

Improving in-season estimation of rice yield potential and responsiveness to topdressing nitrogen application with Crop Circle active crop canopy sensor

Qiang Cao^{1,2} · Yuxin Miao¹ · Jianning Shen¹ · Weifeng Yu¹ · Fei Yuan³ · Shanshan Cheng¹ · Shanyu Huang^{1,4} · Hongye Wang¹ · Wen Yang⁵ · Fengyan Liu⁵

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Abstract In-season site-specific nitrogen (N) management is a promising strategy to improve crop N use efficiency and reduce risks of environmental contamination. To successfully implement such precision management strategies, it is important to accurately estimate yield potential without additional topdressing N application (YP_0) as well as precisely assess the responsiveness to additional N application (RI) during the growing season. Previous research has mainly used normalized difference vegetation index (NDVI) or ratio vegetation index (RVI) obtained from GreenSeeker active crop canopy sensor with two fixed bands in red and near-infrared (NIR) spectrums to estimate these two parameters. The development of three-band Crop Circle active sensor provides a potential to improve in-season estimation of YP_0 and RI. The objectives of this study were twofold: (1) identify important vegetation indices obtained from Crop Circle ACS-470 sensor for estimating rice YP_0 and RI; and (2) evaluate their potential improvements over GreenSeeker NDVI and RVI. Four site-years of field N rate experiments were conducted in 2012 and 2013 at the Jiansanjiang Experiment Station of China Agricultural University located in Northeast China. The GreenSeeker and Crop Circle ACS-470 active canopy sensor with green, red edge, and NIR bands were used to collect rice canopy reflectance data at different key growth stages. The results indicated that both the GreenSeeker (best $R^2 = 0.66$ and 0.70 , respectively) and Crop Circle (best $R^2 = 0.71$ and 0.77 , respectively) sensors worked well for estimating YP_0 and RI at the stem elongation stage. At the booting stage, Crop Circle red edge optimized soil adjusted vegetation index (REOSAVI, $R^2 = 0.82$) and green ratio

✉ Yuxin Miao
ymiao@cau.edu.cn; ymiao2007@gmail.com

¹ International Center for Agro-Informatics and Sustainable Development (ICASD), Center for Resources, Environment and Food Security, China Agricultural University, Beijing 100193, China

² National Engineering and Technology Center for Information Agriculture, Nanjing Agricultural University, Nanjing 210095, China

³ Department of Geography, Minnesota State University, Mankato, MN 56001, USA

⁴ Institute of Geography, University of Cologne, 50923 Cologne, Germany

⁵ Jiansanjiang Institute of Agricultural Sciences, Jiansanjiang, Heilongjiang, China

vegetation index ($R^2 = 0.73$) explained 26 and 22 % more variability in YP_0 and RI, respectively, than GreenSeeker NDVI or RVI. At the heading stage, the GreenSeeker sensor indices became saturated and consequently could not be used for YP_0 or RI estimation, while Crop Circle REOSAVI and normalized green index could still explain more than 70 % of YP_0 and RI variability. It is concluded that both sensors performed similarly at the stem elongation stage, but significantly better results were obtained by the Crop Circle sensor at the booting and heading stages. Furthermore, the results revealed that the Crop Circle green band-based vegetation indices performed well for RI estimation while the red edge-based vegetation indices were the best for estimating YP_0 at later growth stages.

Keywords Precision nitrogen management · Crop Circle sensor · In-season nitrogen management · Active crop canopy sensor · GreenSeeker sensor · Response index

Introduction

The major challenges for global food security and sustainable development are how to double food production while improving resource use efficiencies and reducing environmental consequences (Tilman et al. 2011; Zhang et al. 2013; Chen et al. 2014). Increase in fertilizer nutrient input, especially nitrogen (N) fertilizer, has contributed significantly to the increase of crop yields in the world (Cassman et al. 2003). However, the rates of cereal yield growth have slowed down in the past 20–30 years, and even become stagnated in many regions, despite increases in N fertilizer input (Zhang et al. 2012; Grassini et al. 2013). The high rates and improper timing of N application are major problems in crop production, which have resulted in low N use efficiency and high environmental costs (Nosengo 2003; Guo et al. 2010; Good and Beatty 2011; Miao et al. 2011). Rice (*Oryza sativa* L.) is the most important staple cereal crop in the world. To feed growing populations, global rice yield needs to be increased to 116 million tons by 2035 (Seck et al. 2012). Globally, China is by far the largest producer of rice and consumed 36 % of total N fertilizer used for rice production on 19 % of world's rice planting area (Heffer 2008; FAOSTAT 2013). The current N partial factor productivity (PFP) for rice was reported to be only 41 kg kg⁻¹ based on surveys of 6592 farmers (Chen et al. 2014). Technologies and methods for effective N management strategies are urgently needed in rice production areas of China.

Chlorophyll meter and leaf color chart have been commonly used in site-specific N management (SSNM) to improve rice N use efficiencies (Dobermann et al. 2002; Peng et al. 2010). In addition to these point measurement tools, there is increasing interest in developing active crop canopy sensor-based precision N management strategies because they are more efficient and suitable for large area applications (Xue and Yang 2008; Harrell et al. 2011; Yao et al. 2012; Cao et al. 2013). A commonly used active crop canopy sensor for precision N management is the GreenSeeker handheld sensor (Trimble Navigation Limited, Sunnyvale, CA, USA) with two fixed wavebands (red and NIR) (Raun et al. 2002; Li et al. 2009; Bijay-Singh et al. 2011; Cao et al. 2012). This sensor provides two vegetation indices, normalized difference vegetation index (NDVI) and ratio vegetation index (RVI). Yao et al. (2012) developed a practical GreenSeeker sensor-based precision N management strategy for rice based on the regional optimum N rate (RONR) strategy and the N fertilization optimization algorithm (NFOA) developed by Raun et al.

(2002, 2005) for winter wheat (*Triticum aestivum* L.). In this strategy, a RONR of 90–110 kg N ha⁻¹ was used as an initial total N rate, and 45 and 20 % were applied as basal and tillering fertilizers, respectively. The GreenSeeker sensor was used at the stem elongation stage to estimate yield potential with no additional topdressing N (YP₀) and yield response index (RI, responsiveness to additional topdressing N application). The potential yield with added N fertilization (YP_N) can be estimated by multiplying YP₀ by RI. The N topdressing rate can then be estimated by considering the difference between YP_N and YP₀, grain N concentration, and N use efficiency (Yao et al. 2012). This approach was tested in rice and increased N PFP by 48 % over farmer's practice without reducing yield (Yao et al. 2012). The key to the success of this strategy is the capability to estimate YP₀ and RI accurately before topdressing. However, the relationships between RI at harvest (RI_{Harvest}) and RI calculated using GreenSeeker NDVI (RI_{NDVI}) and RVI (RI_{RVI}) were poor whether at the stem elongation stage, booting stage or across growth stages, with R² being less than 0.3 (Yao et al. 2012), which may result in inaccurate estimation of topdressing N application rate. This may be caused by the saturation problem of GreenSeeker NDVI at moderate to high biomass conditions, which may be reduced by using wavelengths with similar penetration into the plant canopy (Gnyp et al. 2014; Yao et al. 2014).

Active canopy sensors with more spectral bands may have better potential to improve in-season prediction of rice YP₀ and RI under high-yielding conditions. The Crop Circle ACS-470 sensor (Holland Scientific Inc., Lincoln, Nebraska, USA) is user configurable with a choice of up to 6 spectral bands: blue (450 ± 20 nm), green (550 ± 20 nm), red 1 (650 ± 20 nm), red 2 (670 ± 11 nm), red edge (730 ± 10 nm), and NIR (>760 nm). Three of them can be used at a time. As a result, a variety of spectral vegetation indices can be derived. Some of these indices have been found to be better than the traditional NDVI and RVI indices for estimating crop N status. In a recent study conducted in Northeast China, Cao et al. (2013) systematically evaluated 43 vegetation indices derived from three Crop Circle ACS-470 bands (green, red edge, and NIR) for estimating rice N status. The results revealed that the modified chlorophyll absorption reflectance index 1 (MCARI1) had consistent high correlations with rice biomass and plant N uptake (R² = 0.79–0.83) across site-years, varieties, and growth stages. Four red edge-based indices performed equally well for estimating rice N nutrition index (NNI) (R² = 0.76) under high-yielding conditions. By contrast, Yao et al. (2014) found that GreenSeeker NDVI and RVI explained more than 70 % of rice aboveground biomass and plant N uptake variability at early growth stages, whereas less than 40 % of NNI variability were explained. However, NDVI became saturated at approximately 4 mg ha⁻¹ biomass or 100 kg ha⁻¹ plant N uptake. In a comparison study, Cao et al. (2015) found that the Crop Circle ACS 470 sensor could improve the estimation of winter wheat plant N concentration, uptake, and NNI by 53, 7–11, and 30 %, respectively, compared with the GreenSeeker sensor.

It was hypothesized that the three-band Crop Circle ACS470 sensor could improve in-season prediction of rice YP₀ and RI compared with two-band GreenSeeker sensor. The objectives of this study were to: (1) identify important vegetation indices obtained from Crop Circle ACS-470 sensor for estimating rice yield potential and responsiveness to topdressing N application, and (2) evaluate their potential improvements over GreenSeeker NDVI and RVI.

Materials and methods

Study site description

This study site is located in the Sanjiang Plain (43.8°N–48.5°N, 129.2°E–135.1°E), which is an alluvial plain of the Heilong, Songhua, and Wusuli Rivers and it covers approximately 108 900 km² in Heilongjiang Province, Northeast China. The Sanjiang Plain is a leading region of modern agriculture and is strategically important for China's food security (Zhao et al. 2013). It is characterized by a temperate humid or sub-humid continental monsoon climate with a warm summer and cold winter (Wang et al. 2006). The mean annual temperature is about 2 °C. The annual average precipitation ranges from 500 to 650 mm and 70 % of the precipitation falls from July to September (Wang and Yang 2001). The annual sunshine hours are about 2300–2600, and the frost-free period is only about 120–140 days (Yan et al. 2002). During the past two decades, rice farming has been expanding very fast and has become dominant in this region due to climate warming, abundant water resources, and fertile soils (Zhao et al. 2013).

The field experiments were conducted at Jiansanjiang Experiment Station of the China Agricultural University (47.2°N, 132.6°E). The experimental field has been devoted to rice production since 1992. The soil type is Meadow Albic bleached soil. The chemical parameters of the 0–0.3 m soil layer before transplanting in 2011 were as follows: organic matter content—35 g kg⁻¹, pH—6, total N—145 mg kg⁻¹, Olsen-phosphorus—36 mg kg⁻¹, and exchangeable potassium—111 mg kg⁻¹.

Nitrogen rate experiments

A total of four N rate field experiments (Exp. 1–4) were conducted in two rice seasons (2012 and 2013) to develop models for predicting rice yield potential and response index at harvest (RI_{Harvest}) from in-season optical sensor measurements. Each experiment had the same five N rates (0, 70, 100, 130, and 160 kg N ha⁻¹) using a randomized split block design with three replications. Each plot was divided into two parts: 6 m × 9 m as the main plot and 3 m × 9 m as the subplot. The main plot received the application of fertilizer N as urea in three splits: 40 % as basal N before transplanting, 30 % of N at the tillering stage, and the remaining 30 % of N at the stem elongation stage. In order to evaluate the capability of using Crop Circle sensor to estimate rice yield potential, the subplot did not receive the third N application. For all the treatments, 50 kg P₂O₅ ha⁻¹ in the form of Ca(H₂PO₄)₂ was applied before transplanting and 105 kg K₂O ha⁻¹ was applied as two splits: 50 % before transplanting and 50 % at the stem elongation stage. In each year, one experiment used the rice variety Kongyu 131 (11 leaves, 127 maturity days) and the other experiment used the variety Longjing 21 (12 leaves, 131 maturity days). Rice seedlings were prepared in a greenhouse and transplanted into the experimental fields. Transplanting density, seeding age, and irrigation were the same in all treatments. The rice was transplanted in mid-May and harvested in mid to late September each year. Modified alternate wetting and drying irrigation as described in Zhao et al. (2013) was adopted this study.

Active canopy sensor data collection

Reflectance data were collected across each plot at four different growth stages, including the panicle initiation, stem elongation, booting, and heading stages. The third topdressing N is usually applied at the stem elongation, and there is a possibility of delayed application

to the booting stage due to weather, labor, or other practical limitations in agricultural production. In order to further increase grain yield, a fourth topdressing N can be applied at the heading stage (Zhao et al. 2013). Therefore, data from the stem elongation, booting, and heading stages were used for this study.

Two crop canopy sensors were used in this study. The first sensor was GreenSeeker handheld sensor detecting reflection in red (650–670 nm) and NIR (755–785 nm) spectral regions. It has a nadir viewing angle with a field of view of 0.0052–0.0145 m² and acquisition interval ranging from 20 to 1500 ms (Raper et al. 2013). Sensor readings were collected by holding the GreenSeeker sensor approximately 0.7–0.9 m above the canopy and walking at a constant speed in all experimental plots. The sensor path was parallel to the seed rows or the beam of light was perpendicular to the seed row. The GreenSeeker sensor uses built-in software to calculate NDVI and RVI directly and generates ten NDVI and RVI determinations per second.

The second sensor was the Crop Circle ACS-470 active sensor, which incorporates three optical measurement channels and is user configurable (440–800 nm) using 12.5 mm interference filters. In this study, we selected three bands based on literature reviews and previous research (Cao et al. 2013): green (550 ± 20 nm), red edge (730 ± 10 nm), and NIR (>760 nm). Spectral reflectance data can be easily and quickly recorded to a text file on a SD flash card using the Holland Scientific GeoSCOUT GLS-400 data logger. The field of view of the Crop Circle ACS-470 sensor is an oval of ~32° by ~6° range, resulting in an area of approximately 0.09 m². Sensor readings were collected approximately 0.7–0.9 m above rice canopy at a rate of 10 readings per second and walking at a constant speed in each plot (Fig. 1). The average reflectance values were computed to represent each plot for both sensors. The calculated spectral vegetation indices evaluated in this study are listed in Table 1.

Grain yield determination

Grain yield was determined by hand harvesting three 1 m² areas in each plot where spectral reflectance data were collected. Grains were separated from straw using a small grain thresher and weighed. Grain moisture was determined immediately after weighing. Grain weight for rice was adjusted to a moisture content of 140 g kg⁻¹.



Fig. 1 Collecting rice canopy reflectance data using Crop Circle ACS-470 active canopy sensor

Table 1 Vegetation index selected for Crop Circle multispectral active canopy sensor

Index	Formula	Reference
Normalized green index (NGI)	$G/(NIR + RE + G)$	Modified from Sripada et al. (2006)
Normalized red edge index (NREI)	$RE/(NIR + RE + G)$	Modified from Sripada et al. (2006)
Normalized NIR index (NNIR)	$NIR/(NIR + RE + G)$	Modified from Sripada et al. (2006)
Red edge ratio vegetation index (RERVI)	NIR/RE	Jasper et al. (2009)
Green ratio vegetation index (GRVI)	NIR/G	Buschmann and Nagel (1993)
Red edge green ratio vegetation index (REGRVI)	RE/G	Modified from Buschman and Nagel (1993)
Green difference vegetation index (GDVI)	$NIR - G$	Tucker (1979)
Red edge difference vegetation index (REDVI)	$NIR - RE$	Modified from Tucker (1979)
Red edge green difference vegetation index (REGDVI)	$RE - G$	Modified from Tucker (1979)
Normalized difference red edge (NDRE)	$(NIR - RE)/(NIR + RE)$	Barnes et al. (2000)
Green normalized difference vegetation index (GNDVI)	$(NIR - G)/(NIR + G)$	Gitelson et al. (1996)
Red edge GNDVI (REGNDVI)	$(RE - G)/(RE + G)$	Gitelson et al. (1996)
Green wide dynamic range vegetation index (GWDRVI)	$(a*NIR - G)/(a*NIR + G)$ ($a = 0.12$)	Modified from Gitelson (2004)
Red edge wide dynamic range vegetation index (REWDRVI)	$(a*NIR - RE)/(a*NIR + RE)$ ($a = 0.12$)	Modified from Gitelson (2004)
Optimized vegetation index 1 (VIopt1)	$100*(\ln NIR - \ln RE)$	Jasper et al. (2009)
Modified double difference index (MDD)	$(NIR - RE) - (RE - G)$	Modified from Le Maire et al. (2004)
Modified normalized difference index (MNDI)	$(NIR - RE)/(NIR - G)$	Modified from Datt (1999)
Green chlorophyll index (CI_G)	$NIR/G - 1$	Gitelson et al. (2005)

Table 1 continued

Index	Formula	Reference
Red edge chlorophyll index (CI _{RE})	$NIR/RE - 1$	Gitelson et al. (2005)
Modified red edge simple ratio (MSR _{RE})	$(NIR/RE - 1)/SQRT(NIR/RE + 1)$	Modified from Chen (1996)
Modified green simple ratio (MSR _G)	$(NIR/G - 1)/SQRT(NIR/G + 1)$	Modified from Chen (1996)
Modified enhanced vegetation index (MEVI)	$2.5*(NIR - RE)/(NIR + 6*RE - 7.5*G + 1)$	Modified from Justice et al. (1998)
Modified normalized difference red edge (MNDRE)	$[NIR - (RE - 2*G)]/[NIR + (RE - 2*G)]$	Modified from Wang et al. (2012)
Modified chlorophyll absorption in reflectance index 1 (MCARI1)	$[(NIR-RE) - 0.2*(NIR - G)](NIR/RE)$	Modified from Daughtry et al. (2000)
Modified chlorophyll absorption in reflectance index 2 (MCARI2)	$\frac{1.5[2.5(NIR-RE) - 1.3(NIR-G)]}{\sqrt{(2NIR+1)^2 - (6NIR - 5\sqrt{RE}) - 0.5}}$	Modified from Haboudane (2004)
Modified transformed CARI (MTCARI)	$3*[(NIR - RE) - 0.2*(NIR - G)(NIR/RE)]$	Modified from Haboudane et al. (2002)
Green soil adjusted vegetation index (GSAVI)	$1.5*[(NIR - G)/(NIR + G + 0.5)]$	Sripada et al. (2006)
Red edge soil adjusted vegetation index (RESAVI)	$1.5*[(NIR - RE)/(NIR + RE + 0.5)]$	Modified from Sripada et al. (2006)
Modified GSAVI (MGSAVI)	$0.5*[2*NIR + 1 - SQRT((2*NIR + 1)^2 - 8*(NIR - G))]$	Modified from Qi et al. (1994)
Modified RESAVI (MRESAVI)	$0.5*[2*NIR + 1 - SQRT((2*NIR + 1)^2 - 8*(NIR - RE))]$	Modified from Qi et al. (1994)
Green optimal soil adjusted vegetation index (GOSAVI)	$(1 + 0.16)(NIR - G)/(NIR + G + 0.16)$	Modified from Rondeaux et al. (1996)
Red edge optimal soil adjusted vegetation index (REOSAVI)	$(1 + 0.16)(NIR - RE)/(NIR + RE + 0.16)$	Modified from Rondeaux et al. (1996)
MCARI1/GOSAVI	MCARI1/GOSAVI	Modified from Zarco-Tejada et al. (2004)
MCARI2/GOSAVI	MCARI2/GOSAVI	Modified from Daughtry et al. (2000)
MTCARI/GOSAVI	MTCARI/GOSAVI	Modified from Haboudane et al. (2002)

Table 1 continued

Index	Formula	Reference
Modified canopy chlorophyll content index (MCCCI)	NDRE/GNDVI	Modified from Barnes et al. (2000)
NDRE/GOSAVI	NDRE/GOSAVI	Cao et al. (2013)
Red edge transformed vegetation index (RETVI)	$0.5*[120*(NIR - G) - 200*(RE - G)]$	Modified from Broge and Leblanc (2000)
Green re-normalized different vegetation index (GRDVI)	$(NIR - G)/SQRT(NIR + G)$	Modified from Roujean and Breon (1995)
Red edge re-normalized different vegetation index (RERDVI)	$(NIR - RE)/SQRT(NIR + RE)$	Modified from Roujean and Breon (1995)
Modified RETVI (MRETVI)	$1.2*[1.2*(NIR - G) - 2.5*(RE - G)]$	Modified from Haboudane (2004)
MCARI1/MRETVI	MCARI1/MRETVI	Modified from Eitel et al. (2007)
MTCARI/MRETVI	MTCARI/MRETVI	Cao et al. (2013)

Statistical analysis

In-season estimate of yield (INSEY) can be regarded as an estimate of average daily growth rate or biomass production from the time of planting to the day of sensing (Raun et al. 2002). It was calculated as NDVI divided by the number of growing degree days (GDD) (Yao et al. 2012). In this study, however, the number of days from transplanting to sensing (DAT) was used instead of GDD to calculate INSEY. The selected Crop Circle vegetation indices were used to replace the GreenSeeker NDVI or RVI.

The response index at harvest (RI_{Harvest}) indicates the actual crop response to additional N within a given year (Johnson and Raun 2003; Mullen et al. 2003) and was calculated as follows:

$$RI_{\text{Harvest}} = \frac{\text{Yield}_{\text{N}_{\text{rich}}}}{\text{Yield}_{\text{CK}}},$$

where $\text{Yield}_{\text{N}_{\text{rich}}}$ is the average yield of plots receiving sufficient N application (the 160 kg N ha⁻¹ treatment in this study), and Yield_{CK} is the average yield of a check plot or plot without receiving the third N application at the stem elongation stage.

In-season prediction of response to N fertilization based on vegetation index (RI_{VI}) was calculated in the same way as RI_{Harvest} , with the exception that vegetation indices derived from GreenSeeker and Crop Circle ACS-470 sensors were used instead of yield. The yield potential with additional N (YP_{N}) was calculated by multiplying YP_0 and RI_{Harvest} estimated by RI_{VI} .

Table 2 Relationships between yield potential without additional topdressing N application (YP₀) and in-season estimate of yield calculated with vegetation indices derived from GreenSeeker and Crop Circle ACS-470 sensors at different growth stages across varieties and site-years

Sensor	Stem elongation stage			Booting stage			Stem elongation & booting stages			Heading stage		
	Index	Model	R ²	Index	Model	R ²	Index	Model	R ²	Index	Model	R ²
GreenSeeker	NDVI	Q	0.63	NDVI	E	0.56	NDVI	P	0.47	NDVI	-	NS
	RVI	L	0.66	RVI	P	0.41	RVI	Q	0.52	RVI	-	NS
Crop Circle ACS-470	NNIR	L	0.71	REOSAVI	Q	0.82	MRESAVI	Q	0.63	REOSAVI	Q	0.75
	GSAVI	P	0.68	MEVI	Log	0.80	RESAVI	Q	0.63	RESAVI	L	0.74
	GRDVI	P	0.67	Cl _{RE}	Log	0.80	RERDVI	L	0.62	MRESAVI	L	0.74
	MGSAVI	P	0.67	MSR_RE	Log	0.80	REOSAVI	L	0.60	RERDVI	Q	0.74
	GOSAVI	P	0.66	NDRE	L	0.79	MEVI	L	0.60	MCARII	Log	0.74
	GDVI	P	0.66	Vlopt1	L	0.79	MCARII	Q	0.60	MEVI	Q	0.73
	GNDVI	E	0.62	MCARII	Q	0.79	MTCARI	Q	0.58	MTCARI	Q	0.70
	RERVI	Q	0.60	NNIR	L	0.78	REDVI	Q	0.57	MCARII/GOSAVI	Log	0.70
	GRVI	P	0.60	RERDVI	L	0.78	MSR_RE	L	0.56	Vlopt1	Log	0.69
	REDVI	Q	0.59	MRESAVI	L	0.77	Cl _{RE}	L	0.56	NDRE	L	0.68

L denote linear, Q quadratic, E exponential, P power, log logarithmic fit, NS no significance at P < 0.05

Linear, quadratic, exponential, power, and logarithmic models were evaluated for describing the relationships between INSEY and Y_{P0} or RI_{VI} and $RI_{Harvest}$ using the SPSS 18.0 software (SPSS Inc., Chicago, IL, USA). The corrected coefficients of determination (R^2) values were used for model selection in addition to visual inspection of each curve.

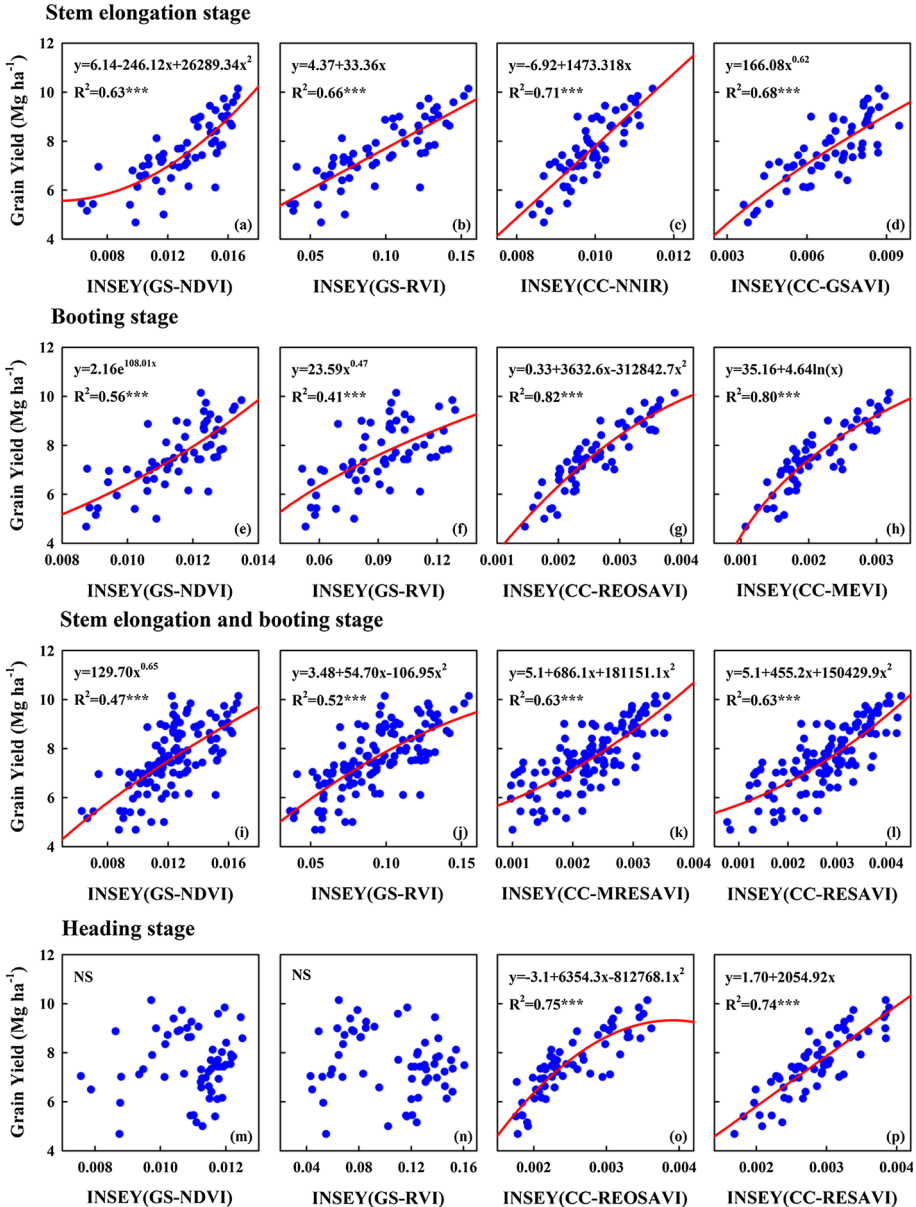


Fig. 2 The relationships between yield without additional topdressing N application (Y_{P0}) and in-season estimate of yield (INSEY) calculated with vegetation indices derived from GreenSeeker (NDVI, RVI) and Crop Circle ACS-470 (*Top two indices*) at different growth stages (stem elongation, booting, stem elongation + booting, and heading stages) during 2012 and 2013

Results and discussion

In-season estimation of rice yield potential

Across site-years and crop varieties, the Crop Circle sensor performed consistently better than the GreenSeeker sensor for estimating YP_0 at different growth stages (Table 2).

The stem elongation stage is the key stage to apply panicle fertilizer for rice in Northeast China. The INSEY calculated with GreenSeeker NDVI (INSEY(GS – NDVI)) and RVI (INSEY(GS – RVI)) explained 63 and 66 % of YP_0 variability, respectively (Table 2). This is similar to the findings of Yao et al. (2012) at Site 1 ($R^2 = 0.67$ – 0.69), which is the same site as this study. The INSEYs calculated with the top 6 Crop Circle indices performed similarly as that derived from the GreenSeeker sensor. The top two Crop Circle indices, normalized near infrared index (NNIR) ($R^2 = 0.71$) and green soil adjusted vegetation index (GSAVI) ($R^2 = 0.68$) explained slightly more YP_0 variability than the GreenSeeker indices (Fig. 2a–d).

At the booting stage, rice aboveground biomass was generally greater than 4 mg ha^{-1} , and the saturation effect started to become a problem (Gnyp et al. 2014; Yao et al. 2014). The performance of the GreenSeeker sensor at this stage was worse than that at the stem elongation stage. The INSEY (GS – NDVI) and INSEY (GS – RVI) explained 56 and 41 % of YP_0 variability, respectively (Fig. 2e, f). Conversely, the INSEYs calculated with the top 10 Crop Circle indices explained 77–82 % of YP_0 variability, which was 21–26 % higher than INSEY (GS – NDVI). These ten indices were all red edge-based indices, indicating the importance of red edge band for estimating yield potential at this stage. The INSEY calculated with the Crop Circle red edge optimal soil adjusted vegetation index (INSEY (CC – REOSAVI)) performed the best, explaining 82 % of YP_0 variability (Fig. 2g). The INSEY calculated with Crop Circle modified enhanced vegetation index (INSEY (CC – MEVI)) (Fig. 2h), red edge chlorophyll index (INSEY (CC – CI_RE)), and modified red edge simple ratio (INSEY (CC – MSR_RE)) had the same performance, all explaining 80 % of YP_0 variability.

Across the stem elongation and booting stages, INSEY (GS – NDVI) and INSEY (GS – RVI) explained 47 and 52 % of YP_0 variability, respectively (Fig. 2i, j). These observations are similar to the results of Yao et al. (2012). On the other hand, the INSEYs calculated with the top 10 Crop Circle indices explained 56–63 % of YP_0 variability (Table 2). They were all red edge-based vegetation indices. Particularly, the INSEYs calculated with the best Crop Circle indices, modified red edge soil adjusted vegetation index (INSEY (CC – MRESAVI)) and red edge soil adjusted vegetation index (INSEY (CC – RESAVI)) ($R^2 = 0.63$) (Fig. 2k, l), explained 11 % more YP_0 variability than INSEY (GS – RVI) ($R^2 = 0.52$).

At the heading stage, crop canopy was closed, and the average biomass was around 7 t ha^{-1} (Gnyp et al. 2014). The GreenSeeker NDVI and RVI became saturated. Hence, no significant relationship existed between the corresponding INSEYs and YP_0 (Fig. 2m, n). By contrast, the INSEYs calculated with the top 10 Crop Circle indices explained 68–75 % of YP_0 variability at this stage (Table 2). Likewise, they were all red edge-based vegetation indices. The INSEY (CC-REOSAVI) (Fig. 2o) and INSEY (CC-RERDVI) indices were quadratically related to YP_0 , while INSEY (CC RESAVI) (Fig. 2p) and INSEY (CC MRESAVI) were linearly related to YP_0 .

The performance of GreenSeeker for estimating YP_0 at the stem elongation and booting stage were better than the result of (Harrell et al. 2011), who found that GreenSeeker NDVI

explained 36 and 42 % of Y_{P_0} variability at the panicle initiation and panicle differentiation stages, respectively. This may be caused by stage difference or attributed to the problem of NDVI saturation in high biomass conditions. The yield level ($>10 \text{ mg ha}^{-1}$ for many data points) was high in the study of Harrell et al. (2011), while it was mainly below

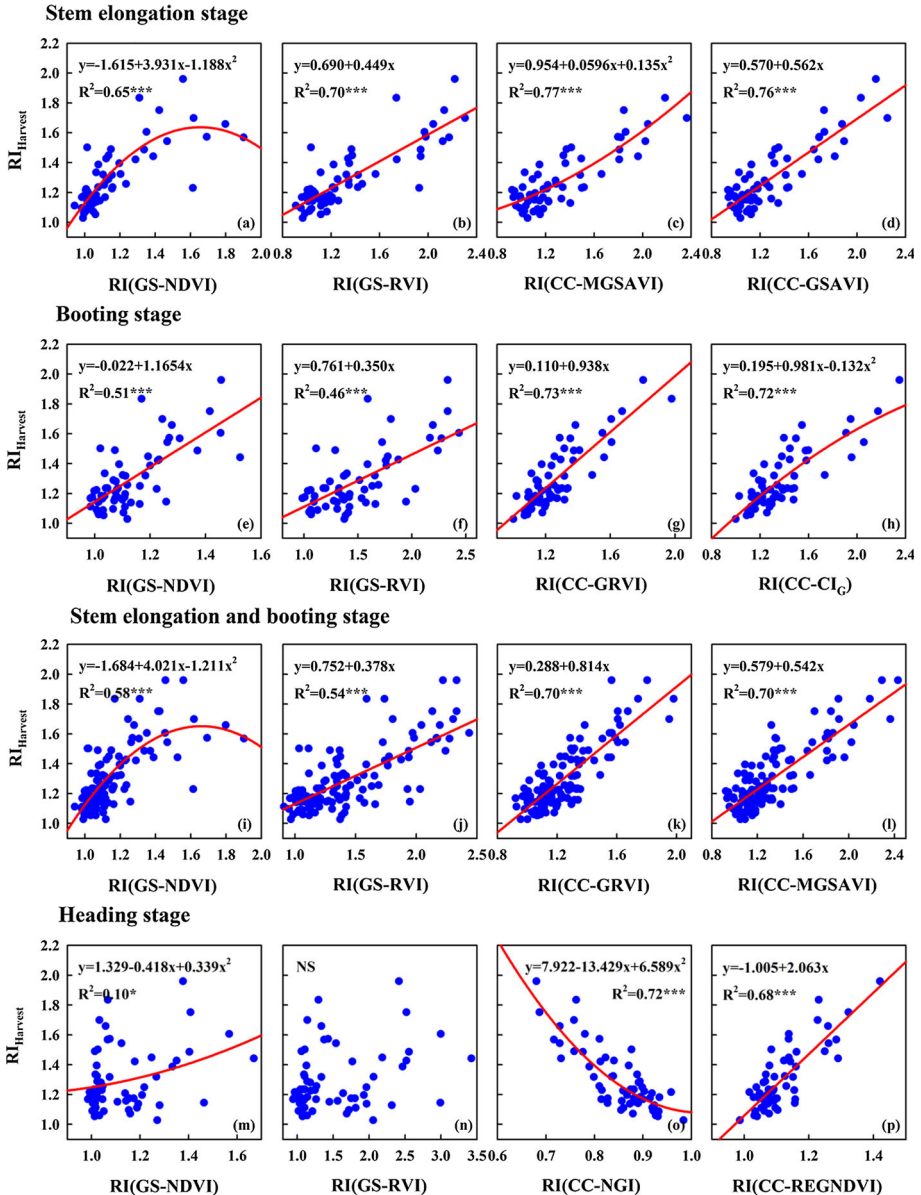


Fig. 3 The relationships between response index calculated with yield ($RI_{Harvest}$) and response index calculated with vegetation indices derived from GreenSeeker (NDVI, RVI) and Crop Circle ACS-470 (top two indices) at different growth stages (stem elongation, booting, stem elongation + booting, and heading stages) during 2012 and 2013

Table 3 Relationships between response index calculated with yield ($RI_{Harvest}$) and response index calculated with vegetation indices derived from GreenSeeker (NDVI, RVI) and Crop Circle ACS-470 (Top 10 indices) at different growth stages across varieties and site-years

Sensor	Stem elongation stage			Booting stage			Stem elongation & booting stage			Heading stage		
	Index	Model	R ²	Index	Model	R ²	Index	Model	R ²	Index	Model	R ²
	GreenSeeker	NDVI	Q	0.65	NDVI	Q	0.51	NDVI	Q	0.58	NDVI	Q
	RVI	L	0.70	RVI	Q	0.46	RVI	L	0.54	RVI	-	NS
Crop Circle ACS-470	MGS AVI	Q	0.77	GRVI	L	0.73	GRVI	L	0.70	NGI	Q	0.72
	GSAVI	L	0.76	Cl _G	Q	0.72	MGS AVI	L	0.70	REGNDVI	L	0.68
	GRDVI	L	0.75	GWDRVI	Q	0.72	GSAVI	L	0.69	GOSAVI	L	0.67
	GDVI	L	0.75	MSR_G	Q	0.72	GRDVI	L	0.69	GRVI	L	0.67
	GOSAVI	L	0.74	GOSAVI	L	0.71	Cl _G	Q	0.69	Cl _G	Q	0.67
	GWDRVI	Q	0.72	NGI	Q	0.71	NGI	Q	0.69	MSR_G	L	0.66
	Cl _G	Q	0.71	GRDVI	L	0.70	GOSAVI	Q	0.69	GWDRVI	Q	0.66
	GNDVI	Q	0.71	GNDVI	Q	0.70	MSR_G	Q	0.68	GNDVI	Q	0.66
	MSR_G	Q	0.71	RESAVI	Q	0.70	GDVI	Q	0.67	REGRVI	L	0.63
	GRVI	Q	0.71	GSAVI	L	0.69	GNDVI	Q	0.67	GRDVI	L	0.62

L linear, Q quadratic fit, NS no significance at P < 0.05

10 mg ha⁻¹ in the present study. In addition, their results were based on multi-site-year and variety data collected from two states in US, while the present data only covered 2 years, one site, and two varieties. At the heading stage, none of the GreenSeeker indices were significantly related to YP₀, which conforms to the findings of Harrell et al. (2011). However, in the study of Xue et al. (2014) conducted in Jiangxi Province in East China, the relationships between GreenSeeker NDVI and rice yield potential were consistently strong across the growing season, with R² being 0.95, 0.87, 0.84 and 0.77 at the tillering, panicle initiation, heading and grain filling stages, respectively. Their results were based on 1 year's data for early rice, and the yield level was lower than this study. Therefore, GreenSeeker NDVI saturation may not be a limiting factor in their study.

In-season estimation of the responsiveness to topdressing N application

Similar to yield potential, the Crop Circle sensor performed consistently better than the GreenSeeker sensor for RI_{Harvest} estimation. The GreenSeeker sensor performed the best at the stem elongation stage, with the RI calculated with NDVI (RI(GS – NDVI)) and RVI (RI(GS – RVI)) explaining 65 and 70 % of RI_{Harvest} variability (Fig. 3a, b). The RI calculated with the top 10 Crop Circle indices explained 71–77 % of RI_{Harvest} variability (Table 3). The RI calculated with Crop Circle modified green soil adjusted vegetation index (RI(CC – MGSAVI)) and GSAVI (RI(CC – GSAVI)) explained 6–7 % more variability than RI(GS – RVI) (Fig. 3c, d).

At the booting stage, both RI (GS – NDVI) and RI (GS – RVI) were linearly related to RI_{Harvest}, with R² of 0.51 and 0.46, respectively (Fig. 3e, f). The RI calculated with the top 10 Crop Circle indices performed similarly, with R² ranging from 0.69 to 0.73 (Table 3). Particularly at this stage, the RI calculated with Crop Circle green ratio vegetation index (RI(CC – GRVI)) explained 22 % more variability in RI_{Harvest} than RI(GS – NDVI) (Fig. 3g).

Across the stem elongation and booting stages, RIs calculated with the top 10 Crop Circle indices performed similarly (R² = 0.67–0.70), explaining 9–12 % more variability than RI (GS – NDVI) (Table 3). Both RI (CC – GRVI) and RI (CC – MGSAVI) were linearly related to RI_{Harvest}, with R² being 0.70 (Fig. 3k, l).

At the heading stage, RI (GS – NDVI) could only explain 10 % of RI_{Harvest} variability, while RI (GS – RVI) was not significantly related to RI_{Harvest} (Fig. 3m, n). However, the RIs calculated with top 10 Crop Circle indices still performed quite well, explaining 62–72 % of RI_{Harvest} variability (Table 3). Again, they were all green band-based indices. RIs calculated with Crop Circle normalized green index (RI(CC – NGI)) and red edge green NDVI (RI(CC – REGNDVI)) explained 62 and 58 % more variability, respectively, in RI_{Harvest} (Fig. 3o, p).

It should be noted that all the top 10 RIs calculated with Crop Circle indices at different growth stages used green band, except for RESAVI at the booting stage. This result indicated the importance of green band for estimating rice responsiveness to additional N application.

The GreenSeeker-based RI_{Harvest} estimation results are better than those reported by Yao et al. (2012), who also conducted rice field experiments in the same study area. They also found that the GreenSeeker sensor performed better at the stem elongation (R² = 0.43–0.59) than the booting stage (R² = 0.17–0.22). In the study of Tubaña et al. (2012), which was conducted in US with multi-site-year and variety data, the R² for the relationship between RI(GS – NDVI) and RI_{Harvest} was 0.52, 0.49 and 0.43 at the panicle initiation, panicle initiation plus 1 week, and panicle initiation plus 2 weeks, respectively.

The patterns were similar; the relationship became weaker at later growth stages, mainly due to NDVI saturation. It should be noted that they used data from N_{rich} plots and check plots or different N rate plots and check plots to calculate RI, while N_{rich} plots and different N rate plots (including check plots) were used in the present study to calculate RI, which may be more applicable when developing in-season N recommendation algorithms.

Implications for precision N management of rice

Yield goal is central in many N recommendation methods or algorithms; however, actual yield varied significantly from field to field, year to year and within fields. Consequently, it is hard to reliably estimate yield at the beginning of the growing season. Therefore, it is advisable to set an initial yield goal based on historical yield information, soil conditions, variety characteristics, and management practices under normal weather conditions and get a rough estimate of total N application rate or simply use regional optimum N rate as the initial total N application rate (Peng et al. 2010; Harrell et al. 2011; Yao et al. 2012). Next, a moderate amount of N can be applied in the early stages (e.g. 45 % before planting or transplanting and 20 % at the tillering stage). Then, before topdressing application at the panicle initiation or stem elongation stage, the yield goal can be adjusted based on in-season crop growth conditions, which can be used to further estimate topdressing N application rate (Yao et al. 2012). Such a dynamic in-season site-specific precision N management strategy can better match N supply to crop N demand and result in improved N use efficiencies.

Two key components in the above-mentioned strategy are YP_0 and RI_{Harvest} . The YP_0 can be used to estimate how much N has already been accumulated in the plant before topdressing plus the amount of soil N supply in the later part of the growing season (Yao et al. 2012). RI_{Harvest} is an indicator of the responsiveness of rice yield to additional topdressing N application (Mullen et al. 2003; Yao et al. 2012). Both of these influence crop N demand, but they are independent of each other, and should be combined to determine in-season topdressing N application rates (Raun et al. 2011).

The results of this study indicated that the GreenSeeker sensor worked well for estimating YP_0 ($R^2 = 0.63\text{--}0.66$) and RI_{Harvest} ($R^2 = 0.65\text{--}0.70$) at the stem elongation stage. The Crop Circle sensor only slightly improved the estimation of these parameters by 5–7 % at the best. Therefore, both sensors can be used in the precision N management strategy for rice as discussed previously. The advantage with GreenSeeker sensor is its simplicity, because NDVI and RVI are automatically calculated and the users don't need to do any calculations. The Crop Circle ACS 470 sensor is more suitable for researchers rather than farmers. The users need to calculate different vegetation indices by themselves. However, once the most suitable indices are determined, the Crop Circle sensor can be programmed to calculate the desired indices automatically for practical applications.

To meet the double challenges of food security and sustainable development, integrated precision rice management systems need to be developed to increase both grain yield and N use efficiencies simultaneously (Zhao et al. 2013). For such high yield rice management systems, N application may need to be split into four doses: basal fertilizer before transplanting, tiller fertilizer during the tillering stage, panicle fertilizer during the stem elongation stage, and grain fertilizer during the heading stage (Zhao et al. 2013). The GreenSeeker sensor will not be able to estimate YP_0 and RI_{Harvest} at the heading stage, as indicated by the results of this study. One alternative approach is to use GreenSeeker sensor to determine topdressing N application rate at the stem elongation stage, and then split that in two doses, 2/3 as panicle fertilizer and 1/3 as grain fertilizer. The Crop Circle

ACS 470 sensor, however, can still be used to reliably estimate both YP_0 (highest $R^2 = 0.75$) and RI_{Harvest} (highest $R^2 = 0.72$) at the heading stage. Therefore, this sensor can be used to develop precision N management strategy for high yield rice management system with four N split applications. On the basis of the precision N management strategy with three split N applications, the Crop Circle sensor can be used to estimate topdressing N rate and 2/3 can be applied as panicle fertilizer at the stem elongation stage. Then at the heading stage, the sensor can be used again to estimate YP_0 and RI_{Harvest} , as well as to determine if and how much grain N fertilizer is needed.

More studies are needed to further evaluate GreenSeeker and Crop Circle active sensors-based precision N management strategies for improving rice N use efficiencies under on-farm conditions, especially in high yield rice management systems.

Conclusions

This study demonstrated that the GreenSeeker active canopy sensor performed the best for estimating rice yield potential and responsiveness to topdressing N application at the stem elongation stage, and became unusable at the heading stage. The Crop Circle ACS 470 sensor performed consistently well at different growth stages. It improved the estimations of these two parameters by 5–7, 22–26 and 62–75 % at the stem elongation, booting, and heading stages, respectively, compared to the GreenSeeker sensor. In general, Crop Circle green band-based vegetation indices performed the best for estimating responsiveness to topdressing N application, whereas red edge-based vegetation indices were the best for estimating rice yield potential at the booting and heading stages. The Crop Circle ACS-470 sensor would be more suitable for precision N management of high yield rice systems. Future studies are needed to develop and evaluate GreenSeeker and Crop Circle active sensor-based precision N management strategies for improving rice N use efficiencies under diverse on-farm conditions, especially for high yield rice management systems.

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