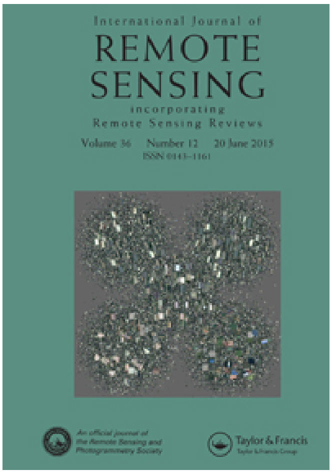

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Modified vegetation indices for estimating crop fraction of absorbed photosynthetically active radiation

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Modified vegetation indices for estimating crop fraction of absorbed photosynthetically active radiation

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The fraction of absorbed photosynthetically active radiation (FPAR) is an important biophysical parameter of vegetation. It is often estimated using vegetation indices (VIs) derived from remote-sensing data, such as the normalized difference VI (NDVI). Ideally a linear relationship is used for the estimation; however, most conventional VIs are affected by canopy background reflectance and their sensitivity to FPAR declines at high biomass. In this study, a multiplier, the ratio of the green to the red reflectance, was introduced to improve the linear relationship between VIs and crop FPAR. Three widely used VIs – NDVI, the green normalized difference VI (GNDVI), and the renormalized difference VI (RDVI) – were modified this way and were called modified NDVI (MNDVI), modified GNDVI (MGNDVI), and modified RDVI (MRDVI), respectively. A sensitivity study was applied to analyse the correlation between the three modified indices and the leaf area index (LAI) using the reflectance data simulated by the combined PROSPECT leaf optical properties model and SAIL canopy bidirectional reflectance model (PROSAIL model). The results revealed that these new indices reduced the saturation trend at high LAI and achieved better linearity with crop LAI at low-to-medium biomass when compared with their corresponding original versions. This has also been validated using *in situ* FPAR measurements over wheat and maize crops. In particular, estimation using MNDVI achieved a coefficient of determination (R^2) of 0.97 for wheat and 0.86 for maize compared to 0.90 and 0.82 for NDVI, respectively, while MGNDVI achieved 0.97 for wheat and 0.88 for maize, compared to 0.90 and 0.81 for GNDVI, respectively. Algorithms based on the VIs when applied to both wheat and maize showed that MNDVI and MGNDVI achieved a better linearity relationship with FPAR (R^2 = 0.92), in comparison with NDVI (R^2 = 0.85) and GNDVI (R^2 = 0.82). The study demonstrated that applying the green to red reflectance ratio can improve the accuracy of FPAR estimation.

1. Introduction

The fraction of absorbed photosynthetically active radiation (FPAR), defined as the fraction of photosynthetically active radiation (PAR) absorbed by vegetation in the 0.4–0.7 μm spectral range, is a critical biophysical parameter for crop growth monitoring and productivity estimation (Dong, Meng, and Wu 2012; Gitelson 2011; Gitelson, Peng, and Huemmrich 2014; Gitelson et al. 2012; McCallum et al. 2010; Wu, Niu, and Gao 2012; Zhang et al. 2014). Satellite-based FPAR estimation, with the advantages of temporal and spatial continuity, has been extensively exploited by many researchers. Methods of FPAR

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estimation from satellite data are generally based on empirical or physical models (Dong, Meng, and Wu 2012). The empirical models are based on regression analysis between vegetation indices (VIs) and ground measured FPAR (Dong, Meng, and Wu 2012; Gitelson, Peng, and Huemmrich 2014; Huemmrich and Goward 1997; Myneni and Williams 1994), whereas the physical models are based on inversion of canopy reflectance models (Bacour et al. 2006; Baret et al. 2007; Gitelson, Peng, and Huemmrich 2014; Gobron et al. 2004; Knyazikhin et al. 1998; Myneni et al. 2002). Many studies showed that FPAR can be estimated from VIs using linear or quasi-linear equations (Epiphanio and Huete 1995; Myneni and Williams 1994; Verger, Baret, and Camacho 2011; Viña and Gitelson 2005). Given its simplicity and computational efficiency, the empirical approach has been widely used for FPAR estimation. For example, the normalized difference VI (NDVI), one of the most commonly used indices that incorporates the near-infrared (NIR) and the red reflectance (Roujean and Breon 1995), has been used and validated for FPAR retrieval in various vegetation types (Gitelson, Peng, and Huemmrich 2014; Myneni and Williams 1994; Roujean and Breon 1995; Rouse et al. 1973; Viña and Gitelson 2005). In practice, the empirical approach has been adopted as a back-up algorithm in generating the Moderate Resolution Imaging Spectroradiometer (MODIS) FPAR/leaf area index (LAI) product when the model based on canopy reflectance modelling fails (Gitelson, Peng, and Huemmrich 2014; Myneni et al. 1997). In the past two decades, it has been acknowledged that FPAR comprises contributions from both photosynthetically active and non-photosynthetically active components of the canopy (Huemmrich and Goward 1997; Knyazikhin et al. 1998; Viña and Gitelson 2005; Zhang et al. 2014, 2009). Several studies have attempted to develop methods for estimating PAR absorbed by green tissues of plants (Huemmrich and Goward 1997; Ogutu and Dash 2013; Viña and Gitelson 2005; Zhang et al. 2014, 2012, 2009). It was observed that both the green LAI and leaf chlorophyll content (LCC) determine FPAR (Di Bellat et al. 2004; Viña and Gitelson 2005), and FPAR from canopy chlorophyll provides more accurate estimation of gross primary productivity (Gao et al. 2006; Zhang et al. 2014, 2012, 2009). Thus, it is advantageous for a VI to be sensitive to both green LAI and LCC.

Different VIs have been used for estimation of FPAR, and an ideal VI should be sensitive to FPAR through the whole dynamic range. However, the relationships between most VIs and FPAR are not stable due to impacts from several external factors such as the illumination geometry (Epiphanio and Huete 1995; Ogutu and Dash 2013; Roujean and Breon 1995), canopy background reflectance (Goward and Huemmrich 1992; Huemmrich and Goward 1997), and canopy structure parameters (Asner and Wessman 1997; Cristiano et al. 2010; Dong et al. 2015; Goel and Qin 1994; Goward and Huemmrich 1992). The relationships are also significantly affected by the saturation effect (Di Bellat et al. 2004; Ridao, Conde, and Minguez 1998; Viña and Gitelson 2005). For example, it is observed that the sensitivity of NDVI decreases when FPAR is greater than 0.7 (Di Bellat et al. 2004; Gitelson, Kaufman, and Merzlyak 1996; Viña and Gitelson 2005). This is partially due to the fact that light absorption by leaf chlorophyll is very strong in the red wavelength region, so that the red reflectance of a canopy becomes invariant easily due to the absorption saturation at high LAI. NIR reflectance also tends to saturate due to stronger light scattering at high LAI (Chen et al. 2004; Epiphanio and Huete 1995; Myneni and Williams 1994). This leads to saturation in VIs that rely on the contrast between the red and the NIR reflectance, and hence degrades the sensitivity to FPAR at moderate to high biomass (Gitelson, Kaufman, and Merzlyak 1996; Gitelson, Kaufman, et al. 2002; Ridao, Conde, and Minguez 1998; Viña and Gitelson 2005). Much effort has been focused on modifying the existing VIs or developing new VIs to reduce the uncertainties in biophysical parameter estimation (Cristiano et al. 2010; Gitelson, Kaufman, et al. 2002; Roujean and Breon 1995; Viña and Gitelson 2005). For example, the renormalized difference VI (RDVI), which combines the advantages of the difference VI (DVI) and NDVI for low and high vegetation cover fraction, respectively, has proved to be better for FPAR estimation, because it is more sensitive to low vegetation cover and less affected by the effect of solar angle than the other VIs (Roujean and Breon 1995; Zhang et al. 2009). The soil-adjusted VI (SAVI), which incorporates an adjustment factor into NDVI to account for background reflectance, can obtain a stronger linear correlation with FPAR than NDVI, especially in low LAI (Epiphanio and Huete 1995; Ridao, Conde, and Minguez 1998). The green NDVI (GNDVI) (Pinter 1993), with the red band reflectance replaced by the green reflectance, exhibits an increased sensitivity to moderate-to-high FPAR in comparison to NDVI; however, its sensitivity decreases as FPAR continues to increase (FPAR > 0.8) (Gitelson, Kaufman, and Merzlyak 1996; Viña and Gitelson 2005). The study by Cristiano et al. (2010) showed that the red-edge NDVI ($NDVI_{red\text{-}edge}$) and the wide dynamic range VI (WDRVI) (Viña and Gitelson 2005) have the highest sensitivity to green FPAR over the entire variation range in a growing season. The red-edge reflectance is more sensitive to high chlorophyll content than the red band reflectance (Gitelson, Kaufman, and Merzlyak 1996). In addition, $NDVI_{red\text{-}edge}$ is also relatively invariant with respect to vegetation species for LAI or LCC estimation (Gitelson, Merzlyak, and Lichtenthaler 1996; Viña et al. 2011). The aim of a weighting factor α in WDRVI is to attenuate the disparity contributions from the NIR and red band reflectance at moderate-to-high biomass (Gitelson 2004; Nguy-Robertson et al. 2012). Other VIs such as the enhanced VI (EVI) and the Medium Resolution Imaging Spectrometer terrestrial chlorophyll index (MTCI) have also proven to be more sensitive than NDVI in the estimation of green FPAR due to their higher sensitivity to green LAI or LCC (Viña and Gitelson 2005; Zhang et al. 2009).

Even though the modified VIs can provide improved performance in FPAR estimation, uncertainties still exist. For example, when using SAVI and the optimized soil-adjusted VI (OSAVI), the adjustment factor to reduce the soil effect is difficult to set because it varies among different vegetation covers (Ogutu and Dash 2013; Ridao, Conde, and Minguez 1998). A default value of 0.5 is used in SAVI, whereas an optimal value of 0.16 is recommended for OSAVI for agricultural applications. Similarly, the weighting factor α in WDRVI also varies over different canopy types and environments as α is a function of sensor characteristics, atmospheric conditions, and vegetation species (Baret and Guyot 1991; Gitelson 2004). Although $NDVI_{red\text{-}edge}$ is superior, its application is still limited as it requires a red-edge band that many broadband multispectral sensors, such as the Advanced Very High Resolution Radiometer (AVHRR), the MODIS, and the Landsat sensors (Thematic Mapper/Enhanced Thematic Mapper Plus/Operational Land Imager (TM/ETM+/OLI)), do not have.

The objective of this study is to develop a method to improve crop FPAR estimation using VIs derived from data acquired by broadband multispectral sensors. To achieve a stronger linear correlation with crop FPAR, a multiplier, the ratio of the green to red reflectance, was introduced to modify the existing broadband VIs. The combined PROSPECT leaf optical properties model and SAIL canopy bidirectional reflectance model (PROSAIL model) (Jacquemoud et al. 2009) was employed to analyse the sensitivities of VIs to impacting factors (e.g. LAI). Validations of the new VIs were also conducted using field measured FPAR over two common crops, the wheat (C3) and maize (C4).

2. Materials and methods

2.1. The study site

The study site is located in agricultural areas of Yucheng (36° 50′ N, 116° 33′ E), a county-level city in northwest Shandong Province, China (Figure 1). It is representative of a typical irrigated cropping system in the North China Plain. The study site is characterized by a temperate semi-arid monsoon climate with a mean annual total solar radiation of 5225 MJ m^{-2}, mean annual daily temperature of 13.1°C, and mean annual precipitation of 582 mm (Zhang, Wu, and Meng 2014). A crop rotation of wheat–maize is followed each year. The winter wheat is usually seeded in early October, with the main growing season from March to early June of the following year, followed by harvest in early or mid-June. Maize is planted immediately following the wheat harvest, and the main growing period is between late June and October. Maize harvest in October is followed by the seeding of winter wheat again.

2.2. Field data collection

Field data of winter wheat and maize were collected over the study site during the 2012 growing season. Ten large plots, each with an area of 60 m × 60 m, were established in the study site, and five smaller 3 m × 3 m sub-plots were deployed along the diagonal for intensive field measurements. The large plots were deployed to accommodate satellite observations whereas the sub-plots were selected for intensive field measurements. According to the crop calendar of 2012 (http://www.sdtfw.gov.cn/) (Figure 1), field data collection was scheduled corresponding to key growth stages and the measurements included canopy spectral reflectance and FPAR. For winter wheat, field data were collected in a few periods, from 25 to 28 March (the jointing stage), 16 to 19 April (the booting stage), and 10 to 14 May (the flowering stage). For maize, field data were

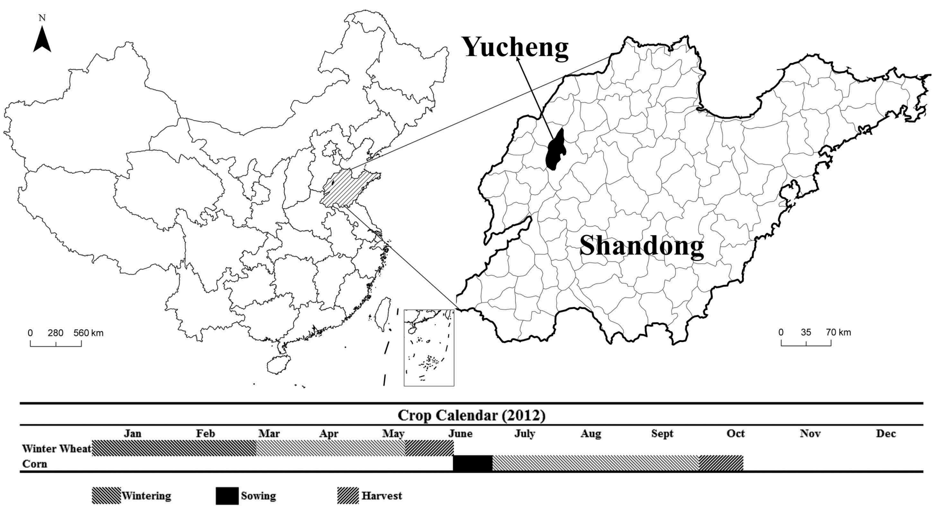

Figure 1. Location of the study site in Yucheng, Shandong Province, China.

collected in periods from 12 to 15 July (the third leaf collar stage), 16 to 19 August (the seven leaf collar stage), and 7 to 9 September (the tassel emergence stage). Canopy reflectance and FPAR were measured in each sub-plot under clear and stable air conditions. In general, the FPAR was collected after finishing the canopy reflectance measurements.

2.2.1. Canopy reflectance

Canopy reflectance measurements were taken using a portable field spectroradiometer (HR-786, Spectra Vista Corporation (SVC), Poughkeepsie, NY, USA). The instrument provides continuous spectral measurements in the 350 to 2500 nm range, with 1.5 nm bandwidth from 350 to 1000 nm, 7.5 nm bandwidth from 1000 to 1850 nm, and 5 nm bandwidth from 1850 to 2500 nm. A fibre optical cable of 25° field-of-view was used for spectral measurements at a a zenith angle of 0° (Zhang, Wu, and Meng 2014) and kept at a constant height of 1.5 m above the canopy. The canopy reflectance was calculated as the ratio between the reflected radiation from the canopy and the incident radiation based on a barium sulphate ($BaSO_4$) standard white panel. For each sub-plot, five readings were taken and averaged to reduce noise and account for spatial heterogeneity. The spectra processing was conducted using the Savitzky–Golay filter (width 3 and polynomial order 2) (Savitzky and Golay 1964) to reduce the noise caused by the measurements (Zhang, Wu, and Meng 2014). The collected canopy reflectance spectra were then converted to four multi-spectral bands corresponding to the blue (450–520 nm), green (520–600 nm), red (630–690 nm), and NIR (760–900 nm) bands based on the spectrum response function of the Landsat TM/ETM+ sensors for the intended application of calculating VIs using data acquired by satellite-based broadband optical sensors (e.g. AVHRR, Landsat sensors, MODIS).

2.2.2. Fraction of absorbed photosynthetically active radiation

The FPAR was measured using the SUNSCAN Canopy Analysis system (Delta-T Devices, Cambridge, UK). The SUNSCAN system is a combination of a probe and a handheld personal digital assistant (PDA). The one-metre-long probe is embedded with 64 quantum sensors and is connected *via* an RS-232 cable to the PDA. As a reading is taken, all the sensors are scanned and the measurements are transmitted to the PDA. Four PAR measurements are required to derive FPAR: the incoming PAR (PAR_c) is measured with the SUNSCAN facing the sky about 1 m above the canopy, the canopy reflected PAR ($RPAR_c$) is measured at the same height but with the sensors facing downward, the PAR transmit through the canopy (TPAR) is measured with the sensors facing upward about 0.02 m above the soil, and the PAR reflected from the background soil ($RPAR_g$) is measured with the sensors facing downward at 0.02 m above the canopy ground. FPAR is then calculated using the following equation (Viña and Gitelson 2005):

$$\mathrm{FPAR} = \frac{\left((\mathrm{PAR_c} - \mathrm{RPAR_c}) - \left(\mathrm{TPAR} - \mathrm{RPAR_g}\right)\right)}{\mathrm{PAR_c}}. \tag{1}$$

Previous study of Johnson, Kiniry, and Burson (2010) compared three ceptometer deployments (plant method, transect method, and cross method) for FPAR measurements and found that the measured FPAR using the three methods were significantly different at

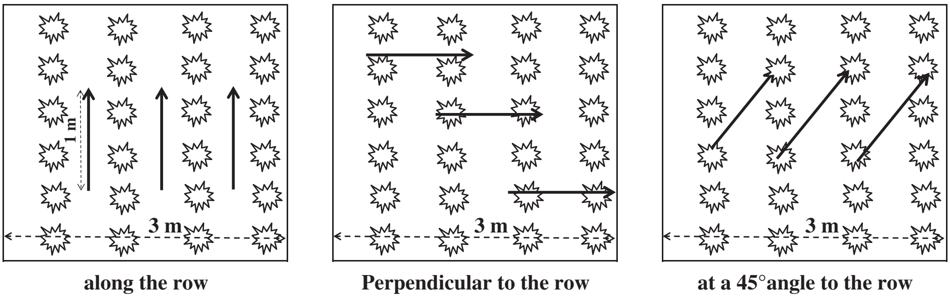

Figure 2. Illustration of fraction of absorbed photosynthetically active radiation (FPAR) measurement.

low LAI. This was due to the combined effects of row direction, sun zenith angle (SZA), and canopy structure (e.g. LAI and leaf angle distribution (LAD)). However, these effects tend to diminish at high LAI when the canopy appears to be homogeneous so that FPAR measured using the three are about the same (Johnson, Kiniry, and Burson 2010). For obtaining good quality FPAR, three sets of measurements were made at each sub-plot with the probe oriented in three directions respective to the crop row direction, i.e. along the row, perpendicular to the row, and at a 45° angle with the row (Figure 2), according to the methods by Johnson, Kiniry, and Burson (2010). FPAR of a sub-plot was represented as the average of the three measurements.

2.3. Vegetation indices

Most of the broadband VIs, such as NDVI, show declined sensitivity to FPAR, LAI, and LCC at medium to high LAI because of the saturation of indices using visible and NIR reflectance. Fortunately, the green reflectance remains sensitive to chlorophyll absorption at high LAI. This phenomenon has been reported in several studies (Gitelson and Kaufman 1998; Gitelson, Kaufman, and Merzlyak 1996). It is concluded that information content in the green or red reflectance can be exploited to improve the detection of vegetation stress and monitoring growth dynamics such as fraction of green vegetation cover and LCC (Gitelson, Kaufman, and Merzlyak 1996; Gitelson, Kaufman, et al. 2002; Wu et al. 2008). The study by Koide and Koike (2012) showed that reflectance in the green region at around 550 nm can be used to improve the performance for vegetation fraction (VF) estimation when VF is greater than 60%. The study also found that the new VIs based on the visible range of the spectrum (e.g. the visible atmospherically resistant index (VARI)) have greater potential for VF estimation (Gitelson, Kaufman, et al. 2002; Gitelson, Stark, et al. 2002). Another advantage of using the green and red reflectance is to minimize the sensitivity of VI to crop types (Gitelson, Kaufman, et al. 2002; Kanemasu 1974; Vincini, Frazzi, and D'Alessio 2008) as the visible region is mainly governed by leaf pigments of crops (Jacquemoud et al. 2009). Previous studies also indicated that the ratio between the two bands was helpful to maximize sensitivity to the variable of interest (e.g. LAI/FPAR) and minimize variation caused by extraneous factors (Daughtry et al. 2000; Haboudane et al. 2002, 2008; Vincini, Frazzi, and D'Alessio 2008). For these reasons, the format of the ratio of green to red reflectance ($(R_{green}/R_{red})^c$) was incorporated into the NDVI, GNDVI, and RDVI in an attempt to increase sensitivity to FPAR at high

Table 1. Vegetation indices (VIs) evaluated in the study.

Index	Formula	Reference
Normalized difference vegetation index	$\mathrm{NDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{red}}}{R_{\mathrm{NIR}} + R_{\mathrm{red}}}$	Rouse et al. (1973)
Green normalized difference vegetation index	$\mathrm{GNDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{green}}}{R_{\mathrm{NIR}} + R_{\mathrm{green}}}$	Gitelson, Kaufman, and Merzlyak (1996)
Renormalized difference vegetation index	$\mathrm{RDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{red}}}{\sqrt{R_{\mathrm{NIR}} + R_{\mathrm{red}}}}$	Roujean and Breon (1995)
Modified normalized difference vegetation index	$\mathrm{MNDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{red}}}{R_{\mathrm{NIR}} + R_{\mathrm{red}}} \times \left(\frac{R_{\mathrm{green}}}{R_{\mathrm{red}}}\right)$	This study
Modified green normalized difference vegetation index	$\mathrm{MGNDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{green}}}{R_{\mathrm{NIR}} + R_{\mathrm{green}}} \times \left(\frac{R_{\mathrm{green}}}{R_{\mathrm{red}}}\right)$	This study
Modified renormalized difference vegetation index	$\mathrm{MRDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{red}}}{\sqrt{R_{\mathrm{NIR}} + R_{\mathrm{red}}}} \times \left(\frac{R_{\mathrm{green}}}{R_{\mathrm{red}}}\right)$	This study

Note: R_{NIR} is the reflectance at near-infrared (NIR) wavelength; R_{green} is the reflectance at green wavelength; R_{red} is the reflectance at red wavelength.

LAI and minimize the effects of canopy non-photosynthetic materials in this study. The value of the correction factor (c) was set as 1.0 and the $(R_{\mathrm{green}}/R_{\mathrm{red}})^c$ becomes a simple ratio as the optimal correction factor for broadband VIs under different crops and soil conditions, according to the sensitivity study by Vincini, Frazzi, and D'Alessio (2008). The modified indices are called the modified NDVI (MNDVI), modified GNDVI (MGNDVI), and modified RDVI (MRDVI), respectively. The formulas of these indices are listed in Table 1.

The PROSAIL model (Feret et al. 2008; Jacquemoud et al. 2009; Verhoef 1984) has been widely used for VI analysis and biophysical variable estimation in agriculture (Jacquemoud et al. 2009). To evaluate the sensitivity of the VIs to FPAR, the PROSAIL model was employed in this study. Six parameters are used in the latest version of PROSPECT (Feret et al. 2008): the leaf mesophyll structure parameter (N), the leaf chlorophyll-*a* and -*b* content (C_{ab}), the leaf equivalent water thickness (C_{w}), the dry matter content (C_{m}), the leaf brown pigment content (C_{br}), and the carotenoid content (C_{ar}). In the SAIL model, the top of canopy (TOC) reflectance is simulated as a function of two kinds of parameters, the canopy parameters and the external parameters (Jacquemoud et al. 2009). The canopy parameters include LAI, average leaf angle (ALA), hotspot parameter (hotspot), and soil brightness parameter (psoil). The external parameters include the fraction of diffused incoming solar radiation (skyl) and the view and illumination geometry parameters: the sun zenith angle (tto), the sensor zenith angle (tts), and the relative azimuth angle (phi). The parameters used in the PROSAIL model and their values are listed in Table 2.

2.4. Sensitivity analysis of VI

The coefficient of determination (R^2), the mean squared error (MSE), and the root mean squared error (RMSE) are global metrics used to assess the overall correlation between a VI and a biophysical parameter. However, the sensitivity of a VI to a biophysical parameter is not constant across the whole dynamic range of the parameter; thus it may be misleading by using the global metrics alone (Vincini, Frazzi, and D'Alessio 2008).

Table 2. Ranges for input parameters used for simulating canopy reflectance in the PROSAIL model.

Parameter	Abbreviations	Unit	Default value	Range
Leaf				
Leaf mesophyll structural parameter	N	Dimensionless	1.55	–
Leaf chlorophyll content	C_{ab}	μg cm^{-2}	40	–
Dry matter content	C_m	g cm^{-2}	0.0035	–
Equivalent water thickness	C_w	g cm^{-2}	0.015	–
Leaf brown pigments content	C_{br}	-	0.0	–
Leaf carotenoid content	C_{ar}	g cm^{-2}	10.5	–
Canopy				
Leaf area index	LAI	m^2 m^{-2}	2.5	0.2–7.0
Mean leaf inclination angle	ALA	Degrees	57.3	–
Hot spot size parameter	hotspot	Degrees	0.2	–
Soil brightness parameter	Psoil	Dimensionless	0.5	–
External				
Sun zenith angle	tts	Degrees	45	–
Sensor zenith angle	tto	Degrees	0	–
Relative azimuth angle	phi	Degrees	0	–
Fraction of diffuse incoming solar radiation	skyl	Dimensionless	0.1	–

For this reason, the noise equivalent (NE) of FPAR (NEΔFPAR) was used in this study (Govaerts et al. 1999; Nguy-Robertson et al. 2012; Peng, Gitelson, and Sakamoto 2013):

$$\mathrm{NE\Delta FPAR} = \delta_{\mathrm{VI}} \times \left(\frac{\partial(\mathrm{FPAR})}{\partial(\mathrm{VI})}\right), \qquad (2)$$

where δ_{VI} is the RMSE of the best fit-function between VI and FPAR; $\partial\mathrm{FPAR}/\partial\mathrm{VI}$ is the inverse of the first partial derivative of this relationship. The NEΔFPAR is a better metric as it takes into account both the deviation of the samples and the local sensitivity between VI and a biophysical parameter (Gitelson 2013; Peng, Gitelson, and Sakamoto 2013; Viña et al. 2011). An ideal VI should have a lower and consistent NEΔFPAR across the dynamic range of FPAR.

3. Results and discussion

3.1. Dependency of VIs on LAI

The relationship between the VIs and LAI is shown in Figure 3 using the data simulated with the PROSAIL model. NDVI and GNDVI became saturated when LAI is larger than 2.0, although this is slightly less apparent for GNDVI than for NDVI. RDVI remains sensitive to LAI at a much larger LAI (LAI > 4.0) than NDVI and GNDVI. The three new VIs show a large improvement over their respective original forms in terms of sensitivity to LAI at high LAI values (LAI > 3.0). MNDVI and MGNDVI showed a greater improvement than MRDVI as NDVI and GNDVI had a more severe saturation issue than RDVI. This result is mostly due to the effect of the green/red ratio (Figure 4). The red reflectance drops more rapidly than the green reflectance when LAI is less than 3 and saturates at a high value of LAI; thus, the total trend of the green/red ratio is to increase as LAI increases and also to saturate at higher LAI than NDVI, GNDVI, and RDVI (Figure 3 and Figure 4). These results indicate that an improvement for crop FPAR estimation could be anticipated using the three new VIs.

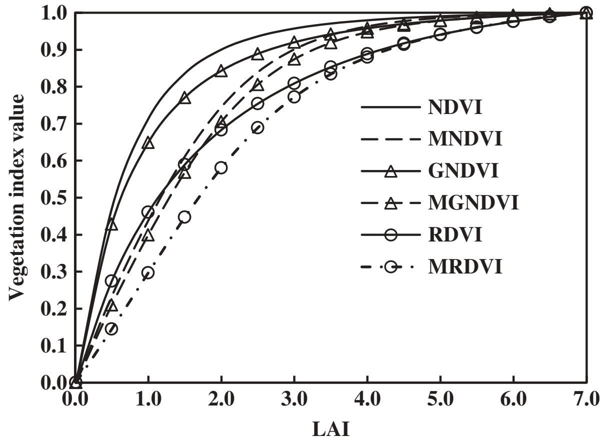

Figure 3. Relationships between vegetation indices (VIs) and leaf area index (LAI). Indices were scaled to the range of 0 to 1 for better comparison with each other.

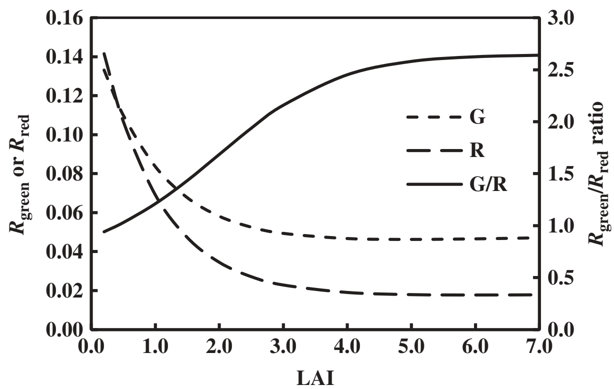

Figure 4. The effect of LAI on green (G) and red (R) reflectance and their ratio (G/R).

3.2. Correlation between field-measured FPAR and VIs

As analysed above (Figure 3 and Figure 4), the three modified VIs derived from the data simulated by the PROSAIL model showed a better linearity with LAI at higher LAI values. This was validated using the ground-measured canopy reflectance and FPAR in two distinct types of crops, winter wheat and maize. A preliminary assessment using the correlation between the VIs and FPAR was conducted in this section, and then a stricter and intuitive evaluation through sensitivity analysis using scatter plots between the VIs and FPAR was conducted in Section 3.3.

The results obtained from linear regression between VIs and crop FPAR are given in Table 3 for winter wheat and Table 4 for maize. The three original VIs were strongly correlated with FPAR for the two crops, with $R^2 = 0.90$ for winter wheat and between 0.79 and 0.82 for maize. The three modified VIs achieved a higher R^2 and a lower RMSE than their respective original versions for both maize and winter wheat crops. The correlation

Table 3. Results of linear regression analysis between vegetation indices (VIs) and fraction of absorbed photosynthetically active radiation (FPAR) for winter wheat; x = VI, y = FPAR, and the RMSE is the root mean square error of FPAR estimation.

Index	Equation	R^2	RMSE
NDVI	$y = 1.454x - 0.519$	0.90	0.099
MNDVI	$y = 0.683x - 0.105$	0.97	0.055
GNDVI	$y = 1.855x - 0.798$	0.90	0.099
MGNDVI	$y = 0.771x - 0.171$	0.97	0.056
RDVI	$y = 2.054x - 0.446$	0.90	0.098
MRDVI	$y = 0.977x - 0.071$	0.96	0.068

Table 4. Results of linear regression analysis between VIs and FPAR for maize; x = VI, y = FPAR, and the RMSE is the root mean square error of FPAR estimation.

Index	Equation	R^2	RMSE
NDVI	$y = 1.095x - 0.243$	0.82	0.098
MNDVI	$y = 0.643x - 0.037$	0.86	0.086
GNDVI	$y = 1.371x - 0.393$	0.81	0.101
MGNDVI	$y = 0.766x - 0.108$	0.88	0.079
RDVI	$y = 1.728x - 0.194$	0.79	0.107
MRDVI	$y = 0.985x + 0.010$	0.81	0.101

between the modified VIs and FPAR for the winter wheat crop each had an R^2 of 0.97, an increase of 0.07 over that obtained from the original indices. Similarly, the linear correlation between the three modified indices and FPAR for the maize crop increased over the original indices, with a large increase of 0.07 for MGNDVI and a smaller increase of 0.02 for MRDVI. This further indicated that the modified VIs show improved crop FPAR estimation.

It is observed that the correlation between all the VIs and FPAR is stronger for the winter wheat crop than for the maize crop (Tables 3 and 4). This could be attributed to two reasons. First, the FPAR of the maize canopy was affected more by stalks and canopy background than that of the wheat canopy (Peng, Gitelson, and Sakamoto 2013). Second, it was more difficult to take measurements over the maize canopy at a height above 2 m, leading to degraded quality of measurements.

For comparison, both linear and non-linear correlation analyses were conducted and are shown in Figure 5. It is observed that both NDVI and GNDVI are better correlated with FPAR using a non-linear relationship (i.e. with a higher R^2) than a linear relationship, while RDVI shows comparable performance using either linear or non-linear regression, but with more dispersion. This is because RDVI has a higher saturation point with LAI. For all three modified indices, the higher R^2 than their original forms and the comparative R^2 with the non-linear regression indicate that they have a relatively consistent sensitivity to FPAR over the whole dynamic range and thus are better for FPAR estimation. FPAR could be estimated from RDVI and the three modified indices using linear regression models, as they were very close to correspondent non-linear regression models (Figure 5).

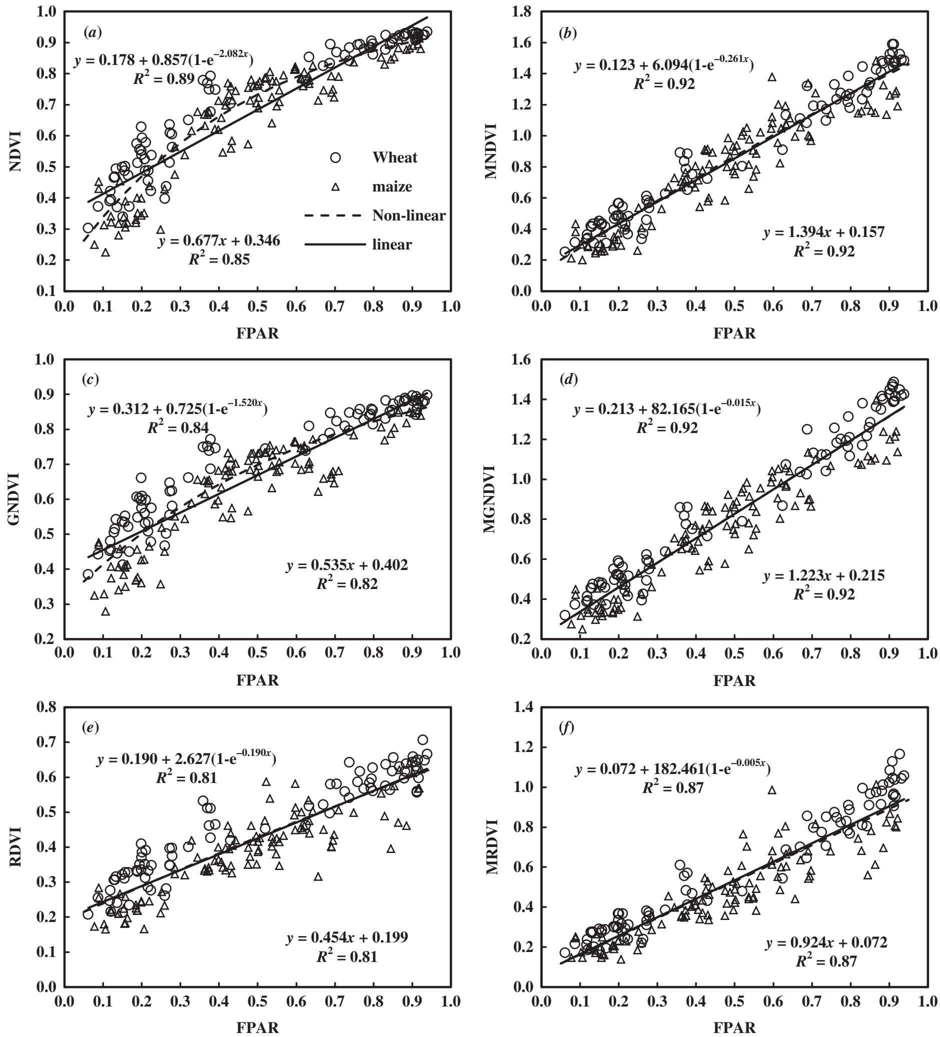

Figure 5. Scatter plots of VIs *versus* FPAR: (*a*) NDVI, (*b*) MNDVI, (*c*) GNDVI, (*d*) MGNDVI, (*e*) RDVI, and (*f*) MRDVI. The solid line is the linear regression and the dashed line is the best-fit regression function for both wheat and maize.

Ideally, the best VIs should have the best linear relationship with canopy biophysical parameters and minimal dependency on crop types (Viña et al. 2011; Wu et al. 2008). However, the vegetation species have significant influence on most VIs and hence limit their applications (Myneni and Williams 1994; Viña et al. 2011). Regression results in Table 3 and Table 4 showed that FPAR of different crops were correlated differently with VIs, consistent with the studies by Cristiano et al. (2010) and Viña and Gitelson (2005). This suggests that under the same atmospheric conditions different crop types with different canopy architectures might have the same FPAR but different LAI. ALA is an important factor for determining the area and direction of PAR interception (Viña et al. 2011). Similarly, different crops with the same LAI might have different FPAR. The maize

Table 5. ANOVA of the VIs; a p-value of less than 0.001 ($p < 0.001$) indicates that the VI *versus* FPAR is affected by the effect of the crop type.

Vegetation index	F-value	p-Value
NDVI	11.476	0.001
GNDVI	24.909	0.000
RDVI	39.911	0.000
MNDVI	3.399	0.066
MGNDVI	6.367	0.012
MRDVI	16.322	0.000

and wheat plants have different canopy architectures. This means that the strength of the relationship between VIs and crop FPAR values could be reduced by the differences among crop types. In Figure 5, MNDVI and MGNDVI show a more linear relationship than MRDVI and the three original VIs. For assessing the effect of the crop type on the relationship between FPAR and VIs, a factorial analysis of variance (ANOVA) based on the linear and non-linear models as depicted in Table 5 was conducted. The result revealed that the regressions of all VIs, with the exception of MNDVI and MGNDVI, show significantly ($p < 0.001$) different residuals for maize and wheat FPAR (Table 5). This suggests that MNDVI and MGNDVI have better ability to reduce the effect of the crop type and achieve a non-parameterized model of FPAR for different crop types, while other VIs tested in this study require different model coefficients for estimating FPAR for different crop types.

3.3. *Sensitivity analysis*

Sensitivity analysis was conducted using the NEΔFPAR, as calculated using Equation (1) from the best-fit function obtained between the field-measured FPAR and VI (Figure 5). The results are shown in Figure 6. The NDVI had the minimum NEΔFPAR when FPAR is

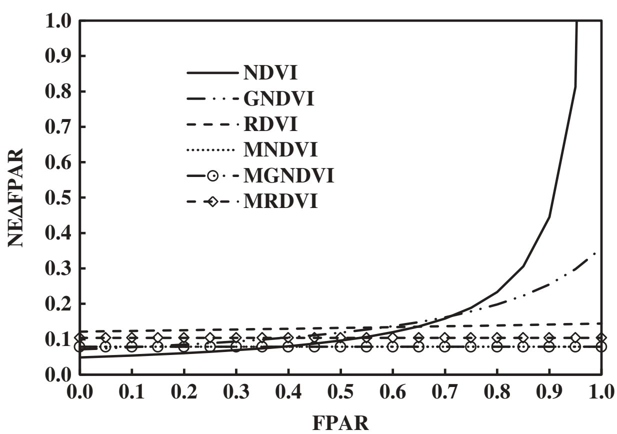

Figure 6. Sensitivity of the three original VIs and their corresponding modified version examined plotted against FPAR of maize and winter wheat during the growing season of 2012. Sensitivity was evaluated using the NEΔFPAR based on the best-fit function.

smaller than 0.40 but increased rapidly with FPAR when FPAR exceeds 0.6. The GNDVI had a slightly higher NEΔFPAR than NDVI when FPAR < 0.7, but had a much lower value of NEΔFPAR when FPAR > 0.7. This suggests that the GNDVI has a better ability to reduce the saturation effect. The RDVI showed the best linearity among the three original indices across the whole dynamic range of FPAR. A possible reason might be that RDVI is less affected by the background reflectance and performs slightly better for denser canopies (Vincini, Frazzi, and D'Alessio 2008). All the modified VIs showed a more stable and lower NEΔFPAR across the whole dynamic range of FPAR, indicating that they have better linearity and sensitivity to FPAR. The MNDVI and MGNDVI are the most accurate VIs for estimating FPAR beyond 0.4 and have better ability to reduce the effect of saturation at medium-to-high biomass.

4. Conclusions

To take advantages of the combination of green and red reflectance for detecting photosynthetic materials of vegetation, in this study, a multiplier, the ratio of the green to red reflectance, was incorporated into the VIs; NDVI, GNDVI, and RDVI to derive three modified indices; MNDVI, MGNDVI, and MRDVI; for crop FPAR estimation using broadband optical remote-sensing data. Sensitivity analysis using data simulated by the PROSAIL model showed that the three modified VIs had better linearity with LAI, with a higher value of saturation than the original VIs. Validation using the ground measurements of FPAR and canopy reflectance over winter wheat and maize showed that the modified VIs had improved performance for winter wheat and maize FPAR estimation. Linear regression analysis showed that incorporating the green to red reflectance ratio into the conventional VIs, NDVI, GNDVI, and RDVI improved their correlations with the FPAR for both the winter wheat and maize crops, i.e. the coefficients of determination (R^2) of the modified indices were higher than that of the original indices. A sensitivity analysis also showed that the three modified indices were more stable for FPAR estimation across the whole growing season than the original indices. In particular, MNDVI and MGNDVI were less affected by crop types than the other VIs for FPAR estimation. Further study may be needed to assess the modified indices on different crops, data sets, and under different environmental conditions.

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