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SPECTRAL REFLECTANCE FEATURES IN WHEAT CROP ASSESSMENT MODELS

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ABSTRACT. Agricultural monitoring is among the priorities of operational remote sensing. The application of hyperspectral data to precision farming is related to the supply of information on crop growth and to the possibility of yield prediction. This paper presents the results of a study aimed at the implementation of multispectral and multitemporal data in wheat crop assessment models.

СПЕКТРАЛНИ ОТРАЖАТЕЛНИ ХАРАКТЕРИСТИКИ В МОДЕЛИТЕ ЗА ОЦЕНКА НА СЪСТОЯНИЕТО НА ПШЕНИЧНИ ПОСЕВИ И ПРОГНОЗИРАНЕ НА ДОБИВА

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РЕЗЮМЕ. Аграрният мониторинг е сред приоритетите на дистанционните методи. Използването на хиперспектрални данни за цалите на селското стопанство е свързано с получаването на информация относно развитието и състояниетона посевите и възможността за прогнозиране на добивите. В работата са представени резултати от изследвания за приложението на многоспектрални данни в модели за оценка на състоянието на пшенични посеви и прогнозиране на добива.

Introduction

Remote sensing is an important source of information in environmental sciences. Agricultural monitoring is among the priorities of Earth observations supplying early information on crop growth and state (Thenkabail, 1992; Bouman, 1991). Various approaches have been implemented to provide quantitative information for crop behaviour assessment and yield prediction (Thenkabail et al., 1994a; McMurtrey et al., 1994). On the other hand, continues the research to improve the reliability of the results by implying different sampling strategies and statistical data analysis, by integrating agro-meteorological and remotely sensed data from various sources (Bouman, 1991; McMurtrey et al., 1994; De Brisis et al., 1991).

A major application of remote sensing involves the characterization of agricultural vegetation canopies using multispectral measurements (Thenkabail et al., 1994b; Rundquist, 2002). Spectral data collected over vegetative targets are analyzed to estimate key agronomical variables which are bioindicators of crop state. Monitoring of farmland dynamics during plant growth period is performed with the goal to track crop development and forecast crop production.

In this paper, we investigate an approach for providing crop state assessment and yield forecasts. The study has been carried out over field-grown winter wheat. High-resolution visible and near-infrared spectral data have been acquired at different moments throughout plant ontogenetic season, along with ground-truth data on crop parameters, such as leaf area index, biomass, density and others.

Materials and methods

The main attention in the study was concentrated on the following work: • development of phonologically–specific regression models between crop spectral reflectance and biophysical properties; • development of yield forecasting models from single-date and time-accumulated spectral data; • establishment of relationships between plant bioparameters and yield. The first step is used for the estimation of crop state variables from radiometric data and along with the third one for accuracy assessment and verification of spectral yield predictions performed by the second set of models.

In-situ high-resolution visible and near-infrared reflectance data have been acquired throughout the growing season, along with detailed measurements of crop bioparameters. These data served to establish empirical relationships between crop reflectance, agronomic variables, and grain yield. The relationships have been used to estimate crop bioparameters from airborne remotely sensed spectral data. The retrieved crop bioparameters have been implemented then into yield-predicting models.

In validation purpose, the prediction results have been compared to the results from using ground-truth biophysical-yield models as well as with the prediction results of using reflectance features temporal behavior in yield assessment.

The present study was taken for winter wheat field-grown crops. Crop spectral and growth data were acquired throughout the growing period at the main phenological stages. Plant parameters were recorded per unit area basis and comprised vegetation canopy cover (C), leaf area index (LAI), plant height (h), stem number (N), fresh and dry total M_w, M_d and leaf biomass M_L, M_{Ld}. The in-situ spectral measurements were performed with a portable multichannel radiometer within the 400-800 nm wavelength band.

Various ratio vegetation indices (Qi et al., 1994; Dusek et al., 1985; Li et al., 1993; Kancheva, Borisova, 2006a) were calculated from spectral data and related to crop parameters through regression analysis. Some of them are presented in Table 1. Such spectral indices are a more stable baseline to detect crop growth variations than reflectance factors in single bands. They exploit the contrasting high and low reflectance in specific for green vegetation spectral bands (G – green, R – red, NIR – near infrared).

Table 1. *Vegetation İndices (VI)*

№	VI	№	VI
1	(NIR-R)/(NIR+R)	11	(G-R)/(G+R)
2	NIR/R	12	G/R
3	G.NIR/R	13	NIR/(G.R)
4	(NIR-G)/(NIR+G)	14	G/(G+R+NIR)
5	NIR/G	15	R/(G+R+NIR)
6	(NIR-R)/NIR	16	NIR/(G+R+NIR)
7	(G-R)/G	17	(NIR-G)/R
8	(NIR-G)/NIR	18	$[(G-R)/(G+R)+0.5]^{0.5}$
9	NIR/(G+R)	19	$[(NIR-R)/(NIR+R)+0.5]^{0.5}$
10	R/(NIR+G)	20	$[(NIR-G)/(NIR+G)+0.5]^{0.5}$

Spectral-biophysical relationships were established relating crop variables and yield to spectral predictors (vegetation indices). Yield models linking crop production with plant agronomical variables were obtained as well. All statistical relationships were derived for particular crop development stages. Temporal spectral data gathered throughout the growing season were analyzed as well. They were correlated with pant state deviations and crop yield.

Results and discussion

In order to obtain predictors of crop state and yield, spectral-biophysical models were developed relating crop bioparameters and yield to different spectral indices. High correlations and good correspondence were found between predicted and actual (ground-truth) values.

In Table 2 and Table 3 results of the correlation and regression analyses of wheat bioparameters and yield at different phenological stages are given. High correlations were obtained as well at other development stages (tillering, heading, ear-filling). The correlation kept high at plant 'green' stages before full maturity. The empirically derived relationships between plant bioparameters presented in Table 4 give additional possibilities for multivariative crop state assessment and prediction verification.

Table 2. *Correlation between wheat bioparameters and yield at stem elongation (1) and milk ripeness (2) stages*

	C	LAI	M_w	M_d	M_L	M_{Ld}	N
1	0.95	0.89	0.9	0.84	0.87	0.88	0.79
2	0.86	0.9	0.86	0.87	0.84	0.86	0.76

To be pointed out is the phenologically-based modeling which means that spectral-biophysical relationships have been fitted at different ontogenetic stages of plant growth. This allows the best observation time to be picked up, improves the predictive accuracy of the models and provides for early crop diagnostics.

Table 3. *Yield prediction models from 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	0.9
M_w	ax+bx²	344.9	-55.58	0.91	162.9	-12.32	0.92
M_d	ax+bx²	1443	-863.6	0.89	466.7	-97.02	0.9
N	a+bx	-7.341	0.338	0.63	-32.71	0.338	0.82
M_L	a+bx	78.49	400.9	0.76	72.34	843.2	0.87
M_{Ld}	a+bx	34.62	2211	0.78	50.13	2792	0.84

Table 4. *Regressions between wheat parameters as changing during plant advanced growth*

predictor	variable	a	b	R^2
stem elongation				
C	M_w	-0.073	2.007	0.90
C	M_L	-0.042	0.999	0.93
M_w	LAI	0.306	2.694	0.92
heading				
C	M_w	0.298	4.067	0.94
C	M_L	0.198	0.478	0.98
M_w	LAI	0.058	0.847	0.88
milk ripeness				
C	M_w	-0.07	4.296	0.77
C	M_L	-0.024	0.495	0.79
M_w	LAI	0.016	0.475	0.9

Agricultural species are dynamic systems whose parameters change during plant growth. This imposes modeling to be performed at different stages of plant development. The changes of the relationships depict the temporal behavior of crop bioparameters with plant physiological changes. Thus, the relationship between the vegetation fraction and leaf biomass reflected the increase of LAI during the vegetative stages and its decrease with plant maturing (Thenkabail et al., 1994a; Kancheva, Borisova, 2006a). Spectral features are higher correlated with green vegetation canopies and this correlation decreases towards crop maturing. In Table V the fitted models of wheat grain yield (Y, kg/dca) on crop parameters and two spectral indices at heading stage are given.

Figure 1 illustrates the application of biophysical (a) and spectral (b) data for yield prediction. This example, along with Figure 2, shows the good correspondence between the two-fold predictions.

Table 5. *Empirical relationships of wheat spectral index VI 1, growth parameters and yield at crop heading stage*

variable	model	a	b	R^2
M_w	exp(a+bx)	-1.4	3.3	0.86
LAI	exp(a+bx)	-1.6	3.73	0.89
Y	a+bx	-323	960	0.91

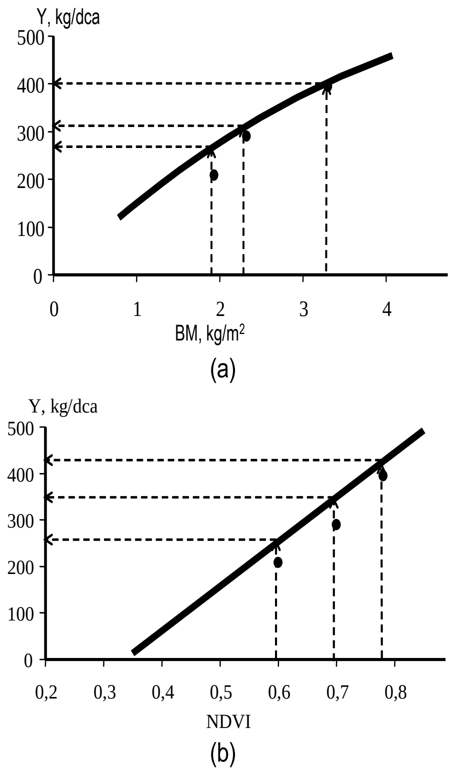

Fig. 1. Biophysical (a) and spectral (b) yield prediction models for winter wheat crops at heading stage

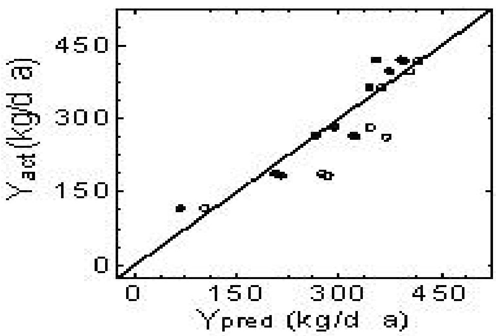

Fig. 2. Correspondence between the actual and predicted yield from airborne-acquired NDVI (●) and ground-measured LAI (○) at wheat milk ripening stage *16 $Y_{LAI} = 68.23 + 0.91Y_{VI\,1}$ (R^2=0.97)*

VI 1 (called Normalized Difference Vegetation Index - NDVI) is the most commonly used but other two or three-band spectral ratios are usable as well (Thenkabail et al., 1994b; Qi et al., 1994; Kancheva and Borisova, 2007). Some of the best performing within our study indices is listed in Table 6 to present their significant correlation with plant bioparameters and yield. The preliminary correlation analysis of the acquired spectral data (Table 6) showed that vegetation indices were confidently related to plant parameters through a big portion of the growth season. Crop yield is highly correlated with VIs.

Table 6. *Correlation of vegetation indices with wheat yield and bioparameters at milk ripeness stage*

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

The same was confirmed by the results of the regression modeling. Through simple regression, each vegetation index was related to each crop state variable. At sample dates before full maturity the results showed statistically significant relationships for most of the examined VIs. In such a way, crop parameters which are descriptors of wheat canopies can be reliably estimated from multispectral data.

Very strong correlation was found between the temporal cumulative behavior of some spectral indices and crop yield as seen from Table 7.

Table 7. *Linear yield prediction models from VI temporal sum throughout the whole wheat development season*

VI	a	b	R^2
1	-554	136	0.95
2	-296	13	0.95
11	40	174	0.91
16	-363	2	0.88

Figure 3 presents the yield prediction model from VI1 (NDVI) values sum throughout the whole growth season from emergence till full maturity. Temporal spectral indices distinctly monitor and depict differences and variations of cropland state during plant development.

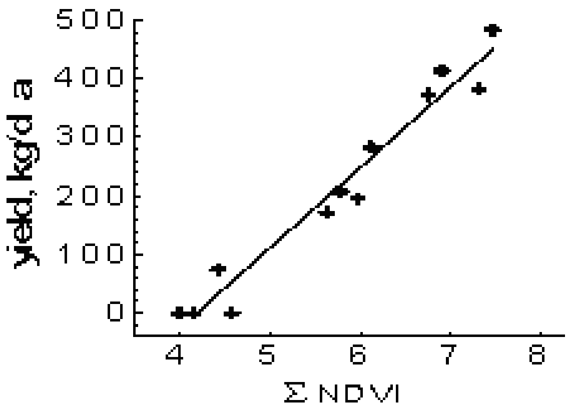

Fig. 3. Empirical relationship between wheat yield and the whole-season temporal sum of VI1

Conclusions

The proposed approach for crop growth and yield assessment is developed on a well-known basis which exploits the close relationships between vegetation biophysical variables and spectral reflectance features. Good correspondence has been found between ground-truth data and crop state assessment and yield prediction made from spectral measurements. The valuable aspect of the work is the verification of the spectral predictions through the implementation of ground-truth derived spectral-biophysical models and seasonal time-dependent relationships. The results highlight the capability of the approach to track the dynamics of crop growth and show the accuracy of the predictions. More work is intended to examine the effects of the site-specific and environmental conditions on the robustness of the models.

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