. The area on the left from the critical range (darker green color on the imagery) was considered sufficient; the area on the right from the critical range (lighter green color on the imagery) was considered deficient. For example, the field with ID 2008045 shown in figure 2 had 34% of the total area predicted as deficient and 66% of the total area predicted as sufficient (figure 4).

Because farmers commonly estimate their optimal N rates based on various field-average GNFR systems, the percent-deficient area within a field may indicate (1) underapplication of N fertilizer or animal manure, (2) application errors (e.g., fertilizer skips), (3) nonuniformity of fertilizer and manure applications, (4) variable N losses due to leaching and denitrification, and (5) other factors that reduce N availability within fields.

A summary of the percentage area predicted as deficient within fields is shown as a box plot for each year (figure 5). The differences among the years are striking. Based on medians, about 60% of the total area was predicted deficient in 2008, about 50% in 2007, but only about 1% in 2006. A partial reason for these large differences could be in the different amounts of rainfall received in each year. For example, in 2006, the average monthly rainfall in May, June, and July was about 50% less than the long-term monthly average rainfalls during those three months across the state (figure 6). In contrast, in 2008,

the average monthly rainfall was above normal in April, May, June, and July. Specifically, fields evaluated in 2008 received about twice as much rainfall in June, compared with the long-term average June rainfall. As a result, many cornfields across the state had saturated soils or had standing water for several days or weeks in June and July of 2008. In 2007, rainfall in May and August was also above the 30 y average. Thus, the large percentage of N-deficient areas within the fields could be partially explained by N losses due to leaching and denitrification in relatively wet 2007 and extremely wet 2008. As indicated by larger interquartile ranges for these two years, compared with that in 2006 (figure 5), the above-average early season rainfall in 2007 and 2008 also increased within-field variability in the percent-deficient area within fields.

The mean percent-deficient area for fields evaluated in 2006 was about 20% higher than the median percent-deficient area (figure 5). Although the median deficient area was almost 0%, some fields had relatively large areas (>80%) predicted as deficient in 2006. These large areas with N-deficient status within some fields could be due to (1) a poor fit of the multilevel BLR to the observed data, (2) problems with the DAI (e.g., the imagery was taken too late and corn plants might have begun senescence, which changed their canopy reflectance characteristics or there might be problems with the digital cameras used to acquire the imagery, (3) management problems not related to N (e.g., herbicide injury or drought stress) that were not identified in the preliminary visual exploratory analysis of DAI, or (4) factors related to N management or soil characteristics that decreased N availability or increased N losses within those fields.

Factors that Affected Percent-Deficient Area. To identify factors that affected the percent-deficient area within fields, we conducted a multiple regression analysis where predictor variables were (1) average monthly

Figure 5

Box plots summarizing percent-deficient area within 565 cornfields evaluated in 2006, 473 in 2007, and 573 in 2008. Fields were not used in the analysis if they had more than one corn hybrid planted, problems not related to N management, many water ways, buffer strips, or flooded areas. Whisker bars indicate 5th and 95th percentiles and boxes indicates 25th and 75th percentiles.
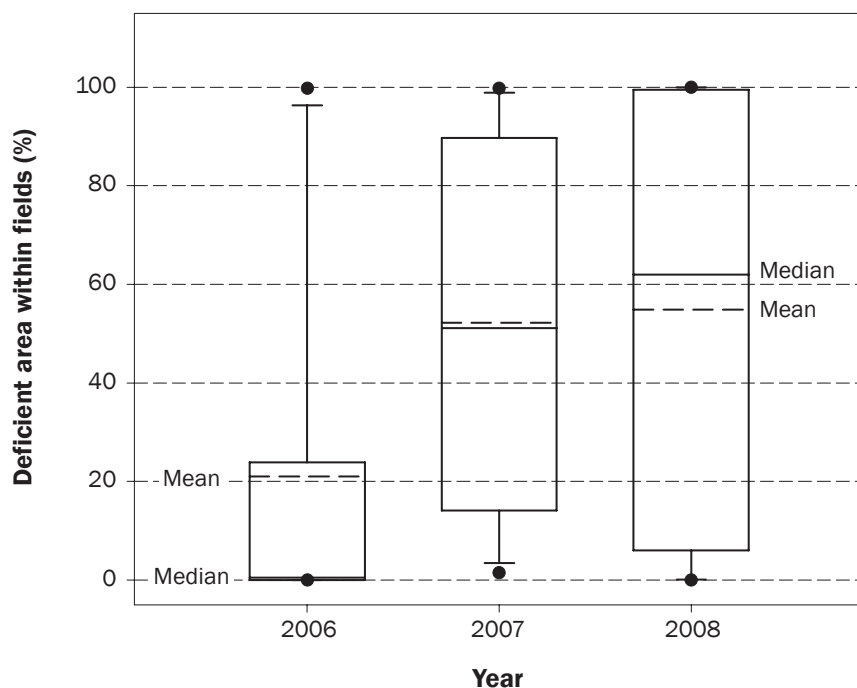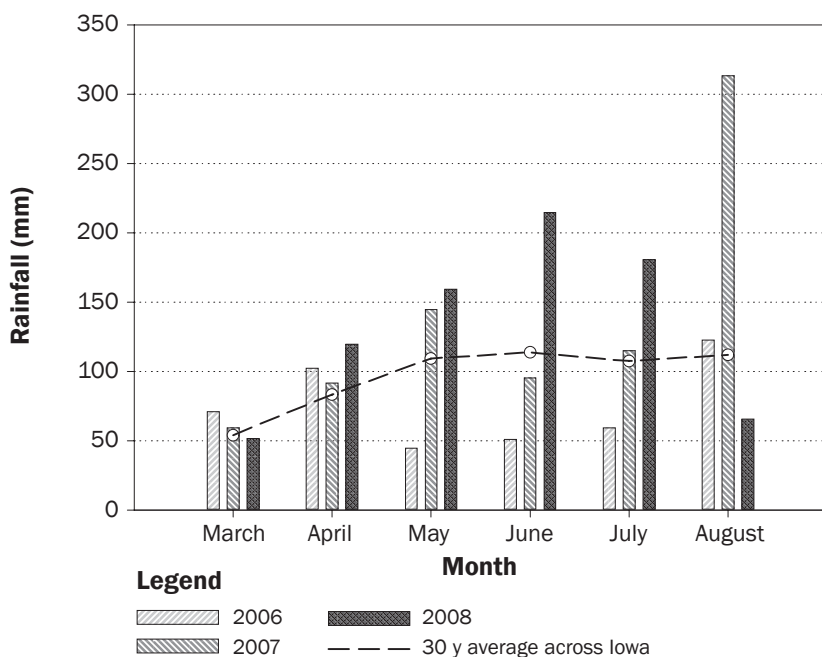

Figure 6

Monthly average rainfall for fields evaluated during three years and 30 y average monthly rainfall across Iowa.

rainfall or spring cumulative rainfall (cm), (2) field size (ha), (3) total N rates applied with commercial N and animal manure (kg N ha⁻¹), (4) date the DAI was taken (days after August 15), (5) the previous crop (corn or soybeans), and (6) the N management category. The N management categories were created by combining the major forms and timing of N fertilizer and manure applications. We used only those categories in the analysis that had >3% of fields from the total number of fields evaluated during each year. The N management categories were (1) AA Fall (fall-applied anhydrous ammonia), (2) AA Spring (spring-applied anhydrous ammonia), (3) Swine Fall (fall-injected swine manure), (4) UAN SD (sidedress UAN), and (5) UAN Spring (spring-applied urea-ammonium nitrate solution).

Parameters for the best multiple regression model for each year are summarized in table 2. The best regression model for the the 2006 data explained 8% of the total variation in predicted percent-deficient area. Date of taking the imagery, field size, the previous crop, and interaction between N management category and the previous crop were not statistically significant, but N management category, total N rate applied, and rainfall in June had statistically significant effects ($p < 0.1$). While all other factors were held constant, each additional 1 cm (0.39 in) of rainfall in June increased the percent-deficient area by about 1.5%, and each additional 10 kg N ha⁻¹ (9 lb N ac⁻¹) applied with commercial N and liquid swine manure decreased percent-deficient area by 1.6%.

Comparisons between N management categories for the 2006 data are shown in figure 7a. Because the effect of the previous crop and an interaction between N management category and previous crop were not statistically significant, corn-after-corn and corn-after-soybean fields were combined in one group to compare the N management categories. Fields receiving AA Fall and AA Spring, as one group, had a statistically significant ($p < 0.1$) lower percent-deficient area than fields receiving Swine Fall, UAN SD, and USN Spring, as the other group. The sidedress applications of UAN had the largest percent-deficient area. This can be partially explained by the unusual dry conditions in May and June during sidedress UAN applications (figure 6). It is likely that N sidedressed as UAN in 2006 was unavailable for plant uptake or that it was partially immobilized

by crop residues, especially in fields planted to corn after corn (figure 7a). These observations partially explained why some fields had a relatively large percent-deficient area in relatively dry 2006 (figure 5).
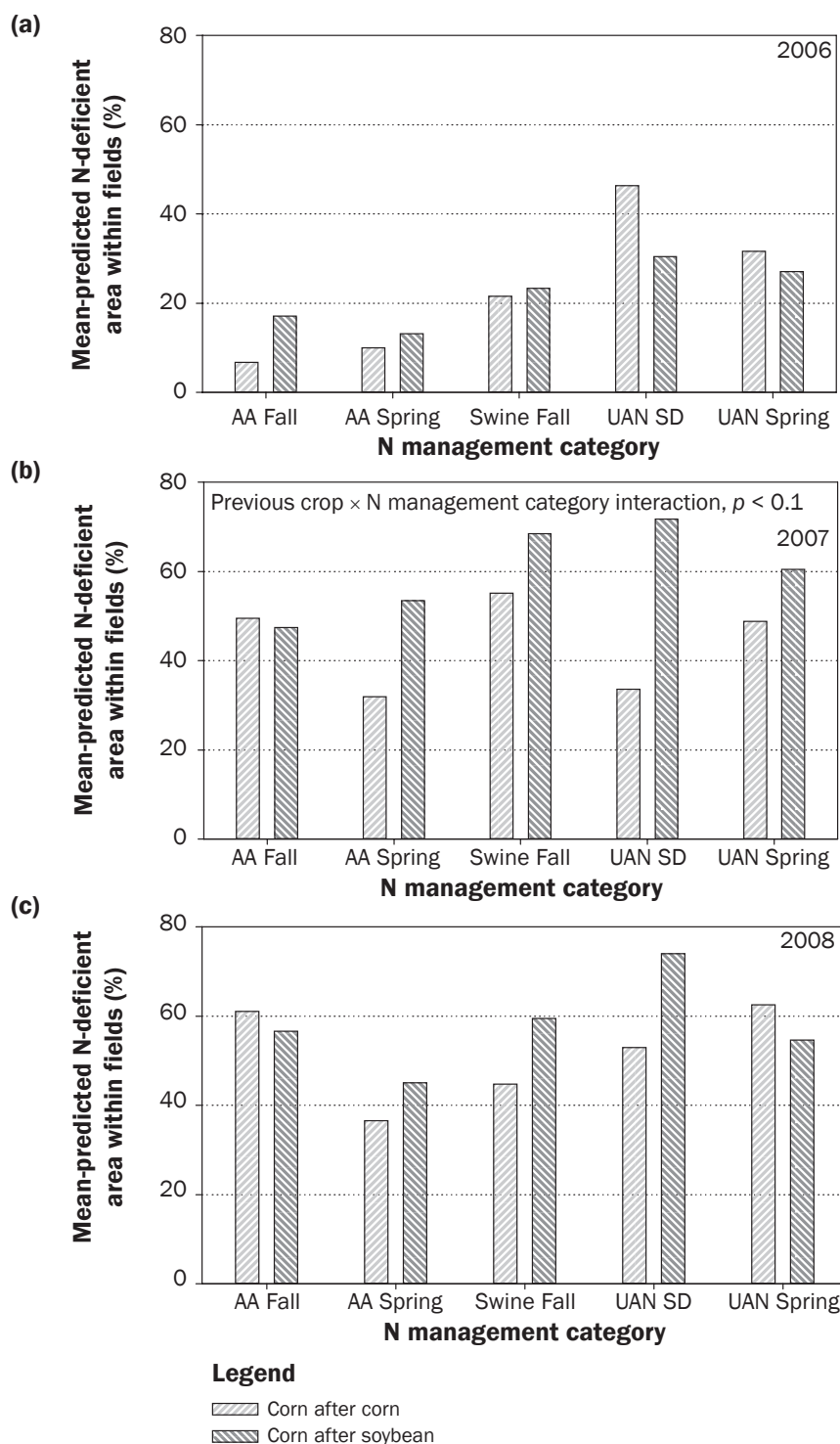
The best multiple regression model for the 2007 data explained 13% of the total variation in the size of deficient area. Only effects of N management category, previous crop, and their interactions were statistically significant. The effect of total N rate was negative, and the effect of May rainfall was positive, suggesting that N losses also increased with more rainfall in May.

Comparisons between N management categories for the 2007 data are shown in figure 7b. For all N management categories, except AA Fall, corn after corn had a smaller percentage of deficient area than corn after soybean. For corn after soybean, AA Fall and AA Spring (as one group) had a statistically significant ($p < 0.1$) smaller percent-deficient area than Swine Fall, UAN SD, and UAN Spring (as the other group). These differences among the categories can be partially explained by differences in N losses attributed to different N forms and to different timing of the nitrogen application. Fields that received UAN SD had the largest percent-deficient area. This finding is not surprising because UAN has 25% nitrate–nitrogen, which can be leached with heavy rainfalls immediately after UAN applications.

It is important to note, however, that the average total N rates applied with the commercial N sources and with liquid swine manure among the N management categories were different in 2007. For example, fields with UAN sidedress and UAN Spring applications received, on average, 140 to 150 kg N ha^{-1} (125 to 134 lb N ac^{-1}), which was approximately 10 kg N ha^{-1} (9 lb N ac^{-1}) less than those with AA Spring applications. The Swine Fall and AA Fall categories received, on average, about 200 kg of total N ha^{-1} (179 lb ac^{-1}) for corn after soybean. Despite the higher N rates applied, injected swine manure applications had the largest percent-deficient area. The last finding can be explained by potentially large N losses within fields that received liquid swine manure and the uncertainty in N availability from the organic fraction of the manure (Balkcom et al. 2009; Hansen et al. 2004). These data suggest the need for large-scale studies to evaluate N availability from swine manure in the Midwest. Such studies are

Figure 7

Mean percentage area predicted as deficient in corn nitrogen (N) status within fields for five N management categories (a combination of forms and timing of N fertilizer and animal manure applications) in (a) 2006, (b) 2007, and (c) 2008. Only management categories that had >3% of samples from the total number of samples were used in the analysis.

(a)

(b)

Previous crop × N management category interaction, $p < 0.1$

(c)

Legend
Corn after corn
Corn after soybean

Notes: AA Fall = fall-applied anhydrous ammonia. AA Spring = spring-applied anhydrous ammonia). Swine Fall = fall-injected liquid swine manure. UAN SD = sidedress urea-ammonium nitrate solution. UAN Spring = spring-applied, preplant UAN.

Table 2
Summaries of the best multiple regression models for identifying factors affecting percent-deficient area within 565 fields evaluated in 2006, within 473 fields in 2007, and within 573 fields in 2008.

Predictor variable	Slope (% unit^{-1})	Probability of significance based on *F* test	Multiple coefficient of determination (r^2)
2006			
N management category*		0.002	0.08
Total N rate (kg N ha^{-1})	–0.16	0.001	
June rainfall (cm)	1.5	0.02	
2007			
N management category		0.001	0.13
Previous crop		0.01	
N management category × previous crop		0.07	
Total N rate (kg N ha^{-1})	–0.11	0.08	
May rainfall (cm)	1.3	0.004	
2008			
N management category		0.004	0.07
Total N rate (kg N ha^{-1})	–0.05	0.25	
Cumulative March through June rainfall (cm)	0.6	0.0001	

Note: N = nitrogen.

* A combination of N form and timing of application.

needed because states in the Midwest use different values for the percent of total N available to corn in the first year after swine manure is injected in the soil.

For corn after corn in 2007 (figure 7b), fields that received Swine Fall and AA Fall had the largest percent-deficient area. Both of these N management categories had the largest average amount of N applied (data not shown). This suggests that substantial N losses occurred within fields that received AA Fall and Swine Fall applications in 2007. Sidedress UAN applications had a much smaller percent-deficient area for corn after corn than for corn after soybean in 2007 (figure 7b), but the number of fields with UAN SD for corn after corn was relatively small (data not shown).

The best multiple regression model for 2008 data explained 7% of the total variation in percentage of deficient area within fields (table 2). Only the effects of the N management category and cumulative rainfall from March through June were statistically significant. Similar to the data observed in 2006 and 2007, early-season rainfall increased percent-deficient area, but the slope for rainfall (percentage increase in deficient area per cm of rain received) was about two times smaller in 2008 than the slopes in 2006 and 2007. The effect of the total N application rate was not statistically significant, but this potential predictor was kept in the final regression model.

Neither the effect of the previous crop nor the interaction between the N management category and the previous crop was statistically significant in 2008 (figure 7c). Across both corn after corn and corn after soybean, fields with AA Spring had the lowest percentage of deficient area. Similar to 2007, the largest percent-deficient areas in 2008 were for UAN SD, UAN Spring, and AA Fall, which suggests the possibility of substantial N losses within fields in those N management categories. On average, AA Spring had only about 10 to 20 kg N ha^{-1} (9 to 18 lb N ac^{-1}) more N applied than fields receiving UAN SD and UAN Spring and only about 10 kg N ha^{-1} (9 lb N ac^{-1}) less N than AA Fall. However, the fields receiving AA Spring had about 30 to 50 kg N ha^{-1} (27 to 45 lb N ac^{-1}) less N than fields receiving Swine Fall applications (data not shown).

The data presented in table 2 suggest that a large percentage of the total variation in percent-deficient area was not explained by the predictor variables used in the multiple regressions. This could be because our analyses did not include soil characteristics observed within fields sampled across the state. In the future studies, it would be desirable to evaluate the potential effects of soil drainage class, soil organic matter level, or field topography on spatial variability on predicted categorical N status within all fields across the state. The relatively low observed r^2 values in table 2 could also be due to a small number of observations used for calibrating DAI to the binary corn N status within each field. However, the low predictability of the multiple regressions

did not diminish the finding that N fertilizer forms and timing of application along with early-season rainfall were the most important factors when quantifying the size of deficient area within fields.

The date of taking the DAI and field size did not have statistically significant effects on percent-deficient area in each year (table 2). The first observation is important because it suggests that the time for taking the imagery is less critical and is relatively flexible as long as DAI is acquired before plants start senescence and before the corn canopy reflectance characteristics begin to change. The relatively similar slopes for the statewide multilevel models (table 1) also suggest that other sources of DAI imagery (Iowa and some other states provide DAI for free) may be used for guiding CSNT sampling and calibrating the imagery for stalk test results, but future studies are needed for exploring this possibility.

Deficient Area for Major Soil Types within the Des Moines Lobe. Among eight landform areas, the Des Moines Lobe (north central Iowa) had the largest number of cornfields sampled in each year (figure 1). Percent-deficient area was estimated for each soil type within each field, but comparisons were completed only among five major soil types (figure 8). These major soil types create a common toposequence with well-drained Clarion soils located at the summit, somewhat poorly drained Nicollet soils located at the shoulder, poorly drained calcareous

Figure 8

Mean percentage area predicted as deficient in corn N status for five major soil types within (a) 217 fields sampled in 2006, (b) 126 fields in 2007, and (c) 185 fields in 2008 for the Des Moines Landform Area. Clarion soils are well drained, Nicollet soils are somewhat poorly drained, Canisteo and Webster soils are poorly drained, and Okoboji soils are very poorly drained. Differences among the soil types were not statistically significant at $p < 0.1$ in each year.
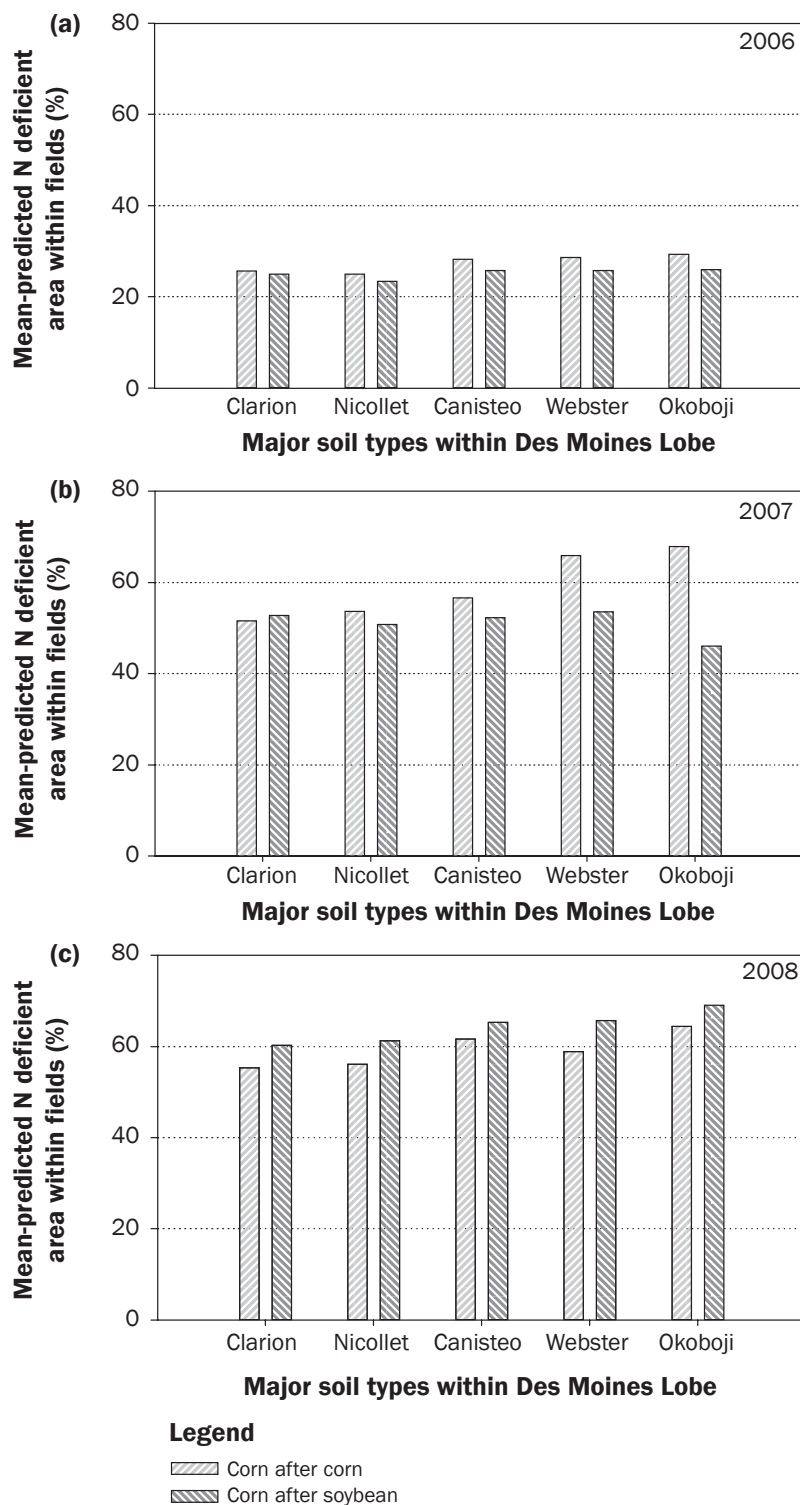
Canisteo soils and poorly drained Webster soils located at the backslope, and with very poorly drained high organic matter Okoboji soils located at the footslope.

Means for estimated percent-deficient area for Clarion, Nicollet, Canisteo, Webster, and Okoboji soil types for the two previous crops (corn after corn and corn after soybean) are shown in figure 8. The effects of soil types and the previous crops and their interactions were not statistically significant at $p < 0.1$. However, percent-deficient area within Webster and Okoboji soils, which are located in areas of lower topography, was about 10% to 15% higher than percent-deficient area for Clarion, Nicollet, Canisteo soils, which are located in areas of higher topography (figure 8b). For the 2008 data (figure 8c), the size of deficient area also slightly increased as elevation and slope within the fields decreased. These observations may indicate that larger N losses occurred in lower topography areas in relatively wet 2007 and excessively wet 2008.

The data shown in figure 8 also illustrate that spatial variability observed on DAI of the corn canopy is often too complex to be adequately classified by information from the digital soil maps. For example, three major soil types for field 2008045 shown in figure 2 had the following percent-deficient area: Clarion had 34%, Nicollet had 38%, and Webster had 32%, but the large difference in soil drainage among these soils indicates that there should be a larger difference in the size of N-deficient area. Because of the complexity of N losses within fields, the approach described here of utilizing low cost, uncalibrated DAI together with measuring the N status by using the CSNT as feedback about the effectiveness of N management has a great potential to improve site-specific N management and to make both economic and environmental improvements.

Summary and Conclusions

About 30 groups of farmers, lead by local agronomists and crop consultants, utilized late-season DAI of the corn canopy and CSNT for evaluating common N management practices within >600 cornfields sampled across Iowa during a three-year period between 2006 and 2008. This type of on-farm evaluation, called adaptive management, differs from the traditional controlled small-plot N studies because farmers and agronomists participating voluntarily identify the critical management problems for evalu-

ations, and the evaluations are completed by the participants. The advantage of such evaluations is that farmers can use their normal application equipment and their common N fertilizer practices, including forms and timing of applications. Also, the results and feedback from these evaluations can be used to develop more accurate site-specific N fertilizer recommendations for fields evaluated and for similar management categories across the state. These site-specific recommendations are based not only on the feedback information from the DAI and CSNT results but also on the farmers' knowledge of previous field history, soil properties, and rainfall patterns.

We developed and tested a methodology for calibrating DAI to a binary N status of corn, expressed as deficient and sufficient (a combination of marginal, optimal, and excessive categories of CSNT) and for estimating the percent of area that is deficient in N within each field based on green reflectance of the corn canopy. Also, we identified major factors that influenced the percent-deficient area within fields evaluated each year. A relatively small effect was found for the total N rate applied with commercial fertilizer or liquid swine manure. A small effect was also found for the previous crop. The field size and timing of taking the imagery did not have statistically significant effects on the percent-deficient area. The largest effects on percent-deficient area had a variable that described N management practice (a combination of N form and timing of application) and early season rainfall (May, June, or cumulative from March through June). During each year, fields receiving AA Spring had a smaller percent-deficient area than fields receiving Swine Fall, UAN Spring, or UAN SD, even if AA Spring received, on average, lower N rates than Swine Fall.

Our image calibration methodology and discussions were mainly focused on the percent-deficient area within fields because DAI works the best when identifying N deficiencies and because one of the four sampling areas was intentionally selected within a target-deficient area within each field. Although estimating the size of the area with excessive N status would also have practical significance when evaluating N management practices, percent-deficient area is especially important because it is usually attributed to (1) underapplication of N, (2) application errors (fertilizer skips), (3) nonuniformity of application, (4) variable N losses (leach-ing and denitrification), or (5) other factors that limit N availability within fields. Future evaluation methodology should be focused more on predicting excessive corn N status and factors that contribute to persistently excessive N applications within fields.

Acknowledgements

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