Современные проблемы дистанционного зондирования Земли из космоса.
2012. Т. 9. № 4. С. 265–273

Wheat canopy biophysical and spectral features seasonality

R. Kancheva, G. Georgiev

Institute for Space Research and Technologies - Bulgarian Academy of Sciences
rumik@abv.bg, ggeorgie@stil.bas.bg

Agricultural monitoring is an important and continuously spreading application of remote sensing observations. It supplies valuable information on crop condition and growth processes. Much research has been carried out on vegetation phenology issues. These issues are related to using remotely sensed data for phenology monitoring, assessment of vegetation types distribution, predicting ecosystems, quantifying the carbon budget, evaluation of year-to-year spatial and temporal variations of vegetation seasonality, and the dependence of these changes on environmental factors. 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. However, the correct interpretation of remote sensing data and the increasing demand for its reliability require ground-truth study of the seasonal spectral behaviuor of different species and their link to crop vigour. For this reason, we performed ground-based experiments to investigate the seasonal response of various winter wheat vegetation indices (VIs) to crop growth patterns. The utility of spectral vegetation indices for monitoring crop seasonal dynamics, health condition, and yield potential was examined. The goal was to quantify crop seasonality by establishing empirical relationships between plant biophysical and spectral properties in different ontogenetic periods. Suchlike phenologically-specific relationships allow to assess crop condition during different portions of the growth cycle and thus effectively track plant development and predict yield.

Keywords: winter wheat, spectral features, vegetation indices, seasonal dynamics, phenology, growth variables, yield prediction

Introduction

Remote sensing has entered into a stage when the goal is to bring investigation results to an operational use. Vegetation monitoring is, with no doubt, 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. In agriculture, mapping farm-land use, crop area estimates, and spatial and temporal distributed information on crop growth are preconditions for improving the efficiency of agricultural policies and management. Remote sensing-based monitoring is a major source of relevant data. Within Earth observation activities agricultural monitoring supplies information on crops development and health condition [1-5]. Various approaches are being implemented for crop performance assessment in order to provide objective and quantitative yield forecasts at regional and national scales [5-7].

Much research is carried out on vegetation phenology issues. These issues are related to using remotely sensed data for phenology monitoring [8-10], spatial distribution assessmeцnt of vegetation types [11, 12], ecosystem forecasting [13, 14], predicting carbon fluxes and quantifying the carbon budget [15, 16], and evaluating year-to-year spatial-temporal variations of vegetation seasonality and their dependence on environmental factors [17]. Knowledge of phenology and taking into account phenological events are a crucial element in vegetation data interpretation. Crop phenology studies have many aspects. In agricultural remote sensing observations, the timing of seasonal cycles of crop activity is important for identifying species and assessing plant development, condition, and potential yield. However, the correct interpretation of remotely sensed data and the increasing demand for data reliability requires ground-truth knowledge of the seasonal spectral patterns of various species and their link to crop vigour. This paper focuses on the establishment of empirical relationships between winter wheat growth variables and spectral-temporal responses. Both depend on plant phenology as well as on plant condition. Ground-based radiometric and agronomical data was used to attribute time-series spectral patterns to the variance of crop condition and yield. The goal was to assess the capability of different spectral features to effectively monitor plant development process, distinguish crop health condition, and associate it with yield. Relating plant spectral and biophysical variables in a phenology-based manner allows crop diagnosis and predictions to be performed multiple times during plant ontogenesis.

Materials and Methods

The study was undertaken for winter wheat crops on grey forest soil. Ground-based field experiments were conducted. The application of different nitrogen fertilization forms in varying rates as well as different irrigation regimen ensured a variety of crop state patterns by affecting plant vigor during the ontogenetic process. All treatments were planted on the same date and replicated twice. Multispectral data in narrow wavebands (400 to 820 nm) were acquired after sowing at weekly intervals starting from emergence to full physiological maturity. Concurrent measurements of crop physiological parameters were performed. They were recorded per unit area basis and comprised: vegetation canopy cover (C), leaf area index (LAI), stem height (H) and number (N), total above-ground and leaf biomass - fresh (M_w, M_L) and dry (M_d, M_{Ld}), chlorophyll (Chl) and grain yield (Y). In addition, accurate characterization of crop phenology was made. Spectral and growth data were acquired throughout the whole growing period appoiximately twice at each phenological phase. Due to the sampling number in terms of frequency and replicates available, and the sample pattern variability in terms of crop condition, the collected datasets had an amount and a range width sufficient to process them in a statistically meaningful way. Spectral characteristics were examined by utilizing vegetation indices (VIs). Various VIs were calculated from spectral data and related to crop state-indicative variables. We chose to present here the 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 ratio indices and the possibility the obtained results to be compared with the results of other studies.

In the paper, we investigate the performance of an approach for crop state assessment and yield forecast on a time-series basis. The first motivation is that ground-truth spectral-biophysical modelling is needed in order *trustworthy* crop information to be obtained from remotely sensed data. The second reason is that accounting for phenology is obligatory for obtaining reliable and accurate interpretation results. That is why the approach comprises: • development of phenologically-specific empirical models between crop biophysical properties and spectral reflectance response (serving for the retrieval of crop state variables from remote sensing radiometric data); • development of yield forecasting regression models from single-date (phenological event) and time-series (phenological interval) spectral data; • establishment of physiological relationships among variuos plant growth variables and between growth variables and yield; • verification of remote sensing predictions through comparison with estimations from the obtained ground-based relationships (not illustrated here).

Herein we present only a part of the obtained results. The main effort was put into empirical modeling as an effective technique to discriminate between the vigour of the treatments using radiometric data. The time-series spectral data gathered during plant ontogenesis were analyzed with the above-mentioned bioparameters. The latter are indicators of plant condition and determine the overall crop performance. For assessing crop condition, the agronomic variables are compared to average statistical values or some other criteria. Simple regression analysis was employed to the biophysical and spectral datasets. The statistical relationships were established for particular development stages. Spectral-biophysical relationships were derived by relating plant growth variables at different phenological phases to various spectral predictors (vegetation indices). Prediction models linking grain yield with crop agronomic characteristics and spectral response at different plant development stages or growth intervals (e.g., active vegetative growth, mid-season or whole-season period, etc.) were obtained as well. The goal of the study was to characterize plant seasonal development by multispectral and multitemporal spectral data and to use crop spectral response for distinguishing and assessing variations in crop condition.

Results and Discussion

Spectral data, agronomic variables and yield showed variation between the plots due to the applied treatment. Our purpose, however, was not to discriminate between the impact of the different growing conditions, but to obtain predictors of crop state and yield from biophysical and spectral relationships. The biometrical and spectral measurements were used to examine and describe by correlation and simple regression analyses two groups of relationships: first, physiological - among various crop growth variables, and between crop growth variables and yield; second, spectral-biophysical - between plant spectral features and agronomic variables including yield. The first group of relationships, besides physiologically defining crop condition and being associated with the potential yield, is a reliable basis for verifying the retrieval of crop growth variables and yield predictions from spectral data.

Various spectral indices were statistically related to vegetation canopy fraction, leaf area index, total and leaf fresh and dry biomass, crop density, plant chlorophyll, and grain yield in order to quantitatively link appropriate spectral indicators to crop state-indicative variables. Strong correlation with spectral indices derived from the green, red and near-infrared reflectance were observed. Ratio and normalized differences were found sensitive to crop growth variables at different phenological stages characterizing plant seasonal development. All treatments showed a bowl shape of the temporal spectral response but with different amplitudes. The most pronounced differences were for mid-season values around heading. Correlation results between winter wheat biophysical parameters and yield are presented in Table 1 and Table 2. As seen, high correlations exist at vegetative, reproductive and early maturation stages. With further maturing the relations weaken or become insignificant.

Table 1. Linear correlation matrix of winter wheat growth variables and yield at stem elongation (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	0.93
LAI	0.88	0.72	0.91		0.96	0.93	0.92	0.96	0.89
M_w	0.81	—	0.89	0.93		0.93	0.97	0.98	0.9
M_d	0.77	—	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	

Table 2. Linear correlation matrix of winter wheat growth variables and yield at jointing (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	—	0.72	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	—	084	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	

Agricultural species are dynamic systems whose bioparameters change during plant growth. For this reason, the empirical modeling was performed at different phenological phases. Some of the derived relationships among plant bioparameters are presented in Table 3. Their changes depict crop dynamics during the physiological development. Thus, the slope and strength variations of the relationship between LAI and the total biomass reflects LAI increase during the vegetative period and its decrease with plant maturing and leaf senescence. Plant biomass, 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 also indicators of crop condition. Crop condition is assessed by evaluating the growth-stage values of the agronomic variables and comparing them to a certain criterion in absolute terms or on a relative basis.

Table 3. Linear regressions of winter wheat bioparameters as varying with plant advanced growth

predictor	variable	a	b	R^2	predictor	variable	a	b	R^2
jointing					stem elongation				
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
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

Table 4. Correlation between vegetation indices and bioparameters of winter wheat at heading stage

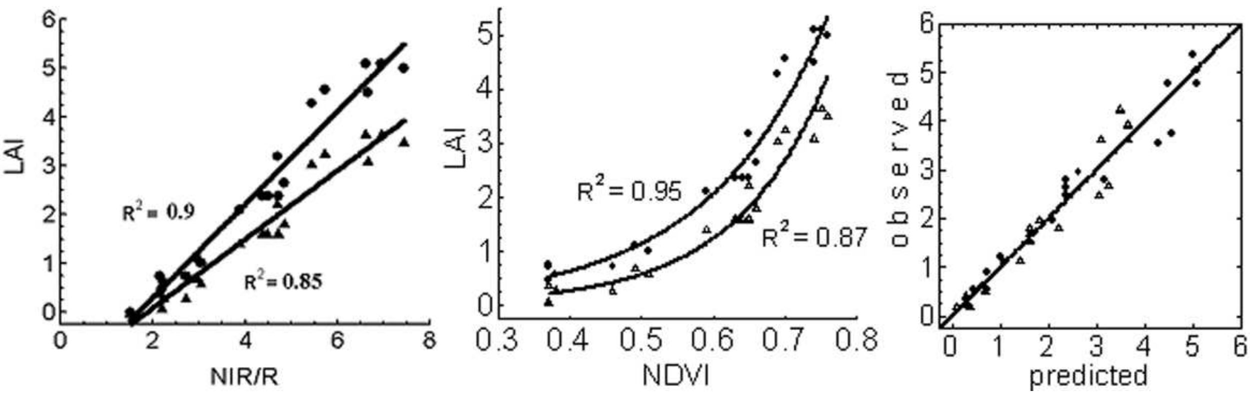
No	VI	C	N	H	LAI	M_w	M_d	M_L	Y
1	(NIR-R)/(NIR+R)	0.95	0.86	0.93	0.93	0.88	0.80	0.87	0.96
2	NIR/R	0.97	0.92	0.93	0.95	0.94	0.84	0.92	0.94
3	G.NIR/R	0.84	0.60	0.54	0.81	0.70	0.52	0.78	0.72
4	(NIR-G)/(NIR+G)	0.88	0.89	0.92	0.91	0.91	0.85	0.92	0.9
5	NIR/G	0.97	0.95	0.75	0.98	0.96	0.88	0.98	0.92
6	(NIR-R)/NIR	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

Vegetation indices (VIs) are routinely used to monitor spatial and temporal changes in vegetation biophysical characteristics. The most common VIs are normalized differences (NDVI) and diverse ratio indices. Usually the red and near-infrared bands are considered but other spectral bands are used as well. We examined a big number of VIs for the strength of their correlation with plant growth variables. Some of them (in the form of two or three-band combinations: G-550 nm, R-670 nm, NIR-800 nm) that produced the highest correlation when related to the biometrical datasets are given in Table 4 and Table 5.

Table 5. Correlation of vegetation indices with winter wheat bioparameters 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	—	0.81
13	0.77	0.78	0.78	0.84	0.64	—	0.84	0.79
14	-0.70	—	-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

The temporal VIs values varied significantly between treatments with varying plant biophysical properties. This provided for reliable discrimination and assessment of crop condition during the season. Through simple regression, each vegetation index was related to each crop growth variable. The regression results for most of the examined VIs gave statistically significant relationships with very good accuracy. This is illustrated by Fig 1a and Fig 1b where LAI prediction models from spectral reflectance data are presented. Fig. 1c shows the correspondence between LAI predicted (estimated from the models) and actual (observed) values. LAI is an essential descriptor of wheat canopies. As seen, it can be reliably estimated from multispectral data. 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. In Table 6 the empirical relationships between some VIs and crop variables at ear-filling stage are given.



a) *b)* *c)*

Fig. 1. VI_1 (a) and VI_2 (b) as spectral predictors of LAI at pre-heading (●) and post-heading (Δ); correspondence of LAI actual and predicted by VI_1 values for both periods (c)

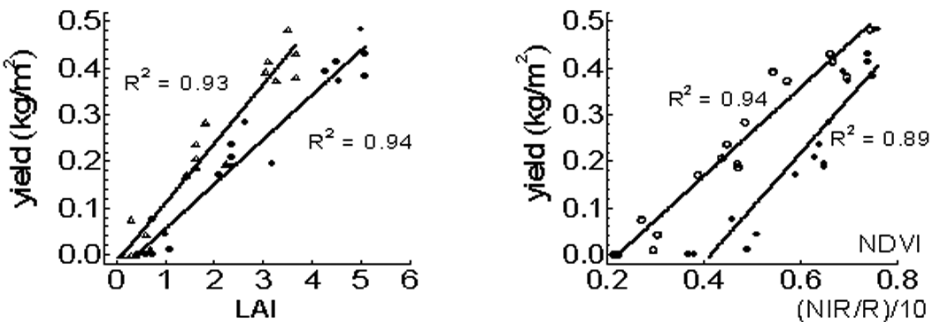
Table 6. Empirical relationships between VIs and crop variables at ear-filling stage

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

Quantitative relationships linking winter wheat biophysical variables at two phenological phases to grain yield are given in Table 7. The correlation kept high at plant ‘green’ stages before advanced and full maturity. The established dependences can be useful in verification of remote sensing yield forecasts. In Fig. 2a the yield dependence on LAI at stem elongation and early-heading is plotted. At later stages this dependence trends to curvilinear.

Table 7. Yield prediction models from winter wheat bioparameters at two phenological stages

stem elongation					heading		
predictor	model	a	b	R^2	a	b	R^2
C	a+bx	24.44	483.2	0.9	18.56	496.9	0.88
N	a+bx	-7.341	0.338	0.62	-32.71	0.338	0.69
H	a+bx	-157.6	1321	0.86	-116.6	470.6	0.83
M_w	$ax+bx^2$	344.9	-55.58	0.91	162.9	-12.32	0.92
M_d	$ax+bx^2$	1443	-863.6	0.89	466.7	-97.02	0.9
M_L	a+bx	78.49	400.9	0.76	72.34	843.2	0.87
M_{Ld}	a+bx	34.62	2211	0.77	50.13	2792	0.71



a *b*

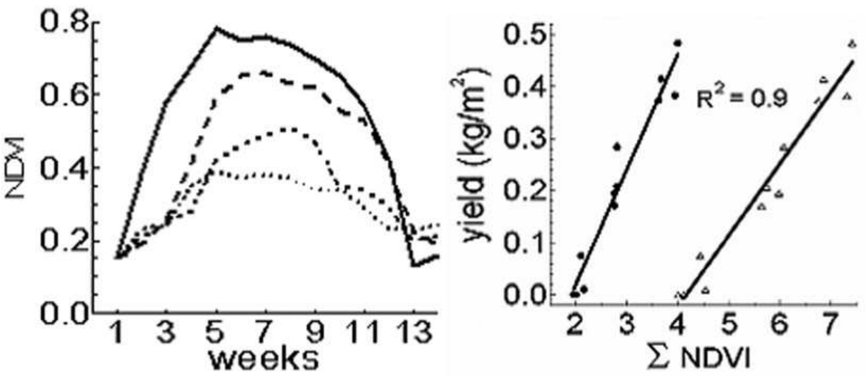
Fig. 2. Winter wheat yield prediction models: physiological (a) from LAI at stem elongation (Δ) and heading (●) stages, and spectral (b) from VI_1 (●) and VI_2 (○) at heading stage

Besides monitoring pant growth deviations, VIs were suitable for yield predictions being highly correlated with the grain yield of the treatments. Fig. 2b presents the yield prediction models fitted from VI_1 and VI_2 at heading stage.

The performance of VIs was a function of plant state and growth stage. Time-series VI_1 patterns of winter wheat treatments are shown in Fig. 3a. This figure contains data from emergence through ripening and full maturity taken on 14 dates during the growing season. As seen, the temporal behaviour of the spectral index (and of other indices as well) tracks crop phenological development and distinctly monitors temporal deviations in plant condition throughout the season. Accumulated VIs values (sums) during different growth periods produced significant correlations with crop yield. In Fig. 3b the derived spectral fits for yield prediction from VI_1 half-season and whole-season sums are plotted. The integrated during plant growth VIs values appeared to be a reliable yield prediction tool. The important is that partial-season predictors also gave good results. This provides for early predictions.

Table 8 Linear yield predictionmodels from VIs whole-season sum

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



a *b*

Fig. 3. Temporal patterns of winter wheat VI_1 indicating crop different condition during the growth cycle (a); yield prediction fits from temporally integrated VI_1 values (b): half-season sums (●) and whole-season (Δ) sums

Regression analysis between VIs temporal sums (ΣVI) and yield was performed to fit the empirical equations. Linear relationships with very good statistical confidence were obtained for different time intervals. Some of these relationships for yield prediction from multitemporal spectral data are summarized in Table 8.

Conclusions

Reflectance (vegetation indices) temporal behaviour revealed increased sensitivity to crop condition. The derived spectral-biophysical relationships allowed extraction of quantitative information about crop growth variables and yield at different stages of the phenological development. During earlier vegetative periods spectral data was highly indicative of plant growth trends and yield. The temporal sums of spectral indices contributed to accurate yield prediction and showed very good correspondence with the estimates from the biophysical models. For sample dates before full maturity most of the VIs were meaningful statistical predictors of crop condition. Sensitivity to red, near-infrared and green reflectance showed both vigorous and depressed plants. The highest correlations were obtained for canopy cover fraction and LAI. 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 approach to track the dynamics of crop growth and illustrate the accuracy of the predictions. 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. *Darvishzadeh R., Skidmore A., Schlerf M., Atzberger C.* Inversion of a radiative transfer model for estimating vegetation LAI and chlorophyll in a heterogeneous grassland // Remote Sensing of Environment, 112 (5), pp. 2592-2604, 2008.
2. *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), pp. 45-57, 2002
3. *McNairn, H.* Deriving percent crop cover over agriculture canopies using hyperspectral remote sensing // Canadian Journal of Remote Sensing 34(1), 2008.
4. *González-Sanpedro M.C., Le Toan T. , Moreno J., Kergoat L., Rubio E.* Seasonal variations of leaf area index of agricultural fields retrieved from Landsat data // Remote Sensing of Environment, 112 (3), pp. 810-824, 2008.
5. *Doraiswamy P.C., Hatfield J.L., Jackson T.J., Akhmedov B., Prueger J., Stern A.* Crop condition and yield simulations using Landsat and MODIS // Remote Sensing of Environment, 92, pp. 548–559, 2004.
6. *Serrano L., Filella I., Penuelas J.*, Remote Sensing of Biomass and Yield of Winter Wheat under Different Nitrogen Supplies // Crop Sci., 40, pp. 723–731, 2000.
7. *Anup K. Prasad A.K., Chai L., Singh R.P., Kafatos M.* Crop yield estimation model for Iowa using remote sensing and surface parameters // International Journal of Applied Earth Observation and Geoinformation, 8, pp. 26–33, 2006.
8. *Jolly, W. M., Nemani, R., Running, S. W.* A generalized, bioclimatic index to predict foliar phenology in response to climate // Global Change Biology, 11, pp. 619−632, 2005.
9. *Schwartz M. D., Reed B., & White M. A.* Assessing satellite-derived start-of-season (SOS) measures in the conterminous USA // International Journal of Climatology, 22, pp. 1793−1805. 2002.
10. *Zhang X.Y., Friedl M.A., Schaaf C.B. et al.* Monitoring vegetation phenology using MODIS // Remote Sensing of Environment, 84, pp. 471−475, 2003.
11. *Ferreira L.G., 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), pp. 1837–1860, 2004.
12. *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, pp. 534–550, 2003.
13. *White, M. A., Nemani, R.R.* Soil water forecasting in the continental United States: Relative forcing by meteorology versus leaf area index and the effects of meteorological forecast errors // Canadian Journal of Remote Sensing, 30, pp. 717−730, 2004.
14. *Stockli R., Rutishauser T., Dragoni D., O'Keefe J., Thornton P. E., Jolly M., Lu L., Denning A.S.* Remote sensing data assimilation for a prognostic phenology model // *J.* Geophys. Res., 113, G04021, doi:10.1029/2008JG000781, 2008.
15. *White M. A., Brunsell N., Schwartz M.D.* Vegetation phenology in global change studies // In M. D. Schwartz (Ed.), Phenology: An integrative environmental science (pp. 453−466). NY: Kluwer Academic Publishers, 2003.
16. *White M. A., Hoffman F., Hargrove W.W., Nemani R. R.* A global framework for monitoring phenological responses to climate change // Geophysical Research, 32, L04705, doi:10.1029/2004GL021961, 2005.
17. *Jenkins J.P., Braswell B.H., Frolking S.E., Aber J.D.*, Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S. // Geophysical Research Lett, 29 (24) 2201, doi:10.1029/2001GL014008, 2002.

Сезонность биофизических и спектральных характеристик озимой пшеницы

Р. Кынчева, Г. Георгиев

Институт космических исследований и технологий – Болгарская академия наук
rumik@abv.bg, ggeorgie@stil.bas.bg

Сельскохозяйственный мониторинг является важным и широко распространенным применением дистанционного зондирования, предоставляя ценную информацию о состоянии посевов и процессе их развития. Вопросам фенологии посвящено множество исследований. Эти вопросы связаны с использованием дистанционных данных для слежения за ходом вегетации, картирования растительных видов, прогнозирования развития экосистем, количественного определения углеводородных потоков, оценки межгодовых пространственных и временных изменений сезонных циклов растительности и зависимости этих изменений от условий окружающей среды. В сельском хозяйстве дистанционные данные о сезонной активности посевов используются для классификации культур, для оценки их развития и условий прорастания, для прогнозирования урожая. Правильная интерпретация данных дистанционного зондирования и растущие запросы к их надежности требуют, однако, тщательного наземного изучения сезонного хода различных культур и их связей с состоянием посевов. Для того, чтобы проследить сезонность биофизических и спектральных характеристик озимой пшеницы, мы провели полевой эксперимент с целью количественно описать взаимосвязи биофизических и спектральных свойств посевов в отдельных фенологических фазах растений. Такие связи позволяют оценку состояния посевов в различные периоды их развития, чем обеспечивается эффективное слежение за ходом их роста и бóльшая точность прогнозирования урожая.

Ключевые слова: озимая пшеница, спектральные характеристики, вегетационные индексы, сезонная динамика, фенология, параметры состояния, прогнозирование урожая.