Field Crops Research 157 (2014) 111–123

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Improving estimation of summer maize nitrogen status with red edge-based spectral vegetation indices

Fei Li[a,b], Yuxin Miao[a,*], Guohui Feng[c], Fei Yuan[d], Shanchao Yue[a], Xiaowei Gao[a], Yuqing Liu[a], Bin Liu[a], Susan L. Ustin[e], Xinping Chen[a]

[a] International Center for Agro-Informatics and Sustainable Development (ICASD), College of Resources and Environmental Sciences, China Agricultural University, Beijing 100193, China

[b] College of Ecology and Environmental Science, Inner Mongolia Agricultural University Hohhot, Inner Mongolia 010019, China

[c] Department of Agriculture, Qingfeng Farm, Hulin, Heilongjiang 158421, China

[d] Department of Geography, Minnesota State University, Mankato, MN 56001, USA

[e] Center for Spatial Technologies and Remote Sensing (CSTARS), Department of Land, Air, and Water Resources, University of California, Davis, CA 95616 USA

ARTICLE INFO

Article history:
Received 1 December 2013
Received in revised form
19 December 2013
Accepted 19 December 2013

Keywords:
Canopy chlorophyll content index
Nitrogen status
Red edge vegetation index
Crop Circle sensor
WorldView-2 satellite
Precision nitrogen management

ABSTRACT

In recent decades, many spectral indices have been proposed to estimate crop nitrogen (N) status parameters. However, most of the indices based on red radiation lose their sensitivity under high aboveground biomass conditions. The objectives of this study were to (i) evaluate red-edge based spectral indices for estimating plant N concentration and uptake of summer maize (*Zea mays* L.) and (ii) study the influence of bandwidth and crop growth stage changes on the performance of various vegetation indices. Nitrogen rate experiments for maize were conducted in 2009 and 2010 at Quzhou Experimental Station of China Agricultural University in the North China Plain. The spectral indices were calculated from hyperspectral narrow bands, simulated Crop Circle ACS-470 active crop canopy sensor bands and simulated WorldView-2 satellite broad bands. The results indicated that red edge-based canopy chlorophyll content index (CCCI) performed the best across different bandwidths for estimating summer maize plant N concentration and uptake at the V6 and V7 and V10–V12 stages. The second best index was MERIS terrestrial chlorophyll index (MTCI). The four red edge-based indices, CCCI, MTCI, normalized difference red edge (NDRE) and red edge chlorophyll index ($CI_{red\ edge}$), performed similarly better across bandwidths for estimating plant N uptake ($R^2 = 0.76$–0.91) than normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) ($R^2 = 0.54$–0.80) at the V10–V12 and V6–V12 stages. More studies are needed to further evaluate these red edge-based vegetation indices using real Crop Circle ACS 470 sensor and satellite remote sensing images for maize as well as other crops under on-farm conditions.

© 2013 Elsevier B.V. All rights reserved.

1. Introduction

Maize (*Zea mays* L.) production is becoming increasingly important in resolving the pressure of per-capita food demands with China's growing population. Compared with 2001, China's planting area and total yield of maize in 2011 increased by 38.1% and 69.0%, respectively (China Agricultural Yearbook, 2001, 2011). It has become the second staple food crop since its total amount of production exceeded that of wheat in 1998. However, over- and under-application of nitrogen (N) fertilizers have been commonly reported, especially in the North China Plain (NCP) (Miao et al., 2011). The average household field was about 0.1 ha (Chen et al., 2011), and N fertilizer was applied manually based on local farmers' experience (Miao et al., 2011). The applied N rates varied significantly among different farmers, and large variability in indigenous N supply was found between and within fields (Cui et al., 2008; Cao et al., 2012). As a result, timely and effective methods or tools for guiding farmers to implement in-season site- or field-specific N management practices are urgently needed.

In recent decades, active crop canopy sensors, such as GreenSeeker (Trimble Navigation Limited, Sunnyvale, California, USA) and Crop Circle (Holland Scientific Inc., Lincoln, Nebraska, USA), have been developed to estimate crop N status non-destructively. Coupled with corresponding N fertilizer recommendation algorithms, the crop sensors have been used to recommend in-season N application rates (Raun et al., 2005; Sripada et al., 2008; Dellinger et al., 2008; Roberts et al., 2009; Solari et al., 2008, 2010; Shaver et al., 2011; Barker and Sawyer, 2012). Compared with traditional practice, the N fertilizer use efficiency (NUE) was significantly increased using active sensor-based in-season

* Corresponding author. Tel.: +86 10 62732865.
E-mail addresses: ymiao@cau.edu.cn, ymiao2007@gmail.com (Y. Miao).

0378-4290/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.fcr.2013.12.018

N management strategies for winter wheat (*Triticum aestivum* L.) (Raun et al., 2002; Li et al., 2009; Bijay-Singh et al., 2011) and rice (*Oryza sativa* L.) (Yao et al., 2012). A profit of \$25–50 ha^{-1} has been reported for active sensor-based variable rate N management of maize (Kitchen et al., 2010). Similarly, Scharf et al. (2011) noted that sensor-based N application increased partial profit and yield by \$42 ha^{-1} and 110 kg ha^{-1}, respectively, while N application rate was reduced by 16 kg N ha^{-1} compared to local farmers' practice. These results suggest that active sensor-based technology has a high potential for improving crop N management. However, the commonly used normalized difference vegetation index (NDVI) in these sensor-based strategies easily becomes saturated at moderate to high canopy coverage conditions (Erdle et al., 2011; Nguy-Robertson et al., 2012; Gnyp et al., 2014). Li et al. (2010) reported that NDVI lost sensitivity when aboveground biomass of winter wheat was higher than 3736 kg ha^{-1}. Particularly for corn, the challenge is that the aboveground biomass increases rapidly after the V6 crop growth stage, and the red and green spectra based indices lose sensitivity at the V10-VT growth stages under moderate to high aboveground biomass and high N rate conditions (Freeman et al., 2007; Martin et al., 2007; Mistele and Schmidhalter, 2008; Shaver et al., 2010).

One reason for the saturation of NDVI is due to the normalization effect embedded in the calculation formula of this index (Nguy-Robertson et al., 2012; Gnyp et al., 2014). Alternatively, the ratio vegetation index (RVI, NIR/R) can partially avoid the saturation problem, as revealed in several studies (Li et al., 2010; Nguy-Robertson et al., 2012; Yao et al., 2012; Gnyp et al., 2014). Another reason is because of the different transmittance of red and NIR radiation through the crop canopy leaves; therefore, the saturation effect of NDVI can be partially addressed by using wavelengths similar to NIR's penetration into the canopy (Van Niel and McVicar, 2004).

Green NDVI (GNDVI) has been found to be more sensitive than NDVI in differentiating maize canopy variability as the vegetation increased with the advancing growing season (Shanahan et al., 2001). Gitelson et al. (2005) reported that the chlorophyll index (CI_{green}) (NIR/G − 1) was more sensitive to total canopy chlorophyll content under moderate-to-high crop biomass conditions than GNDVI. Solari et al. (2008) also found CI_{green} was more sensitive than GNDVI for estimating maize canopy greenness and was more suitable for guiding variable rate N applications.

The red edge (700–40 nm), a transition region of rapid change in leaf reflectance caused by the strong pigments absorption in the red spectrum and leaf scattering in the NIR spectrum, has been found to be sensitive to crop canopy chlorophyll and N status (Hatfield et al., 2008; Nguy-Robertson et al., 2012). Radiation in the red edge region penetrates deeper into the crop canopies and leaves than the visible light (especially blue and red radiation) because of the much lower chlorophyll absorption in the region. In other words, the sensitivity of absorbance related to crop chlorophyll content is much higher in the red edge region. Therefore, to certain degree, red edge-based spectral indices can overcome the saturation problems as reported with NDVI (Van Niel and McVicar, 2004; Nguy-Robertson et al., 2012). Kanke et al. (2012) compared red edge position (REP) and NDVI for detecting differences in winter wheat N status. They found that the sensitivity of NDVI decreased with N rate, while the sensitivity of REP increased with N rate and advancing growth stages, indicating the potential of REP to overcome the saturation problem. However, at early growth stages, NDVI performed better in detecting plant growth differences at the same N rates. Red edge inflection point (REIP) based on four bands (R_{670}, R_{700}, R_{740} and R_{780}) has also been found to be linearly related to N supply (R^2 = 0.97) (Heege et al., 2008). Fitzgerald et al. (2006) found normalized difference red edge index (NDRE), taking the form of the NDVI but with the red band being replaced by a red edge band, was a reliable indicator of chlorophyll or N status. Gitelson et al. (2005) developed a red edge chlorophyll index ($CI_{red\ edge}$), which successfully predicted canopy chlorophyll content of maize and soybean. Based on the theory of two-dimensional planar domain illustrated by Clarke et al. (2001), the CCCI with a red edge band was proposed as a superior method to estimate N-related indicators for cotton (*Gossypium hirsutum* L.) (El-Shikha et al., 2008), wheat (Rodriguez et al., 2006; Tilling et al., 2007; Fitzgerald et al., 2006, 2010; Perry et al., 2012) and broccoli (*Brassica oleracea*) (El-Shikha et al., 2007). However, little detailed research of the relationship between CCCI and maize canopy N status exists. Wu et al. (2008) noted that a combination of indices based on the Modified Chlorophyll Absorption Ratio Index (MCARI), Transformed Chlorophyll Absorption in Reflectance Index (TCARI), and the Optimized Soil-Adjusted Vegetation Index that using NIR, red edge, and green bands, such as MCARI/OSAVI and TCARI/OSAVI, were more linearly related to maize chlorophyll content than indices based on NIR, red and green bands. Similarly, Hatfield et al. (2008) concluded that indices using red edge and NIR bands are more sensitive to maize canopy N indicators than those using NIR and red bands.

Recently developed Crop Circle sensors (e.g., Crop Circle ACS-470 and 430) include a short red edge band (730 ± 10 nm). In this study, we define short band as band width of 20–40 nm to distinguish Crop Circle sensor bands from narrow hypersepctral bands (1 nm band width) and satellite sensor broad bands (40–125 nm band width). Cao et al. (2013) systematically evaluated Crop Circle ACS-470 sensor with the configuration of NIR, red edge and green bands for estimating rice N status. They calculated 43 different vegetation indices and found modified MCARI index using NIR, red edge and green bands performed best for estimating aboveground rice biomass (R^2 = 0.79) and plant N uptake (R^2 = 0.83), and four red edge-based indices performed equally well for estimating rice N nutrition index (NNI) (R^2 = 0.76). Erdle et al. (2011) found the red edge ratio index (NIR/Red edge) that can be calculated with Crop Circle ACS 470 sensor was the most powerful and temporally stable index for estimating winter wheat N status. Shiratsuchi et al. (2011) found that two 3-band red edge-based vegetation indices calculated with Crop Circle ACS-470 bands, including DATT index ((NIR-Red edge)/(NIR-R)) and MERIS terrestrial chlorophyll index (MTCI, (NIR-Red edge)/(Red edge-R)), were the best indices for differentiating N rate effects on maize N status and were least affected by water stress. In addition, newly launched high spatial resolution satellites involving broad red edge bands, such as WorldView-2 (705–745 nm) and RapidEye (690–730 nm) can be important platforms for regional crop growth monitoring and precision N management. Li et al. (2012) used hyperspectral data to simulate the spectral bands of WorldView-2 and RapidEye. They found CCCI and N planar domain index (NPDI) were more stable and could better predict plant N concentration of winter wheat after the heading stage and plant N uptake before the heading stage than NDVI and RVI.

So far, little has been reported on evaluating the potential of using red edge-based spectral indices for improving estimation of maize plant N concentration and uptake at critical growth stages for in-season N status diagnosis and management, as compared with commonly used vegetation indices such as NDVI, RVI, GNDVI and chlorophyll index (CI_{green}). Studies are even rare to determine the potential impact of different bandwidth sensors (e.g. narrow band hyperspectral sensor, short band Crop Circle sensor and broad band WorldView-2 satellite sensor) on the performance of the red edge-based indices. Therefore, the objectives of the present study were to (i) evaluate red edge-based spectral indices for estimating plant N concentration and uptake of summer maize and (ii) study the influence of bandwidth and crop growth stages on the performance of spectral vegetation indices using hyperspectral narrow bands,

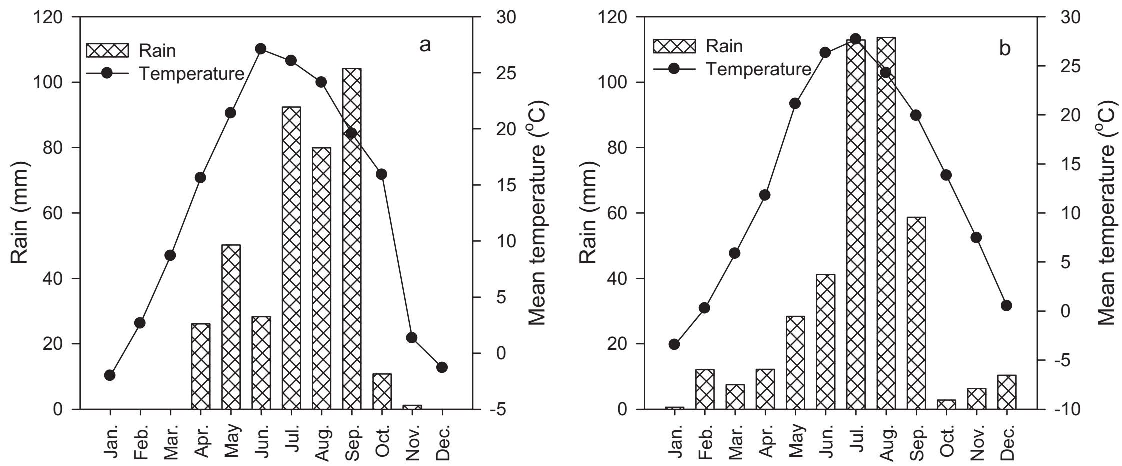

Fig. 1. Monthly rainfall and average temperature in Quzhou in (a) 2009 and (b) 2010.

simulated Crop Circle short bands, and simulated WorldView-2 satellite broad bands.

2. Materials and methods

2.1. Site description

The experiments were conducted at the Quzhou Experimental Station of China Agricultural University (CAU) (36.87 °N, 115.02 °E) in Quzhou County of Hebei Province located in the NCP. Quzhou County lies in the warm-temperate subhumid-continental monsoon zone and was characterized by cold winters and hot summers. The yearly mean temperature was 13.3 °C and 13.0 °C in 2009 and 2010, respectively. More than 300 mm rainfall occurs between sowing of summer maize in the middle of June and harvesting in the middle of October (Fig. 1). The weather in this area is hot (24–8 °C) and wet, with more than 70% yearly precipitation occurring in summer maize growing season. Commonly only one irrigation is applied at sowing of summer maize in this region.

2.2. Experimental design

Three experiments involving three maize cultivars were conducted from June through October in 2009 and 2010, at the CAU Quzhou Experimental Station. Experiment 1 adopted a randomized complete block design with four replications and was conducted in 2009. There were five N treatments: (i) control (no N was applied), (ii) 50% of the optimum N rate (Opt), (iii) 150% of Opt, (iv) optimum (Opt), and (v) conventional N rate fertilization (Con). The maize cultivar was Zhengdan958 (maturity days 96). The plot size was 15 m × 20 m. Experiment 2 was a split-plot design with four replications conducted in 2010. The main plot consisted of five N treatments: (i) control (no N was applied), (ii) 70% of the optimum N rate (Opt), (iii) 130% of Opt, (iv) optimum (Opt), and (v) conventional N rate fertilization (Con), and the subplot consisted of three summer maize cultivars, Xianyu335 (maturity days 98), Yedan20 (maturity days 97) and Zhengdan958. The main plot size was also 15 m × 20 m. The Opt was determined to be 150 and 105 kg N ha^{-1} for 2009 and 2010, respectively, based on the soil mineral N (N_{min}) test following Cui et al. (2008). The conventional N treatment represents the local farmer's practice and had an application rate of 250 kg ha^{-1} for both years. Experiment 3 was conducted in both 2009 and 2010, adopting a randomized complete block design with four replications. It evaluated six different N management strategies, where the N application rate was determined by the management strategy. The N management strategies were: (i) control (no N was applied), (ii) soil N_{min}-based N management same as the Opt. Treatment in experiment 1 and 2, (iii) GreenSeeker sensor-based N management based on a self-developed algorithm, (iv) Green Window-based N management based on visual examination of reference plots receiving different N supplies, (v) regional optimum N management at 180 kg N ha^{-1} and (vi) local farmers' practice at 300 kg N ha^{-1}. The cultivar for experiment 3 was Zhengdan958 and the plot size was 6 m × 8 m. The planting density for all the experiments were 75000 plants ha^{-1}, with a row spacing of 60 cm. These experiments were conducted in different projects for other purposes and will be published in separate papers, but this study took advantage of the wide range of applied N rates and resulting N levels of maize to evaluate the potential of different vegetation indices for estimating maize plant N status.

2.3. Canopy spectral data collection and vegetation indices calculation

Canopy spectral reflectance was measured using an ASD Fieldspec3 optical sensor (Analytical Spectral Devices, Inc., Boulder, CO, USA) from 10:00 am to 14:00 pm local time under cloudless conditions. The reflectance of the target is calculated with the calibration measurements of dark current and a white Spectralon reference panel with known reflectance properties. The ASD FieldSpec® 3 spectrometer covers 350–2500 nm spectral range, with 1.4 nm and 2 nm sampling interval for the UV/VNIR (350–1000 nm) and SWIR (1000–2500 nm) region, respectively. The hyperspectral data were re-sampled to 1 nm bandwidth using a self-driven interpolation method of the ASD spectrometer and then saved. The spectral measurements were taken randomly at three sites in each plot with a 25° field of view at a height of 50 cm above plant canopy. The measurements were averaged to represent the canopy reflectance of each plot. Calibration was performed every 30 min to correct the potential effects caused by changes in illumination conditions. Canopy reflectance was collected at the summer maize growth stages of V6 and V7 and V10–V12 during the growing season in 2009 and 2010. These growth stages are key time windows for sidedressing N fertilizers.

In this study, canopy spectral reflectance data were used for calculating twelve vegetation indices, many of which have been reported in the literature for crop N status estimation (Table 1). Specifically, the spectral indices investigated include: NDVI, GNDVI, NDRE, $CI_{red\ edge}$, CI_{green}, RVI, and MTCI. We also tested several combined spectral indices including CCCI, TCARI/OSAVI, and MCARI/OSAVI.

Table 1
Spectral vegetation indices evaluated in this study.

Vegetation index	Formula*	Reference
Normalized difference vegetation index (NDVI)	$(NIR-R)/(NIR+R)$ $(R_{790}-R_{670})/(R_{790}+R_{670})$	Rouse et al. (1974)
Green normalized difference vegetation index (GNDVI)	$(NIR-G)/(NIR+G)$ $(R_{790}-R_{550})/(R_{790}+R_{550})$	Gitelson and Merzlyak (1996)
Normalized difference red edge index (NDRE)	$(NIR-RE)/(NIR+RE)$ $(R_{790}-R_{720})/(R_{790}+R_{720})$	Fitzgerald et al. (2010)
Red edge chlorophyll index ($CI_{red\ edge}$)	$NIR/RE-1$ $R_{790}/R_{720}-1$	Gitelson et al. (2005)
Green chlorophyll index (CI_{green})	NIR/G-1 $R_{790}/R_{550}-1$	Gitelson et al. (2005)
Ratio vegetation index (RVI)	NIR/R R_{790}/R_{670}	Jordan (1969)
MERIS terrestrial chlorophyll index (MTCI)	$(NIR-RE)/(RE-R)$ $(R_{750}-R_{710})/(R_{710}-R_{680})$	Dash and Curran (2004)
Canopy chlorophyll content index (CCCI)	$(NDRE-NDRE_{MIN})/(NDRE_{MAX}-NDRE_{MIN})$	Fitzgerald et al. (2010)
Transformed chlorophyll absorption in reflectance index/Optimized soil-adjusted vegetation index (TCARI/OSAVI)	$3^*[(RE-R)-0.2^*(RE-G)(RE/R)]/[(1+0.16)(NIR-R)/(NIR+R+0.16)]$ $3^*[(R_{700}-R_{670})-0.2^*(R_{700}-R_{550})(R_{700}/R_{670})]/[(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)]$	Haboudane et al. (2002)
Modified chlorophyll absorption in reflectance index index/Optimized soil-adjusted vegetation index (MCARI/OSAVI)	$\{[(RE-R)-0.2^*(RE-G)](RE/R)\}/[(1+0.16)(NIR-R)/(NIR+R+0.16)]$ $\{[(R_{700}-R_{670})-0.2^*(R_{700}-R_{550})](R_{700}/R_{670})\}/[(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)]$	Haboudane et al. (2002)
Red edge-based transformed chlorophyll absorption in reflectance index/Optimized soil-adjusted vegetation index (TCARI/OSAVI_RE)	$3^*[(NIR-RE)-0.2^*(NIR-G)(NIR/RE)]/[(1+0.16)(NIR-RE)/(NIR+RE+0.16)]$ $3^*[(R_{750}-R_{705})-0.2^*(R_{750}-R_{550})(R_{750}/R_{705})]/[(1+0.16)(R_{750}-R_{705})/(R_{750}+R_{705}+0.16)]$	Wu et al. (2008)
Red edge-based modified chlorophyll absorption in reflectance index index/Optimized soil-adjusted vegetation index (MCARI/OSAVI_RE)	$\{[(NIR-RE)-0.2^*(NIR-G)](NIR/RE)\}/[(1+0.16)(NIR-RE)/(NIR+RE+0.16)]$ $\{[(R_{750}-R_{705})-0.2^*(R_{750}-R_{550})](R_{750}/R_{705})\}/[(1+0.16)(R_{750}-R_{705})/(R_{750}+R_{705}+0.16)]$	Wu et al. (2008)

* G, R, RE and NIR represent green, red, red edge and near infrared bands of Crop Circle ACS 470 or WorldView-2 sensor, respectively. The specific band positions for the narrow band vegetation indices are given below the corresponding general formulas.

In order to evaluate the influence of bandwidth on the performance of spectral indices for estimating maize N concentration and uptake, the aforementioned indices were calculated using the ASD hyperspectral narrow bands, simulated Crop Circle ACS-470 sensor short bands (green: 530–570 nm, red: 630–670 nm, red edge: 720–740 nm, NIR: 760–780 nm) and simulated WorldView-2 satellite broad bands (green: 510–580 nm, red: 630–690 nm, red edge: 705–745 nm, NIR: 770–895 nm).

2.4. Field sampling and measurements

To obtain a representative plant sample, aboveground biomass were destructively sampled at the V6 and V7 and V10–V12 stages by randomly cutting 3–6 consecutive rows in 2 m length in the middle of each plot after canopy reflectance measurements were taken. All plant samples were oven dried at 70 °C to constant weight and then weighed and ground for chemical analysis later. A subsample was taken from the ground samples for Kjeldahl-N determination. The plant N uptake ($kg\,N\,ha^{-1}$) was determined by multiplying plant N concentration (%) and aboveground dry biomass.

2.5. Data analysis

The correlations between plant N concentration and uptake of summer maize and different bandwidth spectral indices were analyzed using SAS software (SAS Institute Inc., Cary, NC, USA). Data collected from different growth stages were used to develop regression models. Relationships between spectral indices of the canopy and plant N concentration and uptake were established. The stabilities of different spectral indices under different growth stages, cultivars, locations and years were tested. Sensitivities of the different spectral vegetation indices for detecting changes in plant N uptake across growth stages was tested through the use of the Noise Equivalent (NE) as the method reported by Viña et al. (2011).

$$NE = \frac{RMSE\{VI\ vs.\ Plant\ N\ uptake\}}{[d(VI)/d(Plant\ N\ uptake)]} \quad (1)$$

where $d(VI)/d(Plant\ N\ uptake)$ is the first derivative of the best-fit function of the relationship "spectral indices vs. Plant N uptake". RMSE is the root mean square error of the best-fit function of this relationship. The lower the NE, the higher the sensitivity of the vegetation index to N uptake. It allows the direct comparison among different spectral indices with different scales and dynamic ranges (Viña et al., 2011).

3. Results

3.1. Variation of plant N concentration and uptake

Across growth stages, applied N rates, locations, and years, plant N concentrations of maize ranged from 1.18% to 3.61%, with a mean of 2.58%, and plant N uptakes varied from 6 $kg\,N\,ha^{-1}$ to 105 $kg\,N\,ha^{-1}$, with a mean of 49 $kg\,N\,ha^{-1}$. As shown in Fig. 2,

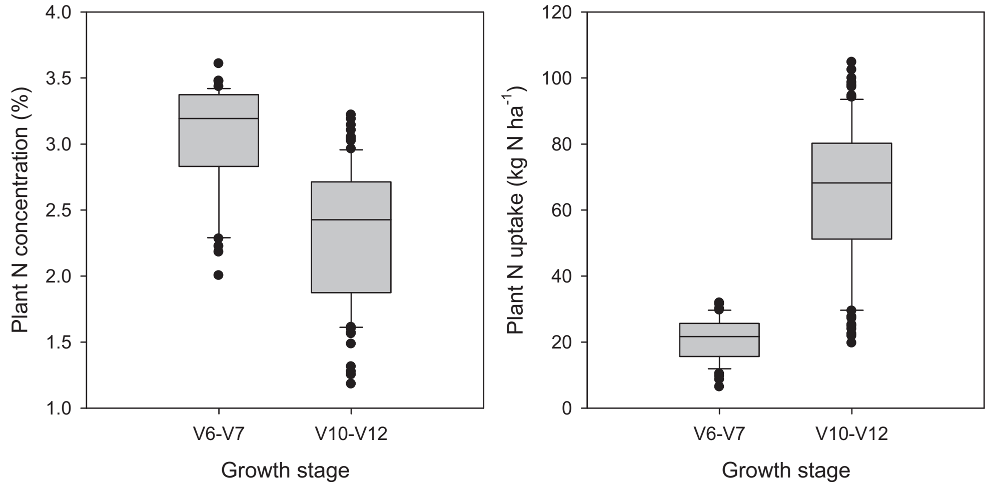

Fig. 2. The variation of (a) plant N concentration and (b) plant N uptake at different growth stages.

the plant N concentration was affected by the "dilution effect" as described by Plénet and Lemaire (2000). The average plant N concentration decreased from 3.07% at the V6 and V7 growth stage to 2.33% at the V10–V12 growth stage while the average plant uptake increased dramatically from 22 kg N ha^{-1} to 70 kg N ha^{-1}. With the development of the growth stages, coefficients of variation (CV) for plant N concentration and uptake increased (Fig. 2).

3.2. At the V6 and V7 stage

The red edge index CCCI performed the best for estimating both maize plant N concentration and uptake at the V6 and V7 stage, with R^2 ranging from 0.65 to 0.68 (Table 2; Figs. 3 and 4). The results were consistent across the three levels of bandwidths. The second best performing index was MTCI, explaining 51–62% and 60–68% of plant N concentration and uptake variability, respectively (Table 2; Figs. 3 and 4). The short and broad band MTCI performed slightly better than the narrow band index. The narrow band TCARI/OSAVI index performed well (R^2 = 0.50–0.57); however, the index lost its sensitivity when the narrow bands were replaced with short and broad bands (R^2 = 0.03–0.18) (Table 2). MCARI/OSAVI was also significantly affected by bandwidth differences. NDVI and RVI only explained 3–19% of plant N concentration and N uptake variability. GNDVI and CI_{green} (R^2 = 0.26–0.47) performed similarly better than NDVI and RVI. Narrow band NDRE and $CI_{red\ edge}$ performed similarly as narrow band NDVI and RVI, but short and broad band NDRE and $CI_{red\ edeg}$ (R^2 = 0.38–0.55) had better performance than corresponding NDVI and RVI (R^2 = 0.04–0.19). The TCARI/OSAVI_RE index performed worse than TCARI/OSAVI, except for short bands, while MCARI/OSAVI_RE performed better than MCARI/OSAVI with both short and broad bands (Table 2).

3.3. At the V10–V12 stage

The performance of NDVI and RVI was better for estimating plant N concentration (R^2 = 0.15–0.19) and uptake (R^2 = 0.54–0.64) at the V10–V12 stage than at the V6 and V7 stage (Table 2). However, the red radiation based indices performed the worst at the V10–V12 stage, as compared with other green and red edge based indices. The CCCI and MTCI indices performed similarly and consistently across bandwidths for estimating plant N concentration (R^2 = 0.33–0.34) (Fig. 5) and uptake (R^2 = 0.77–0.82) (Fig. 6). These two indices explained more variability in plant N uptake, but less viability in plant N concentration at the V10–V12 than at the V6 and V7 stage. Two other red edge indices, NDRE and $CI_{red\ edge}$ (R^2 = 0.30–0.31 for plant N concentration, and R^2 = 0.76–0.80 for plant N uptake) had compatible performance as CCCI and MTCI across bandwidths. The GNDVI also performed quite well for estimating plant N uptake (R^2 = 0.76–0.78). GNDVI and CI_{green} performed similarly for estimating plant N concentration, but CI_{green} had slightly worse performance in plant N uptake estimation (R^2 = 0.70–0.72). The TCARI/OSAVI, MCARI/OSAVI and the red edge counterparts were inconsistent across different bandwidths (Table 2).

3.4. Across growth stages

For plant N uptake estimation, NDVI and RVI performed similarly across growth stages (R^2 = 0.74–0.78) (Fig. 7), with better relationships than at the V6 and V7 or V10–V12 growth stages. However, the red edge indices, including NDRE, CCCI, $CI_{red\ edge}$, MTCI, MCARI/OSAVI_RE, all performed significantly better (R^2 = 0.84–0.91) than NDVI and RVI across bandwidths (Figs. 8–10). The green radiation based indices, GNDVI and CI_{green}, also had better performance than NDVI and RVI for assessing plant N uptake (R^2 = 0.85–0.88) (Figs. 8 and 9). TCARI/OSAVI had similar performance as NDVI and RVI across bandwidths; however, MCARI/OSAVI and TCARI/OSAVI_RE were highly sensitive to bandwidth changes.

For plant N concentration, none of the indices performed satisfactorily. The best performing index was MCARI/OSAVI (R^2 = 0.30–0.44) (Table 2). The red edge indices did not improve model performance over red or green radiation-based indices.

3.5. Sensitivity analysis of regression models

Similar R^2 were achieved in the regression models based on eight vegetation indices for estimating plant N uptake across growth stages. To further evaluate these indices, a sensitivity analysis was performed using NE as presented by Viña et al. (2011) (Fig. 11). Results indicated that NDVI based models showed the highest NE values when plant N uptake exceeded 45 kg N ha^{-1} and 36 kg N ha^{-1} for narrow and short band data and broadband data, respectively. The GNDVI-based models consistently had the second or third high NE for assessing plant N uptake exceeding 60 kg N ha^{-1}. The narrow band CI_{green} model had quite high NE, while short and broadband CI_{green} had similar NE as the red edge indices. The narrow band RVI model had quite low NE, but the short and broad band RVI had similar NE as GNDVI. In contrast, NDRE, CCCI, $CI_{Red\ edge}$, and MTCI exhibited consistent low NE for plant N uptake estimation.

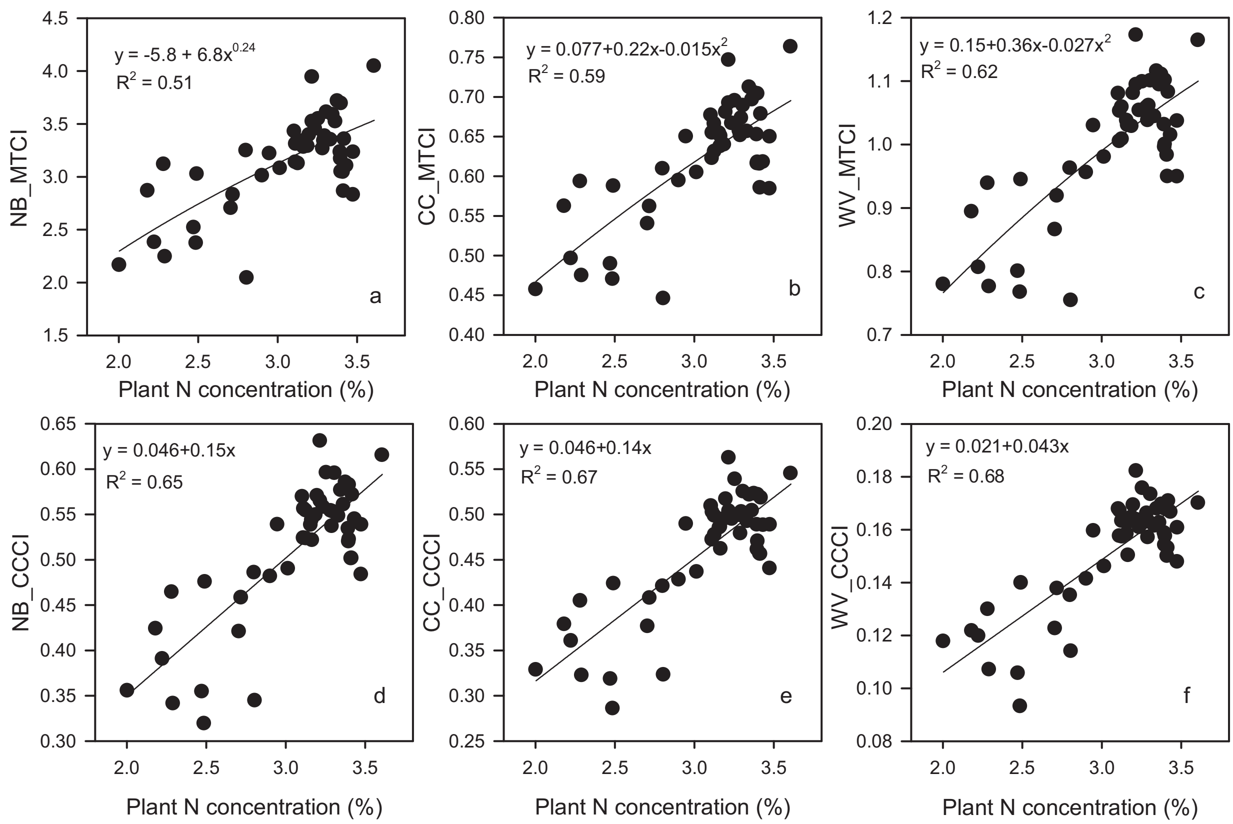

Fig. 3. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_MTCI, (b) CC_MTCI, (c) WV_MTCI, (d) NB_CCCI (e) CC_CCCI and (f) WV_CCCI vs. plant N concentration for summer maize at the V6 and V7 growth stages.

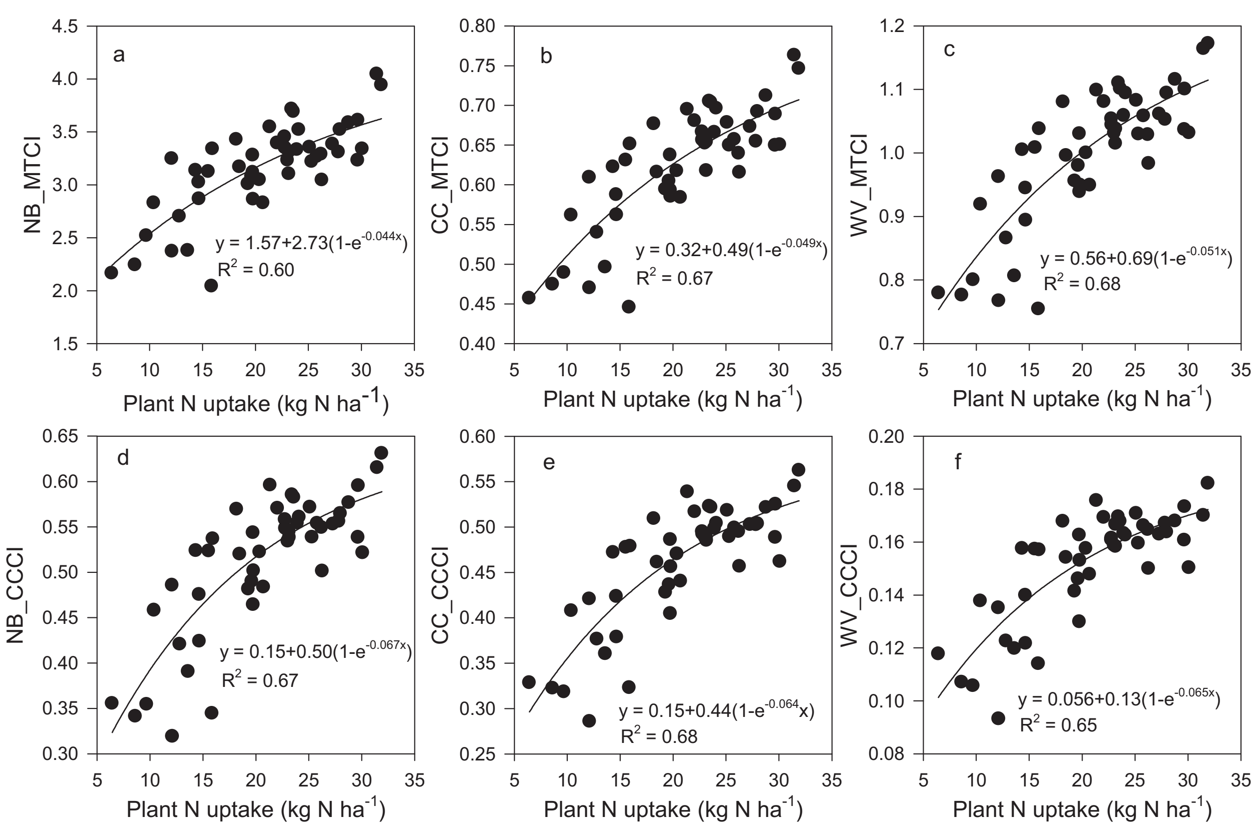

Fig. 4. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_MTCI, (b) CC_MTCI, (c) WV_MTCI, (d) NB_CCCI (e) CC_CCCI and (f) WV_CCCI vs. plant N uptake for summer maize at the V6 and V7 growth stages.

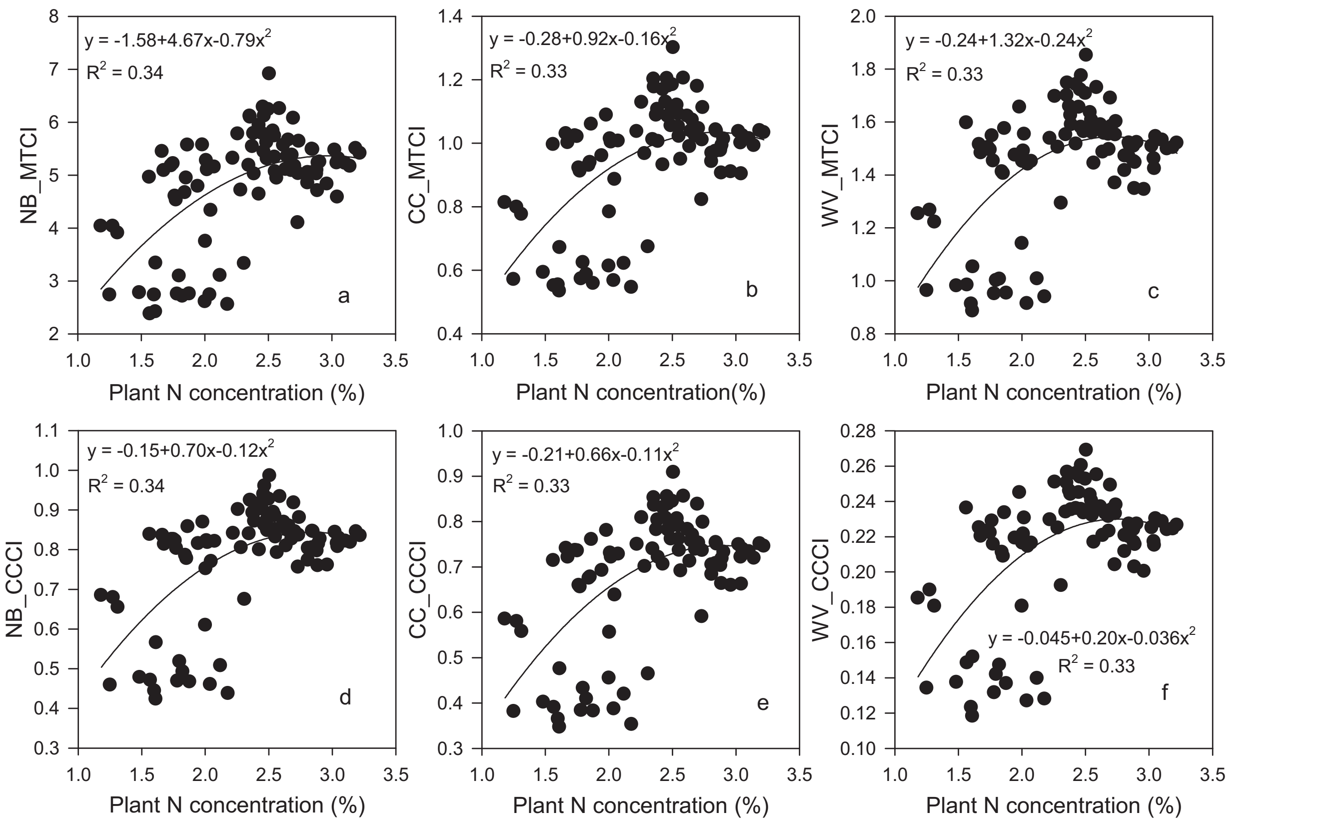

Fig. 5. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_MTCI, (b) CC_MTCI, (c) WV_MTCI, (d) NB_CCCI (e) CC_CCCI and (f) WV_CCCI vs. plant N concentration for summer maize at the V10–V12 growth stages.

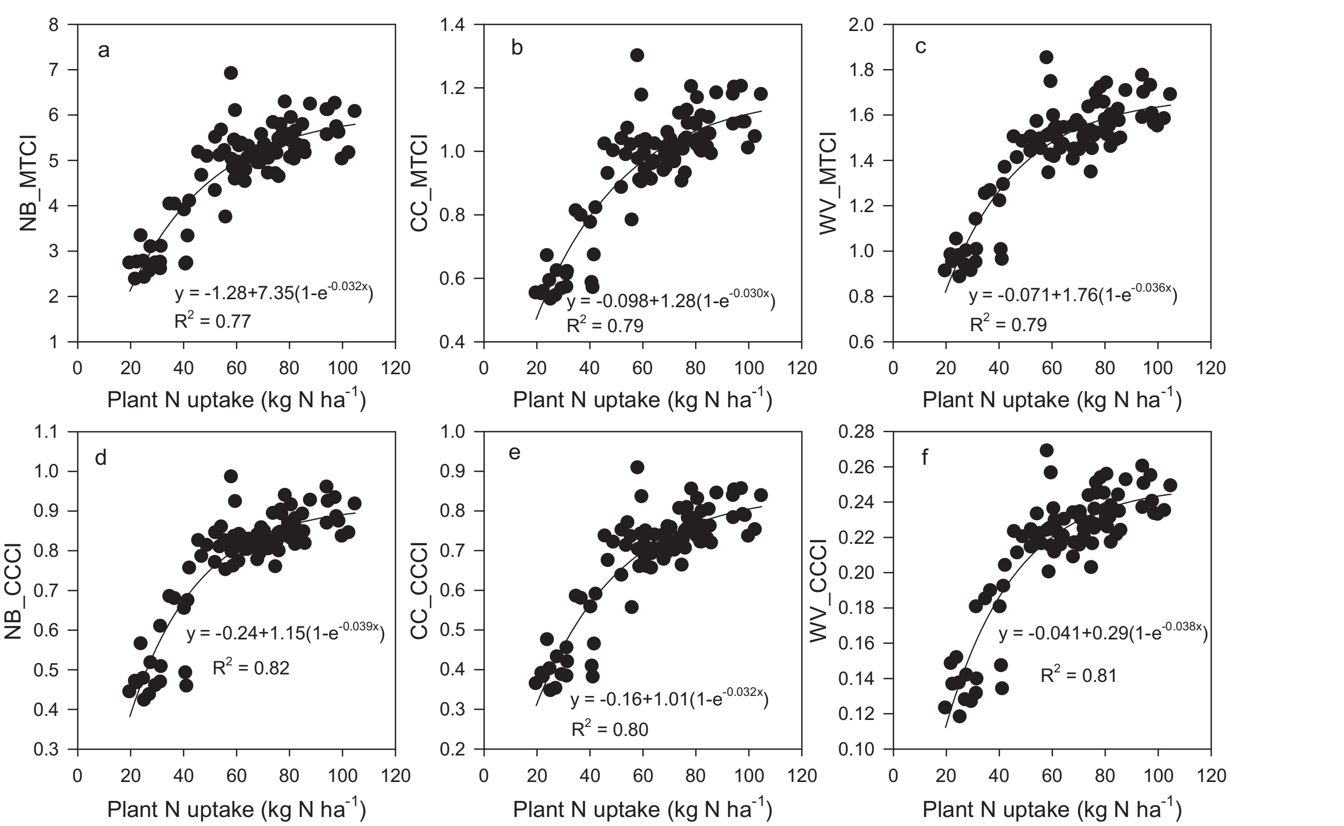

Fig. 6. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_MTCI, (b) CC_MTCI, (c) WV_MTCI, (d) NB_CCCI (e) CC_CCCI and (f) WV_CCCI vs. plant N uptake for summer maize at the V10–V12 growth stages.

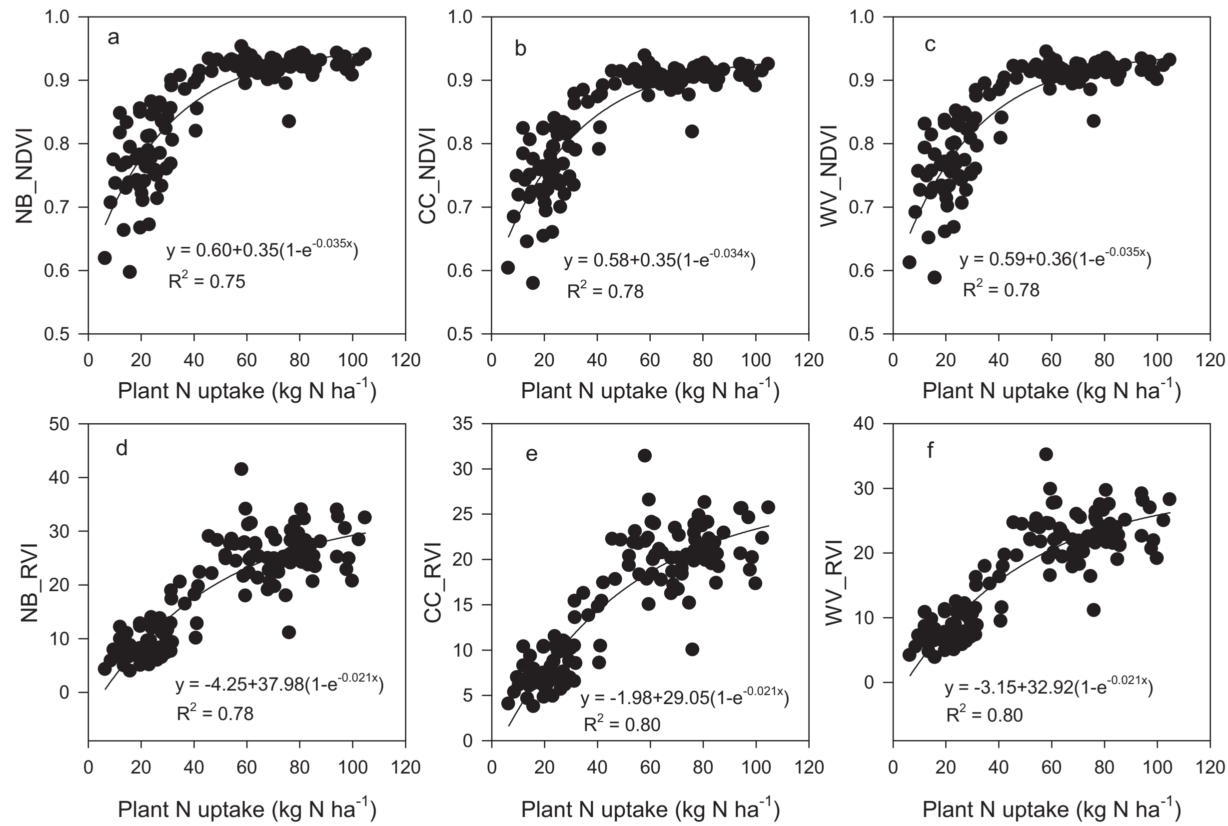

Fig. 7. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_NDVI, (b) CC_NDVI, (c) WV_NDVI, (d) NB_RVI (e) CC_RVI and (f) WV_RVI vs. plant N uptake for summer maize across growth stages (V6–V12).

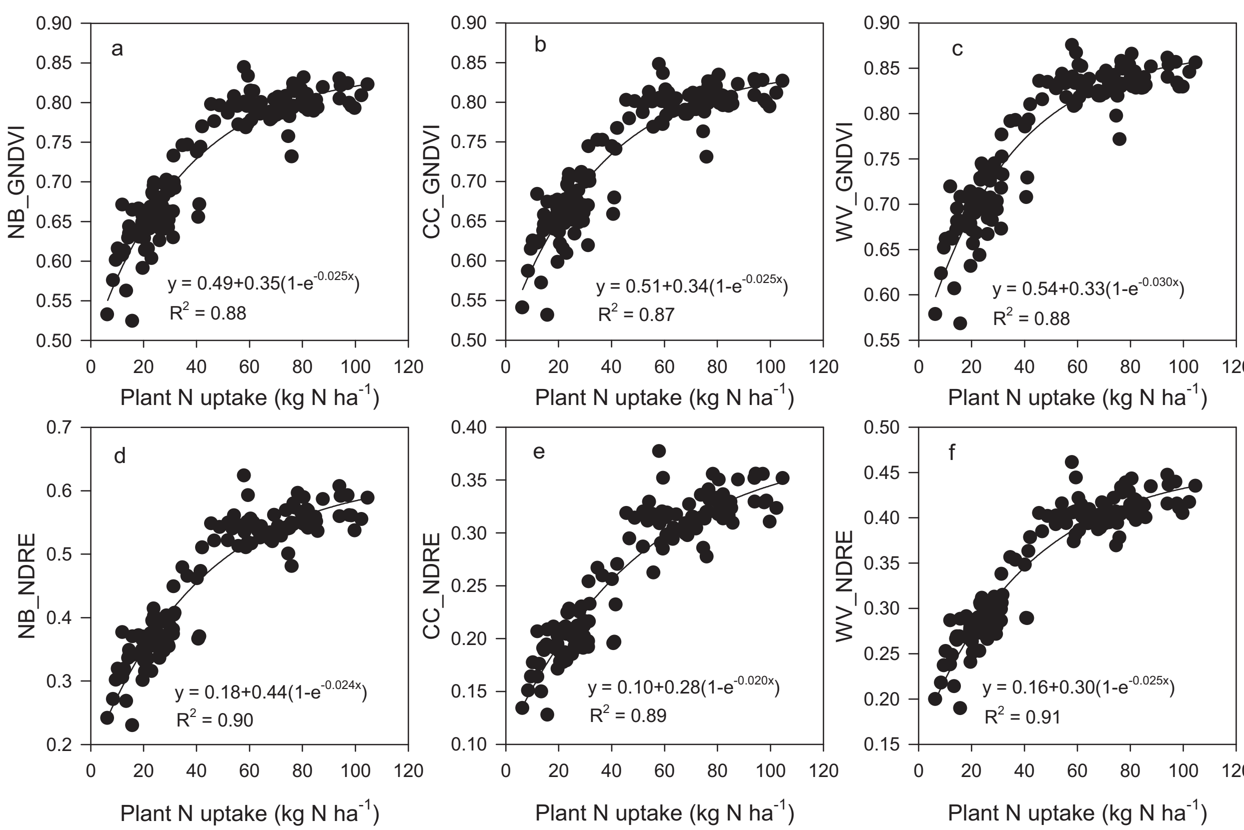

Fig. 8. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_GNDVI, (b) CC_GNDVI, (c) WV_GNDVI, (d) NB_NDRE (e) CC_NDRE and (f) WV_NDRE vs. plant N uptake for summer maize across growth stages (V6–V12).

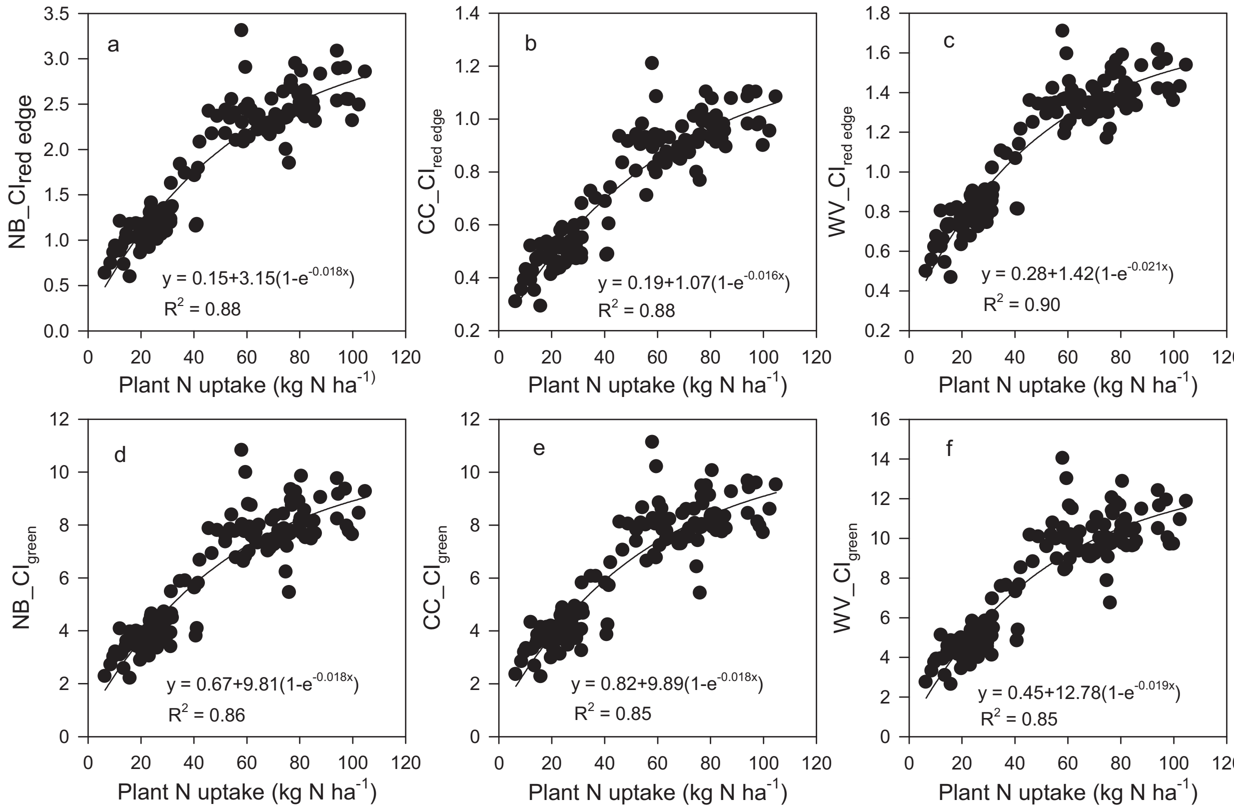

Fig. 9. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_$CI_{red\ edge}$, (b) CC_ $CI_{red\ edge}$, (c) WV_$CI_{red\ edge}$, (d) NB_CI_{green} (e) CC_CI_{green} and (f) WV_ CI_{green} vs. plant N uptake for summer maize across growth stages (V6–V12).

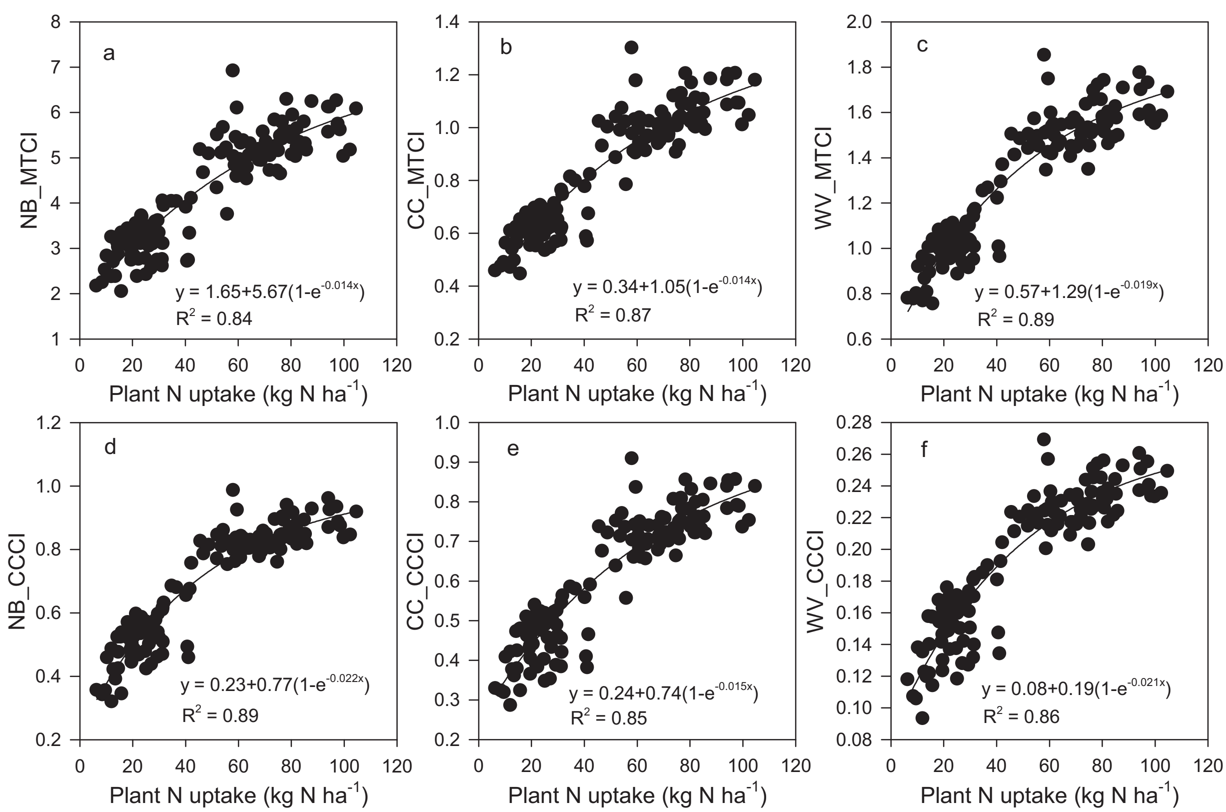

Fig. 10. Relationships between narrow band (NB), short band (simulated bands of Crop Circle ACS-470 sensor, CC) and broad band (simulated bands of WorldView-2 satellite, WV) spectral indices (a) NB_MTCI, (b) CC_MTCI, (c) WV_MTCI, (d) NB_CCCI (e) CC_CCCI and (f) WV_CCCI vs. plant N uptake for summer maize across growth stages (V6–V12).

Table 2
Coefficient of determination (R^2) for the best fitting models between spectral indices and plant N concentration and uptake at different growth stages.

Spectral indices	Narrow band				Short band				Broad band			
	N concentration (%)		N uptake (kg N ha^{-1})		N concentration (%)		N uptake (kg N ha^{-1})		N concentration (%)		N uptake (kg N ha^{-1})	
	Model	R^2	Model	R^2	Model	R^2	Model	R^2	Model	R^2	Model	R^2
V6 and V7 growth stage												
NDVI	P	0.04	Q	0.14	P	0.06	P	0.17	P	0.06	P	0.17
GNDVI	P	0.32	P	0.47	P	0.29	P	0.44	P	0.27	P	0.42
NDRE	P	0.34	P	0.49	P	0.40	P	0.55	P	0.39	Q	0.53
$CI_{red\ edge}$	P	0.33	P	0.49	P	0.40	P	0.55	P	0.38	Q	0.53
CI_{green}	P	0.31	L	0.47	P	0.28	Q	0.45	P	0.26	Q	0.43
RVI	Q	0.03	Q	0.16	P	0.04	Q	0.19	P	0.04	Q	0.19
MTCI	P	0.51	E	0.60	Q	0.59	E	0.67	Q	0.62	E	0.68
CCCI	L	0.65	E	0.67	L	0.67	E	0.68	L	0.68	E	0.65
TCARI/OSAVI	Q	0.57	Q	0.50	Q	0.03	Q	0.17	Q	0.03	Q	0.18
MCARI/OSAVI	Q	0.39	Q	0.27	Q	0.01	Q	0.06	Q	0.02	Q	0.05
TCARI/OSAVI_RE	L	0.16	Q	0.36	P	0.26	Q	0.35	Q	0.01	Q	0.04
MCARI/OSAVI_RE	P	0.09	E	0.22	P	0.29	P	0.42	P	0.25	P	0.37
V10–V12 growth stage												
NDVI	Q	0.16	E	0.59	Q	0.19	E	0.64	Q	0.18	Q	0.64
GNDVI	Q	0.27	E	0.78	Q	0.26	E	0.77	Q	0.25	Q	0.76
NDRE	Q	0.30	E	0.79	Q	0.31	E	0.79	Q	0.30	E	0.80
$CI_{red\ edge}$	Q	0.30	P	0.76	Q	0.31	P	0.78	Q	0.30	Q	0.77
CI_{green}	Q	0.27	P	0.72	Q	0.26	P	0.72	Q	0.24	P	0.70
RVI	Q	0.15	P	0.54	Q	0.18	P	0.59	Q	0.17	P	0.58
MTCI	Q	0.34	E	0.77	Q	0.33	E	0.79	Q	0.33	E	0.79
CCCI	Q	0.34	E	0.82	Q	0.33	E	0.80	Q	0.33	E	0.81
TCARI/OSAVI	Q	0.03	Q	0.11	Q	0.13	Q	0.50	Q	0.13	Q	0.49
MCARI/OSAVI	Q	0.27	Q	0.51	P	0.08	Q	0.32	P	0.08	Q	0.31
TCARI/OSAVI_RE	Q	0.28	Q	0.70	Q	0.16	Q	0.24	Q	0.08	Q	0.23
MCARI/OSAVI_RE	Q	0.30	P	0.66	Q	0.33	P	0.70	Q	0.28	P	0.63
V6–V12 growth stage												
NDVI	Q	0.24	E	0.75	Q	0.23	E	0.78	Q	0.24	E	0.78
GNDVI	Q	0.18	E	0.88	Q	0.17	E	0.87	Q	1.18	E	0.88
NDRE	Q	0.21	E	0.90	Q	0.19	E	0.89	Q	0.20	E	0.91
$CI_{red\ edge}$	Q	0.24	E	0.88	Q	0.21	E	0.88	Q	0.23	E	0.90
CI_{green}	Q	0.23	E	0.86	Q	0.23	E	0.85	Q	0.24	E	0.85
RVI	Q	0.27	E	0.78	Q	0.26	E	0.80	Q	0.27	E	0.80
MTCI	Q	0.18	E	0.84	Q	0.19	E	0.87	Q	0.20	E	0.89
CCCI	Q	0.17	E	0.89	Q	0.16	E	0.85	Q	0.22	E	0.86
TCARI/OSAVI	Q	0.33	Q	0.74	Q	0.25	Q	0.77	Q	0.25	Q	0.77
MCARI/OSAVI	E	0.44	Q	0.05	Q	0.30	Q	0.71	Q	0.31	Q	0.71
TCARI/OSAVI_RE	Q	0.21	Q	0.81	Q	0.18	Q	0.72	L	0.15	Q	0.14
MCARI/OSAVI_RE	Q	0.24	E	0.84	Q	0.24	E	0.87	Q	0.26	E	0.86

E, L, P, Q = Exponential, Linear, Power, Quadratic fit.

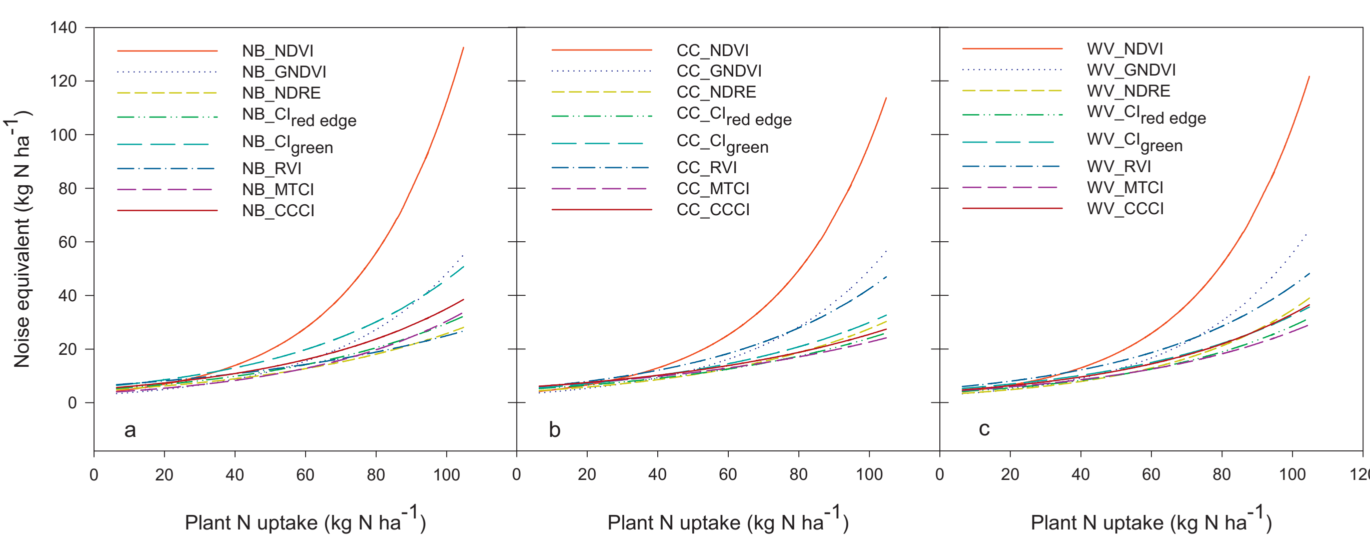

Fig. 11. Noise equivalent of plant N uptake estimation by the (a) narrow band (NB), (b) simulated Crop Circle (CC) ASC-470 short band and (c) simulated WorldView-2 (WV) broadband spectral indices of NDVI, GNDVI, NDRE, $CI_{red\ edge}$, CI_{green}, RVI, MTCI and CCCI across growth stages (V6–V12).

4. Discussion

Plant N concentration and uptake are important crop N status indicators, which can be used to guide farmers for N management. As the product of plant N concentration and aboveground biomass per unit ground area, plant N uptake increases with the development of the growth stage. In contrast, plant N concentration decreases with crop development due to the dilution effect. Since 50–70% of total corn leaf N is associated with chloroplast, more N supply can increase leaf chlorophyll concentration, which absorbs more light and decreases reflectance of visible wavebands (Dwyer et al., 1995; Heege et al., 2008). On the other hand, more N supply increases plant biomass and LAI, resulting in more scattering back of incident solar radiation in the NIR region by the plant canopy (Heege et al., 2008). It should be pointed out that the relationship between leaf N and chlorophyll concentration is not linear (Dwyer et al., 1995), so vegetation indices best for estimating leaf chlorophyll concentration may not be the best indices for estimating leaf and plant N concentration.

The CCCI index was consistently among the best indices for estimating plant N uptake at the V6 and V7 (R^2 = 0.65–0.68), V10–V12 (R^2 = 0.80–0.82) and across growth stages (R^2 = 0.85–0.89). Based on NDRE and NDVI, the CCCI index uses three bands (red, red edge and NIR). The NDVI is used as a surrogate for ground cover to separate soil signal from plant signal and the NDRE is used as a measure of canopy N status (Fitzgerald et al., 2010). It therefore permits a relative measure of N status without being significantly affected by ground cover (Fitzgerald et al., 2006, 2010). This may explain why it had the best correlation with plant N concentration at both the V6 and V7 (R^2 = 0.65–0.68) and the V10–V12 (R^2 = 0.33–0.34) stages. At the V6 and V7 stage, soil background influence on canopy reflectance could be strong, but CCCI could isolate crop signal from soil reflectance as a function of canopy cover changes (Cammarano et al., 2011). Consequently, CCCI had the best performance as compared with all other evaluated vegetation indices. However, across growth stages, it only explained 17% model variability. This may be caused by the fact that from V6 to V12, plant biomass increased rapidly, and N uptake could not keep pace with biomass increases, and canopy reflectance was dominated by biomass (Li et al., 2012). Therefore, growth stage-specific models will be preferred for estimating plant N concentration, while a general model across growth stages will be sufficient for estimating plant N uptake. This index was also very stable across different bandwidths (narrow, short and broad bands), showing great potential for estimating plant N concentration and uptake using Crop Circle ACS 470 canopy sensor at ground level or WorldView 2 satellite remote sensing at regional level. Perry et al. (2012) evaluated the potential of using RapidEye satellite remote sensing and CCCI to estimate wheat canopy N at the whole paddock scale in Australia and achieved promising results. However, more studies are needed to further evaluate the CCCI index for precision N management using both actual Crop Circle ACS 470 and WorldView 2 or RapidEye satellite remote sensing technologies.

The MTCI index and CCCI had comparable performance for estimating maize plant N uptake and concentration, with the exception at the V6 and V7 stage when MTCI explained 6–14% less variability in plant N concentration. Dash et al. (2010) noted MTCI was strongly correlated with chlorophyll content across different crops (R^2 = 0.62-0.80). The MTCI and DATT had the best ability to differentiate the effect of N fertilizer rate on maize canopy status, with MTCI showing less saturation with increasing N rate (Shiratsuchi et al., 2011). They were also least affected by water stress among the indices tested (Shiratsuchi et al., 2011). At early growth stages (V6 and V7), MTCI index could be affected by soil background, resulting in lower R^2 for the relationship with plant N concentration in this study relative to CCCI, which accounted for ground cover information. In addition, MTCI was much easier to calculate compared with REP and CCCI, and was also sensitive to high values of chlorophyll content (Dash and Curran, 2004). It was quite stable across growth stages and bandwidths and can be easily automated, showing a great potential for monitoring maize N status. More studies are needed to further test this index for monitoring crop N status under high yielding intensive farming conditions, especially using WorldView 2 or RapidEye satellite images.

The NDRE used two bands (NIR and red edge). It had similar performance as CCCI at the V10–V12 stage and across growth stages. However, at the V6 and V7 stage, it explained 27–31% and 12–18% less variability in plant N concentration and uptake, respectively than CCCI in this study. This result indicated that at the V6 and V7 stage, soil background had strong influence on this index, while CCCI reduced this influence by accounting for ground cover factions using NDVI. At later growth stages (V10–V12), the soil influence was smaller, and the performance of NDRE and CCCI was similar. The NDRE explained 30–33% and 35–38% more variability in plant N concentration and uptake, respectively, relative to NDVI at the V6 and V7 stage. At the V10–V12 stage, NDRE explained 12–14% and 15–20% more variability in plant N concentration and uptake, respectively, than NDVI. Across growth stages, NDRE did not perform better than NDVI for estimating plant N concentration, but explained 11–15% more variability in plant N uptake than NDVI (Table 2). The performance of NDRE was also very consistent across bandwidths. Therefore, at later growth stages, NDRE would also be a suitable index, but CCCI or MTCI would be preferred at early growth stages when soil background has strong influence. Long et al. (2009) developed a simplified CCCI (NDRE/NDVI) to estimate dryland winter wheat N status, and found that this simplified CCCI had higher correlations with wheat chlorophyll (R^2 = 0.46) and leaf N concentration (R^2 = 0.31) than NDRE ($R^2 \leq 0.16$) or NDVI ($R^2 \leq 0.09$). It explained chlorophyll and leaf N concentration variability well in two farm fields ($R^2 \leq 0.79$), while NDRE or NDVI only performed well in one field. This simplified CCCI was easier to calculate than the original CCCI based on the theory of two-dimensional planar domain, and should be further evaluated against the original CCCI.

The GNDVI also performed significantly better than NDVI in estimating plant N concentration or uptake at both stages, especially at the V6 and V7 stage. It performed similarly as or slightly worse than NDRE. These results support the findings that green and red edge reflectance's are sensitive to a wider range of chlorophyll levels than red reflectance (Carter, 1993; Carter and Knapp, 2001). Additionally, the red edge band could be influenced by stress induced increase in fluorescence, and thus is more sensitive to stress induced chlorophyll changes than the green band (Carter and Miller, 1994).

The ratio vegetation indices (RVI, CI_{green} and $CI_{red\ edge}$) performed similarly as their NDVI counterparts in this study, as evaluated with R^2. However, R^2 is an indicator of how well the best-fit function captures the relationship between vegetation index and an N status parameter. It can be misleading if the best-fit function is not linear, because sensitivity of the vegetation index to the N status indicator will not be constant (Gitelson, 2013). Under such conditions, NE is a better indicator of vegetation index performance in estimating plant N status, because it accounts for both scattering of the points and the slope of the best-fit function (Gitelson, 2013). Some spectral vegetation indices can have similar R^2 but very different shapes of relationships with plant N uptake. When evaluated with NE, RVI was more sensitive than NDVI after plant N uptake reached 40 kg ha^{-1}, and CI was more sensitive than GNDVI after plant N uptake reached about 50 kg ha^{-1} with the short and broad bands. The $CI_{red\ edge}$ and NDRE had very similar NE. This is different from Nguy-Robertson et al. (2012) finding that that normalized difference indices (NDVI, GNDVI and NDRE, etc.) were most sensitive to green leaf area index (gLAI) below 2, while ratio indices

(RVI, CI_{green} $CI_{red\ edge}$) were most sensitive to gLAI above 2. Our results indicated that the short- and broad-band CCCI, MTCI, NDRE, $CI_{red\ edge}$, and CI_{green} all performed similarly for estimating plant N uptake form V6 to V12 stage.

All these results indicated the importance of adding the red edge band in the short band active crop canopy sensors and broadband satellite borne sensors for monitoring crop N status. More studies are needed to evaluate the actual Crop Circle ACS 470 sensor and WorldView 2 or RapidEye satellite remote sensing images for in-season crop N status diagnosis, as well as the combination of ground and satellite or aerial remote sensing technologies as suggested by Miao et al. (2009). More importantly, red edge vegetation index-based algorithms for in-season N recommendation and management also need to be developed.

5. Conclusions

The results of this study showed that CCCI performed most consistently across different bandwidths for both N concentration and uptake estimations. The best model for assessing summer maize plant N concentration at the early growth stage (V6 and V7) was found with CCCI since it accounts for ground cover fractions. For estimating plant N uptake at this stage, CCCI and MTCI based models were the best. For plant N uptake at the V10–V12 and V6–V12 stages, all the four red edge indices – CCCI, MTCI, NDRE and $CI_{red\ edge}$ – performed similarly and constantly better than NDVI and RVI. The latter two indices were also consistently worse than GNDVI and CI_{green}. These results demonstrated the importance of red edge vegetation indices for estimating summer maize N status. This study also provides insights for in-season variable rate N management using commercial active crop sensors and newly launched satellite remote sensing platforms with red edge bands. Further studies may investigate the stability and transferability of the best performing spectral indices at heterogeneous maize production agro-ecosystems using actual Crop Circle active canopy sensors and satellite remote sensing images.

Acknowledgements

This research was financially supported by the Natural Science Foundation of China (31060273), National Basic Research Program (973-2009CB118606), The Innovative Group Grant of Natural Science Foundation of China (31121062), and Special Fund for Agro-scientific Research in the Public Interest (201103003).

References

Barker, D.W., Sawyer, J.E., 2012. Using active canopy sensing to adjust nitrogen application rate in corn. Agron. J. 104, 926–933.

Bijay-Singh, Sharma, R.K., Jaspreet-Kaur, Jat, M.L., Martin, K.L., Yadvinder-Singh, Varinderpal-Singh, Chandna, P., Choudhary, O.P., Gupta, R.K., Thind, H.S., Jagmohan-Singh, Uppal, H.S., Khurana, H.S., Ajay-Kumar, Uppal, R.K., Vashistha, M., Raun, W.R., Gupta, R., 2011. Assessment of the nitrogen management strategy using an optical sensor for irrigated wheat. Agron. Sustain. Dev. 31, 589–603.

Cammarano, D., Fitzgerald, G., Basso, B., O'Leary, G., Chen, D., Grace, P., Fiorentino, C., 2011. Use of the canopy chlorophyll content index (CCCI) for remote estimation of wheat nitrogen content in rainfed environments. Agron. J. 103, 1597–1603.

Cao, Q., Cui, Z., Chen, X., Khosla, R., Dao, T.H., Miao, Y., 2012. Quantifying spatial variability of indigenous nitrogen supply for precision nitrogen management in small scale farming. Precis. Agric. 13, 45–61.

Cao, Q., Miao, Y., Wang, H., Huang, S., Cheng, S., Khosla, R., Jiang, R., 2013. Non-destructive estimation of rice plant nitrogen status with Crop Circle multispectral active canopy sensor. Field Crops Res. 154, 133–144.

Carter, G.A., 1993. Response of leaf spectral reflectance to plant stress. Am. J. Bot. 80, 239–243.

Carter, G.A., Knapp, A.K., 2001. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. Am. J. Bot. 88, 677–684.

Carter, G.A., Miller, R.L., 1994. Early detection of plant stress by digital imaging within narrow stress-sensitive wavebands. Remote Sens. Environ. 50, 295–302.

Chen, X., Cui, Z., Vitousek, P.M., Cassman, K.G., Matson, P.A., Bai, J., Meng, Q., Hou, P., Yue, S., Römheld, V., Zhang, F., 2011. Integrated soil–crop system management for food security. Proc. Natl. Acad. Sci. U. S. A. 108, 6399–6404.

2001. China Agricultural Yearbook. China Agricultural Press, Beijing, China.

2011. China Agricultural Yearbook. China Agricultural Press, Beijing, China.

Clarke, T.R., Moran, M.S., Barnes, E.M., Pinter, P.J., Qi, J., 2001. Planar domain indices: a method for measuring a quality of a single component in two-component pixels. In: Proc. IEEE International Geosci. Remote Sens. Sympos. [CD ROM], Sydney, Australia, 9–13 July.

Cui, Z., Chen, X., Miao, Y., Zhang, F., Sun, Q., Schroder, J., Zhang, H., Li, J., Shi, L., Xu, J., Ye, Y., Liu, C., Yang, Z., Zhang, Q., Huang, S., Bao, D., 2008. On-farm evaluation of the improved soil N_{min}-based nitrogen management for summer maize in North China Plain. Agron. J. 100, 517–525.

Dash, J., Curran, P.J., 2004. The MERIS terrestrial chlorophyll index. Int. J. Remote Sens. 25, 5403–5413.

Dash, J., Curran, P.J., Tallis, M.J., Llewellyn, G.M., Taylor, G., Snoeij, P., 2010. Validating the MERIS Terrestrial Chlorophyll Index (MTCI) with ground chlorophyll content data at MERIS spatial resolution. Int. J. Remote Sens. 31, 5513–5532.

Dellinger, A.E., Schmidt, J.P., Beegle, D.B., 2008. Developing nitrogen fertilizer recommendations for corn using an active sensor. Agron. J. 100, 1546–1552.

Dwyer, L.M., Stewart, D.W., Gregorich, E., Anderson, A.M., Ma, B.L., Tollenaar, M., 1995. Quantifying the nonlinearity in chlorophyll meter response to corn leaf nitrogen concentration. Can. J. Plant Sci. 75 (1), 179–182.

El-Shikha, D.M., Barnes, E.M., Clarke, T.R., Hunsaker, D.J., Haberland, J.A., Pinter Jr., P.J., Waller, P.M., Thompson, T.L., 2008. Remote sensing of cotton nitrogen status using the canopy chlorophyll content index (CCCI). Trans. ASAE 51, 73–82.

El-Shikha, D.M., Waller, P., Hunsaker, D., Clarke, T., Barnes, E., 2007. Ground-based remote sensing for assessing water and nitrogen status of broccoli. Agric. Water Manage. 92, 183–193.

Erdle, K., Mistele, B., Schmidhalter, U., 2011. Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. Field Crops Res. 124, 74–84.

Fitzgerald, G., Rodriguez, D., O'Leary, G., 2010. Measuring and predicting canopy nitrogen nutrition in wheat using a spectral index – the canopy chlorophyll content index (CCCI). Field Crops Res. 116, 318–324.

Fitzgerald, G.J., Rodriguez, D., Christensen, L.K., Belford, R., Sadras, V.O., Clarke, T.R., 2006. Spectral and thermal sensing for nitrogen and water status in rainfed and irrigated wheat environments. Precis. Agric. 7, 233–248.

Freeman, K.W., Girma, K., Arnall, D.B., Mullen, R.W., Martin, K.L., Teal, R.K., Raun, W.R., 2007. By-plant prediction of corn forage biomass and nitrogen uptake at various growth stages using remote sensing and plant height. Agron. J. 99, 530–536.

Gitelson, A.A., Merzlyak, M.N., 1996. Signature analysis of leaf reflectance spectra: algorithm development for remote sensing of chlorophyll. J. Plant Physiol. 148, 494–500.

Gitelson, A.A., Viña, A., Ciganda, V., Rundquist, D.C., Arkebauer, T.J., 2005. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32, L08403.1–L08403.4.

Gitelson, A.A., 2013. Remote estimation of crop fractional vegetation cover: the use of noise equivalent as an indicator of performance of vegetation indices. Int. J. Remote Sens., 1–13.

Gnyp, M.L., Miao, Y., Yuan, F., Ustin, S.L., Yu, K., Yao, Y., Huang, S., Bareth, G., 2014. Hyperspectral canopy sensing of paddy rice aboveground biomass at different growth stages. Field Crops Res. 155, 42–55.

Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., Dextraze, L., 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sens. Environ. 81, 416–426.

Hatfield, J.L., Gitelson, A.A., Schepers, J.S., Walthall, C.L., 2008. Application of spectral remote sensing for agronomic decisions. Agron. J. 100, 117–131.

Heege, H.J., Reusch, S., Thiessen, E., 2008. Prospects and results for optical systems for site-specific on-the-go control of nitrogen-top-dressing in Germany. Precis. Agric. 9, 115–131.

Jordan, C.F., 1969. Derivation of leaf-area index from quality of radiation on the forest floor. Ecology 50, 663–666.

Kanke, Y., Raun, W., Solie, J., Stone, M., Taylor, R., 2012. Red edge as a potential index for detecting differences in plant nitrogen status in winter wheat. J. Plant Nutri. 35, 1526–1541.

Kitchen, N.R., Sudduth, K.A., Drummond, S.T., Scharf, P.C., Palm, H.L., Roberts, D.F., Vories, E.D., 2010. Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. Agron. J. 102, 71–84.

Li, F., Miao, Y., Zhang, F., Cui, Z., Li, R., Chen, X., Zhang, H., Schroder, J., Raun, W.R., Jia, L., 2009. In-season optical sensing improves nitrogen-use efficiency for winter wheat. Soil Sci. Soc. Am. J. 73, 1566–1574.

Li, F., Miao, Y., Chen, X., Zhang, H., Jia, L., Bareth, G., 2010. Estimating winter wheat biomass and nitrogen status using an active crop sensor. Intell. Autom. Soft Comput. 16, 1221–1230.

Li, F., Mistele, B., Hu, Y., Yue, X., Yue, S., Miao, Y., Chen, X., Cui, Z., Meng, Q., Schmidhalter, U., 2012. Remotely estimating aerial N status of phenologically differing winter wheat cultivars grown in contrasting climatic and geographic zones in China and Germany. Field Crops Res. 138, 21–32.

Long, D.S., Eitel, J.U., Huggins, D.R., 2009. Assessing nitrogen status of dryland wheat using the canopy chlorophyll content index. Crop Manag., http://dx.doi.org/10.1094/CM-2009-1211-1001-RS.

Martin, K.L., Girma, K., Freeman, K.W., Teal, R.K., Tubana, B., Arnall, D.B., Chung, B., Walsh, O., Solie, J.B., Stone, M.L., Raun, W.R., 2007. Expression of variability in

corn as influenced by growth stage using optical sensor measurements. Agron. J. 99, 384–389.
Miao, Y., Mulla, D., Randall, G., Vetsch, J., Vintila, R., 2009. Combining chlorophyll meter readings and high spatial resolution remote sensing images for in-season site-specific nitrogen management of corn. Precis. Agric. 10, 45–62.
Miao, Y., Stewart, B., Zhang, F., 2011. Long-term experiments for sustainable nutrient management in China. A review. Agron. Sustain. Dev. 31, 397–414.
Mistele, B., Schmidhalter, U., 2008. Spectral measurements of the total aerial N and biomass dry weight in maize using a quadrilateral-view optic. Field Crops Res. 106, 94–103.
Nguy-Robertson, A., Gitelson, A., Peng, Y., Viña, A., Arkebauer, T., Rundquist, D., 2012. Green leaf area index estimation in maize and soybean: combining vegetation indices to achieve maximal sensitivity. Agron. J. 104, 1336–1347.
Perry, E.M., Fitzgerald, G.J., Nuttall, J.G., O'Leary, G.J., Schulthess, U., Whitlock, A., 2012. Rapid estimation of canopy nitrogen of cereal crops at paddock scale using a canopy chlorophyll content index. Field Crops Res. 134, 158–164.
Plénet, D., Lemaire, G., 2000. Relationships between dynamics of nitrogen uptake and dry matter accumulation in maize crops. Determination of critical N concentration. Plant Soil 216, 65–82.
Raun, W.R., Solie, J.B., Johnson, G.V., Stone, M.L., Mullen, R.W., Freeman, K.W., Thomason, W.E., Lukina, E.V., 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agron. J. 94, 815–820.
Raun, W.R., Solie, J.B., Stone, M.L., Martin, K.L., Freeman, K.W., Mullen, R.W., Zhang, H., Schepers, J.S., Johnson, G.V., 2005. Optical sensor-based algorithm for crop nitrogen fertilization. Commun. Soil Sci. Plant Anal. 36, 2759–2781.
Roberts, D.F., Adamchuk, V.I., Shanahan, J.F., Ferguson, R.B., Schepers, J.S., 2009. Optimization of crop canopy sensor placement for measuring nitrogen status in corn. Agron. J. 101, 140–149.
Rodriguez, D., Fitzgerald, G.J., Belford, R., Christensen, L.K., 2006. Detection of nitrogen deficiency in wheat from spectral reflectance indices and basic crop eco-physiological concepts. Aust. J. Agric. Res. 57, 781–789.
Rouse, J.W., Has, R.H., Schell, J.A., Deering, D.W., 1974. Monitoring vegetation systems in the great plains with ERTS. In: Third ERTS Symposium, NASA SP-351, Vol. 1, NASA, Washington, DC, pp. 309–317.
Scharf, P.C., Shannon, D.K., Palm, H.L., Sudduth, K.A., Drummond, S.T., Kitchen, N.R., Mueller, L.J., Hubbard, V.C., Oliveira, L.F., 2011. Sensor-based nitrogen applications out-performed producer-chosen rates for corn in on-farm demonstrations. Agron. J. 103, 1683–1691.
Shanahan, J.F., Schepers, J.S., Francis, D.D., Varvel, G.E., Wilhelm, W.W., Tringe, J.M., Schlemmer, M.S., Major, D.J., 2001. Use of remote sensing imagery to estimate corn grain yield. Agron. J. 93, 583–589.
Shaver, T.M., Khosla, R., Westfall, D.G., 2010. Evaluation of two ground-based active crop canopy sensors in maize: growth stage, row spacing, and sensor movement speed. Soil Sci. Soc. Am. J. 74, 2101–2108.
Shaver, T.M., Khosla, R., Westfall, D.G., 2011. Evaluation of two crop canopy sensors for nitrogen variability determination in irrigated maize. Precis. Agric. 12, 892–904.
Shiratsuchi, L., Ferguson, R., Shanahan, J., Adamchuk, V., Rundquist, D., Marx, D., Slater, G., 2011. Water and nitrogen effects on active canopy sensor vegetation indices. Agron. J. 103, 1815–1826.
Solari, F., Shanahan, J., Ferguson, R., Schepers, J., Gitelson, A., 2008. Active sensor reflectance measurements of corn nitrogen status and yield potential. Agron. J. 100, 571–579.
Solari, F., Shanahan, J.F., Ferguson, R.B., Adamchuk, V.I., 2010. An active sensor algorithm for corn nitrogen recommendations based on a chlorophyll meter algorithm. Agron. J. 102, 1090–1098.
Sripada, R.P., Schmidt, J.P., Dellinger, A.E., Beegle, D.B., 2008. Evaluating multiple indices from a canopy reflectance sensor to estimate corn N requirements. Agron. J. 100, 1553–1561.
Tilling, A.K., O'Leary, G.J., Ferwerda, J.G., Jones, S.D., Fitzgerald, G.J., Rodriguez, D., Belford, R., 2007. Remote sensing of nitrogen and water stress in wheat. Field Crops Res. 104, 77–85.
Van Niel, T.G., McVicar, T.R., 2004. Current and potential uses of optical remote sensing in rice-based irrigation systems: a review. Aust. J. Agric. Res. 55 (2), 155–185.
Viña, A., Gitelson, A.A., Nguy-Robertson, A.L., Peng, Y., 2011. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. Remote Sens. Environ. 115, 3468–3478.
Wu, C., Niu, Z., Tang, Q., Huang, W., 2008. Estimating chlorophyll content from hyperspectral vegetation indices: modeling and validation. Agric. Forest Meteorol. 148, 1230–1241.
Yao, Y., Miao, Y., Huang, S., Gao, L., Ma, X., Zhao, G., Jiang, R., Chen, X., Zhang, F., Yu, K., Gnyp, M., Bareth, G., Liu, C., Zhao, L., Yang, W., Zhu, H., 2012. Active canopy sensor-based precision N management strategy for rice. Agron. Sustain. Dev. 32, 925–933.