ACTIVE OPTICAL SENSORS TO DEVELOP NITROGEN FERTILIZER RECOMMENDATIONS FOR POTATO CROP

Ahmed. A. Z.[1] L. Sharma[2] S. Bali[3] A. Buzza[4] A. Alyokhin[5]
Lecturer Asst. Prof . Asst. Prof. Asst. Prof. Prof.
[1]Remote Sensing Unit, College of Science, University of Baghdad, 10070 Iraq;
[2]University of Florida, Soil and Water Science, Gainesville, FL 32611, USA;
[3]University of Florida, Agroecology, Gainesville, FL 32611, USA;
[4]University of Maine, Aroostook Research Station, Presque Isle, ME 04769 USA.
[5]University of Maine, Department of Biology, Orono, ME 04469 USA.
[1]E-mail: ahmed.asaad@sc.uobaghdad.edu.iq

ABSTRACT

This study was performed to determine whether active optical sensors could develop an algorithm for N recommendation for the potato crop (*Solanum tuberosum* L.). The experiment was conducted in Maine State, (USA) during the growing season of 2018-2019. Six N rates (0-280 kg ha^{-1}) were applied on eleven locations under a randomized complete block design (RCBD), with four replications. Data of normalized difference vegetation index-(NDVI) were collected via active sensors, GreenSeeker-(GS), and Crop Circle-(CC). Sensors measurements collected at the 20th of the leaf stage were significantly associated with tuber yield, where the exponential model exhibited a better fit for the regression curve. Conventionally, 168 kg N ha^{-1} produced the maximum potato yield. The N rate computed based on in-season sensors reading reduced by about 12-14% from the total N rate that growers use to apply based on the conventional approach. Studying potato cultivars separately in the same soil properties can improve the algorithm accurately.

Keywords: nitrogen, greenseeker, crop circle, in-season estimated yield

توصية السماد النيتروجيني لمحصول البطاطا باستخدام أجهزة الاستشعار البصرية النشطة

احمد اسعد زعين[1] لاكيش شارما[2] سكوندر بالي[3] ارون بازا[4] اندري اليخون[5]
مدرس استاذ مساعد استاذ مساعد استاذ مساعد استاذ
[1]وحدة الاستشعار عن بعد – كلية العلوم – جامعة بغداد، [2]جامعة –امريكا– قسم التربة والمياه –فلوريدا ، [3]جامعة فلوريدا– قسم البيئة–امريكا، [4]محطة بحوث ارستوك–جامعة مين–امريكا، [5] قسم البايولوجي–جامعة مين–امريكا.

المستخلص

إجريت هذا البحث لتحديد ما إذا كانت المستشعرات الضوئية النشطة يمكن أن تولد خوارزمية لتوصية النتروجين لمحصول البطاطا (*Solanum tuberosum* L.). نفذت التجربة في ولاية مين في الولايات المتحدة الامريكية للموسم الزراعي 2018–2019. تم تطبيق ستة معدلات نيتروجين (0–280 كغم هكتار$^{-1}$) على أحد عشر موقعًا بتصميم القطاعات العشوائية الكاملة، مع أربعة مكررات. تم الحصول على بيانات فهرس الغطاء النباتي (NDVI) المعياري بواسطة المستشعرات الضوئية النشطة، GreenSeeker و Crop Circle. ارتبطت قياسات المستشعرات التي تم الحصول عليها في المرحلة العشرين (عدد اوراق) ارتباطًا وثيقًا بإنتاجية الدرنات، حيث أظهر الانموذج الأسي ملائمة أفضل لمنحنى الانحدار. تقليديًا ، أنتج المعدل 168 كغم Nهكتار$^{-1}$ أقصى إنتاجية من البطاطا. معدل النيتروجين المحسوب على أساس قراءة أجهزة الاستشعار في الموسم انخفض بنسبة 12–14٪ تقريبًا من إجمالي معدل النيتروجين الذي استخدمه المزارعون لتطبيقه بناءً على النهج التقليدي. يمكن أن تؤدي دراسة أصناف البطاطا بشكل منفصل في خصائص التربة المماثلة إلى تحسين الخوارزمية بدقة.

الكلمات المفتاحية: المتحسس كرين سيكير، كروب سيركل، الانتاجية المحسوب في الحقل.

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INTRODUCTION

It has been a fact that unreasonable application of N fertilizer to the potato crop causes low tuber production due to excessive vegetative growth, lower tuber quality (low specific gravity, large size with hollow heart, delay in maturity, etc.), and lower N use efficiency (NUE) that causes the leaching of a large part of N to groundwater and leads to a high risk of environmental contamination (of the atmosphere by nitrous oxides and water by nitrate, etc.) (6, 17, 51). N deficiency, in contrast, can considerably decrease crop yield (68). Furthermore, the potato production system is well known for low NUE, varying between 50 and 60% (14,55), and this could be due to shallow and poorly developed root systems. Typically, loss of N occurs when mineral N (NH_4^+ and NO_3^-) is present in the soil, in amounts higher than plant requirements (28). Consequently, inadequate synchronization between soil N supply and crop demand is one of the main reasons for low N fertilizer use efficiency (3,4,14,41,38). Potato growers in developed countries are under immense pressure to keep profitability against new environmental restrictions, such as the commitment to the nitrate directive (91/676/EEC) and a recent increment in N fertilizer prices, to motivate them for precise input management. Nevertheless, having adequate food supplies globally is a challenge that fertilizer application cannot be achieved (56). In such a meaning, it is essential to develop instruments and procedures for potato growers that could help them determine "the right N fertilizer rate at the right time and place." It is generally acknowledged that a temporary field-specific N recommendation for potato at planting time can never be accurate. Furthermore, it is challenging to predict crop N requirements during the growing season (61) due to numerous predictable or unpredictable factors, such as chemical, physical, and biological soil characteristics, soil organic matter, cultural practices, crop maturity time, and weather conditions. Nitrogen fertilization recommendation with estimated requirements during crop growing seasons can essentially aid in matching crop N requirement times and rates with supplies. Accordingly, N fertilizer efficiency can be improved (5,61). Precision agriculture technology allows growers to apply the correct quantity of fertilizer in real-time based on the crop's current growth status without negatively affecting the final yield. A modeling strategy (N recommendation at field-specific scale) of crop N status monitoring can lead to helpful decision-support methods to enhance N fertilizer use efficiency. It has been found that the approach of using crop N status assessment to determine crop demands is more reliable than predicting the available soil N supply (48). Plants are often considered a good indicator (mirror) of growing conditions (45). Most of the available crop monitoring techniques depend on the magnitudes of reflected light above the crop canopy (49). A remote sensing approach can be performed at several spatial scales: ground-based, airborne, or space-borne (31,57). All these scales focus on measuring plant canopy formation factors, such as the leaf area index (LAI) and leaf chlorophyll, among others, with well-established science that these factors are strongly related to each other and plant N status (47). The most common precision agriculture tools used for grain crops, such as corn (*Zea mays* L.), wheat (*Triticum aestivum* L.), and sunflower (*Helianthus annuus* L.), among others, are ground-based active optical sensors such as GS, Cropscan, N-sensor, and Holland CC (12). The GS and CC are the most prevalent ground-based sensors in North America for research and commercial use. GreenSeeker (GS) has been widely used for developing N recommendations (46), and with which an algorithm for wheat crop increased nitrogen use efficiency by more than 15% (23). In another study in Oklahoma, the coefficient of variation (CV) from NDVI data was used to evaluate plant density in wheat (11). Similar techniques were used in wheat and rice (*Oryza sativa* L.) grown in Northwest India and attained higher NUE than conventional methods (20,47). The CV was further used to adjust the algorithm in wheat (19). Another in-season N uptake was developed for rice, which increased the NUE and yields (9). Crop characteristics have been used in various methods to calculate optimum N requirements (20). Several other research studies have used plant biomass (11,19) and plant N content (9, 10) to determine N requirements. Spectral measurements have also been used to assess yield potential (YP0) (43,54). Yield potential is a function of the growing environment (28) and is essential for fertilizer N calculation methods. The YP0 has been predicted in-season utilizing optical sensors (49). In addition, the NDVI has been used to determine in-season estimated yield (INSEY) (49), which is a measurement of biomass produced per day as NDVI; (Large, 1954) (34) divided by the number of growing degree days (GDD). A few studies have utilized active optical sensors to predict leaf N content (8,25) and yield (47) studies developed an algorithm for N recommendations for potato crops. Therefore, this study aimed to use the data of active optical sensors (NDVI) to develop N recommendation and compare it with what potato growers commonly applied in Maine, USA.

MATERIALS AND METHODS

Research locations: The experimentation was performed in Aroostook County, Maine, USA (Figure1), in the period of 2018 and 2019. Eleven investigation locations, six of them in Presque Isle, Aroostook Farm (AF1, Lat.46.66134° and Long.-68.01808°), New Sweden-1 (NS-1, Lat.46.95156° and Long.-68.14779°), Frenchville (FV, Lat. 47.21676° and Long. -68.41153°), and New Sweden-2 (NS-2, Lat.46.95271° and Long.-68.14572°), Caribou (CA1, Lat. 46.88227° and Long.-68.02895°), and Wood Land (WL,Lat. 46.88520° and Long.-68.12577°), were selected to experiment in 2018. In 2019, five research sites were chosen to conduct the investigation, two in Presque Isle, Aroostook Farm (AF2 and AF3, Lat. 46.66134° and Long. -68.01808°), Limestone (LM, Lat: 46.96186° and Long. -67.83333°), two in Caribou (CA2, Lat. 46.89628° and Long. -68.07750°), and (CA3, Lat: 46.89180° and Long.-68.04055°). All locations have a separate average annual precipitation and temperature, where AF1, 2, and 3 locations had yearly average precipitation of 91.0 cm and an annual mean temperature of 5.15 °C. The sites WL, NS (1 and 2), as well as CA1, 2, and 3 had average yearly rainfall of 97.9 cm and a yearly mean temperature of 4.3 °C, whereas FV had average annual precipitation of 85.5 cm and an annual mean temperature of 3.6 °C (59).

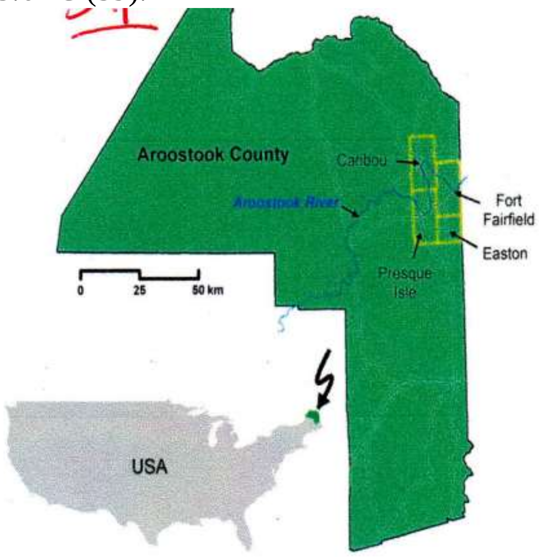

Figure 1. The study area, Aroostook County within Maine state, USA (62).

Experimental materials

The investigation covered three potato cultivars: Russet Burbank, Shepody, and Superior. Russet Burbank was planted in all sites, while Shepody and Superior were planted in AF. The planting space was 30 cm within rows, where the row width was about 90 cm.

Experimental treatments and design

Six N rates of fertilizer, 0, 56, 112, 168, 224, and 280 kg ha^{-1}, as ammonium sulfate ($(NH_4)_2SO_4$) in the first year and ammonium nitrate (NH_4NO_3) in the second year, were used on all the locations a randomized complete block design, RCBD, with four replications. Phosphorus (P), potassium (K), and sulfur (S) were used as instructed by the University of Maine Soil Laboratory (Maine). Each subplot was 9.14 m long × 3.65 m wide and had four rows. A distance of 1.50 m was left between replicates as a buffer zone. All managing procedures, such as disease, pest, insect control, and weeding, were employed for all locations. Planting was conducted between the middle and end of May; harvesting was accomplished between September and October.

Soil properties

Pre-plant soil samples were sampled from each location, and then samples were examined at the University of Maine Soil Laboratory. The USDA-Natural Resources Conservation

Service-NRCS (United States Department of Agriculture) was utilized for physical soil properties (Table 1). The locations NS-1, NS-2, and WL were subjected to three-year crop rotation (potato-grain-cover crop), whereas CA1 and FV locations had a two-year crop rotation (potato-grain). The AF1, 2, and 3 locations did not follow any crop rotation plan, where the grass was grown continually over seven years. The locations CA2, CA3, and LM locations subjected to two-year crop rotation (potato, (mustard, radish)), (potato, (red, white clover), rye), and (potato, (clover, oat-grains)) respectively, (Table 1).

Measurements

Active sensors and data collection: Active optical sensors (GS and CC) (Figure 2) were employed to assemble NDVI data weekly, where sensing began once plants reached the fourth leaf stage till the twentieth (4, 8, 10, 12, 16, and 20) (22). The NDVI data were acquired at 60 cm over the top of the plant from the middle row of each plot, where about 40–60 readings were collected from each plot. The excel and in-house macro programs for Visual Basic were utilized to compute the mean of sensing data (21). The NDVI data were normalized by calculating in-season yield estimation (INSEY) and then combined according to leaves number (22), counted during each sense date. Data collection was continued until completing the twentieth leaf stage. After that, plants start laying down, and greenness declines, preparing to enter the maturing stage. Table 2 shows how sensors provided NDVI data during walk-throughs of plant rows; due to the long Excel columns, the table has been truncated to indicate the beginning and end of the data series. Table 2 a shows the beginning of collecting data, while (Table 2 b) with a marked row represents a new data collection for the following plot in the RCBD.

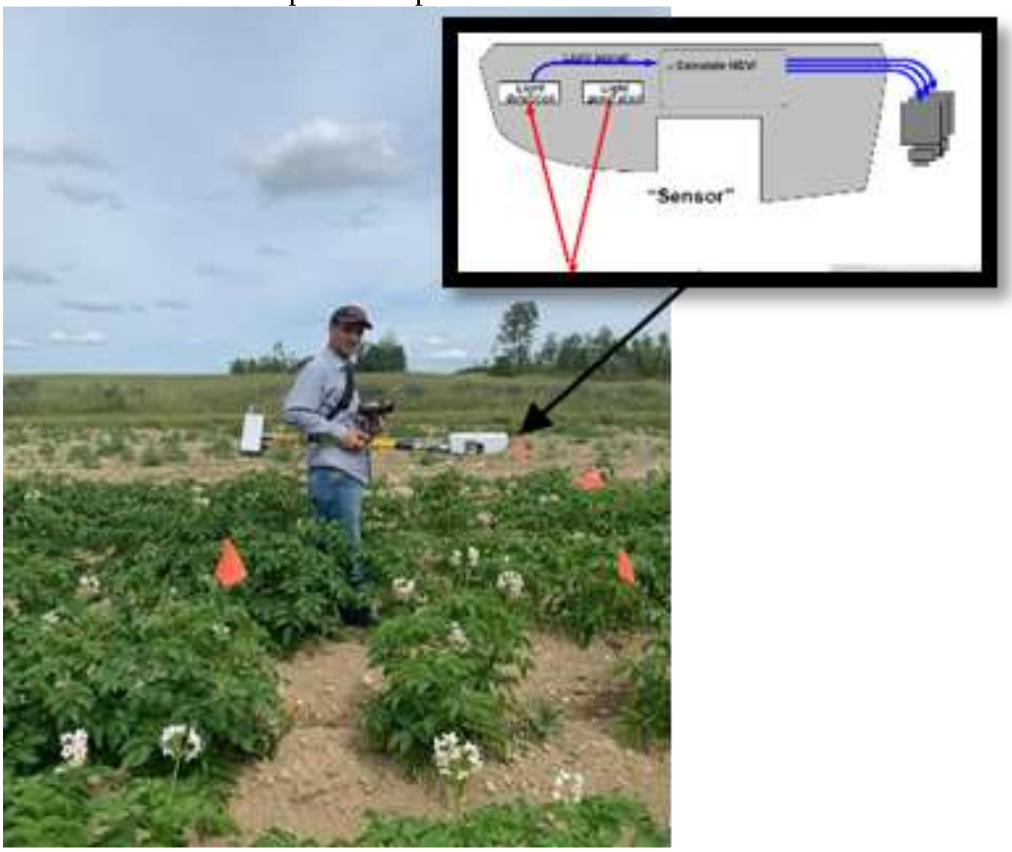

Figure 2. GreenSeeker sensor that was used in the experiment

Table 1. Soil chemical data, crop rotation, and soil series (66)

Site	pH	OM g kg^{-1}	NO_3	NH_4	P	K_{sat}	Ca_{sat}	Mg_{sat}	S	Bo	Cu	Fe	Mn	Zn	CEC me $100g^{-1}$	Crop Rotation	Soil Series
			--------	--------	--------	--------	--------	mg kg^{-1}	--------	--------	--------	--------	--------	--------			
AF1	6.5	27	7	4.0	21.5	98000	680000	222000	4.0	0.2	0.42	2.0	2.9	0.3	7.0	>3 yrs	Fine-Loamy, mixed, Frigid Typic Haplorthods
AF2	7.0	18	6	9.0	17.0	80000	660000	250000	4.0	0.1	0.38	3.3	2.7	0.7	6.2	>3 yrs	Fine-Loamy, mixed, Frigid Typic Haplorthods
AF3	6.0	18	12	8.0	15.0	70000	430000	162000	5.0	0.2	0.57	8.9	4.9	0.5	6.3	>3 yrs	Fine-Loamy, mixed, Frigid Typic Haplorthods
CA1	6.5	37	6	1.0	23.6	128000	692000	180000	8.0	0.3	0.67	5.0	3.2	1.3	7.9	2 yrs	Fine-Loamy, mixed, Frigid Aquic Haplorthods
CA2	5.0	41	8.0	3.0	19.4	90000	270000	96000	19.0	0.4	1.69	23	8.1	2.6	7.8	2 yrs	Gravelly loam, Isotic, Frigid, Typic Haplorthods
CA3	6.0	30	7.0	2.0	19.5	80000	800000	125000	9.0	0.3	0.95	6.2	1.3	1.4	6.2	2 yrs	Gravelly loam, Isotic, Frigid, Typic Haplorthods
FV	5.9	49	5	1.0	19.8	93000	771000	136000	15.0	0.3	0.85	10.0	4.2	1.3	7.3	3 yrs	Fine-Loamy, mixed, Frigid Aquic Haplorthods,
LM	6.0	33	3.0	2.0	19.0	90000	7700000	1370000	7.0	0.2	2.96	8.7	3.4	0.8	6.5	2 yrs	Gravelly loam, Isotic, Frigid, Typic Haplorthods
NS-1	5.4	45	21	6.0	18.2	46000	476000	127000	10.0	0.3	1.12	8.4	7.3	1.9	8.7	3 yrs	Fine-Loamy, mixed, Frigid Typic Haplorthods
NS-2	5.6	41	16	6.0	19.3	66000	541000	138000	6.0	0.3	1.33	11.0	8.8	1.7	7.9	3 yrs	Coarse-Loamy, Isotic, Frigid Oxyaquic Haplorthods
WL	5.8	41	15	5.0	16.5	99000	626000	147000	9.0	0.3	0.71	6.0	8.4	1.6	7.3	3 yrs	Fine-Loamy, mixed, Frigid Aquic Haplorthods

Soil reaction was estimated in a 1:1 ratio of soil to deionized water (63), organic matter was estimated utilizing loss on ignition (LOI) approach (7), micro and macronutrients and were extracted utilizing modified Morgan extraction approach (38), and estimated by ICP-OES (Inductively coupled plasma optical emission spectroscopy) (25), but phosphorus was estimated utilizing colorimetric (34), NO3 was extracted utilizing KCL (33), cation exchange capacity (CES) was estimated utilizing ammonium acetate approach (25).

Table 2. Represents data (NDVI) collected by the GS*, a) starting a plot, b) ending the previous plot, and starting the next, as the marked row showing.

(a) A Time	B Plot	C Count	D NDVI
37010	27	1	0.689
437110	27	2	0.798
437210	27	3	0.829
437310	27	4	0.832
437410	27	5	0.852
437510	27	6	0.722
437610	27	7	0.828
437710	27	8	0.847
437810	27	9	0.851
437910	27	10	0.871
438010	27	11	0.855
438110	27	12	0.871
438210	27	13	0.864
438310	27	14	0.842
438410	27	15	0.838
438510	27	16	0.856
438610	27	17	0.866
438710	27	18	0.865
438810	27	19	0.881
438910	27	20	0.878
439010	27	21	0.856
439110	27	22	0.878
439210	27	23	0.872
439310	27	24	0.876
439410	27	25	0.861
439510	27	26	0.811
439610	27	27	0.874
439710	27	28	0.845
439810	27	29	0.828
439910	27	30	0.809
440010	27	31	0.815
440110	27	32	0.854
440210	27	33	0.828
440310	27	34	0.809
440410	27	35	0.815

(b) A	B	C	D
440510	27	32	0.854
440610	27	33	0.828
440710	27	34	0.815
440810	27	35	0.864
440910	27	36	0.847
441010	27	37	0.856
441110	27	38	0.868
441210	27	39	0.875
441310	27	40	0.837
441410	27	41	0.839
441510	27	42	0.853
441610	27	43	0.842
441710	27	44	0.795
441810	27	45	0.836
441910	27	46	0.769
442010	27	47	0.43
442110	27	48	0.256
442210	27	49	0.258
442310	27	50	0.256
442410	27	51	0.456
442510	27	52	0.514
442610	27	53	0.589
442710	27	54	0.682
442810	27	55	0.764
442910	27	56	0.668
443010	27	57	0.767
443110	27	58	0.689
444610	27	59	0.874
444710	28	60	0.821
444810	28	61	0.878
444910	28	62	0.787
445010	28	1	0.846
445110	28	2	0.847
445210	28	3	0.846
445310	28	4	0.835
445410	28	5	0.819

***GreenSeeker**

Sensor description and sensing procedure: Two handheld active optical sensors (GS-Trimble Navigation Limited, Sunnyvale, CA, USA) and (CC-ACS-430 sensor Holland Scientific, Inc., Lincoln, NE, USA) were used in this investigation. The GS sensor estimates incident and reflected light from the plant canopy at a wavelength in R and NIR bands (Table 3) (50). In GreenSeeker, a ray is transmitted from light-emitting diodes at different duration, such that the visible source pulses for 1.0 ms, and then the NIR diode source pulses for 1.0 ms with 40,000 Hz. The light covers about 60 cm in width by 1.0 cm in length, with a long dimension positioned vertically in the running path. The Crop Circle sensor emits white light and employs three types of filters, which are R, red-edge, and NIR (Table 3), in order to segregate the reflected light. The sensor collects nearly 2–20 of NDVI readings per second, so with each recorded value in a 6.0 m plot length with 5.0 km hr^{-1} of walking speed, there is an average of 4000 NDVI readings. Sensor outputs are reflectance values that allow the calculation of vegetation indices (50).

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

Red NDVI $=\frac{NIR-Red}{NIR+Red}$ ….(1) Red Edge NDVI $= \frac{NIR-Red\ Edge}{NIR+Red\ Edge}$ ..(2) Where NIR=near-infrared band

Red= red band

RedEdge= rededge band

Table 3. Spectral properties for sensors

Properties	Sensors	
	GreenSeeker	Crop Circle
R (nm)	656	630
Red-edge (nm)	-	730
NIR (nm)	774	780
Total covered area (cm^2)	92	741

Due to the insignificant differences in the growth stages among locations, NDVI data were normalized employing the INSEY procedure. The in-season estimate of yield (INSEY) could be beneficial if NDVI data were combined from different sites and years. The in-season estimate of yield (INSEY) (43) was calculated by dividing NDVI data on the GDD that started from the planting date to the date of taking sensor readings (58), as shown in equation (3).

$GDD = [(T\_max+T\_min)/2]- C$ ..…(3)

where: Tmax. and Tmin. describes the daily maximum and minimum temperatures, which is the base growing temperature for potato (10°C). Sensing was performed by passing GS and CC at an approximate space of 60 cm over the plant canopy, resulting in a similar portion of reflectance at all locations and each growth stage (21).

Yield harvesting and calculation

A three 3.0-m random plot length selected from the two middle rows (6.0 m total) of each subplot was harvested mechanically utilizing a potato digger machine. Potato tubers were collected into individual paper containers of 23 kg capacity, then cleaned from plant and soil debris, and graded to four different sizes using a potato grading machine. The length of the two middle rows (6.0 m total length) of each subplot was converted to 3.0 m length and then utilized to estimate total yield production employing the equation supplied by North Dakota and Minnesota (equation 4) (16). The certain weight/acre (cwt/acre) = [lb/(10 ft). × multiplication Factor] ….(4) The multiplication factor relies on the row width, where 14.5 is used when planting a row at a width of 36 inches (90cm). Equation (4) was used to calculate the total yield per area and then converted to the standard units (Mg ha^{-1}). The total weight per plant was estimated by dividing the total weight of tubers from each subplot by the number of plants in a row. Tuber yield data has been combined from the two years of research based on N rates and statistical analysis.

Data analysis

Analysis of variance test (ANOVA) was used to examine the effect of nitrogen rates on potato tuber yield using SPSS software (52). Microsoft Excel (40) was used to plot the relationships between potato tuber yields and a series of nitrogen rates. The bar graph (Figure 1) shows the difference between the control treatment (0 N kg ha^{-1}) and other treatments in addition to the N rate that maximized the potato yield and the rate after which potato yield did not respond significantly. Regression analysis was conducted between potato yield and sensors data (INSEY) to generate models for yield prediction.

RESULTS AND DISCUSSION

A large gap was noticed among yield data from the 11 sites. Therefore, a multiple regression analysis was conducted (data not shown) among soil characteristics and yield, where OM was found to be the main factor that had a high correlation with crop yield (R^2= 0.78**) at P-value <0.01. Therefore, all sites were divided into soil OM ≤30 g kg^{-1} and ≥30 g kg^{-1}. The sites LM, WD, NS-1, NS-2, FV, CA1, CA2, and CA3, were categorized as ≥ 30.0 g kg^{-1} OM, while the sites AF1, AF2, and AF3 were categorized as ≤30 g kg^{-1} OM. It is crucial to note that the Superior and Shepody potato cultivars had only one location each that came under ≤30 g kg^{-1} OM.

Yield responses to nitrogen rates

Potato yields at various N rates are shown in (Figure 3), showing the association between N rates and potato yields for locations with ≤ 30 g kg^{-1} of OM, ≥ 30 g kg^{-1} of soil OM, and an average of all locations combined. The potato yield remarkably enhanced with N fertilizer applications at all the abovementioned locations. Compared with the control remedy, 0 kg N ha^{-1}, the yields under 56, 112, 168 kg ha^{-1} treatments were enhanced by 10.75%, 20.71%, and 18.76%, concerning the rates of 56 kg N ha^{-1}; 13.3%, 28.8%, and 25.4%, respectively, for 112 kg N ha^{-1}, 21.72%, 42.73%, and 37.74%, respectively for 168 kg N ha^{-1}. For all locations, potato yields enhanced as the N rate increased from 0 kg N ha^{-1} to 168 kg N ha^{-1}. Nonetheless, no substantial increase was seen for 224 kg N ha^{-1}, indicating that the 168 kg N ha^{-1} was the highest economic rate for potato yield production.

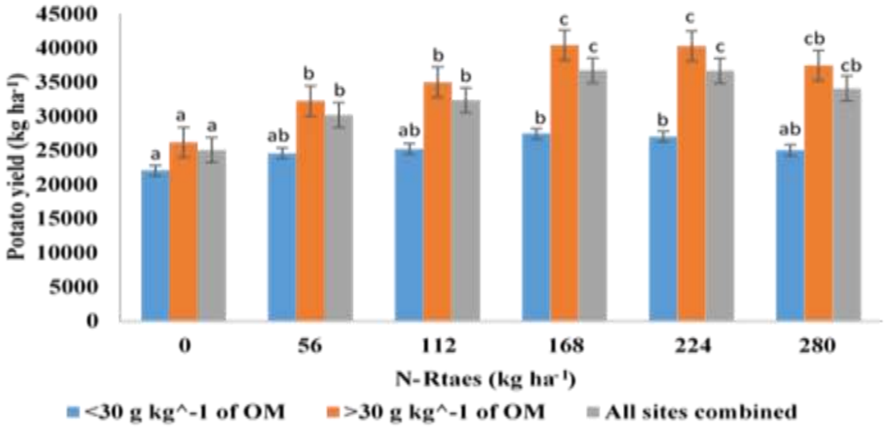

Figure 3. The potato yield response to various N fertilizer rates from all locations during two growing seasons (2018-2019) when P-value < 0.05 (2).

Procedure (1) for nitrogen recommendation

Generating the nitrogen fertilizer optimization algorithm (NFOA)

Algorithms for managing N rates for numerous crops and regions have been established (28). They can be practiced in a sensor-based N rate calculator produced by agronomists at Oklahoma State University to feed in zone-specific sensor data for determining the in-season crop yield and N response index (RI). The algorithm of N rate recommendation for sensor-based information is (41);

$$\mathbf{N_{rate}} = \frac{[(YP0 \times RI) - YP0] \times N\%}{\mathbf{NUE}} \quad \mathbf{....(5)}$$

where YP0 is the maximum achievable crop yield with no applied N.

RI is the response index

N% is the percentage of N in the yield, 0.026 (2.6%) (1).

NUE is the nitrogen use efficiency (yield ratio to fertilizers) (18).

Yield potential (YP0)

YP0 is defined as the maximum achievable crop yield with no applied N. Considered the backbone of any N fertilizer rate measurements, YP0 can be predicted from the relationship between crop yield and INSEY (35,43). The yield potential (YP0) is presented by

$$\mathbf{YP0 = Ae\ b\ \frac{NDVI}{GDD}} \quad \mathbf{.....(6)}$$

where: A and b indicate the intercept and slope, respectively, of the exponential function due to the regression analysis between potential yield and INSEY (43,52). The regression analysis between tuber yield (kg ha^{-1}) from the plots of 0 N kg ha^{-1} and INSEY data was used to generate the prediction equation. All growth stages were tested to generate the best-fitted model. The end of the tuber initiation of growth stage (20th of leaves stages) was the best time to produce a significant coefficient of determination (R^2=0.24) at P-value <0.05. The tuber initiation stage is when that plant uptake more N for tuber growth, while the stage before (vegetative growth) is the time to leave and stems from growing, so most of the N is only for vegetative growth. Next is the tuber bulking, where the N uptake is less than the tuber initiation stage (66). The INSEY derived from GS-NDVI data showed a significant relationship between the INSEY derived from CC-NDVI and CC-NDRE data.

Response index

The NDVI readings from the high N (N-rich) plot divided by the NDVI of the test plot is referred to as the response index (RI), which refers to the possibility of increment in crop yield with added N (30). The RI also is a valuable indicator of crop yield response and a guide to reduce Type II errors (31,41).

Hodgen et al. (2005) (27) concluded that when $1 < RI < 1.1$, N application will likely result in no yield response to any added fertilizer

$1.1 < RI < 1.25$, N application will likely result in marginal responses

$RI > 1.25$, N application will result in a response

Johnson and Raun (2003) (31) first defined yield response to applied N as the proportion of crop yield of an N-reference plot to that of a non-N treated plot given by,

$$\mathbf{RI}_{\mathbf{Harvest}} = \frac{\mathbf{Yield}_{\mathbf{N-Reference\ strip}}}{\mathbf{Yield}_{\mathbf{non-treated\ strip}}} \quad \mathbf{......(7)}$$

The mean tuber yield produced from the N-rich plot (280 kg N ha^{-1}) was 34080.91 kg ha^{-1}, while untreated plots (0 kg N ha^{-1}) produced a mean of 25071.85 kg ha^{-1}. As a result, the response index (RI) was equal to 1.36, more than 1.25; the N application will respond. Raun et al. (2002) (44) stated that the combined advantage of the RI concept and INSEY allowed an accurate top-dressed N rate for wheat. Total grain (yield) N removed from each area is measured, and the difference between the N-rich and farmer's application values were divided by a calculated NUE value.

$$\mathbf{RI}_{\mathbf{NDVI}} = \frac{\mathbf{NDVI}_{\mathbf{-Reference\ strip}}}{\mathbf{NDVI}_{\mathbf{non-treated\ strip}}}$$

Nitrogen use efficiency

The most fundamental description of nutrient use efficiency is a crop yield per unit of available nutrients (52), while Teboh et al. (2012) (53) described it as the portion of N input, indicating that it corresponds to the portion of N taken up to fulfill further yield needs. The information can be utilized to assess the nutrient use efficiency of a given cropping operation on an annual or multi-year basis. Nitrogen use efficiency (NUE) can be computed as defined by Baligar et al. (2001) (6) as follows:

$$\mathbf{NUE} = \frac{(\mathbf{Crop\ yield\ in\ N\ fertilized\ plot - Crop\ yield\ in\ no\ N\ plot})}{(\mathbf{Quantity\ of\ N\ fertilizer\ applied\ in\ N\ fertilized\ plot})} \quad \mathbf{......\ (9)}$$

Thus, applying the data of potato yield and sensors in equation (5) resulted in 195 kg ha^{-1} being the N recommendation for the potato crop, which is about 14% lower than the amount that potato growers have previously applied, 224 kg N ha^{-1}.

Procedure (2) nitrogen recommendation

This procedure differs from procedure number (1) mathematically; however, the materials (yield and sensor data) are still the same. Sharma (2014) (47) used procedure number (2) to generate an N recommendation for the corn crop, as in equation (10).

$$\text{N rate in kg ha}^{-1} = \frac{[(\mathrm{Y1-Y2})\times \mathrm{N\%}]}{\mathrm{NUE}} \text{ ....(10)}$$

where: Y1 is the predicted yield from the N-rich plot in kg ha^{-1}

Y2 is the predicted yield from farmer practice plot in kg ha^{-1}

N% is nitrogen percent in potato tuber, 0.026 (2.6%) (1).

NUE is the nitrogen use efficiency. As mentioned before, the N-rich plot is the plot that has been provided with a complete fertilizer to be an unlimited N area. Nitrogen (N) at 280 kg N ha^{-1} was applied to fulfill the N-rich plot, while 224 kg N ha^{-1} was the rate practiced by potato growers in Maine. A regression analysis was conducted between potato tuber yield and sensor data (INSEY) to generate an algorithm for potato yield prediction at p-value <0.05. The exponential model was the best to fit that curve for both Y1 and Y2, respectively. The twentieth leaf stage was most likely to have a significant relationship between yield data and INSEY. The GS and CC sensors showed a significant association with yield data, but the determination coefficient for the CC-NDRE was higher than those for other wavelengths (NDVI from GS and CC) (Figure 5 a-d). At the 20th leaf stage, the plant vegetation density is maximum, called the NDVI saturation condition. The red (R) wavelength from GS and CC is sensitive only for a low range of chlorophyll (3–5 µg.cm^{-2}) in comparison to the CC red-edge wavelength that is sensitive to a wider range (0.3–45 µg cm^{-2}) (23). As a result, applying the potato yield data and sensor data in equation (10) resulted in 199 kg ha^{-1} being the N recommendation for potato crops, which is about 12% lower than the amount that potato growers used to apply, 224 kg N ha^{-1}. Although the coefficient of determination (R^2) was statistically significant but not very strong (0.13, 0.24, 0.27, and 0.38), it could still be considered a step toward utilizing active optical sensors for the nitrogen recommendation potato crop. Experimenting with sites with different soil properties is a reason to have representative samples from multiple locations. However, having a massive gap among sites could be a problem, especially for statistical analysis. That was our problem; there was a significante gap in the yield data between locations. Classifying or grouping sites is an excellent idea to overcome this issue, but running a regression analysis for a single N rate (0, 224, 280 kg N ha^{-1}) using a few points are considered insufficient. Therefore, experimenting with enough numbers sites would be the solution to this issu

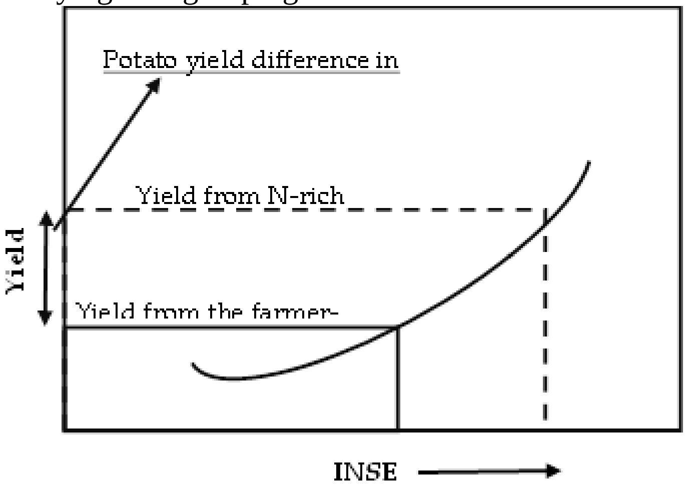

Figure 4. The schematic demonstrates the algorithm of nitrogen recommendation's work

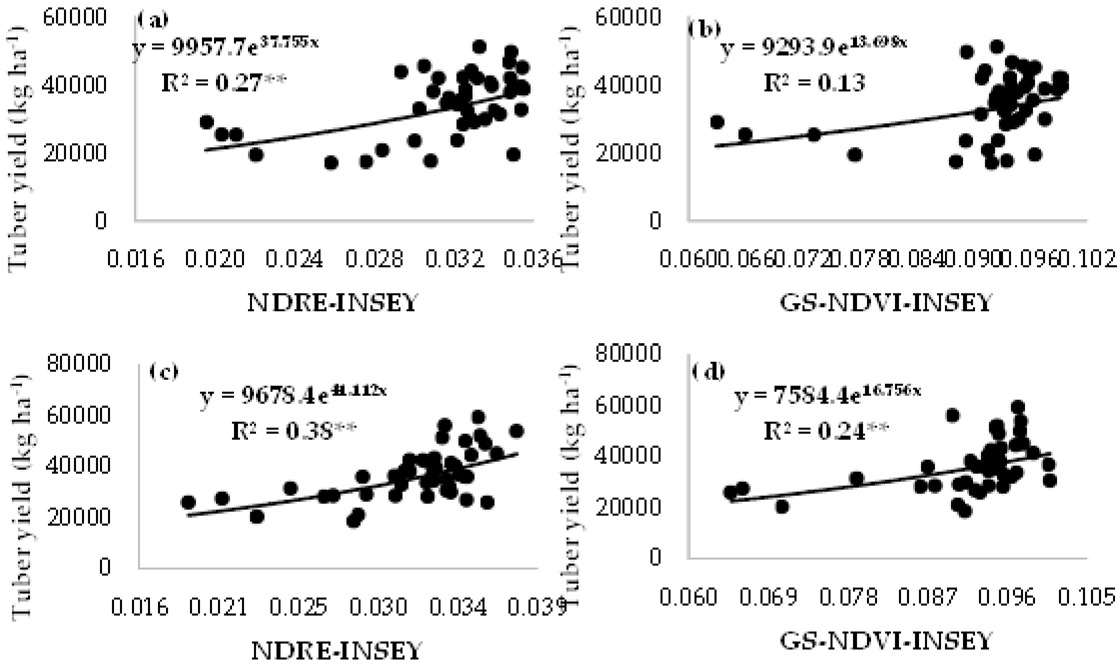

Figure 5. The relationship between potato tuber yield (kg ha^{-1}) and the sensor reading (INSEY) derived from a) NDRE, b) GS-NDVI for the N-rich plots, and c) NDRE, d) GS-NDVI for the farmers practiced rate r, at p-value<0.05

CONCLUSIONS

At the twentieth leaf stage, the sensing time has been observed to give a significant yield estimation. Although the determination coefficient between tubers yield and sensor data is not very strong due to uncontrolled factors such as temperature and rain, it still can give good results regarding yield prediction. Despite satellite and aerial images covering large areas; still, there are some uncontrolled restrictions, such as clouds issues and temporal resolution (16 days for Landsat-8). Ground-based sensors have advantages that let users overcome some of these disadvantages. For instance, there is no problem with cloudy day's condition that affects the sunlight to reach ground targets, where ground-based sensors do not depend on sunlight as a source of light; it sends and collects its lights. Ground-based sensors can be used anytime unless there is no rain or muddy soil (64). The disadvantages of active sensors are the high initial cost. The used sensors may be somewhat expensive ($4000.0), but a small GS can do the same job. GS provides only the NDVI resulting from the NIR and R wavelengths, and it is cheap ($400.0) and easy to use. There is news that Trimble, the producer of the handheld GS, is working on updating the sensor; we hope that they will add the red edge wavelength as well. In procedure (1), the calculation depended totally on the predicted yield from the control treatment (0 kg N ha^{-1}). There was no chlorophyll saturation issue, so the R wavelength showed a considerable association with yield data. In contrast, procedure (2) calculations depended on the N-rich and farmer-practice plots (280 and 224 kg N ha^{-1}), respectively. The chlorophyll saturation issue happens commonly, so the red-edge wavelength was the best to overcome this issue and showed a significant relationship with yield data. The N-recommendation rates from both procedures (1&2) (195 and 199 kg N ha^{-1}), respectively, were lower than the average rate that potato growers in Maine are applying annually (224 kg ha^{-1}). Procedure (1) can save about 14% of the rate that potato growers apply, while procedure (2) can save about 12%. So far, these were valuable results and a good step toward utilizing active optical sensors to generate N recommendations. However, to be more accurate, the sites had to be classified into the soil with high OM content and soils with low OM content, but according to literature from other crops, calculations cannot be conducted with a small number of sites. Therefore, separating our sites into two classes will be scientifically a good idea, but when we have at least ten to fifteen sites experimenting with different soil types can help determine whether soil properties have a significant effect on the N-recommendation outcome or not. The same issue holds for potato cultivars when planting specific cultivars in a particular soil type; it can expose whether potato cultivars significantly affect the N-recommendation outcome.

Conflicts of Interest: The authors declare no conflict of interest

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