DERIVING INFORMATION ON WINTER WHEAT PERFORMANCE FROM IN-SEASON VARIATIONS OF CROP CANOPY REFLECTANCE

Rumiana Kancheva, Denitsa Borisova, Georgi Georgiev

Space Research and Technology Institute – Bulgarian Academy of Sciences
e-mail: rumik@abv.bg, dborisova@stil.bas.bg, ggeorgie@stil.bas.bg

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Abstract: *Agricultural monitoring is an important and continuously spreading activity in remote sensing and applied Earth observations. It supplies valuable information on crop condition and growth processes. Much research has been carried out on vegetation phenology issues. In agriculture, the timing of seasonal cycles of crop activity is important for species classification and evaluation of crop development, growing conditions and potential yield. The correct interpretation of remotely sensed data, however, and the increasing demand for data reliability require ground-truth knowledge of the seasonal spectral behaviour of different species and their relation to crop vigour. For this reason, we performed ground-based study of the seasonal response of winter wheat reflectance patterns to crop growth patterns. The goal was to quantify crop seasonality by establishing empirical relationships between plant biophysical and spectral properties in main ontogenetic periods. Phenology and agro-specific relationships allow to assess crop condition during different portions of the growth cycle and thus effectively track plant development and make yield predictions. The applicability of different vegetation indices for monitoring crop seasonal dynamics, health condition, and yield potential was examined.*

ИЗВЛИЧАНЕ НА ИНФОРМАЦИЯ ЗА РАЗВИТИЕТО НА ЗИМНА ПШЕНИЦА ПО СЕЗОННИ ИЗМЕНЕНИЯ НА СПЕКТРАЛНОТО ОТРАЖЕНИЕ НА РАСТЕНИЯТА

Румяна Кънчева, Деница Борисова, Георги Георгиев

Институт за космически изследвания и технологии – Българска академия на науките
e-mail: rumik@abv.bg, dborisova@stil.bas.bg, ggeorgie@stil.bas.bg

Ключови думи: *зимна пшеница, спектрални характеристики, вегетационни индекси, сезонна динамика, фенология, параметри на състоянието, прогнозиране на добивите*

Резюме: *Мониторингът в селското стопанство е важно и широко разпространено приложение на дистанционните изследвания, което предоставя ценна информация за състоянието на посевите и процеса на развитието им. Множество изследвания са посветени на въпроси на фенологията. Сроковете и ходът на вегетационната активност са важни при използването на дистанционни данни за класификация на културите, за оценка на тяхното развитие, условията на отглеждане и потенциалния добив. Правилната интерпретация на данните от дистанционните изследвания, както и изискването за по-голяма надеждност на информацията, налагат подробно наземно изучаване на сезонната динамика на спектралните характеристики на различните култури и установяване на връзката им със състоянието на посевите. Поради тази причина са проведени полеви експерименти, чрез които да се проследи сезонния ход на биофизичните и спектралните отражателни характеристики на зимна пшеница. Целта е да се изследват и опишат количествените връзки между биометричните параметри и спектралните свойства на посевите в различни фенологични фази на развитие. Тези зависимости позволяват оценка на състоянието на растенията в различни периоди на вегетаиця, което осигурява ефективно проследяване на сезонната динамика на растежа и по-голяма точност на прогнозирания добив.*

Introduction

The rapid advances of space technologies concern almost all scientific areas from aeronautics to medicine and a wide range of application fields from communications and hazard warning to crop yield prediction. Without a doubt, vegetation monitoring is the most essential application of remote sensing techniques. Vegetation plays a vital role in Earth's hydrological, biogeochemical, and ecological processes and helps in maintaining the balance of the carbon-dioxide level in nature. Remote sensing is an accepted source of information in environmental studies for ecosystems change detection, natural resources management, environment preservation and other problems of global importance.

Agriculture is a continuously spreading application area of remote sensing. Within Earth observation activities, agricultural monitoring supplies information on crop performance. Agricultural remote sensing involves characterization of plant canopies through multispectral and multitemporal measurements. Spectral response data collected over vegetative targets are analyzed to derive information on plant growth stage and physiological condition. Mapping farm-land use, crop area estimates, and spatial and temporal distributed information on crop development are preconditions for improving the efficiency of agricultural policies and management. This is especially important in the context of site-specific precision agriculture running. Remote sensing is a major source of relevant data. Monitoring agricultural fields during the growing season plays a significant role in precision farming [1, 2] provided that reliable phytodiagnostics is obtained. Regular and timely information is needed for tracking plant phenological development [3-5], evaluating the growth process [6, 7], and assessing crop health [8-11] in order to adjust farmland management and make yield predictions at different scales [12-16]. Particular efforts are put into the elaboration of methods for assimilation of remote sensing data of high spatial-temporal resolution in agronomical models [14, 17-19] to produce information needed in agricultural practice. Various data and data processing algorithms are applied to provide quantitative crop information. The acquired multispectral data are especially effective in deriving crop biophysical parameters used in growth models. A large amount of work has been published on the derivation of vegetation biomass, leaf area index and chlorophyll content from optical data [2, 6, 7, 20-22].

Much research is carried out on vegetation phenology issues. Phenology studies have many aspects. They are related to using remotely sensed data for phenology monitoring [23, 24], assessment of vegetation types distribution [25, 26], ecosystems forecasting [27], quantifying the carbon budget [28], evaluation of year-to-year spatial and temporal variations of vegetation seasonality, and the dependence of these variations on environmental factors [29, 30]. Knowledge of phenology and taking into account phenological events are crucial elements in vegetation data interpretation. In agricultural remote sensing observations, the timing of seasonal cycles of crop activity is important for species classification [31], evaluation of plant development and growing conditions, identifying stresses, and evaluating potential yield.

However, the use of airborne and satellite data in agricultural monitoring requires detailed knowledge of species spectral behaviour under different conditions. For this reason, ground-based empirical studies complement the vast array of geo-spatial data products providing a reference data source and being associated with site-specific conditions. All the more so since data integration and sharing between different sources has become recently a leading concept [32] in remotely sensed data application and an answer to the question about the reliability of data interpretation results. Ground-based studies are an appropriate way of aiding and verifying the interpretation of remotely sensed data and a tool for validation of data processing and retrieval algorithms. Entering wider into their operational stage, remote sensing technologies face higher requirements to the accuracy of the information they provide. Because of this raising need, ground-based observations are considered one of the pillars of remote sensing observations. In-situ spectral modeling activities [33-36] are an integral part of remote sensing technologies. In vegetation studies, especially advantageous is the ability to vary and control the experimental conditions getting a precise picture of plant spectral response to different factors (species type, soil background, agricultural practices, stress impacts, etc.) as well as to track in detail the temporal behaviour of plant spectral properties during the ontogenetic cycle.

In the context of all this, our paper is devoted to in-situ observations of crop spectral response during plant growth and the performance of ground-derived spectral-biophysical relationships for the retrieval of crop canopy variables and yield prediction from multispectral and multitemporal data.

Materials and methods

The correct interpretation of remote sensing data along with the increasing demand for high reliability of the derived information require precise ground-truth study of the seasonal performance of different species, knowledge of the phenology-resolved behaviour of their spectral response and the relationship of species seasonal spectral patterns with crop vigour and productivity. For this reason, we conducted ground-based field and greenhouse experiments with the intention to investigate the multispectral response of winter wheat at different phenological stages and to relate reflectance patterns to crop seasonal development and yield. The focus of the work was on quantifying crop seasonality by establishing empirical relationships between plant biophysical and spectral properties in different periods during the ontogenetic process. Both, growth variables and spectral-temporal response, strongly depended on crop phenology and condition.

The application of different nitrogen rates and fertilization forms as well as different water supply ensured varying growing conditions and provided for a wide range of crop performance by affecting plant vigour during the phenological development. All treatments were planted on the same date and replicated twice. Whole-season measurements of canopy reflectance were carried out with a multichannel spectrometer in the visible and near infrared region (400 to 820 nm). Multispectral data in 43 narrow wavebands were acquired at weekly intervals starting from emergence to full physiological maturity and harvest (Figure 1). Concurrent measurements of crop biophysical parameters were performed. They were recorded per unit area basis and comprised: vegetation canopy fraction (C), leaf area index (LAI), plant height (H, m), stem number (N), total above-ground and leaf biomass (kg/m^2): fresh (M_w, M_L) and dry (M_d, M_{Ld}), chlorophyll concentration (Chl), and grain yield (Y, kg/m^2). In addition, precise characterization of crop phenological events was made.

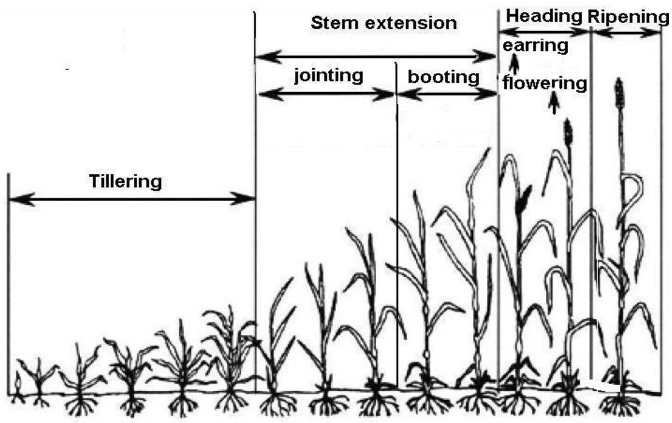


Fig. 1. Winter wheat growth stages: emergence, tillering, stem elongation (jointing, booting), heading (earring, flowering), ripening (milk, dough, and full physiological maturity)

Spectral and growth data were gathered throughout the entire growing cycle 2-3 times per each phenological stage. Due to the sampling number in terms of frequency and replicates available, and the samples variation range in terms of crop condition, the collected datasets had an amount and a range width sufficient to process them in a statistically meaningful way. Canopy spectral behaviour as a function of plant condition and phenology was statistically related to crop growth variables and yield using single-date data or datasets referring to a whole phenophase (see Fig. 1).

The measured spectral signatures were analyzed by employing vegetation indices (VIs). Various VIs were calculated from reflectance data and related to crop condition-indicative variables. We chose to present here mainly results of using ratio indices which exploit the contrasting high and low reflectance in specific for vegetation spectral bands. This choice was prompted by the most common implementation of various ratio indices and the possibility the obtained results to be compared with the results of other studies. The performance of VIs as spectral predictors of crop biophysical parameters and yield was examined. Their capability to effectively monitor plant development, to distinguish health condition and associate it with yield was assessed.

Results and discussion

Spectral data, growth patterns and yield showed variation between the trials due to the different treatment. Our purpose, however, was not to discriminate between the impact of the growing conditions, but to obtain spectral predictors of crop performance. The biophysical and multispectral measurements were used to examine by correlation analysis and describe by simple regression analysis the following relationships: first, physiological relationships - between crop growth variables, and between them and yield; second, spectral-biophysical relationships - between canopy spectral patterns, growth variables and yield.

In Table 1 and Table 2 results of the correlation analysis between winter wheat growth parameters at four phenological stages are presented as well as their correlation with yield. The strength of correlation between the examined variables revealed dependence on plant phenology and depicted crop physiological development and morphological changes. The correlation was higher in the periods of most intensive vegetative growth and at early reproductive stages before full maturity.

Table 1. Linear correlation coefficients of winter wheat growth variables and yield at tillering (up right) and heading (down left) stages

	C	N	H	LAI	M_w	M_d	M_L	M_{Ld}	Y
C		0.9	0.69	0.96	0.93	0.73	0.98	0.98	0.91
N	0.86		0.67	0.92	0.87	0.76	0.88	0.85	0.93
H	0.86	0.62		0.72	0.63	0.73	0.72	0.68	0.71
LAI	0.96	0.83	0.82		0.86	0.64	0.96	0.95	0.94
M_w	0.96	0.89	0.8	0.97		0.88	0.95	0.95	0.87
M_d	0.92	0.71	0.86	0.91	0.98		0.75	0.74	0.75
M_L	0.94	0.88	0.77	0.94	0.98	0.85		0.99	0.9
M_{Ld}	0.82	0.8	0.84	0.76	0.74	0.9	0.68		0.88
Y	0.94	0.83	0.91	0.92	0.9	0.86	0.83	0.84	

Table 2. Linear correlation coefficients of winter wheat growth variables and yield at booting (up right) and milk ripeness (down left) stages

	C	N	H	LAI	M_w	M_d	M_L	M_{Ld}	Y
C		0.89	0.96	0.89	0.93	0.87	0.91	0.94	0.95
N	0.64		0.76	0.76	0.87	0.77	0.89	0.87	0.79
H	0.92	0.62		0.92	0.9	0.91	0.84	0.92	0.96
LAI	0.88	0.72	0.91		0.96	0.93	0.92	0.96	0.89
M_w	0.81	0.77	0.89	0.93		0.93	0.97	0.98	0.9
M_d	0.77	0.73	0.85	0.88	0.98		0.85	0.96	0.84
M_L	0.84	0.64	0.9	0.98	0.9	0.84		0.94	0.87
M_{Ld}	0.85	0.64	0.91	0.99	0.95	0.89	0.99		0.88
Y	0.86	0.76	0.89	0.9	0.86	0.87	0.84	0.86	

Agricultural species are dynamic systems whose bioparameters change during plant growth. For this reason, the empirical modeling was performed at different stages of the phenological development. Single-date, phenophase-relevant and time-series spectral patterns were attributed to the set of crop variables. Some of the obtained relationships between winter wheat growth parameters are presented in Table 3. As it can be seen, high correlations existed at vegetative, reproductive and early maturation stages. With further maturing the relations weakened or became negligible.

Table 3. Linear relationships between winter wheat biophysical parameters as dependent on plant advanced growth

predictor	variable	a	b	R^2	predictor	variable	a	b	R^2
tillering					booting				
C	M_w	-0.327	2.29	0.86	C	M_w	-0.073	2.007	0.86
C	M_L	-0.119	1.918	0.96	C	M_L	-0.042	0.999	0.83
M_w	LAI	-0.678	1.209	0.74	M_w	LAI	0.031	2.694	0.92
M_L	Y	0.078	0.401	0.76	C	Y	0.024	0483	0.9
heading					milk ripeness				
C	M_w	0.298	4.067	0.92	C	M_w	-0.07	4.296	0.66
C	M_L	0.198	0.478	0.88	C	M_L	-0.024	0.495	0.71
M_w	LAI	0.058	1.211	0.94	M_w	LAI	0.016	0.611	0.86
M_L	Y	0.072	0.843	0.87	C	Y	0.019	0.497	0.88

The varying values of the regression parameters depicted crop dynamics during the physiological development. Thus, different slopes and correlation strength of the relationship between, for instance, LAI and the total biomass reflected LAI increase during the most active vegetative periods and its decrease with plant maturing and leaf senescence. Plant biomass, dry matter accumulation, leaf area index and canopy density are key parameters for assessing crop condition and productivity. The temporal patterns of these variables characterize not only crop phenological development but are as well indicators of plant health condition. Crop condition is assessed by evaluating the stage-specific values of growth variables and comparing them to a certain criterion in absolute terms or on a relative basis. Biophysical relationships can serve for verification of vegetation parameters retrieval and yield predictions from remote sensing spectral data.

Vegetation indices (VIs) are routinely used to monitor spatial and temporal changes in vegetation performance. The most common VIs are normalized differences (NDVI) utilizing visible and infrared spectral bands, and diverse ratio indices. We examined a big number of VIs for the strength of their correlation with plant growth variables. The formulae of some of them (mainly in the form of two or three-band combinations) that produced highest degree of correlation are presented in Table 4. The spectral indices were statistically related to crop canopy fraction, leaf area index, total and leaf fresh and dry biomass, crop density, plant chlorophyll, and grain yield. Strong correlation with spectral indices derived from the green (G=550 nm), red (R=670 nm) and near-infrared (NIR=800 nm) reflectance factors were observed (Table 4 and Table 5). Crop spectral response at different phenological stages was found to be sensitive to the variations of the growth variables that characterized plant vigour and seasonal development.

Table 4. Correlation between vegetation indices and winter wheat growth variables and yield of at heading stage

No	VI	C	N	H	LAI	M_w	M_d	M_L	Y
1	(NIR-R)/(NIR+R)	0.95	0.86	0.93	0.93	0.88	0.80	0.87	0.96
2	NIR/R	0.97	0.92	0.93	0.95	0.94	0.84	0.92	0.94
3	G.NIR/R	0.84	0.60	0.54	0.81	0.70	0.52	0.78	0.72
4	(NIR-G)/(NIR+G)	0.88	0.89	0.92	0.91	0.91	0.85	0.92	0.9
5	NIR/G	0.97	0.95	0.75	0.98	0.96	0.88	0.98	0.92
6	(NIR-R)/NIR	0.79	0.80	0.96	0.81	0.82	0.76	0.82	0.9
7	(G-R)/G	0.87	0.82	0.85	0.85	0.85	0.75	0.85	0.83
8	(NIR-G)/NIR	0.83	0.85	0.95	0.86	0.87	0.81	0.87	0.86
9	NIR/(G+R)	0.99	0.95	0.74	0.98	0.96	0.87	0.99	0.96
10	R/(NIR+G)	-0.83	-0.83	-0.94	-0.84	-0.86	-0.78	-0.85	-0.83
11	(G-R)/(G+R)	0.89	0.82	0.80	0.85	0.85	0.74	0.85	0.79
12	G/R	0.89	0.80	0.73	0.85	0.83	0.71	0.84	0.82
13	NIR/(G.R)	0.90	0.94	0.65	0.89	0.95	0.94	0.93	0.77
14	G/(G+R+NIR)	-0.94	-0.93	-0.85	-0.95	-0.95	-0.88	-0.96	-0.93
15	R/(G+R+NIR)	-0.88	-0.86	-0.92	-0.88	-0.89	-0.81	-0.88	-0.8
16	NIR/(G+R+NIR)	0.91	0.90	0.90	0.92	0.92	0.84	0.92	0.94
17	(NIR-G)/R	0.91	0.82	0.82	0.95	0.94	0.75	0.85	0.86
18	$[(G-R)/(G+R)+0.5]^{0.5}$	0.88	0.82	0.82	0.85	0.85	0.75	0.85	0.72
19	$[(NIR-R)/(NIR+R)+0.5]^{0.5}$	0.83	0.84	0.94	0.85	0.86	0.79	0.85	0.92
20	$[(NIR-G)/(NIR+G)+0.5]^{0.5}$	-0.87	-0.88	-0.93	-0.89	-0.90	-0.83	-0.90	-0.83

Table 5. Correlation between vegetation indices and winter wheat growth variables and yield at milk ripeness stage

VI	C	N	H	LAI	M_w	M_d	M_L	Y
1	0.94	0.89	0.95	0.92	0.81	0.78	0.71	0.93
2	0.97	0.93	0.82	0.93	0.95	0.90	0.97	0.91
4	0.88	0.71	0.88	0.92	0.90	0.88	0.94	0.89
5	0.86	0.95	0.70	0.85	0.89	0.84	0.94	0.87
6	0.94	0.84	0.86	0.87	0.86	0.84	0.74	0.94
8	0.81	0.71	0.87	0.92	0.85	0.83	0.92	0.87
9	0.95	0.79	0.93	0.98	0.94	0.89	0.95	0.93
10	-0.93	-0.83	-0.84	-0.84	-0.84	-0.83	-0.71	-0.86
12	0.86	0.77	0.71	0.71	0.74	0.72	0.73	0.81
13	0.77	0.78	0.78	0.84	0.64	0.8	0.84	0.79
14	-0.70	-0.83	-0.79	-0.89	-0.76	-0.73	-0.90	-0.78
16	0.95	0.83	0.93	0.96	0.93	0.90	0.90	0.95
17	0.93	0.85	0.87	0.95	0.92	0.88	0.95	0.93
19	0.93	0.83	0.84	0.84	0.84	0.83	0.71	0.92

Subsequently, in order to quantitatively link spectral indicators to crop state-indicative parameters regression analysis was run over the datasets. Through simple regression, each vegetation index was related to each crop growth variable. The regression results for most of the examined VIs produced well-fitting models with predicted values close to the observed data values. This is illustrated by Figure 2a and Figure 2b where LAI empirical models derived from spectral reflectance data at two phenological intervals are presented. Figure 2c and Figure 2d shows the good correspondence between LAI predicted (estimated from the regression fits) and actual (measured) values. LAI is an essential descriptor of wheat canopies. As illustrated, it can be reliably estimated from multispectral data provided that phenology is taken into account. The same refers to other essential crop parameters such as canopy cover, and total and leaf biomass. The analysis of the acquired spectral data showed that VIs were confidently related to plant variables through the bigger portion of the growing season before advanced maturity. The obtained empirical equations for some vegetation indices and crop yield and biophysical variables at earring stage are given in Table 6.

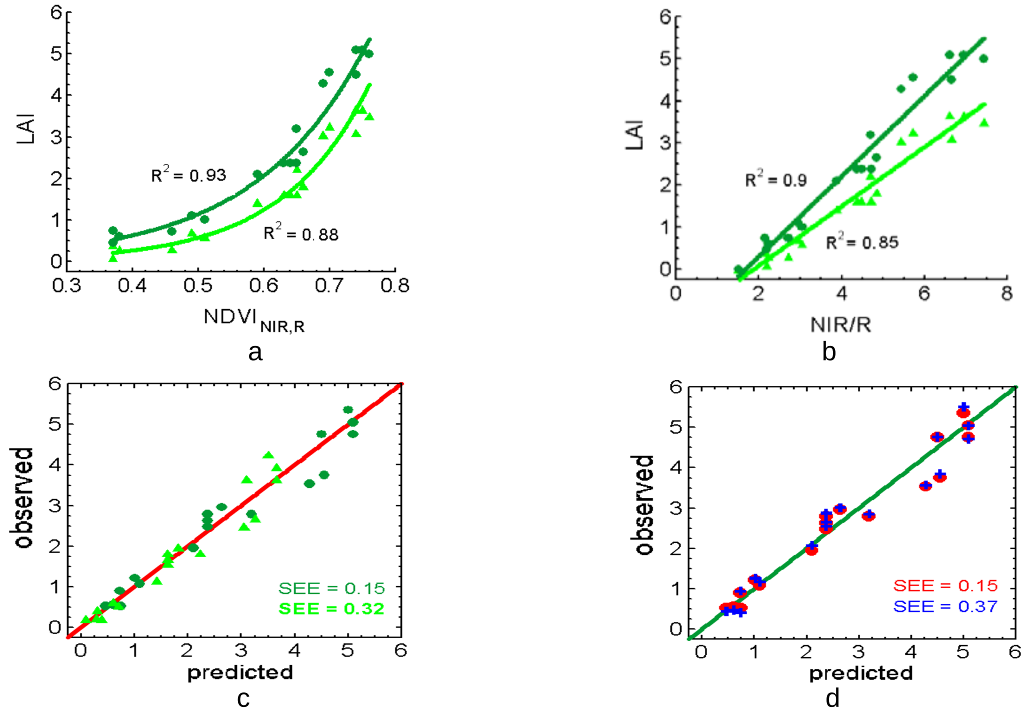
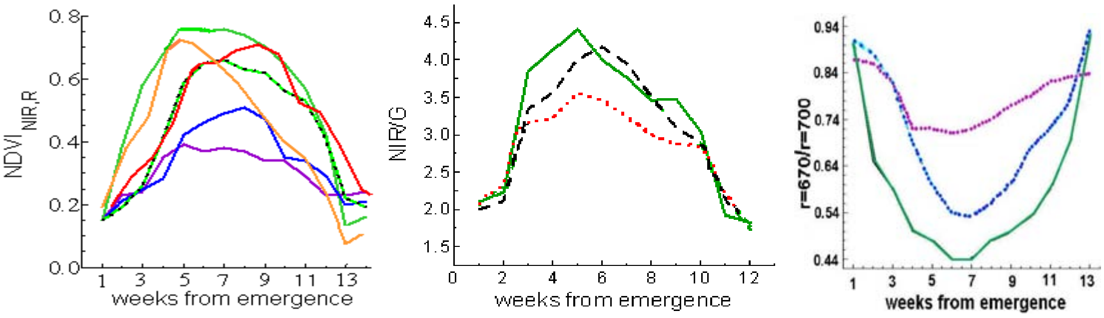


Fig. 2. VI_1 (a) and VI_2 (b) as spectral predictors of LAI for pre-heading (●) and post-heading (Δ) period; correspondence of LAI actual and predicted values: by VI_1 for both periods (c), and by VI_1 (●) and VI_2 (✚) at pre-heading (d)

Table 6. Empirical relationships of VIs with crop variables and yield at earring stage

VI	variable	model	a	b	R^2	VI	model	a	b	R^2
1	C	a+bx	-0.531	1.563	0.93	9	a+bx	-0.1	0.243	0.91
	M_w	e^{a+bx}	-1.252	3.123	0.9		a+bx	-0.92	1.22	0.94
	LAI	e^{a+bx}	-1.72	3.675	0.86		a+bx	-1.592	1.087	0.91
	Y	a+bx	-0.373	1.058	0.9		a+bx	-0.054	0.131	0.9
2	C	a+bx	0.062	0.077	0.88	14	a+bx	1.816	-7.34	0.87
	M_w	a+bx	-0.493	0.441	0.95		a+bx	7.842	-30.3	0.9
	LAI	a+bx	-0.421	0.386	0.93		a+bx	3.807	-14.9	0.91
	Y	a+bx	-0.006	0.047	0.89					
4	C	a+bx	-0.588	1.813	0.81	16	a+bx	-1.173	2.426	0.91
	M_w	a+bx	-5.928	13.08	0.82		a+bx	-9.003	15.87	0.88
	LAI	a+bx	-5.66	12.22	0.88		a+bx	-8.449	14.7	0.93
	Y	a+bx	-344.9	1018	0.83		a+bx	-0.856	1.616	0.91
5	C	a+bx	-0.205	0.162	0.84	17	a+bx	0.074	0.094	0.88
	M_w	a+bx	-1.506	0.827	0.91		a+bx	-0.079	0.476	0.95
	LAI	a+bx	-1.385	0.74	0.91		a+bx	-1.385	0.74	0.91
	Y	a+bx	-0.039	0.052	0.88		a+bx	0.039	0.050	0.88

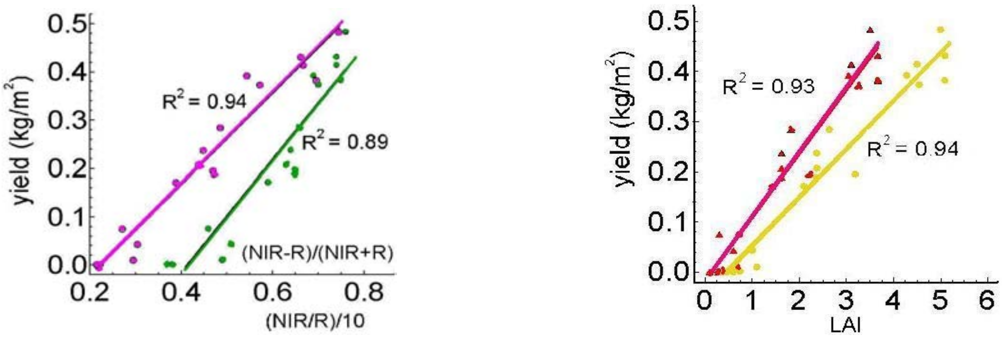
The seasonal performance of VIs was a function of plant condition and growth stage. Examples of time-series VIs patterns of winter wheat trials are shown in Figure 3 for $NDVI_{NIR,R}$ (VI_1) and the simple ratios NIR/G (VI_5) and R/700 nm. These multitemporal profiles contain data from emergence to ripening and full maturity taken on 13 dates during the growing season. They tracked crop phenological development and distinctly monitored the temporal deviations in plant condition throughout the season. VIs temporal behaviour varied significantly between the trials depending on crop vigour. This provided for reliable discrimination between crop conditions during the season. Plant development rates and stages duration could also be distinguished from VIs profiles. The most pronounced amplitude differences were observed for mid-season values around heading. All trials showed uni-modal temporal spectral response during plant development. The temporal VIs curves had a bell (Figure 3a and Figure 3b) or bowl (Figure 3c) shape depending on the positive or negative correlation with plant growth variables. Bell-shaped and bowl-shaped pattern could be found in the blue, red and NIR wavebands.



a b c

Fig. 3. Seasonal patterns of winter wheat vegetation indices:
a – $NDVI_{NIR,R}$ (VI_1),b – NIR/G (VI_5), c – 670 nm/700 nm

Besides monitoring pant growth performance, VIs was suitable for yield forecasts being strongly correlated with the grain yield within plant active growth and early reproductive periods. Figure 4a shows yield spectral models fitted from VI_1 and VI_2 values at heading stage. Verification of yield spectral predictions was performed through phisiological yield models linking yield to crop growth variables. Figure 4b presents the derived linear dependences of winter wheat grain yield on LAI values at two phenological stages. At later stages and higher LAI this relationship tends to curvilinear.



a b

Fig. 4. Winter wheat yield prediction models: from VI_1 (●) and VI_2 (●) values at heading stage (a); from LAI values at stem elongation (Δ) and early-heading (●) stages (b)

Accumulated VIs values (temporal sums) during different growth periods produced high correlations with crop yield. Regression analysis between VIs temporal sums (ΣVI) and yield was performed to fit the empirical equations. Linear models with good statistical confidence were derived for the entire season sums as well as for different time intervals. Best performed in terms of yield prediction VI 1, 2, 4, 11, 13, 15 and 16. The R^2 values of their relationship with grain yield were above 0.9 (Table 7).

Table 7. Linear yield prediction models from VIs whole-season sums

ΣVI	a	b	R^2
1	-0.554	0.136	0.95
2	-0.296	0.013	0.95
3	-0.363	0.002	0.88
11	0.040	0.174	0.91
13	-0.209	0.068	0.91
15	1.254	-0.374	0.94
16	-1.733	0.275	0.9

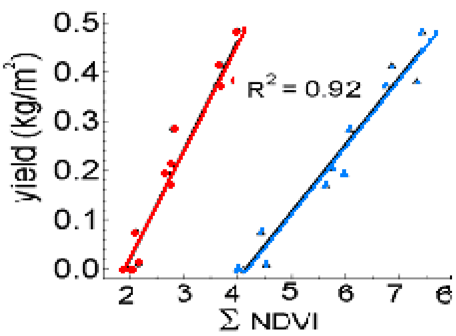


Fig. 5. Winter wheat yield prediction models from VI_1 half-season (●) and whole-season (Δ) temporal sums

In Figure 5 the derived spectral models for yield prediction from VI_1 half-season and whole-season sums are plotted. The integrated during plant growth VIs values proved to be a reliable yield prediction tool. The important point is that partial-season predictors also gave good results showing almost equally close relation with crop yield. This fact provides for early yield forecasts before the end of season.

Conclusions

The performance of various vegetation indices for monitoring crop seasonal dynamics, condition, and yield potential was examined. The temporal behaviour of vegetation indices revealed increased sensitivity to crop growth. The derived spectral-biophysical relationships allowed extraction of quantitative information about crop variables and yield at different stages of the phenological development. Relating plant spectral and biophysical variables in a phenology-based manner allows crop monitoring, that is crop diagnosis and predictions to be performed multiple times during plant ontogenesis. During active vegetative periods spectral data was highly indicative of plant growth trends and yield potential. The temporal sums of VIs values contributed to reliable yield prediction and showed very good correspondence with the estimates from biophysical models. For dates before full maturity most of the examined VIs proved to be meaningful statistical predictors of crop state-indicative biophysical variables. High correlations were obtained for canopy cover fraction, LAI, and biomass. Sensitivity to red, near-infrared and green reflectance showed both vigorous and depressed plants. As crops attained advanced growth stages, decreased sensitivity of VIs and weaker correlations with bioparameters were observed, yet still significant in a statistical sense. The results highlight the capability of the presented approach to track the dynamics of crop growth from time-resolved and time-integrated spectral data, and illustrate the prediction accuracy of the spectral models. The results of this paper may be useful in assessing the efficiency of various spectral band ratios and other vegetation indices often used in remote sensing studies of natural and agricultural vegetation. They suggest that the algorithm is particularly suitable for airborne cropland monitoring and could be expanded to similar sites at local or regional scale.

References:

1. Santhosh, K. S.n, Soizik. L., Casady, G. M. and Seielstad, G. A., "Remote sensing applications for precision agriculture: A learning community approach", Remote Sensing of Environment, 88 (1-2), 157-169 (2003).
2. Haboudane, D., Miller, J. R., Pattey, E., Zarco-Tejada, P. J. and Strachan, I. B. "Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture", Remote Sensing of Environment, 90, 337-352 (2004).
3. Jihua Meng, Bingfang Wu, Qiangzi Li, Xin Du, and Kun Jia, "Monitoring crop phenology with MERIS data: A case study of winter wheat in North China Plain", Proceedings of Progress In Electromagnetics Research Symposium, Beijing, China, 1225-1228 (2009).
4. Viña, Andrés; Gitelson, Anatoly A.; Rundquist, Donald C.; Keydan, Galina P.; Leavitt, Bryan; and Schepers, James, "Monitoring maize (Zea.mays L.) phenology with remote sensing" Papers in Natural Resources. Paper 264 (2004) http://digitalcommons.unl.edu/natrespapers/284.
5. Xingzhi You, Jihua Meng, Miao Zhang and Taifeng Dong, "Remote sensing based detection of crop phenology for agricultural zones in China using a new threshold method", Remote Sensing. 5, 3190-3211 (2013).
6. González-Sanpedro, M.C., Le Toan. T., Moreno, J., Kergoat, L. and Rubio, E., "Seasonal variations of leaf area index of agricultural fields retrieved from Landsat data", Remote Sensing of Environment, 112 (3), 810-824 (2008).
7. Hatfield, J.L. and Prueger, J.H., "Value of using different vegetative indices to quantify agricultural crop characteristics at different growth stages under varying management practices", Remote Sensing, 2,562-578 (2010).
8. Cagatay Tanrverdi, "Improved agricultural management using remote sensing to estimate water stress ındices", Applied Remote Sensing Journal, 1(2), 19-24 (2010).
9. Baret, F., Houle`s, V. and Guer'rif, M., "Quantification of plant stress using remote sensing observations and crop models: the case of nitrogen management", Journal of Experimental Botany, 58 (4), 869–880 (2007).
10. Franke, J. and Menz, G., "Multi-temporal wheat disease detection by multi-spectral remote sensing". Precision Agriculture, 8(3), 161-172 (2007).
11. Cagatay Tanrverdi, "Improved agricultural management using remote sensing to estimate water stress ındices", Applied Remote Sensing Journal, 1(2), 19-24 (2010).
12. Bolton, D. K. and Friedl, M. A., "Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics", Agricultural and Forest Meteorology 173, 74– 84 (2013).
13. Jianqiang Ren, Zhongxin Chen, Qingbo Zhou, Huajun Tang, "Regional yield estimation for winter wheat with MODIS-NDVI data in Shandong", China, International Journal of Applied Earth Observation and Geoinformation, 10 (4), 403-413 (2008).

14. Prasad, A. K., Lim Chai, Ramesh P. Singh, Menas Kafatos, “Crop yield estimation model for Iowa using remote sensing and surface parameters”, International Journal of Applied Earth Observation and Geoinformation, 8, 26–33, (2006).
15. Doraiswamy, P. C., Akhmedov, B., Beard, L., Stern, A., Mueller, R ., “Operational prediction of crop yields using MODIS data and products”, ISPRS Archives, XXXVI, 8/W48, 45-49, (2006).
16. Uttam Kumar Mandal, U.S. Victor, N.N. Srivastava, K.L. Sharma, V. Ramesh, M. Vanaja, G.R. Korwar, Y.S. Ramakrishna, “Estimating yield of sorghum using root zone water balance model and spectral characteristics of crop in a dryland Alfisol”, Agricultural water management, 87, 315–327 (2007).
17. Jianmao Guo, Weisong Lu, Guoping Zhang, Yonglan Qian, Qiang Yu, et al. "Incorporating remote sensing data in crop model to monitor crop growth and predict yield in regional area", Proc. SPIE 6411, Agriculture and Hydrology Applications of Remote Sensing, 64111C (2006) http://dx.doi.org/10.1117/12.692756
18. Dente, L., Satalino, G., Mattia, F., Rinaldi, M., “Assimilation of leaf area index derived from ASAR and MERIS data into CERES-Wheat model to map wheat yield”, Remote Sensing of Environment, 112 (4), 1395-1407 (2008).
19. Clevers, J. G. P. W., Vonder, O. W., Jongschaap, R. E. E., Desprats, J. F., King, C., Prévot, L.and Bruguier, N., “Using SPOT data for calibrating a wheat growth model under mediterranean conditions”, Agronomie, 22, 687-694 (2002).
20. Thenkabail, Prasad S., Smith, Ronald B., De Pauw, Eddy, “Hyperspectral vegetation indices and their relationships with agricultural crop characteristics, Remote Sensing of Environment, 71 (2), 158-182 (2000
21. Broge, N. H., Mortensen, J. V., “Deriving green crop area index and canopy chlorophyll density of winter wheat from spectral reflectance data”, Remote Sensing of Environment, 81, (1), 45-57 (2002).
22. McNairn, H., Deriving percent crop cover over agriculture canopies using hyperspectral remote sensing. Canadian Journal of Remote Sensing, 34(S1), S110-S123 (2008).
23. Motohka, T., K.N. Nasahara, H. Oguma, S. Tsuchida, “Applicability of green-red vegetation index for remote sensing of vegetation phenology”, Remote Sensing, 2, 2369-2387 (2010).
24. Zhang, X. Y., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C. F., Gao, F., et al.. “Monitoring vegetation phenology using MODIS”, Remote Sensing of Environment, 84, 471−475 (2003).
25. Ferreira, L. G. and Huete, A. R., “Assessing the seasonal dynamics of the Brazilian Cerrado vegetation through the use of spectral vegetation indices’, Int. J. Remote Sensing, 25, (10), 1837–1860 (2004).
26. Ferreira, L.G., Yoshioka, H., Huete, A., Sano, E.E., “Seasonal landscape and spectral vegetation index dynamics in the Brazilian Cerrado: An analysis within the Large-Scale Biosphere–Atmosphere Experiment in Amazonia (LBA)”, Remote Sensing of Environment, 87, 534–550 (2003).
27. Stockli, R., Rutishauser, T., Dragoni, D., O’Keefe,J., Thornton, P. E., Jolly, M., Lu, L. and Denning, A. S., “Remote sensing data assimilation for a prognostic phenology model”, J. Geophys. Res., 113, G04021 (2008)/
28. Jenkins, J. P., Braswell, B. H., Frolking, S. E. and Aber, J. D., “Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S.”, Geophysical Research Letters, 29 (24) 2201 (2002).
29. White, M. A., Brunsell, N., and Schwartz, M. D., “Vegetation phenology in global change studies”, In M. D. Schwartz (Ed.), Phenology: An integrative environmental science, NY: Kluwer Academic Publishers, 453−466 (2003).
30. White, M. A., Hoffman, F., Hargrove,W.W., and Nemani, R. R., “A global framework for monitoring phenological responses to climate change”, Geophysical Research, 32, L04705 (2005).
31. Vieira, C., Mather, P. and McCullagh, M., “The spectral-temporal response surface and its use in the multi-sensor, multitemporal classification of agricultural crops”, International Archives of Photogrammetry and Remote Sensing. XXXIII (B2), 582-589 (2000).
32. Teillet, P M., Gauthier, R P., Chichagov, A., Fedosejevs, G., “Towards integrated Earth sensing: Advanced technologies for in situ sensing in the context of Earth observation”. Canadian Journal of Remote Sensing, 28 (6), 713-718 (2002).
33. Kancheva, R., Borisova, D., “Validation of crop spectral models”, Proc. 11th International Scientific Conference “Solar-Terrestrial Influences”, Sofia, Bulgaria, 125-127 (2005).
34. Sharma, A. R., Badarinath, K.V.S., Roy, P. S., “Comparison of ground reflectance measurement with satellite derived atmospherically corrected reflectance: A case study over semi-arid landscape”, Advances in Space Research, 43 (1), 56-64 (2009).
35. Kancheva, R., Borisova, D., “Vegetation ground-level spectral modelling in support of remotely sensed data interpretation,” Proceed of the 4th Workshop “Imaging Spectroscopy. New Quality in Environmental Studies”, Warsaw, 817-825 (2006).
36. Numata, I. D., Roberts, A., Chadwick, O. A., Schimel, J. P., Galvão, L. S., Soares, J. V., “Evaluation of hyperspectral data for pasture estimate in the Brazilian Amazon using field and imaging spectrometers”, Remote Sensing of Environment, 112 (4), 1569-1583 (2008).