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Geostatistical Methods as a Tool Supporting Revitalization of Industrially Degraded and Post-Mining Areas

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INTRODUCTION

Post-industrial and post-mining areas have often been under strong anthropogenic pressure for a long time. As a result, such areas, after the end of industrial activity, require taking steps to revitalize them. It may cover many elements of the natural environment, such as water, soil, and vegetation. To carry out revitalization, it is necessary to determine the initial state of such areas, most often based on a variety of selected chemical, geophysical or ecological indicators. After that it is also important to properly monitor the state of such areas to assess the progress of the revitalization process.

Post-industrial areas are very often characterized by a large extent, complicated land cover, and high spatial variability of numerous environmental factors. For this reason, it is crucial to choose appropriate methods for effective characterization of such areas. These methods should be cheap, fast and reliable suited for complicated and scarce data. A very desirable feature of such methods is that they should allow a quick assessment of the large areas. Modern geostatistical methods and contemporary remote sensing can be effective for this purpose. Using a variety of remote sensing sensors, it is possible to gather information simultaneously from even vast area with reasonable spatial, radiometric and time resolutions. Geostatistics in turn provides many sophisticated tools that are useful for rapid analyses and inference based on even very complicated spatial data sets, and what is more to combine different environmental data such as geochemical, geophysical, biological or even social with remotely sensed ones. This is a case of revitalization challenge when usually numerous, different chemical, geological, geophysical parameters have to be monitored together. Geostatistics offers huge potential in terms of various data integration (David, 1977; Vauclin et al., 1983), which is essential for ground validation of satellite observations. It is possible to integrate the data from numerous ground measurements with satellite information obtained by means of Landsat, Sentinel or other satellites (D'Emilio, 2018).

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Geostatistics offers many tools for the analysis of spatially correlated data, which is the case of almost all environmental data, and it is exceptionally well-suited to the study of phenomena occurring in natural or anthropogenic environment. Primarily, it should be noted that geostatistical methods were developed for mining and ore exploration industry. The main goals of geostatistics are describing and analyzing spatial variability using different measures of spatial variability. The majority of classical statistics do not utilize the spatial information, which is a natural characteristic of environmental data.

It is important to outline how geostatistics can be useful in supporting the management and revitalization of degraded and post-mining areas. Since geostatistical methods compromise numerous techniques of analyzing spatial data and determining spatial variability or calculating spatial distributions, there are many issues common with management and revitalization of degraded and post-mining areas, such as:

i. identification of areas with high or low spatial variability of studied phenomena,
ii. overlying the spatial models with other GIS maps of roads, building, water bodies, etc.
iii. monitoring changes in selected indicators of environment,
iv. in particular - determination of selected soil parameters such as soil moisture, vegetation indices, also using open access data from numerous satellites,
v. identification of major sources that still influence remediated area,
vi. enhanced spatial characterization of the degraded area,
vii. change detection, in particular comparison before and after reclamation,
viii. studies of parameters that influence remediation effectiveness,
ix. creation of precise spatial distributions for the supervised accurate classification of studied area,
x. enhanced integration of spatial models with satellite information, etc.

Summarizing, geostatistical methods have many advantages which make them still a forensic methodology for solving above-mentioned problems, and what is even more important allow to embrace new exciting possibilities offered by present-day and future remote sensing technics.

Remote sensing offers unprecedent advantage in systematic monitoring of large areas, and what is more using satellite techniques it is possible to observe parameters which measuring directly in the field is difficult, often impossible in systematic way. There are numerous studies where various indexes were calculated from remote sensing imagery, such as comprehensive evaluation index that combines remote sensing data related to a concentration of fine particulate matter, land surface temperature, vegetation cover, vegetation indices (He et al., 2017; Musse et al. 2018). Moreover, as it was studied, infrared bands can be effectively used to remote sense of methane and nitrous oxide fluxes that originate from waste incineration (Galfalk & Basteviken, 2018). The use of remote techniques also has great potential in urban and highly urbanized environment. For instance, it is possible to classify urban areas on the basis of many criteria and indicators at the same time, and all this can be done without the need for field measurements (Seto & Christensen, 2013; Neocleous et al, 2016; Cheng et al, 2018). As it was studied so far, remote sensing can be used not only to monitor the mining industry and its impact on the environment, but also to identify sites where small-scale or even illegal mining activities were attempted (Isidro et al., 2017).

METHODOLOGY OF RESEARCH

One of the most important measure of geostatistics is the semivariance function (Isaaks & Srivastava, 1989; Zawadzki, 2011), which plot is commonly called a semivariogram. It is used to analyze spatial continuity of phenomena. Semivariance can be calculated separately for different directions, which produce anisotropic semivariance or combined to produce an omnidirectional semivariance. The experimental semivariance is calculated as one-half of the average squared difference in data values for every pair of data locations separated by ***h*** vector.

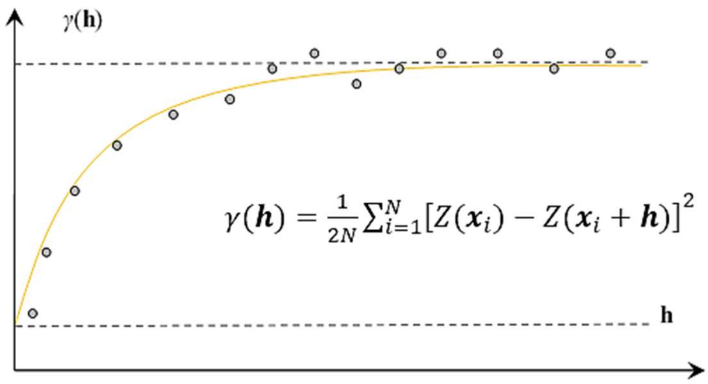

Fig. 1 Semivariance equation and semivariogram plot

Geostatistics also enables accurate estimation of spatial distributions based on measurement data. Compared to the usual interpolation methods, in the case of geostatistical estimation, also the information on the spatial variability is additionally used, which is usually obtained using the aforementioned semivariograms. Among the many geostatistical methods used to determine spatial distributions, we can mention: varieties of kriging, co-kriging or simulations (Journel & Ying, 2001), such as conditional sequential Gaussian simulations (SGS). In simulation, a covariance model of measured values is used to calculate kriging estimates, and these values are used to center the normal distribution from which values are sampled and assigned to simulation grid. The advantage of simulations over the classic estimation methods is that simulation include some local variability, which can be done by running even several hundreds of realizations. Consequently, it is also possible to calculate some statistics of simulated values, such as average, minimum, maximum or standard deviation.

In this paper several types of soil measurements were used. Generally, soil cores were collected using a Humax sampler equipped with plastic tubes with a length of about 30 cm. These soil samples were later used in the laboratory for chemical and in-profile magnetometric measurements (Dearing, 1994).

Determination of element concentration in soil was performed using soil samples that were cut from collected soil cores. Soil samples were air dried, homogenized, and sieved through 2 mm mesh to separate the soil skeleton or artifacts. After that, about 250 mg of dried soil sample was digested using 50% (v/v) HNO_3. Each soil sample was then placed in a Teflon bottle, diluted to 108 ml, and transferred to 15-ml vials for ICP-MS analysis.

Apart from chemical measurements, selected magnetometric measurements were also used. Soil magnetic susceptibility κ was measured using the Bartington MS2 Magnetic Susceptibility System, equipped with an MS2D, MS2C or MS2B sensors. MS2D sensor was used to measure soil magnetic susceptibility on soil surface. The penetration range of the MS2D sensor is equal to 10 cm, however about 90% of the total signal is collected from a depth of 6 cm. In the laboratory, an MS2C Bartington sensor was used to measure the distribution of κ values along the collected soil cores. Mass soil magnetic susceptibility was determined in the laboratory using soil samples that were cut from the part of soil cores located between 0 and 10 cm below the soil surface. The volume of soil samples was equal to about 10 cm^3.

RESULTS OF RESEARCH

This part of the article presents a synthetic description of the results of selected studies that have been carried out so far by the Authors, and are related to the use of geostatistics and remote sensing for analyses of the state of the environment in post-industrial areas.

Study case 1

The study was carried out in Upper Silesian Industrial Area, and its goal was to determine the area that is degraded or polluted, basing on the chemical measurements of selected elements, in this case Zn and Pb (Zawadzki & Fabijańczyk, 2013).

Spatial distributions were calculated using kriging while concentrations of these elements were used to calculate geoaccumulation index (IG). This indicator was previously used to assess the soil pollution (Rubio et al. 2000, Cukrov et al. 2011), and depending on its values soil can be classified into several classes, ranging between not polluted (IG < 1) and very highly polluted (IG > 5).

The study area covered almost 150 km^2 and was located in the vicinity of an old mining town Sławków in Silesian district, in southern Poland (Zawadzki & Fabijańczyk, 2013). The highest values of IG were observed in the vicinity of the mines, areas used for mining purposes and also near the town Sławków. At this part of the study area values of IG were 3 or higher which reveals that the contamination intensity was ranging from strong to very strong. Analogous values and spatial distributions of IG were observed for levels 1 and 2 for concentration of Pb and Zn and also similar likeness was observed for concentrations of both metals on the same level. It confirmed that the soil pollution at this parts of study area is strongly connected with the extraction of ores, in which concentration of Pb and Zn ores is highly correlated. At the remaining parts of the study area, mostly forests in the northern and north-eastern part and post-mining area in the south-western part, values of IG were low, ranging from 0 to 1 (practically uncontaminated up to moderately contaminated).

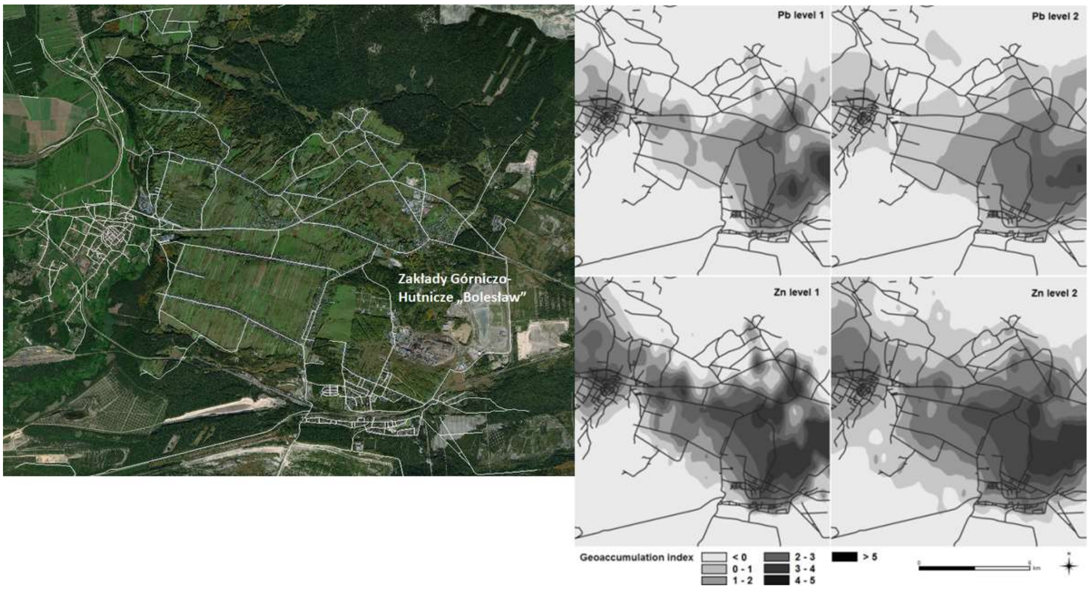

Fig. 2 Study area near Sławków town and spatial distributions of geoaccumulation index calculated for concentrations of Pb and Zn on soil levels 1 (0 cm to 30 cm) and 2 (30 cm to 60 cm),
Source: (Zawadzki and Fabijańczyk, 2013)

Study case 2

As it was studied by Zawadzki et al. (2012), 3D geostatistical spatial estimation can be effectively used to determine the volume of degraded/polluted soil. Frequently, it is not enough to determine only the extent of polluted area, but also the volume of polluted soil e.g. for remediation purposes.

The study area was located within the Upper Silesian Industrial Area, near the town of Tarnowskie Góry, in a large forest park surrounding the Repty Rehabilitation Center.

Two series of magnetometric measurements were performed. The first one consisted of magnetic susceptibility measurements on the surface of the soil by a MS2D sensor. The measurements were carried out without removing the forest litter. In the point location from 10 to 15 individual measurements of magnetic susceptibility were performed. Then the measured values were averaged and the average was taken as the value measured at the data point. The second series included measurements of magnetic susceptibility in the soil profile performed with a SM400 device.

The calculated 3-dimensional spatial distribution of soil magnetic susceptibility covered the part of the soil profile from the surface to a depth of 15 cm. Figure 3 presents the volumes of soil where the magnetic susceptibility exceeded values of 55×10^{-5} magnetic units.

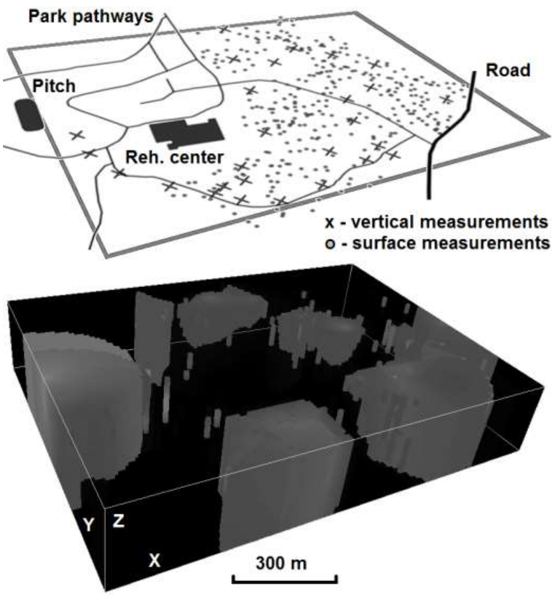

Fig. 3 The 3-dimensional spatial distribution of those volumes of soil where magnetic susceptibility exceeded value of 55×10^{-5} SI. The distances along the Z axis – the depth in the soil profile where scaled by exaggerate factor in order to make the figure more
Source: (figure from Zawadzki et al., 2012)

Accordingly to previous studies (Magiera, 2004) such a value can be used as an indicator of potential soil pollution with heavy metals. In the majority of study area, especially in the vicinity of public road and near the building of Rehabilitation Center, the κ values exceeded 55×10^{-5} SI magnetic units. In some profiles, the increased κ values were observed up to 10 cm below surface whereas in other even up to 15 cm. The maximum of κ value was observed within the layer of 3-5 cm below the surface. In this sub-horizons the majority of anthropogenic contaminants, including technogenic ferromagnetic particles and related heavy metals were accumulated. Such observations suggest that the increased values of magnetic susceptibility were caused by anthropogenic pollution.

In the northern part of the study area, heightened κ values exceeding 55×10^{-5} SI magnetic units were observed through the entire soil profile. However, the soil volumes where magnetic susceptibility exceeded 55×10^{-5} magnetic units were mostly located in the upper 10 cm of soil profile. At depth from 10 cm to 20 cm, κ values were not higher than 60×10^{-5} SI magnetic units. The decreasing tendency towards the deeper horizons means that the magnetic particles were accumulated in the topsoil as a result of anthropogenic dust fall.

Study case 3

In this study (Zawadzki & Fabijańczyk, 2012) the goal was to evaluate the parameters of spatial variability of soil magnetic susceptibility in varying types of areas: forest, arable field and urban park, all neighboring to each other to ensure that the anthropogenic pressure was the same at each site.

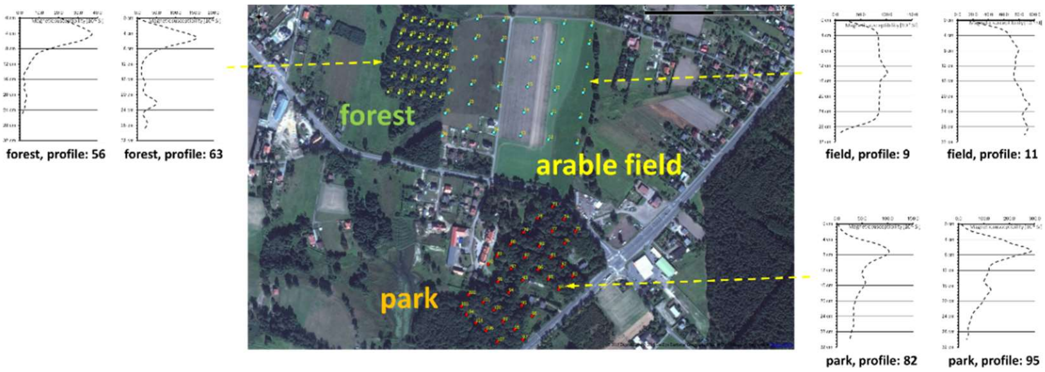

Fig. 4 Study area encompassing natural forest, park and arable field, located in Upper Silesian Industrial Area

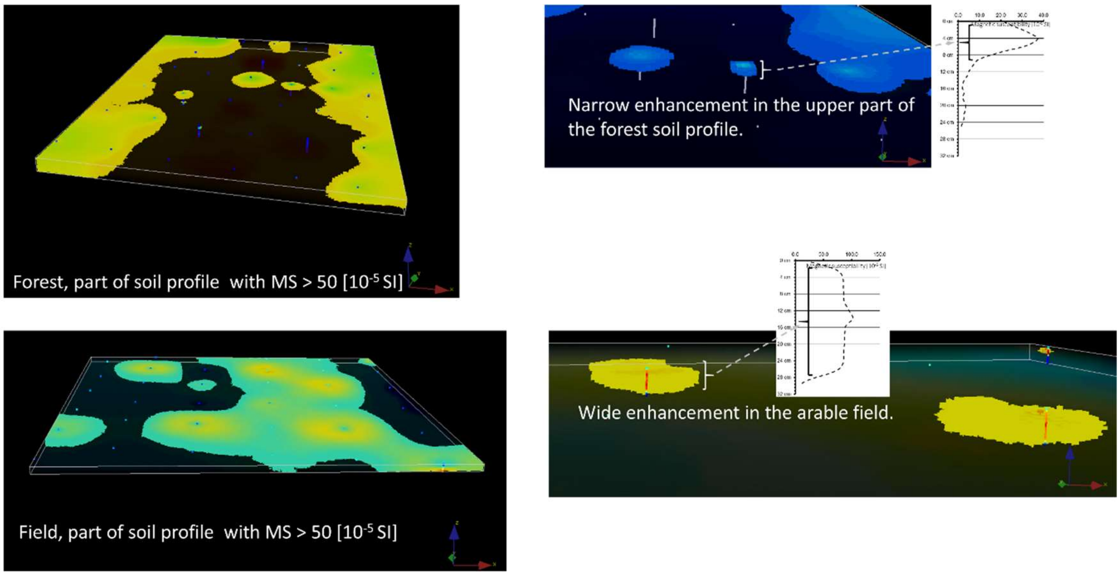

Fig. 5 Simulated spatial distributions of soil magnetic susceptibility in topsoil; only these volumes of soil where soil magnetic susceptibility exceeded 50×10^{-5} SI were displayed

As it was analyzed, distributions of magnetic susceptibility in soil profiles varied depending on the type of area. In the arable field it had a specific shape, and values of soil magnetic susceptibility were almost constant, equal to about 80×10^{-5} SI, through the soil profile. In the forest and the park distributions of soil magnetic susceptibility were characterized by well-visible peak at the depth of about 6 cm.

Similarly like in the study case 2, simulated 3D spatial distributions make it possible to estimate the volume of soil that is characterized by heightened magnetic susceptibility and simultaneously potentially polluted with heavy metals.

Study case 4

The last presented in this paper study case is related to a determination of the area of influence of depression cone in the vicinity of one of the largest open pit mine Bełchatów using remote sensing techniques (Zawadzki et al., 2015; Przeździecki et. al. 2018).

This analysis was performed using data from TM and ETM+ sensors of Landsat 5 and Landsat 7 satellites. For validation purposes ground data were also used, specifically spatial maps provided by Kujawsko-Pomorski Research Centre of Institute of Technology and Life Sciences in Falenty (KPRC). Remote sensing data can be used to calculate selected vegetation indices as well as land surface temperature (e.g. Zawadzki J., 2005; Zawadzki et al., 2005; Przeździecki et. al., 2017). These parameters were later used to calculated combined parameter Temperature Vegetation Dryness Index (TVDI) that merges the information about the ground surface temperature and conditions of vegetation. Next, depending on the 50% and 60% percentile values of TVDI spatial distribution of cone of depression was calculated, as it was presented in the Figure 6.

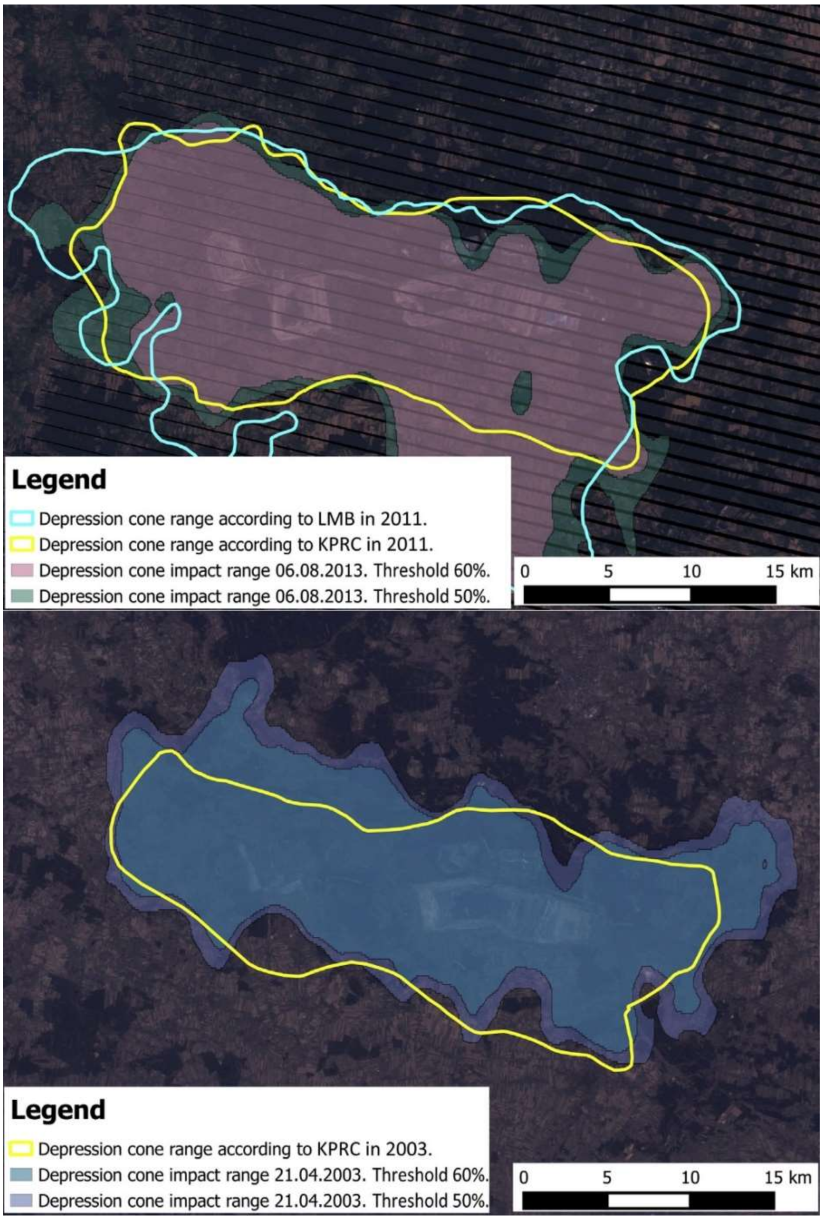

Fig. 6 The comparison of the areas of the depression cone in the vicinity of the Bełchatów mine calculated using: remote sensing data of 50% and 60% percentile values of TVDI and ground reference data, for two selected years 2003 and 2011

Source: (figure from Zawadzki et al., 2015)

As it was analyzed by Authors for several, selected years, the estimation of the area of a cone of depression done using remote sensing was very accurate, comparing with a ground data. Considering that the area of depression was almost over 40 km in size, performing frequent ground measurements can be both costly and time-consuming. For objects of such a large size, the use of remote sensing is much more effective, because it is possible to check the changes in the depression cone with an interval of even up to several days. It was found that TVDI could be very effective if appropriate grid density is determined from a variogram.

CONCLUSIONS

Industrially degraded and post-mining areas may be often extremally complex in various respects. For this reason, monitoring, evaluation and management of such areas can be also difficult and complicated and need support with the latest geoinformation technologies going far beyond traditional measurements and analyzes. Nowadays, for these purposes, it is necessary to use both spatial statistics and modern satellite observations.

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Abstract.
Post-industrial and post-mining areas have often been under strong anthropogenic pressure for a long time. As a result, such areas, after the ending of industrial activity require taking steps to revitalize them. It may cover many elements of the natural or urban environment, such as water, soil, vegetated areas, urban development etc. To carry out revitalization, it is necessary to determine the initial state of such areas, often using selected chemical, geophysical or ecological. After that it is also important to properly monitor the state of such areas to assess the progress of the revitalization process. For this purpose a variety of change detection technics were developed. Post-industrial areas are very often characterized by a large extent, are difficult to access, have complicated land cover. For this reason, it is particularly important to choose appropriate methods to assess the degree of pollution of such areas. Such methods should be as economical as possible and time-effective. A very desirable feature of such methods is that they should allow a quick assessment of the entire area. Geostatistics supplemented by modern remote sensing can be effective for this purpose. Nowadays, using remote sensing, it is possible to gather information simultaneously from the entire, even vast area, with high spatial, spectral and temporal resolution. Geostatistics in turn provides many tools that are able to enable rapid analysis and inference based on even very complicated often scarce spatial data sets obtained from ground measurement and satellite observations. The goal of the article was to present selected results obtained using geostatistical methods also related to remote sensing, which may be helpful for decision makers in revitalizing post-industrial and post-mining areas. The results described in this paper were based mostly on the previous studies, carried out by authors.

Keywords: geostatistics, Landsat, post-mining areas, post-industrial areas, remote sensing, revitalization, soil pollution