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Comparison of Satellite Imagery and Ground-Based Active Optical Sensors as Yield Predictors in Sugar Beet, Spring Wheat, Corn, and Sunflower

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ABSTRACT

Algorithms using active-optical (AO) sensors have been developed to direct in-season N application to crops. Many farmers in the United States have a large number of farm fields to manage. Farmers using AO technology must visit each field and operate the sensor across the entire field in order to conduct in-season N application. A field might be driven over with an on-the-go N fertilizer applicator, but the application might not be required. The objective of this study was to determine whether satellite imagery might be used to predict yield in sugar beet, spring wheat, corn and sunflower similar to the yield prediction possible using AO sensors. If so, the algorithms produced could be used to select fields that would benefit from in-season N application. Two N-rate studies in sugar beet, spring wheat, corn and sunflower, were conducted with experimental unit size of 9 by 9 m large enough to fit a satellite pixel of 5 by 5 m size within each unit. The AO sensor and satellite imagery data were related to yield of sugar beet, spring wheat, corn and sunflower in some site-years. The problem is the ability to acquire the satellite imagery early enough in the season to be useful as a screening tool. These results indicate that even though satellite imagery could be used as a field screening tool, a better option may be to mount an AO sensor on a farm implement for an early season activity, or to explore the use of unmanned aerial vehicles (UAVs).

Core Ideas

- Satellite imagery could be used to predict yield the study crops.
- Satellite imagery could be used to screen fields for in-season N application.
- Obtaining satellite imagery early enough in the season to screen fields for in-season N is a problem.

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The original use of remote sensing using infrared photography for yield variation was conducted by Colwell (1956). Since the launch of the Landsat 1 imaging satellite in 1972 (Mulla, 2013), satellite imagery has been widely used in agriculture for yield prediction and most lately for site-specific N management. Bhatti et al. (1991) used Landsat imagery and auxiliary data to estimate wheat yield potential. On 11 Feb. 2013, NASA launched Landsat 8, which provides moderate-resolution imagery from 15 to 100 m and operates in the visible, near-infrared, short wave infrared and thermal infrared spectrums (NASA, 2013). Additional satellite imaging systems include: SPOT (SPOT, 2016), MODIS (MODIS, 2016), QuickBird (QuickBird, 2015), RapidEye (RapidEye, 2016), GeoEye (GeoEye, 2016), WorldView (WorldView, 2016), and NOAA-AVHRR (NOAA-AVHRR, 2016). Newer satellite remote sensing systems provide higher spatial resolution, a greater variety of spectral bands, and higher revisit frequency. Satellite imagery in the visible and near infrared (NIR) bands is useful only during daylight when cloud cover does not interfere with the groundcover image. Shou et al. (2007) found that the individual red, green, and blue spectral band reflectance values from QuickBird satellite imagery were highly correlated with winter wheat total N concentration and aboveground biomass.

Although in small areas individual spectra can be related to crop biomass, differences in angle of light reflection and other interferences led to the use of vegetation indices, especially normalized differential vegetation index (NDVI), derived from satellite imagery for greatly improved relationships to crop biomass and its use to predict crop grain yield (Rouse et al., 1973) and N status. The NDVI formula is:

$$\text{NDVI} = (\text{red} - \text{NIR})/(\text{red} + \text{NIR})$$

where NIR is near infrared reading.

The NDVI formula can be used to calculate red edge NDVI by substitution of red edge values for red in the formula (Gitelson et al., 1996a; Gitelson et al., 1996b) An effective method for predicting crop yield or N status using remote sensing data perhaps is to construct the empirical regression

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Abbreviations: AO, active optical; CC, Crop Circle; GS, GreenSeeker; NDVI, normalized differential vegetation index; NIR, near infrared; UAV, unmanned aerial vehicle.

relationships between crop yield or N status and the vegetation indices from sensing data. To improve prediction accuracy, additional ancillary measurements are sometimes incorporated into the regression models.

Satellite spectra derived vegetation indexes have been useful in relating satellite imagery to yield in corn (*Zea may.* L.) (Mkhabela and Mashinini, 2005; Prasad et al., 2006; Bognár et al., 2011), winter wheat (*Triticum aestivum,* L.) (Salazar et al., 2007; Ren et al., 2008; Becker-Reshef et al., 2010; Bognár et al., 2011;), potato (*Solanum tuberosum*, L.) (Bala and Islam, 2009), barley (*Hordeum vulgare,* L.), canola (*Brassica napus,* L.), field pea (*Pisum sativum,* L.), spring wheat (*Triticum aestivum.* L.) (Mkhabela et al., 2011), and sorghum (*Sorghum bicolor,* L.) (Shamseddin and Adeeb, 2012). Satellite imagery has also been found to be related to sugar beet (*Beta vulgaris*, L.) sucrose concentration at harvest (Humburg et al, 2006).

Use of satellite imagery for site-specific N application requires a within field or near field comparison for algorithms relating imagery to yield, and then to N status (Schepers et al., 1992). Shanahan et al. (2001) placed white-painted sheets of plywood at the four corners of their research field as a reference to correct for differences in imagery over the area.

The improvement of farm nitrogen use efficiency (NUE) is an important issue due to economic and environmental concerns. For many crops there is a relationship between leaf N and chlorophyll concentration (Blackmer and Schepers, 1995; Evans, 1983; Olfs et al., 2005). Therefore, chlorophyll content of a plant can be a good indicator for leaf N concentration. Red NDVI is most useful in yield prediction and in determining N status of crops before the leaves cover the row. Later in the season after the leaf canopy closes, red edge NDVI is more useful, since red edge NDVI is more related to chlorophyll content, while red NDVI is more related to leaf area index (LAI) (Horler et al., 1983).

GREENSEEKER

Raun et al. (2001) developed the GreenSeeker (GS) ground-based AO sensor with engineering colleagues at Oklahoma State University, which sold the rights to N-Tech (Ukiah, CA), which was acquired by Trimble (Sunnyvale, CA) in 2009 (Trimble, 2009). The GS uses red NDVI and NIR active light sources and detectors to record readings. Raun et al. (2001) found that dividing the red NDVI readings by growing degree days from winter wheat planting normalized the data so that algorithms developed were not specific for an exact growth stage, but were valid over a range of growth stages. The product of this calculation was named INSEY (in-season estimate of yield). Based on INSEY, Lukina et al. (2001) developed a winter wheat in-season N fertilization recommendation algorithm. The basic method for in-season N application using AO sensors is to establish an N-nonlimiting area in the field of interest immediately before planting, then comparing the yield predicted by sensing the N-nonlimiting area to the yield predicted in other areas of the field. The difference in yield prediction multiplied by the N content anticipated in the grain divided by an N fertilization efficiency factor provides the N rate in the area of the field being sensed. Variations of this basic method include the response index (RI) of the soil through empirical experiments (Johnson and Raun, 2003; Mullen et al., 2003). Algorithms for use of the GS are available for corn (Raun et al., 2008; Reiter et al., 2014; Franzen et al., 2014; Tubana et al., 2008) and wheat (Raun et al., 2002; Murdock et al., 2013; Reiter et al., 2014).

CROP CIRCLE

The Holland Scientific Crop Circle (CC) sensors (Holland Scientific, Lincoln, NE) are a series of ground based AO sensors that use red, NIR, and red-edge wavelengths simultaneously. The use of the CC sensors has been directed toward development of algorithms for in-season N application. Relationships of sensor readings to yield and in-season N status, as well as algorithms for use in determining in-season N rates have been developed by several researchers (Dellinger et al., 2008; Solari et al., 2008; Sripada et al., 2008; Scharf and Lory, 2009; Barker and Sawyer, 2010; Solari et al., 2010; Oliviera et al., 2013; Franzen et al., 2014).

COMPARISON OF VEGETATIVE INDEXES FROM SATELLITE IMAGERY COMPARED TO GROUND-BASED ACTIVE SENSORS

Several studies have compared imagery from satellites to ground-based AO sensor data and found the correlation between the two sources to be high. Caturegli et al. (2015) found that the GeoEye-1 NDVI was correlated to GS NDVI, with the conclusion that either could be used to estimate N status of turfgrasses. Several spectral bands from Quickbird satellite imagery and multi-spectral imagery from a Portable Field Spec Handheld Spectroradiometer (Analytical Spectral Devices, Inc., Boulder, CO) were highly correlated in winter wheat N rate experiments in Turkey (Genc et al., 2009). Bausch and Khosla (2010) extracted green normalized normalized differential vegetation index (NGNDVI) from QuickBird satellite multi-spectral data to estimate the N status of irrigated corn and proved the feasibility of using QuickBird satellite multi-spectral imagery for in-season N management of corn at the V12 and later growth stage.

Although these studies demonstrated that satellite imagery could be used to direct in-season N application, there are practical challenges in utilizing satellite imagery for real-time or near real-time N application. Available satellite image pixel size is larger than the scene exposed for readings with the GS and CC sensors. GeoEye has the greatest resolution of any present imagery satellite at 0.5 by 0.5 m, while the GS and CC sensors have resolutions of about 0.5 by 0.15 m. RapidEye has a resolution of approximately 5 by 5 m, while LandSat has a resolution of approximately 30 by 30 m. In addition, in-season N application is conducted within each crop at specific time periods. In corn, application from V5 to V9 is important to provide N to the plant before major physiological components of yield are determined, such as the number of kernel rows per ear, length of ear, and kernels in a row.

Cloud cover that obscures or partially obscures a satellite imagery target is always a concern. Dai (2006) determined that the probability of cloud cover directly over a monitoring station was about 65% at Huntsville, AL, 75% at Albany, NY, and about 45% at Tucson, AZ. Although it might be possible to obtain a cloud-free image of a given field sometime in the 10 d prior to an intended in-season N application, the probability of obtaining an image the day of application would be low. In June in North Dakota, when corn would be in the V5 to V9 growth stages, the probability of obtaining a cloud-free image on a given day in summer would be less than 50% (Ju and Roy, 2008).

In North Dakota, farm size is large, with an average farm size of 510 ha from about 30,000 farm units. The average farm size statistic is misleading, since any land can be classified as farm with income from the land of at least US$2500 ha^{-1} or potential to reach or exceed that income. The number of commercially viable and independent farm units is about 10,000 farms, with average size of 1000 ha. The highest economic class of farm unit in North Dakota has an average size of about 1700 ha (NASS, 2014). This means that many farmers do not farm fields in a concentrated area. There are many farm field locations within a commercial farming unit, and some are separated by as much as 80 km. Distance between fields is a logistical problem for the farmer or the business charged with application of in-season N. If an AO sensor is utilized to deliver in-season N, every field must be visited and even if the field does not have a sensor reading difference with the N-sufficient standard, every hectare of the field must be covered to discover that. If a satellite image obtained within 10 d of the in-season N application was obtained, and the satellite image analysis could analyze differences in readings between an N-sufficient standard area of sufficient size, fields requiring no in-season N application could be eliminated from the list of fields, the area and locations of areas within fields that could benefit from in-season N could be identified, and the total N fertilizer required for in-season N application could be calculated prior to a visit with the AO sensor-equipped in-season N applicator.

The objective of these experiments were to determine whether RapidEye satellite NDVI is related to yield similar to GS and CC NDVI in sugar beet, spring wheat, sunflower, and corn, so it might be considered as a logistical aid to identify fields that might benefit from in-season N application directed by AO sensors.

MATERIALS AND METHODS

Field N rate experiments were conducted in 2012 and 2013 on four crops; sugar beet, spring wheat, corn, and sunflower. Site and agronomic information is provided in Table 1. The experiments were organized using a randomized complete block design (RCBD) with four replications and six N rate treatments as ammonium nitrate (34–0–0) granules applied pre-plant within a week of seeding. The N treatments for corn, spring wheat, and sunflower were 0, 45, 90, 135, 180, and 225 kg ha^{-1}, and the treatments for sugar beet were 0, 34, 67, 101, 135, and 168 kg ha^{-1}. For all site-years, each experimental unit was 9.1 by 9.1 m, which is large enough to accommodate several RapidEye imagery pixels. Soil samples from the 0 to 15 cm and 15- to 60-cm depths were collected at each site in each year before fertilizer application to determine residual soil nitrate, plant available P, K, and other relevant soil chemical properties (Table 2).

Two AO sensors were used to collect crop canopy optical reflectance data; the Holland CC ACS-470 and the GS. The CC sensor has six narrowband interference filters but only three optical measurement channels, so each measurement records using three filters which are chosen prior to use by the operator. The 670 nm (red), 730 nm (red edge), and 760 nm (NIR) were used to calculate red NDVI and red edge NDVI. The GS used 660 nm (red) and 770 nm (NIR) channels. Optical reflectance was measured using the sensors positioned about 50 cm above the crop canopy, with the operator walking along a representative middle row within the defined area of each experimental unit. Sensing date, growth stage, and other important dates are provided in Table 3.

Growing degree days (GDD) from time of planting to time of sensing was obtained from the North Dakota Agricultural Weather Network (NDAWN) website using the closest NDAWN station relative to the experimental site (NDAWN 2015). The GDD for each sensing date and planting data are listed in Table 3. To compare and combine data, INSEY was determined using the following equation (Raun et al., 2001):

$$\text{INSEY} = \text{Sensor reading}/(\text{GDD from planting to sensing date})$$

RapidEye Ortho Products (Level 3A) satellite imagery was obtained (Blackbridge AG, Berlin, Germany), which were already subjected to radiometric, sensor and geometric corrections before release (RapidEye, 2016). The RapidEye imagery has a 5 m spatial resolution and includes five broad spectral bands, including Red (630–685 nm), Red Edge (690–730 nm), and NIR (760–850 nm). The NDVI extraction was performed using GRASS GIS 6.4.2 (2012) and MATLAB 8.0 (The Mathworks, Inc., 2012). The dates of the satellite imagery are provided in Table 3. The regression coefficient (r^2) of satellite imagery and AO sensor imagery with yield, and crop quality components was determined using SAS 9.2 for Windows (SAS Institute, Cary, NC).

The harvest dates of each site-year crop are listed in Table 2. The middle 1.22 m width of each spring wheat experimental unit was harvested using a small plot combine. Wheat was cleaned using a mechanical grain cleaner before weighing for plot yield and moisture measurement. Moisture readings for wheat, corn, and sunflower were obtained using a Dickey-John GAC 500XT moisture meter (Dickey-John Corporation, Auburn, IL). A single 9.1 m row, less the ear/head from each of the row, near the middle of each experimental unit of corn and sunflower was hand harvested, removing the ears in corn and cutting off the sunflower head at the junction of head and stem. Harvest stand was also recorded for sunflower. Late germinating corn or sunflower plants that did not produce grain were not counted. The ear corn was dried to about 10% moisture in a dryer set at 50°C for 48 h before shelling using an Almaco (Almaco, Nevada, IA) corn sheller. Sunflower heads were threshed using a stationary plot combine. Sunflower seed was cleaned, then weighed, and moisture recorded.

Corn and sunflower yield were further adjusted using the corresponding plant stand information based on the following formula:

$$\text{Adjusted yield} = \text{yield}/\text{stand coefficient}$$

where

$$\text{Stand coefficient} = \text{plant stand of individual plot}/\text{average of plant stand over all plots.}$$

In 2012, Amenia sugar beet were harvested at two dates and Crookston sugar beet at three dates, with each harvest consisting of 3.05 m of row that was hand-harvested in each experimental unit. Commercial harvest at Amenia was early, and a

Table 1. Background information for crops, soil and agronomic factors for N-rate and imagery experiments conducted in North Dakota and Crookston, MN, in 2012 and 2013.

Year	Crop	Cultivar	Site	NW corner GPS coordinate	Previous crop	Soil types and slopes	Row width	Seeding rate
							cm	1000 seed ha^{-1}
2012	spring wheat	Kelby	Gardner	47°10′19.425″ N, 96°55′12.471″ W	soybean	Fargo-Enloe silty clays†, 0–2% slopes	20	3850
2012	spring wheat	Argent	Valley City	46°52′58.656″ N, 97°54′52.072″ W	sunflower	Barnes-loams, 3–6% slopes	20	2970
2013	spring wheat	Kelby	Gardner	47°10′12.322″ N, 96°54′03.359″ W	soybean	Fargo-Enloe silty clays, 0–2% slopes	20	2470
2013	spring wheat	Argent	Valley City	46°52′41.906″ N, 97°54′46.331″ W	sunflower	Barnes-loams, 3–6% slopes	20	2570
2012	corn	DeKalb 42-72	Durbin	46°50′59.021″ N, 97°09′29.045″ W	corn	Fargo-Hegne silty clay, 0–1% slopes	56	84
2012	corn	NK 17P	Valley City	46°53′04.814″ N, 75°54′55.421″ W	spring wheat	Barnes loams, 3–6% slopes	76	70
2013	corn	DKC 43-10	Arthur	47°02′04.176″ N, 97°07′48.268″ W	soybean	Fargo silty clay loam, 0–1% slopes	56	86
2013	corn	NK 17P	Valley City	46°53′26.218″ N, 97°55′05.695″ W	spring wheat	Barnes loams, 3–6% slopes	76	65
2012	sugar beet	Vander Have 36813RR	Crookston	47°47′58.426″ N, 96°35′55.436″ W	spring wheat	Bearden silty clay loams, 0–1% slopes	56	141
2012	sugar beet	Crystal 095	Amenia	46°58′34.623″ N, 97°15′04.762″ W	spring wheat	Fargo silty clay, 0–1% slopes	56	167
2013	sugar beet	Crystal 875	Casselton	46°51′43.782″ N, 97°18′47.800″ W	spring wheat	Fargo silty clay, 0–1% slopes	56	150
2013	sugar beet	Seedex Xavier	Thompson	47°45′00.656″ N, 97°05′23.046" W	spring wheat	Bearden silty clay loams, 0–1% slopes	56	148
2012	sunflower	CHS RH 1121 confection	Cummings	47°31′45.677″ N, 97°06′52.330″ W	corn	Glyndon silt loams, saline, 0–1% slopes	76	44.5
2012	sunflower	Croplan 555 NSCLDR	Valley City	46°52′35.815″ N, 97°56′27.728″ W	spring wheat	Fordville loams, 0–2 % slopes	76	64
2013	sunflower	CHS RH 1121 confection	Cummings	47°32′31.989″ N, 97°01′41.687″ W	corn	Divide loams, 0–2% slopes	55	44.5
2013	sunflower	Syngenta 3495	Valley City	46°52′45.234″ N, 97°54′15.948″ W	corn	Barnes loams, 3–6% slopes	76	66.7

† Soil series taxonomic designations:
Barnes- fine-loamy, mixed, superactive, frigid Calcic Hapludoll.
Bearden- fine-silty, mixed, superactive, frigid Aeric Calciaquoll.
Divide- fine-loamy over sandy or sandy-skeletal, mixed, superactive, frigid Aeric Calciaquoll.
Enloe- fine, smectitic, frigid Argiaquic Argialboll.
Fargo- fine, smectitic, frigid Typic Epiaquert.
Fordville- fine-loamy over sandy or sandy-skeletal, mixed, superactive, frigid Pachic Hapludoll.
Glyndon- coarse-silty, mixed, superactive, frigid Aeric Calciaquoll.
Hegne- fine, smectitic, frigid Typic Calciaquert.

Table 2. Background soil analysis prior to spring wheat, corn, sunflower, and sugar beet experiments, 2012–2013.

Crop	Year, Site	Nitrate-N, 0–60 cm	P	K	Organic matter	pH
		———	mg kg^{-1}	———	g kg^{-1}	
Spring wheat	2012, Gardner	81	24	185	53	7.5
	2012, Valley City	68	32	128	54	5.4
	2013, Gardner	132	31	460	61	7.6
	2013, Valley City	146	16	245	48	5.6
Corn	2012, Durbin	44	40	650	74	5.4
	2012, Valley City	87	8	275	39	6.3
	2013, Arthur	66	11	270	47	7.9
	2013, Valley City	88	18	150	45	6.1
Sunflower	2012, Cummings	80	15	420	49	7.8
	2012, Valley City	46	12	170	40	6.2
	2013, Cummings	44	24	160	49	8.2
	2013, Valley City	152	21	270	31	6.0
Sugar beet	2012, Amenia	152	9	380	49	7.6
	2012, Crookson, MN	94	20	320	42	7.4
	2013, Casselton	153	7	370	54	7.6
	2013, Thompson	88	10	225	57	7.8

third date of harvest was not possible given early grower harvest of the field. In 2013, the Casselton and Thompson sugar beet sites were harvested on three dates. Sugar beets were pulled by hand from the soil, and the tops were removed using a modified machete and all beets were placed in a leather bag provided by American Crystal Sugar Cooperative and delivered the same day for subsequent weights and quality analysis by the East Grand Forks American Crystal Sugar Tare Laboratory, East Grand Forks, MN.

Regression analysis of crop yield and satellite and ground-based sensor NDVI was conducted using SAS 9.3. Except sunflower, ground-based or satellite-based sensing data for the two sites of each of the other crops in each individual year were pooled for analysis. Sunflower data were first analyzed for each individual site-year, then analyzed for 2-yr pooled data of each different type of sunflower seed (oilseed or confectionery).

RESULTS AND DISCUSSION

Sugar Beet

A summary of the first (V6) and second (V12–V14) GS and CC sensing statistically significant ($P < 0.05$) regression analysis results is provided in Table 4. In sugar beet N management, in-season N application should be conducted early in the growing season to avoid low sugar production (Lamb and Moraghan, 1993). The coefficients of determination (r^2) from the linear regressions of GS and CC INSEY with sugar beet root yield indicate that either of these instruments might be used to direct a variable-rate N application to sugar beet should readings indicate N stress. The INSEY values at V12 to V14 would be used more to estimate final yield and recoverable sugar content for logistical benefit, but not to conduct an N application. Multiplying INSEY by canopy height improved the model at V6, but not at V14.

In 2013, the sensor data for the GS and CC AO sensors for Casselton and Thompson were pooled and linear regression analysis conducted with first, second, and third harvest sugar beet root yields. The coefficients of determination of the linear regressions of pooled data with sugar beet root yields were not significant. The lack of significance was probably due to high initial residual soil nitrate at Casselton and incidence of root disease at Thompson.

The INSEY data from GS and CC AO sensors for each sensing period for the two 2012 sugar beet sites were pooled and linear regression relationships determined with first and second harvest sugar beet root yield. The coefficients of determination of the linear regressions of pooled 2012 V6 to V8 and V12 to V14 INSEY and first and second harvest sugar beet recoverable sugar yield were significant (Table 5). The sensors tended to have the greatest significance at the V12 to V14 growth stage, and the CC red edge INSEY tended to be more highly significant compared with the GS and CC red light sources.

Four site-years of data from 2012 and 2013 experiments were pooled for linear regression analysis (Table 6). The coefficients of determination of the linear regression between the GS and CC sensors at V6 to V8 and recoverable sugar yield were highly significant except for the CC red edge INSEY at V6 to V8. The r^2 values of the linear regression of the GS and CC V12 to V14 INSEY and recoverable sugar yield at the second harvest dates were all highly significant.

The satellite imagery INSEY from Amenia and Crookston in July 2012 was pooled and the coefficients of determination of the linear regression of INSEY and sugar beet root yield at first and second harvest dates were significant (Table 7). Data were also pooled from the satellite INSEY obtained in August 2012 and the r^2 values of the linear regressions of INSEY and sugar beet root yield were also significant for red and red edge INSEY. Although the July satellite image might aid in identifying fields with an in-season N fertilizer requirement, the August image would be too late for such an application, but might help to better predict final root and sugar yield.

In 2013, only the Casselton 24 June satellite imagery and the Thompson 13 August satellite imagery were clear enough to provide adequate data for comparing imagery with sugar beet yield and quality. The quality of Casselton 24 June imagery was slightly affected by cloud haze. The INSEY data obtained from these two imageries were pooled. The coefficients of determination of the linear regression between the pooled INSEY and

Table 3. Ground-based active-optical (AO) sensor reading and RapidEye satellite image information for spring wheat, sugar beet, corn, and sunflower, 2012 and 2013.

Site, Year	Crop	Plant date	First AO sensing date	First AO sensing growth stage	Second AO sensing date	Second AO sensing growth stage	Satellite image access date	Harvest date(s)
Gardner, 2012	spring wheat	7 Apr.	23 May	Feekes 4	6 June	Feekes 9	3 July	26 July
Valley City, 2012	spring wheat	31 Mar.	24 May	Feekes 4	6 June	Feekes 9	Not available	26 July
Gardner, 2013	spring wheat	6 May	24 June	Feekes 6	25 June	Feekes 9	24 June	12 Aug.
Valley City, 2013	spring wheat	7 May	17 June	Feekes 5	25 June	Feekes 9	15 June	13 Aug.
Durbin, 2012	corn	3 May	15 June	V6	29 June	V12	16 Aug.	22 Sept.
Valley City, 2012	corn	3 May	15 June	V6	29 June	V12	16 Aug.	22 Sept.
Arthur, 2013	corn	10 May	20 June	V6	23 July	V14	24 June	24 Sept.
Valley City, 2013	corn	15 May	25 June	V6	17 July	V12	21 July	8 Oct.
Crookston, 2012	sugar beet	25 Apr.	4 June	V6	21 June	V14	11 July; 16 Aug.	15 Aug., 29 Aug., and 15 Sept.
Amenia, 2012	sugar beet	12 Apr.	24 May	V6	13 June	V14	1 July; 16 Aug.	15 Aug. and 28 Aug.
Casselton, 2013	sugar beet	13 May	20 June	V8	10 July	V12–V14	24 June	27 Aug., 16 Sept., and 30 Sept.
Thompson, 2013	sugar beet	14 May	20 June	V8	10 July	V12	13 Aug.	27 Aug., 17 Sept., and 1 Oct.
Cummings, 2012	sunflower	7 May	19 June	V8	3 July	V14	1 July; 16 Aug.	24 Sept.
Valley City, 2012	sunflower	16 May	19 June	V8	10 July	V12	10 Aug.	28 Sept.
Cummings, 2013	sunflower	29 May	2 July	V8	18 July	V16	24 June	17 Oct.
Valley City, 2013	sunflower	3 June	3 July	V8	22 July	V18	24 June	8 Oct.

first, second, and third harvest sugar beet root yield were significant (Table 7). The normalizing effect of the growing degree days within INSEY made pooling these data possible. Two-year, four-site satellite INSEY values were pooled and the coefficients of determination of the linear regressions of the pooled INSEY and sugar beet root yield and sugar beet recoverable sugar yield at the first and second harvest dates were significant (Table 8). The pooled satellite red edge INSEY linear regressions with sugar beet root yield and sugar beet recoverable sugar yield were not significant.

The INSEY values were calculated from pooled 2013 satellite imagery and the coefficients of determination of the linear regressions with each harvest recoverable sugar yield were significant (Table 8). Two-year, four-site INSEYs calculated from satellite imageries were pooled and the coefficients of determination of the linear regressions of red INSEY with sugar beet recoverable sugar yield at the first and second harvest periods were significant (Table 8).

The coefficients of determination of the linear regressions of satellite imagery, using red and red edge INSEY with sugar beet root yield and recoverable sugar yield were highly significant for 2013 pooled site, and 2012–2013 pooled site data at the first and second harvest dates. The coefficients of determination of the linear regression of 2013 pooled site INSEY with third harvest root yield and recoverable sugar yield were also significant. If the satellite imagery was acquired about V6, as it was when June dates were available for some sites, the imagery could be used as a logistics tool to screen fields for the need for in-season N application. Imagery acquired later in the growing season would not be suitable for use in scheduling in-season N application due to reduction in sugar beet recoverable sugar content with late N application; however, the late-season imagery would help logistics related to harvest to estimate trucking and processing needs.

Spring Wheat

The pooled data from the two 2012 wheat experimental sites were pooled. The coefficients of determination of the linear regression of the GS red INSEY with wheat yield was significant, but not from the CC red or red edge INSEY. In 2013, the coefficients of determination of the linear regression for all pooled AO sensor INSEYs and wheat yield were significant (Table 9). The coefficients of determination of the linear regression of the pooled data from both years were significant for the INSEYs of both AO sensors. With the pooled 2012, pooled 2013, and 2-yr pooled data, each data set from both sensors at Feekes 9 INSEY was significantly related to spring wheat protein concentration (Table 9).

In 2012, only the Gardner satellite imagery was available for analysis. The coefficients of determination of the linear regression of the red edge INSEY and wheat yield and protein were significant, but not the red INSEY. Thin cloud cover confounded the use of earlier images. In 2013, pooled data from both sites resulted in no significant r^2 values of the linear regression of INSEY to wheat yield. However, the linear regression of red INSEY and wheat protein was highly significant. Pooling satellite INSEY from 2012 and 2013, the coefficients of determination of the linear regression with protein were highly significant, but not yield (Table 10). The

Table 4. Coefficients of determination (r^2) of the linear regressions and the probabilities of $P > F$ between pooled 2012 GreenSeeker (GS) and Crop Circle (CC) INSEY and first and second harvest sugar beet root yield.

	V6 red INSEY†		V6 red edge INSEY		V12–V14 red INSEY		V 12–V14 red edge INSEY	
Sensor/Harvest	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$
GS/First	0.47	0.0002	na‡	–	0.67	<0.0001	na	–
GS/Second	0.40	0.0003	na	–	0.65	<0.0001	na	–
CC/First	0.56	<0.0001	0.63	<0.0001	0.72	<0.0001	0.72	<0.0001
CC/Second	0.42	0.0003	0.45	0.0001	0.68	<0.0001	0.66	<0.0001

† INSEY is normalized differential vegetation index (NDVI)/(growing degree days from planting).

‡ na means data unavailable because red edge is not available in the GS.

Table 5. Coefficients of determination (r^2) and probabilities of $P > F$ between pooled V6 to V8 and V12 to V14 GreenSeeker (GS) and Crop Circle (CC) INSEY from 2012 sugar beet first and second harvest recoverable sugar yield.

		GS red INSEY†		CC red INSEY		CC red edge INSEY	
Harvest	Growth stage	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$
First	V6–V8	0.35	0.0011	0.43	0.0002	0.49	<0.0001
	V12–V14	0.42	0.0002	0.46	0.0001	0.48	<0.0001
Second	V6–V8	0.39	0.0003	0.40	0.0003	0.43	0.0002
	V12–V14	0.68	<0.0001	0.68	<0.0001	0.65	<0.0001

† INSEY is NDVI/(growing degree days from planting).

Table 6. Coefficient of determination (r^2) of the linear regression and probabilities of $P < F$ of pooled 2012 and 2013 GreenSeeker (GS) and Crop Circle (CC) INSEY at V6 to V8 and V12 to V14 and first and second sugar beet harvest recoverable sugar yield.

	GS red INSEY† V6–V8		CC red INSEY V6–V8		CC red edge INSEY V6–V8		GS red INSEY V12–V14		CC red INSEY V12–V14		CC red edge INSEY V12–V14	
Harvest	r^2	$P < F$	r^2	$P < F$	r^2	$P < F$	r^2	$P < F$	r^2	$P < F$	r^2	$P < F$
First	0.48	<0.0001	0.69	<0.0001	ns‡	–	0.73	<0.0001	0.76	<0.0001	0.70	<0.0001
Second	0.74	<0.0001	0.94	<0.0001	ns	–	0.92	<0.0001	0.96	<0.0001	0.89	<0.0001

† INSEY is normalized differential vegetation index (NDVI)/(growing degree days from planting).

‡ ns denotes nonsignificance.

Table 7. Coefficients of determination (r^2) of the linear regression and the probabilities of $P > F$ between the July 2012 and August 2012 pooled RapidEye INSEY and first and second harvest sugar beet root yield.

	First harvest root yield				Second harvest root yield			
	red INSEY		red edge INSEY		red INSEY		red edge INSEY	
Satellite imagery date	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$
July	0.77	<0.0001	0.86	<0.0001	0.59	<0.0001	ns†	–
August	0.86	<0.0001	0.90	<0.0001	0.69	<0.0001	0.47	<0.0001

† ns denotes nonsignificance.

Table 8. Coefficients of determination (r^2) between linear regression and the probabilities of $P > F$ of 2013 pooled RapidEye INSEY with sugar beet root yield at three harvest dates, and 2012–2013 pooled INSEY with sugar beet root yield and recoverable sugar yield.

	2013 pooled root yield		2013 pooled recoverable sugar yield						2012–2013 root yield		2012–2013 recoverable sugar yield	
	red INSEY†		red edge INSEY		red INSEY		red edge INSEY		red INSEY		red INSEY	
Harvest	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$
First harvest	0.41	<0.0001	0.60	<0.0001	0.26	<0.0001	0.36	<0.0001	0.55	<0.0001	0.55	<0.0001
Second harvest	0.43	<0.0001	0.56	<0.0001	0.29	<0.0001	0.29	<0.0001	0.44	<0.0001	0.54	<0.0001
Third harvest	0.54	<0.0001	0.58	<0.0001	0.45	<0.0001	0.43	<0.0001	na‡	–	na	–

† INSEY is normalized differential vegetation index (NDVI)/(growing degree days from planting).

‡ na denotes not available due to only two harvest dates in 2012 at Amenia.

Table 9. Coefficients of determination (r^2) of the linear regression of pooled 2012 and pooled 2013 GreenSeeker (GS) and Crop Circle (CC) INSEY at Feekes 5 with spring wheat yield and at Feekes 9 with spring wheat protein concentration. Where values are provided, the r^2 values are highly significant at $P < 0.0001$.

	GS red INSEY†		CC red INSEY		CC red edge INSEY	
Year	Yield	Protein‡	Yield	Protein	Yield	Protein
2012	0.76	0.76	ns§	0.74	ns	0.78
2013	0.89	0.80	0.94	0.71	0.97	0.77
2012–2013	0.96	0.80	0.96	0.78	0.96	0.82

† INSEY is NDVI/(growing degree days from planting).

‡ Active optical (AO) INSEY for yield was obtained at Feekes 5; INSEY for protein was obtained at Feekes 9.

§ ns denotes nonsignificance.

Table 10. Coefficients of determination (r^2) for the linear regression of RapidEye red normalized differential vegetation index (NDVI) and red edge NDVI INSEY and spring wheat yield and grain protein concentration. Where values are provided, the r^2 values are highly significant at $P < 0.0001$.

	red INSEY†	red edge INSEY	red INSEY	red edge INSEY
Year	Yield		Protein	
2012	ns‡	0.83	ns	0.77
2013	ns	ns	0.80	ns
2012–2013 pooled	ns	ns	0.68	0.79

† INSEY is NDVI/(growing degree days from planting).

‡ ns denotes nonsignificance.

satellite image in 2012 was obtained in early July, nearly a month past flag leaf emergence. Despite the late date, the coefficient of determinations of the linear regressions of red edge INSEY with yield and protein were significant (Table 10). The imagery in 2013 was a month later than necessary to predict spring wheat yield to screen for fields where in-season N application might help improve yield, but it was obtained at the time of flag leaf emergence. The problem for satellite imagery in North Dakota for wheat is that decisions on in-season N application for yield improvement must be made in May in most years, and May is the wettest month of the season with cloud cover common. Although satellite imagery would be a useful logistical tool for spring wheat, cloud cover would often be a problem, and perhaps a better early screening logistic tool would be to attach an AO sensor to a herbicide applicator during normal ground application activities at the Feekes 4 to Feekes 5 growth stages.

Corn

The coefficients of determination of the linear regression of 2012 pooled, 2013 pooled, and 2012–2013 pooled GS INSEY and CC red and red edge INSEY were significant at V6, but not V12 (Table 11). The INSEY values were probably affected at V12 by drought in 2012, and by excessive rain in 2013.

Two 2012 RapidEye satellite imagery data sets, one from Durbin 16 August and the other from Valley City 10 August, were pooled for regression analysis. The coefficient of determination of the linear relationship of the pooled red INSEY with corn yield using red INSEY was 0.71 ($P < 0.0001$). The r^2 of the red edge INSEY was not significant 2012. In 2013, the Valley City data was compromised with thin cloud cover, so the 2013 imagery data only includes the Arthur site, obtained 24 June. The r^2 of the linear regression of the red INSEY with yield was 0.81 ($P < 0001$), and that of yield with the red edge INSEY was 0.84 ($P < 0.0001$). Pooling the 2012 sites and the 2013 Arthur site,

Table 11. Coefficients of determination (r^2) of the linear regressions between 2012 pooled, 2013 pooled and 2012–2013 pooled GreenSeeker (GS) and Crop Circle (CC) INSEY at V6 and V12 and corn yield.

		GS red INSEY†		CC red edge INSEY		CC red INSEY	
Year	Growth stage	r^2	$P < F$	r^2	$P < F$	r^2	$P < F$
2012 pooled	V6	0.37	0.006	0.56	<0.0001	0.46	0.0001
	V12	ns‡	–	ns	–	ns	–
2013 pooled	V6	0.37	0.006	0.67	<0.0001	0.40	0.0003
	V12	ns	–	ns	–	ns	–
2012–2013 pooled	V6	0.84	<0.0001	0.80	<0.0001	0.82	<0.0001
	V12	ns	–	ns	–	ns	–

† INSEY is normalized differential vegetation index (NDVI)/(growing degree days after planting).

‡ ns denotes nonsignificance.

Table 12. Coefficients of determination (r^2) values and probabilities of $P > F$ of the linear regressions between 2012 confection sunflower yield and GreenSeeker (GS) red INSEY at V8 and RapidEye imagery.

GS V8 red INSEY		Satellite July 02 Red INSEY		Satellite Aug 16 red INSEY		Satellite Aug 16 red edge INSEY	
r^2	$P > F$	r^2	$P > F$	r^2	$P > F$	r^2	$P > F$
0.31	0.0004	0.24	0.02	0.35	0.0003	0.27	0.02

the r^2 of the red INSEY with yield was 0.77 ($P < 0.0001$) and that of yield and the red edge INSEY was 0.78 ($P < 0.0001$). The use of satellite imagery in August in corn to be used as a logistical tool to screen fields for in-season N application is too late. If satellite imagery were obtained in late May or early June, it might be used for this purpose. However, as in spring wheat, late May and early June is the period of greatest cloud cover and rain in the region. The AO sensors might be a better choice of a logistics tool if the sensor was attached to a herbicide applicator at V4 to V6 to screen fields that might benefit from in-season N application.

Sunflower

The coefficients of determination of the linear regressions of 2012 and 2013 oil seed sunflower and GS INSEY and CC INSEY at V6 to V8 and V12 were not significant. However, the coefficients of determination of the linear regression of satellite red INSEY and red edge INSEY obtained 10 Aug. 2012 and yield were significant with r^2 values of 0.75 ($P < 0.0001$) and 0.71 ($P < 0.0001$), respectively. The r^2 of the linear regression of the pooled 2012 and 2013 oil sunflower yield with satellite red INSEY was 0.75 ($P < 0.0001$). Lack of relationship from the AO sensors might be due to the abundance of corn residue left from the previous year that interfered with sensor readings at V6. However, this would not explain the lack of relationship at V12.

In confection sunflowers in 2012, the only significant linear regression model using AO INSEY was the GS red V8 INSEY (Table 12). The significant coefficient of determination from satellite red INSEY with yield at 1 July was early enough to be used as a logistic tool for screening fields that might benefit from in-season N application. The August dates would be too late to be used for that purpose. The 2013 satellite imagery was confounded by haze in the images and could not be used at any date.

CONCLUSIONS

These experiments indicate that sugar beet root yield, sugar beet recoverable sugar yield, spring wheat yield, spring wheat grain protein, corn yield, and sunflower yield can be predicted by both AO sensors and RapidEye satellite red and red edge imagery. The results suggest that if a satellite image were obtained before a possible in-season N application, the image could be used as a logistic tool to screen fields so that only those fields that would benefit from an in-season N application were visited with the application equipment fitted with an AO sensor. This system could work quite well in regions where cloudless days are common, such as parts of California, Colorado, or Idaho. The problem of cloud cover and haze interference in this 2-yr study also suggests that satellites might not be a primary tool for use in logistical screening in the northern plains of the United States; rather, fitting an AO sensor on a herbicide applicator or another farm tool that will be used in the field prior to in-season N application might be a more reliable strategy. Also, the lack of consistently being able to obtain a timely satellite image might serve as an incentive for exploring the use of UAV's for this logistical use, particularly if they were fitted with an AO sensor.

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