Sensor-Based Nitrogen Applications Out-Performed Producer-Chosen Rates for Corn in On-Farm Demonstrations

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Soil Fertility & Crop Nutrition

ABSTRACT

Optimal N fertilizer rate for corn (*Zea mays* L.) and other crops can vary substantially within and among fields. Current N management practices do not address this variability. Crop reflectance sensors offer the potential to diagnose crop N need and control N application rates at a fine spatial scale. Our objective was to evaluate the performance of sensor-based variable-rate N applications to corn, relative to constant N rates chosen by the producer. Fifty-five replicated on-farm demonstrations were conducted from 2004 to 2008. Sensors were installed on the producer's N application equipment and used to direct variable-rate sidedress N applications to corn at growth stages ranging from V6 to V16. A fixed N rate chosen by the cooperating producer was also applied. Relative to the producer's N rate, sensors increased partial profit by \$42 ha^{-1} ($P = 0.0007$) and yield by 110 kg ha^{-1} ($P = 0.18$) while reducing N use by 16 kg N ha^{-1} ($P = 0.015$). This represents a reduction of approximately 25% in the amount of N applied beyond what was removed in the grain, thus reducing unused N that can move to water or air. Our results confirm that sensors can choose N rates for corn that perform better than rates chosen by producers.

Economically optimal nitrogen fertilizer rate (EONR) for corn and other crops can vary substantially within fields (Schmidt et al., 2002; Mamo et al., 2003; Scharf et al., 2005; Kitchen et al., 2010) and among fields (Schmitt and Randall, 1994; Bundy and Andraski, 1995). Current N management practices do not address this variability. Most U.S. corn producers apply the same rate of N fertilizer to whole fields and often to whole farms.

The adoption of tools to diagnose fertilizer N need has been slow (Kitchen and Goulding, 2001). In the past 10 yr, prices for both N fertilizer and corn have increased substantially, increasing the financial incentive to apply no more N than the crop needs but also to make sure that N is supplied in sufficient amounts. In addition to the agronomic and economic benefits, diagnosing and applying the EONR produces environmental benefits by reducing nitrate levels left in the soil after harvest (Hong et al., 2007). Accurate, convenient, and affordable methods to diagnose EONR are needed now more than in the past.

Understanding why the EONR varies will help us to devise more effective strategies for managing N. It appears that variability in crop yield and demand for N is usually not a major factor determining the EONR (Lory and Scharf, 2003; Nafziger et al., 2004; Scharf et al., 2006b). This leaves variability in the soil N supply as the probable controlling factor, although it would be desirable to have a body of evidence that directly supports this hypothesis. Many lab tests for soil N availability have been devised, and some have performed well in small data sets, but in large data sets they have performed poorly (Scharf et al., 2006a; Laboski et al., 2008).

It has long been known that N-deficient corn reflects more visible and often less near-infrared light than N-sufficient corn (Walburg et al., 1982). Scharf et al. (2006a) showed in a large and geographically-dispersed study that chlorophyll meter (transmittance) measurements of corn leaves provided much better prediction of the EONR than any of 26 soil N tests. Improved diagnostic accuracy is the main justification for pursuing canopy-sensor-based N management in preference to soil-test-based management.

Technological advances have enabled us to use spectral measurements of crops to diagnose and control N fertilizer rates. Reflectance sensors have logistical advantages over other potential spectral measurements. They can manage spatial variability in N need more easily than hand-held meters, and can operate under conditions that prevent the acquisition of aerial images. These advantages have led to the development of methods to translate sensor data into N rate decisions (Mullen et al., 2003; Dellinger et al., 2008; Scharf and Lory, 2009; Barker and Sawyer, 2010; Kitchen et al., 2010). Although there is still a need for decision systems to be improved and differences between them resolved, reflectance sensors are commercially available to guide variable-rate N applications. They can diagnose crop N needs and control N application rates at a fine spatial scale. The expected benefits are identification of places where N rate can be reduced without hurting yield; the identification of places where

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Published in Agron. J. 103:1683–1691 (2011)
Posted online 15 Sep 2011
doi:10.2134/agronj2011.0164

Abbreviations: EONR, economically optimal nitrogen fertilizer rate; GIS, geographic information system; GPS, global positioning system; NIR, near-infrared; Rel V/NIR, relative visible/near-infrared; V/NIR, visible divided by near-infrared.

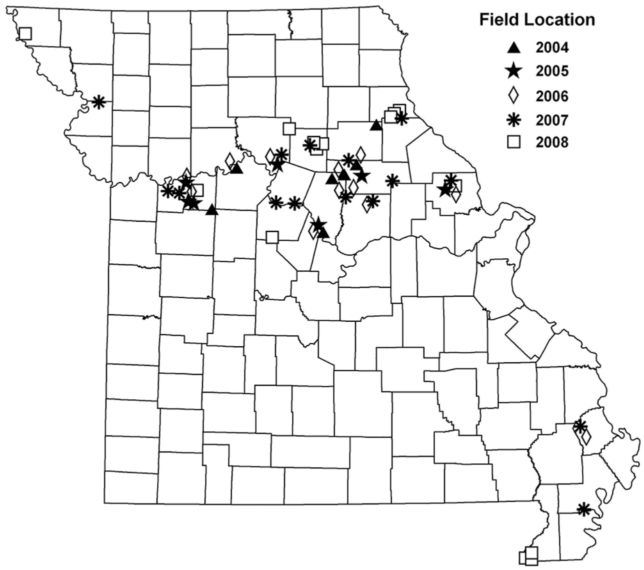

Fig. 1. Locations of sensor demonstration fields, 2004–2008.

additional N is needed to achieve full yield; lower residual soil nitrate after harvest that can be lost to water; and less in-season loss of N to water and air than with preplant N application.

Our objective was to evaluate the agronomic, economic, and implied environmental performance of sensor-based variable-rate N applications relative to constant N rates chosen by corn producers.

MATERIALS AND METHODS

Fifty-five on-farm demonstrations were conducted from 2004 to 2008. These demonstrations were distributed widely across the corn-growing regions of Missouri (Fig. 1) and included a range of soil parent materials and climatic zones. In central Missouri, three major soil groups are represented that are widely used for corn production: claypan, deep loess, and Missouri River alluvial. All demonstration fields in northwest and southeast Missouri were located on alluvial soils. These two regions are underrepresented in our data set relative to the area cropped to corn in those regions. The only major region/parent material combination used for corn production in Missouri that is missing from our data set is deep loess soils in northwest Missouri; however, average conditions for corn production on deep loess soils in central Missouri are nearly identical.

Preplant N rate was chosen by the cooperating producer and varied from 0 to 168 kg N ha^{-1} of available N, with an average value of 51 kg N ha^{-1}. This value includes all N in P fertilizer, calculated available manure N, starter N fertilizer, and N fertilizer applied with preplant herbicides. Background information on the demonstration sites and preplant N management practices is given in Table 1.

High-N reference areas were created in all demonstration fields between 4 and 8 wk before sidedress N application. Some reference areas were field-length strips, while others were small areas in which the N was applied by hand. Usually the N rate in these reference areas was 220 kg N ha^{-1}.

In 2004, all sidedress N applications were made with a Spra-Coupe sprayer that we transported to the demonstration fields. Beginning in 2005, many sidedress N applications were made using the producers' (or service providers') N application equipment. Over the 5 yr of the project, 19 demonstrations were conducted with the Spra-Coupe (sites 1–19 in Tables 1 and 2) and 36 with the producers' applicators (sites 20–55). A range of N sources and placements were used due to the diversity of equipment used by producers (Table 1). Plots were field-length, ranging from 140 to 1165 m (Table 1) with an average of 450 m. Their width varied from 4.5 to 24 m (Table 1), depending on equipment used and number of passes per plot.

Reflectance sensors were installed on the N application equipment (two or three per applicator; Roberts et al., 2009) and used to direct variable-rate sidedress N applications to corn at growth stages ranging from V6 to V16 (Abendroth et al., 2011) (Table 1). Sensors were positioned on the front of the applicator and directly over the corn row (nadir orientation) at a height of 50 cm above the canopy. A fixed N rate chosen by the cooperating producer was also applied on the same day. In most demonstrations, these were the only two treatments. In some demonstrations, additional treatments were included but are not reported here. A replicated complete-block design was used in all demonstrations with at least 3, and up to 15, replications (Table 1).

Two types of crop reflectance sensor were used: Crop Circle 210 (Holland Scientific, Lincoln, NE) and Greenseeker (NTech Industries, Ukiah, CA) (Table 1). These sensors measure reflectance of pulsed light emanating from the sensor, and effective "field of view" is determined by light source geometry, not the geometry of the light-measuring component. For the Crop Circle sensor, the light source projects over an area of 29 by 9 cm at the top of the canopy with the mounting height (50 cm) that we used. For the Greenseeker sensor, product information says that "optical masking and position of the sensor LEDs allows the sensor to view only a 60-cm wide strip regardless of the sensor height". This strip is narrow, approximately 1 cm, giving an illuminated area with dimensions of 60 by 1 cm at canopy height.

For both sensors, N rate was calculated from visible/near infrared (NIR) reflectance values in the target area divided by the visible/NIR value for the high-N reference area. We will refer to this parameter as relative visible/near infrared (Rel V/NIR):

$$\text{Rel V/NIR} = (\text{Visible/NIR})_{\text{target}}/(\text{Visible/NIR})_{\text{reference}} \quad [1]$$

When the target corn is N-deficient, this value will be >1, since the visible reflectance of N-deficient corn is higher than that of high-N corn, while the NIR reflectance is usually lower than that of high-N corn.

When the Crop Circle 210 sensor was used with corn at the V6 or V7 growth stages, Scharf and Lory's (2009) equation relating EONR to green/NIR for the Cropscan sensor (Cropscan, Inc., Rochester, MN) was used to calculate N rates:

$$\text{Crop Circle V6–V7 N rate (kg N ha}^{-1}) = (363 \times \text{Rel V/NIR}) - 303 \quad [2]$$

This equation appeared to perform well despite sensor differences and was used throughout the duration of the demonstrations. Dellinger et al. (2008) developed a very similar calibration relationship between Crop Circle 210 reflectance measurements and optimal N rates at growth stage V6, supporting the validity of this approach.

As corn growth stage advances, the difference in spectral properties between N-sufficient and N-stressed corn gets larger

Table 1. Details of on-farm demonstrations of sensor-based N sidedressing. Applications at sites 1 to 19 were conducted using our Spra-Coupe sprayer, while those at sites 20 to 55 were conducted using N applicators owned by the producers or their retailers.

Site no.	Year	Latitude	Longitude	Dominant soil great group	Pre-plant N			Plot		Number of Reps	Sensor used†	Sidedress N		
					Rate	Form‡	Placement	Length	Width			Form‡	Placement	Growth stage§
					kg ha^{-1}			—— m ——						
1	2004	39°13'39"	–92°7'19"	Albaqualfs	32	MAP	broadcast	720	4.5	6	Crop Circle	UAN	dribble	10
2	2004	39°17'11"	–93°15'57"	Udifluvents	0	—	—	590	4.5	6	Crop Circle	UAN	dribble	7
3	2004	38°45'24"	–92°23'8"	Hapludolls	0	—	—	475	4.5	7	Crop Circle	UAN	dribble	7
4	2004	39°38'9"	–91°46'27"	Albaqualfs	30	DAP	broadcast	765	4.5	3	Crop Circle	UAN	dribble	8
5	2004	38°56'33"	–93°31'44"	Argiudolls	0	—	—	200	4.5	6	Crop Circle	UAN	dribble	7
6	2004	39°12'49"	–92°13'37"	Epiaqualfs	41	MAP	broadcast	320	4.5	6	Crop Circle	UAN	dribble	8
7	2004	39°18'39"	–91°59'30"	Epiaqualfs	45	DAP	broadcast	410	4.5	6	Crop Circle	UAN	dribble	7
8	2005	38°44'57"	–92°22'41"	Hapludolls	0	—	—	470	4.5	6	Crop Circle	UAN	dribble	11
9	2005	39°19'4"	–92°50'0"	Argialbolls	0	—	—	380	4.5	6	Crop Circle	UAN	dribble	11
10	2005	39°9'56"	–93°48'19"	Endoaquolls	0	—	—	200	4.5	4	Crop Circle	UAN	dribble	12
11	2006	39°14'23"	–92°6'51"	Albaqualfs	39	DAP	broadcast	760	4.5	3	Crop Circle	UAN	dribble	10.5
12	2006	39°17'32"	–93°16'7"	Udifluvents	28	DAP	broadcast	515	4.5	3	Crop Circle	UAN	dribble	9.5
13	2006	38°45'9"	–92°22'53"	Hapludolls	0	—	—	360	4.5	3	Crop Circle	UAN	dribble	9
14	2006	39°22'35"	–92°54'33"	Argiudolls	12	MAP	broadcast	360	4.5	4	Crop Circle	UAN	dribble	10
15	2006	39°6'27"	–92°7'6"	Albaqualfs	30	DAP	broadcast	400	4.5	3	Crop Circle	UAN	dribble	9.5
16	2007	36°24'52"	–89°42'0"	Argiudolls	0	—	—	310	4.5	4	Crop Circle	UAN	dribble	9
17	2007	39°19'9"	–92°50'6"	Argialbolls	12	DAP	broadcast	410	4.5	4	Crop Circle	UAN	dribble	9.8
18	2007	38°59'42"	–92°51'4"	Udifluvents	0	—	—	400	9	3	Crop Circle	UAN	dribble	9
19	2007	38°59'18"	–92°39'9"	Hapludolls	0	—	—	555	4.5	3	Crop Circle	UAN	dribble	9
20	2005	39°7'49"	–90°58'48"	Hapludalfs	56	Urea + DAP	broadcast	175	9	8	Crop Circle	UAN	injected	6
21	2005	38°59'46"	–93°43'18"	Endoaquolls	90	chicken litter	broadcast	430	24	5	Crop Circle	UAN	injected	8
22	2005	39°0'57"	–93°45'1"	Hapludolls	67	UAN	Injected	270	12	6	Crop Circle	UAN	injected	7
23	2005	39°15'9"	–91°58'8"	Epiaqualfs	39	DAP	broadcast	760	18	3	Crop Circle	NH_3	injected	7
24	2006	39°7'22"	–90°59'43"	Hapludalfs	56	Urea + DAP	broadcast	560	9	5	Crop Circle	UAN	injected	6.5
25	2006	39°4'11"	–92°5'4"	Epiaqualfs	7	MAP	broadcast	800	9	6	Crop Circle	NH_3	injected	7
26	2006	39°5'6"	–93°44'39"	Hapludolls	90	chicken litter	broadcast	265	12	10	Crop Circle	UAN	injected	7
27	2006	39°2'1"	–93°47'7"	Hapludolls	67	UAN	injected	195	12	13	Crop Circle	UAN	injected	6
28	2006	39°18'51"	–91°59'28"	Epiaqualfs	22	DAP	broadcast	450	18	4	Crop Circle	NH_3	injected	8
29	2006	37°3'36"	–89°42'14"	Udipsamments	62	UAN	broadcast	320	18	6	Greenseeker	UAN	dribble	6
30	2007	39°7'22"	–90°59'43"	Hapludalfs	56	Urea + DAP	broadcast	250	9	6	Crop Circle	UAN	injected	7.5
31	2007	39°9'18"	–92°8'2"	Albaqualfs	34	MAP	broadcast	1165	9	3	Crop Circle	NH_3	injected	7
32	2007	39°48'51"	–94°44'60"	Endoaquolls	112	DAP	broadcast	1020	9	3	Crop Circle	UAN	dribble	15
33	2007	39°42'18"	–91°33'29"	Albaqualfs	50	hog pit slurry	injected	140	18	6	Crop Circle	UAN	dribble	16
34	2007	39°1'34"	–93°48'22"	Argiudolls	56	UAN	injected	185	12	5	Crop Circle	UAN	injected	7
35	2007	39°1'30"	–93°48'32"	Argiudolls	56	UAN	injected	325	12	5	Crop Circle	UAN	injected	7
36	2007	39°29'30"	–92°26'17"	Albaqualfs	84	UAN + DAP	broadcast	350	12	15	Crop Circle	UAN	injected	15
37	2006	39°0'6"	–91°49'27"	Epiaqualfs	45	DAP	broadcast	370	24	6	Greenseeker	UAN	dribble	9
38	2007	39°9'58"	–91°36'44"	Epiaqualfs	168	hog pit slurry	injected	170	24	7	Greenseeker	UAN	dribble	8
39	2007	39°0'6"	–91°49'27"	Epiaqualfs	45	DAP	broadcast	360	24	6	Greenseeker	UAN	dribble	6
40	2007	37°6'20"	–89°41'32"	Fluvaquents	56	DAP	broadcast	560	12	3	Greenseeker	Urea	broadcast	7
41	2007	39°15'29"	–92°0'18"	Epiaqualfs	0	—	—	380	24	4	Greenseeker	UAN	dribble	8
42	2008	39°36'23"	–92°42'29"	Argialbolls	120	NH_3	injected	865	12	7	Crop Circle	UAN	injected	14
43	2008	40°21'51"	–95°33'36"	Hapludolls	112	NH_3	injected	410	18	3	Crop Circle	Urea	broadcast	10
44	2008	39°7'17"	–90°59'57"	Hapludalfs	45	Urea + DAP	broadcast	445	9	7	Crop Circle	UAN	injected	7
45	2008	38°42'37"	–92°53'28"	Argialbolls	112	NH_3	injected	720	6	6	Crop Circle	NH_3	injected	7
46	2008	39°43'35"	–91°32'8"	Albaqualfs	67	UAN	injected	550	12	6	Crop Circle	UAN	injected	15
47	2008	39°43'2"	–91°33'33"	Albaqualfs	67	UAN	injected	420	12	8	Crop Circle	UAN	injected	13
48	2008	39°42'31"	–91°33'16"	Albaqualfs	134	hog pit slurry	injected	200	12	12	Crop Circle	UAN	injected	12
49	2008	39°5'20"	–93°44'36"	Hapludolls	146	NH_3	injected	150	12	8	Crop Circle	UAN	injected	10
50	2008	39°27'42"	–92°24'54"	Epiaqualfs	78	UAN + DAP	broadcast	540	12	7	Crop Circle	UAN	injected	14
51	2008	39°26'42"	–92°24'13"	Epiaqualfs	78	UAN + DAP	broadcast	610	12	5	Crop Circle	UAN	injected	12
52	2008	39°29'34"	–92°26'42"	Epiaqualfs	78	UAN + DAP	broadcast	370	12	4	Crop Circle	UAN	injected	14
53	2008	36°1'36"	–90°18'48"	Hapludalfs	69	UAN	injected	370	10	7	Crop Circle	UAN	dribble	8
54	2008	36°0'43"	–90°17'27"	Hapludalfs	69	UAN	injected	335	10	6	Crop Circle	UAN	dribble	7
55	2008	36°0'56"	–90°17'27"	Hapludalfs	69	UAN	injected	340	10	5	Crop Circle	UAN	dribble	7

† Crop Circle = Crop Circle 210; Greenseeker = Greenseeker 505 (red and near-infrared).

‡ MAP = monoammonium phosphate; DAP = diammonium phosphate; UAN = urea-ammonium nitrate solution.

§ Number of collared leaves including the seed leaf (Abendroth et al., 2011); in the text, this number is preceded by V for vegetative.

(Scharf et al., 2006a). This means that different equations are needed for different growth stages to convert sensor reflectance measurements to N rates. We used Crop Circle 210 measurements from stage V6 to V10 in an N rate experiment (data not shown) to assess the change in Rel V/NIR with advancing growth stage. Based on our observations in that experiment, we modified Eq. [2] to be suitable for growth stages V8 to V10:

$$\text{Crop Circle V8–V10 N rate (kg N ha}^{-1}\text{)} = (280 \times \text{Rel V/NIR}) - 225 \quad [3]$$

This equation was validated in a series of on-farm N rate response experiments as being near-optimal at typical price ratios between corn grain and N fertilizer (Kitchen et al., 2010).

In the same N rate experiment used to assess the effects of growth stage on Rel V/NIR, we compared measurements of Rel V/NIR from the two sensors. We observed that Rel V/NIR varied more widely when measured with the Greenseeker than when measured with the Crop Circle on the same corn. By mathematically describing the relationship between Rel V/NIR for Crop Circle 210 and Greenseeker, then applying this relationship to Eq. [2] and [3], we produced the N rate equations for demonstrations where the Greenseeker sensor was used:

$$\text{Greenseeker N rate V6–V7 (kg N ha}^{-1}\text{)} = (245 \times \text{Rel V/NIR}) - 190 \quad [4]$$

$$\text{Greenseeker N rate V8–V10 (kg N ha}^{-1}\text{)} = (190 \times \text{Rel V/NIR}) - 135 \quad [5]$$

The Crop Circle 210 sensor was used in all 13 fields in which N was applied at corn growth stages V11 to V16. Equation [3] was used to calculate the variable N rate for 10 of these fields. However, results from Scharf et al. (2006a) suggest that the EONR associated with a relative spectral value of 1.0 goes down as the season progresses. Therefore, Eq. [3] was modified to reflect this observation for the last three demonstrations at growth stage V11 or later:

$$\text{Crop Circle V11–V16 N rate (kg N ha}^{-1}\text{)} = (265 \times \text{Rel V/NIR}) - 230 \quad [6]$$

We wrote custom software that averaged the V/NIR value for the high-N reference area, stored this value for use during fertilization, continuously collected sensor and global positioning system (GPS) data, calculated the N rate based on the appropriate equation (see above), and sent a new rate command to the controller once per second. Either two or three sensors were used, each collecting approximately 10 reflectance measurements per second, so that each N rate command was based on an average of 20 to 30 data points. In 2007, a filter was added to the software that discarded measurements from bare soil before calculating average V/NIR and N rate. Sensors were mounted on the front of the N applicator. In cases where the time from when the sensor passed a point until the fertilizer reached that point was longer than the processing and control time, an appropriate delay was introduced. Minimum and maximum N rates were selected in consultation with the producer. If the calculated N rate was below the minimum or above the maximum, the software would change it to these preselected values. Sensor data, GPS data, and N rate commands were logged continuously during the fertilization operation. The average N rate for each sensor (variable-rate N) plot was calculated using ArcView geographic information systems (GIS) software. Maps of N rate command were also produced for each site using ArcView.

When liquid N sources (anhydrous ammonia or urea-ammonium nitrate solution) were used, the minimum N rate was usually set near half of the maximum N rate. This kept the minimum pressure high enough to distribute the fertilizer evenly. In some cases when urea-ammonium nitrate solution was the N source, we used Veri-Flow nozzles to allow a wider range of N rates while maintaining appropriate pressure.

All cultural practices other than N application were performed or contracted by cooperating corn producers following their normal management practices and decision processes. In one demonstration, the yield data were obtained using a weigh wagon. In all other demonstrations, yield monitor data co-collected with GPS data were used. ArcView GIS software was used to delineate treatment areas (based on N application data files), identify yield data that were unambiguously within those areas, and calculate average yield for each area. Yield data were cleaned using Yield Editor software (Sudduth and Drummond, 2007) or ArcView. Data were discarded from specific "problem" locations where aerial images revealed unusual patterns, where standard deviation was high, and where the combine was accelerating or decelerating. When data were discarded for these reasons, they were also discarded from the adjacent area of the other treatment in the same replication. Extreme yield data points were also removed, on the assumption that they were erroneous measurements. Typically values that were more than two standard deviations from the field mean were discarded.

Outcomes were analyzed by considering each demonstration field as an independent observation. Average yield and N rate were calculated for each treatment (sensor-based variable-rate N and producer-chosen N rate) at each site (Table 2). Yield and N were assigned economic values using prices of \$200 Mg^{-1} corn and \$1.30 kg^{-1} N. These are representative prices at the time of writing and give the best current estimate of the value of sensor technology. Partial profit was calculated for each location as:

$$\text{Partial profit} = (\text{Value of corn grain}) - (\text{Cost of N fertilizer applied}) \quad [7]$$

A *t* test was performed on the entire population of location data to test the hypothesis that sensor impact on yield, N rate, and partial profit was zero. *t* tests were also used to determine whether specific subpopulations were different or similar. Regression analysis was used to examine the impact of independent location variables on yield, N rate, and partial profit.

RESULTS AND DISCUSSION

Production Conditions and Yield Levels

Production conditions were generally favorable during the 5 yr of this study, resulting in an average yield of 9.8 Mg ha^{-1} with the producer-chosen N rates (Table 2). This is well above the average corn yield in Missouri for these years, and slightly above

Table 2. Comparison of outcomes with producer-chosen and sensor-based N rates in 55 replicated demonstrations.

Site no.	Year	Nitrogen rate, kg ha^{-1} †			Yield, Mg ha^{-1}			Partial profit, \$ ha^{-1}		
		Producer	Sensor	Difference	Producer	Sensor	Difference	Producer	Sensor	Difference
1	2004	234	195	−39	12.3	11.8	−0.5	2111	2064	−47
2	2004	168	196	28	7.3	7.8	0.4	1223	1272	49
3	2004	202	137	−65	13.5	12.5	−1.0	2388	2277	−112
4	2004	198	137	−62	13.0	11.9	−1.1	2294	2166	−128
5	2004	202	101	−101	13.9	14.1	0.2	2463	2633	170
6	2004	209	152	−57	10.9	10.5	−0.4	1872	1861	−11
7	2004	179	217	38	11.2	12.3	1.1	1974	2133	160
8	2005	202	147	−55	4.5	4.2	−0.3	610	633	23
9	2005	202	92	−110	10.6	10.2	−0.4	1820	1879	59
10	2005	202	113	−88	13.4	13.5	0.1	2376	2506	129
11	2006	207	176	−31	11.7	11.5	−0.3	2035	2027	−8
12	2006	196	241	45	8.6	8.9	0.3	1433	1423	−10
13	2006	202	139	−63	9.1	9.5	0.4	1524	1693	169
14	2006	214	146	−68	11.6	11.3	−0.3	2002	2030	29
15	2006	198	127	−72	10.5	10.1	−0.4	1800	1821	21
16	2007	273	142	−131	11.2	10.0	−1.2	1849	1788	−61
17	2007	214	114	−100	12.2	11.1	−1.1	2113	2035	−78
18	2007	235	223	−12	10.7	10.2	−0.5	1801	1718	−82
19	2007	202	170	−31	10.6	10.8	0.2	1820	1899	79
20	2005	157	189	32	6.4	6.3	−0.2	1058	985	−74
21	2005	166	181	16	8.4	8.9	0.5	1436	1520	84
22	2005	230	217	−12	7.9	7.7	−0.1	1240	1232	−8
23	2005	174	179	6	3.8	4.0	0.1	524	541	17
24	2006	146	108	−38	7.0	6.8	−0.2	1178	1192	13
25	2006	158	158	0	9.5	9.5	0.0	1668	1668	0
26	2006	162	157	−6	9.7	9.4	−0.3	1687	1633	−54
27	2006	230	213	−17	10.4	10.3	−0.1	1734	1736	2
28	2006	157	185	28	8.2	8.0	−0.2	1396	1319	−78
29	2006	241	236	−4	12.6	12.7	0.2	2151	2194	43
30	2007	142	129	−13	8.1	8.2	0.1	1405	1447	42
31	2007	179	205	26	6.9	6.9	0.0	1121	1087	−34
32	2007	291	267	−25	13.7	13.9	0.2	2307	2377	70
33	2007	143	146	2	11.0	10.9	−0.1	1976	1951	−25
34	2007	213	237	25	9.9	10.4	0.5	1657	1724	66
35	2007	213	237	25	7.2	7.6	0.4	1126	1180	54
36	2007	226	271	45	7.9	9.2	1.3	1257	1444	188
37	2006	196	122	−74	9.1	9.4	0.3	1531	1679	147
38	2007	280	250	−30	13.1	13.2	0.1	2211	2263	52
39	2007	196	141	−55	6.7	6.9	0.3	1050	1172	122
40	2007	291	269	−22	12.3	12.2	−0.1	2035	2053	17
41	2007	134	155	20	8.5	9.3	0.8	1502	1623	122
42	2008	187	183	−4	10.3	10.4	0.2	1772	1812	41
43	2008	157	215	58	8.5	9.3	0.8	1467	1551	83
44	2008	131	118	−13	10.2	10.1	−0.1	1841	1839	−2
45	2008	207	190	−17	12.0	11.9	−0.1	2085	2082	−2
46	2008	125	170	45	9.2	10.4	1.3	1637	1825	188
47	2008	158	206	48	10.4	12.2	1.8	1841	2136	294
48	2008	189	203	13	11.2	11.3	0.1	1948	1955	7
49	2008	193	207	14	9.4	9.8	0.4	1590	1649	59
50	2008	158	167	9	7.7	8.0	0.3	1310	1360	50
51	2008	146	187	41	8.1	9.2	1.1	1396	1563	167
52	2008	146	175	29	8.3	9.5	1.2	1442	1637	195
53	2008	209	230	20	9.7	9.8	0.1	1633	1629	−4
54	2008	209	181	−28	8.8	9.0	0.2	1452	1526	74
55	2008	209	188	−21	10.4	10.5	0.1	1773	1813	41
Avg.		194	179	−16*	9.8	9.9	0.1	1672	1714	42***

*Different than zero with $\alpha = 0.05$

***Different than zero with $\alpha = 0.001$

† Nitrogen rates include the pre-plant N shown in Table 1

the national average. Two sites were drought-affected in 2005, resulting in treatment mean yields of 3.8 and 4.4 Mg ha^{-1} with the producer-chosen N rates. The highest mean yield obtained using producer-chosen N rates was 13.9 Mg ha^{-1}.

Sensor Impact on Nitrogen Rate

Over all 55 demonstration fields, an average of 16 kg ha^{-1} less N was applied when sensors chose N rates than when cooperating producers chose them ($P = 0.015$) (Table 2). This is identical to the average reduction in N rate seen when sensors were used to choose fixed N rates in 15 production wheat (*Triticum aestivum* L.) fields in Oklahoma (Butchee et al., 2011). Although sensors chose average N rates higher than the producer's rate in some fields, more often the average N rate was lower than the producer's. At 21 sites, the sensor-based rates were more than 25 kg N ha^{-1} below the rates chosen by the cooperating producer, with an average savings in these fields of 63 kg N ha^{-1}. On the other hand, at 14 sites, the sensor-based rates were more than 25 kg N ha^{-1} above producer-chosen rates, and the average rate increase was 37 kg N ha^{-1} in these fields.

The effect of sensor-based N management on average N rate was related to the year and the weather. In 2008, excessive spring rainfall across much of the Midwest created the potential for N loss. Eleven of the 14 demonstration fields in 2008 received more than 40 cm of rainfall from April through June. That year the sensor-based N rates were, on average, 14 kg N ha^{-1} above the rates chosen by producers ($P = 0.09$). In contrast, for 2004 through 2007 sensor-based rates were 37, 30, 25, and 19 kg N ha^{-1} below producer-chosen rates, respectively ($P = 0.11$, 0.19, 0.05, and 0.16, respectively). Average N rate reduction for combined data from 2004–2007 was 26 kg N ha^{-1} ($P = 0.0011$) with no effect on yield (see next section). Taken together, our results suggest that the rate decisions produced by the sensors compensated for weather-related N losses more than did the rate decisions made by the producers.

Several other researchers have found that using sensors to guide N rates has reduced N use compared to conventional or producer-chosen N rates without reducing yield. These outcomes have mostly been accomplished with recurrent sensor measurements that trigger N application through irrigation water when the relative sensor value falls below a critical value. Bausch and Delgado (2005) used this approach to lower N rates applied to corn through pivot irrigation by more than half without reducing yield. The amount of N saved in two field zones being managed was related to the amount of soil nitrate present before planting in these zones. Bausch and Diker (2001) lowered N rate by 39 kg N ha^{-1} with no effect on corn yield, and Bronson et al. (2011) lowered N rate by 22 kg N ha^{-1} with no effect on cotton (*Gossypium hirsutum* L.) yield. Stone et al. (1996) used sensors to guide a single in-season N application to wheat, reducing N rates by 32 and 57 kg N ha^{-1} in two 70-m transect experiments without influencing yield. Our results extend these findings to a much larger population of fields, and augment the evidence that sensors-based N rates can save N without yield penalty even when in-season N will be applied only once.

The effect of sensor-based N management on N rate was also dependent on the amount of N applied before planting. In fields that received <75 kg N ha^{-1} before planting (including manure, P fertilizer, starter fertilizer, and fertilizer applied with herbicides), the use of sensors reduced average N rate by 24 kg N ha^{-1} ($P = 0.002$). In fields that received more than 75 kg N ha^{-1} before planting, the use of sensors did not affect N rate ($P = 0.49$). In our sensor interpretations (Eq. [2–5]), a minimum of 55 to 65 kg N ha^{-1} is recommended even when the target corn has the same appearance as the high-N reference corn (i.e., Rel V/NIR = 1.0). With a pre-plant N rate above 75 kg N ha^{-1} and a minimum of 55 kg N ha^{-1} sidedress, there is little potential to save N unless the producer's normal rate is quite high. Why do our sensor interpretations recommend a minimum sidedress of 55 kg N ha^{-1}? During our calibration research (Scharf and Lory, 2009), corn with Rel V/NIR = 1.0 sometimes needed low or moderate additional N rates to achieve optimal yield. The implication is that reflectance sensors cannot reliably distinguish between corn that is slightly N-deficient and corn that is N-sufficient. This is consistent with other calibration research relating EONR values to spectral measurements of corn (Scharf and Lory, 2002; Sripada et al., 2005; Scharf et al., 2006a; Dellinger et al., 2008), which has generally found an average EONR of 30 to 45 kg N ha^{-1} when the relative spectral value = 1.0. In our system, low pre-plant N rates (below 75 kg N ha^{-1}) increase the opportunity for sensors to reduce total N use and save money on N.

Sensor Impact on Yield

Relative to the producer's N rate, we found weak evidence ($P = 0.18$) that sensors increased yield by 110 kg ha^{-1} over all demonstration sites. Raun et al. (2002) found a similar level of evidence for a 270 kg ha^{-1} wheat yield increase with sensor-based variable-rate N in three small-plot experiments when no pre-plant N was applied.

In 2008, with a wet spring and sensors recommending (on average) higher N rates than those used by producers, average grain yield with the sensor system was 526 kg ha^{-1} greater than with producer-chosen N rates ($P = 0.007$). This confirms that higher N rates were justified under the weather conditions of 2008. There was essentially no evidence of any sensor influence on yield during any of the other 4 yr ($0.52 \leq P \leq 0.78$ by *t* test). A two-sample difference of means test showed that the yield effect of using sensors in 2008 was different than the effect in all other years combined ($P = 0.002$). Our results from 2008 indicate that sensors can identify times and places in which yield can be increased by putting on more N than the producer's normal rate. This is an important factor favoring profitability and adoption. Even more important for adoption is that when N rates are reduced, as happened on average in 2004–2007, that this does not negatively impact yield. This is, on average, what we observed.

Yield was usually increased when sensor-based N rates exceeded producer-chosen rates. In the 19 fields where sensor-based N rates were more than 10 kg N ha^{-1} higher than producer rates, yield was increased by an average of 620 kg ha^{-1} ($P = 0.0001$) above the yield achieved with the producer's N rate.

Sensor Impact on Partial Profit

Relative to the producer's N rate, sensors increased partial profit by \$42 ha^{-1} ($P = 0.0007$) averaged over all locations (Table 2). This effect was a product of both reduced N use (2004–2007) and increased yield (2008). Among years, only in 2008 did sensor use convincingly increase partial profit ($P = 0.004$); this was due to increased yield ($P = 0.007$). The consistent N use reductions from 2004–2007 ($P = 0.0011$) also contributed to the increase in partial profit observed over all 55 fields.

For producers who currently apply sidedress N, the observed level of profit advantage ($42 ha^{-1}) is probably enough to pay for the sensors and the management time required to learn to use them effectively. However, this level of profit advantage may not be enough to generate fast or enthusiastic adoption. For producers who do not currently apply sidedress N, it is almost certainly not enough to motivate them to change their application timing.

A full economic analysis is beyond the scope of this paper, but a rudimentary analysis may help give some perspective on economic benefits to the user. A simple case would be a full-time farmer who grows 200 ha of corn annually. If that producer achieves the same level of profit advantage that we did in our 55 demonstration fields, the gross benefit of sensor use each year will be 200 ha × $42 ha^{-1} = $8400. Assuming that the producer already owned a fertilizer applicator with a controller and a GPS (true for many producers), only sensors and associated electronics would need to be purchased. The cost to purchase three Ag Leader OptRx sensors and associated electronics is currently about $10,500, or for four Greenseeker sensors and associated electronics is about $16,500. Either system would be paid for within a few average years at these prices. As with other emerging technologies, prices are likely to come down as the market matures and as adoption increases. The value of the management time to get the system set up and to learn to use the sensors well is difficult to quantify but is also an important component of overall economic outcome. Economic return would be greater for producers with more than 200 ha of corn, and lower for those with less. Profitability would also hinge on whether the sensors can be used profitably to manage N on other N-requiring crops in the producer's operation (such as wheat or cotton), and whether they can be used profitably to variably manage other inputs (such as growth regulators in cotton). For sensors mounted on fertilizer applicators owned by retailers, the economics are more complex, with more fields covered, less cost per field, and benefits split between the producer and the retailer.

We found that the effect of sensors on partial profit was greatest when they recommended either more N or substantially less N than the producer-chosen rates (Fig. 2). Identifying fields that need either more or less total N than the producer's rate appears to be one important benefit of sensor use. It is difficult to assess the value of simply redistributing the same amount of N (i.e., sensor N rate change = 0 in Fig. 2). However, our data suggest that this redistribution would give partial profit increases in the range of $16 ha^{-1} (average for all fields with $-20 <$ sensor N rate change <20 kg N ha^{-1}) to $35 ha^{-1} (from regression in Fig. 2). The value from the regression equation may be pulled up by the large positive values on the right side of Fig. 2.

The sensor interpretations that we used produced, on average, N rate decisions that were economically superior to the rates chosen by the producer both when they recommended more N and when they recommended less N than the producer's rate. However, the rates chosen by the sensors were not always better than those chosen by producers. There were fields where the sensors recommended a higher N rate than the producer's rate without producing higher yield, resulting in lower partial profit (lower right quadrant of Fig. 2; Table 2). More often, the higher N rate produced a yield benefit that more than offset the cost of

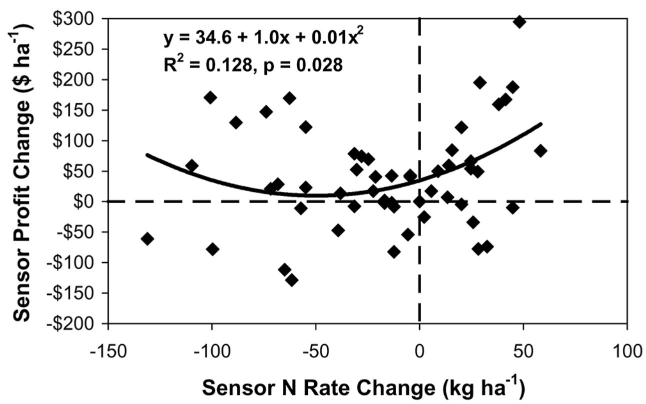

Fig. 2. Sensor profit change (partial profit with sensor-based N rates minus partial profit with producer-based N rates) as a function of sensor N rate change (average N rate with sensors minus the producer's N rate in the same field). Sensor-based management was most profitable when sensors recommended more N than the amounts chosen by producers, or when sensors recommended substantially less N than producers chose. When sensors recommended more than 10 kg N ha^{-1} above the rate chosen by the producer, yield was increased by an average of 620 kg ha^{-1} ($P = 0.0001$), enough to pay for the extra N and to increase profit. Over all 55 locations, sensors increased partial profit by an average of $42 ha^{-1} ($P = 0.0007$) relative to producer-chosen N rates applied at the same timing.

the N (upper right quadrant). Similarly, there were fields where sensors reduced the N rate relative to the producer's rate but this was an incorrect decision, reducing yield and partial profit (lower left quadrant). Again, it was more common when sensors recommended a reduced N rate that this did not affect yield and partial profit was increased (upper left quadrant). We were not able to identify any common factors associated with poor N rate decisions based on sensor measurements.

The economic advantage of sensors over the producer-chosen N rate was higher ($P = 0.008$ from linear regression; quadratic term not significant) in fields where N was applied at later growth stages. This is probably in part an artifact. In 2008, the average partial profit advantage was higher than in any other year and demonstrations were conducted at later growth stages than in any other year. This confluence contributes to the significant regression result without being based on a causal relationship between the two variables. However, it does make sense that N-need diagnoses would be more accurate at later growth stages when the roots have explored a greater soil volume and the unpredictable processes of soil N mineralization and N loss have had time to occur. Added to the timing effect on sensor accuracy is any effect of N timing on yield. Across this group of experiments, there was no significant effect of the growth stage at which N was applied on yield ($P = 0.48$). To the extent that there was a trend, it was that yield was higher with later application.

The partial profits associated with sensor use were evaluated using prices of $200 Mg^{-1} corn and $1.30 kg^{-1} N. These are representative prices at the time of writing and thus give the best current estimate of the value of sensor technology. Future price changes could substantially alter that value. Because the partial profit advantage due to sensors in this study resulted from both N savings and yield increases, high prices for both corn and N favor the economics of sensor adoption. If corn and/or N prices go up, the economic advantage of sensor use will increase; conversely, if prices go down, the advantage of sensor use will decrease.

Sensor Impact on the Environment

Nitrogen escaping from corn production systems is known to have negative effects on water quality (Rabalais et al., 1996) and air quality (Robertson et al., 2000). We do not have any direct measures of N escape to water or air from the fields we studied. This section will briefly address the potential environmental implications of changes in N rate due to sensor use.

Sensor use reduced the average N fertilizer rate in this study by 16 kg N ha^{-1} (Table 2), which is within the likely range of 10 to 50 kg N ha^{-1} suggested by Roberts et al. (2010). This represented an 8% reduction in the total amount of N (all fertilizer and manure N) applied. However, a great deal of N ends up in the crop and is carried away during harvest. This N is not escaping to other environments where it may have undesirable effects. A more useful metric for environmental impact is "surplus N": the fertilizer (and manure) N applied in excess of the N removed in grain during harvest. This represents a pool of N that is vulnerable to loss to the environment.

Use of sensors to guide N rates reduced surplus N by an estimated 24 to 26% in our demonstration fields. This represents our best estimate of how much sensor-based management reduced the potential for N escape to the environment. With producer-chosen N rates, average total N applied was 194 kg N ha^{-1}. Using the National Research Council (2000) value for corn grain protein content, we estimated average N removal in grain to be 129 kg N ha^{-1}, giving a surplus of 65 kg N ha^{-1}. Use of sensors reduced total N applied to 179 kg N ha^{-1} while increasing estimated N removal to 131 kg N ha^{-1}, giving a surplus of 48 kg N ha^{-1}, a 26% reduction. The lack of actual measured grain N concentrations in our study introduces uncertainty into this estimate, but for average behavior over 55 fields, the National Research Council value should be relatively robust. Nitrogen rate also affects grain N concentration, again introducing uncertainty. We used data from Shepard et al. (2011) to estimate the influence of N rate on grain N concentration for both treatments at all locations. These corrections did not change our estimate of "surplus N" for producer N rates, but increased surplus N for sensor-based N rates by 1 kg N ha^{-1}. This analysis suggests low sensitivity of average surplus N estimates to varying grain N concentration due to N rate within the range we encountered. Our estimate of the reduction in surplus N due to sensor use changed slightly when we corrected grain N concentration for N rate, dropping to 24%.

Another useful metric is the proportion of applied N that is removed in grain, which is one measure of N efficiency. Sensor use increased the proportion of applied N removed in grain from 67 to 73% with either the National Research Council (2000) grain N value or with that value adjusted for N rate based on data from Shepard et al. (2011).

These results are consistent with earlier research showing that applying the EONR reduces soil nitrate levels found after harvest (Andraski et al., 2000; Hong et al., 2007). This effect is usually not linear. Nitrogen overapplication (above the EONR) changes postharvest soil nitrate more than N underapplication. Similar results have been found in potato (*Solanum tuberosum* L.) production (Bélanger et al., 2003).

As a result of the environmental benefits that we observed, the Natural Resources Conservation Service in Missouri has approved sensor-based sidedressing as a practice available for cost-share payments from their Environmental Quality Incentives Program (EQIP). This can add to the modest economic benefits that we observed for sensor use, potentially increasing adoption rate and environmental benefits.

Adoption

The economic benefits to sensor use that we saw mean that lower incentive levels will be needed to get adoption than for practices that have costs but no economic returns. At the time of writing, we are aware of 6 of the 27 cooperating producers who have adopted sensor-based N sidedressing. Five of the six have received EQIP cost-share payments on at least some fields. All six of these producers used and operated their own equipment to conduct the sensor demonstrations. One possible interpretation is that participating in the demonstrations and watching the sensors control N rates convinced producers to adopt this approach. However, producers who agreed to conduct sensor-based N demonstrations using their own equipment made a larger time commitment (installation and removal of sensors, computer, and so on) than the other producers. They may have been willing to make this commitment because they were already more disposed than the others to adopt sensor technology.

Sensor Interpretation: Context, Options, and the Future

Reflectance sensors are a relatively new technology for diagnosing crop N status and need. Although the body of research associated with this technology is steadily increasing, we are still far from a consensus about how to best convert sensor values to N rates. This study showed that one system for interpreting sensor values produced yield, economic, and environmental benefits. A different algorithm for interpreting sensor measurements may have produced larger benefits, no benefits, or "negative benefits". The sensor and the interpretation of the sensor data create an integrated package that is evaluated as a whole; it is not possible to evaluate the sensors without evaluating the interpretations. The fact that one system produced benefits is encouraging for the future of reflectance sensors for controlling N application rates. Comparing different interpretation systems and refining them to optimize outcomes is still needed to maximize sensor utility and adoption.

One approach that may help to improve the performance of sensor-based N rate recommendations is the incorporation of additional relevant information in making the N rate decision. Zillmann et al. (2006) found that sensor-based N rates for winter wheat performed well except in areas where other factors limited yield, such as shallow soils with low water-supplying capacity.

CONCLUSIONS

Using sensors to control sidedress N rates for corn produced yield, economic, and environmental benefits in 55 on-farm demonstrations. The real-world scale of these demonstrations, and the wide range of production environments encountered, suggest that our results give relatively robust estimates of the outcomes that can be expected when corn producers adopt sensor-based N sidedressing. Our results confirm that reflectance sensors combined with our interpretation system were able to choose N rates for corn that performed better than rates chosen by producers.

ACKNOWLEDGMENTS

We thank Tom Becker, Bob Benoit, Kenny Brinker, Ryan and Randy Britt, David Copeland, Steve and Robert Diederich, Charles Ellis, Ronnie Flatt, Dolph and Ryan Flurry, Jeff Gebhardt, Ronald Hackman, Tony Hayes, Bill and Nathan Holmes, Steve Jackson, Brandon and Carl Kliethermes, Mark Lehenbauer, Tim Lichte, Mark Nuelle, Mark Peterson, Gary Riedel, Garret and Gary Riekhof, Ted Sander, Gene Sandner, Brian Schnarre, Terry and Pat Seyer, and Bruce Wilson for conducting these demonstrations with us even though it slowed down their sidedress operation. We are also grateful to MFA Inc. (Paul Tracy, Kenny Schlitt, Joe Haskins, Scott Wilburn, and Jason Brown) and to Delta Growers (Kendal Mouser) for allowing us to install sensors on their applicators and for conducting demonstrations for their customers. Matt Volkmann, Bob Mahurin, Ray Benson, and Kurt Holiman helped carry out the demonstrations with the USDA-ARS Spra-Coupe and we appreciate their efforts. This work was supported by the Conservation Innovation Grants program of the USDA-NRCS, the Nonpoint Source Pollution Control program of the Missouri DNR, and the Special Grants program of the USEPA.

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