Published May 3, 2018

Use of Rainfall Data to Improve Ground-Based Active Optical Sensors Yield Estimates

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ABSTRACT

Ground-based active optical sensors (GBAOS) have been successfully used in agriculture to predict crop yield potential (YP) early in the season and to improvise N rates for optimal crop yield. However, the models were found weak or inconsistent due to environmental variation especially rainfall. The objectives of the study were to evaluate if GBAOS could predict YP across multiple locations, soil types, cultivation systems, and rainfall differences. This study was carried from 2011 to 2013 on corn (*Zea mays* L.) in North Dakota, and in 2017 in potatoes in Maine. Six N rates were used on 50 sites in North Dakota and 12 N rates on two sites, one dryland and one irrigated, in Maine. Two active GBAOS used for this study were GreenSeeker and Holland Scientific Crop Circle Sensor ACS 470 (HSCCACS-470) and 430 (HSCCACS-430). Rainfall data, with or without including crop height, improved the YP models in term of reliability and consistency. The polynomial model was relatively better compared to the exponential model. A significant difference in the relationship between sensor reading multiplied by rainfall data and crop yield was observed in terms of soil type, clay and medium textured, and cultivation system, conventional and no-till, respectively, in the North Dakota corn study. The two potato sites in Maine, irrigated and dryland, performed differently in terms of total yield and rainfall data helped to improve sensor YP models. In conclusion, this study strongly advocates the use of rainfall data while using sensor-based N calculator algorithms.

Core Ideas

- Optical sensors are commonly used by the researchers to improve yield estimated in commercial crops.
- This study was carried out in two states in two different crops, corn and potatoes, 2011–2013 and 2017, respectively.
- The objectives of the study were to evaluate ground based optical sensors to predict yield potential across multiple locations, soils types, cultivation systems, and rainfall differences.

Published in Agron. J. 110:1561–1571 (2018)
doi:10.2134/agronj2017.12.0696
Available freely online through the author-supported open access option

Ground-based active optical sensors (GBAOS) display promising results in their ability to predict crop yields. The GBAOS based on red and near-infrared (NIR) ratios or normalized difference vegetative index (NDVI), which are defined as[(NIR − red)/(NIR + red)], measure the density of leaves on current living vegetation and chlorophyll status of the crops before the closure of the canopy. Sensor diodes generate modulated light (pulsed at ~40,000 Hz) in wavebands that are then absorbed by plant tissues through chlorophyll and reflected by its biomass. Algorithms based on expected corn yields with both the GreenSeeker (GS) (Trimble, Sunnyvale, CA) and Holland Scientific Crop Circle Sensor ACS 470 (HSCCACS-470) (Holland Scientific, Lincoln, NE) measurements obtained early in the growing season have been developed (Raun et al., 2001; Lukina et al., 2001; Franzen et al., 2015; Holland and Schepers, 2010; Sharma et al., 2015). The GreenSeeker algorithm that was developed for corn (Dellinger et al., 2008; Raun and Johnson, 1999; Shanahan et al., 2008; Sharma et al., 2016a; Raun et al., 2001) correlates the corn yield measured in field experiments with the in-season estimate of yield (INSEY). The INSEY number is a derivative of the GS measurements of NDVI divided by growing degree days (GDD) from the date of planting. The algorithm described by the regression relationship between the INSEY and corn yield is used to vary the rate of N to corn, using an estimate of the difference in corn yield prediction and the corn yield predicted from an N-rich strip within variety and field of interest, multiplied by the 1.25% N in corn grain estimate and divided by a N fertilizer application efficiency factor (values >0–1).

Plant height also has been used as a metric during the vegetative growth of corn. The water content (Sharma et al., 2016b), soil texture (Sharma et al., 2016a), rate of fertilizer application (Sharma et al., 2016c), and cultivation methods (Bu et al., 2016) influence plant height in the soil. Measurement of plant height can be conducted using high-resolution ultra-sound

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Abbreviations: BW, bandwidth; GBAOS, ground-based active optical sensors; GS, GreenSeeker; GY, grain yield; HSCCACS-430, Holland Scientific Crop Circle Sensor ACS 430; HSCCACS-470, Holland Scientific Crop Circle Sensor ACS 470; INSEY, in-season estimate of yield; NDAWN, North Dakota Agriculture Weather Network; NDVI, normalized difference vegetative index; NIR, near-infrared ratios; SM, soil moisture; YP, yield potential.

distance sensing of the crop canopy (Sharma et al., 2016a, 2016b]. The canopy height of the sugar beet was multiplied times a GS reading in an attempt to estimate leaf N concentration, sugar beet top N content, and dry matter yield (Bu et al., 2016). The NDVI measurement is related to leaf area index, a two-dimensional representation of crop development and growth. In NDVI, saturation of readings causes a weak relationship in the later stages of corn growth (Franzen et al., 2016, 2017; Sharma et al., 2017; Sharma, 2014).

Previous studies have deduced the importance of soil moisture (SM) in estimating grain yield (GY). Humphrey and Schupp (2004) concluded that by incorporating soil characteristics like soil texture and SM, could explain more about the growing conditions and thereby enhance the precision of YP prediction utilizing the INSEY method. Kumar et al. (2006) examined the relationship between seasonal crop water stress index (depending on evapotranspiration deficits and NDVI) and sorghum GYs and found that by incorporating spectral indices (i.e., NDVI) with soil water parameters into a mid-season model, they could improve GY estimates.

An essential factor affected by SM is the color of the surrounding soil, in turn affecting NDVI values. Eklundh (1998) indicated that between 10 and 36% of the variation in NDVI values could be attributed to changes in rainfall in 10-d and monthly scales, respectively. The author did mention, however, that the use of rainfall data to predict vegetative growth could be restricted based on the variability in soil characteristics such as soil type, soil water holding capacity, and rainfall duration and density. Detailed research is necessary for SM-NDVI-yield relationship (Eklundh, 1998). It has been suggested that changes in surface SM significantly contribute to differences in crop canopy reflectance and can increase the difficulty in quantifying and identifying plant stress (Wilhelm et al., 2000; Haboudan et al., 2003; Katsvairo et al., 2003a; Daughtry et al., 2000).

Using soil moisture with sensor readings would be a wise choice, but it is highly impractical for growers to put a soil moisture sensor in each field and get the data unless remotely connected to the controller that holds the sensor and fertilizer applicator. To solve this problem, we used rainfall data from weather stations close to the research sites. The objective of this study was to evaluate the sensor-based YP models using rainfall data. This study will investigate if the rainfall data from nearby weather stations could be used in validating the sensor based N calculator algorithms more confidently. The study will also examine which duration of rainfall data will be more useful considering crop growth period from planting to harvesting. In addition, this study will determine whether the rainfall data is useful individually, or in combination with crop height.

MATERIAL AND METHODS

The study was conducted in two states, North Dakota (corn sensor study) and Maine (potato sensor study), to confirm whether rainfall data successfully helped in YP model.

Soil Sampling and Analysis

At the North Dakota study site, five soil-sample cores were obtained from each site using a 2.5-cm diameter hand probe, to a depth of 0–15 cm for P, K, Zn, pH, and organic matter, and 0–60 cm in depth for residual nitrate. Fertilizer P and K were not applied by the cooperator with their pre-plant N requirement. Instead, the researchers applied P as mono-ammonium phosphate and K as potassium chloride at rates consistent with soil analysis based recommendations (Peters et al., 2012). If the site was deficient in Zn, the researchers applied zinc sulfate (36% granules) at a rate of 11 kg ha^{-1} Zn per acre as a broadcast at the time of treatment application. If the site proved to be S deficient at V6, an application of gypsum at 22 kg ha^{-1} S (112 kg ha^{-1} gypsum) was applied as granules over the top of the corn. After obtaining soil samples, they were air-dried, ground to pass through a 2 mm screen, and thoroughly mixed before analysis for soil pH, available P, K, Zn, and organic matter. Soil pH was analyzed using a 1:1 soil/deionized H_2O solution method (Frank et al., 1998); P by the Olsen method (Warncke and Brown, 2012), and K using the 1-N ammonium acetate method (Whitney, 2012). The diethylene triamine pentaacetic acid extraction method (Combs and Nathan, 2012) coupled with atomic absorption spectroscopy detection was used for determination of available Zn. Organic matter was measured by loss of ignition method (Whitney, 2012).

In Maine, soil tests were carried out from 0–18 cm depth using a regular soil probe. The cooperator did not apply fertilizer P and K. Instead, the researchers applied P as mono-ammonium phosphate and K as potassium chloride at rates consistent with soil analysis based on U. Maine Soil Lab recommendations. The soil analysis was carried out using procedures from "Recommended Soil Testing Procedures for the Northeastern United States" (The Northeast Coordinating Committee for Soil Testing-1312, http://extension.udel.edu/lawngarden/soil-health-composting/recommended-soil-testing-procedures-for-the-northeastern-united-states/).

Locations and Treatments

Nitrogen rate trials with field corn were conducted on 50 sites in North Dakota in 2011, 2012, and 2013 (Table 1). The sites were established within larger farm fields with permission from farmer cooperators. The cooperators were a mix of farmers that NDSU researchers had worked previously and those recommended by county agents and farmers, who volunteered after presentations about the project at winter meetings. Each experimental area did not receive supplemental N from the cooperator, but was planted by the cooperator using corn hybrid of their choice, and received herbicide applications at their discretion along with the rest of the field. The experimental design at each site was a randomized complete block with four replications and six treatments; check (no added N), 45, 90, 134, 179, and 224 kg N ha^{-1}; applied as ammonium nitrate by hand pre-plant within a week of planting. Each experimental unit (plot) was 6.1 × 3.05 m. Locations were categorized into eastern high clay (soil survey description) conventional-till sites and eastern medium-textured conventional-till sites (soil survey description) soil types as well as long-term eastern no-till sites and west-river sites (generally no-till) cultivation by using multiple regression analysis. Soil survey data was used to differentiate eastern high clay conventional-till sites from eastern medium-textured conventional-till sites. Eastern high clay conventional-till sites had silty clay loam textures or higher clay, while eastern medium-textured conventional-till sites included fine sandy loams, silt loam, loam, and sandy loam textures. Long-term eastern no-till sites were defined as sites in continuous no-till sites for at least 6 yr.

Table 1. GPS coordinates and soil series for field experiments in 2011 through 2013.

Year	Location	GPS coordinates	Soil Series†
2011	Valley City	46°52'49.090" N, 97°54'46.240" W	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls
	Rutland	45°59'58.051" N, 97°28'43.634" W	Fine-loamy, mixed, superactive, frigid Pachic Argiudolls
	Havana	45°56'04.266" N, 97°35'54.633" W	Fine-silty, mixed, superactive, frigid Pachic Hapludolls
	Durbin	46°51'29.495" N, 97°09'26.907" W	Fine, smectitic, frigid Typic Epiaquerts
	Mooreton	46°12'40.420" N, 96°46'43.259" W	Fine, smectitic, frigid Typic Epiaquerts
	Great Bend	46°07'54.977" N, 96°43'11.481" W	Fine, smectitic, frigid Typic Natraquerts
	Fairmount	45°59'39.021" N, 96°35'46.219" W	Fine-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Christine	46°53'30.423" N, 96°54'05.749" W	Fine, smectitic, frigid Typic Epiaquerts
	Prosper	46°56'55.978" N, 97°02'48.344" W	Fine, smectitic, frigid Typic Calciaquerts
	Milnor	46°16'34.108" N, 97°28'02.389" W	Sandy, mixed, frigid Oxyaquic Hapludolls
	Page 2	47°09'36.755" N, 97°25'48.088" W	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls
	Buffalo	46°56'51.974" N, 97°28'01.950" W	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls
	Page 1	47°09'05.282" N, 97°23'21.552" W	Coarse-loamy, mixed, superactive, frigid Pachic Hapludolls
	Walcott	46°30'02.183" N, 97°02'32.182" W	Coarse-loamy, mixed, superactive, frigid Aquic Pachic Hapludolls
	Arthur	47°03'43.560" N, 97°08'04.248" W	Coarse-silty, mixed, superactive, frigid Aeric Calciaquolls
2012	Rutland East	45°59'36.599" N, 97°27'28.969" W	Fine-loamy, mixed, superactive, frigid Pachic Argiudolls
	Rutland West	45°59'32.671" N, 97°30'15.115" W	Fine-silty, mixed, superactive, frigid Aeric Calciaquolls
	Leonard-North	46°42'04.081" N, 97°16'52.371" W	Fine-silty, mixed, superactive, frigid Aeric Calciaquolls
	Casselton North	46°56'12.417" N, 97°17'00.351" W	Fine-silty, mixed, superactive, frigid Aeric Calciaquolls
	Amenia	47°00' 13.913" N, 97°12'57.025" W	Coarse-silty, mixed, superactive, frigid Aeric Calciaquolls
	Casselton South	46°56'26.922" N, 97°17'00.351" W	Fine, smectitic, frigid Typic Epiaquerts
	Galchutt	46°23'00.519" N, 96°43'48.576" W	Fine, smectitic, frigid Typic Natraquerts
	Fairmount North	45°59'38.268" N, 96°38'18.155" W	Coarse-silty, mixed, superactive, frigid Aeric Calciaquolls
	Fairmount South	45°57'23.964" N, 96°34'35.244" W	Fine-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Great Bend	46°08'20.469" N, 96°44'09.026" W	Fine, smectitic, frigid Typic Natraquerts
	Prosper	46°58'10.307" N, 96°59'20.466" W	Fine, smectitic, frigid Typic Epiaquerts
	Barney	46°10'58.074" N, 96°55'43.331" W	Fine, smectitic, frigid Typic Epiaquerts
	Mooreton	46°18'13.407" N, 96°51'40.672" W	Coarse-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Gardner	47°09'57.820" N, 97°02'59.152" W	Fine, smectitic, frigid Vertic Argialbolls
	Arthur	47°06'25.800" N, 97°14'36.562" W	Fine, smectitic, frigid Vertic Argialbolls
	Wheatland	46°55'06.854" N, 97°23'14.391" W	Fine-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Milnor	46°13'11.317" N, 97°25'31.110" W	Fine-loamy, mixed, superactive, frigid Pachic Argiudolls
	Leonard South	46°40'32.061" N, 97°17'02.579" W	Sandy, mixed, frigid Typic Endoaquolls
	Walcott west	46°30'29.560" N, 97°03'00.760" W	Coarse-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Walcott east	46°29'44.107" N, 96°53'04.456" W	Coarse-silty over clayey, mixed over smectitic, superactive, frigid Aeric Calciaquolls
2013	Casselton	46°52'41.973" N, 97°14'55.894" W	Fine-silty, mixed, superactive, frigid Typic Endoaquolls
	Durbin	46°51'22.072" N, 97°09'28.366" W	Fine, smectitic, frigid Typic Epiaquerts
	Barney	46°15'07.560" N, 96°59'28.627" W	Coarse-loamy, mixed, superactive, frigid Aquic Pachic Hapludolls
	Dwight	46°18'39.335" N, 96°47'12.237" W	Fine, smectitic, frigid Vertic Argialbolls
	Gardner	47°10'28.482" N, 96°54'02.138" W	Fine, smectitic, frigid Typic Epiaquerts
	Leonard-North	46°52'57.807" N, 97°17'44.945" W	Fine, smectitic, frigid Typic Epiaquerts
	Walcott	46°30'02.359" N, 97°02'39.660" W	Coarse-loamy, mixed, superactive, frigid Aeric Calciaquolls
	Leonard West	46°39'10.750" N, 97°18'12.980" W	Coarse-loamy, mixed, superactive, frigid Pachic Hapludolls
	Arthur	47°06'50.963" N, 97°57'55.219" W	Coarse-silty, mixed, superactive, frigid Pachic Hapludolls
	Rutland	45°57'50.176" N, 97°31'44.205" W	Fine, smectitic, frigid Pachic Vertic Argiudolls
	Jamestown	46°45'58.571" N, 98°47'55.930" W	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls
	Mott	46°56'43.583" N, –02°19'10.919" W	Fine-loamy, mixed, superactive, frigid Typic Haplustolls
	Richardton	46°35'0.095" N, –102°21'41.364" W	Fine-loamy, mixed, superactive, frigid Typic Haplustolls
	Beach	46°49'3.0354" N, –03°59'40.451" W	Fine-silty, mixed, superactive, frigid Typic Haplustolls
	New Leipzig	46°26'44.051" N, –01°56'31.379" W	Fine, smectitic, frigid Vertic Natrustolls

† Information collected from Soil Survey Staff, 2013.

Two research trials were established in Aroostook County, Maine: one at MSAD#1 School Farm (dryland) in Presque Isle (46°40'47.4"N, 67°59'40.5"W) and one at the farmer field (irrigated) in Easton (46°35'27.9"N, 67°51'02.5"W). The N was applied at planting. The experimental design at each site was a randomized complete block with four replications and 12 N treatments: (i) C1 (control); (ii) urea (split nitrogen) = 50 kgha^{-1} at planting and 90 kgha^{-1} at 7 leaf stage; (iii) urea (split nitrogen) = 50 kgha^{-1} at planting and 135 kgha^{-1} at 7 leaf stage; (iv) split 1 (ammonium sulfate split) = 50 kgha^{-1} at planting and 90 $kg ha^{-1}$ at 7 leaf stage; (v) AS (ammonium sulfate) = 180 $kg ha^{-1}$ at planting; (vi) urea = 180 $kg ha^{-1}$ at planting; (vii) Ag (agrotain=slow release nitrogen) = 180 $kg ha^{-1}$ at planting; (viii) DAP (diammonium phosphate) = 180 $kg ha^{-1}$ at planting; (ix) NK1 (slow release nitrogen) = 180 $kg ha^{-1}$ at planting; (x) CAN (calcium ammonium nitrate) = 180 $kg ha^{-1}$ at planting; (xi) ESN (slow release nitrogen) = 180 $kg ha^{-1}$ at planting; and (xii) split 2 (ammonium sulfate split) = 50 $kg ha^{-1}$ at planting and 135 $kg ha^{-1}$ at 7 leaf stage.

Sensor Data Collection

Similar procedure for data collection was followed in both the states. In Maine, HSCCACS-430 was used instead of HSCCACS-470 at North Dakota State. Sensor readings were collected four times at 4, 6, 10, and 12 leaf stage of potatoes in Maine, and at 6 and 12 leaf stage of corn in North Dakota State. The GS gave only one NDVI reading using red and infrared wavelengths.

The Holland Scientific sensor is a relatively easy to use instrument that currently comes with a 5-h battery pack. The HSCCACS-470 and HSCCACS-430 simultaneously emit three bands; two in the visible range (red 650 nm, red-edge 730 nm) and one in the NIR (760 nm). The light source of both HSCCACS-470 and HSCCACS-430 is a modulated polychromatic LED array. It can emit and measure the light spectrums in the range from 430 nm to 850 nm bandwidth (BW). The sensor has a measurement filter range includes 450 nm (BW ± 20 nm), 550 nm (BW ± 20 nm), 650 nm (BW ± 20 nm), 670 nm (BW ± 11 nm), 730 nm (BW ± 10 nm), and 760 nm (BW ± 10 nm) wavebands.

Wavelength values that we used for GS, HSCCACS-470, and HSCCACS-430 sensor are defined below.

The GS emits two bands, visible and near infrared:

$$\mathrm{NDVI} = \left(\frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}\right) \mathrm{or} \left(\frac{774\mathrm{nm} - 656\mathrm{nm}}{774\mathrm{nm} + 656\mathrm{nm}}\right) \quad [1]$$

HSCCACS-470 and HSCCACS-430 emit three same bands: visible, red-edge, and near infrared:

$$\mathrm{NDVI} = \left(\frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}\right) \mathrm{or} \left(\frac{760\mathrm{nm} - 670\mathrm{nm}}{760\mathrm{nm} + 670\mathrm{nm}}\right) \quad [2]$$

$$\mathrm{NDVI} = \left(\frac{\mathrm{NIR} - \mathrm{Red-edge}}{\mathrm{NIR} + \mathrm{Red-edge}}\right) \mathrm{or} \left(\frac{760\mathrm{nm} - 730\mathrm{nm}}{760\mathrm{nm} + 730\mathrm{nm}}\right) \quad [3]$$

The GS, HSCCACS-470, and HSCCACS-430 readings were obtained when the corn was at ~V6 stage and again ~10 d to 2 wk later when the corn reached the V12 stage (V = vegetative). Readings were taken over the top of the corn whirl on the same interior row of each plot where harvest was intended. All reflectance data, as applicable, were inserted within the generalized NDVI expression explained earlier.

Crop Height: Manual/SenixView

No height data was used in Maine. For the first 2 yr (2011 and 2012), manual height was used for this experiment; however, during 2013, an automatic height sensor was used to collect the crop height data.

Weather Data Processing

In North Dakota, the multitudes of fields posed a slight difficulty in the changes in accumulated precipitation, as weather monitoring stations are not close. Using the North Dakota Agriculture Weather Network (NDAWN), the fields were best matched to the nearest weather station to record the precipitation in the area as precisely as possible. Several of the fields were located close to the same weather station, resulting in the same precipitation data being used more than once. Using the NDAWN system, archived data logs were searched and compiled for average precipitation recorded by each required weather station, and organized by month. From there, all precipitation data from each specified station was organized by year, and an average taken from a specific range of months only for the years of 2011 through 2013.

The weather station data was processed two ways to evaluate the best representation of actual soil moisture status: (i) Option 1, Average precipitation from date of planting to date of harvesting (corn growth window); and (ii) Option 2, Average precipitation from date of planting to date of sensing.

Table 2 explains the research site and weather station used by the NDAWN. There were two separate crop circle versions of each scan due to a difference in wavelength from 660nm (V1) and 710nm (V2).

In Maine, the rainfall data from planting (May) to harvesting (Sept.) was used. The Caribou weather station used for collecting the data for rainfall.

Statistical Analysis

For the North Dakota State corn study, regression analyses were conducted on sensor readings and yield with yield as the dependent variable, and INSEY or INSEYH (in-season estimation of yield multiplied by crop height) were determined at V6 and V12 as the independent variable to evaluate the relationship between yield and INSEY multiplied with plant height at V6 and V12, respectively. The INSEY was defined as the sensor reading divided by the growing degree days from the date of planting to date of sensor reading (Raun et al., 2001; Frank et al., 1998). The exponential and polynomial relationships were found to have a high frequency of describing the relationships compared to other models. Multiple regression analysis using the method of Sharma (2014) was used to determine whether the data should be segregated into long-term eastern no-till sites, eastern high clay conventional-till sites, and medium texture conventional sites. The analysis confirmed that segregation of the data into those categories improved the relationship between INSEY and yielded overall. The determination coefficient (R^2) was used to evaluate the relationship among crop yield, sensor reading, crop yield with sensor reading multiplied with corn height, and crop yield with sensor readings multiplied by crop height +rainfall data at V6 and V12. The SAS procedure Proc Reg for Windows V9.2 (SAS Institute, Cary, NC) was used to calculate the R^2 and evaluate linear, quadratic, square root, and logarithmic regression models. The SAS Proc GLM procedure was used to compare the N treatments. A P-value of 5% was used to differentiate the treatments from each other regarding statistical differences between treatments.

Table 2. The sites and weather station used for that specific site for rainfall data collection.

Field location	Station	Field location	Station	Field location	Station
2011		2012		2013	
Valley City	Fingal 4W	Rutland West	Oakes 4S	Arthur	Prosper
Rutland	Oakes 4S	Leonard North	Leonard 5N	Wheatland	Prosper
Havana	Oakes 4S	Casselton North	Prosper 5NW	Milnor	Lisbon
Durbin	Fargo NW	Amenia	Prosper 5NW	Leonard South	Leonard
Mooreton	Mooreton 3SW	Casselton South	Prosper 5NW	Walcott West	Leonard
Great Bend	Wahpeton 6N	Galchutt	Mooreton 3SW	Walcott East	Leonard
Fairmount	Wahpeton 6N	Fairmount West	Wahpeton 6N	Casselton	Fargo NW
Christine	Leonard 5N	Fairmount South	Wahpeton 6N	Rutland	Oakes 4S
Prosper	Prosper 5NW	Great Bend	Wahpeton 6N	Jamestown	Jamestown
Milnor	Lisbon 2W	Prosper	Prosper 5NW	Mott	Jamestown
Page Site 2	Galesburg 4SSW	Barney	Mooreton 3SW	Beach	Beach
Buffalo	Fingal 4W	Mooreton	Mooreton 3SW	New Leipzig	New Leipzig
Page Site 1	Galesburg 4SSW	Arthur	Prosper 5NW	Leonard North	Leonard 5N
Walcott	Leonard 5N	Walcott	Leonard 5N	Dwight	Lisbon
Arthur	Prosper 5NW	Leonard	Leonard 5N	Durbin	Prosper 5NW

Table 3: Regression relationship between sensor readings and corn yield with and without rainfall data averaged across months from April to September.

Category	Year	Wavelength†	Original	Original data × weather data (Expo. model)	Original data × weather data (Poly. model)	Original data × weather data (Expo. model)	Original data × weather data (Poly. model)
				Rainfall data date of planting to sensing		Rainfall data date of planting to harvesting	
High clay high yield	2011	CC2V1	0.30**	0.01	0.41***	–	0.44***
Medium high yield	2011	CCV1	0.62***	0.60***	0.70***	–	0.71**
Medium high yield	2011	CCV2	0.59***	0.53***	0.67***	0.53***	0.68***
Medium high yield	2011	GSV1	0.44***	0.43***	0.60***	0.51***	0.67***
Medium low yield	2011	CCV1	0.45***	0.50***	0.51***	0.50***	0.52***
High clay high yield	2012	CCV1	0.56***	0.56***	0.57***	0.42***	0.59***
High clay high yield	2012	CCV2	0.34**	0.38**	0.39***	0.41***	0.44***
High clay high yield	2012	GSV1	0.33*	0.41***	0.44***	0.64***	0.65***
High clay high yield	2012	CC2V2	0.57***	0.61***	0.62***	0.63***	0.63***
High clay high yield	2012	GS2V1	0.55***	0.58***	0.59***	0.58***	0.60***
Medium high yield	2012	CCV2	0.44***	0.44***	0.45***	0.33***	0.33***
Medium high yield	2012	GSV1	0.23*	0.35**	0.34**	–	0.33*
Medium low yield	2013	CCV1	0.44***	0.47***	0.48***	0.48***	0.49***
Medium low yield	2013	CCV2	0.43***	0.41***	0.49***	0.45***	0.51***

*** Denotes significance at 0.001, ** denotes significance at 0.01, and * denotes significance at 0.05, and missing place "–"were found with no relationship.

† CCV1 = CC red edge NDVI readings at V6, CCV2 = CC red NDVI readings at V12, GSV1 = GS red NDVI readings at V6, CC2V1 = red edge NDVI readings at V12, CC2V2 = CC red NDVI readings at V12, GS2V1 = GS red NDVI readings at V12.

For the potato study in Maine, the data were analyzed using a linear model. The R^2 value was used to evaluate the relationship of crop yield, and sensor reading and crop yield with sensor reading multiplied with rainfall data at 4, 6, 10, and 12 leaf stage of potatoes.

RESULTS

North Dakota State Corn Sensor Study

Use of Rainfall Data with Sensor Readings

Option 01: Average Precipitation from Date of Planting to Date of Harvesting (Corn Growth Window). Option 01 (Table 3), in the high clay–high yielding sites in 2011, the NDVI reading CC2V2 (Holland Scientific Crop Circle Sensor red edge reading at V12 stage) explained approximately 30% of the variation in the corn yield. When rain data was multiplied by relationship, sensor reading and corn yield improved to 41% using a polynomial model. In 2012, the relationship between corn yield and NDVI readings Holland Scientific Crop Circle Sensor red wavelength reading at V6 (CCV1), Holland Scientific Crop Circle Sensor red edge reading at V6 stage (CCV2), and Trimble GreeSeeker red wavelength reading at V6, and Holland Scientific Crop Circle Sensor red edge reading at V12 stage (GSV1) improved after using the average rain data from R^2= 0.56, 0.34, 0.33, and 57 to 0.56, 0.39, 0.44, and 0.62, respectively, with the polynomial model.

In medium soil texture–high yielding sites in 2011 and 2012, there is a significant improvement in the relationship between corn yield and NDVI readings CCV1, CCV2, and GSV1 in 2011 and CCV2 and GSV1 in 2012 after using the rain data. The R^2 improved from 0.62, 0.59, and 0.44 in 2011 and 0.44 and 0.27 in 2012 to 0.70, 0.67, 0.60, 0.45, and 0.34, respectively, using polynomial model. In the same treatment but low yield, 2011 and 2013, the relationship between NDVI readings CCV1 in 2011 and CCV1and CCV2 in 2013 were improved from R^2= 0.48, 0.46, and 0.43 to 0.50 (exponential), 0.48, and 0.43 (polynomial), respectively.

Table 4: Regression relationship between sensor readings multiplied with corn height and corn yield with and without rainfall data averaged across months from January to September.

Category	Year	Wavelength†	Original	Original data × weather data (Expo. model)	Original data × weather data (Poly. model)	Original data × weather data (Expo. model)	Original data × weather data (Poly. model)
				Rainfall data date of planting to sensing		Rainfall data date of planting to harvesting	
High clay high yield	2011	CV2 × H1	0.11*	0.25*	0.40***	0.25**	0.41***
High clay high yield	2011	2CV1 × H2	0.23**	0.27**	0.43***	0.27**	0.44***
High clay high yield	2011	Gv1 × H1	0.10	0.31**	0.47***	0.31**	0.47***
High clay high yield	2011	GV2 × H2	0.17*	0.31**	0.48***	0.32**	0.48***
Medium high yield	2011	CV2 × H1	0.54***	0.49***	0.67***	0.56***	0.67***
Medium high yield	2011	2CV1 × H2	0.45***	0.44***	0.64***	0.57***	0.67***
Medium high yield	2011	GV2 × H2	0.68***	0.65***	0.68***	0.44***	0.64***
High clay high yield	2012	GV1 × H1	0.23*	0.23*	0.49***	0.61***	0.65***
High clay high yield	2012	GV2 × H2	0.01	0.23*	0.48***	0.65***	0.68***
Medium high yield	2012	CV1 × H1	0.33***	0.36***	0.36***	0.26**	0.51***
Medium high yield	2012	2CV1 × H2	0.42***	0.50***	0.50***	0.25**	0.51***
Medium high yield	2012	2CV2 × H2	0.47***	0.47***	0.47***	0.46***	0.52***
Medium high yield	2012	GV2 × H2	0.13*	0.26***	0.27**	0.58***	0.59***
High clay low yield	2012	2CV1 × H2	0.46***	0.44***	0.46***	0.44*	0.46**
High clay high yield	2013	GV2 × H2	0.01	–	0.19*	0.47***	0.47***

*** Denotes significance at 0.001, ** denotes significance at 0.01, and * denotes significance at 0.05, and missing place "–"were found with no relationship.
† CCV1 = CC red edge NDVI readings at V6, CCV2 = CC red NDVI readings at V12, GSV1 = GS red NDVI readings at V6, CC2V1 = red edge NDVI readings at V12, CC2V2 = CC red NDVI readings at V12, GS2V1 = GS red NDVI readings at V12.

Option 02: Average Precipitation from Date of Planting to Date of Sensing. Option 02 (Table 3), in high clay–high yielding sites in 2011, the NDVI reading CC2V1 was correlated with weak corn yield (R^2 = 0. 0.01). When averaged rain data was used, the relationship was improved significantly (R^2 = 0.44) using the polynomial model. In 2012, NDVI readings, CCV1, CCV2 GSV1, CC2V2, and GS2V1 and corn yield relationship R^2 was 0.56, 0.34, 0.33, 0.57, and 0.55. However, incorporating averaged rain data significantly improved the relationship with corn yield by using the polynomial model. The relationship between corn yield and sensor readings was improved to R^2 values as 0.57, 0.39, 0.44, 0.62, and 0.59, respectively.

In 2011 medium soil texture–high yielding sites, the relationship between NDVI reading and corn yield increased for CCV1, CCV2, and GSV1 from R^2 = 0.62, 0.59, and 0.44 to 0.70, 0.67, and 0.60, respectively, with the polynomial model. In 2012, the relationship between corn yield and NDVI reading (CCV2 and GSV1) increased from 0.44 and 0.23 to 0.45 and 0.34 with the polynomial model. In 2011 and 2013 medium soil texture–low yielding sites, there was a significant improvement in the relationship between corn yield and NDVI readings. The relationship on corn yield with CCV1 in 2011 and CCV1 and CCV2 in 2012 improved from 0.45, 0.44, and 0.43, to 0.51, 0.48, and 0.49, respectively, using the polynomial model when raindata was multiplied with sensor readings.

Use of Plant Height and Rainfall Data with Sensor Readings

Option 01: Average Precipitation from Date of Planting to Date of Harvesting (Corn Growth Window). Using plant height also improved the relationship between corn yield and NDVI readings. In Option 01 (Table 4) high clay–high yielding sites in 2011, the NDVI reading and CV2 × H1 was weak, R^2 = 0.11, but after incorporating averaged rain data significantly improved the relationship with corn yield with R^2 = 0.41. In 2011, similar results were observed with other wavelengths such as 2CV1 × H2, GV1 × H1, and, GV2 × H2 (Table 4). However, when averaged rain data was incorporated, the relationship significantly improved with R^2 values of 0.44, 0.47, and 0.48, respectively. In 2012 and 2013, the relationship between corn yield and NDVI readings GV1 × H1 GV2 × H2 in 2012 and GV2 × H2, in 2013 increased from R^2 = 0.23, 0.01, and 0.01 to 0.65, 0.68, and 0.47, respectively. In the high clay–low yielding sites in 2012, the relationship stayed the same, R^2 = 0.46 to 0.46 for 2CV1 × H2.

In medium soil texture–high yielding sites in 2011, the NDVI readings CV2 × H1, 2CV1 × H2, and GV2 × H2 were strongly correlated with corn yield of R^2 = 0.54 and 0.45. However, when averaged rain data was used, the relationship was improved further to R^2 values of 0.67 and 0.67. In 2012, the NDVI readings CV1 × H1, 2CV1 × H2, 2CV2 × H2, and GV2 × H2 correlated with corn yield with R^2 values of 0.33, 0.42, 0.47, and 0.13, respectively. When averaged rain data was used, the relationship was improved significantly to 0.51, 0.51, 0.52, and 0.59, respectively.

Option 02: Average Precipitation from Date of Planting to Date of Sensing. Using plant height also improved the relationship between corn yield and NDVI readings. In Option 01 (Table 4) high clay–high yielding sites in 2011, the NDVI reading and CV2 × H1 was weak, R^2 = 0.11; however, incorporating averaged rain data significantly improved the relationship with corn yield with R^2=0.40. In the same year but different NDVI readings from 2CV1 × H2, GV1 × H1, and GV2 × H2, the relationship improved from R^2 =0.23, 0.10, and 0.17 to 0.44, 0.47, and 0.48, respectively. In 2012 and 2013, the relationship between corn yield and NDVI readings GV1 × H1, GV2 × H2 in 2012 and GV2 × H2, in 2013 were increased from R^2 = 0.23, 0.01, and 0.01 to 0.49, 0.48, and 0.36, respectively. In the high clay–low yielding sites in 2012, the relationship stayed the same, R^2 = 0.46 to 0.46 for 2CV1 × H2.

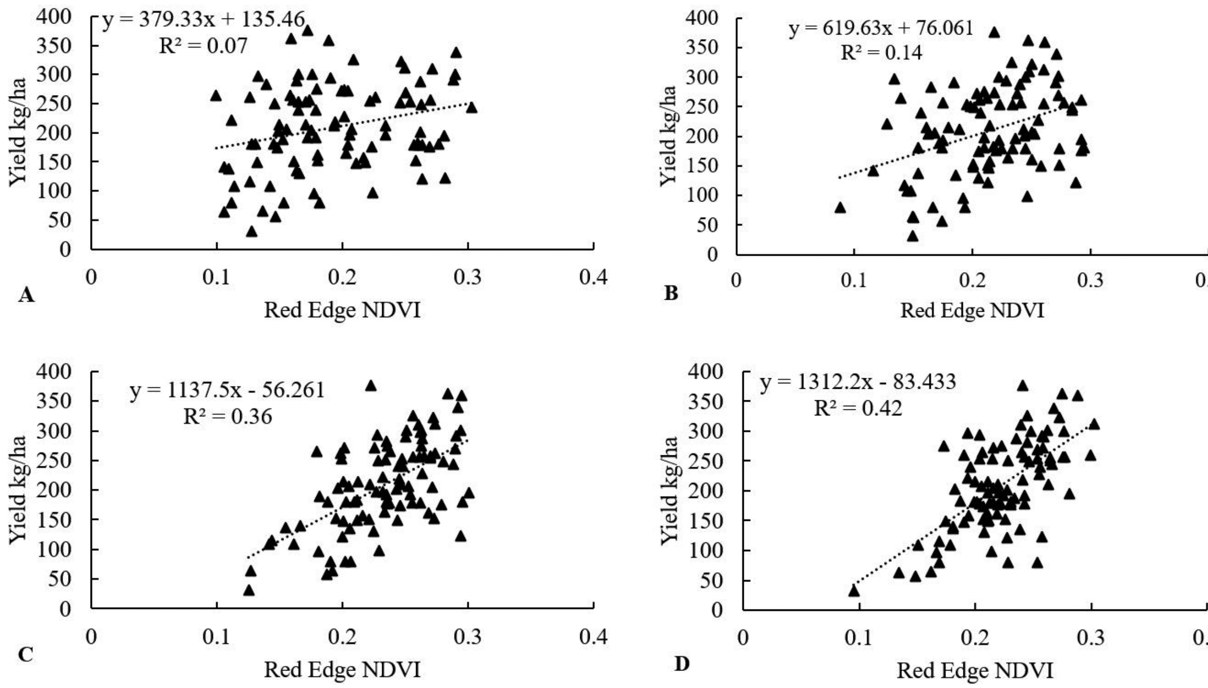

Fig. 1. The Holland Crop Circle-ACS 430 sensor readings (red NDVI) relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D). Potato yield relationship with sensor readings taken at 12 leaf stage.

In medium soil texture-high yielding sites in 2011, the NDVI readings CV2 × H1, 2CV1 × H2, and GV2 × H2 relationship with corn yield were improved from R2 = 0.54 and 0.45. to 0.67 and 0.64. In 2012, the NDVI readings CV1 × H1, 2CV1 × H2, 2CV2 × H2, and GV2 × H2 correlated with corn yield with R^2 values of 0.33, 0.42, 0.47, and 0.13, respectively. When averaged rain data was used, the relationship was improved significantly to 0.36, 0.50, 0.47, and 0.26, respectively.

Maine Potato Sensor Study

The data from three corn studies showed that rainfall data from the entire crop period was better compared to the rainfall data from the date of planting to date sensing. In the potato study, rainfall from date of planting to date of harvesting was used. The total precipitation from May to September was multiplied with the sensor readings. A strong relationship between sensor reading and potato yield was observed, especially during the 10- and 12-leaf stage. The HSCCACS-430 was consistently better in predicting the potato yield compared to GS. When rainfall data was multiplied with the sensor readings, there was a significant improvement in the relationship between sensor readings and potato yield.

The relationship with red edge NDVI was improved from R^2= 0.07, 0.14, 0.36 (Fig. 1), and 0.42 (at 4-, 6-, 10-, and 12-leaf stage, respectively) to R^2 = 0.15, 0.26, 0.51, and 0.45 (Fig. 4) when multiplied with rainfall data. The improvement was higher when data were collected at 10-leaf stage. Similarly, the HSCCACS-430 red NDVI relationship with potato yield improved from R^2= 0.04, 0.07, 0.24 (Fig. 2), and 0.13 to R^2 = 0.10, 0.19, 0.46, and 0.32 (Fig. 5), respectively, at 4-, 6-, 10-, and 12-leaf stage. However, in case of GS, the relationship was very weak when sensor reading was individually used with potato yield, but it improved to significant level when multiplied with rainfall data from R^2 = 0.01, 0.02, 0.15, and 0.11 (Fig. 3) to R^2 = 0.05, 0.13, 0.35, and 0.33 (Fig. 6).

DISCUSSION

There was a significant improvement in sensor relationship with crop yield, as observed when rainfall data was or wasn't used in combination with plant height. Out of two options of collecting rainfall data, Option 01 (average precipitation from date of planting to date of harvesting) and Option 02 (average precipitation from date of planting to date of sensing), the consistent improvement in sensor readings and crop yield was observed in Option 01, because it includes the amount and the intensity of variations incurred by the crop plants between an entire corn growing season compared to Option 02. The YP of any crop does not only depend on the initial growth curve when corn absorbs ~70% of N after/or at V12 growth stage, but also on the environmental changes after fruit set (Bu et al., 2017; Sharma, 2014; Sharma et al., 2017).). The amount of N mineralization that happened during corn growth cycle may compensate any loss of N due to intense rainfall after planting (Sharma, 2014). Any N released in the soil solution was available to the plant only when there is an optimum level of soil moisture (rainfall) available throughout the plant growth period. This fact confirmed in our study when entire rainfall data from corn planting to harvesting was used instead of planting to sensing. The difference in a relationship between sensor reading and corn yield each year could be due to the difference in N mineralizable potential of soils each year as well as the amount of rainfall, which was different during the 3-yr study. The year 2012 was the driest year in North Dakota history. Despite this fact the corn yield was not greatly affected, with a range of 6200 kg ha^{-1} to 15,000 kg ha^{-1}. This could be due to the variations in the timing of rainfall and growing degree-days (Shanahan et al., 2008) which may have influenced the N response in corn and thus affected sensor readings. A possible reason for poor sensor relationships in eastern high clay conventional-till sites in 2012 is the dry growing season. In the highly smectitic clays of the

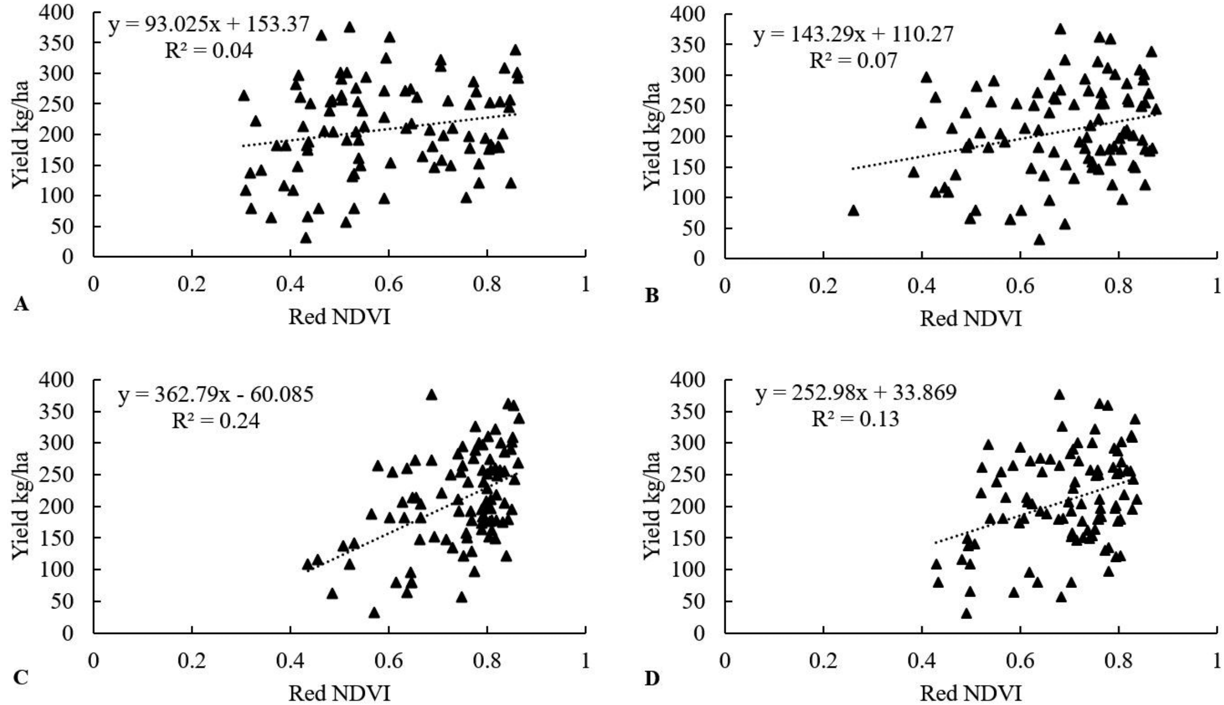

Fig. 2. The Holland Crop Circle-ACS 430 sensor readings (red edge NDVI) relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D) Potato yield relationship with sensor readings taken at 12 leaf stage.

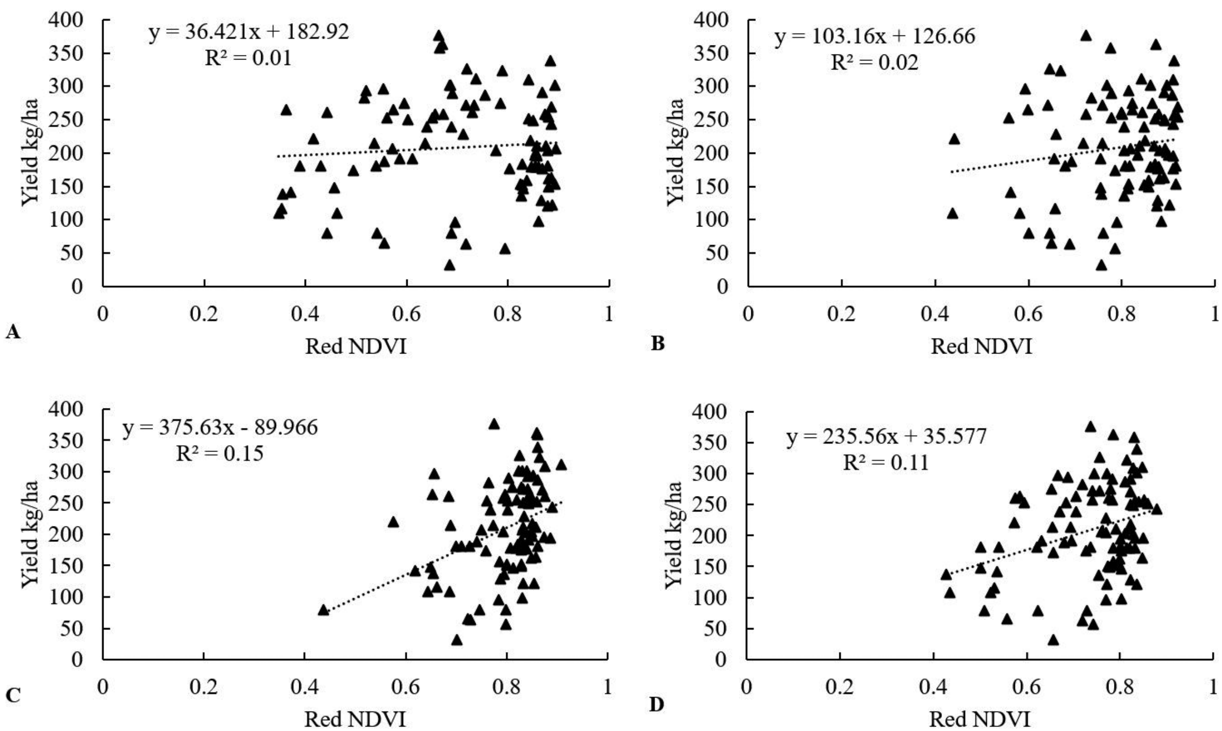

Fig. 3. The Trimble GreenSeeker sensor readings (red NDVI) relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D) Potato yield relationship with sensor readings taken at 12 leaf stage.

Red River Valley, where the eastern high clay conventional-till sites were located, dry soil conditions and corresponding plant water uptake result in large, deep cracks and therefore deep soil drying. Even though capillary movement of water should theoretically supply moisture to corn crop in eastern high clay conventional-till sites textured soils, deep soil cracks result in dryer soil at deeper depths than otherwise possible (Whitmore and Whalley, 2009). Deep soil cracks are not present in eastern medium-textured conventional-till sites during similar dry conditions.

The amount of rainfall during a critical time (high N uptake by corn during July when planted in April) was 100-mm more than usual in 2011(NDAWN records, http://ndawn.ndsu.nodak.edu/). This could result in water saturation of high clay

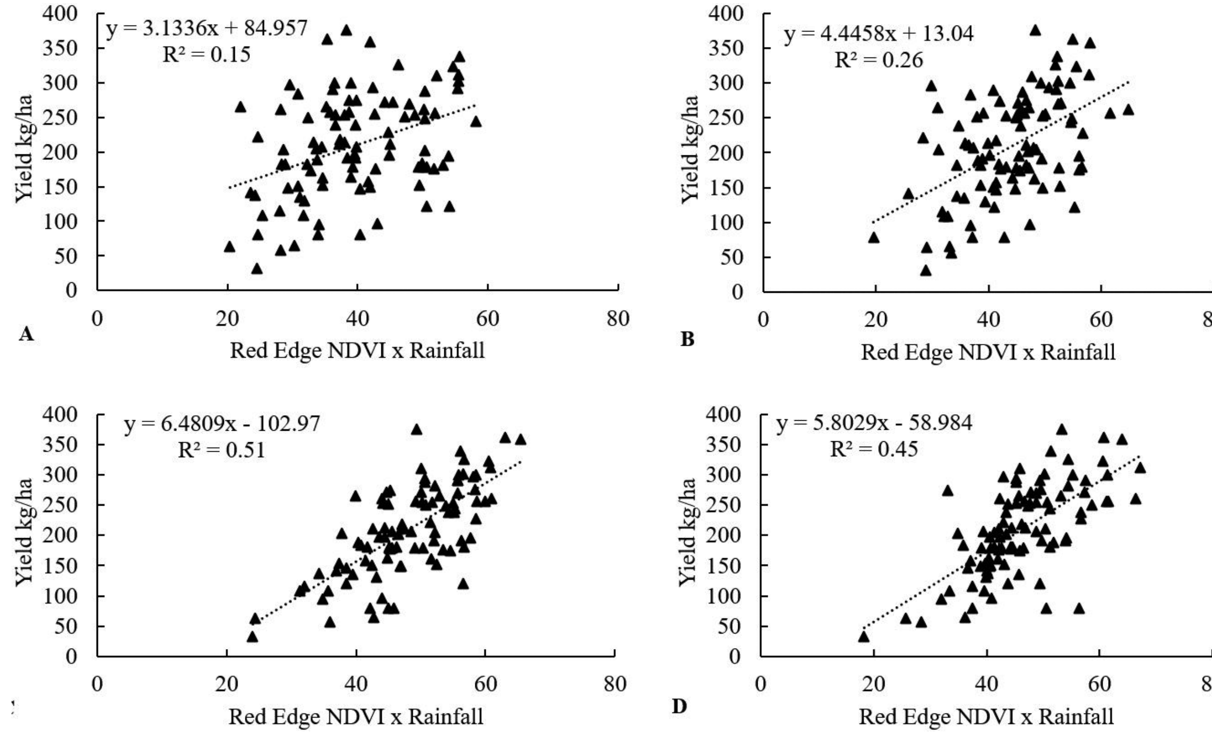

Fig. 4. The Holland Crop Circle-ACS 430 sensor readings (red edge NDVI) multiplied by rainfall data relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D) Potato yield relationship with sensor readings taken at 12 leaf stage.

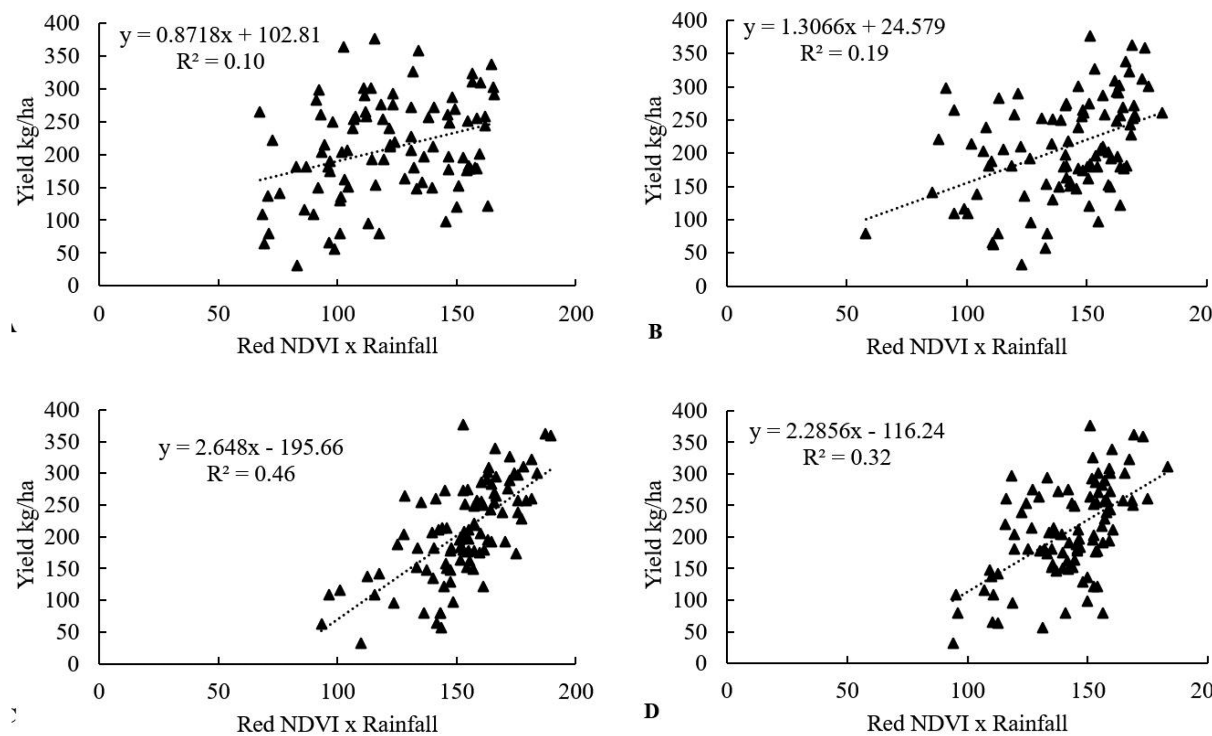

Fig. 5. The Holland Crop Circle-ACS 430 sensor readings (red NDVI) multiplied by rainfall data relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D) Potato yield relationship with sensor readings taken at 12 leaf stage.

sites enhancing high N loss as denitrification (Sogbedji et al., 2001; Katsvairo et al., 2003b). Losing N from the research sites put all N rates at equal risk resulting in high N loss from high N rate lead to uniform N availability across the N rates, thereby making it difficult for sensors to predict any change among N rates. Therefore, when rainfall data was incorporated, it resulted in improvement of the sensor reading relationship with crop yield. Compared to high clay sites, the medium textured sites were mostly dry due to good drainage capacity, thus showed better N response, however there was also N loss happened with N leaching as nitrate into the groundwater. Although the use of rainfall data did not improve the

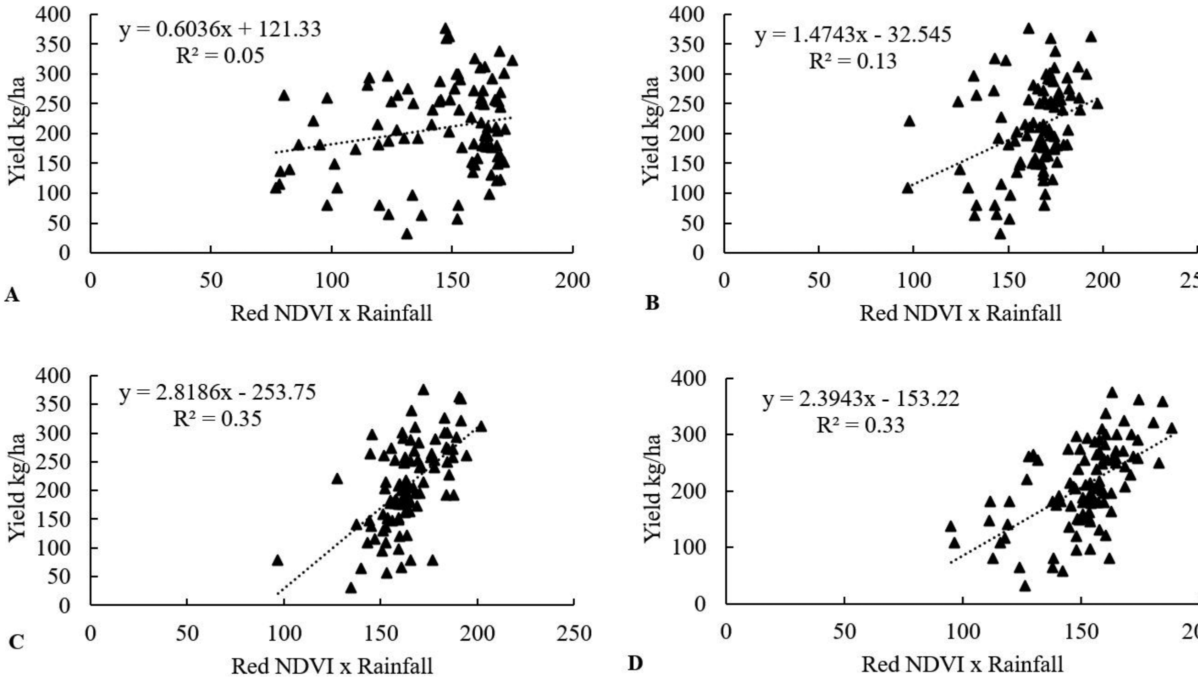

Fig. 6. The Trimble GreenSeeker sensor readings (red edge NDVI) multiplied by rainfall data relationship with potato yield. (A) Potato yield relationship with sensor readings taken at 4 leaf stage. (B) Potato yield relationship with sensor readings taken at 6 leaf stage. (C) Potato yield relationship with sensor readings taken at 10 leaf stage. (D) Potato yield relationship with sensor readings taken at 12 leaf stage.

relationship between sensor readings and corn yield under high clay sites as other soil types, it explained N loss as leaching.

In the case of potato, the rainfall data from the date of planting to date of harvesting was used, and the results were similar to those observed in the three-year corn study in North Dakota.

The crop root system plays a significant role in absorbing nutrients from the soil (Walsh et al., 2013). The corn root system is nodal from where root originates from the lower end of the stem and develop throughout the growth cycle. As soil moisture increases, the root development intensity increases due to the availability of nutrients near root vicinity. Consequently, the amount of soil moisture near the root system drives the absorption of N from the soil, which ultimately helps in defining the N response in crop plants. This makes it easier for the sensors to predict the N response in term of biomass when rainfall data used along with sensor readings. In a potato cultivation system, most of the potato is grown on sandy soils and water is a prime factor that drives the nutrients availability to potato roots. Since Maine's potato is a dryland cultivation similar to North Dakota's corn cultivation, the rainfall intensity and amount largely impact the root zone of both corn and potatoes in terms of nutrient movement.

Considering the environmental and soil variations, neither GS nor HSCCACS-470 and HSCCACS-430 sensors alone or in combination with corn height and rainfall data consistently provide significant yield prediction; however, no other method or prediction of in-season N rates is desirable. Farmers who are interested or doing an in-season corn N application and use one or all of these technologies have at least reduced or protected their N loss period by delaying a percentage of their N fertilizer requirements until later in the season. Also, the complications of developing yield maps using soil data and applying variable rate fertilizer at planting also putting applied N at risk of loss. Therefore, a scientific approach using the relative health of the crop at the time of sensing to calculate in-season application rate of N is perhaps more desirable as compared to a pre-season estimate.

CONCLUSION

The rainfall data was found useful when used with sensor readings, with or without using crop height. However, when crop height was involved in the equation, the relationship between crop yield and sensor was relatively better than sensor reading, rainfall, and crop yield. Since weather is an important factor that impacts nitrogen use efficiency and crop yield, it is rational to install few remotely controlled weather stations; this will not only help in predicting the weather, but also in improvising N rates, with the help of GBAOS. In this study, we used GBAOS as a source to detect plant health, but rainfall data could be used with other available technologies such as satellite imagery and drones. Several studies have been published recently on using leaf area index with NDVI to improve YP models, however, all these vegetative indices measured during the time of sensing, which happens early in the season. The sensor YP models are most affected by the events that happened after the sensing, such as rainfall, temperature, humidity, diseases, and insect attack. Although we cannot control all those factors, the one that affects N response most out of all is rainfall. Therefore, using rainfall data along with the GBAOS may help in improving GBAOS effectiveness and N use efficiency.

REFERENCES

Bu, H., L.K. Sharma, A. Denton, and D.W. Franzen. 2016. Sugar beet yield and quality prediction at multiple harvest dates using active-optical sensors. Agron. J. 108:273–284. doi:10.2134/agronj2015.0268

Bu, H., L.K. Sharma, A. Denton, and D.W. Franzen. 2017. Comparison of satellite imagery and ground-based active optical sensors as yield predictors in sugar beet, spring wheat, corn, and sunflower. Agron. J. 109(1):299–308.

Combs, S.M., and M.V. Nathan. 2012. Soil organic matter. Chapter 12. Recommended chemical soil test procedures for the North Central Region, NCERA-13. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf (accessed 15 Aug. 2015).

Franzen, D., R. Ashley, G. Endres, J. Teboh, L. Sharma, H. Bu, B. Schmidt and E.C. Schultz. 2017. Corn nitrogen calculator https://www.ndsu.edu/pubweb/soils/corn/ (accessed 14 Nov. 2017).

Daughtry, C.S.T., C.L. Walthall, M.S. Kim, E. Brown De Colstoun, and J.E. Mcmurtrey III. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.483.1381&rep=rep1&type=pdf (accessed 15 Nov. 2017).

Dellinger, A.E., J.P. Schmidt, and D.B. Beegle. 2008. Developing nitrogen fertilizer recommendations for corn using an active sensor. Agron. J. 100:1546 doi:10.2134/agronj2007.0386

Eklundh, L. 1998. Estimating relations between AVHRR NDVI and rainfall in East Africa at 10-day and monthly time scales. Int. J. Remote Sens. 19:563–570

Frank, K., D. Beegle, and J. Denning. 1998. Phosphorus. Chapter 8. Chemical soil test procedures for the North Central Region, Missouri Agr. Exp. Sta. SB-1001, Revised August 2015. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf (accessed 15 Aug. 2015).

Franzen, D.W., L.K. Sharma, and H. Bu. 2015. Active optical sensor algorithms for corn yield prediction and a corn side-dress nitrogen rate aid. NDSU Ext. Site Spec. Publ. (SF1176-5). https://www.ag.ndsu.edu/pubs/plantsci/soilfert/sf1176-5.pdf (accessed 3 Apr. 2017).

Franzen, D.W., L.K. Sharma, H. Bu, and A. Denton. 2016. Evidence for the ability of active-optical sensors to detect sulfur deficiency in corn. Agron. J. 108:2158–2162. doi:10.2134/agronj2016.05.0287

Haboudane, D., J.R. Miller, E. Pattey, P.J. Zarco-Tejada, and I.B. Strachan. 2003. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sens. Environ. 90:337–352.

Holland, K.H., and J.S. Schepers. 2010. Derivation of a variable rate nitrogen application model for in-season fertilization of corn. Agron. J. 102:1415–1424. doi:10.2134/agronj2010.0015

Humphrey, L.D., and E.W. Schupp. 2004. Competition as a barrier to establishment of a native perennial grass (*Elymus elymoides*) in alien annual grass (*Bromus tectorum*) communities. J. Arid Environ. 58:405–422.

Katsvairo, T.W., W.J. Cox, and H.M. Van Es. 2003a. Spatial growth and nitrogen uptake variability of corn at two nitrogen levels. Agron. J. 95:1000–1011. doi:10.2134/agronj2003.1000

Katsvairo, T.W., W.J. Cox, H.M. Van Es, and M. Glos. 2003b. Spatial yield response of two corn hybrids at two nitrogen levels. Agron. J. 95:1012–1022. doi:10.2134/agronj2003.1012

Kumar, R., A.K. Sarawgi, C. Ramos, S.T. Amarante, A.M. Ismail, and L.J. Wade. 2006. Partitioning of dry matter during drought stress in rainfed lowland rice. F. Crop. Res. 96(2–3): 455–465.

Lukina, E.V., K.W. Freeman, K.J. Wynn, W.E. Thomason, R.W. Mullen, M.L. Stone, J.B. Solie, A.R. Klatt, G.V. Johnson, R.L. Elliott, and W.R. Raun. 2001. Nitrogen fertilization optimization algorithm based on in-season estimates of yield and plant nitrogen uptake. J. Plant Nutr. 24:885–898.

Peters, J., M. Nathan, and C. Laboski. 2012. pH and lime requirement, Chapter 4. Recommended soil test chemical procedures for the North Central Region, NCERA-13. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf (accessed 15 Aug. 2015).

Raun, W.R., and G.V. Johnson. 1999. Improving nitrogen use efficiency for cereal production. Agron. J. 91:357–363. doi:10.2134/agronj1999.00021962009100030001x

Raun, W.R., J.B. Solie, G.V. Johnson, M.L. Stone, E.V. Lukina, W.E. Thomason, and J.S. Schepers. 2001. In-season prediction of potential grain yield in winter wheat using canopy reflectance. Agron. J. 93:131–138. doi:10.2134/agronj2001.931131x

Shanahan, J.F., N.R. Kitchen, W.R. Raun, and J.S. Schepers. 2008. Responsive in-season nitrogen management for cereals. Comput. Electron. Agric. 61:51–62. doi:10.1016/j.compag.2007.06.006

Sharma, L.K., H. Bu, D.W. Franzen, and A. Denton. 2016a. Use of corn height measured with an acoustic sensor improves yield estimation with ground based active optical sensors. Comput. Electron. Agric. 124: 254–262. doi:10.1016/j.compag.2016.04.016

Sharma, L., H. Bu, A. Denton, and D. Franzen. 2015. Active-optical sensors using red NDVI compared to red edge NDVI for prediction of corn grain yield in North Dakota, U.S.A. Sensors 15:27832–27853.

Sharma, L.K., H. Bu, D.W. Franzen, and A. Denton. 2016b. Use of corn height measured with an acoustic sensor improves yield estimation with ground based active optical sensors. Comput. Electron. Agric. 124: 254–262. doi:10.1016/j.compag.2016.04.016

Sharma, L.K., H. Bu, and D.W. Franzen. 2016c. Comparison of two ground-based active-optical sensors for in-season estimation of corn (*Zea mays*, L.) yield. J. Plant Nutr. 39:957–966.

Sharma, L., S. Bali, J. Dwyer, A. Plant, and A. Bhowmik. 2017. A case study of improving yield prediction and sulfur deficiency detection using optical sensors and relationship of historical potato yield with weather data in Maine. Sensors (Basel Switzerland) 17:1095. doi:10.3390/s17051095

Sharma, L.K. 2014. Evaluation of active optical sensor for yield prediction in corn (*Zea mays*, L). http://search.proquest.com/openview/6a672e359de410e1fd3711df3dda2afc/1?pq-origsite=gscholar&cbl=18750&diss=y (accessed 3 Apr. 2017).

Warncke, D., and J.R. Brown. 2012 Potassium and other basic cations. Chapter 7. Recommended chemical soil test procedures for the North Central Region, NCERA-13 Publ. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf (accessed 15 Aug. 2015).

Whitney, D.A. 2012. Micronutrients: Zinc, iron, manganese and copper, Chapter 9. Recommended chemical soil test procedures for the North Central Region, NCERA-13 Publ. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf (accessed 15 Aug. 2015).

Whitmore, A.P., and W.R. Whalley. 2009. Physical effects of soil drying on roots and crop growth. J. Exp. Bot. 60:2845–2857.

Wilhelm, W., K. Ruwe, and M.R. Schlemmer. 2000. Comparison of three leaf area index meters in a corn canopy. Publ. from USDA-ARS/UNL Faculty. http://digitalcommons.unl.edu/usdaarsfacpub/71 (accessed 14 Nov. 2017).

J.M. Sogbedji, H.M. van Es, S.D. Klausner, and W.J.C. D.R. Bouldin. 2001. Spatial and temporal processes affecting nitrogen availability at the landscape scale. Soil Tillage Res. 58(3–4):233–244. doi:10.1016/S0167-1987(00)00171-9

Walsh, O.S., A.R. Klatt, J.B. Solie, C.B. Godsey, and W.R. Raun. 2013. Use of soil moisture data for refined GreenSeeker sensor based nitrogen recommendations in winter wheat (*Triticum aestivum* L.). Precis. Agric. 14:343–356.