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# VEGETATION GROUND-BASED MODELS IN CROP STATE MONITORING

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## ABSTRACT

The development of efficient algorithms for multispectral and multitemporal data analysis is still one of the most essential issues of remote sensing. The importance of this issue is related to the ever-increasing quantity of data provided by numerous radiometric and imaging sensors. Besides, the necessity to use various geoinformation technologies incorporating remote sensing, in-situ observations, ancillary data etc., imposes information sharing and integration. This paper is devoted to ground-based spectral modeling as an integral part of vegetation remote sensing monitoring. It examines the relationship between agricultural crop spectral and biometrical features with consideration of growing conditions and plant ontogenesis. The influence of soil properties and anthropogenic factors (fertilization, heavy metal pollution) on crop spectral response has been studied. VIS and NIR ground-based reflectance measurements have been related to plant growth features to derive empirical models. Some results of crop state assessment using these models and airborne radiometric data are presented. Good agreement has been found between model estimates and ground-truth data.

## INTRODUCTION

Nowadays the aerospace information gathered by different sensors and numerous Earth observation missions has become a genuine necessity in various investigations and application fields. Vegetation is among the priorities of these investigations which are related to many world significant problems such as environmental changes, anthropogenic impact on ecosystems, desertification processes, etc. In agriculture remote sensing is used for retrieving information about plant development and yield forecasting. Ground-based studies are an integral part of vegetation remote sensing technologies serving as a reference and verification source of remotely sensed data. Especially advantageous is the ability to vary and control experiment conditions getting a precise picture of plant spectral response to different factors as well as to track in detail temporal aspects of plant spectral properties during the ontogenetic process.

A great number of papers is devoted to the possibility of deriving quantitative information about vegetation using reflective and emissive spectra. Many of them deal with plant growth evaluation, biomass estimation and yield prediction (i, ii, iii, iv, v). Empirical modelling is one of the most widely spread technique for vegetation assessment (i, vi, vii, viii, ix) although different conclusions have been made about the applicability of the obtained models, their dependence on local conditions and site-to-site or year-to year discrepancy (vi, x).

This paper is further dedicated to spectral-biophysical modelling of agricultural vegetation. One of the objectives is to examine the impact of soil properties and anthropogenic factors (fertilization and heavy metal pollution) on plant spectral behaviour in relation to stress detection. The other goal is to test the applicability of spectral models for crop state assessment using airborne radiometric data.

## MATERIALS AND METHODS

Reflectance, biometrical and phenological data were gathered from cereals throughout the growing season. A spring barley green-house experiment was conducted which consisted of two parts: $NH_4NO_3$ fertilization treatments over chernozem soil with different nitrogen concentrations (from 0 to 1000 mg/kg) and treatments with $Ca(NO_3)_2$ and $KNO_3$ fertilizers for the nitrogen concentration of

800 mg/kg, and a second part of Ni-polluted plots (with 100, 200, 300 and 400 mg/kg Ni concentration) grown over chernozem soil (pH=7.0-7.5) and grey forest soil (pH=5.0-5.5). The soils were chosen for two reasons - their different reflectance spectra and different response to heavy metal pollution. A field experiment was carried out over winter wheat crops which state varied due to different growth conditions - irrigation and nutrition regimen, soil erosion.

Ground-based VIS and NIR spectral measurements were performed with a multichannel portable spectrometer from the nadir position in the wavelength range 0.4 - 0.8 μm and a 10 nm bandpass. Reflectance data were acquired at weekly intervals during plant development from emergence till full maturity for the barley plots and during wheat main phenological stages. Biometrical sampling included plant canopy cover, total fresh and dried above-ground phytomass, LAI, leaf biomass, plant height, stem and ear number, grain yield after harvest. At the time of ground data acquisition airborne multispectral measurements were performed within several transects over each winter wheat field.

The data sets were statistically analysed to examine the correlations and establish empirical dependences between plant reflectance spectra, growth features and productivity. A regression analysis was run on vegetation spectral indices using band ratios, contrasts, normalized differences as a routinely implemented data transformation (iii, xi, xii, xiii, xiv). The wavelengths selected correspond to absorptions and high reflectance bands of vegetation spectra in the green (550 nm), red (670 nm) and near infrared (800 nm) range. Spectral indices were chosen from those having the best statistical correlation with vegetation bioparameters, the obtained empirical regressions being significant at the 95% level of confidence.

Special attention was paid to temporal aspects of plant spectral properties throughout the growing period. The temporal behaviour of vegetation indices was regarded as a function of plant ontogenesis and used as a crop diagnostic feature and yield predictor. Significant variations in plant state, and consequently in spectral performance, were found associated with the impact of soil properties and anthropogenic factors.

## RESULTS AND DISCUSSION

Various combinations of spectral ratios were examined for their correlation with plant bioparameters, nutrition conditions and Ni contamination. Many of them demonstrated high $R^2$ values from 0.8 to 0.97 (viii, xv). Variations in vegetation reflectance are most attributed to green coverage. This parameter is at the same time a primary indicator of crop state. In Fig. 1 the statistical relationships of NIR/R and R/(G+R+NIR) spectral indices with barley canopy cover at pre-heading stage are shown. The dependences were derived separately for the grey (1) and chernozem soil (2) plots. Soil-integrated regression curves increase estimation errors almost twice, the canopy cover of the brighter grey soil treatments being systematically underestimated and overestimated for the dark chernozem soil treatments.

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Similar spectral models were developed for barley leaf area index. It is explicable considering the high correlation between the two bioparameters described in this phenological stage by the equation: LAI = $-0.052+5.74\times$canopy cover ($R^2$=0.95).

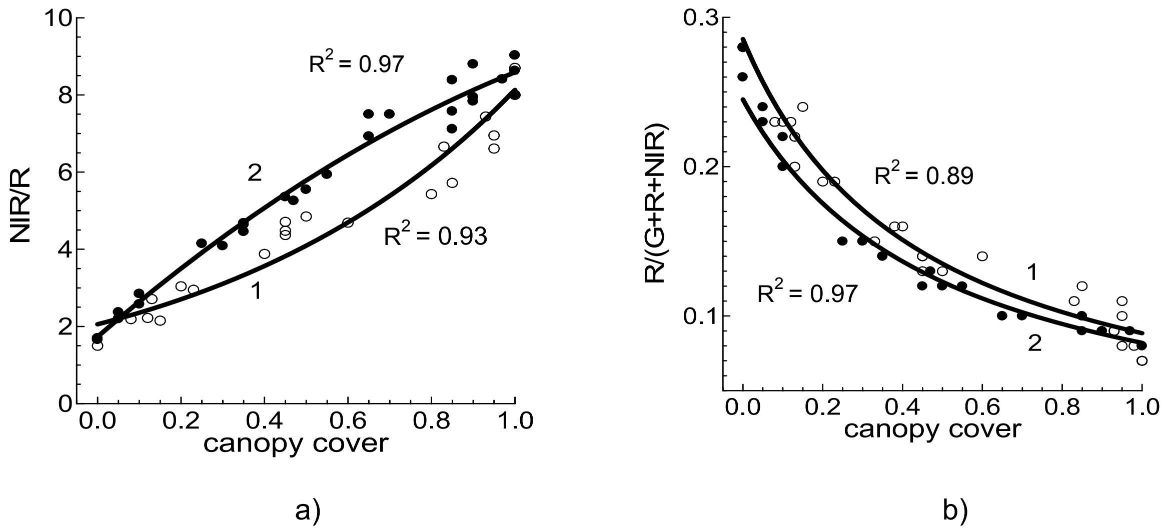



*Figure 1: Dependence of spring barley spectral indices NIR/R (a) and R/(G+R+NIR) (b) on green canopy cover for treatments over grey (1) and chernozem (2) soil*

Since vegetation biometrical variables define plant development processes and yield potential, they serve as crop growth and productivity indicators. Estimated from spectral data and compared to agronomical statistics (maximum, mean or optimal values for given species and territorial-climatic conditions) they can be used as "state indices" evaluated in terms of a certain vegetation parameter, e.g. $SI_{LAI} = LAI_{estimated}/LAI_{statistical}$. For instance, if using as a reference value $LAI_{max}$=5, then for the barley experiment treatment with measured at pre-heading stage LAI of 2.4 the state index was $SI_{LAI}$=2.4/5=0.48. This means that crop state was almost half worst of the best one. Further, estimation of $SI_{LAI}$ from spectral data was performed in the following way. The obtained NIR/R for the same plot was 4.0. The calculated from the established regression equation LAI = $-1.61+0.95\times$NIR/R ($R^2$=0.95) was 2.2, then $SI_{LAI}$=0.44, the ground-true and spectrally-estimated state indices (in terms of LAI) being close enough (with an 8% relative error). This example, as well as the results from more test data, showed a very good correspondence between actually measured and spectrally-retrieved estimates of crop state as well as between state indices obtained in terms of other bioparameters.

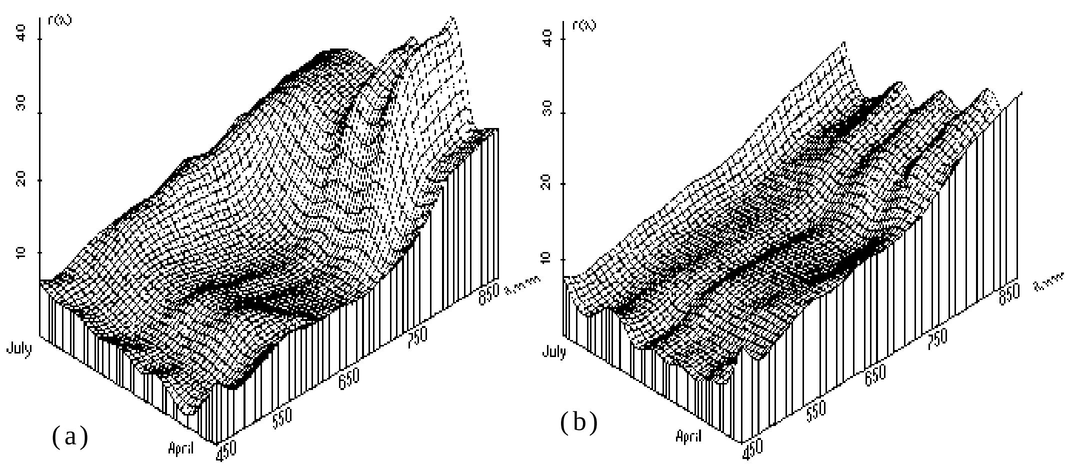
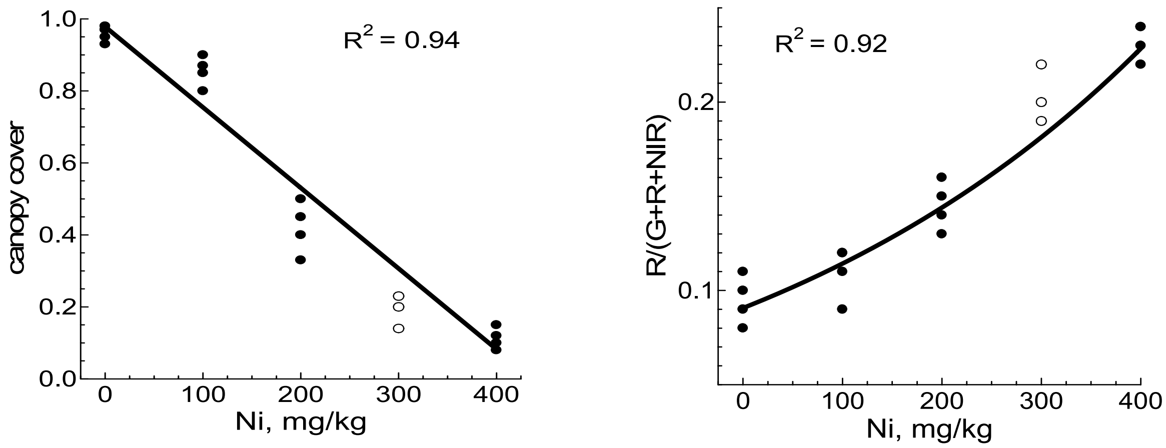



*Figure 2: Spectral reflectance characteristics throughout the growing season of barley control (a) and Ni-polluted (b) plots*

Along with the physiological development, stress factors cause significant variations of plant spectral properties (xiii, xiv, xvii, xviii, xix). This is illustrated by Fig. 2 where the spectral reflectance characteristics of spring barley grey soil plots during the growth period are presented for the control (non-polluted) treatment and the treatment with Ni concentration of 400 mg/kg (see also Fig.4a).

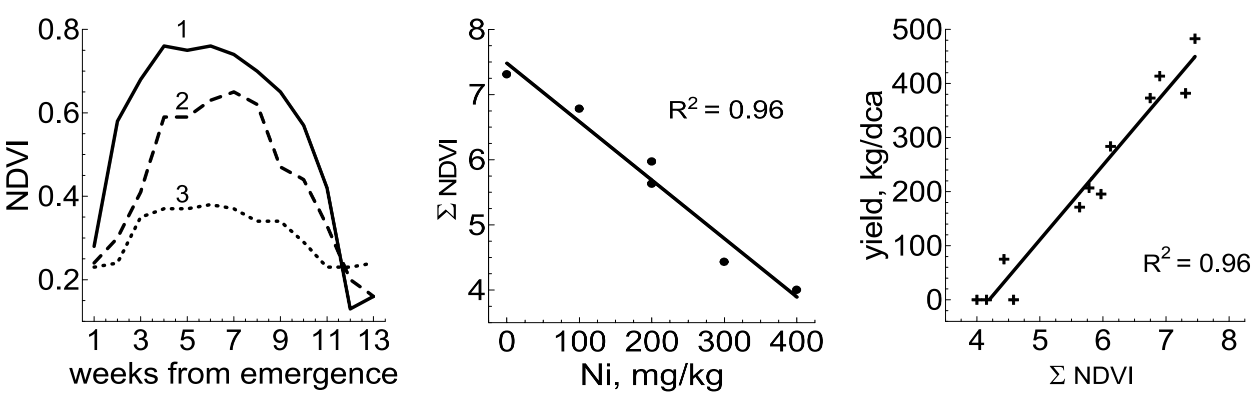
The contamination impact on crop growth and reflectance features was quantitatively examined by regression analysis. Some examples are given in Fig. 3 where the derived dependences of barley canopy cover (a) and R/(G+R+NIR) spectral index (b) on Ni concentration in the grey (acid) soil are shown. The plots with Ni concentration of 300 mg/kg were first excluded from the regressions and used later as a validation data set demonstrating good model predictions.




a) b)

*Figure 3: Statistical dependences of barley canopy cover (a) and R/(G+R+NIR) spectral index (b) on Ni pollution*

Crop reflectance behaviour during the whole phenological period is of particular interest as it provides for plant growth predictions and periodical evaluation of plant state. Temporal spectral data are highly indicative of variations in plant development caused by growing conditions (xix, xx). Fig. 4a presents the temporal NDVI behaviour of barley treatments over grey soil as a function of Ni contamination. The dependence is observed throughout the entire growth period carrying information about the current and previous plant state and showing the development trends. This fact permits early crop diagnostics and stress detection as well as forecasting of plant development process. In Fig.4b the obtained dependence of the NDVI temporal sum on the Ni concentration is given.




a) b) c)

*Figure 4: Dependence of barley NDVI temporal behaviour (a) and temporal sum (b) on the Ni concentration in the grey soil (1 - 0 mg/kg, 2 - 200 mg/kg, 3 - 400 mg/kg); relation between barley grain yield and NDVI temporal sum (c)*

As crop production is an issue of primary interest, barley grain yield was examined to its relationship with plant bioparameters, soil properties and stress conditions. There was not big yield difference between the control treatments over the two soil types. For the rich organic chernozem soil it was with about 10% higher. However, the treatments over the chernozem soil were much less affected by the heavy metal and this did not allow statistically significant relationships or soil-integrated dependences to be developed and used for quantitative assessments. Barley yield was statistically related to various plant variables and spectral indices and showed strong correlations especially during the active vegetative development (in most cases R2>0.9). Accounting for the entire growth process the temporal sum of various spectral indices appears to be very closely related to plant yield (iv,xxi). In our experiment the correlations between yield and temporal sums were higher than the correlations between yield and spectral indices in a given phenological stage. Fig. 4c presents the linear empirical relationship between barley grain yield and NDVI temporal sum during the whole development period from emergence till harvest.

Nutrient deficit is another stress factor clearly manifested and detected by plant reflectance features. Fig. 5a shows the impact of the nitrogen concentration on NIR/G temporal profiles of $NH_4NO_3$ barley treatments over chernozem soil. Differences in crop reflectance were observed also in relation to the fertilizer compound regardless of the equal nitrogen amount. This is seen in Fig. 6b where equal nitrogen concentration of 800 mg/kg was applied but the spectral profiles of the treatments differed due to the nitrogen compound. This is explained most probably by the lower nitrogen accessibility to plants which worsens the nutrient supply and thus the growth conditions.

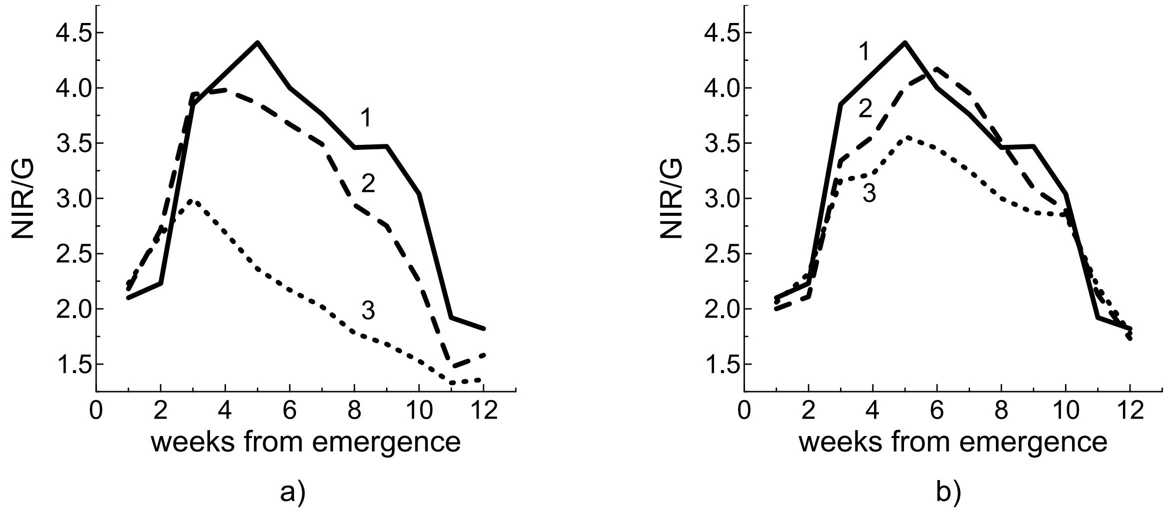



*Figure 5. Temporal behaviour of barley spectral index NIR/G for fertilization treatments: (a) with different nitrogen concentration (1 - 0 mg/kg, 2 – 200 mg/kg, 3 - 800 mg/kg) applied through $NH_4NO_3$; (b) with equal nitrogen concentration (800 mg/kg) applied through $NH_4NO_3$ (1), $KNO_3$ (2) and $Ca(NO_3)_2$ (3)*

In the winter wheat experiment various relationships between plant reflectance characteristics, biometrical variables and yield were established at different stages of the phenological development using ground-based measurements. Some of the statistical models with the regression coefficients and $R^2$ are given in Table 1 and Table 2. These empirical dependences were applied for retrieval of plant growth parameters and for crop state and yield assessment using reflectance data from low-altitude (about 100-150 m) helicopter measurements as model inputs. Because of the subtle atmospheric influence at this flight height no radiometric corrections were made.

*Table 1: Statistical models linking NIR/R spectral index of winter wheat crops with growth parameters (plant canopy cover, leaf area index and above-ground fresh biomass) at ear-filling stage*

| NIR/R = x Bioparameter=y | model | a | b | $R^2$ |
|---|---|---|---|---|
| Canopy cover | a+bx | -0.121 | 0.097 | 0.96 |
| LAI | a+bx | -0.71 | 0.45 | 0.92 |
| Biomass ($kg/m^2$) | a+bx | -0.661 | 0.479 | 0.84 |

*Table 2: Regression models for predicting winter wheat grain yield (kg/dca) as a function of crop growth variables and NIR/R spectral index at ear-filling stage*

| Parameter | yield model | a | b | $R^2$ |
|---|---|---|---|---|
| Canopy cover | a+bx | 18.5 | 497 | 0.9 |
| LAI | $ax+bx^2$ | 204 | -24 | 0.94 |
| Biomass ($kg/m^2$) | $ax+bx^2$ | 162 | -12.32 | 0.92 |
| NIR/R | a+bx | -5.984 | 46.76 | 0.89 |

Using airborne measurments of NIR/R (overpass means for each field were calculated) and the equations from Table 1 the leaf area index (LAI) and total above-ground biomass (M) of five winter wheat fields were retrieved (Table 3). Comparing in a ratio manner the predicted $LAI_{pred}$ and $M_{pred}$ with their mean agrostatistical values for the given phenological stage, assessment of crop state was performed. The results “predicted value/mean statistical value” are presented as State Index in terms of LAI ($SI_{LAI}$) and biomass ($SI_M$). A state index less than 1.0 means that crop state over the examined field is worse than the average observed for the site. Crop state index in terms of the actual yield ($SI_{Yactual}$) estimated after harvest as the ratio “gathered yield/mean yield” served as ground-true data and a verification basis of $SI_{LAI}$ and $SI_M$.

Using the spectrally derived $LAI_{pred}$ and $M_{pred}$ and the yield models from Table 2, the yield of the same fields (each of about 10 dca) was estimated ($Y_{pred(LAI)}$ and $Y_{pred(M)}$) and compared to ground-truth data ($Y_{act}$) to verify predictions. The results of crop state assessment in terms of yield as predicted by growth variabls and spectral data are also presented in Table 3. Good correspondence was found between the various state indices estimated in terms of plant bioparameters, spectral features and ground-true data. Especially high agreement was observed between the yield predictions and yield state indices which can be explained by the better accuracy of the models and probably by the more reliable yield statistical data than the bioparameter statistics. The biggest difference between the predicted and gathered yield was 24 kg/dca. As seen the actual crop state as determined after harvest in terms of the gathered grain yield is very close to the predected yield at ear-forming stage by plant growth variables and remotely sensed spectral data.

*TABLE 3: Results of airborne estimates of crop bioparameters and yield (kg/dca) assessment as predicted by growth variables and spectral data*

| Field | NIR/R | $LAI_{pred}$ | $M_{pred}$ | $SI_{LAI}$ | $SI_M$ | $Y_{actual}$ | $SI_{Yact}$ | $Y_{pr(LAI)}$ | $SI_{Ypr(LAI)}$ | $Y_{pr(M)}$ | $SI_{Ypr(M)}$ | $Y_{pr(NIR/R)}$ | $SI_{Ypr(NIR/R)}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9.0 | 3.34 | 3.65 | 1.34 | 1.3 | 418 | 1.39 | 414 | 1.38 | 427 | 1.43 | 414 | 1.38 |
| 2 | 8.1 | 2.94 | 3.22 | 1.17 | 1.15 | 397 | 1.32 | 392 | 1.31 | 394 | 1.31 | 373 | 1.24 |
| 3 | 4.0 | 1.09 | 1.26 | 0.44 | 0.45 | 188 | 0.63 | 194 | 0.65 | 185 | 0.62 | 193 | 0.64 |
| 4 | 5.7 | 1.85 | 2.07 | 0.74 | 0.74 | 283 | 0.94 | 295 | 0.98 | 283 | 0.94 | 261 | 0.87 |
| 5 | 2.9 | 0.6 | 0.78 | 0.24 | 0.28 | 116 | 0.38 | 114 | 0.38 | 113 | 0.4 | 129 | 0.43 |

## CONCLUSIONS

The performed study does not only illustrate the informational potential of spectral data but attaches to it a quantitative dimension which provides for crop monitoring and detection of stress situations as well as for evaluation of the inhibiting affect of unfavourable factors on plant growth. Good correspondence was observed between measured values and spectral model estimates of plant biometrical features and stress factors. Spectral-temporal data proved to be a good indicator of plant development process and a reliable input in yield-predicting models. Summarizing the results, a conclusion is drawn that ground-level regression models relating plant spectral features to biometrical variables could be successfully applied for crop state evaluation using airborne radiometric data. The knowledge of plant bioparameters is essential because of the strong correlation and direct contribution of these parameters to potential yield. The quantitative agrodiagnostics is then used in crop yield assessment. Indeed, a favourable experimental condition in our investigation haves been the simultaneous ground sampling and aircraft overpassing. However, the accuracy of the results is encouraging and suggests the possibility of developing applicable equations to simply and rapidly estimate growth variables from plant remotely acquired reflectance spectra.

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