Spectral reflectance response of crop canopy to abiotic stress

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Abstract

The expansion of industrial development and rapid urbanization pose serious ecological problems associated with the increasing anthropogenic pressure on the environment. There is a growing concern about the environmental safety and preservation. The problem of soil contamination has received special attention by reason of the degradation effect of various abiotic pollutants on land resources. Significant progress has been made in using remote sensing techniques for monitoring and assessment of vegetation condition. Vegetation is one of the most anthropogenic-affected component of the biosphere. Plants are sensitive biomarkers of world-wide soil and water contamination. Heavy metals are among the most dangerous contaminants because of their high toxicity to organisms, persistent nature, high mobility, and long biological half-life. In this paper multispectral data in the visible and near infrared range is implemented to determine the health status of species under heavy metal-induced stress. Different spectral indicators were statistically related to plant physiological response to contamination. Empirical relationships were obtained between multispectral data and plant growth variables. The applicability of spectral indices to detect and quantify stress effects was examined.

Спектрални характеристики на растителност при абиотичен стрес

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Ключови думи: спектрални отражателни характеристики, вегетационни индекси, растителна покривка, абиотичен стрес, тежки метали

Резюме

Усиленото индустриално развитие и бърза урбанизация пораждат сериозни екологични проблеми, свързани с увеличаващото се антропогенно натоварване върху околната среда. Специално внимание се отделя на почвено замърсяване поради поради деградационния ефект, който имат върху почвата различни абиотични замърсители. С нарастващата загриженост на света относно опазването на природните ресурси дистанционните методи придобиват все по-голямо значение за диагностика и оценка на състоянието на растителната покривка. Растителността е особено чувствителен биомаркер за почти повсеместното замърсяване на почвите и водите в природата. Особено актуален и труден е въпросът на замърсяването с тежки метали поради факта, че те не са биоразградими, остават в почвата за продължителен период от време, не се изнасят от коренообитаемия почвен слой и се съхраняват в него дълго след отстраняване на източника. В настоящата работа се разглежда приложеиието на многоспектрални данни във видимия и близкия енфрамервен диапазон за оценка на състоянието на земеделски култури при стресови условия на отглеждане. Използвани са различни спектрални признаци за установяване на биологичния отговор на растенията при замърсяване на почвата с тежки метали, както и за количествена оценка на стресовото влияние. Изведени са емпирични регресионни модели, свързващи спектралните признаци с растежни параметри на културите. Изследвана е също връзката между стресовия фактор и измененията на спектралните характеристики на растенията. Статистическият анализ на тези стрес-индуцирани изменения цели приложението на спектрални признаци като стрес-индикатори и количествени предиктори за състоянието на растенията.

Introduction

The expansion of industrial development and rapid urbanization pose serious ecological problems associated with the increasing anthropogenic pressure on the environment. Destructive processes caused by human activities are in the focus of the scientific research. Urgent necessity arises for the use of efficient means to assess the effects of anthropogenic factors especially on vegetation land covers. Ecological monitoring and control are an objective of a great variety of projects, multipurpose programs and interdisciplinary research. Many of them focus on environmental pollution and its negative effects on the biosphere with unfavourable short-term and long-term consequences. Industry, agriculture, forestry, and transportation all generate substances and by-products that are considered pollutants and contribute a significant impact on the environmental quality. Contaminated environments are a continuing concern because of the potential risks to natural resources and human health.

In agriculture, abiotic stressors are the most harmful factors concerning species growth and productivity. Abiotic stress is one of the primary causes of crop losses worldwide, The main abiotic stresses that affect plants include drought, salinity, heat, cold, chilling, freezing, nutrient, high light intensity, anaerobic conditions, and pollution by hazardous substances. Heavy metals are among the most dangerous pollutants because of their high toxicity to organisms, persistent nature, high mobility, and long biological half-life [19]. They constitute a group of environmentally hazardous substances whose deposition in soils and easy uptake by species affect soil fertility, plant development and production. In recent time, the desire for food safety and security has stimulated research on the accumulation and danger associated with the consumption of food contaminated with heavy metals [1,2 8, 19, 21, 22]. Soil is the primary recipient of these contaminants. Plants take up and absorb them and then they enter the food chain. Plant damage associated with heavy metals is of great concern throughout the world because of their toxic and mutagenic effects even at low concentration. Therefore, particularly great effort has focused on heavy metal-induced stress in plants, its mechanisms of action, consequences, and prevention [2, 4, 8, 18, 22].

The interrelated nature of environmental problems has imposed the need of data integration and information sharing between different databases. Advanced monitoring, risk detection and early warning techniques, timely information retrieval, modeling and forecasting possibilities are prepositions for successful data application and decision support in developing policies and strategies dealing with environmental issues. In this respect, remote sensing is an essential tool in ecology-related research. It plays an expanding role in vegetation monitoring and especially in diagnosing plant stress. In agriculture, a primary goal of remote sensing is the assessment of crop development throughout the growing season. Agricultural lands are subjected to enormous pressure and their assessment have become an important economic and ecological issue. A lot of attention has been devoted to studying the influence of unfavourable environmental conditions on species performance and the relationship with their spectral behaviour. The impact of stress factors, such as drought, nutrient deficiency and toxic pollution, is described and evaluated from plant spectral response data. Various multispectral features have proven capabilities for crop health assessment and detection of stress situations [3, 6, 9-11, 14, 15, 17, 20].

The interactions between vegetation canopies and incident radiation lie at the root of vegetation remote sensing. Remote sensing of vegetation is based on the analysis of plant reflectance and emittance properties as a function of plant physiology and morphology. Vegetation spectral behaviour depends on plant biophysical and biochemical variables and reveals significant sensitivity to them [5, 10, 12, 13, 16, 17, 20]. Growth variables are defined by plant development processes and health condition. Consequently, variations of plant performance cause changes in plant spectral properties. On the other hand, vegetation health and vigour are an expression of the growing conditions (meteorological, soil properties, agricultural practices) including stress factors. As such, knowledge of plant spectral response to different environments is necessary to interpret remotely sensed data and extract the information content of the acquired multispectral and hyperspectral data. The information is carried by the specifics of vegetation reflectance characteristics which depend on biomass amount, leaf area, canopy cover, chlorophyll content, and etc. The relation “growing conditions - plant condition - spectral response” determines the informational potential of spectral data and provides grounds for vegetation stress detection.

In view of the above, our paper is dedicated to studying the effect of heavy metal (Ni) contamination on agricultural species (spring barley). The main goal is to investigate and analyze the relationship between plant physiological and spectral response to the stress factor and examine the ability of spectral reflectance signatures to detect differences in plant health. Bioindicators of crop performance (growth variables and productivity) were statistically related to the stress factor and multispectral data obtained from ground-based spectrometry measurements. Empirical relationships have been derived that allow not only stress detection from reflectance data but also quantitative assessment of stress-induced changes of growth parameters as well as temporal monitoring during plant development.

Materials and Methods

The paper presents a part of an extended study on the impact of different stressors on crop performance and spectral behaviour. Herein results are presented from a greenhouse experiment with spring barley cultivated on grey forest soil. The pot trial experiment included one control and four Ni-treatments, the soil being contaminated with Ni in concentrations 100, 200, 300 and 400 mg/kg introduced through nickel sulfate $NiSO_4$. The trials were grown from seeding to harvest. Each trial was replicated 4 times. The stress growing conditions influenced plant vigor during the ontogenetic process and ensured a range of plant physiological status thus causing considerable variations of plant spectral behaviour.

Phenology, growth and reflectance data were collected throughout the entire growing season from plant emergence to full maturity and harvest. Visible (VIS) and near infrared (NIR) multispectral measurements were carried out in the wavelength range 400-820 nm. Reflectance measurements were conducted at canopy level at weekly intervals. Crop performance was characterized by key growth variables (canopy cover fraction, height, stem length and stem number, leaf area index, chlorophyll content) and yield components (total biomass dry matter, seed number, seed weight, grain weight). The datasets were statistically analyzed to describe and evaluate variations of plant physiological response as a function of the heavy metal contamination level.

Multispectral reflectance data acquired during plant development were linked to plant attributes and examined for the ability to detect and quantify stress-induced changes in plants. Crop spectral response was examined for its sensitivity to crop performance (growth variables and productivity) and the stress level (Ni concentration). Analysis of variance was conducted to determine the statistical significance of the differences between the trials including within group differences (between replications), and between group variance (between treatments). Correlation analysis of the datasets was performed in order to determine the presence and strength of the relation between plant spectral and biophysical characteristics and to reveal the dependence of these characteristics on the degree of contamination. Through regression analysis conducted on phenology-specific basis, i.e. at a given phenological stage, empirical relationships were derived describing plant physiological response and spectral reflectance sensitivity to the abiotic stress factor. Spectral and biophysical models of plant performance were established quantifying Ni impact.

In fact, spectrometric techniques make use of multispectral data to estimate plant biophysical and biochemical attributes. It is possible because growth attributes determine plant spectral properties. In other words they are factors of plant reflectance response. As such, variations of crop canopy spectral reflectance carry information about plant growth and health status [5, 7, 12-14, 20]. Visible and near infrared data have proven abilities to assess vegetation condition. The reason is that this wavelength range reveals significant sensitivity to growth variables (biomass, canopy fraction, leaf area index. chlorophyll content). These variables are associated with crop development and physiological status. Thus, the information is carried by the specifics of vegetation spectral characteristics.

A common technique for multispectral data processing is the use of spectral transforms called vegetation indices (VIs). They are calculated as various combinations [5, 12-14, 16, 17] of the measured spectral reflectance factors r_λ and are defined usually as different ratios at two or more wavelengths λ (nm), as for instance, $r_{\lambda i}/r_{\lambda j}$, $(r_{\lambda i}-r_{\lambda j})/r_{\lambda i}$, $r_{\lambda i}/(r_{\lambda i}+r_{\lambda j}+r_{\lambda \kappa})$, weighted sums $ar_{\lambda i}+br_{\lambda j}+cr_{\lambda \kappa}$ or normalized differences $(r_{\lambda i}-r_{\lambda j})/(r_{\lambda i}+r_{\lambda j})$. A great number of spectral indices were used in our study to characterize crop performance under abiotic stress. The formulas of some of these spectral transforms (called vegetation indices) are given in Table 1. They were examined in terms of the feasibility to serve as spectral indicators of crop health condition.

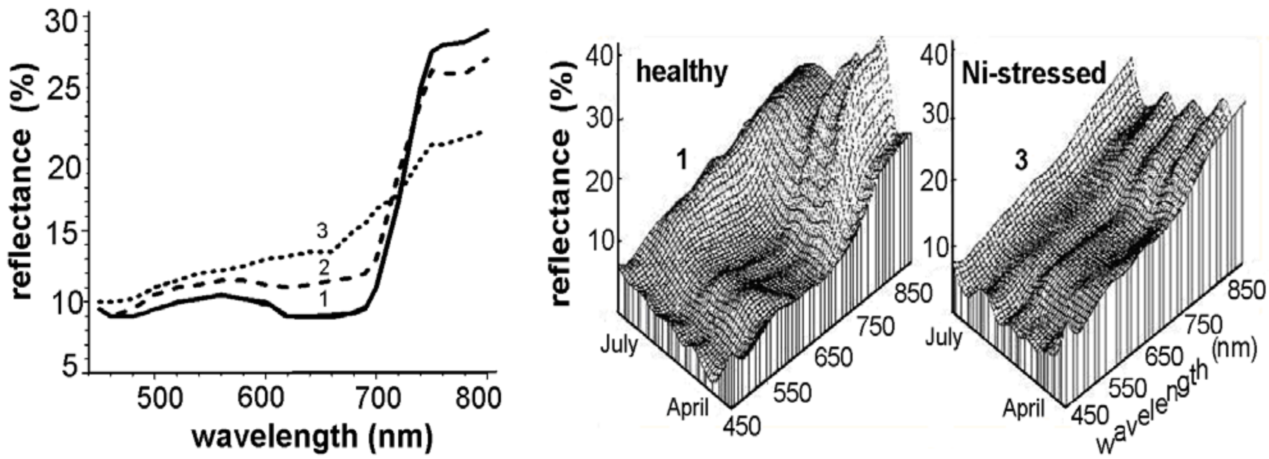
Table 1 Vegetation indices

1	$(r_{800}-r_{670})/(r_{800}+r_{670})$	8	$r_{670}/(r_{800}+r_{550})$	15	$r_{550}*r_{800}/r_{670}$
2	$(r_{550}-r_{670})/(r_{550}+r_{670})$	9	$r_{550}/(r_{650}+r_{670})$	16	$(r_{800}-r_{550})/(r_{800}+r_{550})$
3	$(r_{800}-r_{670})/r_{800}$	10	$r_{670}/(r_{550}+r_{670}+r_{800})$	17	r_{670}/r_{700}
4	$(r_{550}-r_{670})/r_{550}$	11	$r_{800}/(r_{670}+r_{680}+r_{690}+r_{700}+r_{710}+r_{720})$	18	r_{550}/r_{670}
5	$r_{800}(r_{550}-r_{670})/(r_{550}+r_{670})$	12	$r^2_{670}/r_{620}*r_{720}$	19	$r_{550}*r_{670}/r_{450}$
6	$(r_{800}-r_{730})/(r_{800}+r_{730})$	13	r_{800}/r_{670}	20	$r_{670}/(r_{550}-r_{670})$
7	$(r_{720}-r_{670})/r_{720}$	14	r_{800}/r_{550}	21	r_{800}/r_{730}

The proposed vegetation indices (VIs) exploit characteristic wavelengths of vegetation reflectance spectrum in the green, red and red-edge to near infrared spectral bands. The wavelengths correspond to specific absorption and high reflectance regions of vegetation spectrum in the green (G - 550 nm), red (R - 670 nm) and near infrared (NIR - 800 nm) range, or are located within the transition R-NIR interval (680-780 nm) where the reflection increases steeply. The VIs were analyzed for their correlation with plant bioparameters and Ni concentration. The analysis was performed separately on datasets acquired at various phenological stages of crop development.

Results and Discussion

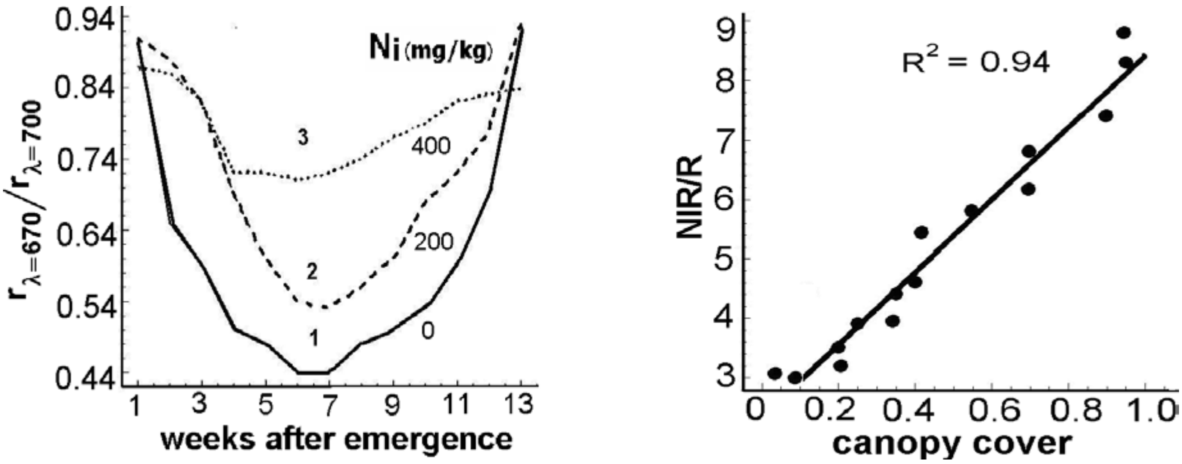
In this section we illustrate the performance of reflectance data for assessing plant condition and detecting heavy metal-induced stress. Significant variations of crop biological and spectral responses were observed associated with the heavy metal impact. The spectral reflectance characteristics of spring barley control and two Ni-treatments at stem elongation stage plotted in Figure 1a provide an evidence for the considerable reflectance differences between healthy (1) and polluted (2 and 3) plants as well as for the reflectance variations due to the stress level (compare 2 and 3). The contamination impact on plant spectral response was observed throughout the entire growing season. This is seen from Figure 1b which presents the reflectance characteristics during plant development of control (1) and 400 mg/kg Ni-polluted treatment (3). In Ni treatments, significant worsening of plant condition was observed. Stress induced by the heavy metal manifested itself in growth depression and resulted in reduction of plant biophysical attributes. Nickel inhibited chlorophyll synthesis as well and accelerated carotenoid accumulation. Stress-induced reduction of growth variables effected in turn plant reflectance features and a consequence of plant depression were significant variations of canopy spectral reflectance.



a) b)

Fig. 1 Spectral reflectance characteristics of spring barley at stem elongation stage (a) and throughout the growing season (b): 1- control, 2, 3 – trials with 200 mg/kg and 400 mg/kg Ni in the soil

Crop monitoring over time is one of the important aspects of remote sensing. Multitemporal data gathered throughout the development cycle or during selected portions of it allow tracking the growth process and crop condition. The temporal profiles of the spectral ratio $r_{\lambda=670}/r_{\lambda=700}$ (VI_{17}) in Figure 2a clearly show the differences between non-stressed and stressed crops (denoted in the same way as in Figure 1). The essential point is that differences in plant spectral response are observed already at the beginning of the vegetative growth. This provides for early stress detection. Besides, the severity of the stress impact can be differentiated from spectral reflectance data as it is seen from VI_{17} temporal profiles of treatments 2 and 3. In this case higher VI_{17} values indicate stronger stress. Further analysis of VIs temporal behavior (onset and duration of phenological events, single values at particular growth stages or time-integrated values over a given period, and etc.) gives quantitative expression of reflectance changes and crop stress-related condition.



a) b)

Fig. 2 Temporal profiles of VI_{17}: control (1), 2 – 200 mg/kg Ni-treatment, 3-400 mg/kg Ni-treatment (a); dependence of VI_{13} on barley canopy cover (b)

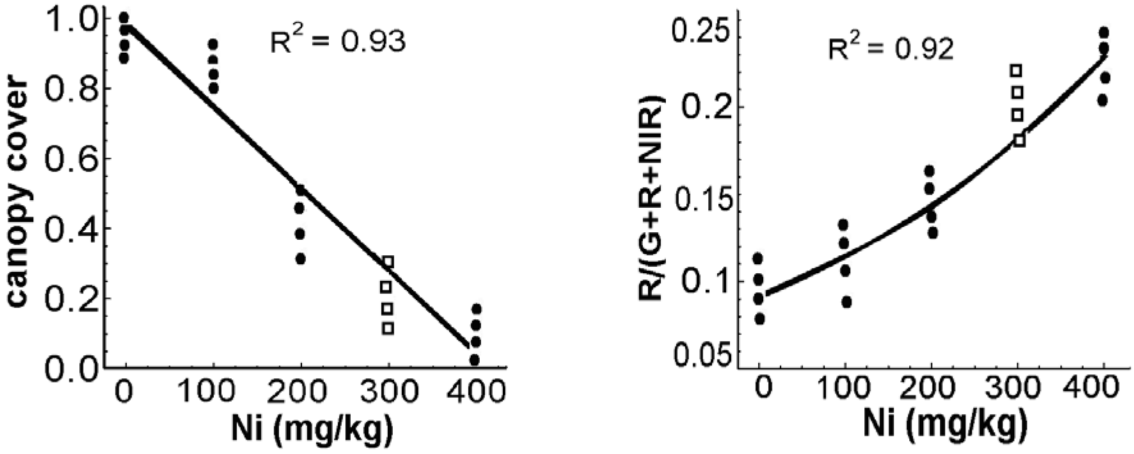
Correlation analysis was run on VIs calculated from the acquired multispectral and multitemporal data. Most any of the VIs were found to be closely linked with plant condition (growth attributes) and Ni concentration in soil. Simple regression analysis was employed to those vegetation indices which showed the best correlation. The contamination impact on crop growth variables and reflectance features was quantitatively described by empirical relationships.

Notable differences in vegetation reflectance, especially in the infrared portion of the spectrum, were attributed to green canopy fraction. This growth variable is an essential factor of vegetation spectral reflectance. On the other hand, it is closely related to other plant biophysical parameters and is an indicator of crop successful growth or worsened vigour under stress conditions. The established dependence of $r_{\lambda=800}/r_{\lambda=670}$ vegetation index (VI_{13}) on canopy cover is presented in Figure 2b. Using suchlike relationships, retrievals of various crop variables can be performed from spectral reflectance data.

Barley canopy attributes and reflectance signatures considerably varied with the level of the stress factor. In Figure. 3a and Figure 3b the obtained strong dependences of plant canopy cover and $r_{670}/(r_{550}+r_{670}+r_{800})$ vegetation index (VI_{10}) on Ni concentration in the soil are plotted.

Ni impact resulted in dramatically decreased vegetation fraction and considerable spectral reflectance variations. The statistical significance of the variations of reflectance data as well as their high correlation with crop growth attributes and stress levels give grounds to consider spectral indices good quantitative predictors of plant response under stress conditions. It is worth mentioning that in Figure 3b the treatments with 300 mg/kg Ni concentration were first excluded from the regression fits and used later as a validation dataset proving the good consistency and prediction accuracy of the models.

Chlorophyll content is a vital plant physiological parameter. It is associated with plant growth and maturing. In the active vegetative stages, chlorophyll depression is a physiological marker of the stress response. As stress increases, chlorophyll content decreases. Variations in chlorophyll were found to be pollution load

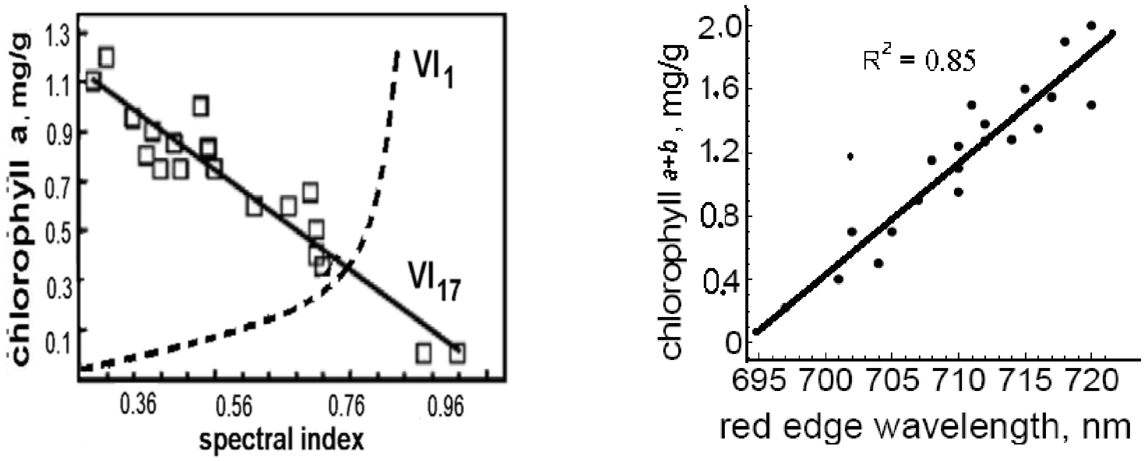


a) b)

Fig. 3 Dependences of barley canopy cover and $r_{670}/(r_{550}+r_{670}+r_{800})$ vegetation index (VI_{10}) on Ni concentration in the soil

dependent. The preformed regression analyses suggested good correspondence between plant chlorophyll content and the degree of the abiotic stress. Thus, chlorophyll deprivation was a reliable marker for physiological damage and estimator of the stress impact.

Plant reflectance spectrum is greatly dominated by leaf pigments. Barley canopy chlorosis as a result of Ni-induced stress leaded to pronounced changes of crop reflectance features, especially in the spectral bands of strong chlorophyll reflectance and absorption. Vegetation indices of barley treatments appeared to be sensitive to chlorophyll variations and exhibited significant correlation with the concentration of chlorophyll a, chlorophyll b and total chlorophyll a+b. An example is shown in Figure 4a where the established through regression analysis statistical relationships of plant chlorophyll-a at stem elongation stage with two vegetation indices are plotted.



a) b)

Fig.4 Relationships of $(r_{800}-r_{670})/(r_{800}+r_{670})$ vegetation index (VI_1) and $r_{670}/(r_{550}+r_{670}+r_{800})$ vegetation index (VI_{10}) with canopy chlorophyl-a concentration at stem elongation stage (a); positive linear relationship between barley total chlorophyll and the red edge position (b)

The linear dependence of the simple ratio VI_{17} on chlorophyll a (C_a=1.88-2.04 VI_{17}) was a better prediction model (R^2=0.88) because it better described the variations of chlorophyll content in the whole range of values. On the contrary, the normalized difference index VI_1 showed a non-linear relationship (R^2=0.67) and responded to initial chlorophyll increase becoming insensitive at higher chlorophyll values. It saturated when chlorophyll content exceeded 0.6 mg/g and was not considered a reliable chlorophyll estimator.The reason of this behaviour of VI_1 is that relatively low chlorophyll is sufficient to saturate absorption in 670 nm region. Therefore, VI wavelength, such as 550 nm, 700 nm, and 720 nm were more suitable for chlorophyll predictions and detection of stress-induced chlorophyll inhibition.

In Table 3 results of the correlation analysis between barley canopy vegetation indices and total chlorophyll at multiple phenological stages are given. High correlation between VIs and plant chlorophyll existed for all vegetative stages before maturing.

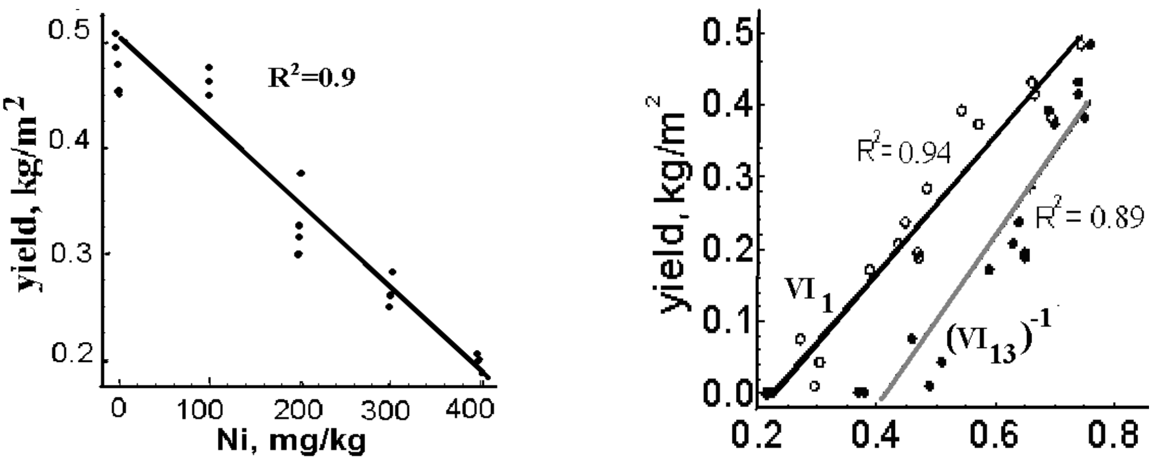
Table 3 Linear correlation coefficients between spring barley vegetation indices and chlorophyll (a+b) at various phenological stages

Growth stage /VI	1	2	6	8	13	14	15	16	17	19	20	21
tillering	0.8	0.82	0.9	-0.81	0.92	0.93	0.84	0.92	-0.93	0.85	-0.83	0.9
stem elongation	0.82	0.85	0.95	-0.85	0.93	0.93	0.87	0.92	-0.94	0.84	-0.85	0.93
booting	0.75	0/81	0.81	-0.78	0.94	0.96	0.88	0.93	-0.94	0.74	-0.8	0.83

The transition spectral region between the red and near infrared bands appeared to be the most suitable spectral region for tracking chlorophyll changes. Decreased absorption along with shift to shorter wavelengths was observed and exploited for assessment of chlorophyll content. Red edge is called the region where there is a sharp change in reflectance between wavelengths 690 and 750 nm. It characterizes the boundary between the strong chlorophyll absorption at 670 nm and high reflectance in the near infrared band. The determination of the red edge position (wavelength) is performed by derivative analysis of plant reflectance spectra. The red edge effectively detects plant stresses.

We used this technique to describe Ni-induced stress in barley crops. The maximum of the first derivative of reflectance spectra in the red-edge region marked the inflection point of canopy reflectance curves. The position of the maximum, i.e. the wavelength at which it occurred, was regressed against plant chlorophyll. The obtained positive regression between chlorophyll and red-edge wavelength at stem elongation stage is shown in Figure 4b (inverse dependence where (the chlorophyll concentration is designated as dependent variable). The red edge shifted to shorter wavelengths due to chlorophyll decline. when stress in plants occurred.

A cumulative expression of plant performance during the growing season is the final yield. Stresses reduce crop production to an extent that depends on the stress factor and species tolerance. The derived dependence of barley grain yield on Ni concentration in the soil is plotted in Figure 5a. Temporal spectral patterns of VIs were found to be very closely related to crop yield. Regression analysis between VIs temporal sums and yield



a) b)

Fig. 5 Dependence of barley grain yield on Ni concentration in the soil (a); relationships of barley grain yield with VI_1 and VI_{13} temporal sums throughout the whole plant development cycle (b)

was performed to fit empirical equations for the whole growing season or parts of it. Regression models linking barley grain yield with VI_1 and VI_{13} temporal sums from plant emergence to maturity are shown in Figure 5b. Suchlike relationships are feasible for yield predictions. It is important to mention that the use of shorter periods did not worsen the predictive ability of the models due to the fact that nickel manifested its adverse impact on plant growth from the very early vegetative stages.

Conclusions

The obtained results indicate that Ni-induced stress causes statistically significant variations of plant spectral response. Thus is associated with the sensitivity of crop reflectance properties to growth characteristics. Various spectral indicators (vegetation indices) are highly correlated with the degree of the stress impact. Multispectral and multitemporal data proves applicable for detection of stress symptoms in crops and reliable health diagnosing. The degree of growth depression is successfully evaluated from spectral reflectance response. Statistically significant empirical relationships were derived that attach a quantitative measure to plant condition and stress assessment.

References

1. Abbas M., Parveen Z., Iqbal M., Riazuddin M., Iqbal S., Mubarik A., Bhutto., 2010, Monitoring of toxic metals (cadmium, lead, arsenic and mercury) in vegetables of Sindh, Pakistan, Kathmandu University Journal of Science, Engineering and Technology, Vol 6, No 2, 50-65.
2. Abii T.A., Levels of Heavy Metals Cr, Pb, Cd Available for Plants within Abandoned Mechanic Workshops in Umuahia Metropolis, Research Journal of Chemical Sciences, Vol. 2 (2), 2012, 79-82.
3. Baret F., V. Houle, M. Guerrif, Quantification of plant stress using remote sensing observations and crop models: the case of nitrogen management. Journal of Experimental Botany, Vol. 58(4), 2007, 869–880.
4. Bavi K., B. Kholdebarin, A. Morad, Effect of cadmium on growth, protein content and peroxidase activity in pea plants, Pak. J. Bot. Vol. 43(3), 2011, 1467-1470.
5. Broge N. H., E. Leblanc, Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density, Remote Sensing of Environment, Vol. 76, 2000, 156-172.
6. Carter G. A., W. G. Cibula, R. L. Miller, Narrow-band reflectance imagery compared with thermal imagery for early detection of plant stress, Journal of Plant Physiology, Vol. 148, 1996, 515– 522.
7. Carter G.A., Knapp A.K., 2001, Leaf optical properties in higher plants: Linking spectral characteristicsto stress and chlorophyll concentration", American journal of botany, 88(4), 677-684.
8. Everhart JL1, McNear D. Jr, Peltier E, van der Lelie D, Chaney RL, Sparks DL., 2006, Assessing nickel bioavailability in smelter-contaminated soils. Science of the Total Environmen,t 31;367(2-3), 732-744.
9. Falkenberg N.R., G. Piccinni, J. T. Cothren, D. I. Leskovar, C. M. Rush, Remote sensing of biotic and abiotic stress for irrigation management of cotton, Agricultural water management, Vol. 87, 2007, 23–31.
10. Filella I., J. Penuelas, L. Llorens, M. Estiarte, Reflectance assessment of seasonal and annual changes in biomass and CO_2 uptake of a Mediterranean shrubland submitted to experimental warming and drought, Remote Sensing of Environment, Vol. 90, 2004. 308–318.
11. Franke J., G. Menz, Multi-temporal wheat disease detection by multi-spectral remote sensing, Precision Agriculture, Vol. 8(3), 2007, 161-172.
12. Glenn E., A. Huete, P. Nagler, S. Nelson, Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape, Sensors, Vol.8, 2008, 2136-2160.
13. Hatfield J.L. J. H. Prueger, Value of using different vegetative indices to quantify agricultural crop characteristics at different growth stages under varying management practices, Remote Sensing, Vol. 2, 2010, 562-578.
14. Kancheva R., D. Borisova, Vegetation stress indicators derived from multispectral and multitemporal data, Space Technology, Vol 26 (3), 2007, 1–8.
15. Kancheva, R., I. Iliev, D. Borisova, S. Chankova, V. Kapchina, Detection of plant physiological stress using

spectral data, Ecological Engineering and Environment Protection, Vol. 1, 2005, 4-9.

16. Osório J., M. Osório, A. Romano, Reflectance indices as nondestructive indicators of the physiological status of Ceratonia siliqua seedlings under varying moisture and temperature regimes, Functional Plant Biology, Vol. 39, 2012, 588–597.
17. Penuelas J., J. Gamon, A. Fredeen, J. MerIno, C. Field, Reflectance indices associated with physiological changes in nitrogen- and water-limited sunflower leaves, Remote Sensing of Environment Vol. 48, 1994, 135-146.
18. Rodrıguez-Serrano M., M. C. Romero-Puertas, D. M. Pazmino, P. S. Testillano, M. C. Risueno, L. A. del Rıo, L. M. Sandalio, Cellular Response of Pea Plants to Cadmium Toxicity: Cross Talk between Reactive Oxygen Species, Nitric Oxide, and Calcium. Plant Physiology, Vol, 150, 2009, 229–243.
19. Sathawara N.G., Parikh D.J. and Agarwal Y.K., 2004, Essential heavy metals in environmental sample from western India: Bull, Environn. Contam. Toxicol., 73, 264-269.
20. Serrano L., I. Filella, J. Penuelas, Remote Sensing of Biomass and Yield of Winter Wheat under Different Nitrogen Supplies. Crop Sci., Vol. 40, 2000, 723–731.
21. Sobukola O. P., Adeniran O. M., Odedairo A. A., Kajihausa O. E., 2010, Heavy metal levels of some fruits and leafy vegetables from selected markets in Lagos, Nigeria, African Journal of Food Science Vol. 4(2),.389-393.
22. Wuana R. A. and OkieimenF. E., 2011, HeavyMetals in Contaminated Soils: A Review of Sources, Chemistry, Risks and Best Available Strategies for Remediation, International Scholarly Research Network ISRN Ecology, Volume 2011, Article ID 402647, 20 pages