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Analysis of vegetation indices derived from hyperspectral reflection measurements for estimating crop canopy parameters of oilseed rape (*Brassica napus* L.)

*Karla Müller**, *Ulf Böttcher, Franziska Meyer-Schatz, Henning Kage*

Institute of Crop Science and Plant Breeding, Christian-Albrechts-University Kiel, Hermann-Rodewald-Strasse 9, D-24118 Kiel, Germany

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Vegetation indices (VIs), which are derived from hyperspectral measurements, may be useful non-destructive measures to estimate crop canopy parameters. A systematic analysis of the reflectance spectrum of winter oilseed rape (OSR) for the derivation of VIs has not been conducted yet. We therefore derived in our study VIs from 61 available wavebands of the spectral range from 400 nm to 1000 nm systematically and compared the best ones to commonly used indices. Hyperspectral reflectance and destructive measurements of crop canopy parameters were therefore carried out in 2005 and 2006 in northern Germany for calibration and in 2006 for validation at the same location. For the derivation of VIs for OSR, three different approaches were tested. The approaches differed in the way of the waveband combinations by combining two wavebands in a simple ratio (SR) form λ_1/λ_2, a normalized difference index (NDI) form $(\lambda_1-\lambda_2)/(\lambda_1+\lambda_2)$ or by using a stepwise forward multiple regression (MR), which identifies the best linear combination of all available bands in a linear combination. The derived VIs were tested for their predictive power for crop canopy parameters like green area index (GAI), shoot dry matter (DM_{shoot}) and total nitrogen amount in the shoot (N_{shoot}) and were compared to commonly used indices.

Waveband combinations of two near infrared bands resulted in the best prediction of the tested crop canopy parameters for calibration and validation data sets. Correlation coefficients (r^2) yielded values up to 0.82 between new indices and N_{shoot}. Especially, NDI 750,740 was best predicting GAI, whereas either NDI or SR forms of 740 nm and 780 nm showed best results predicting DM_{shoot} and N_{shoot} and outperformed commonly used indices. Predicting crop canopy parameters by MR showed good results for calibration, but highest variation for validation among all newly derived indices.

1. Introduction

Spatial knowledge of crop canopy parameters like green area index (GAI), shoot dry matter (DM_{shoot}) and total nitrogen amount in the shoot (N_{shoot}) is an essential prerequisite for many approaches of site-specific management of crops (Tarpley *et al.*, 2000; Hansen and Schjoerring, 2003; Johnson *et al.*, 2003; Lukina *et al.*, 2001; Raun *et al.*, 2002). Non-destructive, sensory measurements may be useful measures to assess those parameters in realtime and for large areas (Xue *et al.*, 2004; Boegh *et al.*, 2002). The use of spectral measurements of canopy reflectance is the most common approach for non-destructive measurements of crop canopy parameters (Elvidge and Chen, 1995; Thenkabail *et al.*, 2001; Behrens *et al.*, 2006; Graeff and Claupein, 2003) by correlating discrete spectral bands or combinations of them, so called vegetation

* *Corresponding author.*
E-mail address: mueller@pflanzenbau.uni-kiel.de (K. Müller).
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Nomenclature

CD	coefficient of determination
DM_{shoot}	shoot dry matter, $g\,m^{-2}$
EF	modelling efficiency
GAI	green area index, $m^2\,m^{-2}$
IR/G	infrared to green ratio
IR/R	infrared to red ratio
LAI	leaf area index, $m^2\,m^{-2}$
λ	wavelength, nm
MR	multiple regression
N	nitrogen
n	sample size
NDI	normalized difference index
NDVI	normalized difference vegetation index
NIRS	near infrared spectroscopy
N_{shoot}	total nitrogen amount in the shoot, $kg\,ha^{-1}$
OSR	winter oilseed rape
r^2	correlation coefficient
REIP	red edge inflection point
RMSE	root mean square error
SAVI	soil adjusted vegetation index
SR	simple ratio
VI	vegetation index

indices (VIs), to crop canopy parameters. The mathematical combinations of VIs can be made of either discrete wavebands from narrowband spectra (5–10 nm intervals) or from broadband spectra (>50 nm intervals). While broadband spectra have been recorded for about three decades, high resolution spectral reflection measurements became more common just recently (Elvidge and Chen, 1995; Thenkabail *et al.*, 2000) and some authors stated that VIs derived by narrowband spectra are supposed to be more sensitive to chlorophyll and other pigments (Broge and Leblanc, 2000; Blackburn, 1998; Thenkabail *et al.*, 2002). Comparisons between broad- and narrowband based VIs showed that the estimation of crop parameters by broadband measurements of canopy reflectance was less accurate than those by narrowband indices (Elvidge and Chen, 1995; Blackburn, 1998; Carter, 1998). For cereal crops and especially for winter wheat, several investigations on the prediction power of different VIs have been conducted (Reusch, 1997; Aparicio *et al.*, 2000; Mistele, 2006). Therefore the commonly used indices are derived from discrete spectral bands of the green, red and near infrared areas of the reflection spectrum (Reusch, 1997; Thiessen, 2002). Reusch (1997) as well as Filella *et al.* (1995) and Aparicio *et al.* (2000) stated that commonly used indices showed good relations to GAI, DM_{shoot} and N_{shoot} of cereal crops. However for winter oilseed rape (OSR) only few studies have been carried out regarding the spectral reflection based estimation of crop parameters. Behrens *et al.* (2006) applied spectral indices commonly used for cereals for OSR, which, however, resulted in less accurate predictions of crop canopy parameters like shoot fresh mass and shoot nitrogen content as compared to cereal crops.

Recent sensors for spectral reflectance measurements allow the discrimination of a large number of wavelength bands resulting in a high spectral resolution, so that methods have to be developed to systematically derive VIs out of all available spectral bands. VIs, which were newly derived, showed better correlations to different crop parameters of cereal crops than commonly used ones (Reusch, 2003), but those have also not been tested for OSR yet. Therefore, there exists the potential to derive new VIs for a more precise prediction of OSR crop canopy parameters as compared to previous approaches.

The aim of our study was the derivation and identification of optimum VIs for the prediction of OSR crop canopy parameters such as GAI, DM_{shoot} and N_{shoot} by a systematic comparison of VIs obtained by three different approaches based on narrowband spectral reflectance measurements.

2. Materials and methods

2.1. *Field experiments*

Field experiments were carried out in 2005 and 2006 at the Hohenschulen experimental farm, 15 km to the west of Kiel. OSR (*Brassica napus* L.) was grown on an 11 ha field in 2005 and on an 18 ha field in 2006. Information on sowing dates, seeding densities, varieties and nitrogen application is shown in Table 1. The fields were fertilized according to usual practice ($200\,kg\,N\,ha^{-1}$) except for two unfertilized strips each year. Four blocks on selected positions within a strip contained four plots with different nitrogen treatments: unfertilized (N0), $80\,kg\,N\,ha^{-1}$ (N1), $200\,kg\,N\,ha^{-1}$ (N2) and $240\,kg\,N\,ha^{-1}$ (N3). The nitrogen was applied as ammonium nitrate/urea solution in two dressings at the beginning of plant growth in spring and the beginning of stem elongation. Otherwise the plants were treated according to best practice German recommendations.

2.2. *Plant sampling*

Plant sampling was carried out twice before winter and weekly from the beginning of the growth period in spring until anthesis, so that an overall sample size of 339 was obtained. At each

Table 1 – Crop management information for the field experiment of spectral analysis on the experimental farm Hohenschulen in the years 2005 and 2006

Vegetation period	Sowing dates	Seeding density (seeds m^{-2})	Variety	Date of 1st N-application	Date of 2nd N-application
2004/2005	4 Sept. 2004	50	Talent	23 March 2005	14 April 2005
2005/2006	24 Aug. 2005	45	Talent	22 March 2006	19 April 2006

sampling date an area of 0.88 m^2 was harvested for analysis of GAI, total dry mass (DM_{shoot}) and total nitrogen content (N_{shoot}). The plants were separated into leaf blades and stem, where the petioles were counted in stem fraction. After drying and weighting, the fractions were ground for near infrared spectroscopy (NIRS) analysis of the nitrogen concentration (NIRSystems 5000 scanning monochromator, FOSS GmbH, Rellingen, Germany). NIRS data were analyzed using the WINISI software package (Infrasoft International, Port Matilda, PA, USA).

2.3. *Spectral reflectance measurements*

Spectral reflectance of OSR was determined using a HandySpec® Field spectrometer of tec5 AG (Oberursel, Germany). The measuring head of this device consists of two optical receive channels, of which the upper one quantifies the incoming light as reference and the lower one records the reflectance by vegetation and ground, if visible. The HandySpec Field spectrometer measures in a spectral range from 400 nm to 1000 nm in 10 nm steps. Both optical channels were calibrated by using a white panel.

Reflectance measurements were carried out in spring 2005, autumn 2005, spring 2006 and autumn 2006. In parallel to intermediate destructive harvests from emergence in autumn to the flowering period, measurements were carried out by holding the measuring head about 1 m above the crop. During flowering the spectral reflectance of OSR changed considerably because of the yellow petals. Furthermore, after flowering the plants were too tall for holding the instrument manually above the crops. In order to obtain comparable reflectance data, the measurements were taken between 2 h before and after solar zenith under consistent sky conditions.

2.4. *Methods for calculation of vegetations indices and statistical analysis*

To investigate correlations between crop parameters like GAI, DM_{shoot}, N_{shoot} and plant reflectance properties three approaches for the derivation of VIs were used. The first and the second approach consisted of linear regressions between destructively measured crop parameters and all 3660 possible two-band combinations of 61 measured bands in a simple ratio (SR) form λ_1/λ_2 and in the normalized difference index (NDI) form $(\lambda_1 - \lambda_2)/(\lambda_1 + \lambda_2)$. These calculations were done using a self-written software implemented in Delphi®, Borland. This tool gives a matrix output with all correlation coefficients (r^2) of the linear regressions (Fig. 1). For the third approach, a stepwise forward multiple regression (MR) was conducted to identify the best linear combination of all available bands for describing the parameters mentioned above. As long as the improvement of the correlation coefficient was better than 5%, more wavebands were added to the MR. Additionally, commonly used VIs were calculated, which are derived from very few discrete red, green and near infrared bands (Table 2). For the commonly used indices normalized difference vegetation index (NDVI) and soil adjusted vegetation index (SAVI), which showed saturation in the curve progression, linear regression was conducted after logarithmical transformation of the measured values. The SAS statistical package (SAS 8.2, SAS Institute Inc.) was used for statistical calculations.

Validation was carried out on an independent data set, containing 89 samples, of the vegetation period 2005/2006 from another experiment field at the same site, which varied by two seeding dates, two varieties and four different N treatments, (N0), 80 kg N ha^{-1} (N1), 120 kg N ha^{-1} (N2) and 200 kg N ha^{-1} (N3). To characterize the predictive force of the derived VIs, slope (*b*) and intercept (*a*) and coefficient of correlation (r^2) of the linear regression ($y = a + bx$) between VIs and destructive measurements, root mean square error (RMSE, Eq. (1)) of the 1:1 line ($y = x$), coefficient of determination (CD, Eq. (2)) and modelling efficiency (EF, Eq. (3)) are given.

$$\mathrm{RMSE} = \sqrt{\frac{\sum (x_i - y_i)^2}{n}}. \tag{1}$$

The CD is

$$\mathrm{CD} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{\sum_{i=1}^{n} (y_i - \bar{x})^2}, \tag{2}$$

and the EF is

$$\mathrm{EF} = 1 - \frac{\sum (x_i - y_i)^2}{\sum (x_i - \bar{x})^2}, \tag{3}$$

where x_i are the measured values; y_i are the estimated values; n is the number of samples; and $\bar{x}$ is the mean of the measured data.

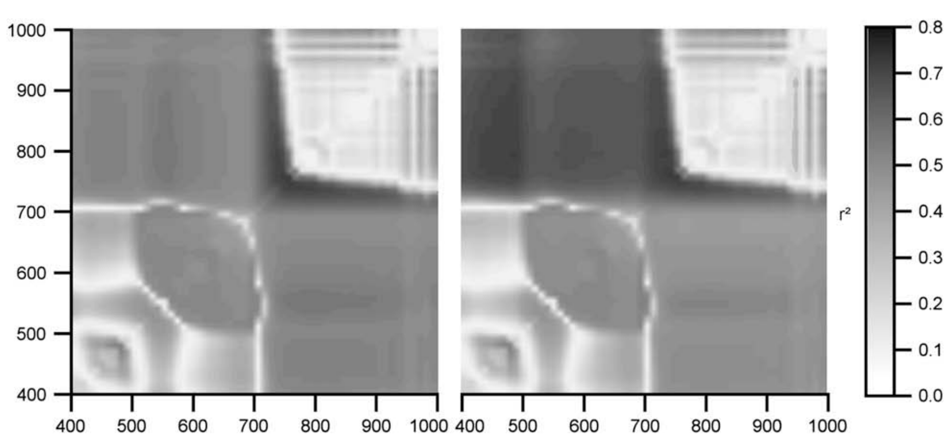

Fig. 1 – Matrix of the correlation coefficient (r^2) of the normalized difference indices (NDI) on the left and the SR indices on the right to total shoot N, respectively. High r^2 values are indicated by dark coloured areas, lower values by brighter ones.

Table 2 – Definition of commonly used VIs of visible and near infrared reflectance for the estimation of crop parameters for winter crops and OSR

Commonly used indices	Equation	Reference
Reflectance at 850 nm	R_{850nm}	Behrens et al. (2006)
SR 810/560	$SR = R_{810nm}/R_{560nm}$	Xue et al. (2004)
Infrared to red ratio	$IR/R = R_{780nm}/R_{670nm}$	Pearson and Miller (1972)
Infrared to green ratio	$IR/G = R_{780nm}/R_{550nm}$	Takebe et al. (1990)
NDVI	$NDVI = (R_{780nm} - R_{670nm})/(R_{780nm} + R_{670nm})$	Bausch (1993)
SAVI	$SAVI = 1.5(R_{780nm} - R_{670nm})/R_{780nm} + R_{670nm} + 0.5)$	Huete (1988)
REIP	$REIP = 700\ nm + 40\ nm((0.5(R_{670nm} + R_{780nm}) - R_{700nm})/(R_{740nm} - R_{700nm})$	Guyot and Baret (1988)

Slope and intercept were tested for being significantly different from one and zero, respectively. Low RMSE values gave best account of the degree of precision of the estimated values. CD values served as a measure of how much the derived values lie under or over the measured ones. It is scaled from zero with no upper limit, whereas one stands for no differences from measured to estimated values. EF reflects the quality of the prediction curve compared to the data points. The values range from $-\infty$ to 1, with higher values indicating better prediction power.

2.5. *Applicability of newly generated VIs to distinguish differences of GAI, DM_{shoot} and N_{shoot}*

To analyze the applicability of the newly generated VIs to indicate differences in crop canopy parameters like GAI, DM_{shoot} and N_{shoot}, an analysis of variance was calculated using the SAS statistical package. This was done for each intermediate harvest date from the first application in spring to anthesis.

3. Results

3.1. *Correlation between VIs and crop canopy parameters of OSR in a calibration data set*

For the NDI form of VI most relevant bands were identified between 720 nm and 800 nm in the near infrared area of the reflection spectrum (Fig. 1, NDI). The SR combinations also showed high correlations in the near infrared area, but there are several combinations of near infrared and visible light reflection areas, which resulted in good correlations (Fig. 1, SR). This applies especially for SR combinations, where the first wavelength is taken from the near infrared and the second from the visible light spectrum.

There were marked differences in the adjusted r^2 and the RMSE values based on linear regressions of crop canopy parameters GAI, DM_{shoot} and N_{shoot} against the five best VIs that were newly derived by approach one and two, the commonly used ones and the best linear waveband combination by the MRs for each crop parameter (Table 3). Since crop parameter values were logarithmically transformed for the commonly used indices NDVI and SAVI, RMSE for these two indices was calculated with retransformed values. New indices achieved higher correlations with all crop canopy parameters from the calibration data set for OSR than commonly used indices. Highest r^2 for correlations of GAI (0.81) and DM_{shoot} (0.76) were calculated with wavebands selected by MR. Correlation coefficients for regressions between these crop canopy parameters and the other newly generated indices lay slightly below these results. For correlations to N_{shoot}, there were three new indices, which yielded an r^2 of 0.82.

IR/G and SR 810/560 achieved highest r^2 (0.71) of the commonly used indices to GAI, regarding DM_{shoot} the IR/G ratio yielded the highest value with 0.66 and for N_{shoot}, red edge inflection point (REIP) showed the best result with $r^2 = 0.73$.

Results for RMSE values were analogous to those of adjusted r^2 for new and commonly used indices. For GAI and DM_{shoot} the MR waveband combinations showed lowest RMSE with 0.43 $m^2\,m^{-2}$ and 58.78 $g\,m^{-2}$, respectively. With regard to N_{shoot}, SR 780/740 yielded the lowest value with 2.10 $g\,m^{-2}$. SR 810/560 achieved the lowest RMSE value among the commonly used indices regarding GAI with 0.53 $m^2\,m^{-2}$, for DM_{shoot} the lowest value was achieved by IR/G with 69.53 $g\,m^{-2}$ and for N_{shoot} REIP showed the best result with 2.57 $g\,m^{-2}$ (Table 3).

Since a large data base, with data from different development phases of OSR over different years, was used for the correlations, it is important to assess the accuracy of several indices for the estimation of crop canopy parameters in differing growth periods based on just one regression over all growth phases. Fig. 2 shows five plots (a–e) for the linear regressions of measured N_{shoot} to estimated N_{shoot} by five new indices, respectively; function parameters for the regressions were taken from Table 4. The data points have different symbols for four different periods: after beginning of spring growth in 2005 and in 2006, before winter 2006 and 2007. The data points for each time period are evenly distributed along the regression line in each figure. No apparent conglomeration for any period could be observed. Between the five VIs, there are marginal differences of distribution.

3.2. *Validation of newly generated VIs for OSR*

To validate the applicability of the VIs, the linear regression parameters (Table 4) for each index and all crop canopy parameters were used to estimate all three crop canopy parameters of an independent data set. In order to rank the different VIs in their predictive power we calculated several statistical parameters like the slope (b), intercept (a) and r^2 of the linear regressions ($y = a + bx$) along with the RMSE values of the reference 1:1 line ($y = x$), CD and EF (Table 5). Since the regression is ideally supposed to have a slope of one and an

Table 3 – Correlation coefficients of linear regressions and RMSE of different indices and GAI, DM_{shoot} and total shoot N (N_{shoot}) of OSR derived from the calibration data set

		Adj. r^2			RMSE		
		GAI [$m^2\,m^{-2}$]	DM_{shoot} [$g\,m^{-2}$]	N_{shoot} [$g\,m^{-2}$]	GAI [$m^2\,m^{-2}$]	DM_{shoot} [$g\,m^{-2}$]	N_{shoot} [$g\,m^{-2}$]
New indices	NDI 780,740	0.74***	0.72***	**0.82*****	0.51	63.06	2.13
	NDI 750,740	0.78***	0.74***	**0.82*****	0.46	61.28	2.13
	SR 780/740	0.75***	0.73***	**0.82*****	0.50	62.58	**2.10**
	SR 740/780	0.73***	0.72***	0.81***	0.51	63.62	2.16
	MR	**0.81*****	**0.76*****	0.81***	**0.43**	**58.78**	2.14
Commonly used indices	R850	0.26***	0.15***	0.16***	0.86	110.31	4.55
	SR 810/560	0.71***	0.65***	0.71***	0.53	70.44	2.66
	IR/R	0.70***	0.60***	0.63***	0.55	75.48	3.00
	IR/G	0.71***	0.66***	0.72***	0.54	69.53	2.63
	NDVI	0.71***	0.57***	0.55***	0.65[a]	86.52[a]	3.59[a]
	SAVI	0.65***	0.52***	0.51***	0.72[a]	100.14[a]	4.03[a]
	REIP	0.66***	0.63***	0.73***	0.58	72.39	2.57

Number of n was 339 for each regression.
Highest r^2 and lowest RMSE are bolded. The limit of significance was $^{***}p < 0.001$, $^{**}p < 0.01$ and $^{*}p < 0.05$, respectively.
a RMSE for logarithmically retransformed values.

intercept of zero, both functional parameters were tested for being significantly different from these values, respectively.

For GAI, MR was the only index whose slope and intercept were not significantly different from one and zero, respectively. However, with regard to the other statistical parameter, this index lays above the average for RMSE of 0.81 $m^2\,m^{-2}$ and under the average for EF of 0.585; regarding CD, MR overestimated the predicted values compared to the measured data to a higher degree than the other indices underestimated them. All other new indices yielded slopes significantly different from one, but intercepts, which did not differ from zero. Although NDI 750,740 showed lowest RMSE with 0.77 $m^2\,m^{-2}$ and highest EF with 0.632 among the new indices, it also underestimated GAI to the highest degree a CD value of 1.416. All commonly used indices showed values significantly different from one and zero for slope and intercept, respectively. As a result, SR, IR/R and IR/G yielded lowest RMSE and highest EF values among all indices. With regard to CD, all commonly used indices showed a higher degree of underestimation of measured GAI values than the new ones, except for NDI 750,740.

For DM_{shoot}, again, MR was the only waveband combination with a slope and an intercept that were not significantly different from one and zero, respectively, whereas RMSE and EF values for this index lay above and under the averaged ones. Also, MR was the only index that overestimated the measured DM_{shoot} among all indices. The rest of the new indices, except NDI 750,740, yielded slopes that differed significantly from one, but the intercepts were not significantly different from zero. All four remaining indices showed similar results for RMSE of about 56 $g\,m^{-2}$ and for EF around 0.83. For this crop parameter, commonly used indices showed higher RMSE and lower EF. SAVI was the only index that had a CD value closer to one than the new indices apart from NDI 750,740. Slopes and intercepts of the regression lines of estimated DM_{shoot} by the old indices to measured DM_{shoot} differed significantly from one and zero, respectively.

For N_{shoot}, there were three new indices that showed either slopes or intercepts significantly different from one and zero, respectively. Among the new indices, these three indices yielded CD values, which were closest to one. Additionally, they showed EF results of about 0.83 and RMSE less than 2.3 $g\,m^{-2}$. Slope and intercept for NDI 750,740 were significantly different from one and zero; slope for MR was significantly different from one, but its intercepts differed not significantly from zero. Again, MR reached highest RMSE and lowest EF among the new indices, whereas NDI 750,740 yielded lowest RMSE and highest EF. In contrast to the CD values for DM_{shoot} and GAI, all new indices, except for NDI 750,740, yielded values lower than one, indicating that they overestimated N_{shoot}. Among the commonly used indices, REIP was the only one with an intercept that did not differ from zero significantly. All other slopes and intercepts were significantly different from one and zero, respectively. Among all indices REIP achieved the second highest EF value and the second lowest RMSE. With regard to CD values, all commonly used indices, except for R850 and NDVI, yielded values closer to one than the new indices.

Since waveband combinations of 780 and 740 in either the SR or the NDI form showed best results among all statistical measures for estimating GAI, DM_{shoot} and N_{shoot}, 1:1 plots for estimated parameter values to measured ones are shown exemplarily for SR 740/780 in Fig. 3(a–c). Regarding the 1:1 lines, highest estimation accuracy was achieved for N_{shoot} (c) and lowest for GAI (a).

3.3. *Efficiency of VIs to indicate relative differences of crop canopy parameters of OSR*

Increasing amounts of nitrogen application to OSR led to increasing values for crop canopy parameters GAI, DM_{shoot} and N_{shoot} (Table 6). This relationship is also depicted in Fig. 4, where increasing amounts of fertilizer N lead to increased reflectance in the near infrared region, which is caused by increased biomass. Analysis of variance was calculated for each date after the second nitrogen application in springtime for all three crop canopy parameters and four different new indices in 2005, only (Table 6). On the first date, there were significant differences between the N0 treatment and the other

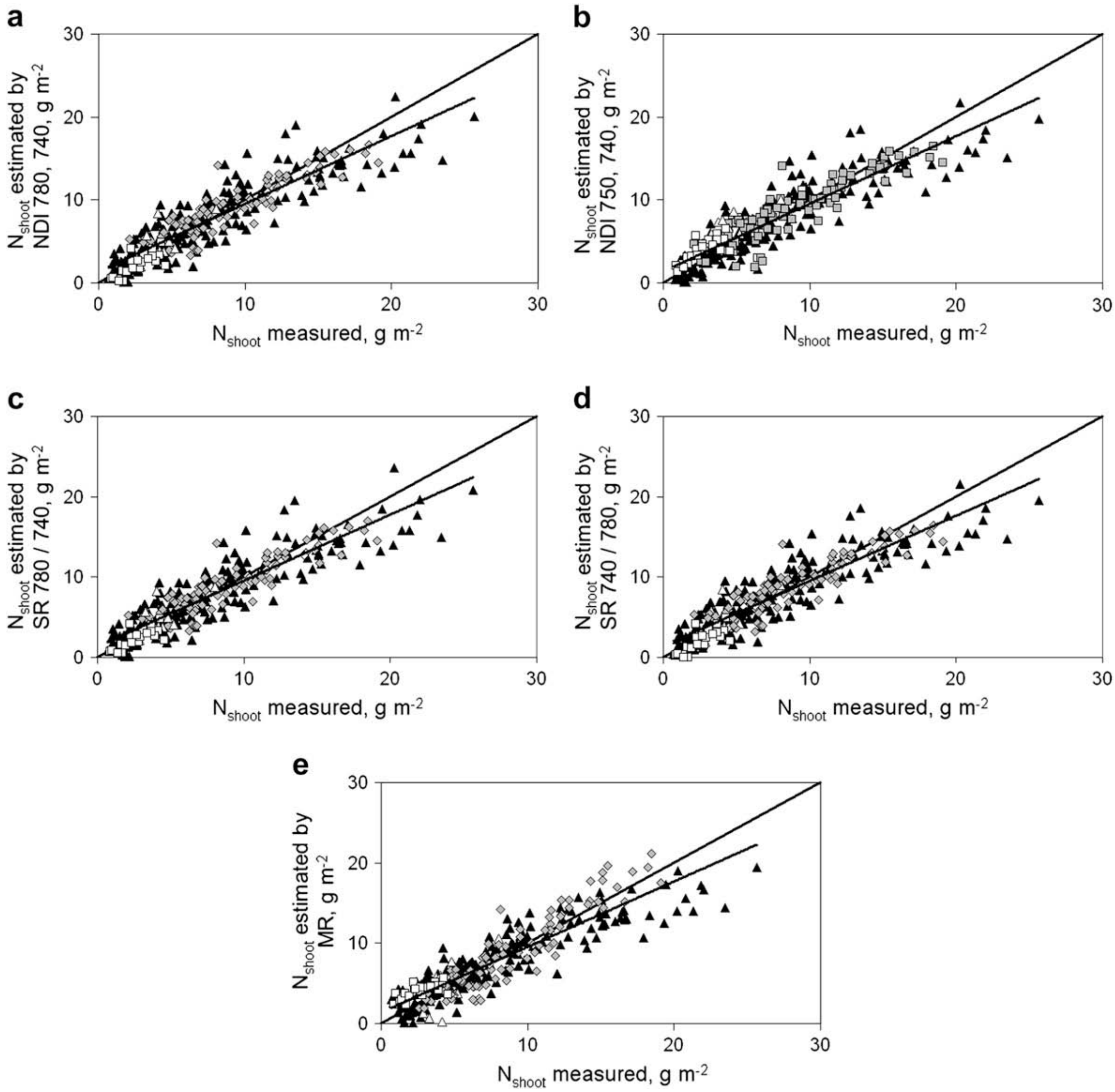

Fig. 2 – Linear regression of the total amount of N in the shoot (N_{shoot}) estimated by five different new indices to measured N_{shoot} values. All regressions contain data from four different time periods: after beginning of spring growth in 2005 (▲) and in 2006 (◇) and before winter 2006 (△) and 2007 (□). The regression functions and r^2 for all subfigures are as follows: (a) NDI 780,740, $y = 0.82x + 1.36$, $r^2 = 0.82$; (b) NDI 750,740, $y = 0.82x + 1.37$, $r^2 = 0.82$; (c) SR 780/740, $y = 0.82x + 1.32$, $r^2 = 0.82$; (d) SR 740/780, $y = 0.81x + 1.41$, $r^2 = 0.81$ and (e) MR, $y = 0.81x + 1.38$, r^2 0.81.

N treatments for GAI, N_{shoot} and the indices, whereas the indices values additionally gave significant differences between the N1 and N3 treatments. For DM_{shoot} no differences could be found. GAI and N_{shoot} showed the same response to N application on the second date as compared to the first date. DM_{shoot} was significantly different between N0 and N3 on the second date. For this date, all indices values resulted in significant differences between N0 and the other treatments and between N1 and the two higher fertilized treatments. On the last date, before anthesis, GAI and N_{shoot} showed the same levels of significance as the indices on the second date. The response of DM_{shoot} was the same as for the second date. For all indices there were significant differences between N0 and the other three treatments, and for N1 and N2 in comparison to N3.

4. Discussion

In our study, newly generated indices of the SR and NDI form showed improvements in estimating all three crop canopy parameters compared to the commonly used ones, though some commonly used indices like the IR/G and the REIP showed stable prediction power for individual crop canopy parameters. Among the newly derived VIs, the waveband combinations of two bands from the infrared region particularly showed good correlations. From these waveband combinations, especially those derived from λ750 und λ740 in the NDI form and from λ740 und λ780 in the NDI form as well as in the SR form, showed stable results for most crop canopy parameters and both calibration and validation. Mainly for

Table 4 – Functional parameters of several indices for estimating GAI, DM_{shoot} and total shoot N (N_{shoot}) of OSR

	Estimation of green area index by $GAI = a + b \times index$ and for NDVI and SAVI $\ln GAI = a + b \times index$		Estimation of dry matter shoot by $DM_{shoot} = a + b \times index$ and for NDVI and SAVI $\ln DM_{shoot} = a + b \times index$		Estimation of total shoot N by $N_{shoot} = a + b \times index$ and for NDVI and SAVI $\ln N_{shoot} = a + b \times index$	
	b	*a*	*b*	*a*	*b*	*a*
NDI 780,740	35.91	−0.71	4243	−92.45	187.3	−4.25
NDI 750,740	56.67	−0.58	6585	−73.04	287.4	−3.27
SR 780/740	15.63	−16.21	1843	−1919	81.36	−84.87
SR 740/780	−20.36	19.51	−2409	2301	−106.3	101.3
R850	2.72	0.27	245.0	58.97	10.52	2.57
SR 810/560	0.42	−0.54	48.03	−63.90	2.08	−2.80
IR/R	0.14	0.27	15.48	32.04	0.66	1.46
IR/G	0.44	−0.61	51.21	−73.99	2.22	−3.23
NDVI	3.02	−1.93	3.05	2.73	2.77	−0.19
SAVI	3.02	−1.41	3.02	3.26	2.77	0.28
REIP	0.35	−247	40.63	−29071	1.81	−1297
Estimations by MR						
$GAI = 0.38 \times \lambda 660 - 24.13 \times \lambda 730 + 18.30 \times \lambda 780 + 1.35$						
$DM_{shoot} = -5565 \times \lambda 400 + 2225 \times \lambda 570 - 3226 \times \lambda 730 + 2220 \times \lambda 780 + 219.7$						
$N_{shoot} = -1.09 \times \lambda 400 - 129.2 \times \lambda 730 + 93.61 \times \lambda 780 + 8.65$						

N_{shoot}, EF as well as RMSE showed best results for these waveband combinations in the range of $0.82\,g\,m^{-2}$ and $2.1\,g\,m^{-2}$, respectively. Correlation coefficients for the MR were highest among all indices for GAI and DM_{shoot} for the calibration, but in the course of validation, this method showed comparable large prediction errors. The reason for this is presumably the higher number of parameters, which can be subject to parameter uncertainty and as a result lead to considerably higher prediction error compared to the description error in the parameterization data set. This explanation is also underlined by the fact that the commonly used less complex indices with a lower number of parameters in the SR or the NDI form show stable results for calibration and validation. Least applicability for estimating crop canopy parameters was the single waveband R850, which had highest RMSE, lowest EF and CD values that were most different from one for all three crop canopy parameters. This may be due to the interference of single wavebands with noise of the measuring instrument, which is sensitive to changes of radiation intensity and sky condition (Reusch, 1997).

Since reflectance in the visible region of the spectrum approaches saturation with leaf area index (LAI) values of higher than three, VIs derived from those wavelengths are not applicable for the estimation of crop canopy parameters in later stages of plant development (Filella *et al.*, 1995; Aparicio *et al.*, 2000). Near infrared light needs a higher LAI to reach saturation of reflectance, and therefore VIs based on these wavelengths can be used to estimate crop canopy parameters like biomass even in late phases of the vegetation period (Tarpley *et al.*, 2000). However, not only the amount of leaves, but also their thickness and structure influence the near infrared reflectance (Slaton *et al.*, 2001; Read *et al.*, 2002). The higher the fraction of spongy tissue inside the mesophyll and thereby the cell surface area which is exposed to intercellular air spaces, the higher the amount of internal reflection (Terashima and Saeki, 1983; Knapp and Carter, 1998) and hence measurable reflectance above the canopy. Reflectance in the visible light region is also influenced by the leaf structure, but mainly by the consistency disposal and amount of photosynthetic pigments (Carter, 2001; Gitelson *et al.*, 2003). In contrast to the mesophyll of OSR leaves, which is separated into palisade and spongy tissues (bifacial leaves), leaves of winter wheat have a non-differentiated mesophyll, leading to fewer structural differences among winter wheat leaves (Gausman and Allen, 1973). Among bifacial leaves, there are strong distinctions concerning the ratios of palisade to spongy tissues caused by age and exposure differences (Vogelmann, 1993; Stefanowska *et al.*, 1999). The uniform structure of winter wheat leaves might be the reason why VIs derived from visible wavebands gave better correlations to crop canopy parameters of winter wheat compared to those of OSR.

Overall, regarding statistical parameters like RMSE, CD and EF, newly derived VIs were firstly well suited to estimate crop canopy parameters (Table 5) and were secondly applicable to detect differences between differently treated OSR crops (Table 6). Their applicability to detect differences between different N treatments was higher than the power of the destructive reference methods we used. This may be attributed to the fact that a larger sampling area is included in each single reflectance measurement and that therefore reflection measurements are less sensitive to local variations in crop canopy parameters caused by plant-to-plant variability. Strongest correlations of VIs were identified with N_{shoot}, but also predictions of GAI and DM_{shoot} with newly derived indices were better than with commonly used ones. In case of N_{shoot} reflectance is not based on one single parameter, but a combination of two different canopy character traits, biomass and amount of chlorophyll in the plant. This combination might stabilize N_{shoot} prediction based on crop reflectance measurements.

Table 5 – Slopes (b), intercepts (a) and correlation coefficients (r^2) of linear regressions ($y = a + bx$), RMSEs of the 1:1 regression line ($y = x$), CD and EF of estimated values of GAI, DM_{shoot} and total shoot N (N_{shoot}) by several indices to measured values derived from the validation data set

		b	a	r^2	RMSE	CD	EF
GAI							
New indices	NDI 780,740	0.712^{***}	0.145	0.71^{***}	0.84 $m^2\,m^{-2}$	1.162	0.563
	NDI 750,740	0.669^{***}	0.283	0.76^{***}	**0.77** $m^2\,m^{-2}$	1.416	**0.632**
	SR 780/740	0.712^{***}	0.157	0.70^{***}	0.84 $m^2\,m^{-2}$	1.165	0.565
	SR 740/780	0.711^{***}	0.137	0.71^{***}	0.84 $m^2\,m^{-2}$	**1.161**	0.560
	MR	0.954	0.029	0.68^{***}	0.84 $m^2\,m^{-2}$	0.744	0.564
Commonly used indices	R850	0.366^{***}	1.317^{***}	0.49^{***}	0.94 $m^2\,m^{-2}$	3.593	0.454
	SR 810/560	0.689^{***}	0.567^{***}	0.72^{***}	**0.68** $m^2\,m^{-2}$	1.501	0.712
	IR/R	0.663^{***}	0.854^{***}	0.73^{***}	**0.68** $m^2\,m^{-2}$	1.630	**0.713**
	IR/G	0.687^{***}	0.549^{***}	0.72^{***}	0.69 $m^2\,m^{-2}$	1.500	0.706
	NDVI	0.355^{***}	1.073^{***}	0.67^{***}	0.94 $m^2\,m^{-2}$	3.894	0.452
	SAVI	0.673^{***}	0.958^{***}	0.62^{***}	0.82 $m^2\,m^{-2}$	1.311	0.583
	REIP	0.664^{***}	0.132^{***}	0.75^{***}	0.89 $m^2\,m^{-2}$	**1.227**	0.513
	Mean	0.655	0.517	0.69	0.81 $m^2\,m^{-2}$	1.692	0.585
DM_{shoot} [$g\,m^{-2}$]							
New indices	NDI 780,740	0.852^{***}	16.72	0.84^{***}	56.22 $g\,m^{-2}$	1.146	0.831
	NDI 750,740	0.755^{***}	41.54^{***}	0.83^{***}	57.65 $g\,m^{-2}$	1.453	0.822
	SR 780/740	0.850^{***}	18.49	0.84^{***}	56.98 $g\,m^{-2}$	**1.145**	0.827
	SR 740/780	0.852^{***}	15.45	0.85^{***}	**55.74** $g\,m^{-2}$	1.149	**0.834**
	MR	1.032	8.95	0.78^{***}	76.70 $g\,m^{-2}$	0.725	0.686
Commonly used indices	R850	0.318^{***}	159.6^{***}	0.52^{***}	103.87 $g\,m^{-2}$	4.708	0.423
	SR 810/560	0.783^{***}	72.91^{***}	0.82^{***}	64.40 $g\,m^{-2}$	1.270	0.778
	IR/R	0.697^{***}	114.1^{***}	0.76^{***}	85.65 $g\,m^{-2}$	1.267	0.608
	IR/G	0.790^{***}	69.32^{***}	0.83^{***}	62.76 $g\,m^{-2}$	1.265	0.790
	NDVI	0.360^{***}	125.0^{***}	0.68^{***}	94.05 $g\,m^{-2}$	5.172	0.527
	SAVI	0.694^{***}	118.0^{***}	0.66^{***}	96.79 $g\,m^{-2}$	**1.126**	0.499
	REIP	0.771^{***}	19.55^{*}	0.84^{***}	**62.23** $g\,m^{-2}$	1.337	**0.793**
	Mean	0.730	64.97	0.77	72.75 $g\,m^{-2}$	1.814	0.702
N_{shoot} [$g\,m^{-2}$]							
New indices	NDI 780,740	0.966	0.424	0.84^{***}	2.29 $g\,m^{-2}$	0.896	0.814
	NDI 750,740	0.855^{***}	1.530^{***}	0.85^{***}	**2.12** $g\,m^{-2}$	1.150	**0.841**
	SR 780/740	0.966	0.480	0.83^{***}	2.31 $g\,m^{-2}$	0.892	0.811
	SR 740/780	0.963	0.388	0.84^{***}	2.27 $g\,m^{-2}$	**0.901**	0.817
	MR	1.193^{**}	−0.116	0.80^{***}	3.60 $g\,m^{-2}$	0.542	0.540
Commonly used indices	R850	0.353^{***}	1.681^{***}	0.53^{***}	5.29 $g\,m^{-2}$	1.429	0.007
	SR 810/560	0.870^{**}	3.009^{***}	0.81^{***}	3.02 $g\,m^{-2}$	0.940	0.676
	IR/R	0.762^{***}	4.858^{***}	0.75^{***}	3.95 $g\,m^{-2}$	0.928	0.446
	IR/G	0.875^{**}	2.870^{***}	0.82^{***}	2.96 $g\,m^{-2}$	0.944	0.690
	NDVI	0.357^{***}	5.583^{***}	0.63^{***}	3.72 $g\,m^{-2}$	4.865	0.509
	SAVI	0.696^{***}	5.185^{***}	0.66^{***}	4.10 $g\,m^{-2}$	**1.012**	0.404
	REIP	0.881^{**}	0.505	0.83^{***}	**2.24** $g\,m^{-2}$	1.062	**0.821**
	Mean	0.811	2.200	0.77	3.16 $g\,m^{-2}$	1.297	0.615

Additionally, the averaged statistical parameter over all indices is given. Number of n was 89 for each regression.
Slopes and intercepts were tested on being significantly different to 1 and 0, respectively. Lowest RMSE, highest EF and CD closest to one are bolded for new and commonly used indices. The limit of significance was $^{***}p < 0.001$, $^{**}p < 0.01$ and $^{*}p < 0.05$, respectively.

Even though the results were calibrated and validated on data from only one location, there is strong evidence that they are also applicable to other locations due to the fact that reflection depends on physical properties of leaves. Since the reflection in the near infrared region is determined mainly by vital biomass, estimation of crop canopy parameters by VIs from near infrared wavebands is likely transferable to other sites.

Because one advantage of this method is the estimation of crop canopy parameters in realtime for a large area with less effort than destructive measurements would take, it can be used in different ranges of application. On the one hand, it can be used for new fertilization techniques, which calculate optimal amounts of nitrogen fertilizer based on different soil and crop canopy parameters, and therefore need information on the current aboveground biomass, which can be derived by VIs. On the other hand, it can be used by plant breeders, who might need to identify crop canopy parameters for many different and differently treated varieties in a time saving way.

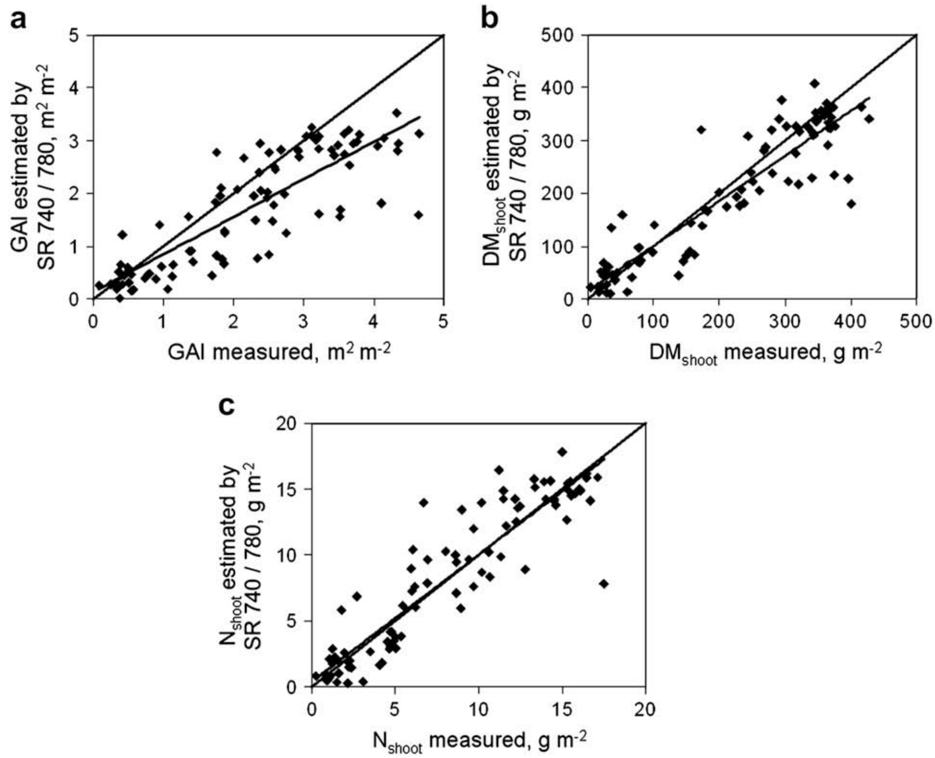

Fig. 3 – Linear regression of estimated crop canopy parameters GAI, DM_{shoot} and total shoot N (N_{shoot}) by SR 740/780 to measured parameter values for the validation data set. The regression functions and r^2 for all subfigures are as follows: (a) $y = 0.71x + 0.14$, $r^2 = 0.71$; (b) $y = 0.85x + 15.45$, $r^2 = 0.85$ and (c) $y = 0.96x + 0.39$, $r^2 = 0.84$.

Table 6 – GAI, DM_{shoot}, total shoot N (N_{shoot}), NDI 780/740, NDI 750/740, SR 780/740 and SR 740/780 as affected by four different N treatments on three different measuring dates

		N rate (kg ha^{-1})			
		0	80	160	240
18.04.2005	GAI	1.01 b	1.60 a	1.79 a	1.82 a
	DM_{shoot} [g m^{-2}]	147.78 a	199.96 a	209.83 a	204.46 a
	N_{shoot} [g m^{-2}]	4.67 b	8.33 a	10.37 a	10.80 a
	NDI 780,740	0.044 c	0.062 b	0.072 ab	0.076 a
	NDI 750,740	0.249 c	0.038 b	0.044 ab	0.046 a
	SR 780/740	1.092 c	1.134 b	1.157 ab	1.165 a
	SR 740/780	0.917 a	0.883 b	0.867 bc	0.860 c
26.04.2005	GAI	1.03 b	1.65 a	2.00 a	2.10 a
	DM_{shoot} [g m^{-2}]	187.27 b	271.16 ab	273.01 ab	297.89 a
	N_{shoot} [g m^{-2}]	5.31 b	9.60 a	13.10 a	13.22 a
	NDI 780,740	0.039 c	0.068 b	0.086 a	0.091 a
	NDI 750,740	0.020 c	0.041 b	0.053 a	0.054 a
	SR 780/740	1.083 c	1.146 b	1.188 a	1.200 a
	SR 740/780	0.925 a	0.874 b	0.843 c	0.834 c
03.05.2005	GAI	1.32 c	2.30 b	3.43 a	3.71 a
	DM_{shoot} [g m^{-2}]	241.58 b	319.26 ab	390.20 a	383.80 a
	N_{shoot} [g m^{-2}]	6.39 c	10.81 b	16.84 a	18.12 a
	NDI 780,740	0.051 c	0.091 b	0.097 b	0.119 a
	NDI 750,740	0.032 c	0.057 b	0.060 b	0.073 a
	SR 780/740	1.108 c	1.200 b	1.215 b	1.270 a
	SR 740/780	0.903 a	0.834 b	0.824 b	0.788 c

Values followed by different letters are significantly different with $p < 0.05$.

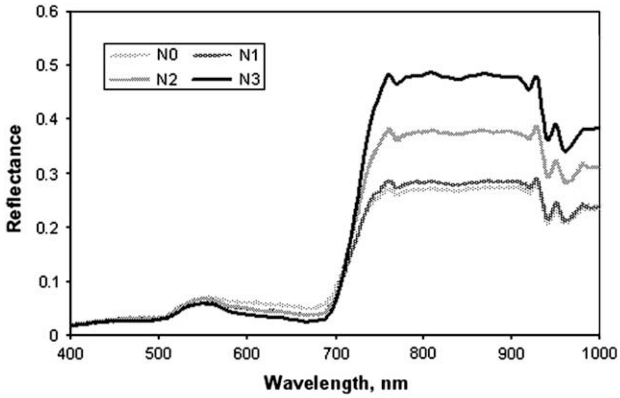

Fig. 4 – Canopy reflectance spectra of four differently fertilized OSR plots of one block on 29 April 2005: 0 kg N ha^{-1} (N0), 80 kg N ha^{-1} (N1), 160 kg N ha^{-1} (N2) and 240 kg N ha^{-1} (N3).

To sum up, the outcomes of this study give strong evidence that VIs derived by narrowband reflectance spectra are not only helpful measures for estimating and predicting crop canopy parameters for cereal crops, but could be applied with a similar accuracy also for OSR. By systematically deriving VIs in different approaches from hyperspectral measurements, new VIs were successfully detected and their applicability was successfully assessed for OSR. For the estimation of GAI, especially NDI 750,740 showed best prediction power according to calibration and validation. DM_{shoot} and N_{shoot} were best predicted by either NDI 750,740 or SR combinations of 780 nm and 740 nm, depending on results of calibration or validation.

5. Conclusions

Systematic analysis of hyperspectral reflectance measurements in the SR and NDI form for OSR was a useful approach for deriving new VIs. These indices were successfully used to estimate crop canopy parameters like GAI, DM_{shoot} and N_{shoot} during the vegetation period and their prediction power exceeded commonly used indices. Particularly, NDI 750,740 served best to estimate GAI and DM_{shoot} and N_{shoot} were best predicted by either NDI or SR forms of 740 nm and 780 nm. Using these indices enables small differences between crop canopy parameters to be identified in realtime and for large areas. Regarding calibration and validation, the indices showed stable results and there is strong evidence that they are also applicable to other locations.

There are several application potentials to transfer this method into practice. Fertilization techniques may benefit from this method as well as plant breeders, who both need to accurately identify crop canopy parameters.

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