Spatial distribution and correlation of soil properties in a field: a case study

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ABSTRACT

Analysis of spatial distribution and correlation of soil properties represents an important outset for precision agriculture. This paper presents an analysis of spatial distribution and mutual correlations, both classical and spatial, of soil properties in an agricultural field in Klučov. Clay and fine silt content, pH, organic carbon content (C_{org}), moisture (Θ), total porosity (P_t), capillary porosity (P_c), and coefficients of aggregate vulnerability to fast wetting (K_{v1}), to slow wetting and drying (K_{v2}), and to mechanical impacts (K_{v3}) were determined. Semivariogram ranges from 206 m (clay content) to 1120 m (K_{v3}) were detected. Many relationships between soil properties were spatially based. Fine silt content and C_{org} proved to be the most important soil properties controlling all the three aggregate vulnerability coefficients, which was not clear for K_{v2} from classical correlation only. Determined spatial correlations and similarities in spatial distribution may serve as groundwork in delineation of different zones for site-specific management.

Keywords: soil heterogeneity; spatial distribution; spatial correlation; soil structure vulnerability; precision agriculture

Spatial heterogeneity of soil properties is a fact we have to deal with. It is caused by a number of factors and processes acting at different spatial and temporal scales. Some of them we know and can describe, many others are unknown. Soil variability thus seems to be random (Webster 2000). Nevertheless, our task is to reveal at least some of these factors and use this knowledge to design agricultural management practices that would be both environment friendly and highly productive. A thorough analysis of spatial distribution of soil properties can make a basis for defining different management zones on a field or on an area. Stafford et al. (1996) reported that the zones could be defined according to the soil survey, namely to soil types. However, soil characteristics can vary significantly even within one soil type which should be taken into account, too.

Certainly, any soil property cannot be completely independent, standing by itself. There exist many interrelations between soil and other properties that we can describe statistically. The data may originate from different sources. Bouma (1997) listed the necessity of integration spatial (and temporal) information of different sources in one operational georeferenced database and decision support system among the principal problems to solve for precision agriculture. This integration, however, cannot consist just in adding further data to the database. On the contrary, analysing the relations and revealing the complex multivariate spatial structures is the right way. Any prediction using substantiated secondary information based on knowledge of the relationships provides better results than univariate prediction methods (Bishop and McBratney 2001).

Precision agriculture or site-specific management is based precisely on the analyses of spatial distribution and relationships. A multidisciplinary research has been conducted on an agricultural field in Klučov, Central Bohemia, aiming at detailed characterisation of the heterogeneity of soil properties, nutrient content (Brodský et al. 2001), crop yields, weeds and pests occurrence, etc. The results will serve as a scientific basis for farming management proposals and methodology. This paper focuses on the soil properties, their spatial distribution and correlations. It follows our previous paper where statistical relationships were analysed (Borůvka et al. 2002). Vulnerability coefficients of soil aggregates were used there as indicators of soil quality. Their relationship to basic soil properties was studied. The aim of this contribution is to describe spatial distribution of basic soil properties and vulnerability coefficients on the Klučov field and to analyse statistical and spatial relationships between soil properties. Potential exploitation of these findings for precision agriculture is briefly discussed.

MATERIAL AND METHODS

A set of 94 soil samples from a 54 ha agricultural field in Klučov, Central Bohemia, was used. The point samples were collected in a regular grid 80 × 80 m. The soil was classified as Orthic Luvisol, with loamy texture. Clay (particles < 0.002 mm in diameter) and fine silt (0.002–0.01 mm) content, soil pH, organic carbon content (C_{org}), soil moisture (Θ), total porosity (P_t) and capillary porosity (P_c) were measured. In addition to the basic soil characteristics, coefficients of aggregate vulnerability to fast wetting (K_{v1}), to slow wetting and drying (K_{v2}), and to mechanical impacts (K_{v3}) were also determined. Details on soil sampling and sample analyses were given in Borůvka et al. (2002).

Table 1. Summary statistics of determined soil properties and parameters of variograms (spherical models with nuggets)

Characteristic	Mean	Variance	Min	Max	Nugget	Sill	Range (m)
Clay (%)	26.30	3.380	20.0	33.0	1.680	3.361	206
Fine silt (%)	14.20	2.167	9.9	17.2	0.595	2.399	481
pH	7.13	0.193	5.76	8.30	0.103	0.206	349
C_{org} (%)	1.16	0.015	0.88	1.44	0.010	0.015	300
P_t (%)	46.51	11.623	35.16	53.65	4.770	11.03	464
P_c (%)	21.47	20.80	15.12	31.73	1.820	23.49	461
Θ (%)	20.41	28.579	11.63	31.63	4.520	32.29	458
K_{v1} – test 1	9.99	2.222	5.44	14.19	0.224	2.487	483
K_{v2} – test 2	3.70	0.923	1.30	6.79	0.850	0.950	800
K_{v3} – test 3	1.67	0.020	1.21	2.00	0.011	0.028	1120

Statistical treatment (summary statistics and correlation analysis) was performed using Statgraphics Plus for Windows, version 4.0 (Manugistics 1997). Geostatistical analysis of data was done using GS^+ software (Robertson 2000). Kriged maps were prepared using Surfer v. 7 software (Golden Software 1999). Structural correlation coefficients, ρ_{uv}, of the spherical variogram components were computed as follows:

$$\rho_{uv} = \frac{b_{uv}}{\sqrt{b_{uu} b_{vv}}}$$

where: b_{uu}, b_{vv} and b_{uv} are coefficients of the structural component of variograms and cross-variogram, respectively, of the two variables investigated (Goovaerts 1992).

RESULTS AND DISCUSSION

Spatial distribution

Basic statistical parameters and parameters of variograms of determined soil properties are presented in Table 1. Spherical models with nuggets were used in all cases (Figure 1). The shortest ranges were found for clay content (206 m), C_{org} (300 m), and pH (349 m). Content of fine silt, soil porosity (P_t, P_c), and Θ had ranges from 458 to 481 m. A similar variogram range was found for K_{v1} (483 m). It indicates some spatial relationship between these variables. K_{v2} and K_{v3} showed the longest ranges (800 and 1120 m, respectively). Variogram ranges were in most cases higher than those reported by Goderya (1998). The sampling density did not enable to detect fine-scale soil variability that was shown by other authors (e.g. Castrignano et al. 2000a, b). Nevertheless, it is the coarse-scale variation that is of use in defining different management zones in the precision agriculture (Sylvester-Bradley et al. 1999). Moreover, as we examine a system at increasingly fine spatial scales, so the problems of understanding and modelling its behaviour become increasingly difficult (Lark 2001). We probably do not have to respond to every fluctuation in soil conditions within a field and we are not able to.

The spatial dependence of most properties can be classified as moderate according to the classification proposed by Cambardella et al. (1994), having the share of nugget on the total sill between 25 and 75%. Higher share (89.5%) and therefore weak spatial dependence was found for K_{v2}. The value of nugget could have been increased here by relatively stronger effect of analytical error. This may be true also for some other characteristics like C_{org} or particle size distribution. Relative homogeneity of the field increases the importance of small analytical deviations. On the contrary, strong spatial dependence (nuggets representing less than 25% of the sill) was found for P_c, Θ, K_{v1}, and fine silt content. It corresponds to the findings of Amador et al. (2000) who reported higher variability of organic matter content than that of soil water content at a small scale. This might have caused relatively higher nugget at C_{org} compared to Θ in our study.

The semivariances of some soil properties tended to further increase. It indicates spatial dependence on a longer distance. However, the limited area of the field did not enable to investigate this long-range spatial dependence more closely. For this reason, no attempt was made to use more complicated variogram models with several spatial structures. Nevertheless, the long range is not so important for the management on a field scale, either.

Some similarities in the spatial distribution between studied soil properties are apparent from the kriged maps (Figures 2 to 4). Some structures are well manifested in the North-South direction (from the top to the bottom on the pictures). There is a general increase of fine silt content and C_{org} towards the South. Brodský et al. (2001) found a similar pattern for nutrient content on this field. This is most probably related to the relief of the field. A slight slope towards the southern direction, that characterises a large part of the field, can cause movement of fine soil constituents including organic matter down the slope. Other spatial structures are apparent in the cross direction (East-West). Those are best manifested for soil P_c and Θ. For most variables, however, both structures

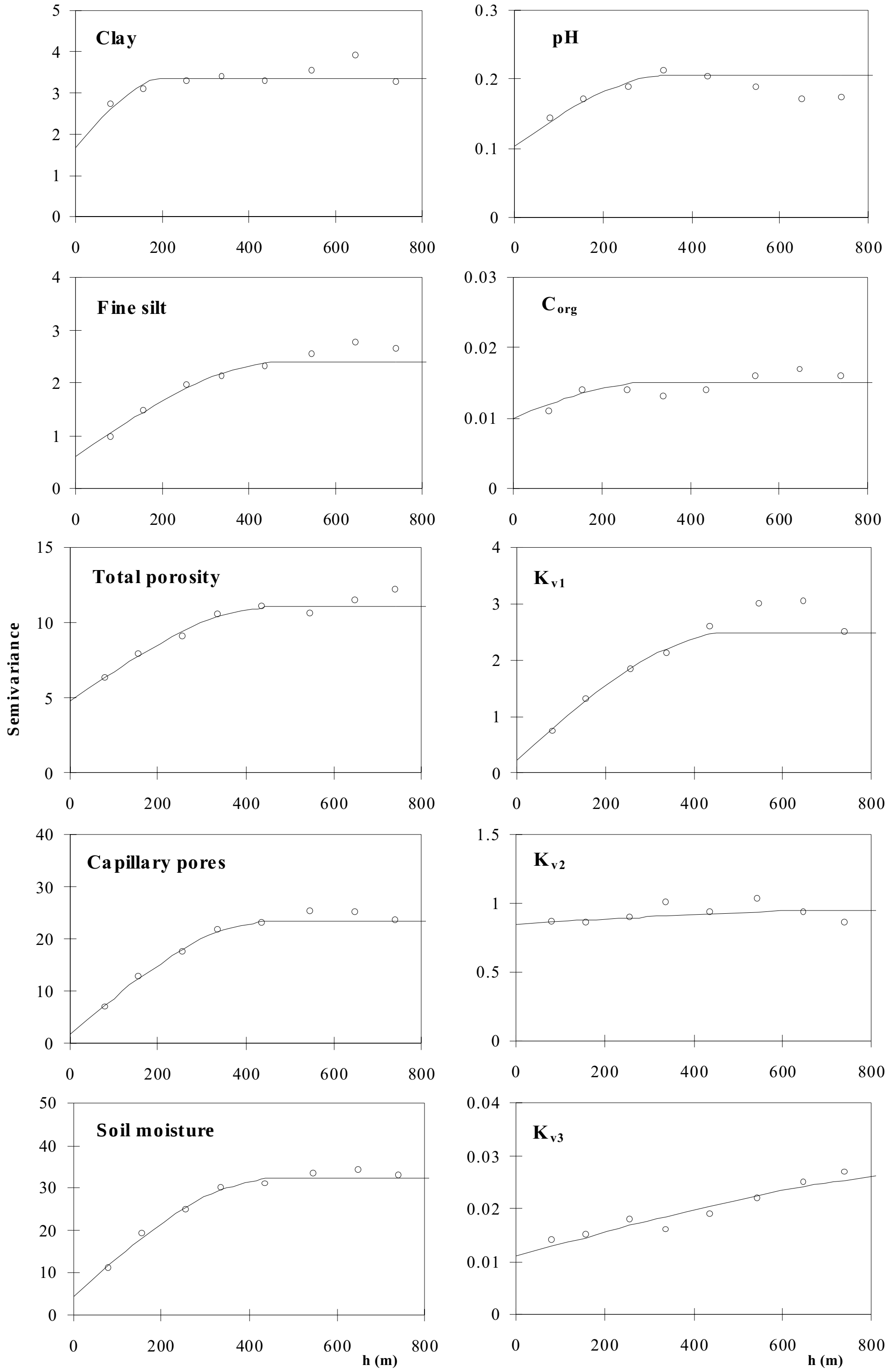

Figure 1. Semivariograms of determined soil properties (spherical models with nuggets)

are mixed. The kriged map of K_{v2} is not very smooth. High share of nugget variance for this variable showed up here.

Correlation between soil properties

Some results from classical correlation analysis were given in our previous study (Borůvka et al. 2002). It was shown that fine silt was the most important soil characteristic decreasing aggregate vulnerability. Aggregate vulnerability and P_t were also related to C_{org}. The correlation coefficients are summarised in Table 2. In addition, this table shows structural correlation coefficients for the spherical part of variogram models wherever it was applicable, that is where semivariograms and cross-variogram could have been calculated and modelled. The structural correlation could not be calculated also if

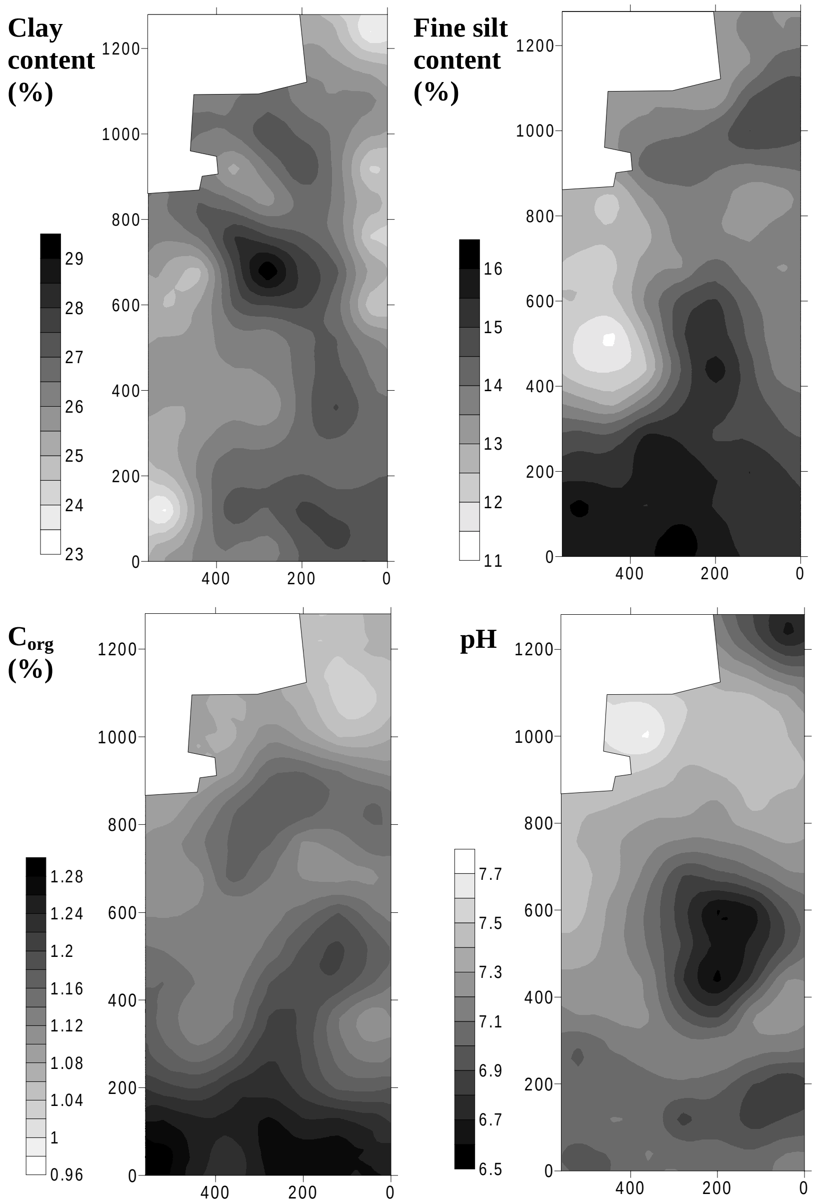

Figure 2. Kriged maps of clay and fine silt content in soil, C_{org} and pH; axis scales are given in metres

Schwarz's inequality did not hold because it would provide structural correlation coefficient in absolute value higher than 1 (Goovaerts and Webster 1994). It was the case for example of the relationship between K_{v1} and K_{v2}. Examples of cross-variograms are presented in Figure 5.

Soil processes controlling variability of the characteristics may be different at different scales (Castrignano et al. 2000b). In most cases, the structural correlation coefficient confirmed the relationship found by means of classical correlation coefficient, having similar or only slightly higher value (Table 2). Very close relationship, both statistical and spatial (coefficients 0.960 and 0.998, respectively), was found between capillary pores and soil moisture. In some cases, the structural correlation coefficient was significantly higher than the classical correlation coefficient (e.g. the relationship of fine silt and vulnerability coefficients, the relationships of P_t to C_{org}, P_c and Θ, etc.). Moreover, the structural correlation coefficients revealed some relationships that were not detected by classical correlation analysis or were not significant. Also Rahman et al. (1996) referred that spatial correlation may be found between properties where conventional correlation analysis did not show any relationship. In our study, this was the case of for example C_{org} and K_{v2}, P_t and K_{v1}, P_t and K_{v2}. That means that the relationships of the pairs of soil properties are rather spatially based. It does not necessarily mean causal relationship. It can be just a parallel effect of an external factor, like slope or water movement, influencing both variables. However, the spatial relationships of K_{v2} with fine silt content (ρ = –0.810), C_{org} (–0.846), or Θ recall similar relationships of K_{v1} and K_{v2} to these basic prop-

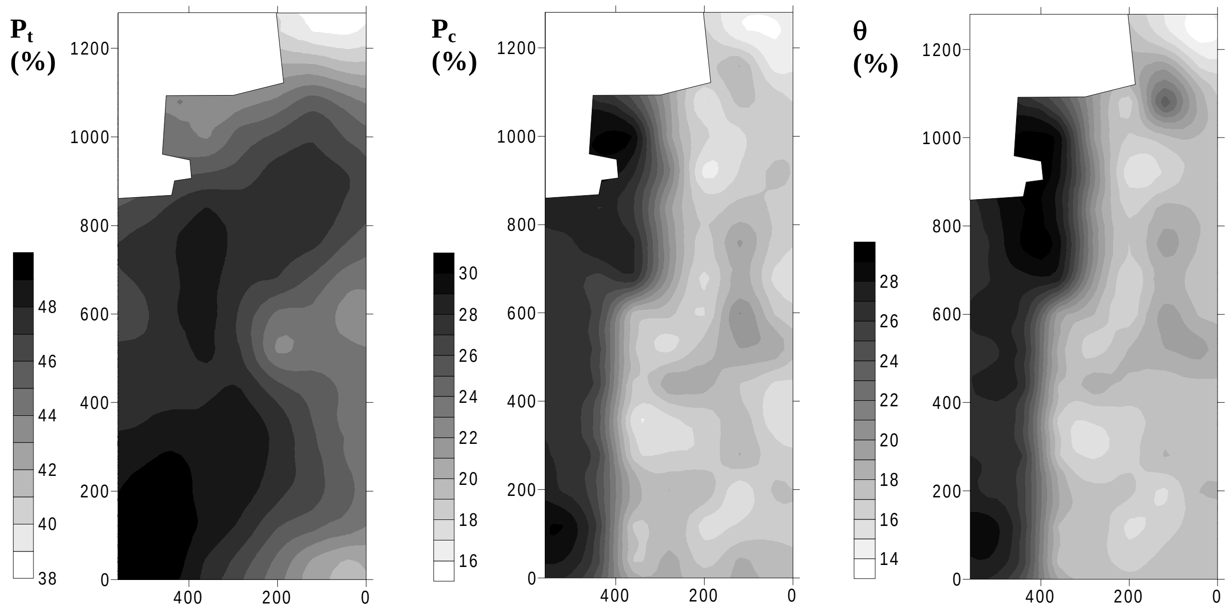

Figure 3. Kriged maps of total and capillary porosity and soil moisture; axis scales are given in metres

erties revealed by classical correlation. Those relationships were discussed previously (Borůvka et al. 2002). That the spatial relationships are valid, it can be seen from the comparison of kriged maps of the variables. There are similar shapes, similar maxima/minima locations etc.

It can be concluded that many relationships between soil properties are spatially based. Spatial correlation with basic soil properties was revealed for soil structure vulnerability coefficients, even if no statistical relationship was detected. It is the case especially of the coefficient of vulnerability to slow wetting and drying. Fine silt content and C_{org} proved to be the most important soil properties controlling soil structure vulnerability. The findings suggest additional prediction ways for soil aggregate vulnerability coefficients as important indicators of soil quality based on basic soil properties, and for other derived soil, agricultural or environmental properties that show spatial dependence and relations. On the other hand, similarities in spatial distribution of different soil

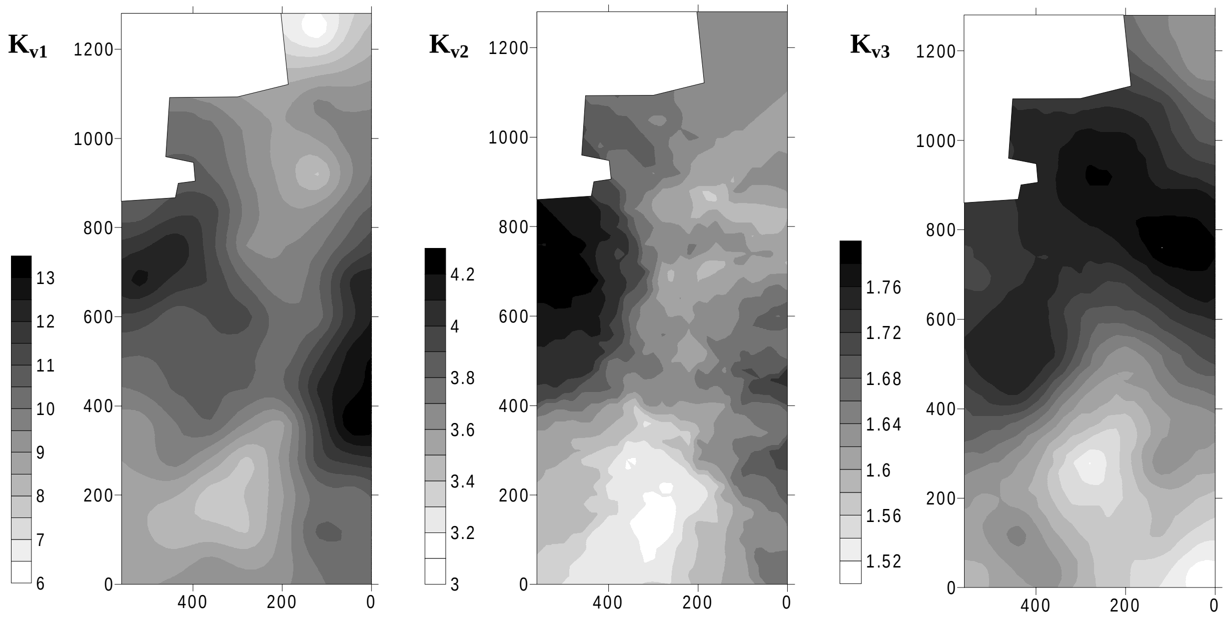

Figure 4. Kriged maps of the vulnerability coefficients of soil structure; axis scales are given in metres

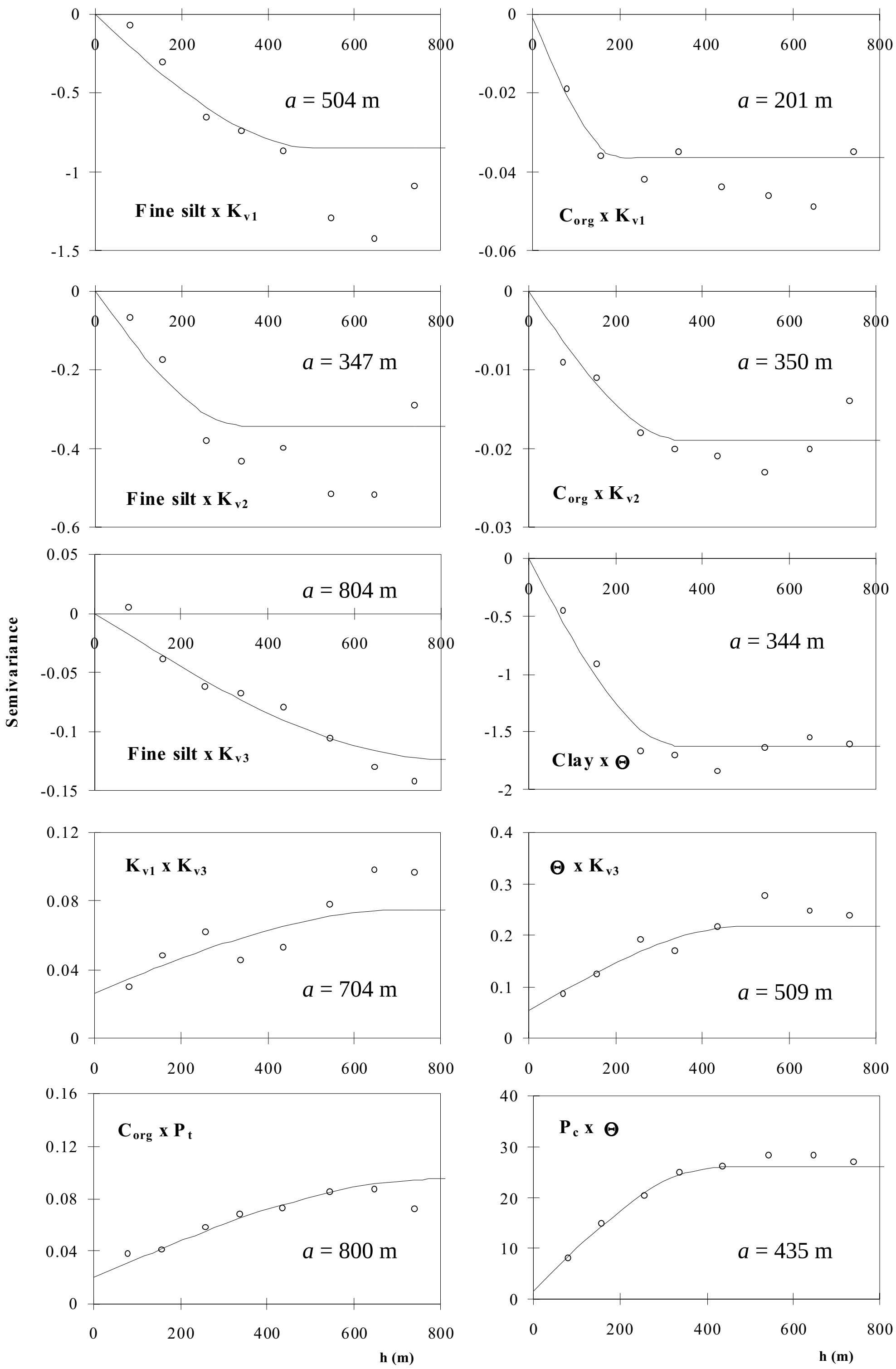

Figure 5. Cross-variograms of selected pairs of soil properties (spherical models with nuggets); variogram ranges (*a*) are shown

and other variables suggest the possibility of clustering and forming zones for site-specific management. Nevertheless, detailed analysis of the relationships between variables, as it was presented in this case study, is the first and necessary stage.

The data used in this study were obtained in the frame of the research plan No. MSM 412100005 of the Ministry of Education, Youth and Sports of the Czech Republic. The pedometrical part was supported by the grant No. 526/02/1516 of the Grant Agency of the Czech Republic.

Table 2. Structural and classical (in parentheses) correlation coefficients of the relationships between determined soil properties; dash is used where no spatial relationship was detected

Variable	Clay	Fine silt	pH	C_{org}	P_t	P_c	Θ	K_{v1}	K_{v2}	K_{v3}
Clay	1.000									
Fine silt	– (–0.038)	1.000								
pH	– (–0.089)	–0.466 (–0.290)	1.000							
C_{org}	– (0.052)	– (0.234)	–0.395 (–0.372)	1.000						
P_t	0.231 (0.150)	–0.119 (0.032)	0.416 (0.022)	0.424 (0.206)	1.000					
P_c	–0.231 (–0.137)	–0.294 (–0.274)	0.245 (0.133)	– (0.105)	0.774 (0.291)	1.000				
Θ	–0.237 (–0.143)	–0.343 (–0.308)	0.397 (0.199)	– (0.011)	0.856 (0.309)	0.998 (0.960)	1.000			
K_{v1}	–0.041 (0.043)	–0.417 (–0.335)	– (0.111)	–0.333 (–0.193)	–0.399 (–0.004)	0.211 (0.164)	0.219 (0.220)	1.000		
K_{v2}	– (–0.012)	–0.810 (–0.248)	– (0.023)	–0.846 (–0.161)	–0.758 (–0.027)	0.384 (0.121)	0.632 (0.181)	– (0.482)	1.000	
K_{v3}	– (–0.041)	–0.714 (–0.393)	0.315 (0.218)	–0.276 (–0.194)	0.182 (0.176)	0.184 (0.205)	0.245 (0.259)	0.250 (0.286)	0.356 (0.149)	1.000

REFERENCES

Amador J.A., Wang Y., Savin, M.C., Görres J.H. (2000): Fine-scale spatial variability of physical and biological soil properties in Kingston, Rhode Island. Geoderma, *98*: 83–94.

Bishop T.F.A., McBratney A.B. (2001): A comparison of prediction methods for the creation of field-extent soil property maps. Geoderma, *103*: 149–160.

Borůvka L., Valla M., Donátová H., Němeček K. (2002): Vulnerability of soil aggregates in relation to soil properties. Rostl. Výr., *48*: 329–334.

Bouma J. (1997): Precision agriculture: an introduction to spatial and temporal variability of environmental quality. In: Precision agriculture: spatial and temporal variability of environmental quality. Wiley, Chichester: 5–17.

Brodský L., Vaněk V., Száková J., Štípek K. (2001): Spatial heterogeneity of soil properties. Rostl. Výr., *47*: 521–528.

Cambardella C.A., Moorman T.B., Novak J.M., Parkin T.B., Karlen D.L., Turco R.F., Konopka A.E. (1994): Field-scale variability of soil properties in central Iowa soils. Soil Sci. Soc. Amer. J., *58*: 1501–1511.

Castrignano A., Giugliarini L., Risaliti R., Martinelli N. (2000a): Study of spatial relationships among some physico-chemical properties of a field in central Italy using multivariate geostatistics. Geoderma, *97*: 39–60.

Castrignano A., Goovaerts P., Lulli L., Bragato G. (2000b): A geostatistical approach to estimate probability of occurrence of *Tuber melanosporum* in relation to some soil properties. Geoderma, *98*: 95–113.

Goderya F.S. (1998): Field scale variations in soil properties for spatially variable control: a review. J. Soil Contam., *7*: 243–264.

Golden Software (1999): Surfer User's Guide. Golden Software Inc., Golden, Colorado.

Goovaerts P. (1992): Factorial kriging analysis: a useful tool for exploring the structure of multivariate spatial soil information. J. Soil Sci., *43*: 597–619.

Goovaerts P., Webster R. (1994): Scale-dependent correlation between topsoil copper and cobalt concentrations in Scotland. Eur. J. Soil Sci., *45*: 79–95.

Lark R.M. (2001): Some tools for parsimonious modelling and interpretation of within-field variation of soil and crop systems. Soil Till. Res., *58*: 99–111.

Manugistics (1997): Statgraphics Plus for Windows User Manual. Manugistics, Inc., Rockville, Maryland.

Rahman S., Munn L.C., Zhang R., Vance G.F. (1996): Rocky Mountain forest soils: Evaluating spatial variability using

conventional statistics and geostatistics. Can. J. Soil Sci., *76*: 501–507.
Robertson G.P. (2000): GS+: Geostatistics for the environmental sciences. Gamma Design Software, Plainwell, Michigan, USA.
Stafford J.V., Ambler B., Lark R.M., Catt J. (1996): Mapping and interpreting yield variation in cereal crops. Comput. Electron. Agric., *14*: 101–119.
Sylvester-Bradley R., Lord E., Sparkes R.K., Wiltshire J.J.J., Orson J. (1999): An analysis of the potential of precision farming in Northern Europe. Soil Use Mgmt, *15*: 1–8.
Webster R. (2000): Is soil variation random? Geoderma, *97*: 149–163.

Received on June 25, 2002

ABSTRAKT

Prostorové rozložení a korelace půdních vlastností pozemku: případová studie

Analýza prostorového rozložení a korelace půdních vlastností představují důležitý počáteční krok pro precizní zemědělství. Příspěvek předkládá analýzu prostorového rozložení a vzájemných korelací, klasických i prostorových, obsahu jílu a jemného prachu, pH, obsahu organického uhlíku (C_{org}), vlhkosti (Θ), celkové pórovitosti (P_t), kapilární pórovitosti (P_c) a koeficientů zranitelnosti agregátů prudkým zatopením (K_{v1}), pomalým ovlhčováním a vysoušením (K_{v2}) a mechanickými silami (K_{v3}) na zemědělském pozemku v Klučově. Byly zjištěny rozsahy variogramů od 206 m (jíl) do 1120 m (K_{v3}). Mnohé vztahy mezi půdními vlastnostmi byly dány prostorově. Jemný prach a C_{org} se ukázaly jako nejvýznamnější půdní vlastnosti ovlivňující všechny tři koeficienty zranitelnosti, což nebylo zřejmé ze samotné klasické korelace. Zjištěné prostorové korelace a podobnosti v prostorovém rozložení mohou sloužit jako základ k vymezení různých zón pro místně specifické hospodaření.

Klíčová slova: půdní heterogenita; prostorové rozložení; prostorová korelace; zranitelnost půdní struktury; precizní zemědělství

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