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DETECTION AND ASSESSMENT OF ABIOTIC STRESS OF CONIFEROUS LANDSCAPES CAUSED BY URANIUM MINING (USING MULTITEMPORAL HIGH RESOLUTION LANDSAT DATA)

ABSTRACT. Remote sensing have become one of decisive technologies for detection and assessment of abiotic stress situations, such as snowstorms, forest fires, drought, frost, technogenic pollution etc. Present work is aiming at detection and assessment of abiotic stress of coniferous landscapes caused by uranium mining using high resolution satellite data from Landsat. To achieve the aim, ground-based geochemical data and were coupled with the satellite data for two periods, i.e. prior and after uranium mining decommissioning, into a file geodatabase in ArcGIS/ArcInfo 9.2, where spatial analyses were carried out. As a result, weak and very weak relationships were found between the factor of technogenic pollution – Z_c and vegetation indices NDVI, NDWI, MSAVI, TVI, and VCI. The TVI performs better compared to other indices in terms of separability among classes, whereas the NDVI and VCI correlate well than other indices with Z_c.

KEY WORDS: remote sensing, high resolution satellite data, abiotic stress, coniferous landscapes, uranium mining, Landsat.

INTRODUCTION

The importance of remote sensing (RS) is noted in a number of key documents and programs such as Global Monitoring for Environment and Security (GMES) of the European Union (EU), Global Earth Observation System (GEOS), Commission for Earth Observation Satellites (CEOS) and networks for calibration and validation of satellite data and satellite products – (Cal/Val). The importance of RS data for governance is underscored also in several EU framework directives, such as INSPIRE (2007/2/EC), Water Framework Directive (2000/60/EC). Forest resources that are part of the European ecological network of habitats – NATURA 2000, which establishment is based on the directives of the European Union (EU) – Directive 92/43/EEC on the conservation of natural habitats and of wild fauna and flora (the Habitats Directive in brief) and Directive 79/409/EEC on the conservation of wild birds (usually called the birds Directive), are subject to conservation measures and restrictions on anthropogenic loading in order to protect habitats and biodiversity.

The importance of stress situations of forest resources for science and society in Europe is outlined in current COST FP0903 action entitled "Climate Change and Forest Mitigation and Adaptation in Polluted Environment" [About COST, 2011]. As noted by [Franklin, 2001] the criteria and indicators for sustainable forest management prepared by the Food and Agrigulture Organization (FAO) of the United Nations (UN), and several national criteria – Canada, Criteria 2 – Element 2.1 "The occurrence of forest disturbances and stress" appear with 8 indicators, which underscore the international importance of monitoring the vegetation stress for sustainable use and conservation of natural resources. In Bulgaria, the adopted National Forest Policy and Strategy "Sustainable Development of Forestry Sector in Bulgaria 2003–2013", subsequently revised and adopted under name "National Strategy for Sustainable Development of Forestry Sector in Bulgaria 2006–2015", outlines three strategic actions, i.e. 2, 4 and 5, which define measures for protection of forests affected by various abiotic and biotic stressors.

On an international level several international organizations, such as the International Atomic Energy Agency (IAEA) and European Commission (EC) are dealing with the determination of Threshold Limit Values (TLVs) for human and nonhuman part of the biota, as a reflection of the guidelines set out in their recommendations and regulations and directives. Some countries have already adopted rules to protect the nonhuman part of the biota, such as UK – England and Wales, which requirements for Environmental Impact Assessment (EIA) concerning NATURA 2000 habitats include ionizing radiation. In United States of America (USA), guidelines for the protection of biota and minimum levels of toxicity are given by the USDOE Orders 5400.5 and 450.1.

In the late 90s of the 20th century, problems with acidification of soil and acid rain have led to the emergence of so-called "New forest decline". For example, as a result of soil acidification in the Ore Mountains in the Sudetenland area, about 8000 ha has developed Mg deficiency [Omasa, Nouchi et al., 2005]. In Bulgaria the proportion of contaminated soils with heavy metals from industrial plants is approximately 90% of total contaminated land, which are about 1% of the total area of the republic [Stoyanov, 1999]. Contaminated agricultural land with heavy metals and metalloids from industrial activities cover an area of 44,900 ha, 61.3% of them are close to industrial enterprises, of which 8160 ha are contaminated five times the TLVs. The most affected are lands into three to four kilometres off the areas around large industrial sites [Staykova, Naydenova, 2008]. Fires and droughts are other stressful situations, which are quoted using RS methods. With low resolution spectrometers from series EOS-MODIS - TERRA and AQUA, NOAA-AVHRR of National Aeronautics and Space Administration (NASA), Medium Resolution Imaging Spectrometer (MERIS) and the Along-Track Scanning Radiomter (ATSR-1) (ATSR-2) aboard the ERS-1 and ERS-2, Advanced Along-Track Scanning Radiomter (AATSR) on board Envisat of European Space Agency (ESA), and SPOT VEGETATION 1 and 2 on board of SPOT 4 and 5 is made the global monitoring of forest fires and their consequences [Garbuk, Gershenzon, 1997; Mardirossian, 2000; Chuvieco, 2008].

The aim of the study is to detect and assess the abiotic stress of coniferous landscapes using High Resolution (HR) Landsat satellite data. The subject of study is coniferous landscapes in Teyna River basin, Novi Iskar Municipality, Sofia-city, Bulgaria.

MATERIALS AND METHODS

Two groups of data have been used to identify the abiotic stress in coniferous plants in the examined regions. The first includes data obtained from independent information sources – field geochemical data, and the second is HR Landsat satellite data.

Field Data

During the ground-based studies conducted in the *Iskra* uranium mining section in 2010 and 2011, the following ground truthing were collected and stored in table.dbf format into a file geodatabase in ArcGIS/ArcCatalog 9.2: 1) GPS measurements; 2) contents of heavy metals and metalloids (Cu, Zn, Pb, Ni, Co, Mn, Cr) and natural and artificial radionuclides (^{235}U, ^{234}Th, ^{226}Ra, ^{40}K) in soils, measured in licensed after the international standards laboratories for the respective elements (Fig. 1). The data collection and sampling scheme is carried out in accordance with Bulgarian Institute for Standardization (BDS) 17.4.5.01 and BDS ISO 18589–2 standards. The content of natural radionuclides is determined by gamma-spectrometric analysis with multichannel analyzer DSA 1000, made by CANBERRA and hyper clean Ge-detector. Analyses were performed in "Accredited Reference Laboratory of Radioecology and Radioisotope Studies" at the Institute of Soil Science "N. Pushkarov" in accordance with IEC 61452 and ISO 18589–3 [Naydenov, Misheva, et al. 2001].

Satellite data

In order to be able to store, visualize and manage the geospatial information required for the purposes of this study, a raster catalog in a file geodatabase was composed. The raster catalog includes images of Landsat 5 TM from the following years (Table 1).

The data stored in the geo-database of Landsat 5 TM, is in GeoTIFF file format for level of processing – Level 1T (terrain corrected), Level 1Gt (systematic terrain corrected) or Level 1G (systematic corrected). QUick Atmospheric Correctiion (QUAC) algorithm was applied on the selected channels in the respective spectral range using the licensed module QUAC in ENVI [ENVI Atmospheric

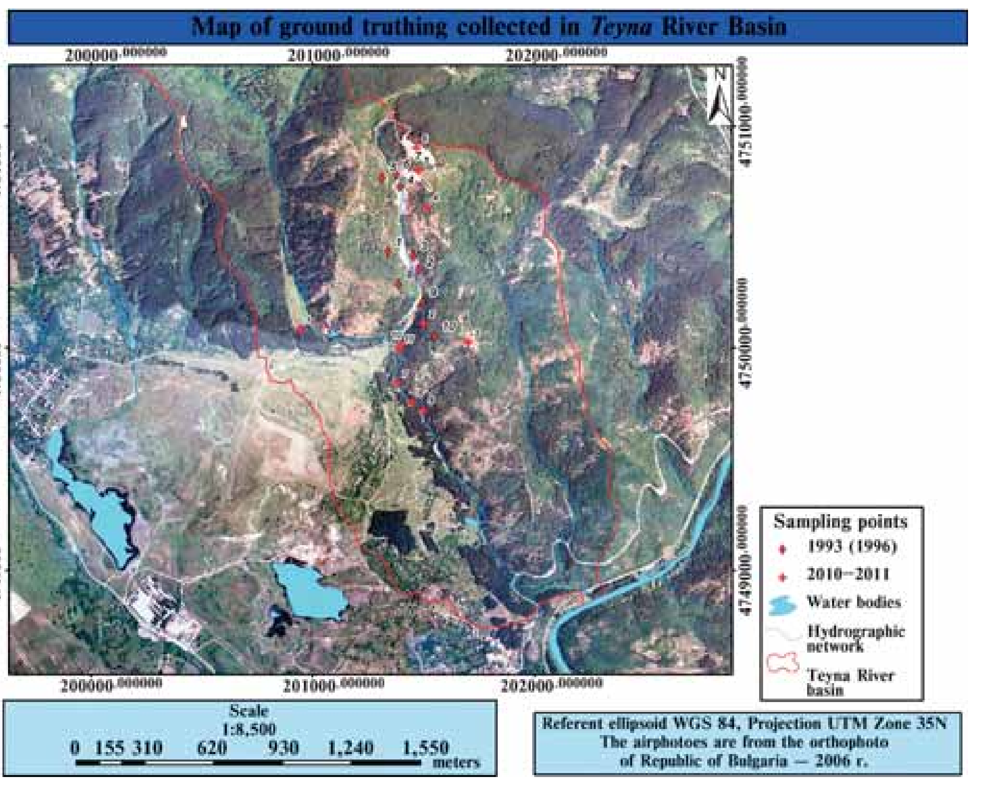

Fig. 1. Map of ground truthing from the catchment area of Teyna River basin

Table 1. List of Landsat images stored into the geo-database

No	Satellite/ radiometer	Date	Solar azimuth	Calibration parameters	Source
1	Landsat 5/TM	11 June 1990	57.07°	In the.MTL file	LPDAAC, USGS
2	Landsat 5/TM	28 June 1991	58.76°	In the.MTL file	LPDAAC, USGS
3	Landsat 5/TM	16 August 2003	53.11°	In the.MTL file	LPDAAC, USGS
4	Landsat 5/TM	23 July 2006	60.18°	In the.MTL file	LPDAAC, USGS
5	Landsat 5/TM	26 July 2007	59.73°	In the.MTL file	LPDAAC, USGS
6	Landsat 5/TM	15 July 2009	60.81°	In the.MTL file	LPDAAC, USGS
7	Landsat 5/TM	3 August 2010	57.69°	In the.MTL file	LPDAAC, USGS
8	Landsat 5/TM	19 June 2011	63.07°	In the.MTL file	LPDAAC, USGS

Correction Module – User's Guide, 2010]. The satellite data is then subdivided and bundled into two time series, i.e. 1990–1991 and 2003–2011, in order to correlate the respective field measurements and geochemical assessments in 1993 (1996) and 2010–2011 with the satellite data.

Methods

In order to establish the heavy metal and radionuclide pollution distribution fields in the examined study area, the landscape approach is adopted. A Digital Landscape Model (DLM) for the river basin of the Teyna River [Filchev, 2009] was created as a result of the unification of the thematic layers according to the LANMAP methodology [Mücher et al., 2010]: 1) Geology – lithology; 2) Relief – aspect and inclination of the slope, geochemical types of landscapes; 3) Climate – climatic type after the climate classification of Koppen-Kottek, [Kottek et al., 2006]; 4) Vegetation – forest types; 5) Soils – main soil types after the soil classification of the FAO, which comprises 452 elementary landscapes united in 98 landscapes after the linear combination method [Filchev, 2009]. The landscapes of coniferous plants were subsequently extracted and a stratified random sampling was made within them to determine the sample sites [McCoy, 2005]. The assessment of the technogeochemical state for 1993 and 2011 was made using the total contamination factor of technogenic pollution with respect to the background – Z_c [Saet et al., 1990]:

$$Z_c = \sum_{i=1}^{n} K_c - (n - 1) \quad (1)$$

where K_c is the technogenic concentration coefficient > 1 (or 1.5) representing the ratio of heavy metal and metalloid concentrations and the specific activities of natural radionuclides in surface soil horizon to the background concentrations and specific activities determined for the examined region; and n – the number of chemical elements with $K_c > 1$ (or 1.5).

$$K_c = C/C_{background} \quad (2)$$

where C is the concentration of the chemical element in the soil sample and $C_{background}$ is the background concentration. The Z_c index is reclassified according to the following classification system: 1) 0-10; 2) 10–20; 3) 20–30; 4) 30–50; 5) 50–60, and 6) > 60. The Z_c values above 50–60 are found to indicate technogeochemical pollution [Penin, 1997]. According to previous research carried out by [Filchev & Yordanova, 2011], it is found that the Z_c values are ranging from 3.13 to 129.24 for 1993 (1996), whereas for 2010–2011 the range is: 2.29–32.18, which indicates fourfold decline in Z_c values between two observation

Table 2. Vegetation indices used for detection and assessment of abiotic stress

Vegetation index	Equation	Source
Normalized Difference Vegetation Index (NDVI)	$NDVI = (RNIR - Rred)/(RNIR + Rred)$	Rouse et al., 1974
Normalized Difference Water Index (NDWI)	$NDWI = \frac{(R_{NIR} - R_{SWIR})}{(R_{NIR} + R_{SWIR})}$	Gao, 1996
Modified Soil Adjusted Vegetation Index (MSAVI)	$MSAVI = \frac{1}{2}\left[2R_{800} + 1 - \sqrt{(2R_{800}+1) - (R_{800} - R_{680})}\right]$	Qi et al., 1994
Triangular Vegetation Index (TVI)	$TVI = \frac{1}{2}\left[120(R_{720} - R_{550}) - 200(R_{670} - R_{550})\right]$	Broge, Leblanc, 2000

periods. This is attributed to the reclamation and restoration measures for mitigation of the anthropogenic impacts from uranium mining activities.

The estimated vegetation indices from Landsat 5 TM dataset used in this study are presented on (Table 2).

The Vegetation Condition Index (VCI), characterize the vegetation condition using the ratio of the differences between the maximum and the minimum value of NDVI, for a period of observation or a certain phenophase. To monitor the signals of abiotic stress caused by drought a multitemporal NDVI data is derived index of vegetation condition – (VCI) [Kogan, 1987; Seiler, Kogan et al., 1998; Unganai, Kogan, 1998]. The formula for calculating the VCI is:

$$VCI = 100(NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min}). \quad (3)$$

The VCI is based on the concept of the ecological potential on natural resources, climate, soil diversity, type and amount of vegetation, and topography of the region [Seiler, Kogan et al., 1998]. Index values range from 0 to extremely adverse conditions to 100 – optimum conditions.

The reclassified thematic layers of Z_c are combined with coniferous landscapes derived from DLM, which new landscapes serve as a basis for the derivation of descriptive statistics from the classes contaminated coniferous landscapes. This statistics is based on the comparison of classes' polluted landscapes and search for similarities and differences in them. Theoretically constructed classes of polluted landscapes are compared in terms of their separability using the VIs of HR satellite data. Then using hierarchical clustering, groups of values of vegetation indices are analyzed for similarities and differences with the theoretical classes of polluted landscapes. Dendrograms are compiled on the basis of the signatures of classes derived from the multitemporal VIs of Landsat 5 TM. The tool "Dendrogram" in ArcGIS/ArcInfo 9.2 (Academic license) use hierarchical clustering algorithm. The construction of the dendrogram begins with the estimation of distances between each pair of classes from the input signature file and iterative collection of all pairs of classes closest to the outermost. Each iteration is merging classes, based on the updated values of the distances, and the average coefficient of variation. The two approaches for construction of a dendrogram in ArcGIS/ArcMap 9.2 are based on: 1) calculating distances based on the class average, and 2) calculating distances using the mean and variance of the values in each class [ArcGIS Desktop Help, 2008]. For purposes of present work the second approach is chosen, as more reliable, as there is no prior knowledge of the statistical distribution of VIs values within each class. In case of coincidence of VIs classes with the Z_c classes, correlations and regression model of dose-effect relationships of the values of Z_c and VIs is built.

RESULTS AND DISCUSSIONS

The comparison of data on the current state of the coniferous landscapes is done in by the Landsat satellite data for the years 1990 and 1991 with modelled environmental fields of total contamination factor of tehnogenic pollution-Z_c for the corresponding period of the ground-based measurements of heavy metals and radionuclides – 1993 (1996). The values of NDVI, NDWI, MSAVI, and TVI for the 1990–1991 are presented on, (Table 3). The table shows that the average between the classes 2 and 3 do not differ significantly for NDWI, the NDVI, indices MSAVI-of the order of 0.03–0.02% of the values of. In TVI the difference in the average of the 2nd and 3rd class is of the order of 0.12.

Differences in the standard deviations (SDs) of the previous group are not a quite bigger 0.003–0.008, while in TVI this difference is 0.12. The grouping of classes in their values (s) from one another is presented (Fig. 2).

The 1990–1991 period shows that the average values of NDVI in the Z_c classes

Table 3. Descriptive zonal statistics of classes contaminated landscapes from time series of NDVI, NDWI, MSAVI, TVI (1990-1991).

No	Zc (classes)	Pixels	Area(m^2)	Min	Max	Range	Average	Standard Deviation (SD)
NDVI								
2	10–20	14	12600	0.524	0.655	0.131	0.576	0.033
3	20–30	16	14400	0.420	0.717	0.297	0.533	0.078
4	30–50	35	31500	0.426	0.660	0.234	0.564	0.060
5	50–60	3	2700	0.458	0.641	0.183	0.568	0.079
NDWI								
2	10–20	14	12600	0.205	0.361	0.155	0.280	0.049
3	20–30	16	14400	0.196	0.408	0.212	0.311	0.048
4	30–50	35	31500	0.183	0.420	0.237	0.306	0.070
5	50–60	3	2700	0.196	0.278	0.082	0.251	0.038
MSAVI								
2	10–20	14	12600	0.687	0.793	0.105	0.730	0.027
3	20–30	16	14400	0.593	0.836	0.243	0.693	0.063
4	30–50	35	31500	0.595	0.798	0.202	0.719	0.052
5	50–60	3	2700	0.627	0.786	0.159	0.725	0.070
TVI								
2	10–20	14	12600	0.673	1.032	0.359	0.907	0.110
3	20–30	16	14400	0.787	1.035	0.248	0.879	0.065
4	30–50	35	31500	–0.236	1.096	1.332	0.819	0.279
5	50–60	3	2700	0.153	1.086	0.933	0.770	0.437

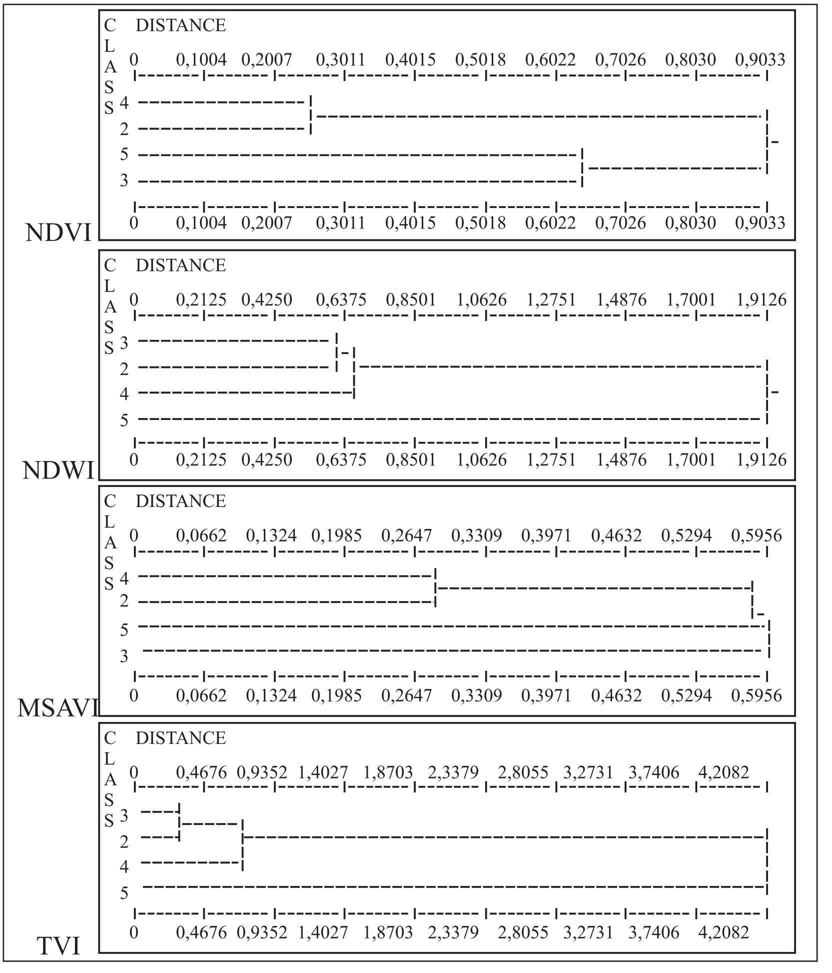

Fig. 2. Dendrograms of zonal statistics extracted from Landsat 5 TM VIs images: NDVI, NDWI, MSAVI, TVI. (1990–1991)

change relatively smoothly in ascending order. The same is for the standard deviation in the class, which is smallest in the 2nd class of relatively uncontaminated landscapes and the highest in the 5th class of technogenical contaminated landscapes. The grouping of classes of values of NDVI is presented (Fig. 2). The figure shows that hierarchical k-means clustering groups the values of the 4th and 2nd class at a distance of 0.26, 5th and 3rd class at 0.65, and the two merged clusters at 0.90. The grouping on the basis of the average and standard deviation of the groups is not sufficiently reliable method for the separation of the groups, and the reliability of NDVI in the determination of stress in one and two-year multispectral satellite data is not that large, which affect the speed and timeliness of detection of abiotic stress with the use of this data type.

The spectral vegetation index MSAVI, which is generally a derivative of NDVI with corrections for topsoil reflectance, shows relative stability in ascending and descending order of the classes. The standard deviation oscillates in increasing order of class 2 to class 5.

The grouping of classes is shown in (Fig. 2) that shows that the classes are grouped similarly to the values of NDVI. This is at distances respectively: 0.28, 0.59, and 0.58. The difference in MSAVI in comparison with the NDVI is that the grouping of the 5th and

3rd class is at a relatively large distance, which indicates that they are more easily separable rather than 2nd and 4th class. However, similarly to the NDVI, classes of pollution do not follow the course of an increase in the values, which witnesses for non-linear dependence of stress effects caused by pollution with heavy metals, metalloids, and radionuclides or non-enforceability of the MSAVI, as an indicator of stressful situations.

In the NDWI average values also increase relatively slowly, along with some of the increase of the SD with the increase of pollution, from class 2 to class 5 (Table 3). (Fig. 2). From the shape of the dendrogramme can be seen that the first two classes, i.e. 2 and 3, group at a distance of 0.61, and then to the first cluster by adding the values of class 4 at a distance of 0.67 and finally the class 5 at a distance of 1.91. This group follows the course of increase in the values of NDWI, proving that the class with the most contaminated landscapes, i.e. 5, is well separated by using NDWI values. As the index is used for assessment of the water status of vegetation, it follows that the total water content of coniferous vegetation in the classes of polluted landscapes is significantly larger, which may be attributed, both to the total water content and the level of the groundwater seepage in landscapes, as well as to the total contamination factor of tehnogenic pollution – Z_c.

The average values of the TVI unlike other indices decline in descending order with the increase in pollution from 2nd to 5th class. It is seen also that with the declining average values the SD increase, although the small sample for class 5, i.e. 3 pixels. The grouping of the values of the TVI classes (Fig. 2), shows that TVI first join the 2nd and 3rd class at a distance of 0.33, and then 4th in 0.75, and finally 5th class at 4.20 similarly to NDWI. The difference of the discriminative power for distinguishing classes of contaminated landscapes in TVI to NDWI is due to the sharp separation of adjacent classes 2 and 3, while the most contaminated landscapes – 5th class is grouped at 4.20.

The time series of NDVI, NDWI, TVI, MSAVI, and VCI VIs from Landsat 5 TM is spanning 9 years, i.e. 2003–2011. Using the so created time series a descriptive statistics on a zone level is retrieved: average, median, minimum and maximum values, range, SD, characterizing the distribution of values in the technogenical contaminated landscape units. The zones are created on the basis of coniferous landscapes of the black pine, in the middle and lower part of Teyna River basin, which are merged with the areas of technogenic pollution, which in turn are derived by reclassifying the values of Z_c (Table 3). The zonal statistics for the 1st and 2nd class is not extracted due to the small size of the test sites of the zones (i.e. about 1 pixel) and due to ignoring zero values in the calculation.

The dendrograms for 2003–2011 VIs, which are built using the extracted signatures from the overlaid reclassified Z_c and coniferous landscapes, are presented on (Fig. 3). From the grouping of the NDVI values, can be inferred that the average of the 2nd and 3rd class resemble one another. The only ungrouped classes remain the 1st and 4th class. The point of clustering of dendrogram is at the distance between the classes 0.780.

The MSAVI shows approximately the same weak distinction between classes, i.e. 0.01 to the average of the classes. Comparing to the NDVI, MSAVI has smaller values of the SD, which shows relatively more stable behavior of the index for registration of changes in the coniferous vegetation. Clusters of signatures of classes of MSAVI are shown in (Fig. 3). The figure shows that clustering of the classes is again at a distance of 0.780 and is similar to the values of NDVI, which indicates that the index has almost the same presentation as regards the discrimination of the classes of landscapes subject to abiotic stress.

Similarly to the dendrogram of the NDVI, NDWI is grouped in 3 classes: 1, 2 and 3, and 4 (Fig. 3).The NDWI values of the 3rd and 4th class approaches one another at 0.816, which shows relatively better representation

Table 4. Descriptive zonal statistics of classes contaminated landscapes from the time series of NDVI, NDWI, MSAVI, and TVI. (2003-2011)

No	Zc (classes)	Pixels	Area(m^2)	Min	Max	Range	Average	Standard Deviation (SD)
NDVI								
1	8.29–10	–	–	–	–	–	–	–
2	10–20	59	53100	0.466	0.816	0.350	0.699	0.070
3	20–30	9	8100	0.504	0.838	0.333	0.721	0.087
4	30–32.18	–	–	–	–	–	–	–
NDWI								
1	8.29–10	–	–	–	–	–	–	–
2	10–20	59	53100	0.109	0.479	0.369	0.293	0.293
3	20–30	9	8100	0.175	0.429	0.254	0.328	0.328
4	30–32.18	–	–	–	–	–	–	–
MSAVI								
1	8.29–10	–	–	–	–	–	–	–
2	10–20	59	53100	0.642	0.901	0.259	0.821	0.051
3	20–30	9	8100	0.658	0.914	0.257	0.834	0.068
4	30–32.18	–	–	–	–	–	–	–
TVI								
1	8.29–10	–	–	–	–	–	–	–
2	10–20	59	53100	–0.340	1.231	1.571	0.576	0.447
3	20–30	9	8100	0.142	1.048	0.906	0.763	0.269
4	30–32.18	–	–	–	-	–	–	–
VCI								
1	8.29–10	–	–	–	–	–	–	–
2	10–20	59	53100	0	76.436	76.436	14.326	17.892
3	20–30	9	8100	0	94.248	94.248	22.576	32.777
4	30–32.18	–	–	–	–	–	–	–

of NDWI in comparison with the NDVI for the separation of contaminated and stressed of heavy metals and radionuclides coniferous landscapes.

Unlike the other indices, TVI shows considerably larger differences of the average values of the Z_c between the 3rd and 4th class – nearly 0.2 (Fig. 3). Grouping in a single cluster of the 1st and 2nd class is at distance between the classes 0.627. The grouping of 3rd and 4th class is logical because there are subtle differences in their values. Lower values of 1st and 2nd class are separated at a little distance of the classes, which shows a better presentation of the TVI in comparison

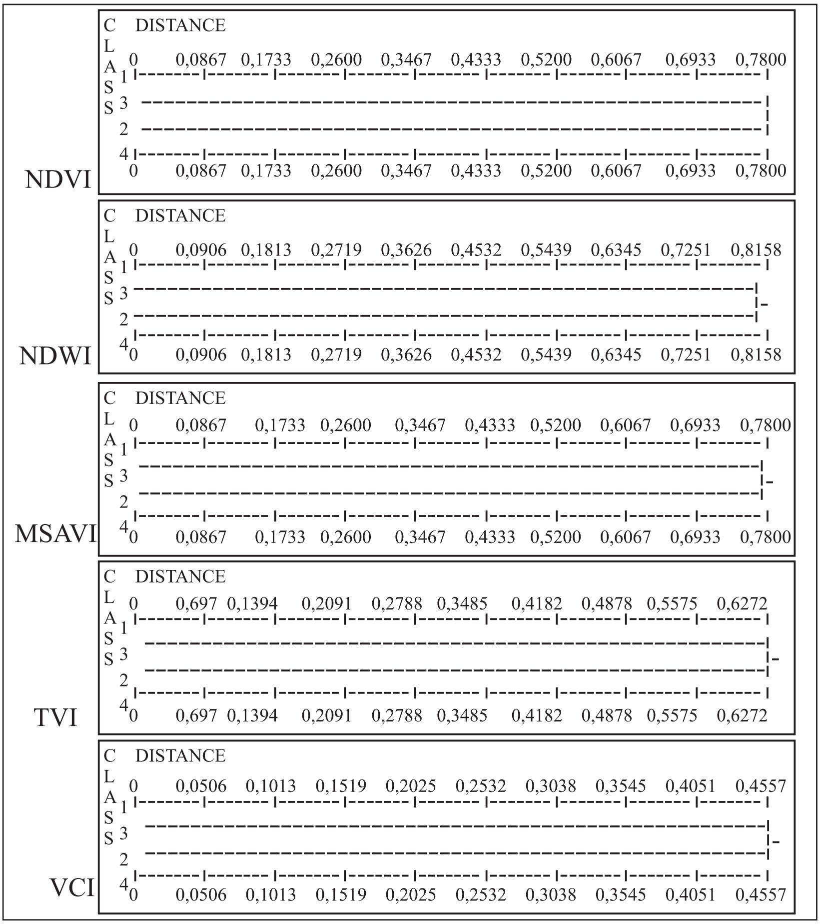

Fig. 3. Dendrograms of zonal statistics extracted from Landsat 5 TM VIs images: NDVI, NDWI, MSAVI, TVI, and VCI. (2003–2011)

with previous indices. This is due to the fact that the index uses the information from 1 additional channel in the green zone of the visible area of the spectrum.

The overall vegetation condition of coniferous landscapes according to preserve VCI index is poor – 2nd grade to 3rd grade on average, which reflects the the NDVI sensitivity regarding the vegetation greenness, which as was noted, is increased by increasing the concentration of tehnogenic pollution in the soil. The phenophase under investigation shows a difference in the average values for the two classes from 14.32 to 22.57 (Table 3). The SD for the same classes varies from 18 to 33, which shows the large variation of values in the 3rd class. The grouping of these classes is at 0.45, which is fairly close to the grouping of the 2nd and 3rd class in the NDVI, and shows greater similarity than difference in classes.

The relationship between the values of VIs for 19900–1991 and the values of the total factor of tehnogeochemical pollution – Z_c are shown in Fig. 4.

The figure shows that between the values of the total index Z_c and VIs, there is a low linear positive correlation, which does not permit the creation of a linear regression model as well as its inversion between the rate of contamination VIs. Correlation of NDVI and Z_c has R^2 = 0.74 (Pearson) and R^2 = 0.675 (Spearman) with the level of significance,

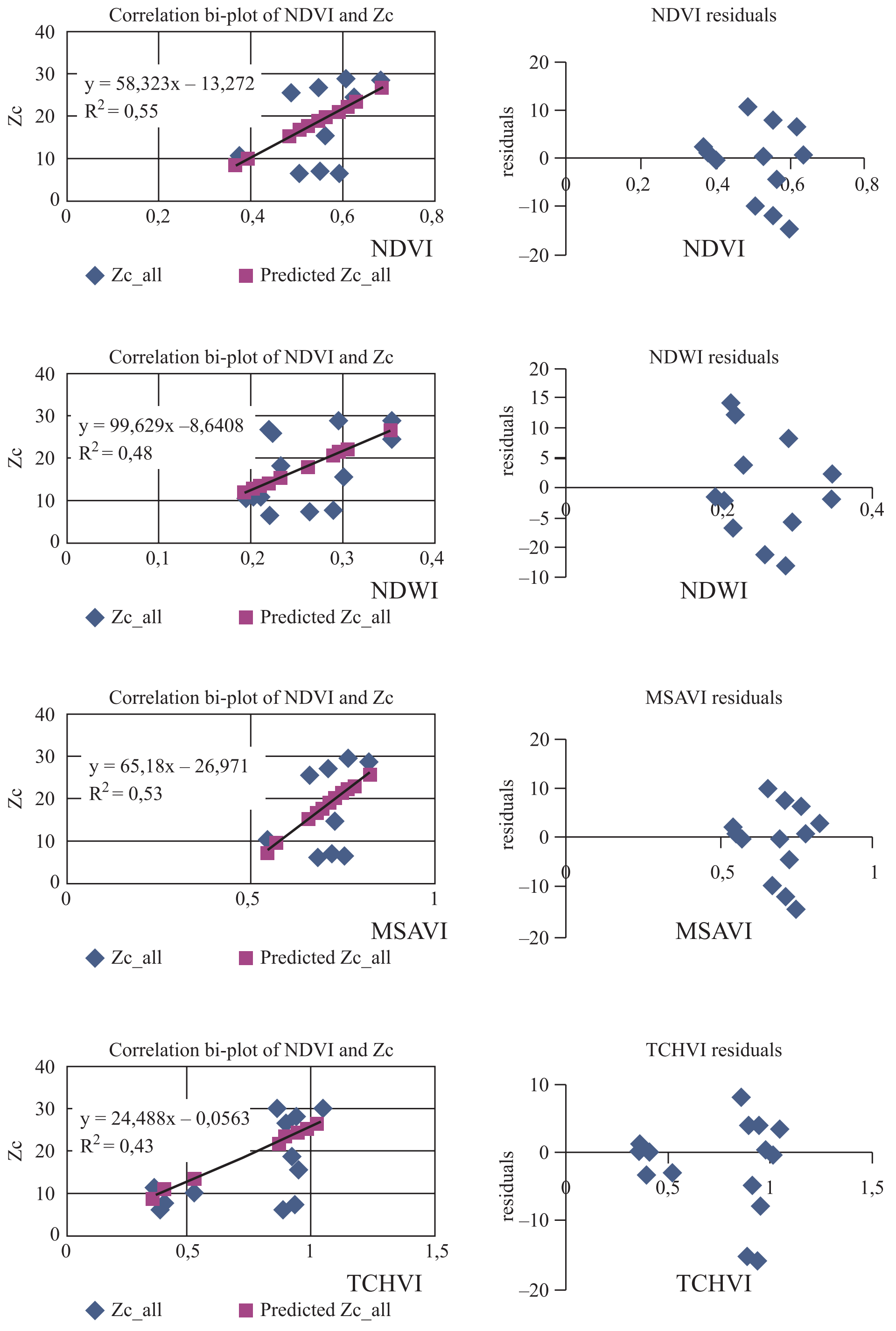

Fig. 4. Correlation bi-plots and residuals of the actual values of NDVI, NDWI, MSAVI, TVI from Landsat and Z_c. (1990–1991)

21.789 for F: < 0.001. Correlation of NDWI and the Z_c has R^2 = 0.695 (Pearson) and R^2 = 0.662 (Spearman) with F = 17.791 for F: < 0.001. For MSAVI and Z_c: R^2 = 0.73 (Pearson) and R^2 = 0.675 (Spearman) at levels of significance F: F: 20.508 for F < 0.001. For the TVI they are R^2 = 0.658 and R^2 = F: 0.373 for F: 13.78 and F: 0.002 respectively.

The relationships between the VIs values of the Landsat TM (2003–2010) and the values of the total factor of technogeochemical pollution – Z_c are shown in Fig. 5. The figure shows that the values of the coefficient of correlation are very low, such as the highest correlation is with VCI, which is derived from the NDVI and NDVI with Z_c. All other indices do not have, or have a very weak correlation with a total coefficient of technogenic pollution. This low value of R^2 is explained by the variation of seasonal dynamics of vegetation during the period of observation by Landsat TM, which dynamics should be tested separately in time, and compared with the dynamics of the Z_c, for the same periods of observation which is beyond the scope of this study. Correlation of NDVI and Z_c has R^2 = 0.41 with level of significance F: 12.60 for F: < 0.002. Correlation of NDWI and the Z_c is R^2 = 0.18 with F = 4.19 for F: < 0.05. For MSAVI and Z_c: R^2 = 0.15 with F: 3.29 in F < 0.08. For the coefficients TVI the R^2 is respectively 0.01 at F: 0.28 and F: 0.60 or lack of correlation.

CONCLUSIONS

In conclusion, it was found that the HR multispectral satellite data from Landsat can be used for detection and assessment of abiotic stress of coniferous landscapes caused by uranium mining. This is based on the established weak relationships between the Z_c and VIs, which however, do not permit for inversion of the derived regression equations between the indices and Z_c. From the analysis of the results it was found also that NDVI and VCI perform better than the index MSAVI. Due to a better presentation of the NDWI in relation to the water content in vegetation, and the resulting physiological abiotic stress, it could be concluded that the water content of the plants is not diminished drastically, while the vegetation greenness is

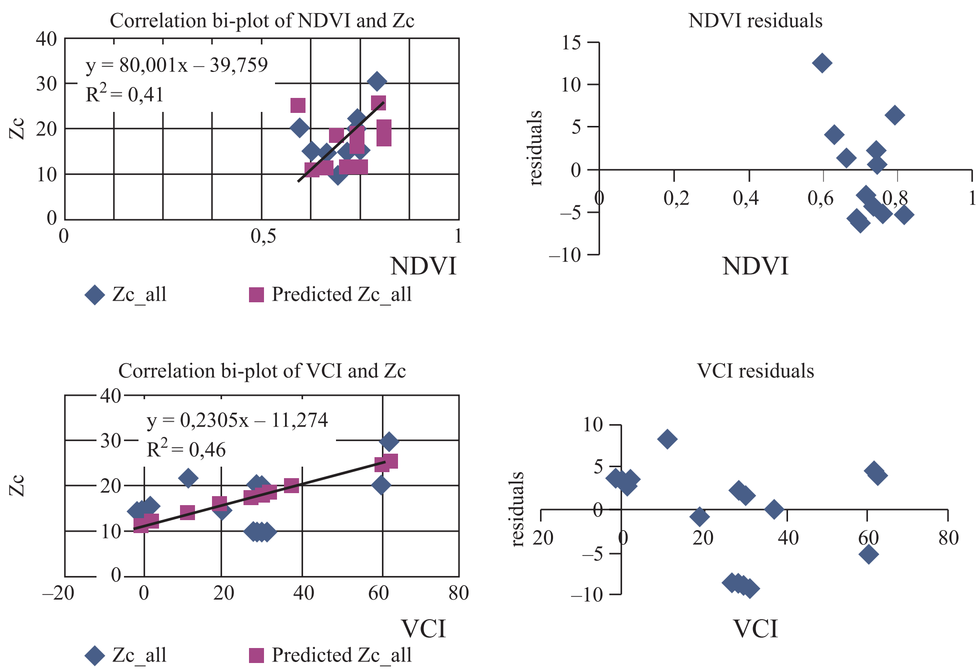

Fig. 5. Correlation bi-plots and residuals of NDVI, VCI from Landsat and Z_c (2003–2011)

more sensitive to this type of stress. As noted, the observed abiotic stress is most likely to be on a physiological level, and one of its manifestations is linked to the increase in the total water content, but also to increase the vegetation greenness of plants. This is better observed by using TVI as an indicator, as it incorporates the green channel in its formula. This argument supports the conclusion of a non-specific reaction of the vegetation renewal and increase in the total water content of conifers discovered in the 1980s of the 20th century [Aronoff et al., 1985]. It can be concluded also that VCI could serve as a relatively good tool for assessment of abiotic stress of coniferous landscapes, in case of availability of a full time series of multispectral HR data.

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