Multispectral Data Related to Cereals Yield

Kancheva R., Borisova D.

Solar-Terrestrial Influences Institute, Bulgarian Academy of Sciences, Sofia, Bulgaria,
rumik@abv.bg, dborisova@stil.bas.bg

Entering wider into their application stage remote sensing technologies face higher requirements to the accuracy of the information they provide. Because of the raising need for reliability of the information products, ground-based observations are considered one of the pillars of remote sensing. This paper presents the results from ground-level studies aimed at the empirical modelling of crop yield using multispectral and multitemporal data.

Introduction

A strong stress is being put in the past years on the application and added-value of remotely sensed data. Agricultural monitoring is an important application of remote sensing technologies associated with plant growth assessment, stress detection, yield forecasting. For precision agriculture running [1], regular and timely information is needed about plant growth in order to assess crop development and predict yield [2-4]. The acquired multispectral data are particularly effective in deriving crop biophysical parameters [5-8].

Ground-level spectral modeling used in land cover studies, data analysis and algorithm validation is an integral part of remote sensing technologies [9-12], all the more that data integration for achieving higher reliability has become recently a leading concept in remotely sensed data application [13, 14].

This paper presents some results of in-situ empirical modeling of the relationship between cereals spectral reflectance and yield. Grain yield is related to plant spectral data acquired at different development stages as well as to spectral data accumulated during the entire growing season. The objective of the study was to develop and test VIS-NIR-vegetation indices as indicators of the variability of the production of cereal crops through plant seasonal reflectance responses. This relation is biophysically justified by the dependence of crop reflectance properties on such agronomic parameters as biomass, leaf area, chlorophyll, etc. [4-8]. Crop parameters determine the variance of spectral features and, on the other hand, are bioindicators of yield [11, 15]. This fact is used here for verification of spectral predictions through biophysical yield models.

Materials and Methods

Field VIS and NIR reflectance was measured with a portable spectrometer in discrete narrow bands between 400 and 800 nm. Spectral measurements were carried out over winter wheat and spring barley crops at week interval during plant development, from emergence till harvest. The objective was to establish empirical relationships between plant reflectance properties and yield. Observed crop characteristics (biometrical variables) included above-ground biomass, leaf area index, density, canopy cover and others.

Yield data were analysed against various spectral (vegetation) indices which are routinely implemented data transformations [16-19], and yield predicting models were developed. Two types of spectral predictors were examined: single-date vegetation indices measured at different phenological stages of plant development, and temporal sums of these indices accumulated during the entire season. The calculated indices were narrow band reflectance ratios including two or more wavelengths, normalized differences (NDVI) involving various two-band combinations. The data sets were statistically analysed to examine the correlations and derive empirical relationships between crop reflectance signatures (vegetation indices) and yield. Simple regression modelling was applied. In order to assess the applicability of the developed models, yield predictions from single-date and multitemporal spectral measurements were validated through comparison with estimations from yield dependences on crop canopy characteristics (bioparameters).

Results and Discussion

Spectral data transformations (vegetation indices VI) were used as inputs in yield prediction models. Data statistical processing included regression analysis for the establishment of empirical relationships between various spectral indices and yield. Additionally, in order to verify spectral predictions, crop variables (biomass, leaf area index, etc.) were linked to yield.

Various vegetation indices have been calculated from plant reflectance factors in spectral bands where the greatest differences in reflectance exist, i.e. in the green (G, 550 nm), red (R, 670 nm) and near infrared (NIR, 800 nm) bands. The wavelengths selected correspond to absorption and peak reflectance of vegetation spectra. The variance of vegetation reflectance properties in these bands is associated with the variance of plant biometrical parameters. Different combinations of spectral ratios were examined for their correlation with crop yield. Many of them demonstrated high r2 values ranging from 0.8 to 0.93 and depending on plant growth stage. For further analysis spectral indices were chosen from those having the best statistical correlation with grain yield, the derived models being significant at the 95% level of confidence. The VIs values varied significantly between crops with varying bioparameters. This provided for reliable statistical modelling. The performance of VIs was a function of plant growth stage as well.

The coefficients of determination (r2) of the linear regression of winter wheat yield with some vegetation indices at two phenological stages of plant development are given in Table I. Similar high correlations were found for spring barley as well. Highest correlations of spectral indices with cereals grain yield were observed at the most active vegetative stages (tillering, stem elongation, heading, ear-filling). This fact is explained by pronounced differences in the spectral reflectance with varying crop state during this period of plant development (see also Fig.2a where the temporal NDVI(R, NIR) behaviour of spring barley treatments throughout the growing season is shown).

TABLE I
Correlation of Winter Wheat Yield with Vegetation Indices at Ear-Filling and Milk Ripeness Phenological Stages

vegetation index VI	ear-filling stage	milk ripeness stage
NDVI (NIR,R))	0.85	0.90
NIR/R	0.81	0.89
NDVI (G, NIR)	0.80	0.83
NIR/G	0.93	0.85
(NIR-G)/R	0.90	0.88
NIR/(G+R)	0.92	0.90
NIR/(G*R)	0.87	0.91
G/(G+R+NIR)	0.88	0.81

In Table II winter wheat yield (kg/dca) prediction models from spectral and biometrical data at plant heading stage are given. The correlation keeps high at plant ‘green’ stages before full maturity. Quantitative relationships linking biophysical variables to yield are useful for verifying spectral yield forecasts.

TABLE II
Winter Wheat Yield Prediction Models from Multispectral and Biometrical Data at Heading Stage

predictor	model	a	b	r^2
NDVI (NIR ,R)	a+bx	-323	959.9	0.91
NIR/R	a+bx	598	46.74	0.89
NIR/(G+R+NIR)	a+bx	856.7	1616	0.91
biomass	$ax+bx^2$	162.9	-12.32	0.92
leaf area index	$ax+bx^2$	151.1	-5.933	0.95

Fig. 1 presents two of the empirical equations from Table II illustrating yield predictions by spectral and biometrical data.

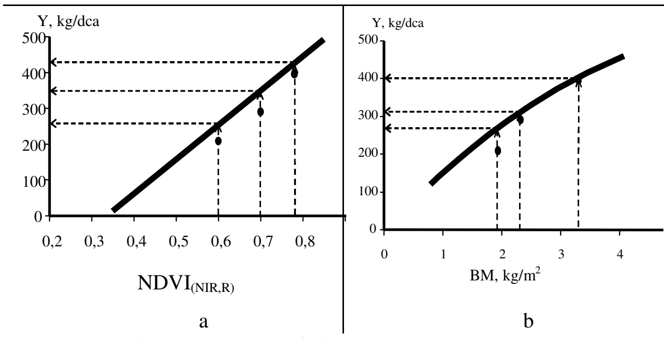

Fig. 1 Empirical regressions of winter wheat yield on $NDVI_{(NIR, R)}$ (a) and biomass (b) at heading stage

Good correspondence was observed between yield predictions from spectral and biophysical estimates. For instance, the following equation was derived to describe the correspondence between yield estimates from leaf area index (LAI) and NDVI(NIR,R) models: YLAI = 68.23+0.91YNDVI(NIR,R) with r2 = 0.97. Using forecasts trough different predictors (spectral as well as biophysical) might improve yield prediction accuracy.

The analysis of the acquired spectral data showed that many VIs were confidently related to crop yield throughout a bigger portion of the growing season. Multitemporal patterns of different spring barley treatments are shown in Fig, 2a. They contain data from emergence through ripening and full maturity taken at weekly intervals on 13 dates during the growing season. Cumulative spectral measurements distinctly monitor plant ontogenetic changes, along with differentiating between crops state. One advantage of using multitemporal predictions is that they account for any unfavorable effects on crop growth that might occur during the development season, and thus serve as “dynamic” predictors. Fig. 2b shows the derived empirical relationship between crop yield and the sum of $NDVI_{(NIR,R)}$ values measured during plant growth.

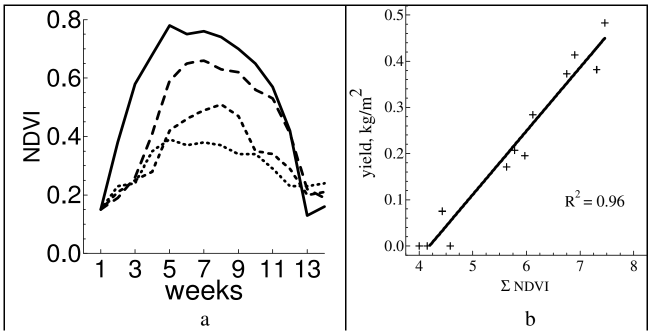

Fig. 2 $NDVI_{(NIR,R)}$ temporal behaviour throughout spring barley growing season (a) and yield prediction model from $NDVI_{(NIR,R)}$ entire season sum (b)

The example in Fig. 3 presents the actual and estimated through $\Sigma NDVI_{(NIR,R)}$ yield from differently fertilized spring barley treatments. Using the relationship from Fig. 2 the grain yield was spectrally predicted and compared to the actually gained.

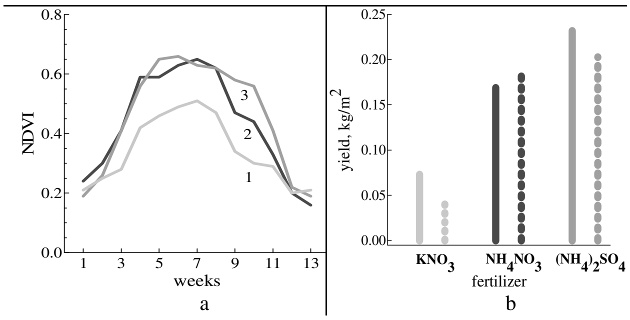

Fig. 3 $NDVI_{(NIR,R)}$ temporal profile (a) of barley treatments with equal nitrogen concentration but different fertilizer: KNO_3 (1), NH_4NO_3 (2), $(NH_4)_2SO_4$ (3); actual grain yield (—) compared to the estimates (---) from $\Sigma NDVI_{(NIR,R)}$ (b)

Regression analysis between various VIs temporal sums (ΣVI) and yield was performed to fit the empirical equations. Linear relationships for different time intervals were obtained with very good statistical confidence (r^2>0.9). Some of the highest ranked indices for yield prediction are summarized in Table III.

TABLE III
Linear Yield Prediction Models from VI Whole-Season Sum

spectral index	a	b	r^2
NDVI (NIR ,R)	-554	136	0.95
NIR/R	-296	13	0.95
NIR/(G+R+NIR)	-1733	275	0.9
NDVI (G, R)	40	174	0.91

Conclusions

The applicability of spectral transformations (vegetation indices) for yield forecasting in reference to cereals production has been examined and analysed for different periods of crop development. Proposing empirical simple least squares regression models to forecast cereals yield, this study proved that the yield variation was well accounted for by spectral single-date and multitemporal data. Statistically significant relationships have been found between spectral reflectance and crop yield. Reflectance temporal behaviour revealed increased sensitivity to crop yield. Spectral temporal sums contributed to yield prediction with as good accuracy as of the estimates from crop biophysical varaiables.

The spectral models allowed discrimination between crop state during plant development and extraction of quantitative information about crop yield. Derived for different phenological stages, the developed models allow to monitor crop production potential and serve as early warning indicators of possible future reductions in yield due to growing conditions. Yield forecasts using different spectral predictors and supported by biophysical relationships improve the accuracy of predictions.

Advantageous aspects of the work are: the simple modeling approach for linking reflectance data with plant yield, the phenological differentiation of the models resulting in early warning possibility, time-integrated data accounting for the growing conditions during the whole plant development.

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