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In-Season Estimation of Corn Yield Potential Using Proximal Sensing

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ABSTRACT

Crop sensing is a promising approach for predicting corn (*Zea mays* L.) yield. Yield prediction is the first step in development of algorithms for sensor-based N management. Here, we evaluated the impact of (i) timing of sensing (growth stage), and (ii) method of reporting sensor data on estimations of corn grain and silage yield in New York. Sensor data were reported as the normalized difference vegetation index (NDVI), in-season estimated yield (INSEY) expressed as NDVI divided by days after planting (DAP; $INSEY_{DAP}$), growing degree days (GGD; $INSEY_{GGD}$), and the inverse simple ratio (ISR; [1–NDVI]/[1+NDVI]) divided by DAP ($INSEY_{ISR}$). To evaluate timing of sensing, corn of six fertility trials was scanned at every growth stage between V4 and V11. The replicated trials had up to six N rates (0, 56, 112, 168, 224, and 336 kg ha^{-1}). The V7 sensor and yield data from zero-N plots of nine additional on-farm trials (varying histories) were added to derive yield algorithms for New York. Drought at three sites in 2016 negatively impacted the accuracy of sensor-based grain yield estimates ($R^2 < 0.27$). Excluding these sites, most accurate yield predictions were obtained from V6 onward. Across different locations and independent of reporting method, INSEY data at V7 predicted yield with an $R^2 > 0.70$ (grain) and >0.77 (silage). We conclude that INSEY data obtained at V7 can be used to accurately predict corn grain and silage yields in non-drought conditions in New York.

Core Ideas

- Accurate yield prediction is needed for effective sensor-based N management.
- Field testing is needed to develop reliable algorithms for silage and grain corn.
- For the most accurate yield prediction, crop sensing should be done at V6 or later.
- Predictions for corn silage were more accurate than for corn grain.
- The use of in-season-estimated yield is preferred across variable sites.

There is a great emphasis on corn grain and silage production because of New York's large dairy industry, ranked fourth in milk production in the United States (National Agricultural Statistics Service, 2015). Corn takes up a significant amount of nitrogen (N) and in soils containing insufficient plant-available N, N addition with fertilizer is needed. Typically in NY, N fertilizer is split-applied between a low rate of starter fertilizer applied at planting followed by side-dressing when the corn is at the V6-V8 growth stage, just prior to the rapid growth phase of the corn plants. The split N application reduces the risk of N loss and increases N use efficiency (Kanwar et al., 1988; Thompson et al., 2015; Walsh et al., 2012; Ma et al., 2005).

During the last decades the development of proximal sensors and variable rate application equipment made it possible to perform mid-season corrections of N deficiencies. Variable rate applications allow farmers to manage field variability and to reduce spatial variation in end-of-season yield (Stone et al., 1996). Crop sensing can aid in identification of areas within fields that require additional N for optimal crop yield and quality, allowing for variable and more precise rate applications (Stone et al., 1996; Lukina et al., 2001; Raun et al., 2002; Tubaña et al., 2008), enhancing N use efficiency. The active proximal sensors emit their own light and measure the reflectance of specific spectra of light, typically in the visible (VIS; green, red, or red-edge) and the near-infrared (NIR), from the plant canopy providing a wide range of vegetation indices such as the NDVI ([NIR–VIS]/[NIR+VIS]) (Rouse et al., 1973) and the inverse simple ratio (ISR; [VIS/NIR]) (Gong et al., 2003). The advantage of the active sensors is that their measurements are not compromised by cloudiness and they can be mounted on N fertilizer applicators making them ideal for on-the-go variable rate N applications (Shanahan et al., 2008).

The first step in the development of an algorithm for variable rate N applications using proximal sensing is the development of an equation to estimate end-of-season yield from mid-season spectral canopy measurements (Moges et al., 2007). The accuracy of yield predictions from sensor data is impacted by the timing of sensing (growth stage) (Raun et al., 2005a), and the way sensor data are interpreted. The NDVI is the most widely used index for deriving yield estimates (Hatfield et al., 2008) but other indices have also been used. For example, Kitchen

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Abbreviations: DAP, days after planting; DM, dry matter; EY, estimated yield; GGD, growing degree days; INSEY, in-season-estimated yield; ISR, inverse simple ratio; MERN, most economic rate of nitrogen; NDVI, normalized difference vegetation index; NIR, near-infrared; VIS, visible.

et al. (2010) used the inverse simple ratio (ISR = [1–NDVI]/[1+NDVI]) instead of NDVI.

Improvements in the use of vegetation indices for yield estimation have been suggested in past years, including some assessment of the growing season since planting. Raun et al. (2001) introduced the "estimated yield (EY)" as the average NDVI acquired in two post dormancy dates divided by the cumulative growing degree days (GDD) for the period from sensing Day 1 to Day 2. This index integrated the early season growing conditions and growth rate in the computation of EY for wheat (*Triticum aestivum* L.) grown for grain. A simplified INSEY was suggested by Raun et al. (2002) as NDVI divided by the days after planting (DAP) for days with GDD > 0. Teal et al. (2006) developed models to predict corn grain yield based on NDVI, $\text{INSEY}_{\text{GDD}}$, and $\text{INSEY}_{\text{DAP}}$ with similarly good results (R^2 ranged from 0.73–0.77). However, the INSEY approach normalized NDVI measurements across time and various environmental conditions (Teal et al., 2006), accounting for the growing conditions from planting to sensing and providing an estimate of the N uptake per day (Lukina et al., 2001) and the biomass produced per day (Raun et al., 2005b). As such, INSEY could be particularly useful when combining data from different site-years.

Over the last few decades proximal sensing and variable rate application technology have been successfully used to predict end-of-season yield and the probability of N responsiveness in grain crops including small grains (Stone et al., 1996; Lukina et al., 2001; Raun et al., 2002) and corn (Tubaña et al., 2008). Limited studies have been conducted for the use of crop sensors for yield prediction and the development of an algorithm for N management of silage crops. One exception is a recent calibration study by Tagarakis et al. (2017) on the use of crop sensor data for predicting yield of forage sorghum (*Sorghum bicolor* L.) in New York. With a growing interest among New York farmers in precision agriculture, the importance of corn silage and grain in the state, and the large diversity in soil types and field fertility histories (with and without manure), field studies are needed to evaluate use of early or mid-season proximal sensing for predicting yield and N responsiveness of corn grown for grain production and corn harvested as silage.

The overall objective in this study was to evaluate the use and performance of proximal sensing for estimating end-of-season yield of grain and silage corn. The specific objectives were to evaluate the impact of (i) timing of sensing (growth stage), and (ii) method of reporting of sensor data on estimations of corn grain and silage yield in New York. Sensor data were reported as NDVI, $\text{INSEY}_{\text{DAP}}$, $\text{INSEY}_{\text{GGD}}$, and $\text{INSEY}_{\text{ISR}}$.

MATERIALS AND METHODS

Field Experiments

Timing of Sensing

Field trials to determine the best timing of sensing (hereafter referred to as "timing of sensing trials") were conducted on research stations at three locations (Varna, NY, 42.461° N, 76.436° W; Ketola, NY, 42.471° N, 76.438° W; and Aurora, NY, 42.725° N, 76.659° W) in 2015 and 2016. The soil type in Varna is a Hudson silt loam (a fine, illitic, mesic Glossaquic Hapludalf) and Collamer silt loam (a fine-silty, mixed, semi-active, mesic Glossaquic Hapludalf), in Ketola is a Langford channery silt loam (a fine-loamy, mixed, active, mesic Typic Fragiudept) while in Aurora it is Lima silt loam (a fine-loamy, mixed, semiactive, mesic Oxyaquic Hapludalf). Fields without recent manure history were selected to ensure crop response to N; yield differences were needed to test the ability of crop sensing to predict yield accurately.

A range of N rates was applied at planting to create ranges in NDVI and yield. In all trials a randomized complete block design was replicated four times to evaluate sensor measurement with growth stage. Five N rates were tested (0, 56, 112, 168, 224 kg of N ha^{-1}) with the exception of the trial at Aurora in 2016 where an additional treatment (336 kg of N ha^{-1}) was added. All trials were planted with a drought tolerant corn hybrid 3316AM (Doebler's, Williamsport, PA) with a 93 d comparative relative maturity. Planting was done in May in both years with actual dates ranging from 10 to 29 May, depending on weather conditions at the various locations (Table 1).

The plots were 30 m long and 3 m wide with four rows per plot. A John Deere 450 grain drill (Deere and Company, Moline, IL) was used to plant corn at 0.76 m row widths and 0.15 m distance between plants within the row (population stand of 87,850 plants ha^{-1}). The N fertilizer (Agrotain treated urea, Koch Agronomic Services LLC., Wichita, KS) was applied directly after planting using a 3-m drop spreader (Gandy Company, Owatonna, MN).

A GreenSeeker 505 Handheld Sensor (NTech Industries, Ukiah, CA) was used to measure the canopy reflectance from the corn plants at the two middle rows in each plot. The sensor was coupled with a NOMAD 900 Handheld Computer (Trimble Ltd., Sunnyvale, CA) to geo-reference, log, and save the NDVI measurements. The trials were scanned eight times during the growing season at each growth stage starting at V4 until V11 (Table 1).

The plots were split lengthwise; half of each plot was harvested for silage when the plant dry matter content was

Table 1. Planting, harvest and crop sensing dates for the timing of sensing field trials with corn in 2015 and 2016.

			Harvest		Crop sensing							
Year	Location	Planting	Silage	Grain	V4	V5	V6	V7	V8	V9	V10	V11
2015	Aurora	29 May	24 Sept.	4 Nov.	24 June	29 June	10 July	14 July	17 July	21 July	24 July	30 July
2015	Varna	15 May	21 Sept.	22 Oct.	10 June	15 June	20 June	23 June	26 June	30 June	7 July	10 July
2015	Ketola	15 May	21 Sept.	26 Oct.	10 June	15 June	23 June	26 June	30 June	7 July	10 July	14 July
2016	Aurora	10 May	2 Sept.	5 Oct.	10 June	15 June	24 June	27 June	6 July	9 July	11 July	14 July
2016	Varna	12 May	2 Sept.	6 Oct.	6 June	13 June	20 June	23 June	1 July	5 July	8 July	12 July
2016	Ketola	12 May	6 Sept.	14 Oct.	17 June	20 June	27 June	1 July	8 July	12 July	15 July	18 July

approximately 350 g kg^{-1} while the rest was harvested for grain when the dry matter content approached 850 g kg^{-1}. The harvest area was 18.3 m^2 (1.5 by 12.2 m; two adjacent rows in the middle of the plots containing 75 plants on average). During silage harvest (in September, Table 1) the plants were chopped at 0.2 m aboveground, weighed in the field, and subsampled for dry matter content. For the grain harvest (in October, Table 1) ears were collected and weighed. The number of ears was also recorded. A sample of 20 ears from each plot was shelled and wet and dry weights of the cobs and grain were obtained.

Precipitation in 2015 was in the normal ranges for the corn growing season with regular precipitation events from planting until harvest. In 2016, trials faced severe drought from planting until tasseling showing only a few insignificant precipitation events (Fig. 1).

Additional Yield Estimation

Nine on-farm trials were conducted in 2014 and 2015 in northern and western New York as part of a statewide study to evaluate impact of sidedress N application on yield of corn grown for silage or for grain. Trials were planted with a small starter N application, ranging from 15 to 34 kg N ha^{-1} (Table 2). Each trial included a zero-N sidedress treatment, in addition to five sidedress N rates. Plot width varied between 18 and 27 m depending on the harvester and fertilizer applicator size at each farm, so that each plot contained at least three even passes with the harvester and one or two complete passes with the fertilizer applicator. The length varied between 100 and 160 m according to the size and shape of each field. In 2014, crop sensing took place using GreenSeeker sensors (NTech Industries, Ukiah, CA) installed on sprayer booms used for the N sidedress application. The NDVI of the plots that did not receive any sidedress N was recorded at the V7 growth stage providing the average NDVI of the sprayer length. In 2015 the GreenSeeker 505 Handheld Sensor was used in all fields to measure the NDVI from three individual passes within each plot. The sensor was coupled with a NOMAD 900 Handheld Computer (Trimble Ltd., Sunnyvale, CA) to geo-reference, log, and save the NDVI measurements. The measurement frequency was set to 1 Hz. The sensor and yield data from the zero N plots were combined with the data from the "time of sensing trials" to develop yield potential equations.

Trials were harvested using each farm's combine harvester (for the trials grown for grain) or forage harvester (for the trials grown for silage) equipped with yield monitors. Yield datasets were cleaned by removing the points where the harvesters were slowing down, accelerating or stopping, and the points with abnormal moisture content.

Data Analysis

The data from the timing of sensing trials were analyzed for each individual timing using regression analysis in SPSS Statistics (SPSS Inc., Chicago, IL). Regression analysis was used to model final yield (independent variable) using NDVI, $INSEY_{DAP}$, $INSEY_{GDD}$, and $INSEY_{ISR}$ as dependent variables. The coefficient of determination (R^2), the root mean square error (RMSE), and the variability of the NDVI measurements expressed as coefficient of variation (CV), were used as the criteria to determine the best timing to scan with the sensor.

To derive models for yield predictions with crop sensing at V7, the data from the timing of sensing trials were combined with the data from the nine on-farm trials. The R^2 and the RMSE were used as the criteria to determine which of the independent variables, NDVI, $INSEY_{DAP}$, $INSEY_{GDD}$, and $INSEY_{ISR}$, provided the most reliable estimation of end-of-season silage and grain yield. Both exponential and power models were tested using regression analysis in SPSS Statistics (SPSS Inc., Chicago, IL).

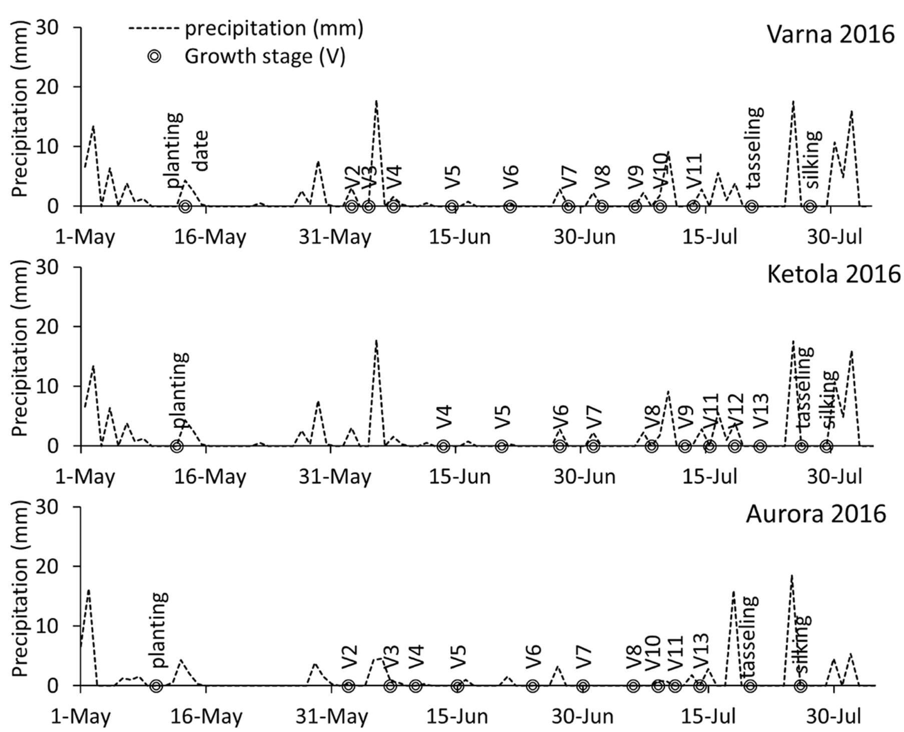

Fig. 1. Precipitation during the corn growing season in Varna, Ketola, and Aurora, NY, in 2016.

Table 2. Location, soil type, soil fertility and amount of starter fertilizer (kg of N ha^{-1}) applied in nine on-farm trials in 2014 and 2015.

		Soil fertility					
Year	Soil type	pH	OM†	P‡	K‡	Mg‡	Starter N
			g kg^{-1}	mg kg^{-1}			kg ha^{-1}
2014	Lima silt loam	6.8	24	5.3 (H)	104 (VH)	193 (VH)	15
2014	Lima silt loam/Honeoye loam	6.7	24	5.6 (H)	101 (VH)	173 (VH)	15
2014	Lima/Cazenovia silt loam	6.5	31	5.7 (H)	111 (VH)	235 (VH)	34
2015	Appleton silt loam	6.2	21	12.0 (H)	145 (VH)	139 (VH)	26
2015	Ontario/Hilton loam	6.8	13	10.5 (H)	101 (VH)	206 (VH)	31
2015	Windsor loamy fine sand	5.2	24	19.1 (H)	160 (VH)	57 (H)	34
2015	Galway loam	6.8	38	36.1 (VH)	190 (VH)	106 (VH)	34
2015	Hudson/Rhinebeck silt loam	6.4	35	9.4 (H)	121 (VH)	270 (VH)	34
2015	Rhinebeck silt loam	6.3	34	4.1 (M)	104 (VH)	255 (VH)	34

† OM, organic matter.

‡ Morgan extractable P, K, and Mg (Morgan, 1941). M = medium; H = high; VH = very high. Interpretations according to Cornell Cooperative Extension (2016).

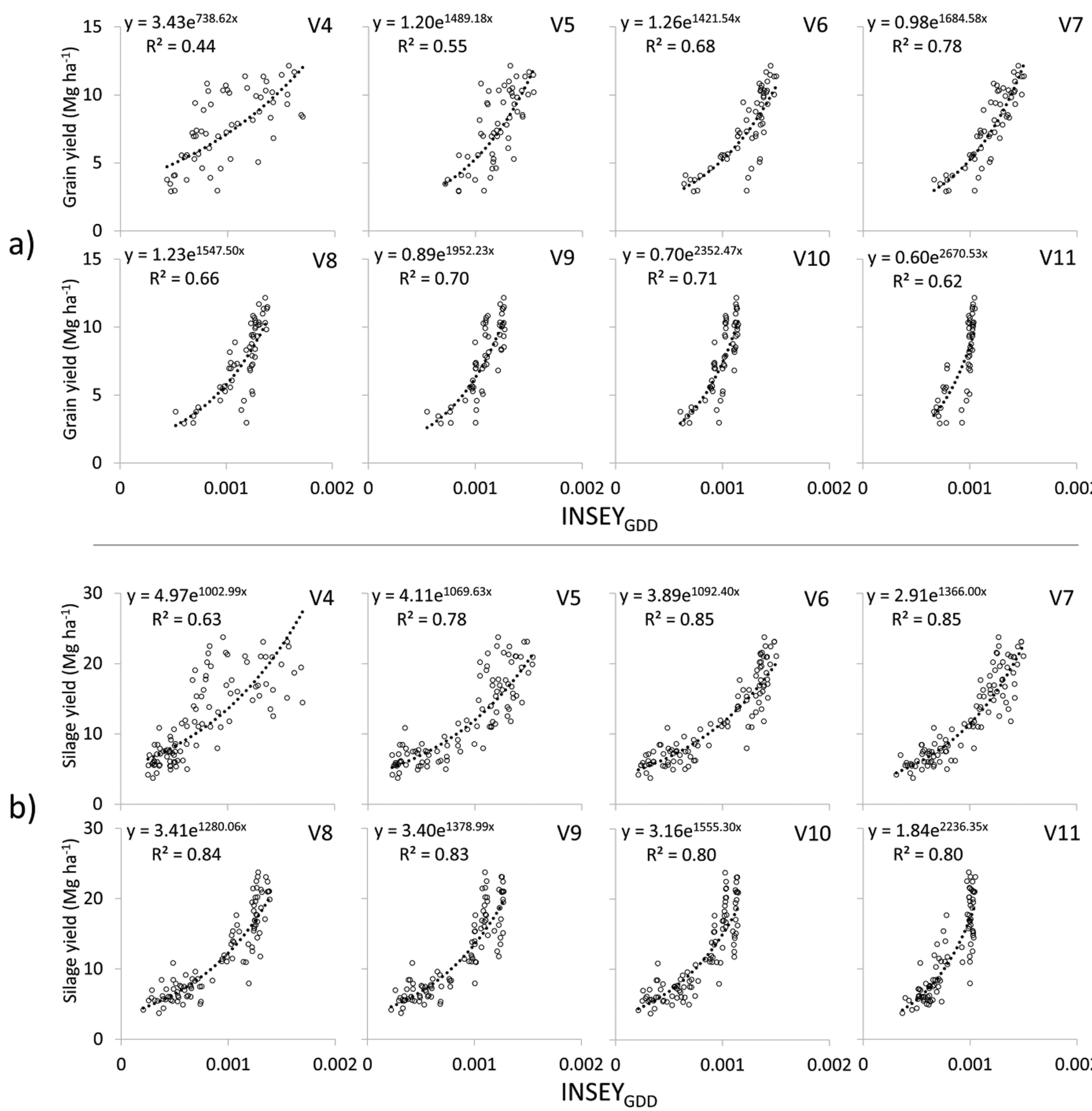

Fig. 2. Relationships between final yield of (a) grain and (b) silage corn and in season estimated yield (INSEY) calculated using days after planting (DAP) and normalized difference vegetation index (NDVI) ($INSEY_{DAP}$ = NDVI/DAP), for trials conducted in Varna, Ketola, and Aurora, NY, with NDVI measured at eight dates in 2015 (V4–V11 growth stages) using the GreenSeeker 505 Handheld Sensor.

Table 3. Regression between end-of-season yield and normalized difference vegetation index (NDVI;), in season estimated yield (INSEY) calculated using the days after planting (DAP) ($INSEY_{DAP}$ = NDVI/DAP), growing degree days (GDD) ($INSEY_{GDD}$ = NDVI/GDD), and the inverse simple ratio (ISR; [1–NDVI]/[1+NDVI]) divided by the growing degree days ($INSEY_{ISR}$ = ISR/GDD) for grain and silage corn (Mg ha^{-1}) in each growth stage from V4 until V11.

	NDVI exponential				$INSEY_{DAP}$ exponential				$INSEY_{GDD}$ exponential				$INSEY_{ISR}$ power			
	R^2	RMSE			R^2	RMSE			R^2	RMSE			R^2	RMSE		
Stage	*a*	*b*	Coefficients		*a*	*b*	Coefficients		*a*	*b*	Coefficients		*a*	*b*	Coefficients	
Grain																
V4	0.34	0.34	3.39***	2.15***	0.37	0.33	3.71***	43.76***	0.44	0.30	3.43***	738.62***	0.39	0.32	46.41**	–0.77***
V5	0.44	0.31	1.23***	3.46***	0.55	0.28	1.46***	84.19***	0.55	0.28	1.20***	1489.18***	0.53	0.29	77.64**	–1.11***
V6	0.67	0.24	0.76***	3.10***	0.66	0.24	1.48***	80.99***	0.68	0.23	1.26***	1421.54***	0.71	0.22	25.34***	–0.73***
V7	0.65	0.25	0.36***	4.00***	0.75	0.21	1.08***	99.50***	0.78	0.19	0.98***	1684.58***	0.77	0.20	31.99***	–0.88***
V8	0.48	0.29	0.86***	2.74***	0.64	0.25	1.36***	91.46***	0.66	0.24	1.23***	1547.50***	0.60	0.26	20.14***	–0.64***
V9	0.46	0.30	0.42*	3.47***	0.65	0.24	0.88***	122.61***	0.70	0.22	0.89***	1952.23***	0.63	0.25	23.13***	–0.78***
V10	0.65	0.24	0.23**	4.18***	0.68	0.23	0.63***	154.11***	0.71	0.22	0.70***	2352.47***	0.74	0.21	24.20***	–0.79***
V11	0.43	0.33	0.08	5.38***	0.61	0.27	0.39**	192.49***	0.62	0.26	0.60***	2670.53***	0.48	0.31	21.94***	–0.75***
Silage																
V4	0.63	0.31	4.38***	3.16***	0.64	0.31	5.21***	61.64***	0.63	0.31	4.97***	1002.99***	0.65	0.30	129.89***	–0.94***
V5	0.78	0.24	3.91***	2.48***	0.81	0.23	4.46***	63.00***	0.78	0.24	4.11***	1069.63***	0.79	0.24	81.78***	–0.80***
V6	0.85	0.20	3.75***	1.91***	0.86	0.19	4.24***	63.77***	0.85	0.20	3.90***	1092.40***	0.87	0.19	39.67***	–0.57***
V7	0.84	0.20	2.53***	2.37***	0.87	0.19	3.32***	77.98***	0.85	0.20	2.91***	1366.00***	0.88	0.18	44.25***	–0.65***
V8	0.82	0.22	2.72***	2.17***	0.85	0.20	3.64***	76.21***	0.84	0.20	3.41***	1280.10***	0.84	0.20	35.24***	–0.55***
V9	0.80	0.23	2.81***	2.04***	0.83	0.21	3.55***	83.27***	0.83	0.22	3.40***	1379.00***	0.84	0.20	31.78***	–0.51***
V10	0.79	0.23	2.55***	2.12***	0.81	0.22	3.18***	97.02***	0.80	0.23	3.16***	1555.30***	0.84	0.21	32.87***	–0.52***
V11	0.79	0.24	0.98***	3.21***	0.84	0.21	1.72***	142.48***	0.83	0.22	1.74***	2291.50***	0.84	0.21	38.65***	–0.64***

* Significant at the 0.05 probability level.

** Significant at the 0.01 probability level.

*** Significant at the 0.001 probability level.

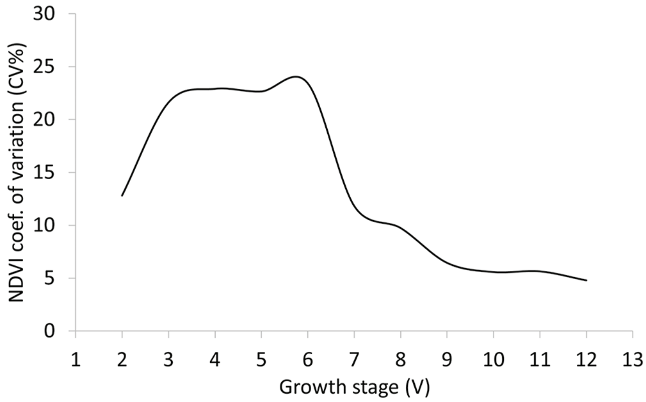

Fig. 3. Relationship between the growth stages and normalized difference vegetation index (NDVI) measurement variability of corn expressed as percentage of coefficient of variation (CV%).

RESULTS AND DISCUSSION

The 2015 timing of sensing trials were responsive to N fertilization. In 2016, the severe drought in spring and summer (Fig. 1) affected yield and N responsiveness. The response indices, defined by Johnson et al. (2000) as the yield in the highest N treatment divided by the yield in the control (zero-N) treatment, were 2.0, 2.5, and 1.4 for the Aurora, Ketola, and Varna sites in 2015, vs. 1.3, 1.1, and 1.2 in 2016. Weed control failed due to the lack of rain at the Aurora site resulting in higher NDVI values than in Varna and Ketola. Due to the weed control issues, this site was excluded from further analysis, consistent with Raun et al. (2005b) who suggested that a model to predict end-of-season yield should be fitted to yields that were not affected by adverse conditions from sensing to maturity. Corn silage yields of the other two sites were consistent with the NDVI measurements, reflecting that when rainfall occurred after mid-July the corn had already entered the reproductive stage. Therefore, data analyses included the 2016 Varna and Ketola trials for the silage yield predictions. Corn grain yield partially recovered during the grain-filling stages assisted by rainfall after mid-July. This caused the NDVI data to underpredict grain yield. Therefore grain yield from these two locations was excluded from the combined analyses. The data from the on-farm trials were not included in the analysis for the timing of sensing as at these trials canopy reflectance was measured only once (at V7).

Timing of Sensing for Grain Corn

Exponential models gave the best fit to the sensor data consistent with findings of previous studies for grain corn (Raun et al., 2005b; Teal et al., 2006), wheat (Lukina et al., 2001; Raun et al., 2005b), and forage sorghum (Tagarakis et al., 2017). Scans before the V6 growth stage showed low correlation to end-of-season yield independent of reporting sensor measurements as NDVI or INSEY ($R^2 < 0.55$; Fig. 2a, Table 3). The R^2 increased as crop growth progressed resulting in a maximum value at V7 growth stage (R^2 ranged between 0.65 and 0.78). This is a growth stage earlier than previous studies which showed high potential to estimate grain corn yield potential from NDVI measurements at V8 (Teal et al., 2006). The RMSE was minimized at V7 indicating that this was the growth stage providing the best prediction of end-of-season yield, consistent with R^2 results (Table 3).

Raun et al. (2005a) suggested that the best time for sensing and to apply in-season N fertilizer was when the variability of the NDVI measurements was maximized stating that treating crops at maximum variability is expected to have the greatest impact. Measurement variability can be expressed as CV in NDVI values. In our study, such NDVI variability was low initially (CV = 12.8% at V2), showed a maximum at V6

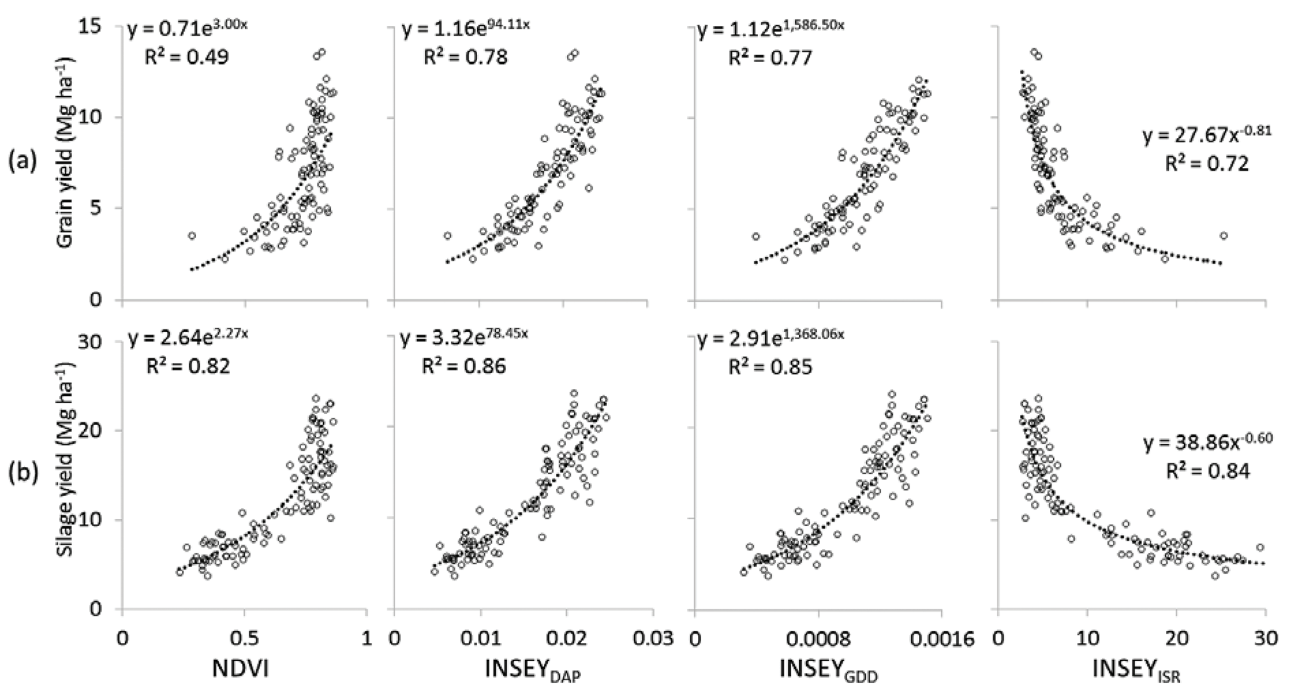

Fig. 4. Relationships between final yield of (a) grain and (b) silage corn and normalized difference vegetation index (NDVI), in season estimated yield (INSEY) calculated using the days after planting (DAP) ($INSEY_{DAP}$ = NDVI/DAP), in season estimated yield (INSEY) calculated using the growing degree days (GDD) ($INSEY_{GDD}$ = NDVI/GDD), and in season estimated yield (INSEY) calculated dividing the inverse simple ratio (ISR) index by the growing degree days ($INSEY_{ISR}$ = ISR/GDD).

(CV = 26.8%), and gradually decreased and leveled off after V10 (CV = 5.6%) (Fig. 3). This result is consistent with the study from Raun et al. (2005a) in corn who concluded that the CV of the NDVI measurements was maximized at V6.

In our work, yield estimations of grain corn were unreliable with scans done prior to V6. The earliest scan that provided acceptable yield predictions across the 4 site-years was at V6 ($R^2 > 0.66$). Predictions providing good estimate of yield were also achieved in later measurements but after V8 the variability of the NDVI, expressed as CV, was significantly lower indicating that the sensor became less efficient in capturing the differences among plants with high and low yields later in the season, and in-field corrections (N addition) would be difficult to do because of the progressed growth of the plants.

Timing of Sensing for Silage Corn

The best fit to the silage data was achieved using exponential models as well (Fig. 2b, Table 3). Scans at the V4 growth stage showed good potential to predict end-of-season yield from NDVI, $INSEY_{DAP}$, $INSEY_{GDD}$, and $INSEY_{ISR}$ ($R^2 > 0.63$) but after V5 the R^2 increased to reach a maximum at V6 and V7 ($R^2 > 0.85$) followed by a small decrease for the later growth stages. The RMSE at V4 was the highest among all growth stages while lowest at V6 and V7 suggesting that sensing at V6–V7 gives the most accurate predictions of silage yield (Table 3). Use of a crop sensor after V9 is not recommended for silage corn either; the CV of the NDVI measurements decreased significantly, and, as mentioned earlier, the corrective N application would be expected to have limited impact (Raun et al., 2005a).

Yield Prediction Models with Sensing at V7

For corn grain, the INSEY-based equations provided more reliable estimations of final yield (R^2 0.72– 0.78) than the raw NDVI measurements ($R^2 = 0.56$) (Fig. 4a). For corn silage, both NDVI and INSEY provided good relationships with silage yield (Fig. 4b). However, it is recommended to use one of the INSEY equations for yield prediction from mid-season sensor measurements across a larger diversity of fields, as these equations adjust the sensor measurements to the specific growing conditions of each field from planting until sensing.

CONCLUSIONS

Sensing timing greatly impacts the accuracy of yield predictions. For grain corn V6 was the earliest growth stage that provided good relationships between sensor measurements and yield but predictions were more accurate (higher R^2 and lower RMSE) for V7. Later sensing resulted in reduced ability to differentiate plants with different yield potentials. The INSEY models fit the data better than the NDVI based model. For silage corn, the NDVI based model performed slightly better than the INSEY based models but also for the INSEY based models the R^2 was 0.77 or higher. Sensing at V6 and V7 resulted in the highest R^2 and lowest RMSE suggesting that crop sensing for corn silage yield predictions might be done one growth stage earlier than sensing for grain yield predictions. The data from the 2016 trials showed that drought can impact the accuracy of yield predictions based on mid-season crop scans. We conclude that crop sensing is a promising technology for determining end-of-season yields of both grain and silage corn. However, timing of scanning needs to be standardized to develop algorithms that can cover a larger region, and scanning in severe drought years will result in less accurate estimates.

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