Eurasian Soil Science, Vol. 34, No. 11, 2001, pp. 1219–1228. Translated from Pochvovedenie, No. 11, 2001, pp. 1365–1376.

AGRICULTURAL CHEMISTRY AND SOIL FERTILITY

Application of Geostatistics in Processing the Results of Soil and Agrochemical Studies

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Received July 28, 2000; in final form, October 30, 2000

Abstract—The advantages of geostatistical techniques in processing the results of soil–agrochemical studies were considered for some objects. The role of variograms in unveiling correlations between the parameters studied, as well as between these parameters and the factors behind their variation, was demonstrated. Enhancement of experimental data processing by the application of kriging, particularly, the advantage of the analysis of smoothed maps, was demonstrated, as well as the tightening of the correlation between the parameters studied because of the partial elimination of the high-frequency variation component. The role of geostatistical techniques in the design of field experiments was shown.

Geostatistics is a method for characterizing the regular component of the variation in natural objects, including soils. The application of geostatistics in soil science ensures a quantitative description of the spatial variation of soils, improves accuracy in the estimation of soil properties for data interpolation and map compilation, and forms the basis for a rational design of soil sampling [25].

With the wide range of geostatistical software available presently, data processing by means of geostatistical tools presents no problems for users without a special mathematical education. In some cases, on the contrary, these procedures significantly simplify the analysis and interpretation of experimental data. However, it should be noted that the choice of point samples and positioning of sampling sites on the plan of the territory are essential requirements for the application of geostatistics.

The aim of this work is to demonstrate the potential of geostatistical techniques in processing the results of soil studies and attendant observations in field experiments.

The paper is based on reported data and results of our experiments. The theoretical principles of the method were described in detail in our paper "Geostatistics: Concepts, Theory, and Software Features" and, hence, will not be reconsidered.

1. Analysis of Variograms

Plotting of variograms for the parameters under study is the first stage in a geostatistical processing of data. We cite some examples when the analysis of variograms leads to important conclusions on the reasons behind the variation in soil parameters and their correlations.

1.1. Determining correlations between parameters from an analysis of variograms. The absence of a pronounced correlation between the parameters studied can be associated with the significant effect of the high-frequency variation of the parameters on the coefficient of correlation because of experimental errors and the variation at short distances. Each point of the variogram, on the contrary, represents an averaged characteristic of the variations in all points located at a specific distance from one another and, hence, is significantly less dependent on the high-frequency variation mentioned above. In this case, a comparison of variograms can unveil correlations between the parameters at a qualitative level. Let us illustrate this statement by the example of a study of the heterogeneity of soil properties in an experiment without impacts, which was carried out on podzolic soil over binary deposits (Sandtieflehm-Fahlerde) 5 km north of Berlin, Germany (the work was performed in cooperation with scientists from the Faculty of Plant Growing, Humboldt University, Berlin). The plot was 240×480 m in size; samples were taken on a regular pattern with a step of 10 m. A statistically significant correlation was found between the content of organic carbon (C_{org}) and the fine particle-size fraction < 0.0063 mm in the plow layer (0–30 cm), with a correlation coefficient of 0.23 ($n = 1148$). This suggested that only 5% of the C_{org} variation was due to the variation in the fine fraction content, which did not allow a definite conclusion to be drawn on the correlation between these parameters. However, the analysis of the variograms of the parameters studied revealed the structural similarity of their spatial distributions. The variograms of C_{org} and the fine

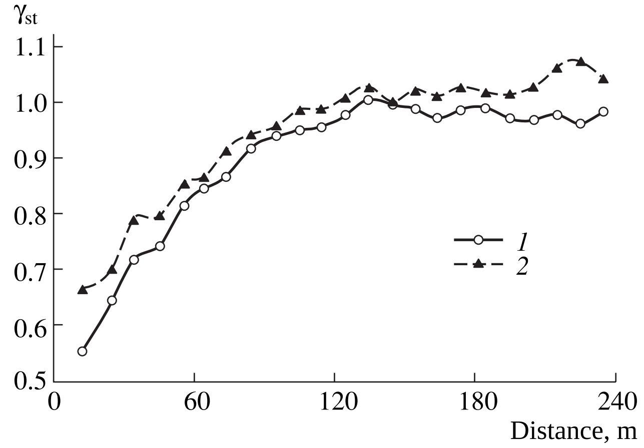

Fig. 1. Isotropic semivariograms of the content of (*1*) organic carbon and (*2*) fine particle-size fraction (<0.0063 mm) in the plow (0- to 30-cm) layer of podzolic soil on binary deposits (Sandtieflehm-Fahlerde, 5 km north of Berlin, Germany); (γ_{st}) standardized semivariances (referred to the sample variance of the corresponding parameter).

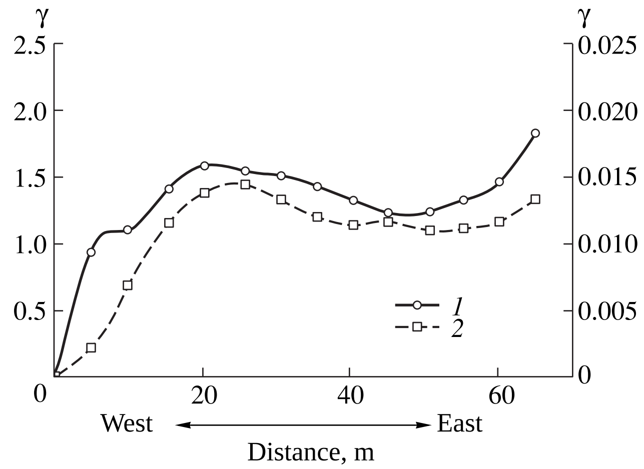

Fig. 2. Anisotropic variograms of (*1*) the C_{org} content in the plow (0- to 20-cm) layer of soddy-podzolic soil and (*2*) logarithm of the temporal water flow intensity (ln Z) across the ln Z slope. A long-term experiment at the Central Experimental Station of the Pryanishnikov Research Institute of Fertilizers and Agricultural Soil Science (Barybino, Moscow oblast): (γ) semivariance.

particle-size fraction (< 0.0063 mm) in the plow (0- to 30-cm) soil layer are presented in Fig. 1. For easy comparison, standardized semivariances, i.e., values referred to the sample variance of the corresponding parameter, were plotted on the ordinate. The parameters were characterized by almost identical variograms, which indicated a similarity between their spatial distribution and its dependence on identical factors of soil cover differentiation. These results are in line with the idea that C_{org} is redistributed in space predominantly in the fine fraction [8, 17].

1.2. Analysis of variograms in the selected directions. Analysis of anisotropic variograms of the parameters studied can be the source of important information. As an example, we cite our work on the determination of the reasons for C_{org} variation in a long-term experiment with two fertilizing systems (organo-mineral and mineral) and herbicides on soddy-podzolic soil established at the Central Experimental Station of the Pryanishnikov Research Institute of Fertilizers and Agricultural Soil Science (VIUA), Moscow oblast, on a plot of 140 × 130 m. The experiment has been described in detail earlier [4, 18]. The analysis of the variance showed that the fertilizer factor determined only 20% of the total C_{org} variance. The effect of erosion–accumulation processes on C_{org} in the plow (0- to 20-cm) layer was not compensated by the complex of agrotechnical measures. The logarithm of the intensity of temporal water flows was used as a characteristic of the potential erodibility of different microrelief positions. This parameter was calculated as the product of the local catchment basin and the local gradient in the nodes of the spatial grid (10 × 10 m). A detailed calculation of the parameter was presented earlier [4]. Variograms of soil C_{org} and logarithms of water flow intensities across the slope are given in Fig. 2. The similar character of the shapes of the curves and the characteristic minima at a distance of 50 m in the variograms of both parameters indicated their similarity. From the analysis of schematic maps, it was found that the highest C_{org} contents across the slopes corresponded to the longitudinal microridges characterized by the minimum intensities of water flows. The distances between microridges averaged 50 m, which was probably associated with the minimas in the variograms.

1.3. Correlation between the shape of the variogram and variation factors. In some cases, the shape of the variogram of soil properties allows one to uncover a correlation between their variation and the main factors of soil cover differentiation on the territory studied. A good example is given in the work of Gummatov *et al.*, who characterized the variograms of some physicochemical parameters of soils: density, natural moisture content, cation exchange capacity, and water-retaining capacity [2]. The work was conducted on gray forest arable soil with the second humus horizon over mantle loams (Pushchino region, Moscow oblast) on a plot 120 × 32 m in size. An oscillatory component with a period of 30–50 m was more or less pronounced on all semivariograms of the soil parameters studied. The authors reckoned that this component was related to the old blocky polygonal structure of soil cover, with polygons 20–60 m in size, which was revealed in the detailed soil survey of the territory performed by Alifanov and Gugalinskaya [1].

1.4. The study of parameter variations at different levels. The total variation in most of the soil parameters depends on the combined effect of pedogenetic factors acting on both short and long distances and controlling the variation in the parameters at the micro-, meso-, and macrolevels. On surveying large territories with high sampling density, one sometimes obtains variograms of soil properties which can be subdivided into segments with different slopes; e.g., segments with increasing semivariances can alternate with relatively flat segments characterized by almost constant semivariance values. The beginning of each plateau corresponds to the attainment of the limiting semivariance values at a specific variation level, either within the limits of an element of soil mantle pattern (pedon, elementary soil area, and elementary soil structure) or within artificial structural elements (separate treatments, fields, etc.). In this case, it is thought that independent sources of spatial variation affect the spatial variation in the parameters analyzed. These variation sources are described by a linear combination of so-called nested functions characterizing the sequence of variation components with characteristic correlation ranges. A thorough analysis of variogram expansion into a series of independent functions for the separate study of variation factors with a short or long range of operation was reported earlier [11, 14–16].

Another method of data transformation is the removal of the trend of the arithmetic mean of the variogram, which is performed by subtracting the polynomial describing this trend from the variogram values. It is suggested that a part of the systematic variation component is thus removed.

We shall illustrate the possibility of such a transformation with variograms of soil parameters characterizing the spatial changes in the acid–base properties of the plow layer in a field experiment performed at the Central Experimental Station of the VIUA on a plot of 22 ha. The experiment was described in detail earlier [5]. Some sections of the plot were natural catchment areas used in different farming systems. Soil samples were taken from the plow layer at depths of 0–20 cm in 120 randomly chosen nodes of a regular square grid with a step of 20 m.

Initial standardized variograms (normalized to the sample variance of the corresponding parameter) for pH, total acidity, and degree of saturation in exchangeable calcium and magnesium are shown in Fig. 3a. As was noted, the similarity of variograms attests to a common set soil-forming processes affecting the parameters analyzed. A regular sinusoidal component with a period of about 100 m is observed in the variograms of continually increasing functions. When the polynomial of the first order is subtracted from the initial variogram values, i.e., after the trend is removed, this dependence is manifested more clearly (Fig. 3b). The transformed variograms also indicate the presence of a local variation [13]. This variation is probably associated with the large-polygonal soil mantle pattern (paragraph 1.3) determining the reproduction of natural processes, which are manifested even under long-term anthropogenic impacts. In this case, the sinusoidal component

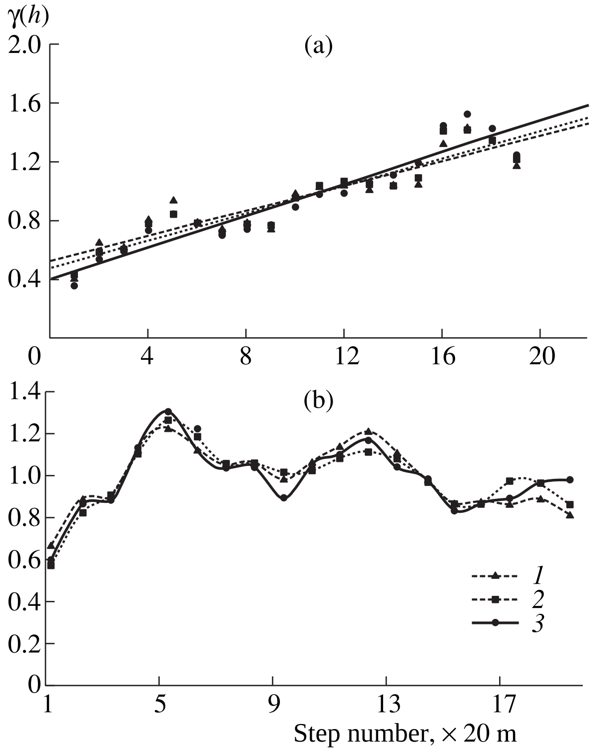

Fig. 3. Semivariograms of the acid–base status parameters of the plow soil layer in a field experiment at the Central Experimental Station of the Pryanishnikov Research Institute of Fertilizers and Agricultural Soil Science in the spring of 1996: (a) initial; (b) after trend removal; (γ) semivariance; (*1*) (Ca + Mg)/CEC; (*2*) total acidity; (*3*) pH.

can be due to the redistribution of calcium and magnesium in the microrelief of paleocryogenic blocks with more homogeneous soil-forming conditions in each [7].

1.5. Use of variograms for the design of field experiments. The calculation of variograms in all space directions can be used in planning field experiments for the substantiation of the experimental design and replications and for the determination of plot shapes and sizes. To illustrate, we cite the geostatistical processing of data on the crop yield obtained from an experimental plot 40 × 48 m in size at the Blumberg experimental station (near Berlin) for five years (1954–1958). The experiment was described in detail earlier [23]. The spatial variation in crop yield was studied in a five-course crop rotation (mustard, winter rye, sugar beet, oats, and mustard) with absolute control. The total estimation of crop yield was conducted on plots 2 × 2 m in size. For all crops, variograms were calculated in all directions ($0° \leq j < 180°$) with a step of 5° ($j = 0°$ corresponds to the south–north direction). From the calculation results, variogram maps of the crop yield variation were composed for all crops in all space directions. The principle of this data representation was described in the literature [25]. The variogram map was composed as follows. For each crop, distances multiple of

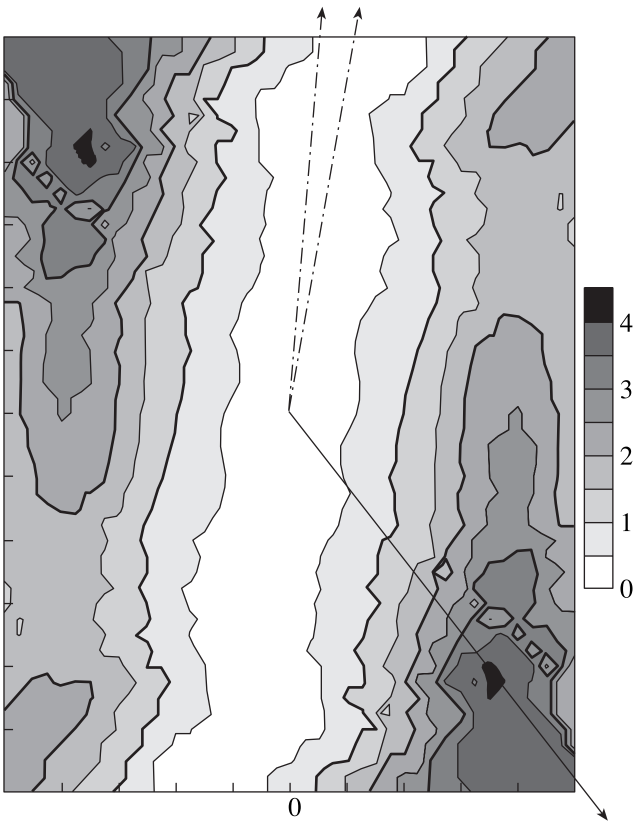

Fig. 4. Variogram map of the variation in winter rye yield in all directions of space at the Blumberg Experimental Station (near Berlin): (0–4) semivariance values multiple of the half sample variance; (dotted line) the direction of minimum changes in crop yield; (full line) the direction of maximum changes in crop yield.

the half-sample variance (i.e., equal to $\sigma^2/2$; σ^2; $3/2\ \sigma^2$, etc.) were laid off in all directions from (20, 24) the center of the plot. Note that $g_j(h) = g^0_{j+180}(h)$. A variogram map for the winter rye yield is presented in Fig. 4. Arrows indicate the directions of the minimum and maximum changes in semivariance, which correspond to the directions of the least and highest trends in the crop yield, respectively. On the basis of this information, an experimental design with rectangular plots elongated in the direction of the highest increase in yield can be recommended. A maximum homogenization of the initial crop yield can be thus attained within each plot, and the effect of the initial natural heterogeneity on the results of an active experiment will decrease.

2. Kriging

A number of important problems concerning the preparation and processing of data, including the application of classical statistical procedures, can be solved by kriging of initial data.

2.1. Determination of the optimal sample size. The number of samples required to estimate a parameter with the prescribed accuracy can be decreased when the spatial pattern of its variation is taken into consideration. In classical statistics, the necessary number of samples N is calculated from the formula

$$N = t^2 s^2/(x-m)^2,$$

where t is the Student's t-criterion; s^2 is the estimate variance; $(x - m)$ is the permissible error. The value of the parameters are considered independent. However, in the case of spatial correlation, this statement is valid only for a set of points remote from one another at least at the correlation range. In practice, the correlation range of soil properties is frequently equal to tens or even hundreds of meters. Therefore, in a large-scale survey, the sampling step is generally lower than the correlation ranges of the properties studied. In this case, if the shape of the variograms for soil parameters is known, the number of soil samples required for obtaining the preset estimate variation can be lower than that derived from the formula above [10, 20–22].

Data interpolation using the kriging procedure makes it possible not only to determine the value of the parameter in the desired point (area), but also to estimate the accuracy of interpolation. For this purpose, the dependence of the standard deviation on the sampling step, the number of samples, and the block size (for block kriging) is studied. In soil studies (with an assumption that the variogram is constant in time), the number of samples necessary for attaining the prescribed accuracy in estimation of the parameters studied can be calculated, and the optimal pattern of sampling sites (or of observation stations) can be determined, as well as the sizes of the plots (blocks) suitable for characterization by a mixed sample.

Let us illustrate the use of the spatial correlation of soil properties in the design of field experiments with the data of an agroecological field experiment performed at the Central Experimental Station of the VIUA (the experiment was described in paragraph 1.4). The sample variance of the available phosphorus content as a function of the number of point samples is given for a catchment area in Fig. 5. Calculation was based on block kriging, with blocks of 20 and 40 m, for two types of block arrangement: in one case, the block centers coincided with the nodes of the sampling pattern grid; in the other case, they were in the centers of the grid squares. It is obvious in the graph that the estimate variance significantly increases when the number of samples drops below 20; about 25 samples are necessary to ensure a measurement accuracy no worse than 60 mg/kg for a block size of 40 m on the given plot. Note that the maximum value of the standard deviation, which was observed at the boundaries of the catchment area, was calculated in this case. For the major part of the territory, the error will be lower by a factor of about 1.5. In the general case, the lower limit of the estimate variance depends on the analytical errors in parameter measurements and the variation at a distance of no longer than the sampling step. In order to discriminate the effects of these variation components, it is advisable to compare the variograms of two parameters with their cross variogram. With an assumption that the analytical errors of each parameter are independent, the cross variogram and individual variograms will be characterized by different values of the residual (nugget) variance.

The use of kriging results for designing the optimal sampling pattern was reported in the literature [2, 3].

2.2. Interpolation of parameter values for the regular sampling pattern. Kriging of initial data allows one to apply a regular spatial sampling pattern for parameters measured on an irregular pattern and to use a unified spatial grid for parameters measured with different steps or in different points or areas. This interpolation allows the subsequent comparison of the parameters studied by classical statistical methods (e.g., correlation and regression analyses). Examples of the calculation of a regular grid and reduction of several soil surveys to a common grid were published previously [4].

2.3. The use of kriging for map smoothing. The obtainment of smoothed maps is an important advantage of kriging. In addition, the values of the parameter studied for a given space area (block) are averaged in block kriging. As applied to soil objects, this implies the smoothing of the high-frequency variation of initial data caused, on the one hand, by experimental errors and, on the other hand, by variation at short distances (less than the block size). Different degrees of smoothing are attained by changing the block sizes, in accordance with the objects and scope of the study. Changing the degree of smoothing presents new opportunities for data presentation and the search for correlations between the parameters studied. So, the use of different degrees of smoothing of topographical survey data makes it possible to clearly discriminate relief forms of different levels (micro-, meso-, and macrorelief forms) and to calculate, from the altitude points, the derivative characteristics of the relief (local gradients, surface curvature, etc.) with different degrees of minuteness.

An example of smoothing is presented in Fig. 6: the maps of plant-available potassium in the plow (0- to 30-cm) and subplow layers of soddy-podzolic soil on binary deposits (the experimental station in the vicinity of Berlin; description of the experiment, see 1.1) based on initial data, with a sampling step of 10 m, and those after kriging. The initial maps are characterized by small units with irregular boundaries, which significantly complicates their visual analysis. The maps compiled after kriging are evidently similar, which attests to a correlation between the parameters considered.

2.4. Enhancing the correlation between the parameters studied after block kriging. The most efficient smoothing of initial data involves averaging

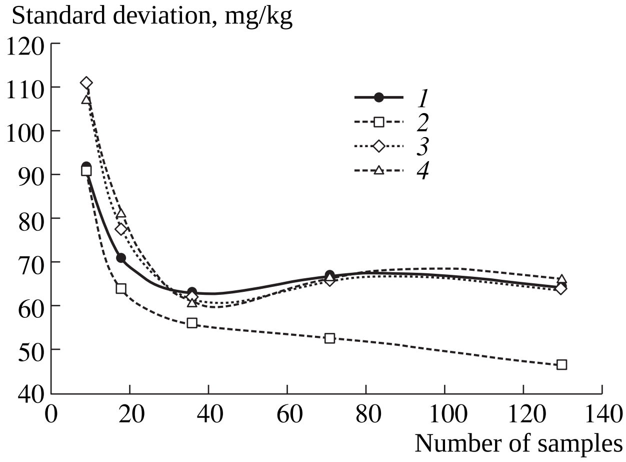

Fig. 5. Sample variance as a function of the number of samples for different block sizes and arrangements in block kriging: (*1*) 20 m; (*2*) 40 m; (*3*) 20 m, shift; (*4*) 40 m, shift.

the variation within the soil cover units (pedon, elementary soil area, and elementary soil structure). Prokhorova and Sorokina showed that, to identify correlations between parameters at a specified level of the variation, averaging of variation at the lower levels is efficient [6]. The enhancement of the correlation is due to the decrease in the portion of the random variation component, which is cased by variation at lower levels, and the corresponding increase in the portion of the regular variation component. In the above-mentioned work, data were averaged by increasing the volume of soil samples and the yield account area. However, this operation can be successfully replaced by block kriging. In some cases, block kriging of initial data increases the coefficients of correlation between the parameters compared because of the decrease in high-frequency variation. As an example, we cite the data on the potassium content in the plow and subplow layers of podzolic soil on binary deposits in the experiment mentioned in paragraphs 1.1 and 2.3 (Fig. 6). Soil samples were taken on a regular grid 10×10 m. The coefficient of correlation between the initial data was 0.46 (significant for the probability level $P_{0.999}$). It should be noted that the potassium content was determined to whole numbers, which also increased the calculation error of the correlation coefficient. After block kriging was performed with blocks of 20 m, the correlation coefficient became 0.88 (for $P_{0.999}$). Thus, kriging of initial data and smoothing of the high-frequency variation component significantly increased the correlation between the parameters studied.

Another example is provided by the dependence of the coefficient of correlation between the yields of mustard and winter rye in a five-course crop rotation on the block size in block kriging. The data were obtained on an experimental plot 40×48 m in size with absolute control at the Blumberg Experimental Station; the total estimation of crop yield was conducted on plots 2×2 m in

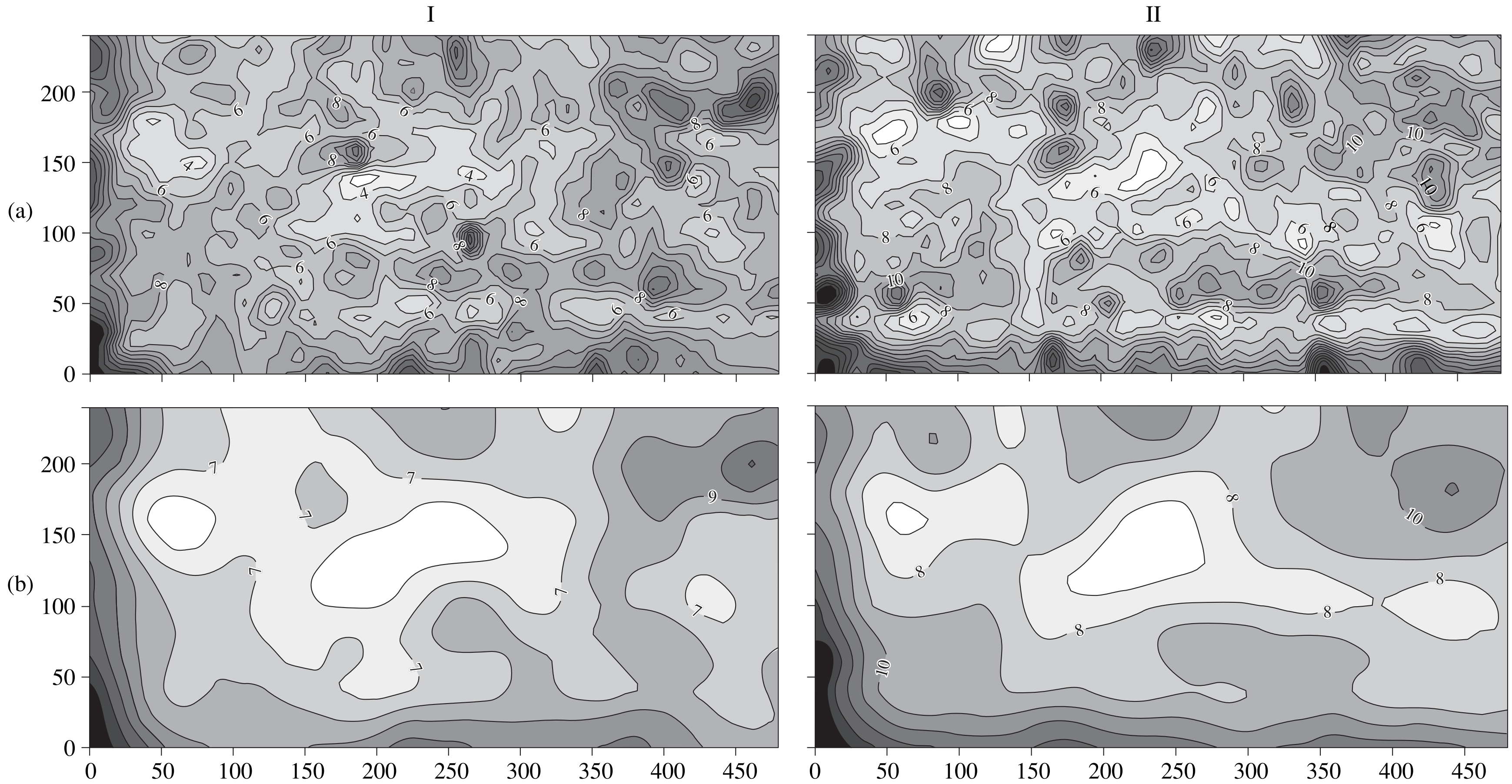

Fig. 6. Variogram maps of the content of plant-available potassium (mg/100 g of soil) in (I) the plow (0- to 30-cm) and (II) subplow (31- to 40-cm) layers of podzolic soil on binary deposits (the Blumberg Experimental Station near Berlin): (a) initial data; (b) after block kriging with blocks of 20 m.

size (description of the experiment, see paragraph 1.5). It is seen in Fig. 7 that the most abrupt increase in the correlation coefficient is observed in going from the initial values of crop yield to the values smoothed by block kriging with blocks 2 m in size (i.e., with block size corresponding to the size of record plots): the correlation coefficient increases from 0.59 (N = 480) to 0.72 (N = 480), respectively. When the block sizes (and, hence, the degree of smoothing) increase, the correlation coefficient continues to increase, in spite of the decreased number of points, and reaches 0.81 at block size of 10 m (N = 25). All correlation coefficients are significant for probability level $P_{0.999}$. Thus, averaging of heterogeneity within blocks smoothes the random component of the crop yield variation and unveils similarity in the spatial distribution of crop yield.

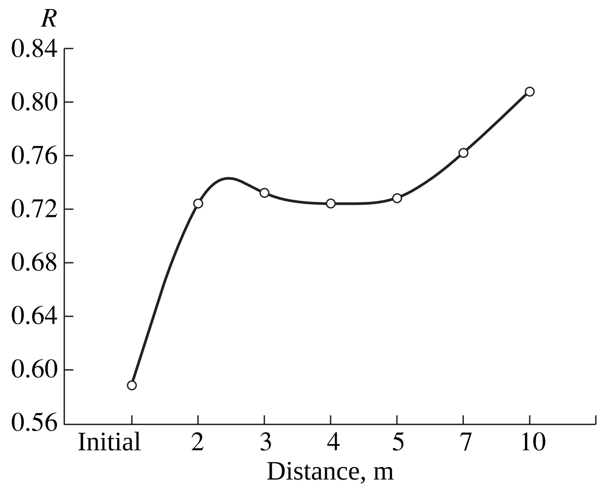

Fig. 7. Coefficient of correlation between the yields of winter rye and mustard as a function of the block size in block kriging (the Blumberg Experimental Station near Berlin).

2.5. The use of smoothed yield maps for the design of field experiments. Map smoothing plays a special role in the design of field experiments based on the test sowing results. Analysis of local trends in crop yield reveals spatial areas with relatively low variations and areas with similar trends hardly depending on the crop and weather conditions. Upon unified field management, the local variation in crop yield depends on the combination of soil and climatic conditions, and the areas with similar trends in yields of different crops in different years can be attributed to areas with a relatively stable combined effect of natural factors.

We elucidate this with the experiment described in paragraphs 1.5 and 2.4. The analysis of variograms in different directions determined the directions of maximum and minimum changes in crop yields. However, the field was considered as a whole, without taking into account the specific features of its separate parts in this case. This approach, evidently, can characterize only the most pronounced trend within the area. More detailed information was derived from smoothed variogram maps. Smoothing made it possible to determine areas with similar spatial distributions of the parameters. At low coefficients of correlation between crop yields for the whole field (0.30–0.56), the determined areas were characterized by correlation coefficients of crop yields of 0.8–0.9. This suggested that the areas with similar trends for all five crops were characterized by the steady effect of natural factors insignificantly affected by weather conditions. These areas are most suitable for the establishment of field experiments.

The plots characterized by pronounced, though dissimilar trends for different crops and years, on the contrary, should be excluded from the experiments, because the effect of experimental treatments is particularly difficult to determine upon uncertain combined effect of natural factors.

Surely, such a thorough preliminary survey and careful exclusion of unsuitable plots from the field experiment is not always possible. However, the demonstrative variogram maps of crop yield on test plots allow to perform a more accurate interpretation of field experiment results, even if optimal design is impossible.

2.6. Quantitative evaluation of soil-forming factors conditions of agrocenosis. The conventional method for solving this problem involves long-term field experiments. However, only active factors in the experiments can be studied using this approach. Other natural and anthropogenic factors, which are not included in the experimental design, are generally not considered, although their effect on the functioning and evolution of an agroecosystem is often significant, as well as their interference with experimental factors. As a rule, the direction and effect of factors not included in the experimental design on the resulting indices vary significantly within the territory studied.

In some cases, these factors can be studied by factor analysis. Combination of factor analysis and kriging also allows the spatial differentiation of factors to be estimated.

Let us briefly recall the main principles of factor analysis [9]. When several parameters are measured in each sampling site, factor analysis can help find some latent general factors, whose effect is significant for all parameters studied (the term “latent parameters” emphasizes the fact that these factors are not known a priori but are discovered when processing initial data). In other words, new factors, which reflect the properties of the plot studied in a generalized form, are discriminated in the set of parameters measured. To solve this problem, the value of each of the parameters studied is represented by a linear combination of general factors multiplied by the corresponding coefficients. Thus, the expressions for different parameters vary only in coefficients (termed “factor loads”) and have the form

$$z(j) = a(j, 1)F1 + a(j, 2)F2 + \dots + a(j, m)Fm,$$

Table 1. Results of factor analysis after the factor matrix rotation

Parameter	Factor			
	1	2	3	4
Variation portion, %	30.8	20.8	14.8	10.1
Accumulated variation, %	30.8	51.6	66.4	76.5
Factor loads				
Exchangeable Ca	**0.94**	–0.01	0.13	–0.03
Total acidity	**–0.57**	–0.43	**0.54**	0.08
log (available K)	–0.28	**0.72**	0.36	–0.14
Exchangeable Mg	**0.95**	–0.03	0.07	–0.02
log NO_3	0.05	0.40	**0.69**	–0.05
log NH_4	0.07	–0.03	**0.67**	0.04
Total N	0.05	**0.68**	0.02	0.22
log (available P)	0.19	**0.80**	–0.11	–0.12
pH	0.62	0.40	**–0.49**	–0.14
Plow layer depth	–0.08	0.01	0.03	**0.96**

Table 2. Internet addresses of geostatistical software or extensive related information

Address: http//:	Program (supplier)	Brief characterization
www.gammadesign.com/	GS+ (Gamma Design Software)	DOS/Windows, variograms (isotropic, anisotropic), kriging (block, point), Jack-Knife, convenient graphics
www.ace.inter.net/	GridstatPro (Applied Computer Engineering)	Windows/Unix, 3D, variograms (isotropic, anisotropic), variogram maps
www.correlations.com/	GViz (Correlations Company)	Windows, variograms (isotropic, anisotropic), kriging (block, point), nearest neighbor analysis, Jack-Knife, convenient graphics
www.geovariances.fr/	Isatis (Geovariances)	
www-sst.unil.ch/geostatistics.html	Variowin	
www-sst.unil.ch/geostatistics.html	Geostatistical Toolbox (Roland Froidevaux)	
triton.cms.udel.edu/~vinton/gis gip/packages/geoeas.ht ml	Geo-EAS	
www-sst.unil.ch/geostatistics.html		
uncert.mines.edu/	Uncert (Department of Geology and Geological Engineering, Colorado School of Mines)	
www.nr.no/sand/wwwSites. html		Extensive review of different commercial and noncommercial geostatistical software
curie.ei.jrc.it/software/index.htm		Extensive review of different commercial and noncommercial geostatistical software

where j is the number of parameters; m is the number of factors; z is the covariance matrix; a denotes the factor loads; $j = 1, 2, \dots n$; and $m \ll n$. A factor load value exceeding 0.3 is generally considered significant, and that exceeding 0.5 is the most significant.

The determination of factor loads for each of the parameters studied is the ultimate aim of mathematical manipulations in factor analysis. The squared factor load corresponds to the contribution of this factor to the general variance of the corresponding parameter. After the calculations, interpretation of the results is performed; i.e., the physical sense of the general factors found is determined.

Using factor analysis in combination with kriging, one can discriminate the most significant factors, characterize their differentiation within the territory studied, and determine the regions of predominant effect for different factors. We illustrate this by the agroecological field experiment at the Central Experimental Station of the VIUA discussed above (paragraph 1.4).

In soil samples taken from 100 sampling sites, ten soil parameters were determined. Next, the data obtained were processed using factor analysis. As a result, four main factors were discriminated, which determined 76% of the total variation in the parameters studied, and the corresponding factor loads were calcu-

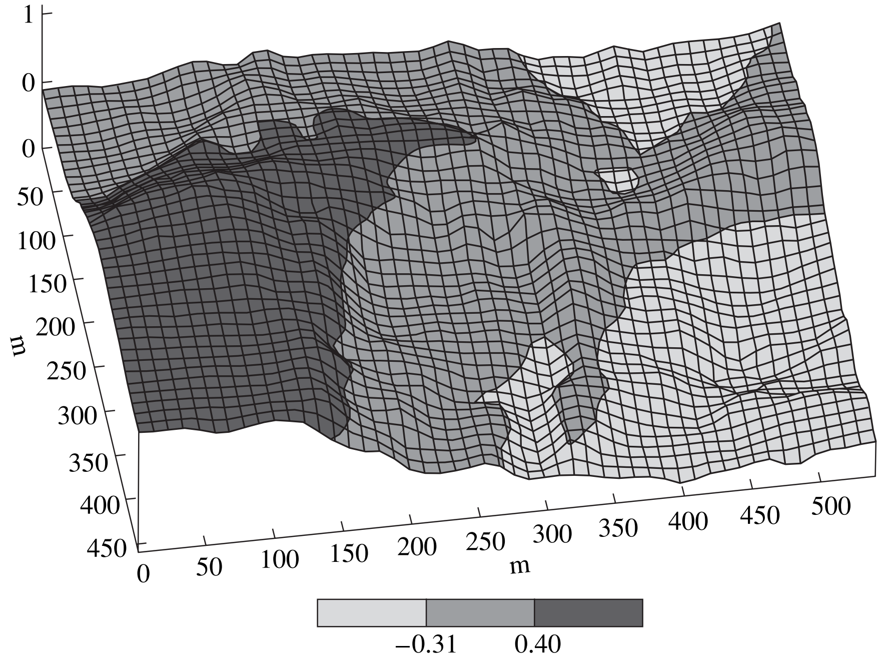

Fig. 8. Three-dimensional projection of the distribution of factor 1 values in the plow layer of experimental plot of the VIUA obtained by the method of block kriging. Size of blocks: 20 × 20 m.

lated for 100 sampling sites [24]. The results averaged for 100 sites are presented in the table (the highest values of factor loads are indicated in bold).

Next, the parameters transformed (factors F1–F4 responsible for the variation in soil properties of the plot studied) were processed geostatistically.

For each factor, semivariograms were calculated (that for factor 1 is described by a linear function), and maps were composed for each factor using block kriging (with blocks 20 × 20 m in size).

The spatial distribution of factor 1 on the territory of the experimental plot is shown in Fig. 8. High factor loads for such soil parameters as exchangeable bases, total acidity, and pH suggest that factor 1 is the factor of the acid–base status of soil. The lower quartile (25% of all minimum factor values) characterizes the areas with the increased acidity; the upper quartile (25% of all maximal factor values) characterizes the areas with highest pH values and base saturation. Thus, the acid–base properties of the areas with low values of this factor are less favorable for agricultural crops, and the areas with increased values have the best properties.

Factor 2, mainly depending on the content of exchangeable P and K and total N, probably characterizes the effect of surface runoff and migration processes on the redistribution of these elements in the relief. In contrast to factor 1, for which only pH exhibits spatial correlation at the given sampling step, an increase in semivariance with the distance between the sampling sites is observed for all parameters of factor 2. The factor 2 values reflect the local level of nutrient supply. By its effect on the total variance, factor 2 is comparable with factor 1 (21 and 31%, respectively).

Thus, it was found that for the selected sampling step, the contribution of migration and redistribution of P, N, and total N to the integral fertility status of the plow soil layer on the territory studied is comparable with the effect of the factor characterizing the acid–base equilibrium in the soil.

It is also evident that it is advisable to allocate the experimental plots on areas with the average level of soil fertility (which corresponds to average values of each factor) in order to obtain more reliable results in the designed experiments. So, for the assessment of the effect of liming systems on the acid–base parameters of soils and plant productivity, the territory of experimental plot can be conventionally limited by the upper and lower quartiles of factor 1 (Fig. 8).

CONCLUSION

In this work, we have shown only some of the potentialities of data processing by means of geostatistical techniques. The development of a theoretical basis and computerization open new possibilities for the application of this promising method in soil science in order to acquire new soil-genetic information. Our prime objective was to demonstrate the relative simplicity of geostatistical methods, and we recommend geostatistical programs for wider use in processing data of soil studies and field experiments.

Geostatistical software programs. Software programs used for most geostatistical calculations significantly differ in their volume of routine operations and, especially, in the quality of result presentation and usability. A complete analysis of the advantages and shortcomings of separate programs is beyond the scope of this work. A brief review was published earlier [12].

Taking into account that data processing by geostatistical techniques is impossible without corresponding software, we gathered information on the software products most frequently used today. Since software purchase is difficult in Russia, we provide Internet addresses for downloading geostatistical freeware: they are presented in Table 2. We shall regularly update this list. In addition, actual information can be obtained at http://www.uni-hohenheim.de/~kuzyakov/geostat.htm.

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