Remote sensing for nitrogen management

P.C. Scharf, J.P. Schmidt, N.R. Kitchen, K.A. Sudduth, S.Y. Hong, J.A. Lory, and J.G. Davis

ABSTRACT: Nitrogen application often dramatically increases crop yields, but N needs vary spatially across fields and landscapes. Remote sensing collects spatially dense information that may contribute to, or provide feedback about, N management decisions. There is potential to accurately predict N fertilizer need at each point in the field. This would reduce surplus N in the crop production system without reducing crop yield, which would in turn reduce N losses to surface and ground waters. Soil spectral properties (color) are related to soil organic matter and soil moisture levels, factors that influence the N-supplying ability of the soil. Plant spectral properties reflect crop N status and soil N availability, and they can be useful for directing in-season variable-rate N applications. Plant color may also be useful for assessing the adequacy of crop nitrogen supply achieved with a given nitrogen management practice. We outline the current status of these approaches, offer examples, discuss several N management contexts in which these approaches might be used, and consider possible future directions for this technology.

Keywords: Aerial, imagery, nitrogen, satellite, soil organic matter, spectral, variable-rate

Current nitrogen management practices for most crops consist of a single application of a uniform rate of N fertilizer over whole fields and, frequently, whole farms. These practices contrast sharply with a substantial and growing body of research that shows that optimum N rate can vary quite widely from field to field (Scharf et al. 1993; Schmitt and Randall 1994; Bundy and Andraski 1995), as well as from place to place within a single field (Malzer et al. 1996; Blackmer and White 1998; Harrington et al. 1997; Schmidt et al., in press). Three of four fields studied by Malzer et al. (1996) had optimum N rates ranging from 0 to 200 kg N ha^{-1} (0 to 180 lb N ac^{-1}). Harrington et al. (1997) found that optimum N rate varied by 94 kg N ha^{-1} (84 lb N ac^{-1}) within a single field in Illinois, and optimum N rate varied by 225 kg N ha^{-1} (200 lb N ac^{-1}) in a Missouri experiment presented later in this paper. However, Bundy (2002) found little variability in optimum N rate in six corn fields in Wisconsin. A better understanding of where and when large spatial variations in optimum N rate occur will help define when remote sensing might contribute to improved N management.

Both soil N supply and crop N demand can vary spatially. Considerable research shows only a weak relationship between optimum N rate and corn yield (Vanotti and Bundy 1994; Scharf 2001; Blackmer et al. 1992) (Figure 1). Because crop N demand is closely related to biomass and yield, this

Peter C. Scharf, John A. Lory, and **J. Glenn Davis** are with the University of Missouri in Columbia, Missouri. **John P. Schmidt** is with Kansas State University in Manhattan, Kansas. **Newell R. Kitchen** and **Kenneth A. Sudduth** are with the U.S. Department of Agriculture's Agricultural Research Service in Columbia, Missouri. **S. Young Hong** is with the National Institute of Agricultural Science and Technology in Suwon, Korea.

Figure 1

In 197 corn N-rate experiments over four states, yield (and therefore, yield goal) was not a good predictor of optimum N fertilizer rate. Yield is a surrogate for N demand. The implication is that variability in optimum N rate is created more by variations in supply than in demand. We thank Bob Hoeft, Dick Fox, and Michael Schmitt for sharing their data with us.
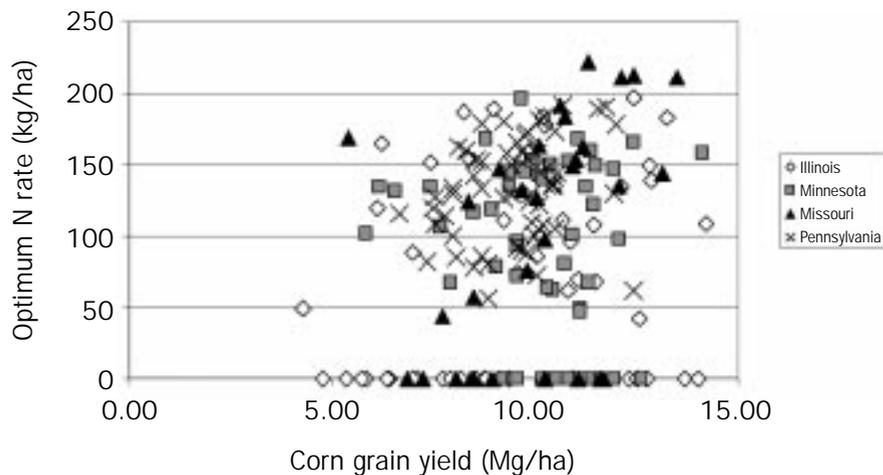
suggests that variability in optimum N fertilizer rate is controlled more by variability in soil N supply than by variability in crop N demand. Spatial variability in soil N supply may be caused by variability in soil organic N content, variability in the rate of release of organic N, and variability in N loss. All of these are controlled primarily by variability in soil water relations: drainage, hydraulic conductivity, landscape position, and water-flow paths and velocities. In semiarid regions, where N loss caused by leaching and denitrification is low, crop factors might play a larger role in controlling spatial variability in need for N fertilizer.

Recent technical advances have made spatially variable applications of nitrogen accessible to many crop producers. The main obstacles to adoption of spatially variable N management are the inconvenience, expense, and limited accuracy of currently available methods for predicting how much N to apply and where. One of the strengths of remote sensing is the ability to collect spatially dense information quickly over large areas, thus creating the potential to supply information about spatial variability of N need that is cheaper and more convenient than currently used sources. A considerable research effort is under way to learn how to translate remotely sensed information into accurate N-rate recommendations.

Predicting N Fertilizer Need with Remote Sensing

Remote sensing from aerial or satellite platforms has long been considered a promising source of information for land management decisions (Johannsen and Barney 1981). Several barriers have impeded the adoption of remote sensing for crop management decisions, including image availability, timeliness, spatial resolution, susceptibility to weather conditions, and limited knowledge of how to translate images into management decisions. As additional infrastructure is developed and new platforms become available, these barriers are slowly being reduced. In addition, progress is being made in understanding how to interpret images to make good management decisions.

Remote sensing of soil N supply to predict N fertilizer need. Soil organic matter (or organic carbon) content and water content are generally the two soil properties most correlated to soil reflectance in bare soil images (Zheng and Schreier 1988). Soils with greater organic matter content or water content will have lower reflectance (Krishnan et al. 1980). Many fields have large variations in soil organic matter content and bare soil color (Figures 2 and 3).

Chen et al. (2000) developed an algorithm using reflectance from a remotely sensed color photograph to predict soil organic carbon. For 31 sample locations within the same field (samples not used in the development of their algorithm), predicted soil organic carbon was very similar to measured soil organic carbon (measured=0.9975[predicted]; r^2= 0.98). They used sophisticated techniques to filter images and segregate pixel values. Even with a simple approach, the relationship between relative radiance from a bare soil image and soil organic matter is quite distinct (Figure 3; r^2=0.47). Although remote sensing may be used to construct maps of predicted soil organic matter content with reasonable accuracy, we are far from having an equation that makes this prediction across a range of soil types and soil moisture levels. The utility of a soil organic matter map is based on the premise that N mineralization, and subsequently N availability to the growing crop, will be proportional to organic matter content. With spatially dense data obtained through remote sensing, a variable N application map that is a function of soil organic matter could then be developed.

This premise is sometimes borne out—soil nitrate levels are higher in areas with darker soil (Blackmer and White 1998; Walters et al. 1999), and economic response to N is greater in areas with lighter soil (White and Blackmer 2001). In other cases, yield response to N may not be consistently related to soil organic matter level or relative soil reflectance (Schmidt et al. 1999; Schmidt et al. 2002). There are several likely reasons for this inconsistency. At low soil organic matter levels, other soil factors may significantly influence reflectance (Baumgardner et al. 1970). Also, availability of N from soil of known organic matter content can vary widely because of other soil characteristics, such as water content, pH, and dissolved organic carbon. These properties have a significant impact on N cycle processes including mineralization, immobilization, denitrification, and leaching. A particular concern is that areas in a field with the highest organic matter content and potentially mineralizable N may also be the wettest areas, with the greatest potential for N loss via denitrification and/or leaching. In wet years, these areas may have lower N-supplying capacity than other parts of the field, and in drier years, they may have greater N-supplying capacity. Year-to-year weather variability will be an obstacle in developing reliable N application maps based on soil organic matter content.

Remote sensing of crop N status to predict N fertilizer need. A considerable research effort has been devoted to detecting crop N stress using remote sensing. This includes a

Figure 2

Bare-soil aerial photograph of a Kansas field with large variations in soil reflectance and soil organic matter content. Organic matter in this field varies from 7 to 33 g kg^{-1}. Darker areas are higher in organic matter. These areas may release more organic N to crops and require less fertilizer N, but research results to date have revealed inconsistencies that need to be resolved before this system could be widely used.
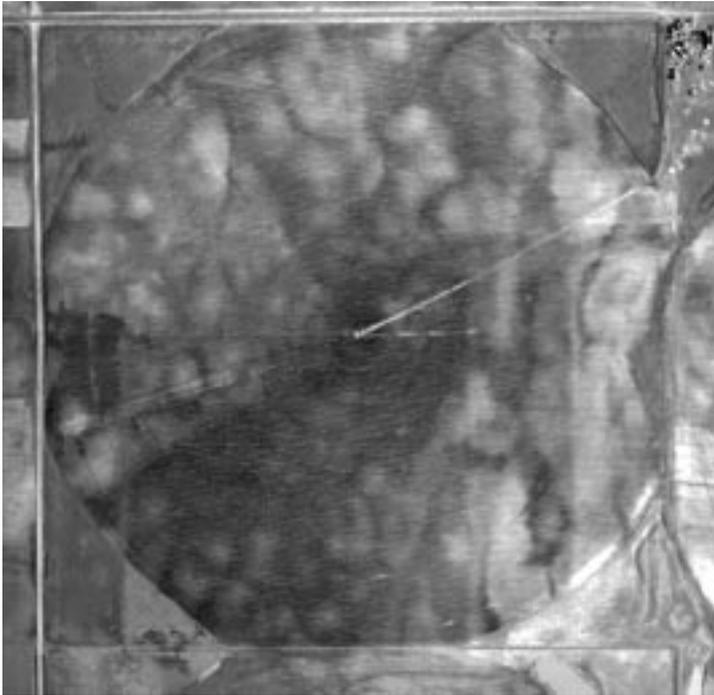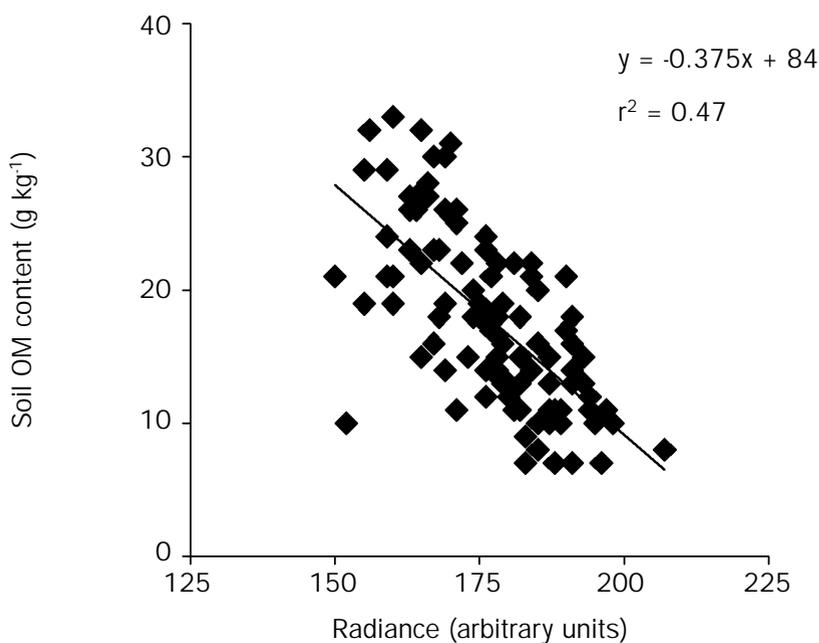
Figure 3

Radiance in the red band measured from the photograph in Figure 2 is predictive of soil organic matter content (n=103).

$$y = -0.375x + 84$$

$$r^2 = 0.47$$

substantial and promising body of work with ground-based sensors, but we will limit the scope of our discussion in this paper to the more traditional meaning of remote sensing: sensing from aerial or satellite platforms. In general, different levels of nitrogen stress can be easily detected in aerial images (Blackmer et al. 1996; Ashcroft et al. 1990; Beatty et al. 2000; Blackmer and White 1998). Nitrogen stress increases canopy reflectance over all visible wavelengths (Blackmer et al. 1996; Beatty et al. 2000) because of a shortage of chlorophyll and other light-absorbing pigments. Nitrogen stress may also decrease canopy reflectance in near-infrared wavelengths (Beatty et al. 2000; McMurtrey et al. 1994). Indexes combining information from visible and near-infrared regions may maximize sensitivity to N stress.

One obstacle to using remotely sensed data to make N management decisions is that many crops have not developed a full canopy at the time that in-season N management decisions are traditionally made. Soil reflectance is often greater than crop reflectance in visible wavelengths and can therefore interfere with remote estimates of crop reflectance. Several groups have begun to develop indexes that are sensitive to plant color in mixed soil-plant scenes (Daughtry et al. 2000; Gitelson et al. 1996; Baret and Fourty 1997; Clarke et al. 2000).

Only recently have attempts been made to develop and evaluate decision algorithms for N management based on remote sensing. Scharf and Lory (2002) have developed a decision algorithm for sidedressing corn based on aerial photographs. This algorithm is based on green light intensity from unfertilized corn relative to well-fertilized corn; the larger the difference in color, the more sidedress N is recommended for the previously unfertilized corn. An aerial view of corn at normal sidedressing time is more than half soil. In order to accurately measure crop spectral properties despite the large soil background, Scharf and Lory (2002) used very high-resolution images (pixel size 5cm or less) and discarded soil pixels from these images. This process greatly increased their ability to predict N need of the corn from measured spectral properties.

Scharf and colleagues at the University of Missouri have begun to evaluate the algorithm of Scharf and Lory (2002) in field-scale experiments, and have completed analysis for one experiment, which we present here. The

Figure 4

Predicting N need of corn in an experiment in southeastern Missouri in 2000. The top panel is an aerial photograph acquired at corn growth stage V8 (very late sidedress). Using the prediction algorithm developed by Scharf and Lory (in press) (graph to the left of the photograph), corn color information from the photograph was used to predict N fertilizer need for each 20 m section. Predictions are shown as grayscale rectangles for each 20 m section. Predicted N need was much higher in the eastern half of the experiment, where the difference in color between fertilized and unfertilized strips was large.

N rate predicted from photo
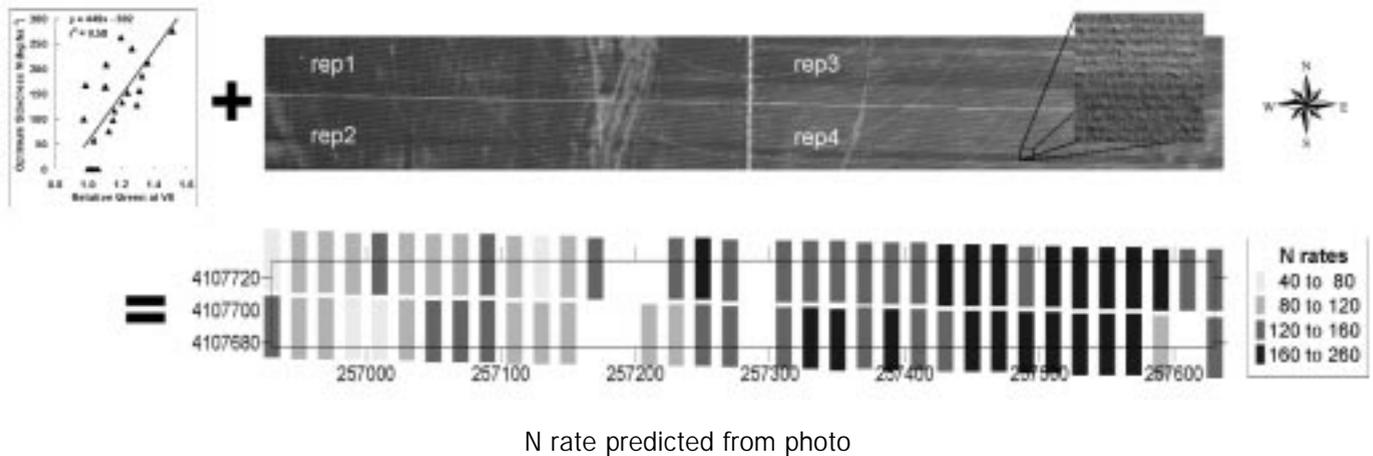
experiment was conducted in southeastern Missouri in 2000 on an alluvial soil. Soil cation exchange capacity ranged from 13 to 27 cmol kg[-1] (13 to 27 meq/100 g). Soybean was the previous crop. Treatments were N rates (0, 56, 112, 168, 224, 280 kg N ha[-1]) (equal to 0, 50, 100, 150, 200, 250 lb N ac[-1]) applied to plots 6 rows wide by 0.4 km (0.25 mi) in length. The experimental design was a randomized complete block with four replications. Corn grain was harvested from the center four rows of each plot using a combine instrumented with a grain yield monitor and global positioning system.

Data was analyzed primarily at a spatial scale considerably smaller than replications. Replications were divided into sections 20 m (65 ft) long, and both yield data and aerial photo data were analyzed separately for each individual 20 m section. The experiment included 65 of these sections.

The aerial photograph in Figure 4 was acquired at corn growth stage V8 (Ritchie et al. 1993). This photograph, while covering an area 0.8 km long, has very fine resolution with a pixel size of 5 cm (2 inches). Individual rows and plants can be clearly seen in the detail view shown in Figure 4. Soil pixels were discarded from the image, and an empirical algorithm analogous to that developed by Scharf and Lory (2002) but specific to growth stage V8 (shown on the left side of Figure 4) was applied to the remaining plant pixels to produce N-rate recommendations. This algorithm is based on the ratio between green-

light radiance from unfertilized strips relative to green radiance from well-fertilized strips. The larger the difference in radiance, the greater the presumed N stress and the higher the N rate recommended. Spatial units were the 20 m (66 ft) sections described above. A class map of the N rates predicted using the aerial photograph is shown at the bottom of Figure 4. Each gray rectangle represents one 20 m (66 ft) section, and the shade of gray indicates the N rate predicted from the aerial photograph for that section. The most noticeable feature of the predicted N rates is that they are much lower in the western half of the field than in the eastern half.

We were able to evaluate the N rates predicted from the aerial photo by comparing them with actual optimum N rates determined by yield response to a range of applied N rates. Each 20 m (66 ft) section contained N-rate treatments ranging from 0 to 280 kg N ha[-1] (0 to 250 lb N ac[-1]), and we measured the corn yield produced by each N rate. Yield response to N rate was described in each section using a quadratic-plateau function. Two examples are shown in the top of Figure 5, and similar functions were produced for all 65 of the 20 m (66 ft) sections in the experiment. Economically optimum N fertilizer rate was then calculated from these yield response functions for each 20 m (66 ft) section. The spatial distribution of optimum N fertilizer rate is shown in Figure 5. Each gray rectangle represents one 20 m (66 ft) section, and the shade of gray indicates the optimum

N fertilizer rate. Sections containing the pivot road and the drainage channel seen in the aerial photograph in Figure 4 are omitted from the analysis.

Optimum N rates varied widely in this experiment and were fairly evenly distributed between 55 and 220 kg N ha[-1] (50 and 200 lb N ac[-1]) with a few higher values (Figure 5). This variation was not due to variability in yield. Yield variability was much smaller, and yields were highest at the west end of the experiment, where optimum N rates were lowest. Neither was variability in optimum N rate attributable to variability in soil mineral N content. Soil samples were taken both pre-plant and sidedress for four main zones. Preplant mineral N to 60 cm (2 ft) depth was 78, 60, 50, and 50 kg N ha[-1] (70, 54, 54, and 45 lb N ac[-1]) for the four zones in order from west to east. Presidedress nitrate to 30 cm (1 ft) depth was 10, 8, 5, and 5 mg N kg[-1] soil (10, 8, 5, and 5 ppm) for the four zones in order from west to east. Although soil mineral N was highest at the west end of the field where optimum N rates were lowest, normal interpretation of these test values would suggest only small differences in N rates recommended from one end of the field to the other.

The wide range of optimum N rates observed suggests that variable-rate application of N would have been appropriate for this field. Nitrogen fertilizer rates predicted from the aerial photo are juxtaposed with actual optimum N rates in Figure 5 for com-

Evaluating the quality of the N-rate recommendations shown in Figure 4. N-rate strips from 0 to 280 kg N ha⁻¹ (0 to 250 lb N ac⁻¹) were applied east to west in this experiment. Yields were collected with a yield-monitor-equipped combine, and yield response to N rate was analyzed for sections 20 m long by one replication wide. Example yield response graphs are shown for two 20 m sections, with an arrow indicating the section corresponding to the graph. Similar graphs were constructed for the other 63 sections, and economically optimum N rates were calculated for each section from these response functions. Actual optimum N rates calculated in this way are coded by color. Optimum N rate was generally less than 120 kg N ha⁻¹ (110 lb N ac⁻¹) in the western half of the experiment and more than 120 kg N ha⁻¹ in the eastern half of the experiment. N rates predicted from the aerial photo also followed this pattern. Sections containing the pivot road and the drainage channel seen in the aerial photograph in Figure 4 are omitted from the analysis.

Optimum N rate from yield response data

N rate predicted from photo
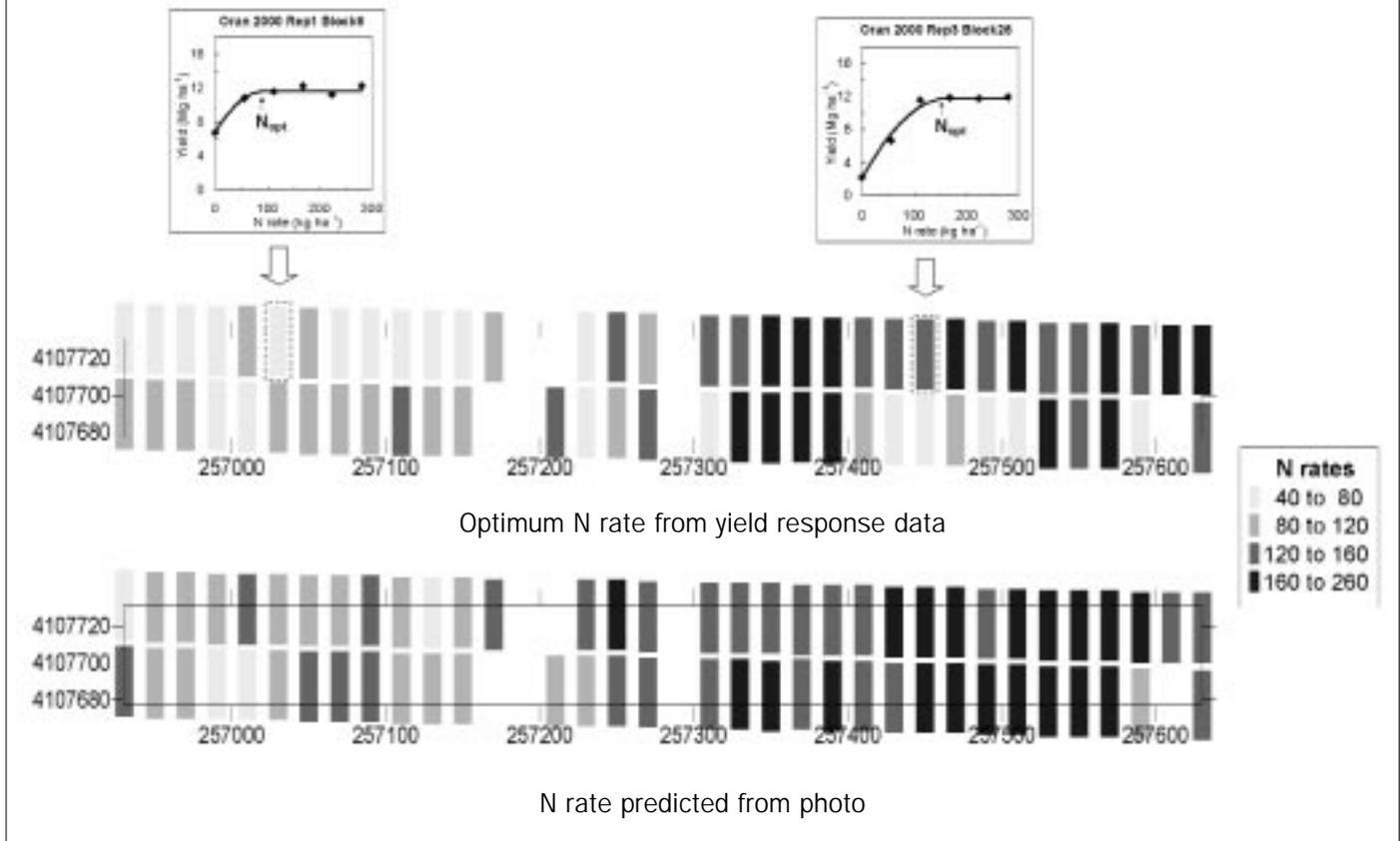
parison. Actual optimum N rates were much lower in the western half of the field, in rough agreement with the pattern of N need predicted from the aerial photo. While there are substantial differences between predicted N need and actual optimum N rate in many of the sections, N rates predicted from the aerial photo performed well economically and environmentally. Photo-predicted N rates were inserted into response equations (e.g. graphs in Figure 5) to derive the yields that would have been produced by these N rates. The average N rate predicted from the photo was very close to the average optimum N rate, but because of under-recommendation in a few areas, a small amount of yield would have been lost by following these predictions (Table 1). Average yield in the experimental area was 11.7 Mg ha⁻¹ (186 bu ac⁻¹). The current University of Missouri N-rate recommendation for this yield level would be 220 kg N ha⁻¹ (195 lb N ac⁻¹) for corn following soybean. The N rates predicted from the aerial photograph were on average 38% lower and resulted in only a 2% reduction in corn yield relative to current recommendations.

This example shows the potential for remote sensing to be used in directing variable-rate in-season N applications that match actual crop needs relatively well. It is only a single example and should be interpreted cautiously. This potential needs to be demonstrated over a range of environments before recommendations based on aerial images could be considered reliable. There do not yet appear to be any other published reports of variable-rate nitrogen recommendations based on aerial or satellite images that would help to evaluate the reliability of this approach. However, there are a number of reports of variable-rate N applications based on measurements of crop spectral properties with ground-based sensors (Bausch and Duke 1996; Stone et al. 1996; Heege and Reusch 1996). Even if N-rate recommendations based on aerial or satellite images are shown to be reliable, there are still many obstacles remaining and details to be worked out for wide-scale commercial application to a range of crops.

Remote Sensing of Crop N Status to Provide Feedback on N Management

Remote sensing is ideal as a feedback tool because of its ability to survey large areas quickly. This type of feedback might be useful when N rates are tightly managed or when in-season losses of N may have occurred. Currently, many producers use

Table 1. Comparison of N rates, yields, and returns for two N recommendation systems relative to optimum N rates for the experiment shown in Figures 4 and 5.

Recommendation system	Mean N rate	Mean yield	Grain value minus N cost
	kg N ha^{-1}	Mg ha^{-1}	$ ha^{-1}
Aerial photo	137 b	11.46 c	826 b
University of Missouri	220 a	11.71 a	783 c
Optimum	130 b	11.68 b	847 a

Values followed by different letters within a column are significantly different (p<0.001) according to a paired t test. N rates recommended by the aerial photo were not significantly different than optimum N rates (p=0.21).

generous N rates that minimize the chances that yield will be limited by N availability. If N rates are managed more tightly for economic or environmental reasons, the incidence of N deficiencies will increase. Detecting these deficiencies, preferably soon enough to respond with additional N applications, will help to minimize risk and make tight N management systems economically competitive. Manure as a nitrogen source has a considerably higher uncertainty and risk than fertilizer N, so feedback on N sufficiency may be particularly important in systems depending on manure N availability. When manure N is managed based on a mandatory nutrient management plan, remote sensing may help to evaluate whether the crop is receiving sufficient N under the management plan.

Advantages and Limitations of Remote Sensing for N Management

The main advantages of remote sensing for N management are the spatial detail of the information that is collected and the speed with which information can be collected and possibly assessed over large areas. The concept that N needs of crops often vary substantially across fields and landscapes is now fairly well-established, and remote sensing may be one of our best tools for understanding and responding to this spatial variability. The ability to cover large areas quickly makes remote sensing an ideal feedback tool for evaluating N management decisions made early in the season.

Limitations of remote sensing for N management include availability, timeliness, spatial resolution, susceptibility to weather conditions, and limited knowledge of how to translate images into management decisions. Currently, there are not enough satellite- or airplane-based sources of remote sensing data to make remote sensing information reliably available to producers. Competition for satellite imagery is keen, particularly for the new generation of higher-resolution satellites. Angle of image acquisition may be an issue with these satellites, as well. Older satellites may have spatial resolution that is too coarse to be effectively used in N management. The remote sensing industry is not accustomed to providing images acquired at specific times and delivered quickly (as would be the case for N management), and it is not currently structured to provide this type of service. Satellites may take too long between successive passes over a specific area to provide information for time-sensitive management decisions. If and when these obstacles are overcome, difficulties with weather will remain. Good images require nearly cloudless conditions, and even then atmospheric corrections can be complex.

Our limited knowledge of how to translate images into management decisions is still a severe limitation to the use of remote sensing for N management. The ability to detect N stress with remote sensing is well-documented in the scientific literature, but a considerable effort is still needed to develop management systems and decision algorithms that can be shown to be reliable enough to justify adoption by producers.

Summary and Conclusions
- Crop N needs are often spatially variable.
- Remote sensing provides spatially dense information that may help us understand and predict spatially variable crop N needs.
- Variable-rate N applications might be based on remote sensing of soil color or crop color.
- Sensing of crop color could provide feedback on the performance of N management decisions.
- Availability, spatial and temporal resolution, and interpretation of remotely sensed images are current limitations on the use of remote sensing for N management that may be overcome in the future.

- Weather will always be an obstacle in acquiring remotely sensed images in a timely manner for use in making N management decisions.

References Cited
Ashcroft, P.M., J.A. Catt, P.J. Curran, J. Munden, and R. Webster. 1990. The relation between reflected radiation and yield on the Broadbalk winter wheat experiment. International Journal of Remote Sensing 10:1821-1836.

Baret, F. and T. Fourty. 1997. Radiometric estimates of nitrogen status of leaves and canopies. Pp. 201-228. In: G. Lemaire (ed.) Diagnosis of the nitrogen status in crops. Springer-Verlag, Berlin.

Baumgardner, M.F., S.J. Kristof, C.J. Johannsen, and A.I. Zachary. 1970. Indiana Academy of Science Proceedings 79:413-422.

Bausch, W.C. and H.R. Duke. 1996. Remote sensing of plant nitrogen status in corn. Transactions of the ASAE 39:1869-1875.

Beatty, M.K., C.J. Johannsen, and K. Ross. 2000. *In situ* detection of leaf chlorophyll content and leaf nitrogen content in *Zea mays* L. with remote sensing. Agronomy Abstracts p. 281.

Blackmer, A.M., T.F. Morris, and G.D. Binford. 1992. Predicting N fertilizer needs for corn in humid regions: Advances in Iowa. In: B.R. Bock and K.R. Kelley (eds.). Predicting N fertilizer needs for corn in humid regions. Bulletin Y-226. National Fertilizer and Environmental Research Center, Tennessee Valley Authority, Muscle Shoals, AL.

Blackmer, T.M., J.S. Schepers, G.E. Varvel, and G.E. Meyer. 1996. Analysis of aerial photography for nitrogen stress within corn fields. Agronomy Journal 88:729-733.

Blackmer, A.M. and S.E. White. 1998. Using precision farming technologies to improve management of soil and fertilizer nitrogen. Australian Journal of Agricultural Research 49:555-564.

Bundy, L.G. 2002. Approaches for implementing variable rate N applications. Proceedings Wisconsin Fertilizer, Aglime, & Pest Management Conference 41:52-54. University of Wisconsin Extension, Madison, WI.

Bundy, L.G. and T.W. Andraski. 1995. Soil yield potential effects on performance of soil nitrate tests. Journal of Production Agriculture 8:561-568.

Chen, F., D.E. Kissel, L.T. West, and W. Adkins. 2000. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Science Society of America Journal 64:746-753.

Clarke, T.R., E.M. Barnes, P.J. Pinter, Jr., B.A. Kimball, J.A. Haberland, E.A. Riley, and T.L. Thompson. 2000. A three-band, two-dimensional reflectance index for wheat and cotton canopy chlorophyll content. Agronomy Abstracts p. 27.

Daughtry, C.S.T., C.L. Walthall, M.S. Kim, E. Brown de Colstoun, and J.E. McMurtrey III. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sensing of the Environment 74:229-239.

Gitelson, A. A., Y. J. Kaufman, and M. N. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of the Environment 58:289-298.

Harrington, P.D., E.D. Nafziger, and R.G. Hoeft. 1997. On-farm evaluation of variable-rate nitrogen fertilizer responses using farmer-owned equipment. 1997 Illinois Fertilizer Conference Proceedings Pp. 57-64.

Heege, H.J. and S. Reusch. 1996. Sensor for on-the-go control of site-specific nitrogen topdressing. ASAE Paper no. 961018. American Society of Agricultural Engineering, St. Joseph, MI.

Johannsen, C. J. and T.W. Barney. 1981. Remote sensing applications for resource management. Journal of Soil and Water Conservation 36:128-131.

Krishnan, P., J.D. Alexander, B.J. Butler, and J. W. Hummel. 1980. Reflectance technique for predicting soil organic matter. Soil Science Society of America Journal 44:1282-1285.

Malzer, G.L., P.J. Copeland, J.G. Davis, J.A. Lamb, P.C. Robert, and T.W. Bruulsema. 1996. Spatial variability of profitability in site-specific N management. Pp. 967-975. In: P.C. Robert et al. (eds.). Precision Agriculture, Proceedings of the Third International Conference. American Society of Agronomy, Madison, WI.

McMurtrey, J.E. III, E.W. Chappelle, M.S. Kim, J.J. Meisinger, and L.A. Corp. 1994. Distinguishing nitrogen fertilization levels in field corn (*Zea mays* L.) with actively induced fluorescence and passive reflectance measurements. Remote Sensing of the Environment 47:36-44.

Ritchie, S.W., J.J. Hanway, and G.O. Benson. 1993. How a corn plant develops. Special report no. 48. Iowa State University, Ames, IA.

Scharf, P. C. 2001. Soil and plant tests to predict optimum N rates for corn. Journal of Plant Nutrition 24:805-826.

Scharf, P.C., M.M. Alley, and Y.Z. Lei. 1993. Spring nitrogen on winter wheat: I. Farmer-field validation of tissue test-based rate recommendations. Agronomy Journal 85:1181-1186, erratum Agronomy Journal 86(1):iv.

Scharf, P.C. and J.A. Lory. 2002. Calibrating corn color from aerial photographs to predict sidedress N need. Agronomy Journal 94:397-404.

Schmidt, J.P., R. Ferguson, R.K. Taylor, C.W. Rice, G.J. Kluitenberg, and J.L. Havlin. 1999. Predicting potential mineralizable nitrogen by remote sensing. Agronomy Abstracts p. 368.

Schmidt, J.P., A.J. DeJoia, R.B. Ferguson, R.K. Taylor, R.K. Young, and J.L. Havlin. 2002. Corn yield response to nitrogen at multiple in-field locations. Agronomy Journal 94:798-806.

Schmitt, M.A. and G.W. Randall. 1994. Developing a soil nitrogen test for improved recommendations for corn. Journal of Production Agriculture 7:328-334.

Stone, M.L., J.B. Solie, W.R. Raun, R.W. Whitney, S.L. Taylor, and J.D. Ringer. 1996. Use of spectral radiance for correcting in-season fertilizer nitrogen deficiencies in winter wheat. Transactions of the ASAE 39:1623-1631.

Vanotti, M.B. and L.G. Bundy. 1994. An alternative rationale for corn nitrogen fertilizer recommendations. Journal of Production Agriculture 7:243-249.

Walters, C.S., B.E. Frazier, B.C. Miller, and W.L. Pan. 1999. Remotely sensed soil organic matter mapping for site-specific N management in dryland winter wheat. In P.C.

Robert et al. (eds.). Precision Agriculture, Proceedings of the Third International Conference. American Society of Agronomy, Madison, WI.

White, S.E. and A.M. Blackmer. 2001. Soil organic matter concentrations influence nitrogen fertilizer needs for

corn in Iowa. Agronomy Abstracts 093053.

Zheng, Feng, and H. Schreier. 1988. Quantification of soil patterns and field soil fertility using spectral reflection and digital processing of aerial photographs. Fertilizer Research 16:15-30.