In-season potato yield prediction with active optical sensors

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Abstract
Crop yield prediction is a critical measurement, especially in the time when parts of the world are suffering from farming issues. Yield forecasting gives an alert regarding economic trading, food production monitoring, and global food security. This research was conducted to investigate whether active optical sensors could be utilized for potato (Solanum tuberosum L.) yield prediction at the middle of the growing season. Three potato cultivars (Russet Burbank, Superior, and Shepody) were planted and six rates of N (0, 56, 112, 168, 224, and 280 kg ha\(^{-1}\)) were applied on 11 sites in a randomized complete block design, with four replications. Normalized difference vegetation index (NDVI) and chlorophyll index (CI) measurements were obtained weekly from the active optical sensors, GreenSeeker (GS) and Crop Circle (CC). The 168 kg N ha\(^{-1}\) produced the maximum potato yield. Indices measurements obtained at the 16th and 20th leaf growth stages were significantly correlated with tuber yield. Multiple regression analysis (potato yield as a dependent variable and vegetation indices, NDVI and CI, as independent variables) could make a remarkable improvement to the accuracy of the prediction model and increase the determination coefficient. The exponential and linear models showed a better fit of the data. Soil organic matter content increased the yield significantly but did not affect the prediction models. The 18th and 20th leaf growth stages are the best time to use the sensors for yield prediction.

1 INTRODUCTION

Potato (Solanum tuberosum L.) contributes to world food security. It supplements or replaces grain-based diets where wheat (Triticum aestivum L.), rice (Oryza sativa L.), and maize (Zea mays L.) availability has declined due to high cost (Camire, Kubow, & Donnelly, 2009). Potato is cheap to buy and easy to grow. It can give a steady yield under different circumstances where other crops might fail (Lutaladio & Castaldi, 2009). Its flexibility in varying environmental circumstances and productive potential also makes it the best crop for food and nutrition security (Kyamanywa et al., 2011).

Regarding its volume of production, potato ranks fourth in the world—after rice, wheat, and maize (Hirpa et al., 2010). Further, it is the most famous tuber crop, listing first in volume produced among tuber and root crops; followed by

Abbreviations: CC, crop circle sensor; CI, chlorophyll index; GDD, growing degree days; GS, greenseeker sensor; INSEY, in-season estimate of yield; LAI, leaf area index; NDVI, normalized difference vegetative index; NIR, near-infrared wavelength; OM, organic matter; RCBD, randomized complete block design; VIF, variance inflation factor.

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cassava [Manihot esculenta (L.) Crantz], sweet potato [Ipomoea batatas (L.) Lam], and yam (Dioscorea spp.) (Cromme, Prakash, Lutaladio, & Ezeta, 2010). The demand for potato crop production is increasing, especially with expanding diet diversity and a need for inexpensive foods. Potato consumption has increased universally due to its ability to grow in a wide range of climates and their adoption by a wide range of cultures (King & Slavin, 2013).

Consequently, potato is the predominant vegetable for sales, production, and consumption (Kolasa, 1993). It is the most valuable crop in developing countries, and its production is increasing more quickly than other food crops (Scott, Rosegrant, & Ringler, 2000). As a result, it is an important source of rural employment, income, and food for a growing population (Guchi, 2015).

Although its yields are considerably lower than the midwestern and western United States, Maine is in the top 10 production areas (DeFauw, Larkin, English, Halloran, & Hoshide, 2012). During the last 10 yr, potato yield in Maine is constant, 38 Mg ha\(^{-1}\), except in 2016, which was 44 Mg ha\(^{-1}\). The consistency of the production for consecutive years explains the difficulty of improving the yield and quality of potato with traditional fertilization practices; therefore, new agronomic procedures are needed to fulfill producers and industry requirements (Sharma, Bali, Dwyer, Plant, & Bhoomik, 2017). Prediction of potato crop yield before the harvest is instrumental in pre-harvest and marketing decision making.

Many types of research (Haverkort & MacKerron, 2012; Reynolds et al., 2000) confirmed that traditional practices of crop yield estimation could lead to inadequate crop yield assessment and inaccurate crop area appraisal. Besides, these methods typically depend on rigorous field data collection of crop and yield, which is a costly and time-consuming process.

These existing strategies have demonstrated to be time-consuming and heavily relied on soil and plant analyses. Because of the restrictions of traditional yield prediction techniques, developing a nondestructive, rapid, and convenient approach to timely estimate yields would help make management decisions and control fertilizer application. Remote sensing technologies have been utilized extensively in agriculture for precise management, nutrition investigation, and in-season yield prediction (Caturegli et al., 2016).

Remote sensing technology can be utilized to estimate the temporal variation in crop dynamics, including crop yield and its spatial variability (Taylor, 1997). Visible (blue, green, and red) and near-infrared (NIR) parts of the electromagnetic spectrum have already confirmed their eligibility in obtaining information on crop type, crop health, soil moisture, N stress, and crop yield (Hassaballa & Matori, 2011; Magri, Van Es, Glos, & Cox, 2005; Hassaballa, A., N., Shafri, & Zulhaidi, 2013; Hassaballa, Althuwaynee, & Pradhan, 2014). Numerous researches have summarized that there could be a good correlation between the vegetation indices provided by the remote sensing techniques and the crop yield and biomass (Liu & Kogan, 2002; Rasmussen, 1997).

Several experiments (Baez-Gonzalez et al., 2005; Baez-Gonzalez, Chen, Tiscareño-López, & Srinivasan, 2002; Funk & Budde, 2009; Taylor, 1997) have focused on crop growth analysis using normalized difference vegetative index (NDVI) to improve precision agriculture. A study in plant life monitoring has confirmed that NDVI is linked with the leaf area index (LAI) and the photosynthetic activity of crops. The NDVI is an indirect method of estimating primary productivity through its correlation with crop yield using the Fraction of Absorbed Photosynthetically Active Radiation (Los, 1998; Prince, 1990).

Numerous plant indices based on multispectral sensors, ratio vegetation index (RVI), perpendicular vegetation index (PVI), the simple ratio (SR), and so on, have confirmed their ability to distinguish plant physiological indexes, such as leaf area accurately, plant N response, and biomass (Aparicio, Villlegas, Araus, Casadesus, & Royo, 2002; Broge & Leblanc, 2001; Hansen & Schjoerring, 2003). Among these indices, the NDVI by the active optical sensor (greenseeker sensor, GS) has shown to be efficient in predicting the in-season yield of many crops (Prasad et al., 2007; Raun et al., 2001). The NDVI measurements are utilized for identifying the N condition or biomass development from plants, sometimes also employed for obtaining nutritional monitoring in field crops of elements like P and K (Pimstein, Karnieli, Bansal, & Bonfil, 2011; Samborski, Tremblay, & Fallon, 2009). The GS hand-held optical sensor is a portable and easy crop research and consulting instrument that provides useful data to monitor plant status (Govaerts et al., 2007).

Erdle, Mistele, and Schmidhalter (2011) represented a study comparing active and passive sensing systems in terms of their capability to identify agronomic parameters. Passive satellite images and three active sensors, including the GS, crop circle sensor (CC), and an active flash sensor (AFS), were examined for their ability to assess six destructively determined crop parameters. The result was that active spectral sensors are more flexible in terms of timeliness and
illuminated by its active light source; the reflected beams from the plant’s canopy would be received again via that sensor, and then it calculates the NDVI value (Kipp, Mistele, & Schmidhalter, 2014). Researches have revealed that the canopy reflectance to the visible beam (400–700 nm) has fundamentally relied on the chlorophyll index (CI) in the palisade layer of the leaf and the NIR reflectance relied on the formation of the mesophyll cell and the cavities between cells (Blackmer, Schepers, & Varvel, 1994; Campbell & Wynne, 2011).

In a past study, Olfs et al. (2005) reported that the visible reflectance reduced, whereas NIR reflectance increased because of N fertilizer supplement. Consequently, the measured NDVI values at nutrient-deficient areas were less than in the areas with sufficient nutrients; also, the NDVI index could discriminate between the N status and plant biomass, which can be employed to predict potential yield. In previous researches, the NDVI values collected by the GS hand-held active optical sensor have been proved to possess the potential to predict in-season yield of several crops, such as winter wheat, corn, rice, and so on (Cao et al., 2015; Lofton et al., 2012; Macnack, Khim, Mullock, & Raun, 2014). A robust relationship was noted between NDVI measurements and the yield of winter wheat. It has been found at Feekes growth stage 4 and 5 (Raun et al., 2001), while with corn crop, the NDVI value taken by the GS at the V8 leaf growth stage has a strong relationship (R² = .77) with the grain yield (Teal et al., 2006).

The GS and CC optical sensors have been favorably employed in predicting yields of grain crops, and the preliminary and accurate estimation of yields would provide ponderable information for building decisions associated with N management (Yao et al., 2012). For potato crop, especially in Maine, there are vast hectares planted with potato; unfortunately, using active sensors is not extensively used, whereas other states and countries are utilizing satellite images for potato yield prediction measurements (Newton et al., 2018). Ji et al. (2017) tested the remote sensing tools for cabbage crop yield prediction; they noticed that the numerous variables and comparatively complicated canopy architecture of cabbage resulted in the uncertainty of whether this precision instrument would be adopted in in-season yield prediction.

Lofton et al. (2012) found some difficulties for the yield prediction of sugarcane crop due to its multi-year cropping cycle combined with the shorter growth period in Louisiana. A similar issue was found with the rice crop, and the robust correlation was not sustained throughout the growth stages. At the heading stage, the GS indices of rice became saturated. Consequently, it could not be used for estimation for in-season yield, whereas at the early growth stages (tillering stage) the rice canopy was not closed, but the soil and water background would have a substantial impact on canopy reflectance (Cao et al., 2016; Kamiji, Yoshida, Palta, Saku-ratani, & Shiraiwa, 2011).

The overall goal of this study was to evaluate the performance of two active optical sensors for in-season potato yield prediction. The specific objectives were to (a) compare the performance of (GS and CC) sensors in yield prediction and (b) evaluate the impact of chlorophyll index in improving the prediction algorithm.

2 | MATERIALS AND METHODS

2.1 | Research locations

The experiment was conducted at Aroostook County, Maine, during 2 consecutive years, 2018 and 2019. Eleven research sites, six in 2018 [Presque Isle, Aroostook Farm (AF1) (46.66134, −68.01808), Frenchville (FV) (47.21676, −68.41153), New Sweden-1 (NS-1) (46.95156, −68.14779), New Sweden-2 (NS-2) (46.95271, −68.14572), Caribou (CA1) (46.88227, −68.02895), and Wood Land (WL) (46.88520, −68.12577)], and five research sites in 2019, [Presque Isle, Aroostook Farm (AF2, AF3) (46.66134, −68.01808), Limestone (LM) (46.96186, −68.07750), (CA1) (46.88227, −68.02895), and Wood Land (WL) (46.88520, −68.12577)], and five research sites in 2019, [Presque Isle, Aroostook Farm (AF2, AF3) (46.66134, −68.01808), Limestone (LM) (46.96186, −67.83333), two in Caribou (CA2) (46.89628, −68.07750), and (CA3) (46.89180, −68.04055)], were selected for the experiment.

All the sites had a different average annual rainfall and temperature, where AF1, 2, and 3 sites are with an average annual rainfall of 91.0 cm and an annual mean temperature of 5.15 °C. The sites WL, NS (1 and 2), and CA1, 2, and 3 are with an average annual rainfall of 97.9 cm and an annual mean temperature of 4.3 °C, whereas FV is with an average annual rainfall of 85.5 cm and an annual mean temperature of 3.6 °C (U. S. Climate Data, 2018).

2.2 | Experimental materials

The experiment included three potato cultivars, which were Shepody, Russet Burbank, and Superior. The Shepody and Superior were planted in AF, and the Russet Burbank was planted in all of the sites. Planting spacing between seeds (tubers) was 30 cm within the rows, and the width of the row was 90 cm.

2.3 | Experimental treatments and design

Six rates of N (0, 56, 112, 168, 224, and 280 kg ha⁻¹) as ammonium sulfate in the first year and ammonium nitrate in the second year, were applied on all the sites in a randomized complete block design (RCBD) manner. The RCBD, with four
replications. Phosphorus, K, and S were applied as recommended by the University of Maine Soil Laboratory. In the experimental design on each site, each subplot was 9.14 m length × 3.65 m width and had four rows. A distance of 1.50 m was maintained between replicates as a buffer zone. Management practices (such as weeding, insect, pest, and disease control) were applied at all sites similarly. Planting was completed between mid-May to the end of May, and harvesting was done between the end of September and beginning of October.

2.4 | Soil properties

The pre-plant soil sample was collected from each site using a soil probe. Soil samples were sent to the University of Maine Soil Laboratory for the chemical tests, and the USDA–NRCS was used to obtain physical soil properties (Table 1). The sites NS-1, NS-2, and WL followed 3 yr of crop rotation (potato–grain–cover crop), whereas CA1 and FV sites had 2 yr of crop rotation system (potato–grain). The AF1, 2, and 3 sites were not under any crop rotation system, and the grass was planted over 7 yr continuously. The sites CA2, CA3, and LM followed a 2-yr crop rotation (potato–[mustard–radish]), (potato–[red + white clover]–rye), and (potato–[clover–oat–grains]), respectively (Table 1).

3 | MEASUREMENTS

3.1 | Sensor description and sensing procedure

Two handheld active optical sensors were employed for this research: GS (Trimble Navigation Limited) and CC (A-470 sensor, Holland Scientific, Inc.). The GS sensor measures incident and reflected beams from the plant canopy at 660 ± 15 nm and 770 ± 15 nm, which were red and NIR bands, respectively (Sharma, Bu, Denton, & Franzen, 2015).

In GS, the beam is transmitted from diodes in alternating emissions at different intervals such that the visible source pulses come out to be 1.0 ms, and the NIR diode source pulses come out to be 1.0 ms at 40,000 Hz. Emission from a given source equals approximately 40 pulses before pausing for the other diode to release its radiation, which is another 40 pulses (Sharma et al., 2015). The light covered area is about 60 cm in width by 1.0 cm in length, with the long dimension positioned vertically in the direction of walking to take readings. The field of view is relatively steady for heights between 60 and 120 cm above the plants’ canopy; the output from the sensors is a red NDVI and simple ratio (red/NIR) (Sharma et al., 2015).

The CC sensor concurrently emits three bands: red, 650 nm; red edge, 730 nm; and the NIR, 760 nm. The sensor collects about 2–20 readings per second, so each recorded

| Site  | pH   | OM  | NO₃⁻ | NH₄⁺ | P    | K    | Ca   | Mg   | Cu   | Fe   | Mn   | Zn   | CEC  |
|-------|------|-----|------|------|------|------|------|------|------|------|------|------|------|
| AF1   | 6.5  | 7   | 2.7  | 2.0  | 2.0  | 2.0  | 2.0  | 2.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.2  |
| AF2   | 7.0  | 1.8 | 6.0  | 6.0  | 0.1  | 2.0  | 2.0  | 2.0  | 0.2  | 0.2  | 0.2  | 0.2  | 0.2  |
| AF3   | 6.0  | 1.8 | 8.0  | 8.0  | 5.0  | 5.0  | 5.0  | 5.0  | 0.2  | 0.2  | 0.2  | 0.2  | 0.2  |
| CA1   | 6.5  | 5.7 | 7.0  | 7.0  | 1.0  | 1.0  | 1.0  | 1.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
| CA2   | 5.0  | 4.1 | 8.0  | 8.0  | 1.0  | 1.0  | 1.0  | 1.0  | 0.2  | 0.2  | 0.2  | 0.2  | 0.2  |
| CA3   | 6.0  | 3.0 | 7.0  | 7.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
| FV    | 5.9  | 4.9 | 5.0  | 5.0  | 1.0  | 1.0  | 1.0  | 1.0  | 0.2  | 0.2  | 0.2  | 0.2  | 0.2  |
| LM    | 6.0  | 3.3 | 2.0  | 2.0  | 1.0  | 1.0  | 1.0  | 1.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
| NS-1  | 5.4  | 4.5 | 21   | 21   | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
| NS-2  | 5.6  | 4.4 | 16   | 16   | 1.0  | 1.0  | 1.0  | 1.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
| WL    | 5.8  | 4.1 | 15   | 15   | 1.0  | 1.0  | 1.0  | 1.0  | 0.3  | 0.3  | 0.3  | 0.3  | 0.3  |
value in a 6.0-m length of the plot, walking about 5.0 km h\(^{-1}\), is the average of about 4,000 readings. Output data of the sensor are reflectance values that allow calculation of vegetation indices. The NDVI involved red and red-edge bands, which is different from GS (Sharma et al., 2015).

The equation for red NDVI and red-edge NDVI follows:

\[
\text{Red NDVI} = \frac{\text{NIR} - \text{red}}{\text{NIR} + \text{red}} \quad (1)
\]

\[
\text{Red edge NDVI} = \frac{\text{NIR} - \text{red edge}}{\text{NIR} + \text{red edge}} \quad (2)
\]

GS emits two bands: red, 660 nm; and NIR, 774 nm,

\[
\text{NDVI} = \frac{(774\ nm - 660\ nm)}{(774\ nm + 660\ nm)} \quad (3)
\]

CC emits three bands: red, 670 nm; red-edge, 730 nm; and NIR, 760 nm:

\[
\text{NDVI} = \frac{(760\ nm - 670\ nm)}{(760\ nm - 670\ nm)} \quad (4)
\]

Or red-edge NDVI

\[
\text{NDVI} = \frac{(760\ nm - 730\ nm)}{(760\ nm + 730\ nm)} \quad (5)
\]

Both the sensors, GS and CC, were used weekly during the growing season, which started directly once the plants completed the fourth leaf (4, 8, 10, 12, 16, 18, and 20). Readings were obtained 60 cm over the top of the potato plant from the middle row of each plot. About 40–60 readings were obtained from every single experimental unit. In-house macro programs for Visual Basic within Excel was used to calculate the mean of the sensing readings data (Franzen, 2012). Due to the small differences in the growth stages between sites, NDVI data were normalized using the INSEY (In-Season Estimate of Yield) approach. The INSEY could be particularly useful when combining NDVI data from different site-years. The INSEY (Raun et al., 2001) was computed by dividing the NDVI data with the growing degree days (GDD), which started from the planting date to the date of taking sensor readings, used (U. S. Climate Data, 2018) to calculate weather data (see Equation 6).

\[
GDD = \frac{(T_{\text{max}} + T_{\text{min}})}{2} - C \quad (6)
\]

where \(T_{\text{max}}\) and \(T_{\text{min}}\) represent the daily maximum and minimum temperature, and \(C\) represents the base growing temperature for potato, which is 10 °C.

Sensing was conducted by placing the GS and CC at an approximate distance of 60 cm above the plant canopy, resulting in a similar magnitude of reflectance at each site and each growth stage reading (Franzen, 2012).

### 3.2 Chlorophyll index

Leaf chlorophyll content, as an index, was measured using an active optical sensor, CC. The CC depends on red-edge and NIR wavelength bands, which is sensitive to a wide range of chlorophyll, to calculate the index (see Equation 7) (Gitelson, Viña, Ciganda, Rundquist, & Arkebauer, 2005).

\[
\text{Cl}_{\text{RE}} = \frac{\text{NIR}}{\text{RE}} - 1 \quad (7)
\]

where \(\text{Cl}_{\text{RE}}\) is red-edge chlorophyll index, NIR is near-infrared wavelength band 850 nm and RE is red-edge wavelength band 730 nm.

### 3.3 Yield harvesting and calculation

A random selection of 3.0 m length from the two middle rows (6.0 m as a total) of each subplot was harvested mechanically using a potato digger machine; potato tubers were collected into special paper bags of 23.0 kg capacity. Potato tubers were cleaned from soil and plant residues and then graded into four different sizes using a potato grading machine. The two middle rows (total of 6.0 m length) of each subplot were converted to 3.0 m length by dividing them by 2.0 and then used to calculate total yield production using the equation provided by North Dakota and Minnesota (see Equation 8) (Donavon, Diane, Todd, Ted, & Andy, 1946).

\[
\text{The certain weight/acre (cwt/acre)} = \frac{\text{lb/10ft} \times \text{multiplication factor}}{\text{acre}} \quad (8)
\]

The multiplication factor depends on the row width, which is equal to 14.5 when planting a row with 90 cm (36 inches) in width. Equation 8 was used to calculate the total yield per area and then converted to standard units, Mg ha\(^{-1}\). The total weight per plant calculated by dividing the total weight of tubers from each subplot by the number of plants in the row.

### 3.4 Data analysis

A correlation analysis via IBM-SPSS v.25 (SPSS-IBM-Corp., 2017) was conducted between total tuber yield and sensor data to understand how leaf chlorophyll content is associated with the yield variation within different potato cultivars. Regression analysis was used to determine the relationship between potato yield data as a dependent variable and sensor data as independent variables. Multiple regressions were conducted between potato yield data and sensors’ data, NDVI, and CI to enhance the determination coefficient \(R^2\) of the yield prediction algorithm. The CI data were utilized with each group
Yield responses to nitrogen rates

(≥3.0, ≤3.0% of soil organic matter [OM], and combined sites), and with each type of sensor data (GS-red, CC-red, and CC-red-edge).

To avoid the multicollinearity between independent variables, variance inflation factor (VIF) used as an index to check the correlation between independent variables. The VIF ≤ 5.0 is the recommended threshold value (Marquardt, 1970; Rogerson, 2001), and values higher than 5.0 would affect negatively the results associated with a multiple regression analysis.

4 | RESULTS

4.1 | Yield responses to nitrogen rates

Potato yields at different N application rates are shown in (Figure 1), which represents the relationship between N rates and potato yields for the sites that have ≤3.0% OM, ≥3.0% soil OM, and an average of all sites combined. The yield of potato significantly improved by N fertilizer applications in all sites (p value < .05). Comparing with the control treatment, 0 kg N ha⁻¹, the yields under 56, 112, and 168 kg ha⁻¹ treatments were increased by 10.8, 20.7, and 18.46%, respectively, for 56 kg N ha⁻¹; 13.3, 28.8, and 25.4%, respectively, for 112 kg N ha⁻¹; 21.7, 42.7, and 37.7%, respectively, for 168 kg N ha⁻¹. For all sites, potato yields increased as N rate increased from 0 to 168 kg N ha⁻¹. However, there was no significant (p value > .05) increase witnessed by applying 224 kg N ha⁻¹, implying that the 168 kg N ha⁻¹ was the maximum economic rate for potato production.

4.2 | Relationships between NDVI measurements and potato yields

The Pearson correlation analysis results of INSEY measurements and yield of potato are shown in (Table 2). The correlation coefficient (r) values exhibited that INSEY measurements had a significant relationship with the potato yield in all sites only after the mid growing season, 16th, and 20th leaf stage (p value were < .01). However, the correlation coefficient values were relatively low at the early growth stages, data not shown. The highest value of correlation coefficient in the sites with ≤3.0% soil OM content was achieved at the 16th leaf growth stage, and the sites that have ≥3.0% soil OM content and all sites combined exhibited the highest value at the 20th leaf growth stage. As a comparison between data obtained from different sensors, the INSEY data derived from the red-edge band exhibited the highest correlation with potato yield data in all sites. However, INSEY derived from the GS and CC using the red band showed a relatively similar correlation with the tuber yield. Still, the correlation was relatively low compared with the red-edge band.

Regression analysis revealed that each of the 16th and 20th leaf growth stages showed the highest values of determination coefficient, R², to explain the relationship between potato yield and sensor data (Table 2). The exponential model showed the best fit for the relationship between potato yield and sensors data (INSEY), especially for the sites characterized by ≥3.0% soil OM content and the combined sites. However, the linear model showed the best fit for the relationship in the sites characterized by ≤3.0% soil OM content. It showed that INSEY data before 25 July, 16th leaf growth stage, exhibited a very low R² with potato yields. Therefore, the regression analysis could not make an adequate forecast of in-season yield with NDVI readings of potato yield before 25 July. The sites of ≥3.0% soil OM and all sites combined showed the highest R² during the 20th leaf growth stage, whereas the 16th leaf growth stage was the best for the sites with ≤3.0% soil OM. In all the sites, the highest R² was achieved using the red edge band at the 16th and 20th leaf growth stage in comparison with INSEY derived from the red band.

4.3 | Predicting potato yields using measured NDVI at the optimum time

The results summarized in the regression analyses exhibited that the 16th and 20th leaf growth stages were the most appropriate time for yield prediction of potato. The fitting curves of measured INSEY values and potato yield at this stage were most significantly associated using the exponential and linear function.

4.4 | Sites with ≤3.0% organic matter

The measured INSEY values could explain the yield variation and predict the in-season yield of potato with R² values .38, .45, and .48 at p value < 0.01 for INSEY that derived...
TABLE 2  Pearson correlation and regression analysis between the sensors measurements and potato yield

| Time of sensing | Leaf stage | Sensor type      | \( r \) | \( R^2 \) |
|-----------------|------------|------------------|----------|----------|
| \( \leq 3.0\% \) OM | 25 July    | GS-red-INSEY     | .67**    | .45** L  |
|                 |            | CC-red-INSEY     | .61**    | .38** Exp|
|                 |            | CC-red-edge-INSEY| .69**    | .48** L  |
|                 | 1 Aug.     | GS-red-INSEY     | .61**    | .38** L  |
|                 |            | CC-red-INSEY     | .57**    | .32** L  |
|                 |            | CC-red-edge-INSEY| .64**    | .41** L  |
| \( \geq 3.0\% \) OM | 25 July    | GS-red-INSEY     | .51**    | .26** P  |
|                 |            | CC-red-INSEY     | .47**    | .22** Exp|
|                 |            | CC-red-edge-INSEY| .60**    | .36** Exp|
|                 | 1 Aug.     | GS-red-INSEY     | .44**    | .25** Exp|
|                 |            | CC-red-INSEY     | .49**    | .27** Exp|
|                 |            | CC-red-edge-INSEY| .60**    | .38** Exp|
| All sites combined | 25 July    | GS-red-INSEY     | .31**    | .12** Exp|
|                 |            | CC-red-INSEY     | .35**    | .15** Exp|
|                 |            | CC-red-edge-INSEY| .48**    | .28** Exp|
|                 | 1 Aug.     | GS-red-INSEY     | .53**    | .28** Exp|
|                 |            | CC-red-INSEY     | .50**    | .25** Exp|
|                 |            | CC-red-edge-INSEY| .62**    | .38** Exp|

Note. OM, organic matter; GS, greenseeker active sensor; CC, crop circle active sensor; red, red wavelength; red-edge, red-edge wavelength; INSEY, in-season estimate of yield; Exp, the Exponential model; P, Power model; L, Linear model for the best fit.

** Significant correlation at the .01 probability level.

FIGURE 2  The relationship between potato yield in the sites with organic matter (OM) content \( \leq 3.0\% \) and sensors data, in-season estimate of yield (INSEY) that (a) derived from CC-red-edge band at 16th leaf stage, (b) obtained from greenseeker sensor (GS)-red band at 16th leaf stage, and (c) obtained from CC-red band at 16th leaf stage. **Denotes significance at the .01 probability level.
from CC-red, GS-red, and CC-red-edge bands, respectively. The INSEY at the 16th leaf growth stage exhibited the highest values of $R^2$, and it was about 15.7, 16.9, and 17.1% higher than what obtained at the 20th leaf growth stage using CC-red-edge, GS-red, and CC-red, respectively (Figure 2a, b, and c).

### 4.5 Sites with ≥3.0% organic matter

The measured INSEY values could explain the yield variation and predict the in-season yield of potato with $R^2$ values .25, .27, and .36 at $p$ value < .01 for INSEY that derived from GS-red, CC-red, and CC-red-edge bands respectively. The INSEY at the 20th leaf growth stage exhibited the highest value of $R^2$, and it was about 3.9, 20.4, and 5.4% higher than what obtained at the 16th leaf growth stage using GS-red, CC-red, and CC-red-edge respectively (Figure 3a, b, and c).

### 4.6 All sites combined

The results of the regression analysis between potato yield and sensor data for all sites combined showed there is a significant correlation that can be utilized to predict the in-season potato yield. The $R^2$ values were .25, .28, and .38 at $p$ value < .01 for INSEY that derived from CC-red, GS-red, and CC-red-edge bands, respectively. The INSEY at the 20th leaf growth stage exhibited the highest values of $R^2$, and it was about 50, 80, and 30% higher than what obtained at the 16th leaf growth stage using CC-red, GS-red, and CC-red-edge respectively (Figure 4a, b, and c).

### 4.7 Chlorophyll measurements to predict yield

The correlation analysis “Pearson” exhibited that CI measurements had a significant relationship with the potato yield in all sites at the 16th and 20th leaf growth stages ($p$ value < .01). However, the $r$ values were relatively lower at the early growth stages. The highest $r$ value (.48) at the sites with ≤3.0% soil OM content was achieved at the 16th leaf growth stage (Figure 5a); whereas the sites that have ≥3.0% soil OM content showed the highest value (.38) at the 20th leaf growth stage (Figure 5b). In the case of all sites combined, it showed a significant correlation at the 20th leaf growth stage, $r = .41$, (Figure 5c).
FIGURE 4  The relationship between potato yield in the sites with all sites combined and sensors data derived from (a) crop circle sensor (CC)-red band at 20th leaf stage, (b) greenseeker sensor (GS)-red band at 20th leaf stage, and (c) CC-red-edge band at 20th leaf stage. **Denotes significance at the .01 probability level

The regression analysis between potato yield as a dependent variable and CI as an independent variable showed that there is an applicable relationship that can be utilized for in-season yield prediction measurements. The significant linear relationship between potato yield and CI is more significant than the yield prediction model based on NDVI measurements.

The exponential model showed the best fit for the relationship between potato yield and CI, especially for the sites characterized by ≥3.0% soil OM content and the combined sites. However, the linear model showed the best fit for the relationship in the sites characterized by ≤3.0% soil OM content.

4.8 Chlorophyll measurements to enhance yield prediction efficiency

The CI beside the NDVI measurements as independent variables enhanced the algorithm of potato yield prediction. Multiple regression analysis results exhibited that at the 16th and 20th leaf growth stages, there were improvements in the $R^2$, whether at the classified (≥3.0%, ≤3.0% soil OM) or combined sites. However, the sites ≤3.0% OM are the only ones that did not show a significant relationship at the 20th leaf growth stage, where $R^2$ improved up to .54**, .52**, and .50** when using GS-red, CC-red-edge, and CC-red, respectively, and VIF 2.0, 1.0, and 1.0, respectively (Figure 6a, b, and c). In the sites ≥3.0% OM, CI improved the $R^2$ up to .38** and .38** and VIF 1.0 and 1.0 when using GS-red and CC-red, respectively, but there was no improvement with CC-red-edge (Figure 6d and e). At the all combined sites, CI improved the $R^2$ for GS-red, CC-red, and C-red-edge by .41**, .41**, and .43** respectively; VIF values were 4.0, 1.0, and 1.0, respectively, (Figure 6f, g, and h).

4.9 Model validation

To validate the yield prediction models, the correlation relationship was conducted between the actual tuber yield and predicted yield by each sensor used, CC, and GS. The correlation analysis results were positive and significant, implying that the relationship between the actual yield and predicted yield with all the models was strong (Table 3). It is necessary to mention that each model predicting the yield under field conditions despite uncertain environmental conditions changes dramatically, such as insect pest damage, high temperature, water stress, and so forth.
The value of correlation confirms that the sensor’s capability to predict the potato yield is strong, particularly red-edge wavelength that excelled over all the wavelengths compared with the red wavelength. In general, the correlation coefficient showed higher values with lower values of root mean square error (RMSE) when using the CC sensor with each band (red and red-edge) compared with GS, which showed lower values of the correlation coefficient. However, multiple regression was different from simple regression, where the correlation coefficient values were high when using all sensors with insignificant differences between them.

4.10 Discussion

Potato yield responded to the different N rates significantly. There was a clear difference between the treatments of 0 kg N ha\(^{-1}\) and the series of N rates in all sites. The 0 kg N ha\(^{-1}\) treatment showed the lowest yield compared with other N rates. Potato yield increased with increasing N rates up to 168 N kg ha\(^{-1}\), after which potato productivity decreased gradually regardless of continuing in supplying N. This is consistent with the findings that over-applying N fertilizer would not increase yield; however, it might direct to high N losses (Ju et al., 2009; Ju, Xu, Wei-Ming, Guang-Xi, & Zhao-Liang, 2011). Yield reduction was observed in all groups (≤3%, ≥3% soil OM, and all combined sites), which could be a result of delayed tuber growth and increased vegetative growth (leaves and stems) compared with tuber growth.

The excessive amount of N applications encouraged a dense vegetative growth, which in turn reduced the amount of the carbohydrates that expected to be going to tubers. As a result, photosynthesis supported a plant’s leaves more than tubers and then reduced the tuber’s quality (Ahmed, El-Baky, Ghoname, Riad, & El-Abd, 2009; Porter & Sisson, 1989). Therefore, timely prediction of yield in the growing season would help to manage N fertilizer application accurately and achieve maximum economic yields.

In this study, the Pearson correlation analysis showed that NDVI measurements had a significant positive relationship with the yields of potato (Table 2) at the 16th and 20th leaf growth stages, indicating that the handy active sensors had a great potential to be utilized for potato yield prediction. At the early stage (before July), the temperature was relatively low and the growth rate was minimal. Consequently, the nutrient uptake was relatively low and this stage did not fully develop potato biomass. After the middle stage of growth (late July), the growth of potato picked up significantly and it was the appropriate stage for collecting reliable sensing data. However, at a later stage (mid to late August) close to maturity,
FIGURE 6 The multiple regression relationship between potato yield as the dependent variable with chlorophyll index (CI) and in-season estimate of yield (INSEY) as independent variables in the (a) sites ≤ 3.0% organic matter (OM) using greenseeker sensor (GS)-red, (b) sites ≤ 3.0% OM using crop circle sensor (CC)-red-edge, (c) sites ≤ 3.0% OM using CC-red, (d) sites ≥ 3.0% OM using GS-red, (E) sites ≥ 3.0% OM using CC-red, (f) combined sites using GS-red, (g) combined sites using CC-red, and (h) combined sites using CC-red-edge. **Denotes significance at the .01 probability level.

the relationship seemed stable but weak, because the potato plant started lying down and turning a yellowish color. Thus, sensing time is crucial for predicting potato yield.

Linear and non-linear regression analyses are usually utilized in past studies to predict crop yields in-season (Cao et al., 2015; Raun et al., 2005). In our research, the best fit of the curves was observed with the linear and exponential equations. The linear model represented the curves in the data generated from the sites with exponential model represented the sites with ≥ 3.0%. Mathematically, Xu et al. (2012) defined the linear function as one that is increasing at a constant rate as \( x \) increases, and the exponential function is one that increases...
| Sites          | Plant index                  | Monitoring stage | $r$  | RMSE  |
|---------------|------------------------------|------------------|------|-------|
| $\leq 3.0$ OM | GS-red-INSEY                 | 16               | .67**| 4.35  |
| $\leq 3.0$ OM | CC-red-INSEY                 | 16               | .61**| 4.64  |
| $\leq 3.0$ OM | CC-red-edge-INSEY            | 16               | .69**| 4.23  |
| $\leq 3.0$ OM | GS-red+CI-INSEY              | 16               | .74**| 3.88  |
| $\leq 3.0$ OM | CC-red+CI-INSEY              | 16               | .71**| 4.07  |
| $\leq 3.0$ OM | CC-red-edge-INSEY+CI         | 16               | .72**| 3.99  |
| $\geq 3.0$ OM | GS-red-INSEY                 | 20               | .44**| 8.32  |
| $\geq 3.0$ OM | GS-red+CI-INSEY              | 20               | .49**| 8.11  |
| $\geq 3.0$ OM | CC-red-edge-INSEY            | 20               | .60**| 7.43  |
| $\geq 3.0$ OM | GS-red+CI-INSEY              | 20               | .62**| 4.72  |
| $\geq 3.0$ OM | CC-red+CI-INSEY              | 20               | .62**| 4.67  |
| $\geq 3.0$ OM | CC-red-edge-INSEY+CI         | 20               | .61**| 4.66  |
| All-combined | CC-red-INSEY                 | 20               | .49**| 8.20  |
| All-combined | CC-red-edge-INSEY            | 20               | .61**| 7.46  |
| All-combined | GS-red-INSEY+CI              | 20               | .64**| 3.33  |
| All-combined | CC-red-INSEY+CI              | 20               | .66**| 3.22  |
| All-combined | CC-red-edge-INSEY+CI         | 20               | .64**| 3.31  |

Note. OM, organic matter; GS, greenseeker active sensor, CC, crop circle active sensor, red, red wavelength, red-edge, red-edge wavelength, CI, chlorophyll index, INSEY, in-season estimate of yield; RMSE, root mean square error.

** Significant correlation at the .01 probability level.

The apparent decrease in the canopy N content, accompanying the onset of rapid tuber bulking, may describe the low leaf chlorophyll content. This decrease was not observed in the sites $\geq 3.0\%$ OM at the 20th leaf growth stage, possibly because the high content of OM supplied more nutrients that extended the growing season compared with $\leq 3.0\%$ OM.

The robust correlation between potato yield and each of INSEY and CI that derived from NDVI red-edge wavelength more than INSEY derived from NDVI-red wavelength is attributed to the chlorophyll saturation condition at that growth stage. The sensor light penetrates the leaf deeply when using the red-edge wavelength compared with using the red wavelength. During the photosynthesis process, about 80% of incident light absorption was observed between the range of 400–700 nm (Moss & Loomis, 1952). Thus, light in the red-edge spectra is more sensitive to changes in chlorophyll content than other bands (Gitelson et al., 2003). The red band can measure plant biomass, but it is sensitive to a low range of chlorophyll content 3–5 $\mu$g cm$^{-2}$, whereas the red-edge band is sensitive to a wide range of chlorophyll 0.3–45 $\mu$g cm$^{-2}$ (Gitelson & Merzlyak, 1997). This property helped to overcome a saturation problem that happens at the end of the growing season, where there is a considerable density of plant biomass.

5 CONCLUSION

The 168 kg N ha$^{-1}$ treatment increased the average fresh tuber production to the maximum yield. Excessive N, more than 168 kg ha$^{-1}$, failed to increase the tuber yield significantly. Soil OM played a significant role in improving potato yield production due to its valuable benefits that support soil chemical, physical, and biological characteristics.

Soil OM content did not influence the prediction calculations and the N rate required for maximum potato yield. Still, there was a considerable difference in the potato yield compared with the sites with $\leq 3.0\%$ OM. The results of the correlation between potato yield and remote sensing data during the growing season indicated that the 16th and 20th leaf growth stages are the optimum time to use these indices for yield prediction. Chlorophyll index either individually or jointly with other spectral vegetation indices (INSEY) enhanced the determination coefficient of the prediction model better than using...
the INSEY data separately. The INSEY obtained from the red-edge wavelength is the best way to overcome the saturation condition caused by heavy canopy density, compared with the INSEY that obtained from the red band. Further work is needed to generalize the results for other varieties of potato individually.

CONFLICT OF INTEREST
The authors declare no conflict of interest.

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