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Integral Methods of Environmental Assessment at Mining Regions Based on Remote Sensing Data

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***Abstract* — The experience of a comprehensive assessment of geo-environmental state of a coal-mining district on the basis of the remote sensing data is described in the article. The example of obtaining the parameters of natural objects by means of the multispectral images and the evaluation of surface displacement on the basis of the radar data are shown.**

***Index Terms*—Remote sensing, environmental.**

I. INTRODUCTION

The current level of human impact on the environment, particularly in regions of substantial tectonic activity, calls for new ways of assessing and regulating the state of the environment in areas of high mineral output. While assessing how mining facilities impact the environment, it is not sufficient to use the results of monitoring a single element, e. g. water bodies. Since mining processes have an integrated effect on all the elements of the environment (i. e. water, vegetation, air, and soil) which are closely interconnected, it is obvious that environmental monitoring requires an integral assessment of environmental compartments and interaction thereof.

II. MATERIALS AND METHODS

An important aspect in the creation of an environmental monitoring system is determining the source of data and methods for data processing. Traditionally, methods used in field works (sampling, botanizing, thematic mapping, etc.), including process modelling in lab conditions, have been used for that end. It should be noted that in the first case there is a limitation in terms of the number of measurements, characteristics and accessibility of locations for field works, and frequency of field works with regard to their isolated nature (measurements of geodata fields are rare). In any case, results of field works can only be used to assess isolated events and their progress over time. Process modelling in lab conditions relies mostly on field works data and is heavily dependent on how adequate and correct a model is used. A short while ago these methods were the only ones to be used in environmental monitoring of mining processes. Today, remote sensing methods that rely on satellite imagery coming from active and passive sensors are being actively developed. Use of remote sensing data rules out the following shortfalls of the traditional research methods:

1. Area and accessibility constraint – dozens, even hundreds of square kilometers are covered at a single point in time;
2. Measurement repeatability – area imaging is performed along the satellite trajectory;
3. Weather constraint – active remote sensing satellites are not affected by atmospheric and weather conditions;
4. Data versatility – the same images can be used to assess various elements (water, vegetation, soil) and interconnections thereof.

In this study, it has been identified that the most comprehensive readings for the purposes of integral geo-ecological assessment in mining regions are provided by remote sensing data sets including multispectral and radar images of medium (50-10 m per pixel) and high resolution (10-5 m per pixel). The key characteristics of these images are listed in Table I.

Table I. Key Characteristics of Images Used for Geo-Ecological Monitoring in Mining Areas

Type of Satellite	Radiometric Resolution, bit/pixel	Spatial Resolution, m	Imaging Mode / Spectral Band
Multispectral image (Landsat 7-8; SPOT 4, 6-7; RapidEye; WorldView-2, etc.)	8 -12	0.46-30	VNIR 0.40-1.40 µm PAN 0.48-0.90 µm TIR 10.40-12.50 µm
Radar image (Cosmo-SkyMed 1-4; ALOS (PALSAR), etc.)	5-8	3-22	X-band 3.1 cm L-band 23.5 cm

Multiple experiments have demonstrated that a minimum time period is 5 years. This interval is appropriate for tracking environmental changes caused by human impact and ruling out those resulting from incidental climatic events (e. g. drought, abundant rainfall, etc.). Multispectral images can be

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used to restore physical indicators and assess the state of such natural elements as water, vegetation, soil, as well as establish possible interconnections thereof. Radar images are primarily used to identify surface changes, i. e. to detect deformation and settlement zones, to assess moisture levels, etc. It should be noted that environmental studies based on a single data type, e. g. multispectral images, may be insufficient for the assessment of the process under consideration or the identification of its dynamics. A typical example would be studying vegetation suppression along a river channel lying close to an edge of the surface coal mine. Apparently, the main factor is the increase in the amount of pollutants washed off into the water from the mine edges. However, the affected area is larger than the river channel area. Radar images of the area of interest show that it is characterized by surface deformations related to the rock mass geodynamics leading to the increased size of the river channel's cone of depression. The resulting integrated effect is that plant roots do not receive the usual water nutrition which is reflected in the overall amount of green biomass. Environmental assessment of mining regions based on remote sensing data generally involves analysis of three natural elements: water, vegetation, and soil. As demonstrated by geo-ecological monitoring practice, it is convenient to start the study by analyzing water bodies. The aquatic medium is the primary indicator of human impact on the environment. A strong interrelation of water, vegetation and soil makes water the main component that has a major impact on the entire system. Water bodies to be analyzed may be selected by an expert who would indicate the potential anomalous zones or may be identified using algorithms for processing textures based on the method developed by R. M. Haralick [1, 2]. These algorithms identify objects characterized by spectral radiance standing out from the natural state of the environment. The state of the objects in the images is further assessed using spectral radiance curves. Spectral properties of the objects in optical images are characterized by integrated and spectral radiance factors. Integrated (achromatic) radiance factor, or radiance factor (r) is a ratio of the integrated radiance of the reflecting surface (B) to the radiance of an ideal diffuse, totally reflective surface (B_0) identically irradiated: $r_0 = \frac{B}{B_0}$. Radiance values should be measured in the same given direction to rule out the impact of irregular reflection in space. Integrated radiance factors for natural features may vary from 1.0 for new-fallen snow to 0.03 for moist black earth. Despite the large interval, only a small number of optically neutral (black and white) objects can be described. Rather than differing in integrated radiance, most natural features have different spectral reflectivity, i. e. they reflect solar radiation differently in various parts of the electromagnetic spectrum. Reflective properties are characterized by the spectral radiance factor which is a ratio of monochromatic radiances: $r_\lambda = \frac{B_\lambda}{B_0}$. [2]. By plotting spectral curves, one can evaluate physical state characteristics of water bodies, such as turbidity and potential pollutant presence. Pollution of water bodies is significantly impacted by meltwater. Snow cover is characterized by accumulation of pollutants that are adsorbed at the surface of crystals as the latter are deposited on the ground; therefore, it can be used as an indicator of pollution of the underlying terrain. Substances accumulated in the snow cover are preserved until snow melting, thus carrying a significant amount of geochemical data. In areas affected by ethnogeny pollution sources, polluted snow cover can be used to evaluate the chemical composition and intensity of atmospheric precipitation, identify zones of dispersion and, supplemented by satellite imagery, obtain information on the level of snow cover pollution near industrial clusters. Accumulation of pollutants in the snow cover is dependent on climatic parameters of a given time period, properties of the underlying surface, soils, rock formations, terrain, vegetation and local ethnogeny pollution sources. Pollutants accumulated in the snow mass increase the pollutant concentration in the spring runoff during the snow melting period. When the snow melts, the pollutants get washed into the runoff water system, water bodies and can contaminate drinking water. It is well known that the atmospheric concentration of pollutants coming from pollution sources plummets as distance from the source increases. The same can be said about pollutant concentration and change in the snow cover. Snow pollution affects brightness on satellite images that, coupled with the results of snow sampling, can be used to plot maps of areas and pollution intensity. Even though originating in winter, differences in the characteristics of snow cover in the polluted and background areas are the most obvious in spring. During the snow melting period, these contrasts stand out the most due to the accumulation of pollutants that are released from snow [3]. Identification of zones with different properties of the snow cover using satellite images is based on the results of field spectrometer measurements that are used to classify snow by its color and on a relatively long list of spectral indices (NDVI, NDSI, NDWI) that are selectively sensitive to water and dust content in the snow, density and other snow characteristics. This process also uses digital terrain models that rule out the influence of surface irregularities on the snow illumination and can be used to calculate the stability of the snow mass. Thus, the existing methods can be applied to spatial irregularities of the snow cover and make a qualitative assessment of the dust content in the snow for horizontal and sloping surfaces. Snow-covered terrain is identified by calculating the

Normalized Difference Snow Index, NDSI (1). NDSI is a relative value characterized by the differences in snow reflectivity in the red (0.66μm) and the short-wave infrared (1.6μm) parts of the spectrum. For snow, NDSI > 0.4.

$$NDSI = \frac{\rho(0,66\,\mu m) - \rho(1,6\,\mu m)}{\rho(0,66\,\mu m) + \rho(1,6\,\mu m)}. \qquad (1)$$

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The main factors that affect the spectral radiance factor of snow are:

- Moisture content;
- Contamination rate;
- Grain size;
- Density.

An increase in the moisture content of snow results in larger snow grain size and density values. At the same time, the spectral radiance factor of snow goes down as water intake increases and multiple scattering is reduced. The contamination rate of snow also decreases the radiance factor. There is a correlation between a decrease in zonal radiance of the contaminated snow cover and concentrations of certain pollutants. The spectral curve for ice is similar to that of snow; however, ice is characterized by lower spectral radiance values and a more dynamic fall of spectral radiance with the increase of pollution levels. Since water intake values are high, the spectral radiance curve of snow in the infrared region is characterized by very low values. A drastic fall in snow radiance in the infrared part of the spectrum as compared to the optical part makes it possible to distinguish between cloud cover and snow using images at these wavelengths. The radiation capacity of snow at infrared wavelengths is, on the contrary, close to 1; therefore, its radiation intensity is primarily dependent on its thermodynamic temperature [3]. The state of vegetation in imagery is assessed using integrated characteristics in the form of vegetation indices. Currently, around 160 index versions are in use. These are selected experimentally (empirically) based on the known peculiarities of spectral reflectivity curves for vegetation and soils. The calculation is based on the two most stable parts of the vegetation spectral reflectivity curve: the red part of the spectrum (0.62-0.75 μm) accounts for maximum absorption of solar radiation by chlorophyll, while the near infrared part (0.75-1.3 μm) represents maximum reflection by the leaf cells. In other words, the high photosynthetic activity coming from large amounts of plant biomass results in lower reflection index values in the red part of the spectrum and higher values in the near infrared part. Depending on the area, researchers may use the traditional Normalized Difference Vegetation Index (NDVI) to analyze normal vegetation or the Soil Adjust Vegetation Index (SAVI) and the Normalized Difference Infrared Index (NDII) to analyze mining sites such as spoil dumps, mine waste piles, etc., i. e. sites with degraded topsoil and little green biomass. The most time-consuming part of the geo-ecological monitoring process, when both conventional methods and remote sensing are used, is identifying changes in the surface of a mountainous area. Radar images and radar interferometry can be used to evaluate the changes on the surface of the Earth. Thus, differential interferometry is applied to detect and track vertical and horizontal motions of the ground surface. The easiest method of assessing motions and temporal variations involves using a couple of radar images taken with a certain time interval. Changes in the ground surface can be seen on interferograms as areas with color transitions from red to blue (phase shift from – π to π). Each transition corresponds to a motion of the ground surface equaling half the radar wavelength. Radar interferometry is used to create digital terrain models and to map vertical surface motions. By processing several couples of images, one can estimate the dynamics of surface changes which is an important factor in studying the geodynamics of rock mass.

III. RESULTS AND CONCLUSIONS

Below is an example of the environmental assessment for a mining region based on remote sensing data. The mining region selected for the study is the town of Polysaevo, Russia (Fig. 1).

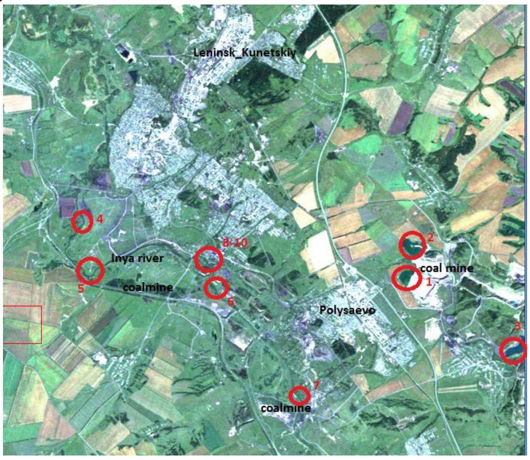

Fig. 1. Area Selected for Remote Geo-ecological Monitoring

Numbers on Fig. 1 represent water bodies which are the primary targets of the study. Some of them are man-made lakes, while others are points along the Inya river channel. Assessing spectral properties of the selected objects resulted in the following spectral curves as shown on Fig. 2.

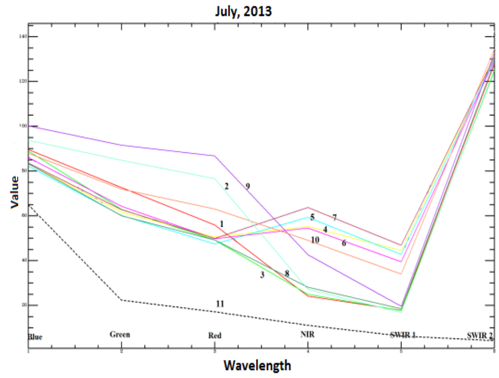

Fig. 2. Spectral Curves for Water Bodies:
1, 2, 3 – lakes; 4, 5, 6, 7 – river; 8, 9, 10 – technogenic reservoirs; 11 – the Baikal Lake (close to the nature reserve)

To assess the state of the water bodies, a reference point for the condition of aquatic medium needs to be introduced. In this study, the spectral curve for the Baikal Lake which is a global benchmark of clean drinking water is used as the reference point. It should be noted that the distilled water curve cannot be used since this is an assessment of water bodies existing in natural conditions. As seen on Fig. 2, all

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spectral curves of the region's water bodies are located above the reference curve which demonstrates significant human impact on the environment. Multiple studies [3-6] confirmed by lab tests of water samples show that presence of suspended solids in water increases the spectral reflectivity in the infrared part of the spectrum, organic matter – in the mid-infrared part. It should be noted that spectral curves of lakes and rivers demonstrate a fundamental difference. As can be seen on the figures, spectral reflectivity curves of enclosed water bodies are wide, with the reflectivity value falling as the wavelength increases. Bodies of flowing water demonstrate a different trend, with a sharp increase in NIR and SWIR values of the electromagnetic spectrum. This results from the sensitivity of these wavelengths to the presence of impurities dissolved in water. In enclosed water bodies impurities tend to settle down on the bottom, while in flowing water particles are continuously mixed due to natural physical factors that cause a spike in reflectivity values. Therefore, it can be seen that the Inya river channel contains the largest amount of pollutants (both organic and inorganic), with the maximum concentration reached near the plant and the Oktyabrskaya mine, while Lake 2 demonstrates algal bloom caused by the increase in phytoplankton volume recorded in the green part (the higher the reflectivity value, the more phytoplankton the water contains) and the red part of the spectrum (chlorophyll in phytoplankton absorbs radiation, thus decreasing radiance). Influence of snow pollutants on the overall environment in the region was based on winter imagery coming from Landsat 7 (Fig. 3).

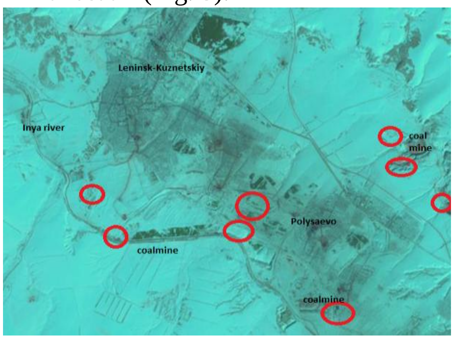

Fig. 3. Assessment of Snow Cover in a Mining Region

The calculation of the snow index, NDSI, helped detect the most polluted areas in the region that are in the buffer zone of the plant and the most unpolluted areas that are located along the Inya River up to the town line. In 2012-2013, the environmental pollution level in the town of Polysaevo was reduced. It is demonstrated by remote sensing data for both water bodies and snow cover. The results have been confirmed by lab tests of water and snow samples which testifies that methods and results of remote distance data analysis are valid. To assess dynamics of the ground surface changes, six pairs of radar images (from ALOS PALSAR and Cosmo SkyMed) were used. The images were processed using the SARscape 5.0 software. They covered a 40x40 km area. The first step was creating a differential interferogram. 6 interferograms were created, allowing the identification of a particular area between the towns of Polysaevo and Leninsk-Kuznetsky where regular motions of the ground surface have been registered during the last 5 years (Fig. 4).

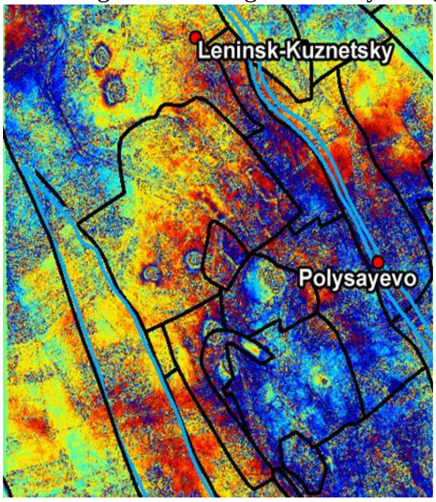

Fig. 4. Differential Interferogram. Black stripes are areas of mine fields and surface mines, blue stripes are shatter zones.

As Fig. 4 demonstrates, changes have been recorded at areas of mining operations. It has also been established that motions of the ground surface are more frequent at earthquake endangered areas of Kuzbass. To assess vertical motions, a digital terrain model was created, and yearly comparisons were made (Fig. 5, Table II).

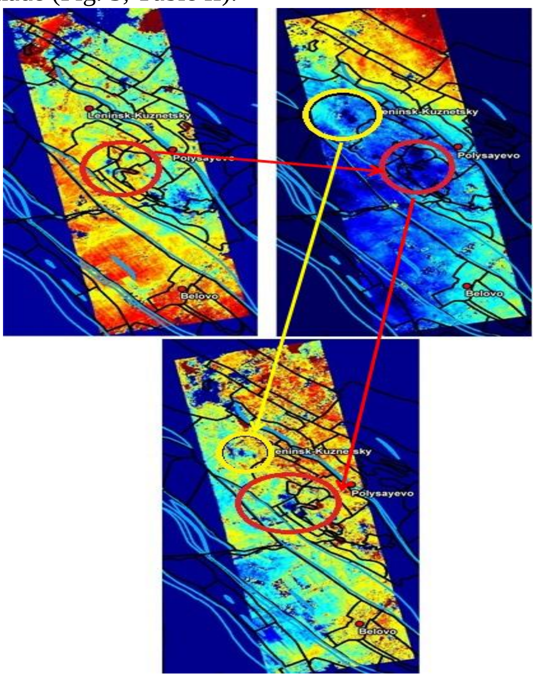

Fig. 5. Maps of Vertical Motions (Based on Data from Cosmo SkyMed for 2011-2013) A) 14/08/2011 – 22/08/2011; B) 15/07/2012 – 23/07/2012 C) 16/06/2013 – 24/06/2013. Black stripes are areas of mine fields and surface mines, blue stripes are shatter zones.

Table II contains values for calculated vertical motions.

Table II. Vertical Motion Values (m)

	2011	2012	2013
Min	-0.038388	-0.042460	-0.031048
Max	0.031386	0.031954	0.027881

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The resulting motion maps have shown that maximum and minimum motion values were recorded in 2012. At areas marked by red circles negative vertical motions of the ground surface were recorded between 2011 and 2013. 2012 saw the appearance of a new area of negative motion (Fig. 5-B, highlighted in yellow). Combining data resulting from radar image processing and the results of the above research demonstrates that the results match in the key measurement points. Thus, we can obtain a comprehensive view of the environmental assessment with areas where mining operations are concentrated and integral changes in the state of natural features are recorded, impacting the environmental and geodynamic state of the entire region.

IV. CONCLUSION

At the current rate of mineral extraction, timely geo-ecological monitoring is an important factor in the successful development of mining regions. Use of remote sensing data provides accurate and up-to-date information. The approach to the comprehensive environmental assessment put forward in the article can be used both to track the impact of human activities on the region's environment in a timely manner and to detect anomalous zones that present the biggest potential danger, making it possible to take timely decisions in order to contain this impact.

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