Nitrogen Fertilizer Recommendation for Waxy Corn Measured by Canopy Reflectance Using UAV Imaging Passive Sensor

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Abstract
Nitrogen (N) is one of the main factors to increasing corn yield. Past research showed that N fertilizer application rates were strongly related to corn yield. The objective of this study was to estimate N fertilizer recommendations with EONR for waxy corn (Zea mays var. ceratina) using NDVI derived from canopy reflectance and images taken by a multispectral camera as a passive sensor mounted on unmanned aerial vehicle (UAV). Three site-years experiments were conducted during two consecutive dry seasons in 2017/18 and 2018/19 at Ban Nong Bua, Nong Bua District, Khon Kaen, Thailand. The experiments were laid out according to randomized complete block design (RCBD) with two replications. Treatments consisted of nine N rates in all site-years; 0, 50, 56.25, 112.50, 125, 168.75, 200, 225 and 281.25 kg N ha^{-1}*. The EONR and N fertilizer rates were determined by fitting quadratic plateau regression models for each whole plot treatment at each site. The relationship between relative NDVI and temporal data of EONR was evaluated to provide N fertilizer recommendation. The EONR was strongly related to relative NDVI (*R^2*= 0.7492). The result presented here suggests that the reflectance data collected with the camera as a passive sensor mounted on UAV has the potential to be a useful tool for N fertilizer recommendation for waxy corn under a variety of management systems and conditions found in Northeastern Thailand.*

1. Introduction

Waxy corn (*Zea mays* var. *ceratina*) is an important vegetable with economic significance that is thought to have originated from cultivated flint corn, a crop mainly consumed as a fresh vegetable in Asian countries such as China, Japan, Korea, and the Philippines, and used as raw material for food industries (Hao et al., 2015). Thailand exports waxy corn hybrid seeds and frozen waxy corn and there is a promising trend for market expansion both locally and internationally (Simla et al., 2010).

Corn yield significantly depends on nitrogen fertilization (Shrestha et al., 2018). In addition, nitrogen fertilization is the most important factor which humans can control the limit of corn yield (Henninger, 2012 and Klimek-Kopyra et al., 2012). Nitrogen (N) is one of the main factors in increasing corn yield (Molla et al., 2014) and it is an essential element for healthy photosynthetic activity in leaves. Due to its role in photosynthetic activity, it is necessary at every stage of its growth. It is involved in many important plant biochemical processes as well as the health of plant components such as amino acids, proteins and chlorophyll. The soil system typically cannot supply the full corn plant N requirement. Therefore, supplemental N is needed to reach economic yield potential. It is possible to estimate the N fertilizer recommendation that results in maximum yield (Zebarth et al., 2009), but guidelines for N fertilizer recommendation have been derived using maximum economic return to determine economic optimum nitrogen rate (EONR) rather than maximum yield (Sawyer and Randall, 2008).

Past research has indicated a strong positive correlation between N fertilization and leaf N concentration, and NDVI in corn (Karki, 2013, Shaver et al., 2014 and Pantoja et al., 2015). Many researchers reported that NDVI derived from a canopy sensor was able to identify crop response to different N rates. The data have been used to monitor crop conditions and forecast yield as well as in the production of many crops, such as rice (Arai et al., 2014 and Liu et al., 2015) wheat (Sultana et al., 2014) sugarcane (Amaral et al., 2014 and Rosa et al., 2015) and turf grasses (Caturegli et al., 2016). This relationship should make it possible to use NDVI to estimate crop N fertilizer recommendation.

Canopy reflectance was measured using active and passive sensors. Active sensors provide their own energy light source and measure light reflectance in real time at the canopy level. On the other hand, passive sensors measures naturally reflected energy or energy emitted by the object from the sun. Dellinger et al., (2008) use the Crop Circle ACS-210 (Holland Scientific, Lincoln, NE, USA) active sensor to measure VIS light at 590 nm and NIR light at 880 nm to study canopy reflectance as a potential tool for assessing the N status and to estimate N requirements in dent corn (*Zea mays* var. *indentata*). Miller et al., (2017) measured NDVI obtained from canopy reflectance using the Green Seeker (NTech Industries Inc., Ukiah, CA, USA) handheld active sensor which operates by directing VIS light at 660 nm and NIR light at 700 nm to estimate N fertilizer recommendation in corn. On the other hand, Mutanga (2005) using a GER 3700 spectrometer (Geophysical and Environmental Research Corporation, Millbrook, NY, USA) as a passive sensor to discriminate tropical grass grown under different N treatments. The objective of this research was to estimate N fertilizer recommendation with EONR for waxy corn using NDVI derived from canopy reflectance and images taken by a multispectral camera as a passive sensor mounted on unmanned aerial vehicle (UAV).

2. Materials and Methods

2.1 Study Area

Three site-years were completed at the Waxy Corn Growing Community Enterprise Group of Ban Nong Bua, Nong Bua District, Khon Kaen, Thailand (Figure 1). Field site experiments were sown with waxy corn hybrid Sweet Wax 254 during two consecutive dry seasons from December 2017 to March 2018 (Y1) and December 2018 to February 2019 (Y2). The climatic condition in the area is semi-arid. Mean temperature during the periods were 24.63 and 25.80 degrees Celsius, while total rainfall was measured at 27.20 and 5.60 mm in Y1 and Y2, respectively. The soil texture of the experimental site was sandy loam and the chemical analysis in laboratory of soil is given in Table 1. Soils were classified as Udon soil series (Coarse-loamy, mixed, active, nonacid, isohyperthermic Typic Halaquepts) in site 1 and Khemarat soil series (fine-loamy over clayey, kaolinitic, isohyperthermic Plinthic Haplustults) in sites 2 and 3. The soils during each of the site-years were at a low fertility level.

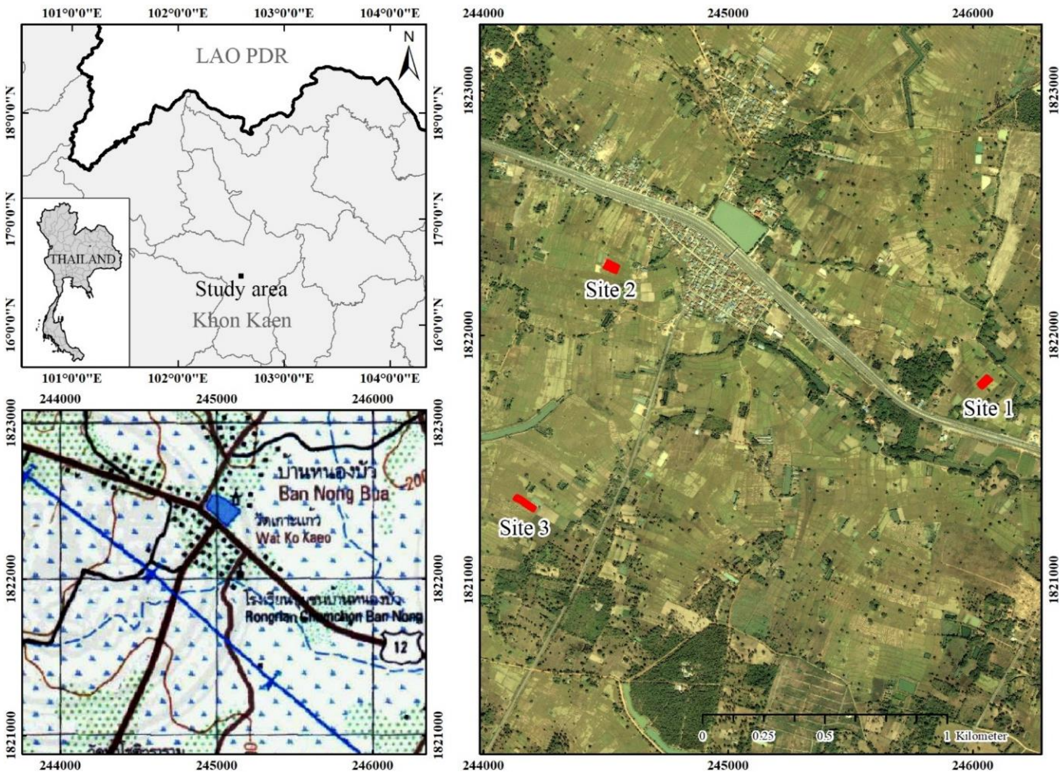

Figure 1: Location of study areas

Table 1: Soil chemicals for each site in 2017/18 and 2018/19

Study areas	Soil series	Sand (%)	Silt (%)	Clay (%)	Texture	NO_3^- (mg/kg)	Available P (mg/kg)	Exchangeable K (mg/kg)	O.M. (%)	pH (1:1)
2017/18										
Site 1	Udon (Ud)	n/a	n/a	n/a	Sandy loam	4.68	54.51	77.03	0.87	5.43
2018/19										
Site 2	Khemarat (Kmr)	74.92	18.17	6.91	Sandy loam	11.78	28	152.11	0.64	5.36
Site 3	Khemarat (Kmr)	52.54	38.13	9.33	Sandy loam	4.88	3.75	129.36	0.57	5.22

NB: n/a = Not available
NO_3^- = Potassium Chloride Extraction, Distillation with devarda Alloy
Available P = Bray No.2 extraction; Spectrophotometry
Exchangeable K = Ammonium acetate extraction; Atomic Absorption Spectrophotometry
Organic Matter (O.M.) = Walkley and Black method
pH = Soil : Water = 1:1; pH meter

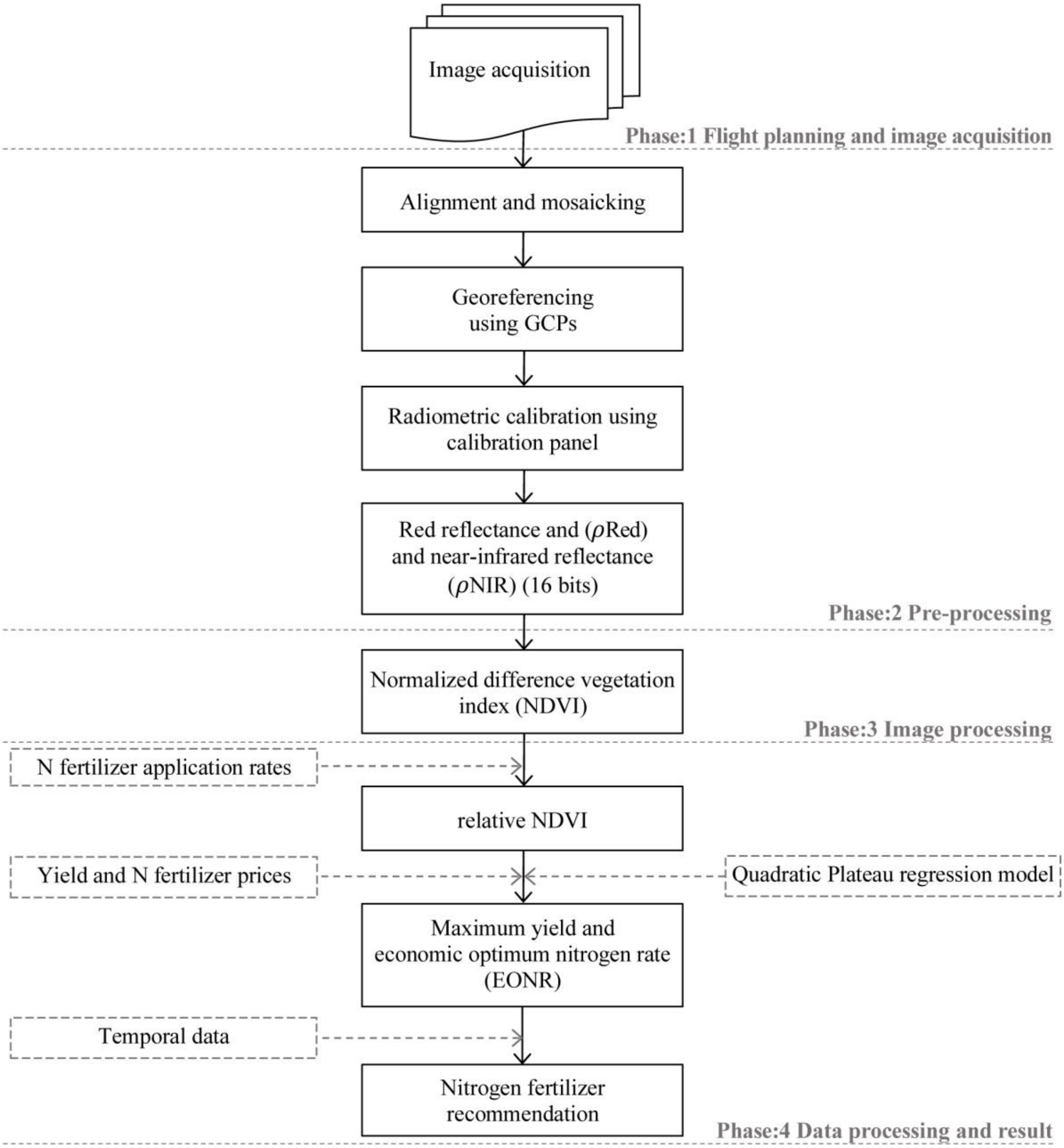

Figure 2: Flow chart for estimating N fertilizer recommendation

2.2 Ground Data and Experimental Design

The experimental design of each field at each site was a randomized complete block design (RCBD) with two replications (Table 2). The sites are under furrow irrigation, conventional tillage management and plant protection, in accordance with standard crop management. The mean areas of each treatment in site 1, 2 and 3 were 137.65, 86 and 87.23 m^2, respectively. Plot sizes measured by width and length were approximately 6.17 m x 23.33 m, 4.33 m x 20.31 m and 6.23 m x 14.44 m, respectively. A summary of site activities for each cropping year including sowing dates, image acquisition dates and harvest dates are reported in Table 3. The flow chart for estimating N fertilizer recommendation is shown in Figure 2.

Corn growth stages and development were divided into two groups: vegetative (V) and reproductive (R) periods. The VE (Emergence) occurs when the seminal roots push through the soil surface. After emergence, the vegetative stages are divided into numerical subdivisions V1, V2, and V3 through Vn where n is the number of leaves with a fully visible collar or fully expanded leaves until the VT (Tasseling). There were six reproductive stages from R1 to R6 that can be identified during the development to maturity for cobs of the corn plant. The R1 or silking stage is the first reproductive stage, and it begins when silks are visible outside the husks of the cob. During the R2 or blister stage, kernels appear white and are blister shaped. During the R3 or milking stage, the kernels inner fluid is milky and thick due to starch accumulation. During the R4 or dough stage, starch accumulation turns the inner contents of the kernel pasty. In the R5 or dent stage, kernels are dented. Lastly, during the R6 or physiological maturity, all kernels in the cob attain full dry weight (Krishna, 2012).

To achieve optimum corn yield, it is recommended to split N fertilizer application into three times (Sitthaphanit, 2010, Hammad et al., 2011 and Sharifi and Namvar, 2016). Thus, this study applied granulated N fertilizer in three splits. The first N application of N-P-K (15-15-15) as basal dressing after final land preparation or in early plant growth improves yield and improves vegetative growth and development (Shrestha et al., 2018). The second N application of urea (46-0-0) as side dressing occurs during the V6 growth stage. The corn plant starts to uptake nutrients significantly from about the V6 stage onward (Schmidt et al., 2009). The third N application as side dressing is applied during the R1 growth stage. The fertilization of ovules occurs during this period. The number of ovules that get pollinated and those that develop into mature kernels are determined at this point (Krishna, 2012). The treatments (T) included four N fertilizer rates; T1 (zero N, control), T2 (50 kg N ha^{-1}), T3 (125 kg N ha^{-1}) and T4 (200 kg N ha^{-1}) in 2017/18 and six N fertilizer rates were T1 (zero N, control), T2 (56.25 kg N ha^{-1}), T3 (112.50 kg N ha^{-1}), T4 (168.75 kg N ha^{-1}), T5 (225 kg N ha^{-1}) and T6 (281.25 kg N ha^{-1}) in 2018/19 (Table 2 and Figure 4). Because the total N fertilizer accumulation was completely applied in the third N application at R1 growth stage, all images of each site were acquired using UAV imaging passive sensor in the same period at R1 growth stage in site 1, 2 and 3 on 26 February 2018, 10 January 2019 and 17 January 2019, respectively (Table 3).

2.3 UAV-Based Description and Image Processing

The UAV used in this study was a quadcopter of Phantom 3 Professional model (Figure 5a). It is equipped with a red (660 nm) - NIR (850 nm) sensor, a 16 Megapixel of Survey 2 camera (Figure 5b) (MAPIR Inc., San Diego, CA, USA). Figure 2 presents the concept workflow for estimating N fertilizer recommendation based on canopy reflectance derived from image processing. The four phases using image processing technique are as follows: (1) flight planning with necessary data using PIX4D Capture (Pix4D, Lausanne, Switzerland) autopilot application to set the UAV flights to region of interest (ROI), flight direction, flight speed and the time of the flight to avoid the effect of shadows during the one to two hours before and after noon. The flight altitude was 40 m above ground. Images were acquired with an 80% side overlap and 75% forward overlap.

(a) (b) (c)

Figure 3: (a) Basal dressing (b) Second N application at V6 stage and (c) Third N application at R1 stage

Table 2: Fertilizer application rates of each treatment

Study areas	Treatments	1st Basal dressing N-P-K (15-15-15) (kg N ha^{-1})	2nd Side dressing N-P-K (46-0-0) (kg N ha^{-1})	3rd Side dressing N-P-K (46-0-0) (kg N ha^{-1})	Total N application (kg N ha^{-1})
Site 1	T1	0	0	0	0
	T2	31.25	9.38	9.37	50
	T3	93.75	15.63	15.62	125
	T4	125	37.50	37.50	200
Site 2 and Site 3	T1	0	0	0	0
	T2	50	3.13	3.12	56.25
	T3	62.5	25	25	112.50
	T4	75	46.88	46.87	168.75
	T5	87.50	68.75	68.75	225
	T6	100	90.63	90.62	281.25

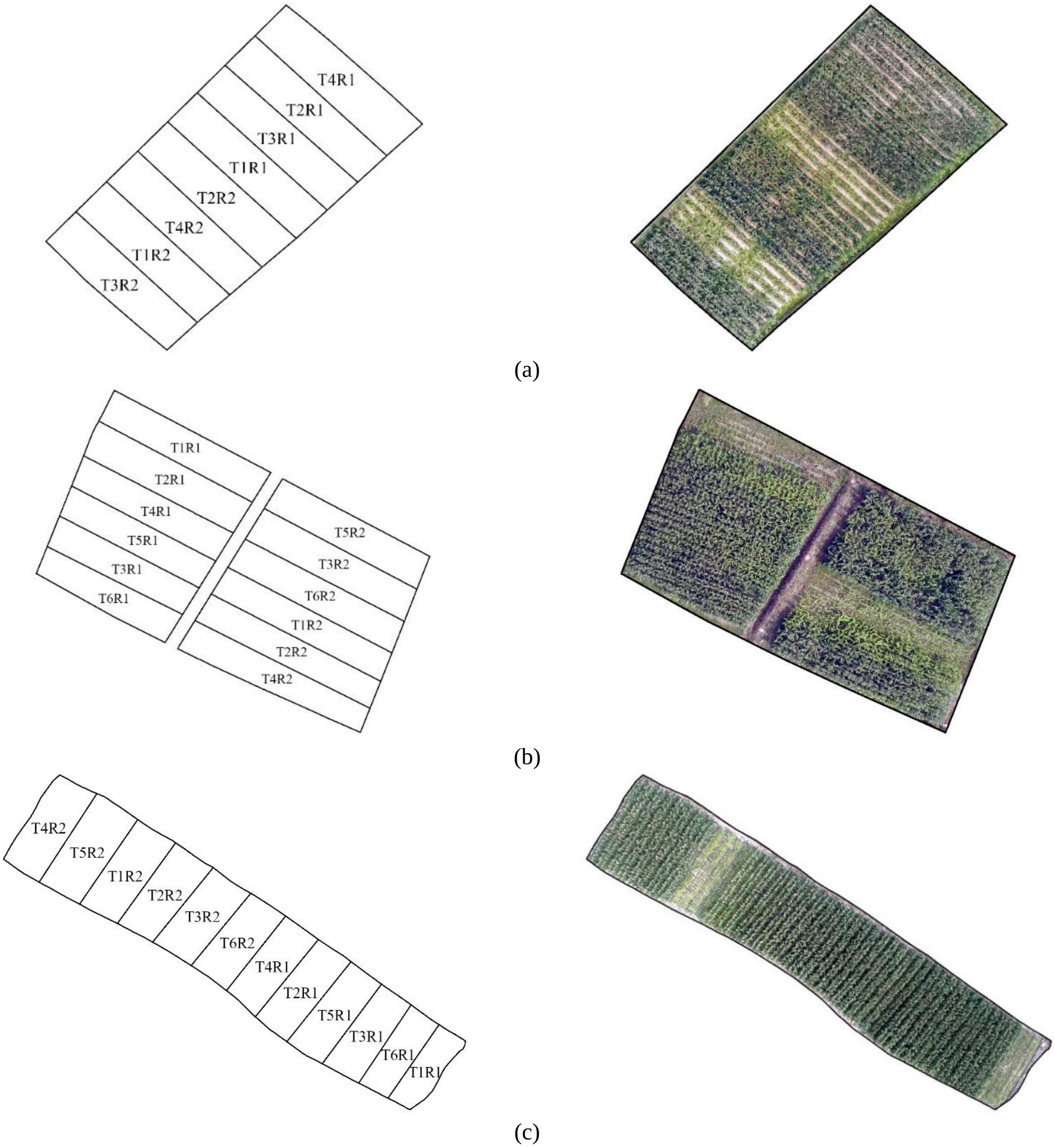

Figure 4: RCBD with two replications and the RGB images of (a) site 1 (b) site 2 and (c) site 3
NB: T = Treatment and R = Replication

Table 3: Activities for each site in 2017/18 and 2018/19

Study areas	Dates		
	Sowing	Image acquisition	Harvest
Site 1	22 December 2017	26 February 2018	13 March 2018
Site 2	19 November 2018	10 January 2019	24 January 2019
Site 3	27 November 2018	17 January 2019	7 February 2019

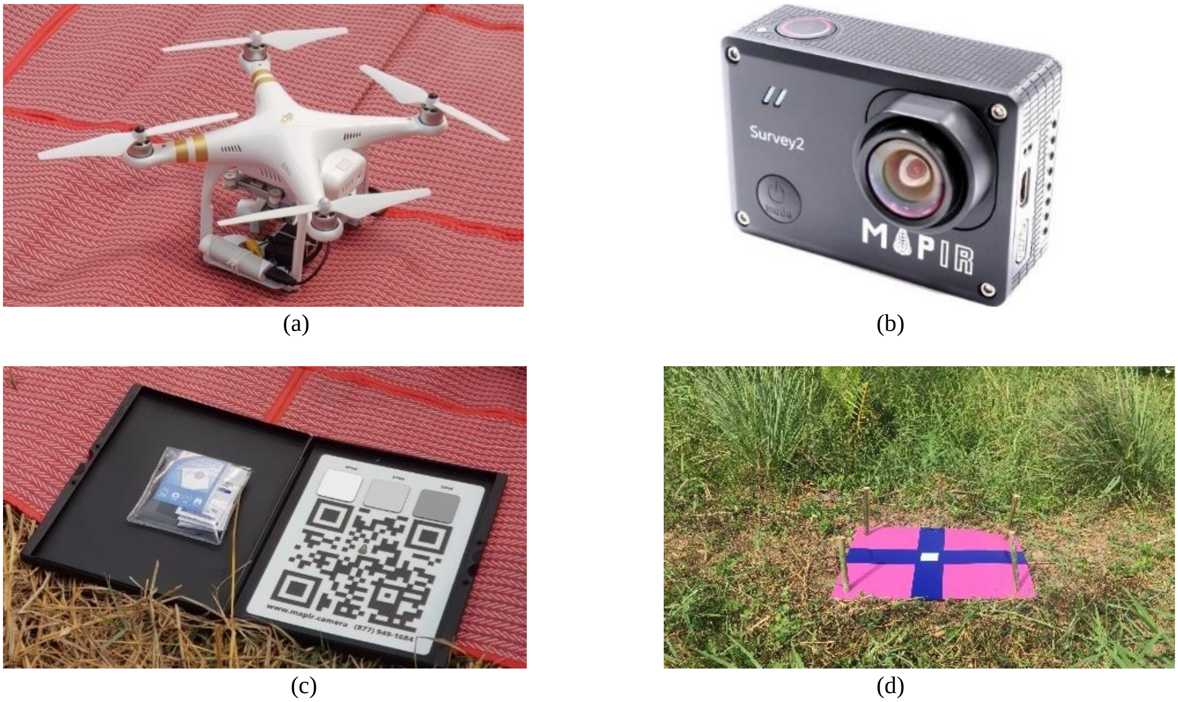

Figure 5: (a) Phantom 3 professional (b) MAPIR Survey 2 camera
(c) Calibration target and (d) Ground control point (GCP)

(2) After the image acquisition, the collected images were transferred for pre-processing. This processing involves alignment and mosaicking, georeferencing and radiometric calibration. Image analysis was performed on both mosaic and single images. Images were mosaicked into a single image with 3 cm pixel resolution using Agisoft PhotoScan (Agisoft LLC, St. Petersburg, Russia). In the next step, georeferencing processes with 9 ground control points (GCPs) focused on the known coordinates of interest in the region using Quantum GIS (QGIS). Next, raw digital number (8 bit) were converted to reflectance values (16 bit) in order to reduce sampling noise and error due to the effect of environmental changes or changes in light conditions due to sunshine or clouds using a standard laboratory calibration panel (Figure 5c) and MAPIR Camera Control Software (MAPIR Inc., San Diego, CA, USA). (3) image processing calculating NDVI and (4) data processing calculating relative NDVI using data between each treatment, and EONR using data between cost and return of yield and N fertilizer prices. Finally, a N fertilizer recommendation model was estimated with temporal data from all site-years using linear regression analysis.

2.4 Canopy Reflectance Measurement

A study by Liu and Wiatrak (2011) reported that NDVI during the R1 growth stage may act as a good predictor to estimate corn grain yield. Similar results were obtained by Sanodiya et al., (2017) who emphasized that the yield prediction equation had a maximum coefficient of determination (R^2) value for NDVI at R1 growth stage.

Moreover, Raun et al., (2005) reported that corn growth between the V6 and R1 growth stage was an important period due to a strong relationship between plant characteristics and corn grain yield. Consequently, this study collected canopy reflectance data during the R1 growth stage. The amount of red reflectance and near-infrared reflectance were obtained from images taken by a Survey 2 MAPIR camera as a passive sensor mounted on a UAV and was used to calculate the Normalized Difference Vegetation Index (NDVI). Measurements were taken with a mean of seven sample representative plants from every row of each plot. The equation for NDVI (Tucker, 1979) is expressed as

$$NDVI = (\rho NIR - \rho Red) / (\rho NIR + \rho Red)$$

Equation 1

where ρNIR is the near-infrared reflectance and ρRed is the red reflectance.

relative Normalized Difference Vegetation Index (relative NDVI) was used for data normalization to allow for the comparison of the variance of the N response among field. Many researchers reported that relative NDVI is better than absolute NDVI values because relative values reduce error from the influence of confounding factors, such as a plant variety factors, cultivation, climate, year of growth, location, irrigation, insect damage, crop rotation and N fertilizer history (Islam and Garcia, 2014). The relative NDVI for each whole plot treatment was determined from the zero N rate treatment (control plot) and the maximum N treatment (reference plot). The equation of relative NDVI (Dellinger et al., 2008) is expressed as:

$$\text{relative NDVI} = NDVI_{control} / NDVI_{reference}$$

Equation 2

where $NDVI_{control}$ is NDVI of zero N rate treatment and $NDVI_{reference}$ is NDVI of maximum N rate treatment.

2.5 Economic Optimum Nitrogen Rate (EONR)

Farmers should apply N fertilizer rates that return the most profitable economic yield, where the yield from N fertilizer application will more than pay for the invested N. Maximum yield N response experimentations are conducted through the application of different N rates, followed by the measurement of yield at each rate. Analysis of that response data allows calculation of site EONR, the rate in which the maximum economic return from the N fertilizer investment is shown. Economic net return is the difference between the price of yield and the cost of N fertilizer (Sawyer and Randall, 2008).

Cob weight with husk yield for each treatment was measured during the harvesting of the crop. Estimates of cob weight with husk yield (11 baht kg^{-1}), N-P-K of 15-15-15 fertilizer (106.92 baht kg^{-1} N) and urea fertilizer (27.32 baht kg^{-1} N) were used with the quadratic plateau yield response model to calculate EONR, based on these prices.

2.6 Statistical Analysis

Analysis of variance (ANOVA) was used to evaluate treatment effects on measured variables as N rates and yield to a randomized complete block design. Scheffe's method with pair-wise comparisons was used to compare means at $P \leq 0.01$ using a program of statistical analysis of sample data (PSPP) (Free Software Foundation Inc., Boston, MA, USA).

Quadratic plateau regression model is the statistical estimation of the optimal plateau, the point at which increases in the input under investigation would have no significant effect on the magnitude of the response. EONR was obtained using quadratic plateau regression model to describe waxy corn yield response to N fertilizer rates. Linear regression model was used to describe the relationship between EONR and relative NDVI in order to evaluate N fertilizer recommendation model using R programming (R Development Core Team, Vienna, Austria). Coefficients of determination were expressed as R^2. The quadratic plateau regression model (Pantoja et al., 2015) (Equations 3, 4) is expressed as:

$$y = a + bx + cx^2, \; x < x_0$$

Equation 3

$$y = a + bx_0 + cx_0^2, \; x \geq x_0$$

Equation 4

where y is yield response to N fertilizer rate (kg ha^{-1}), x is N fertilizer rate (kg N ha^{-1}), a is intercept, b is linear coefficient, c = quadratic coefficient and x_0 = critical N fertilizer rate at the join point. The linear regression model (Zou et al., 2003) (Equation 5) is expressed as:

$$y = a + bx$$

Equation 5

where y is N fertilizer recommendation (kg N ha^{-1}), x is relative NDVI, a is intercept and b is linear coefficient.

3. Results and Discussion

3.1 Yield Response to N Fertilizer Application Rates

Waxy corn is consumed as a fresh or boiled cob. Therefore, yield was determined based on cob weight with husk of each treatment hand-harvested.

Cob weight with husk yield across experimental sites ranged from 1,904.06 to 9,356.38 kg ha^{-1}. Yield consistently increased with N application. The application of N fertilizer at 281.25 kg N ha^{-1} contributed to a mean of maximum yield of 9,202.35 kg ha^{-1}, while the yield in the zero N rate treatment (control plot) was the lowest (Table 4 and Figure 6). There was statistically significant yield response to N rates ($P \leq 0.01$). The ANOVA summary graph (Figure 6) shows that there were not statistical differences between 125 and 281.25 kg N ha^{-1}. Therefore, if there are no canopy reflectance data, this results in an N fertilizer recommendation of 125 kg N ha^{-1}.

Table 4: Mean cob weight with husk yield of each treatment in all site-years

Study areas	**Treatments**	**Total N application (kg N ha^{-1})**	**Cob weight with husk yield (kg ha^{-1})**		
			Rep.1	**Rep.2**	**Mean**
Site 1	T1	0	2,908.56	2,112.06	2,510.31
	T2	50	6,410.50	5,709.90	6,060.20
	T3	125	8,167.81	8,159.88	8,163.85
	T4	200	8,371.56	8,081.40	8,226.48
Site 2	T1	0	1,904.06	2,030.25	1,967.16
	T2	56.25	6,265.38	5,409.03	5,837.21
	T3	112.50	6,686.25	7,121.38	6,903.82
	T4	168.75	9,203.31	7,561.25	8,382.28
	T5	225	7,696.44	7,870.13	7,783.29
	T6	281.25	8,202.13	9,081.94	8,642.04
Site 3	T1	0	2,162.03	2,502.94	2,332.49
	T2	56.25	6,802.88	7,659.03	7,230.96
	T3	112.50	7,384.06	8,198.75	7,791.41
	T4	168.75	8,139.31	8,304.25	8,221.78
	T5	225	7,836.75	7,733.88	7,785.32
	T6	281.25	9,356.38	9,048.31	9,202.35

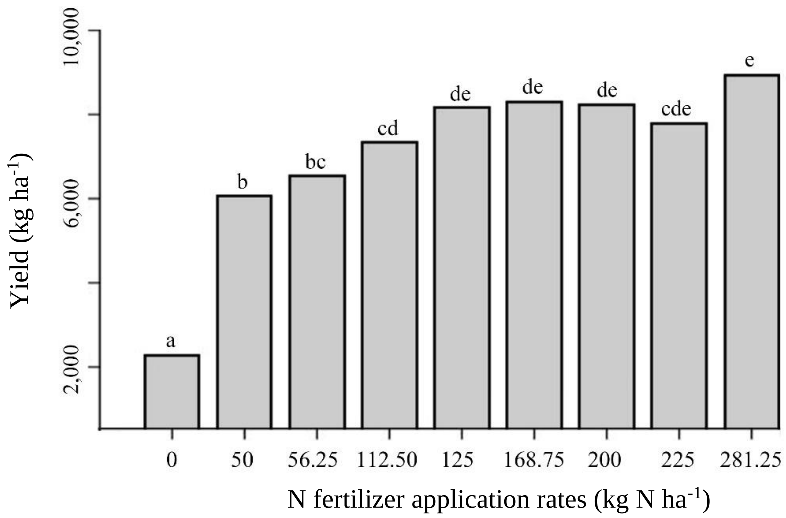

Figure 6: Yield response to different N fertilizer application rates for the treatment sites combined given in Table 4: Different letters on the bars indicate means are statistically different ($P \leq 0.01$)

3.2 EONR

The relationship between yield and N fertilizer application rates was evaluated. The quadratic plateau regression model parameters were used to calculate EONR for each replication in all sites. For example, Figure 7c shows that the fitting curve of quadratic plateau regression model has the equation of yield = 2155.119 + (70.83892 x N rate) - (0.205384 x (N rate)^2) up to the N rate of 172.45 kg N ha^{-1}, the yield remain flat at 8,263.38 kg ha^{-1}.

Further, it shows that overapplying N fertilizer occurs when applying more N fertilizer than 172.45 kg N ha^{-1} with an EONR of 162.50 kg N ha^{-1} and yield of 8,243 kg ha^{-1} at EONR. Table 5 and Figure 7 show the quadratic plateau regression models and equation parameters for the relationship between yield and N fertilizer application rates at each site.

A diverse set of field site management conditions, such as silt content, climate, cultivation, farming experience, previous crop and N fertilizer history provide a wide range of EONR from 81.25 to 190.63 kg N ha^{-1}. Sripada et al., (2005) obtained similar results for a wide range of EONR in corn from 0 to 224 kg N ha^{-1} with a mean of 104 kg N ha^{-1}.

3.3 NDVI and relative NDVI

Figure 8 illustrates the NDVI distribution map from a flight altitude of 40 m. NDVI can be used to quantize crop growth status. The results of NDVI in site 1, 2 and 3 were 0.16-0.96, 0.21-0.99 and 0.28-0.98, respectively. High NDVI values were exhibited by the high nitrogen fertilizer application at more than 125 kg N ha^{-1}, wherein the dark green color in Figure 4 also differed from the color of control treatment and the other areas. It was indicated that NDVI varied with nitrogen application rate. The results were supported by a similar study conducted by Liu and Wiatrak (2011) and Karki (2013) obtained NDVI using an active hand-held sensor GreenSeeker for corn (Table 6).

3.4 N Fertilizer Recommendation

N fertilizer recommendation is based on the relationship between relative NDVI and EONR. The temporal data of EONR from all sites were evaluated by fitting a simple linear regression analysis for N fertilizer recommendation model (Figure 9).

This relationship could then be used to develop N fertilizer recommendation based on relative NDVI. In the more responsive part of the model (Equation 6), the equation for the line is:

$$y = -961.7x + 959.28 \qquad \text{Equation 6}$$

where y is N fertilizer recommendation and x is relative NDVI. This represents the model for the N fertilizer recommendation when relative NDVI is less than 1.0. For example, this model (Equation 6) indicates that a relative NDVI measurement of 0.83, 0.87 and 0.90 corresponds to an N fertilizer recommendation of 161.07, 122.60 and 93.75 kg N ha^{-1}, respectively. The highest limit of relative NDVI was set at 1.0 which causes the N fertilizer recommendation to be zero, or very near zero (no N fertilization is needed). This combined EONR indicates that a gradual increase in relative NDVI was associated with decreasing EONR. It is useful for the site-specific management of agriculture or precision farming. Similar results were reported by Sripada et al., (2005), who conducted similar work during the VT (Tasseling) growth stage with EONR ranged from 0 to 224 kg N ha^{-1} and Dellinger et al., (2008) conducted an experiment during a much earlier corn V6-V7 growth stage while EONR ranged from 0 to 202 kg N ha^{-1}.

The use of a relative NDVI to estimate N fertilizer recommendation requires the availability of the maximum N treatment (reference plot) in the field, which is a potential limitation to the application of this technique. Rather than having one reference plot located at random, a better method may be to have a series of reference plots across the field based on the farmers' knowledge of field variability (Sripada et al., 2005).

Table 5: Quadratic plateau regression models and parameters describing the yield response to N fertilizer rates

Study areas		Quadratic regression models	Join point	Plateau (x_0)	EONR	YEONR	R^2
			kg N ha^{-1}			kg ha^{-1}	
Site 1	Rep.1	$2098.562 + 88.16064x – 0.3624378x^2$	8,269.69	121.62	115.63	8,256.63	0.99
	Rep.2	$2104.534 + 88.88735x – 0.327651x^2$	8,133.02	135.64	128.13	8,114.50	0.99
Site 2	Rep.1	$2155.119 + 70.83892x – 0.205384x^2$	8,263.38	172.45	162.50	8,243.00	0.92
	Rep.2	$2199.046 + 59.35459x - 0.1440487x^2$	8,313.24	206.02	190.63	8,279.06	0.96
Site 3	Rep.1	$2162 + 111.6247x – 0.5176935x^2$	8,179.11	107.81	103.13	8,167.75	0.93
	Rep.2	$2502.938 + 137.0784x – 0.08073789x^2$	8,321.30	84.89	81.25	8,310.63	0.97

NB: x = N fertilizer application rate (kg N ha^{-1})
Join point = Plateau of cob with husk weight waxy corn yield (kg ha^{-1})
Plateau (x_0) = Critical N fertilizer rate (kg N ha^{-1}) which occurs at the intersection of quadratic
EONR = Economic optimum N rate (kg N ha^{-1})
YEONR = Yield at economic optimum N rate (kg ha^{-1})

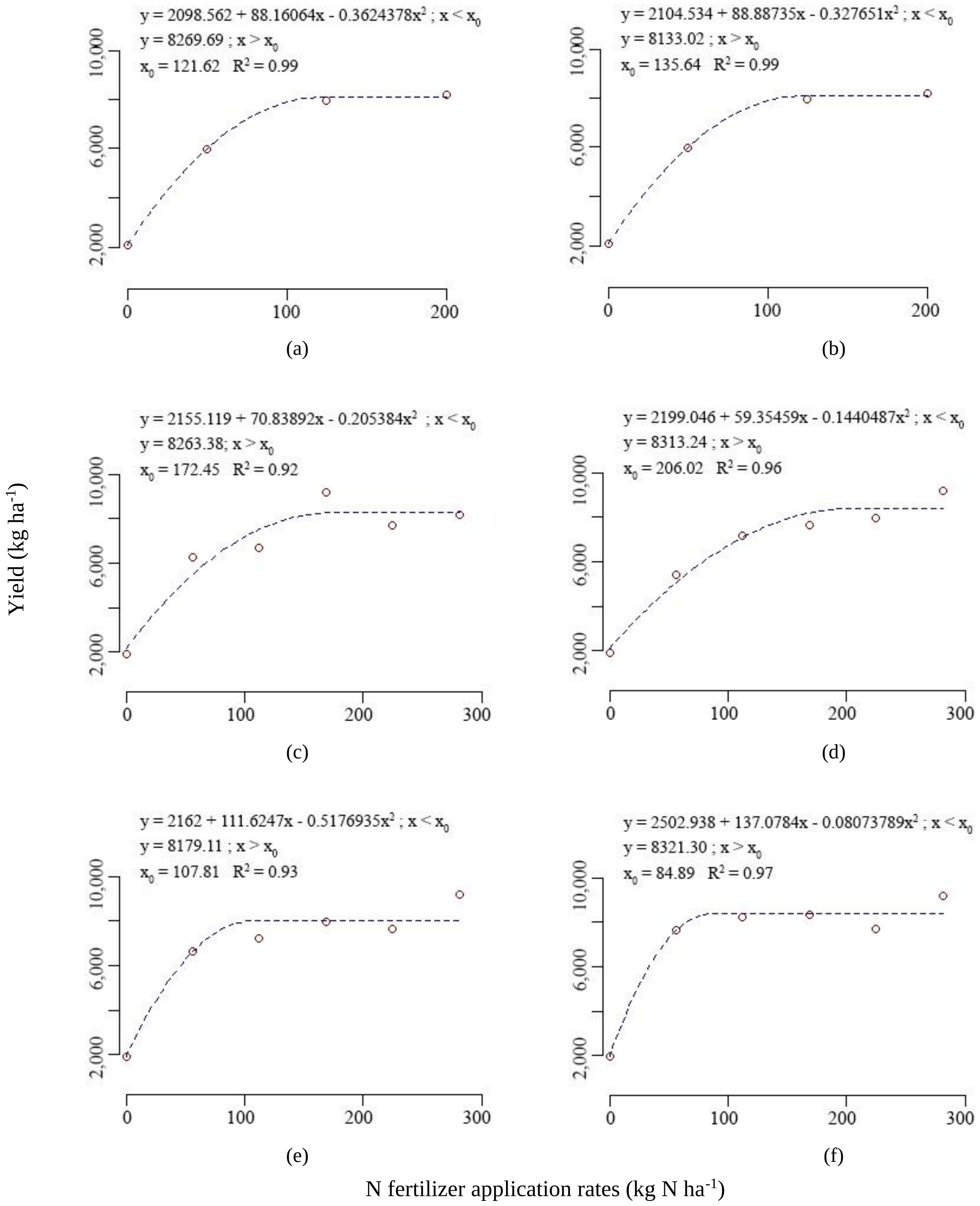

Figure 7: Quadratic plateau regression models and yield response to different nitrogen fertilizer application rates of (a) site 1 in 2017/18 replication 1 (b) site 1 in 2017/18 replication 2 (c) site 2 in 2018/19 replication 1 (d) site 2 in 2018/19 replication 2 (e) site 3 in 2018/19 replication 1 and (f) site 3 in 2018/19 replication 2

Table 6: Mean NDVI and relative NDVI of each treatment in all site-years

Study areas	Treatments	Total N application (kg N ha^{-1})	NDVI		relative NDVI	
			Rep.1	Rep.2	Rep.1	Rep.2
Site 1	T1	0	0.70	0.69	0.85	0.84
	T2	50	0.73	0.73		
	T3	125	0.77	0.78		
	T4	200	0.82	0.82		
Site 2	T1	0	0.71	0.71	0.85	0.86
	T2	56.25	0.79	0.79		
	T3	112.50	0.78	0.77		
	T4	168.75	0.82	0.81		
	T5	225	0.80	0.81		
	T6	281.25	0.84	0.83		
Site 3	T1	0	0.74	0.75	0.88	0.89
	T2	56.25	0.79	0.76		
	T3	112.50	0.81	0.81		
	T4	168.75	0.82	0.81		
	T5	225	0.82	0.81		
	T6	281.25	0.84	0.84		

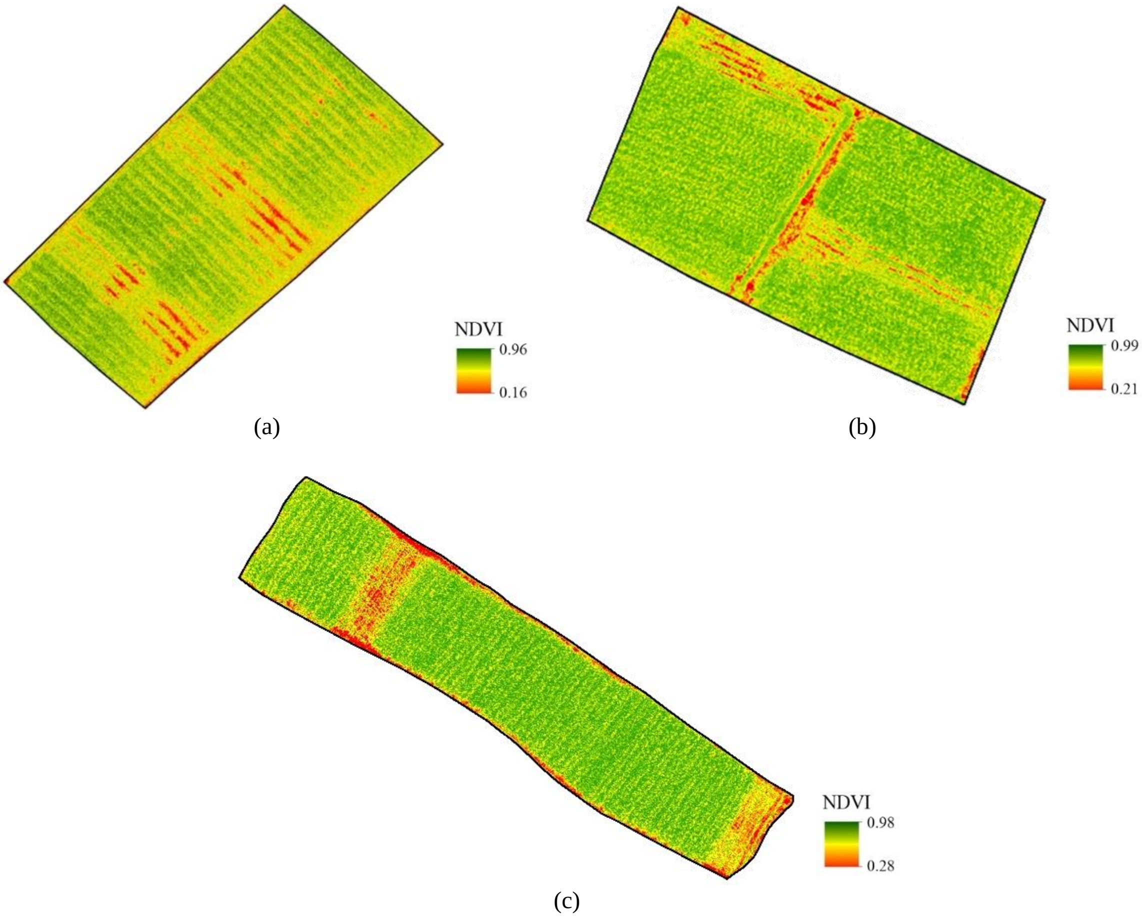

Figure 8: NDVI at R1 growth stage of (a) site 1 (b) site 2 and (c) site 3

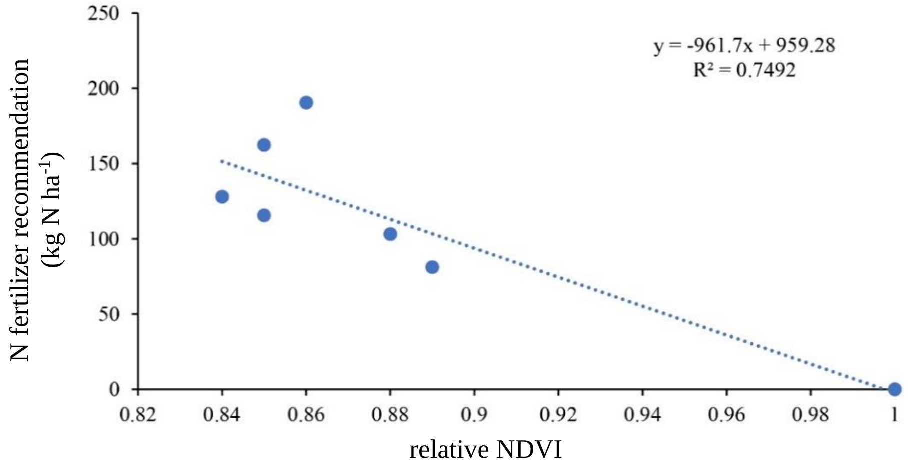

Figure 9: Relationship between EONR and relative NDVI data from 3 site-years were used in developing the model

4. Conclusions

This study demonstrated that relative NDVI at R1 growth stage can be used to estimate N fertilizer recommendation with EONR for the maximum economic return. In addition, waxy corn yields response to N fertilizer application rates and relative NDVI. Spectral reflectance of waxy corn expressed using relative NDVI successfully predicted EONR. These results indicate that if there are no canopy reflectance data, it is possible to estimate yield at the R1 growth stage from the amount of side dress fertilizer in corn. Furthermore, canopy reflectance data have also proven to estimate optimum N fertilizer recommendation and have shown to be more useful for precision farming practices.

Therefore, relative NDVI derived from UAV imaging passive sensor can estimate N fertilizer recommendation for waxy corn under other similar waxy corn growing environments in the country as well as other area. Further work must be conducted with various soils, irrigation systems, tillage practices, types of fertilizer, timing of fertilization, waxy corn varieties and growth stages with any field conditions to verify this relationship or develop the model further. The result presented here suggests that the reflectance data collected with the multispectral camera as a passive sensor mounted on UAV has the potential to be a useful tool for N fertilizer recommendation for waxy corn under a variety of management systems and conditions found in the Northeastern region of Thailand.

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