EKONOMETRIA ECONOMETRICS 32 • 2011
ISSN 1507-3866

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CONDITIONAL TURNING BANDS SIMULATION IN (2D, 3D) FORECASTING OF VARIOUS REGIONALIZED PHENOMENA

Summary: The paper presents the results of a conditional turning bands simulation and a research methodology based on nonlinear geostatistics, applied to the 2D and 3D forecasting of geological and mining parameters, environmental parameters and electrical demand. The turning bands method is used to simulate the stationary values of random functions $Z(x)$, i.e. covariance function C. The input for the investigations were: geological and mining data from the sampling of mining headings in copper ore mines (relating to Cu grade in a recoverable deposit series) and results of chemical analyses of heavy metal (Cr) concentration in soils, representing environmental data and data on power demand in the nodes of 220 and 400 kV transmission networks. The intensity and extent of copper mineralization in the sedimentary rocks in Lubin-Sieroszowice area and those of soil pollution within the area directly affected by the industry in Upper Silesia as well as the distribution of average electrical loads for the whole territory of Poland were determined.

Key words: conditional turning bands simulation, variogram, Gaussian anamorphosis, regionalized phenomena, forecasting.

1. Introduction

The making of many decisions by various enterprises involves short- and long-term area forecasting. Nonlinear geostatistical techniques enabling simulations in surface (2D) or surface-time and spatial (3D) systems can be useful for these purposes. This mainly applies to enterprises which operate over large areas or to phenomena on the basis of which rational decisions developing in a surface, surface-time or spatial system are made. Such enterprises include mines, environmental institutions and network (telecommunications and (electric) power) companies.

The analyzed phenomena often fall within a group of nonlinear problems which can be solved using certain estimation methods, such as multiple indicator kriging, median indicator kriging, disjunctive kriging (DK), uniform conditioning (UC), lognormal kriging and conditional geostatistical simulations [Armstrong 1998; Chauvet 1993; Chiles, Delfiner 1999; *Geostatistical Simulations* 1994; Isaaks, Srivastava 1989; Lantuejoul 2002; Matheron 1973; Namysłowska-Wilczyńska 2006; Rivoirard 1994; Wackernagel 1998].

When it is necessary to estimate the uncertainty associated with the forecasting of a particular regionalized variable or real postprocessing algorithm scenarios (e.g. mining simulation) are needed, a 3D model is suitable rather for simulations than estimations [Chiles, Delfiner 1999; Lantuejoul 2002; Lantuejoul 1994; Matheron 1973]. Unlike kriging, geostatistical simulations are used to generate a series of equiprobable results. Original (input) data is the basis for determining both a 3D model and a data distribution model. There are various simulation algorithms, such as sequential Gaussian simulations (SGS) and turning bands (TB) simulations, which may be applied to continuous variables, e.g. metal content in deposits.

The nonlinear geostatistical method used in this paper is based on the Gaussian anamorphosis function, the Gaussian variogram function and the conditional turning bands simulation technique [Chiles, Delfiner 1999; Lantuejoul 2002; Lantuejoul 1994; Matheron 1973; Namysłowska-Wilczyńska 2006]. In comparison with estimation kriging techniques, the turning bands simulation more accurately describes the variation of regionalized phenomena and better represents the fluctuations of parameter values, especially when the investigated processes vary considerably. Its additional advantage is the possibility of testing the threshold values of investigated parameters, i.e. producing maps of simulated averages or maps of the probability of exceeding different thresholds.

The possibilities of using the turning bands simulation to forecast various phenomena developing in the surface (2D) system and the surface-time (3D) system are demonstrated. The results of the turning bands simulation as applied to different fields, such as deposit geology & mining, environmental protection and the power industry, are presented.

Databases created in 2D and 3D were used for the simulation calculations. The 2D deposit databases and the 2D environmental databases contain data on the Cu content in a recoverable copper ore deposit and the Cr content in soil, as well as the values of geographic coordinates *X*, *Y* and *Z*, specifying the sampling locations.

The 3D energy databases store the values of electrical loads and geographic coordinates *X*, *Y* and *Z*, specifying measurement locations and dates [Kamińska-Chuchmała, Wilczyński 2009]. The energy data represent power values in 101 nodes of the 220 kV and 400 kV power grid, determined through measurements covering the whole territory of Poland and conducted for 20 years. Winter peak (5 p.m.) load node values were used for the forecasts. Since there was not enough original input data on the history of the actual power demand in the nodes, it was necessary to supplement the data with data obtained from simulations [Kamińska-Chuchmała, Wilczyński 2009].

2. Turning bands simulation method

The turning bands method is a stereological tool for the numerical simulation of the stationary values of random functions $Z(x)$, i.e. covariance C [Chiles, Delfiner 1999; Lantuejoul 2002; Lantuejoul 1994; Matheron 1973; Namysłowska-Wilczyńska

2006]. It allows one to reduce a multidimensional simulation to one-dimensional cases whereby one can obtain n-dimensional realizations $z_s(x)$ of multidimensional random Gaussian function $Z_s(x)$, tending towards a Gaussian distribution.

Covariance function C_3 is simulated through the summation of covariances C_1 and the projection of the simulation onto 15 lines. The individual lines are called turning bands. Each realization $z_s(x)$ obtained using the turning bands is a sum of independent one-dimensional realizations created along lines of rotation [Chiles, Delfiner 1999; Lantuejoul 2002; Lantuejoul 1994; Matheron 1973; Namysłowska--Wilczyńska 2006].

If covariance C_3 is replaced with polar covariance C, then in order to generate realizations in space R^3:

$$C(h) = C_3(|h|), \tag{1}$$

it is enough to carry out a simulation of stationary one-dimensional random function X, with the covariance:

$$C_1(h) = \frac{\delta}{\delta r}\left[rC_3(r)\right], \tag{2}$$

Hence X is within the space:

$$Y(x) = X(\langle\theta, x\rangle), \tag{3}$$

where: x – a point in three-dimensional Euclidean space R^3,
r – a radius (a distance from the origin of the Cartesian coordinates to perpendicular projection x onto a particular turning band),
θ – a unit vector in a uniform direction.

Theoretically, the choice of a method of generating random function X is arbitrary. In order to optimize the generation of a given covariance model one can use the spectral method, the dilution method and the migration method.

The principle of the turning bands simulation technique consists in carrying out first a non-conditional simulation and presenting it on a map (reflecting the variogram but without taking the data into account) and then correcting this picture by interpolating the empirical error, i.e. the difference between the original data and the (non-conditional) values simulated in the measuring points. This is referred to as conditioning. This last interpolation takes into account the parameters of the input theoretical variogram model and uses kriging (in the broad sense). The final map of the investigated phenomenon is called a conditional simulation. In the turning bands method the only parameter which needs to be specified is the number of confidence bands (intervals), i.e. turning bands. It is set as, for example, 100, 200, 400, 500 and 2000.

The conditional turning bands simulation method is based on the generator of random numbers, whereby it can be used independently.

3. Investigative methodology

The empirical distributions of the analyzed variables, i.e. the Cu content in the recoverable deposit, the Cr content in the ground's surface layer (soils) and the electric power values, were transformed into normal distributions, i.e. Gaussian variables. For this purpose the transformation function (Gaussian anamorphosis), written as Hermite polynomials, had to be adjusted. The sorted original data and the frequency quantiles on the Gaussian scale are marked on respectively the Y-axis and the X-axis (Figures 1, 5, 9). Isotropic and directional Gaussian variograms were calculated and their courses were approximated by theoretical functions, i.e. geostatistical (linear, spherical, exponential, nugget effect) models (Figures 2, 6, 10).

The copper concentration in mining block R-3 (Rudna mine) and the chromium pollution of the soil in the Dąbrowa Górnicza area were analyzed in 2D while simulated electric power values Z_s for the territory of Poland were forecasted in 3D for a year in advance.

The conditional turning bands simulation was based on a 2D grid of elementary blocks and a 3D grid of elementary nodes, which were superimposed on the investigated areas. The dimensions of the elementary grids were:

- the 2D grid (*mining, geology*): the elementary cell dimensions – 0.5 m × 1 m = 0.5 m^2, the number of grid nodes along axes X and Y: 59 × 48, the number of simulated grid nodes – 2832; *environment*: the elementary cell dimensions – 250 m × 250 m = 62 500 m^2, the number of grid nodes along axes *X* and *Y*: 77 × 55, the number of simulated grid nodes – 4235;
- the 3D grid (*power industry*): the elementary cell dimensions 10 km × 10 km × 1 year = 10 km^2 × 1 year, the number of grid nodes along axes *X*, *Y*, *Z*: 75 × 75 × 25 years, the number of simulated grid nodes – 140 625.

The number of turning bands (confidence intervals) was: 200 (*geology* and *mining, environment*) and 400 (*power industry*).

In total, 100 conditional turning bands simulations were run for each grid node. After the simulations the Gaussian back transformation of the studied parameters into the original values was carried out.

The calculations yielded the values of various geostatistical parameters (co-ordinates *X*, *Y*, *Z* and simulated values Z_s) for particular grid nodes:

- mean of realizations (on the basis of 100 simulated values Z_s),
- standard deviation of realizations of σ_s (on the basis of 100 values of σ_s),
- the largest realization (from among 100 simulated values Z_s),
- the smallest realization (from 100 simulated values Z_s).

The statistics were used to produce raster maps of the conditional turning bands simulation results, presented in section 4.

4. Exemplary applications of (2D, 3D) conditional turning bands simulation

The conditional turning bands simulation has been used in various research areas connected with geological and mining, environmental and power industry problems [Kamińska-Chuchmała, Wilczyński 2009; Namysłowska-Wilczyńska, Wilczyński 1999; Namysłowska-Wilczyńska, Wilczyński 2002; Namysłowska-Wilczyńska 2006; Namysłowska-Wilczyńska 2008].

In the considered case, the application of this technique resulted in the mapping of the variation in Cu content, i.e. in the degree of mineralization of the sedimentary (sandstone, limestone, dolomite and shale) rocks, in Rudna mine (Lubin-Sieroszowice region) and the Cr pollution of the surface soil layers in the Dąbrowa Górnicza region.

In deposit geology and mining, the results of simulation calculations assist making decisions on planning and conducting mineral resource deposits mining, determining prospecting directions and setting company strategic and long-term objectives.

Geostatistical methods, including the conditional turning bands simulation, are also used to solve various problems connected with ecology and environmental protection (also in mining areas), to accurately estimate the degree and extent of soil, air and underground water pollution and to control environment quality. They are particularly useful in the 2D and 3D monitoring of the distribution of (heavy metals, toxic and harmful pollutants) concentration, in detecting pollutant sources and determining their spread and in assessing the environmental hazard. The mathematical modelling of environmental data is essential for ensuring the correctness of natural environment degradation analyses and for making short- and long-term forecasts. Geostatistics is also used in the management of (toxic) wastes (e.g. energy industry ash-slags) deposited on heaps and in sedimentation tanks, and nuclear wastes, during work connected with contaminated land reclamation.

For power engineers the geostatistical methods offer the possibility to forecast power demand and on this basis to plan the operation of power networks and the expansion and building of new energy sources [Namysłowska-Wilczyńska 2006].

4.1. Geological & mining problems

The results of applying the Gaussian anamorphosis function, the Gaussian (isotropic) variogram and the 2D conditional turning bands simulation of Cu content in a recoverable copper ore deposit are presented for mining block R-3 in the Rudna mine (Figures 1-6) [Namysłowska-Wilczyńska 2006, Namysłowska-Wilczyńska 2008].

Variation coefficient V (28%) of the original Cu content data shows that Cu content varies moderately within block R-3 (Table 1). The recoverable deposit series thickness in the area was found to vary more (V − 38 %). The average thickness amounted to 3.52 m (min – 2.00 m, max – 9.26 m) [Namysłowska-Wilczyńska 2006,

Table 1. Basic statistics on copper content in recoverable deposit in Rudna mine block R-3

Analyzed parameter	Sample size n	Min. value X_{min} [%]	Max. value X_{max} [%]	Average value X [%]	Standard deviation S [%]	Variation coefficient V [%]
Cu content	998	0.15	8.04	3.78	1.06	28.00

Source: own calculations.

Namysłowska-Wilczyńska 2008]. It should be noted that the minimum-maximum range is considerable for both parameters.

Taking into account the Gaussian values obtained through the transformation of the original Cu content data (Figure 1), an isotropic Gaussian variogram (Figure 2) was calculated. Its course was expressed using a spherical model with nugget effect C_o (Table 2). The range of influence of the variogram was 118 m. One should note the very high proportion of the random component in the total variation of the analyzed parameter (sill variance C), reflecting the high variation of this parameter within the R-3 block (Table 1).

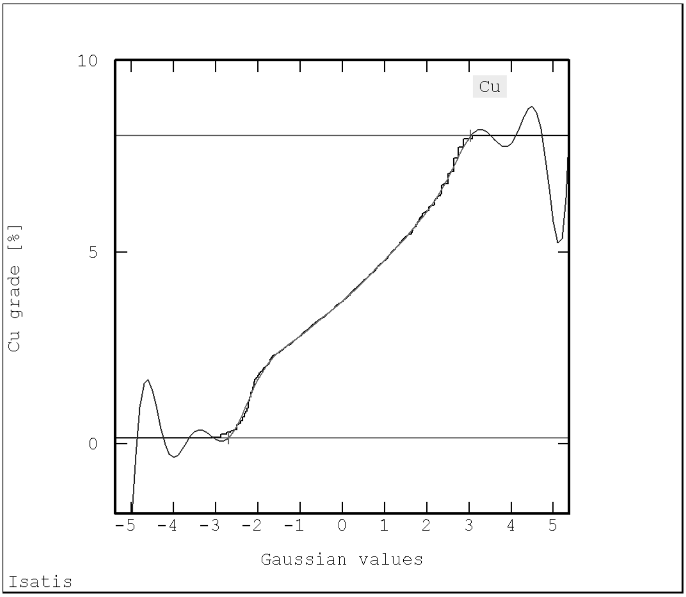

Figure 1. Empirical anamorphosis of Cu content in recoverable deposit, with superimposed theoretical model expanded in Hermite polynomials conditions; Y-axis – original Cu grade [%] data, X-axis – Gaussian values (block R-3 in Rudna mine)

Source: own calculations.

Table 2. Geostatistical parameters of Cu content (isotropic) Gaussian variogram model for Rudna mine recoverable deposit block R-3

Analyzed parameter	Nugget effect C_0 $[\%]^2$	Partial sill variance C' $[\%]^2$	Total sill variance C $[\%]^2$	Range of influence a [m]	Basic model structures
Cu content	0.7227	0.2880	1.0108	118.07	spherical, nugget effect

Source: own calculations.

A conditional turning bands simulation was carried out using the parameters of the theoretical Gaussian Cu content variogram model. Realizations average Z_s and realizations standard deviation σ_s were determined on the basis of the simulated values for 2832 grid nodes. The low value of variation coefficient V (except for the smallest realization Z_s) stands out in the global statistics (Table 3).

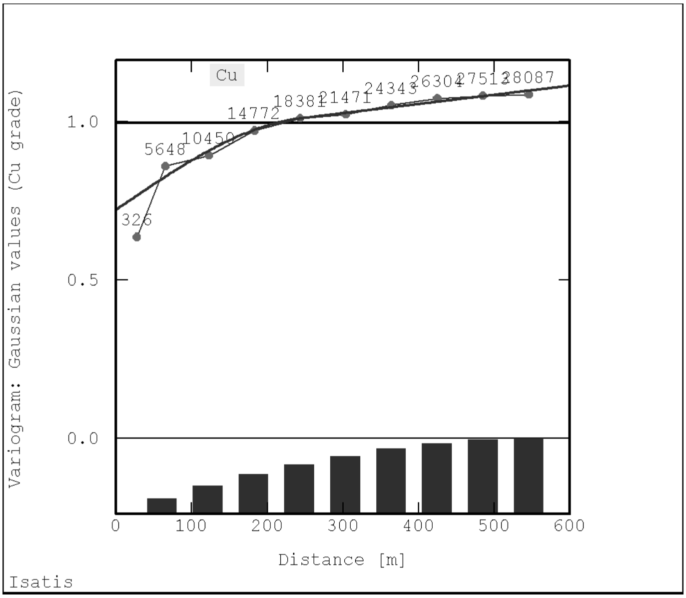

Figure 2. Cu content (isotropic) Gaussian variogram with fitted theoretical model (Rudna mine block R-3)

Source: own calculations.

Raster maps of the conditional turning bands simulation calculation results are shown in Figures 3-6.

A raster map (Figure 3) shows considerable variation in simulated Cu content values Z_s. The high Z_s values reveal areas in which deposit formations rich in Cu

Table 3. Global statistics of simulated (conditional turning bands simulation) values of Cu content in recoverable deposit, in elementary grid nodes for Rudna mine block R-3

Parameter	Number of grid nodes n	Min. value X_{min} [%]	Max. value X_{max} [%]	Average value X [%]	Standard deviation S [%]	Variation coefficient V [%]
Realizations average Z_s	2832	1.55	5.31	3.73	0.53	14.00
Largest realization Z_s	2832	3.68	8.04	6.59	0.95	14.00
Smallest realization Z_s	2832	0.15	3.80	1.05	0.88	84.00
Realizations standard deviation σ_s	2832	0.40	1.71	1.00	0.12	12.00

Source: own calculations.

occur (Figures 3 and 5-6). These are dolomite-clay shales with considerable (between ten and twenty per cent) Cu concentration. The lower Z_s values are associated with the occurrence of less mineralized rocks (sandstone and limestone-dolomite formations). The lowest Z_s values indicate areas in which no copper-bearing shales are deposited (Figures 3 and 5-6).

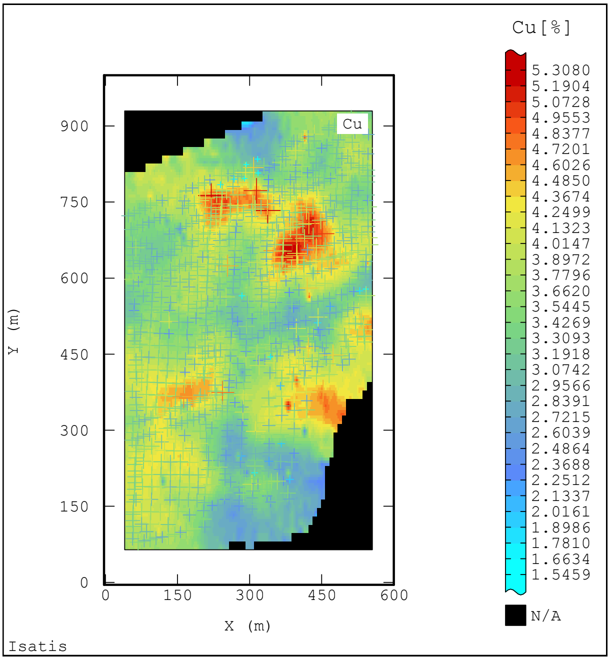

Figure 3. Raster map of surface distribution of simulated values Z_s of Cu grade [%] in recoverable deposit – realizations average (Rudna mine block R-3)

Source: own calculations.

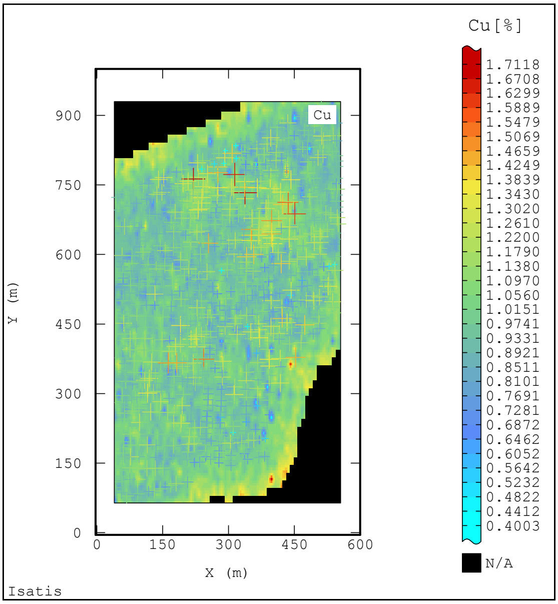

Figure 4. Raster map of surface distribution of realizations standard deviation σ_s of Cu grade [%] in recoverable deposit (Rudna mine block R-3)

Sources: own calculations.

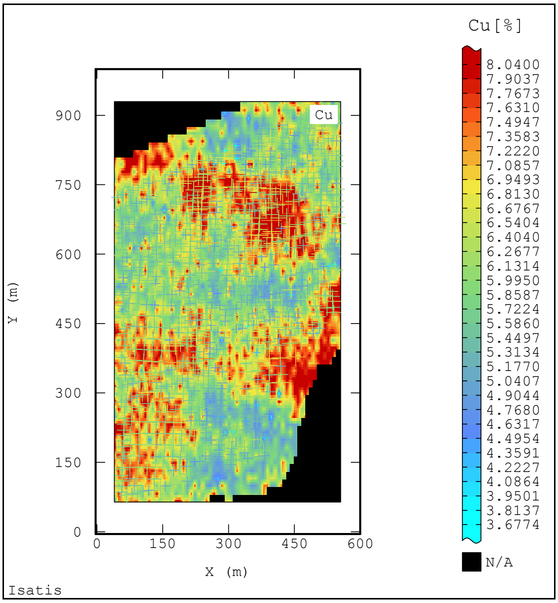

Figure 5. Raster map of surface distribution of simulated values Z_s of Cu grade [%] in recoverable deposit – largest realization (Rudna mine block R-3)

Sources: own calculations.

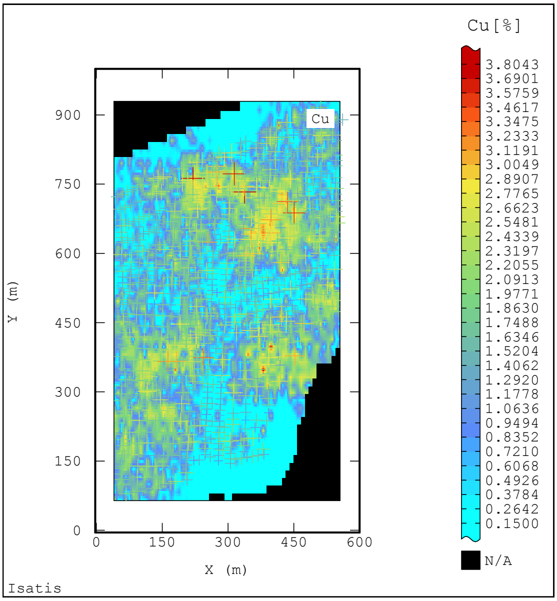

Figure 6. Raster map of surface distribution of simulated values Z_s of Cu grade [%] in recoverable deposit – smallest realization (Rudna mine block R-3)

Source: own calculations.

The simulation of values Z_s is characterized by relatively low values of realizations standard deviation σ_s (Figure 4), undoubtedly owing to the dense sampling of block R-3 (15-20 m spacing of mining headings, size of samples $N = 998$).

4.2. Environmental problems

The results of applying the Gaussian anamorphosis function, the (isotropic) Gaussian variogram and the 2D conditional turning bands simulation of Cr content in the 0.20 m thick surface ground layer (soil) are presented for the Dąbrowa Górnicza area (Figures 7-12).

Variation coefficient V (121.4%) of the original Cr content data shows that Cr content varies greatly in the soil (Table 4).

Table 4. Basic statistics on chromium content in soils in the Dąbrowa Górnicza area

Analyzed parameter	Sample size n	Min. value X_{min} [mg/kg]	Max. value X_{max} [mg/kg]	Average value X [mg/kg]	Standard deviation S [mg/kg]	Variation coefficient V [%]
Cr content	152	0.00	49.00	8.00	9.71	121.40

Source: own calculations.

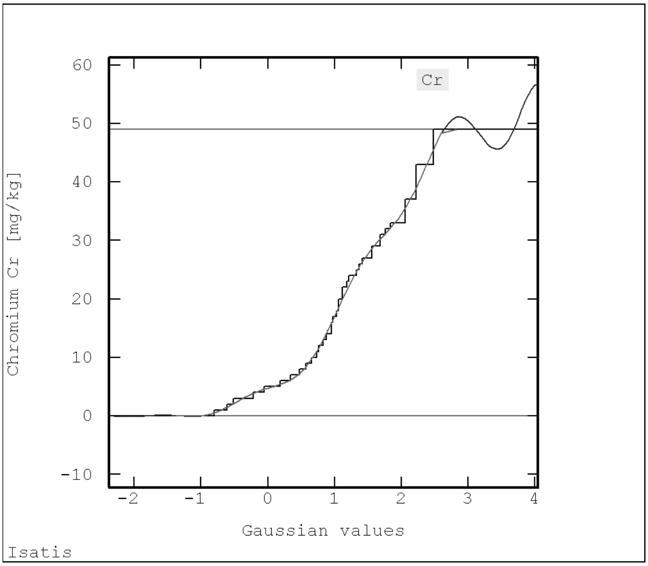

Figure 7. Empirical anamorphosis of Cr content in soils, with superimposed theoretical model expanded in Hermite polynomials conditions; Y-axis – original chromium Cr content [mg/kg] data, X-axis – Gaussian values (Dąbrowa Górnicza area)

Source: own calculations.

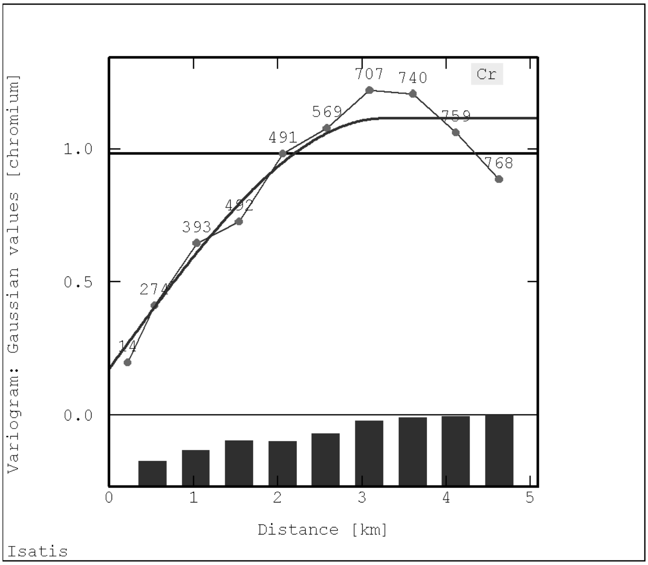

Figure 8. Cr content (isotropic) Gaussian variogram with fitted theoretical model (Dąbrowa Górnicza area)

Source: own calculations.

Taking into account the Gaussian values obtained through the transformation of the original Cr content data (Figure 7), an isotropic Gaussian variogram (Figure 8) was calculated. Its course was approximated using a combination of two spherical models with nugget effect C_o (Table 5). The ranges of influence *a* of the variogram were 3.16 km and 3.25 km. The proportion of the random component (effect C_o) in the total variation of the analyzed parameter (sill variance C) is slight (Table 5).

Table 5. Geostatistical parameters of Cr content (isotropic) Gaussian variogram models for Dąbrowa Górnicza area

Analyzed parameter	Nugget effect C_O [mg/kg]^2	Partial sill variance C' [mg/kg]^2	Total sill variance C [mg/kg]^2	Range of influence *a* [km]	Main components of model
Cr content	0.1750	0.9386 0.0009	1.1145	3.25 3.16	spherical, spherical, nugget effect

Source: own calculations.

A conditional turning bands simulation of Cr content was carried out using the parameters of the composite model approximating the isotropic Gaussian variogram. Realizations average Z_s (Figure 9), based on 100 simulated values Z_s, and realizations standard deviation σ_s (Figure 10) were determined for 4235 elementary grid nodes. The variation coefficients V indicate the strongly varied behaviour of simulated values Z_s (i.e. high variation for realization**s** average Z_s), moderate variation of realization**s** standard deviation σ_s and the largest realization Z_s, and extreme variation of the smallest realization Z_s (Table 6).

Raster maps of the conditional turning bands simulation calculation results are shown in Figures 9-12.

Table 6. Global statistics of simulated (conditional turning bands simulation) Cr content values in soils, in elementary grid nodes for Dąbrowa Górnicza area

Analyzed parameter	Number of grid nodes n	Min. value X_{min} [mg/kg]	Max. value X_{max} [mg/kg]	Average value X [mg/kg]	Standard deviation S [mg/kg]	Variation coefficient V [%]
Realization**s** average Z_s	4235	0.0078	33.1311	8.7104	4.7288	54.29
Largest realization Z_s	4235	0.1405	49.0005	39.1801	11.8306	30.19
Smallest realization Z_s	4235	0.0000	6.7921	0.1641	0.7589	462.35
Realization**s** standard deviation σ_s	4235	0.0239	14.4473	8.7629	3.1367	35.79

Source: own calculations.

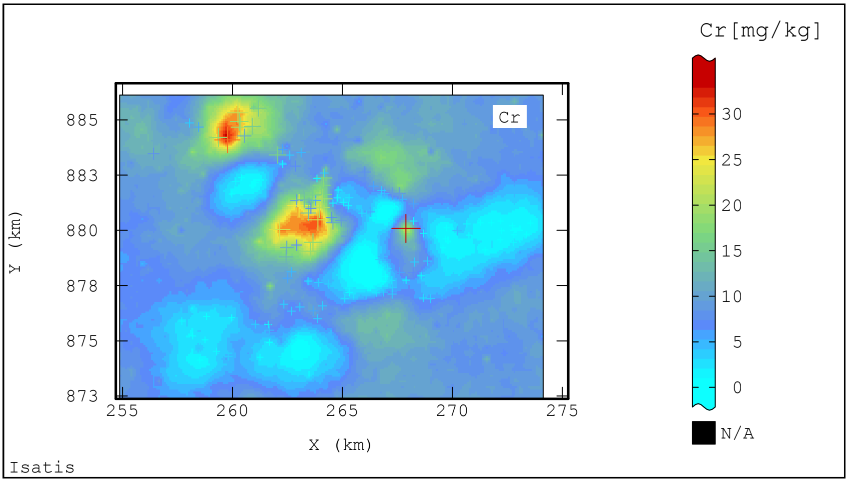

Figure 9. Raster map of surface distribution of simulated values Z_s of Cr content [mg/kg] in soils – realizations average (Dąbrowa Górnicza area)
Source: own calculations.

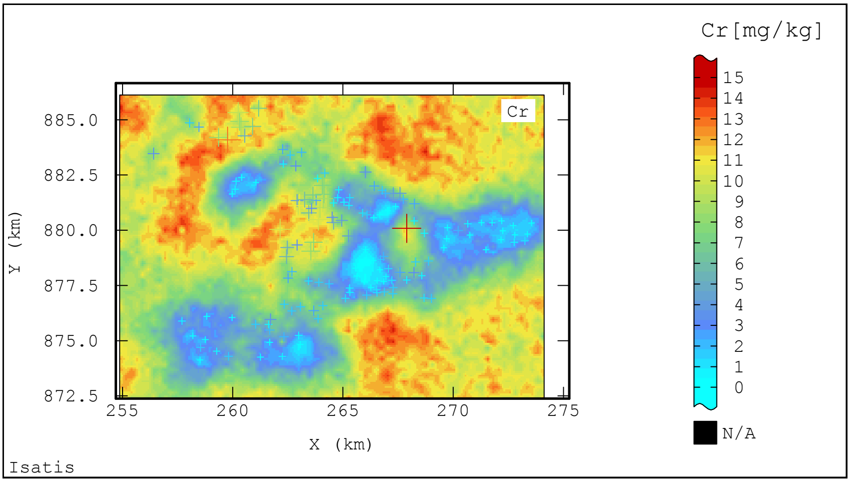

Figure 10. Raster map of surface distribution of realizations standard deviation σ_s of Cr content [mg/kg] in soils (Dąbrowa Górnicza area)

Source: own calculations.

The distinct anomalously elevated Cr concentrations on the raster map are sometimes arranged almost concentrically around the pollution sources (two glassworks and an ironworks) [Namysłowska-Wilczyńska, Wilczyński 1999; Namysłowska-Wilczyńska, Wilczyński 2002; Namysłowska-Wilczyńska 2006].

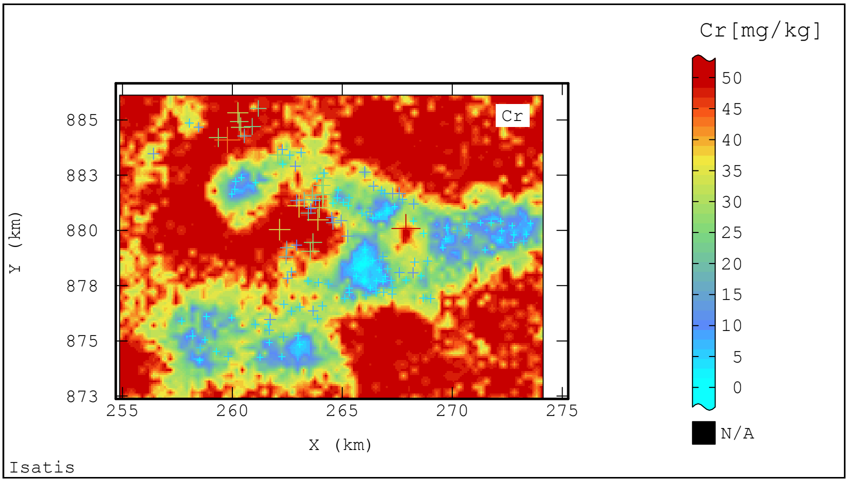

Figure 11. Raster map of surface distribution of simulated values Z_s of Cr content [mg/kg] in soils – largest realization (Dąbrowa Górnicza area)

Source: own calculations.

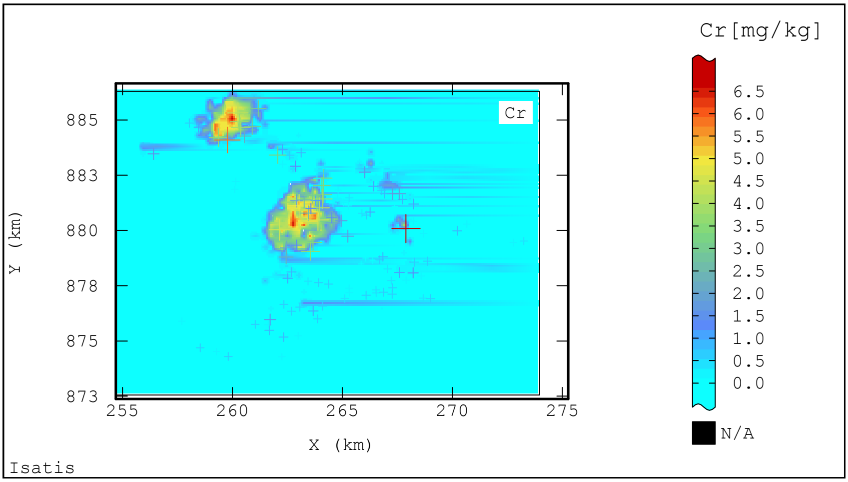

Figure 12. Raster map of surface distribution of simulated values Z_s of Cr content [mg/kg] in soils – smallest realization (Dąbrowa Górnicza area)

Source: own calculations.

4.3. Power industry problems

An attempt was made to apply the conditional turning bands simulation to surface-time forecasting for one year in advance. The results of the application of the Gaussian anamorphosis and the (directional) Gaussian variogram and the 3D conditional turning bands simulation of loads in the nodes of the 220, 400 kV power grid for the whole territory of Poland (Figures 13-18) are presented below.

The coefficient of variation (V) of electric power demand for the territory of the whole country indicates that the power demand varies greatly and that the minimum-maximum power range is wide (Table 7).

Table 7. Basic statistics on electric power demand in nodes of 220, 400 kV power grid for the territory of Poland

Analyzed parameter	Sample size n	Min. value X_{min} [MW]	Max. value X_{max} [MW]	Average value X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Electric power	2021	1.00	666.00	229.57	120.19	52.00

Source: own calculations.

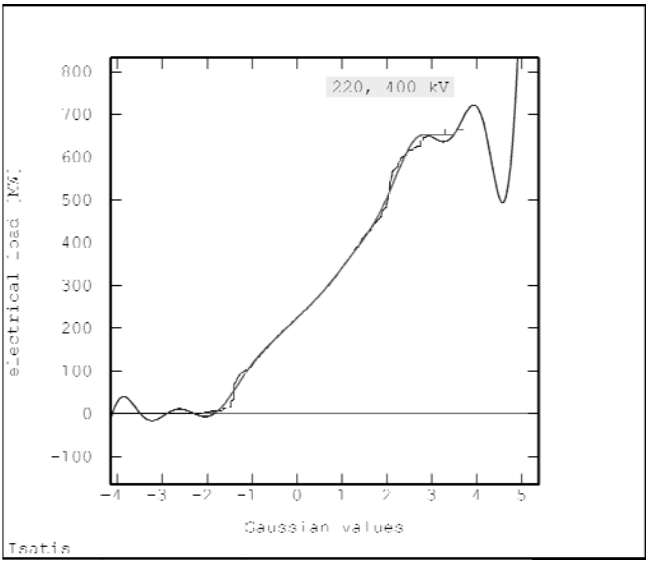

Figure 13. Empirical anamorphosis of power demand in nodes of 220, 400 kV grid, with superimposed theoretical model expanded in Hermite polynomials conditions; Y-axis – original power [MW] data, X-axis – Gaussian values (territory of Poland)

Source: own calculations.

Figure 14 shows a directional Gaussian variogram obtained from the Gaussian anamorphosis – the transformation of the electric demand data (Figure 13) along the time axis for 25 years. One can see some periodicity in the variogram. The latter was approximated with the spherical model combined with the nugget effect (Table 8).

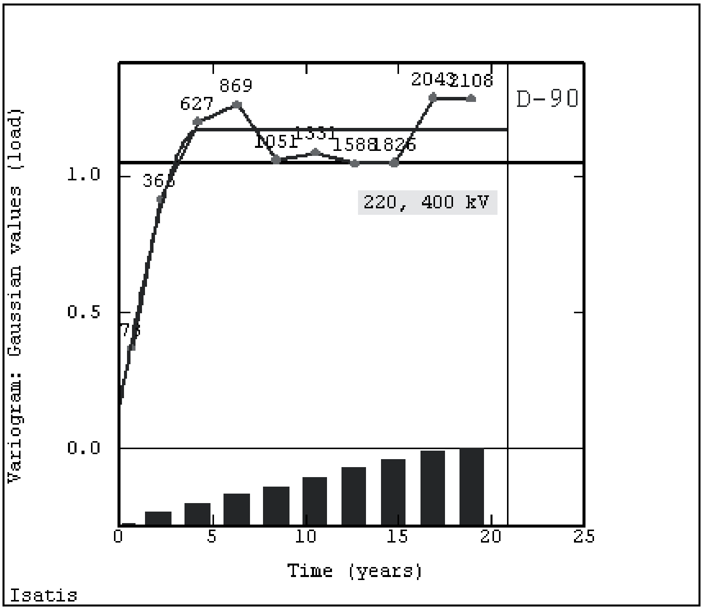

Figure 14. Directional Gaussian variogram of power demand in the nodes of 220, 400 kV grid, with fitted theoretical model (territory of Poland)

Source: own calculations.

Table 8. Values of geostatistical parameters of directional (along Z-axis) Gaussian power demand variogram model for territory of Poland

Analyzed parameter	Nugget effect C_0 $[MW]^2$	Partial sill variance C' $[MW]^2$	Total sill variance C $[MW]^2$	Range of influence a [years]	Main components of model
Electric power	0.157791	1.00977	1.167561	38.62 51.13	spherical, nugget effect

Source: own calculations.

The range of influence **a** of the variogram is 38.6-51 years. The proportion of the random component (nugget effect C_O) in the total power demand variation (sill variance C) is slight.

Summing up the power demand calculations carried out for 140 625 power grid nodes, one should note the low variation coefficient (V) values obtained for three geostatistical parameters (Table 9). The results indicate that the simulated power values Z_s vary little, except for the smallest realization which shows extreme variation (Table 9).

Table 9. Global statistics of simulated values Z_s of electric power demand in nodes of spatial elementary grid (conditional turning bands simulation) – territory of Poland

Analyzed parameter	Number of grid nodes n	Min. value X_{min} [MW]	Max. value X_{max} [MW]	Average value X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Realizations average Z_s	140 625	8.14	512.76	219.98	46.26	21.00
Largest realization Z_s	140 625	83.28	666.01	602.75	76.17	13.00
Smallest realization Z_s	140 625	0.99	300.92	3.35	15.74	470.00
Realizations standard deviation σ_s	140 625	18.68	185.36	129.15	15.07	12.00

Source: own calculations.

The raster maps show distributions of simulated power values Z_s for the territory of Poland for one year in advance, i.e. average Z_s based on 100 realizations (Figure 15) and realizations standard deviation σ_s (Figure 16).

The subareas of elevated forecasted power demand Z_s visible on the map of the realizations average (Figures 15 and 17-18) are connected with large industrial centres and urban agglomerations (Warsaw area, Mazovian Province and Silesia). Also the increased power consumption in some subareas of the NE part of Poland is revealed.

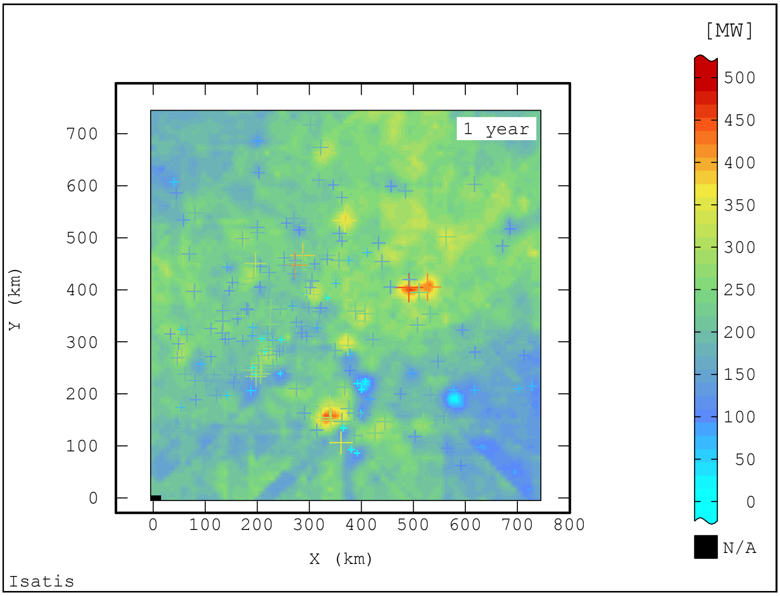

Figure 15. Raster map of surface distribution of simulated electrical load values Z_s [MW] in nodes of 220, 400 kV power grid – realizations average; forecast for one year (territory of Poland)

Source: own calculations.

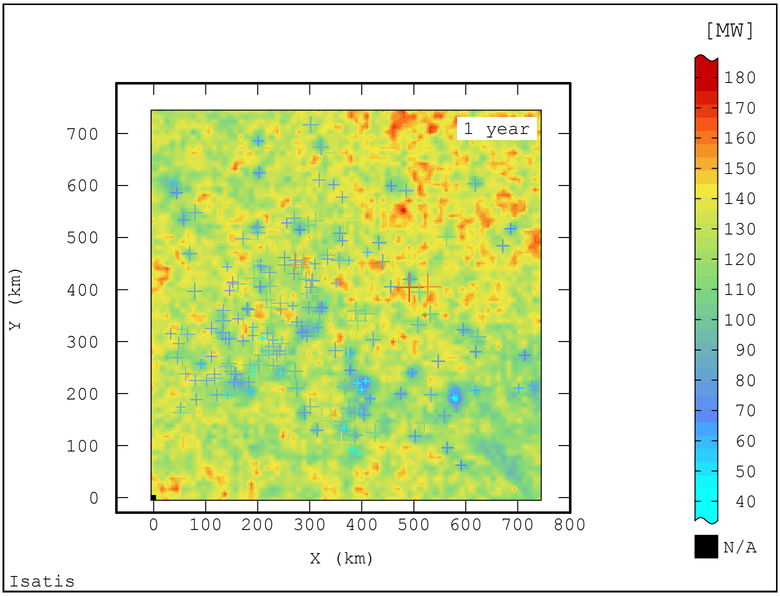

Figure 16. Raster map of surface distribution of electrical load realizations standard deviation σ_s [MW] for nodes of 220, 400 kV power grid; forecast for one year (territory of Poland)

Source: own calculations.

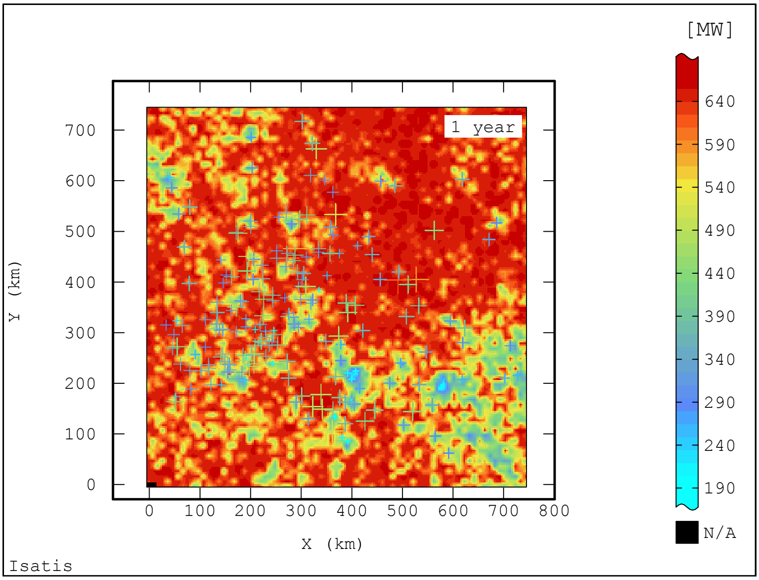

Figure 17. Raster map of surface distribution of simulated electrical load values Z_s [MW] in nodes of 220, 400 kV power grid – largest realization; forecast for one year (territory of Poland)

Source: own calculations.

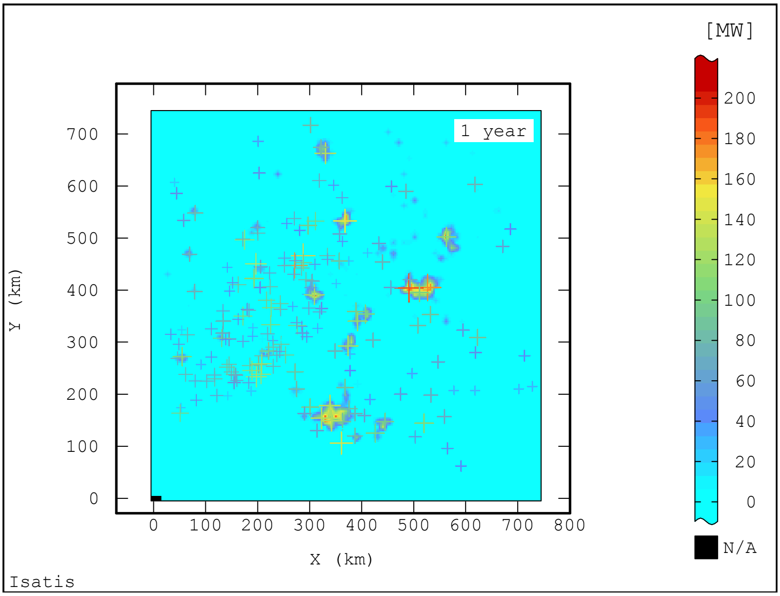

Figure 18. Raster map of surface distribution of simulated electrical load values Z_s [MW] in nodes of 220, 400 kV power grid – smallest realization; forecast for one year (territory of Poland)

Source: own calculations.

The raster map shows that realizations standard deviation σ_s varies little over most of the territory of Poland (Figure 16), with a local marked decrease in standard deviation values σ_s.

5. Conclusion

The conditional turning bands simulation yielded a very rich set of calculation results. Various geostatistical parameters (with 100 realizations for each) were determined for the particular nodes or blocks of the elementary grids covering the investigated areas. As a result of the postprocessing of the simulated values Z_s, raster maps of the variation in the studied phenomena and regionalized processes were obtained. The maps show the pictures averaged on the basis of 100 realizations Z_s, realizations standard deviation σ_s, the largest realization Z_s and the smallest realization Z_s. They can be helpful in decision making for enterprises operating in various industries, such as geology and mining, environmental protection and the power industry. The data obtained from turning bands simulations should also be the basis for other (e.g. economic) analyses, particularly for the testing of different (optimistic or pessimistic) scenarios of business operations by the management.

The presented results have proved the proposed methods to be suitable for the surface and surface-time forecasting of the investigated phenomena. The forecasts can be the basis for making the decisions by company managements. The effectiveness of the methods is particularly valuable in the quickly changing economic and social situation in Poland. This applies to phenomena changing in both time and area.

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SYMULACJA WARUNKOWA *TURNING BANDS* W PROGNOZOWANIU (2D, 3D) RÓŻNYCH ZJAWISK ZREGIONALIZOWANYCH

Streszczenie: W artykule przedstawiono wyniki symulacji warunkowej *turning bands* i metodykę badawczą, wykorzystującą metody geostatystyki nieliniowej (anamorfoza Gaussa, wariogram gaussowski, symulacja warunkowa – *turning bands*), zastosowanej do prognozowania 2D i 3D wartości parametrów geologiczno-górniczych, środowiskowych i zapotrzebo-

wania na moc elektryczną. Metoda *turning bands* jest przeznaczona do symulowania wartości stacjonarnych funkcji losowych $Z(x)$ − kowariancji C. Pozwala ona otrzymać trójwymiarowe realizacje na podstawie jednowymiarowych realizacji symulowanych wzdłuż linii rotacji w przestrzeni. Informacje wejściowe do obliczeń stanowiły dane geologiczno-górnicze, pochodzące z opróbowania wyrobisk górniczych w kopalniach rud miedzi, dotyczące zawartości Cu w złożu bilansowym, następnie wyniki analiz chemicznych koncentracji zawartości chromu Cr w glebach, reprezentujące dane środowiskowe oraz dane energetyczne, związane z zapotrzebowaniem na moc elektryczną w węzłach sieci przesyłowej 220 i 400 kV. Wymienione dane z wartościami współrzędnych X, Y, Z, określających lokalizacje poboru próbek i wykonania pomiarów elektrycznych oraz czas ich realizacji, zamieszczono w tematycznych bazach danych. Zawartości tych baz były podstawą do przeprowadzenia analiz przestrzennych. Określono intensywność i zasięg okruszcowania skał osadowych w rejonie Lubin – Sieroszowice oraz zanieczyszczenia gleb w rejonach znajdujących się w obszarze bezpośredniego oddziaływania przemysłu górniczo-hutniczego na Górnym Śląsku, a ponadto wyznaczono rozkład średnich obciążeń elektrycznych dla całego obszaru Polski. Technika *turning bands* jest użytecznym narzędziem dla celów szczegółowego odwzorowania zróżnicowania wartości badanych parametrów. Pozwala na identyfikację anomalii geochemicznych koncentracji zawartości metali, symulację mineralizacji skał i zanieczyszczenia gruntów, a nawet wartości obciążeń elektrycznych.