Soil depth prediction supported by primary terrain attributes: a comparison of methods

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ABSTRACT

The objective of this study was to investigate the benefits of methods that incorporate terrain attributes as covariates into the prediction of soil depth. Three primary terrain attributes – elevation, slope and aspect – were tested to improve the depth prediction from conventional soil survey dataset. Different methods were compared: 1) ordinary kriging (OK), 2) co-kriging (COK), 3) regression-kriging (REK), and 4) linear regression (RE). The evaluation of predicted results was based on comparison with real validation data. With respect to means, OK and COK provided the best prediction (both 110 cm), RE and REK gave the worst results, their means were significantly lower (79 and 108 cm, respectively) than the mean of real data (111 cm). *F*-test showed that COK with slope as covariate gave the best result with respect to variances. COK also reproduced best the range of values. The use of auxiliary terrain data improved the prediction of soil depth. However, the improvement was relatively small due to the low correlation of the primary variable with used terrain attributes.

Keywords: soil depth; geostatistics; terrain; ordinary kriging; co-kriging; regression-kriging

Geostatistics is a group of methods that has been widely used for prediction of variability of soil properties in last two decades (Utset et al. 2000). This technique provides prediction of soil properties at unobserved locations. However, all interpolation techniques, geostatistical or other, require a fairly dense network of sampling sites from which data are collected. The amount of the data is very often limited due to the cost of collecting soil attributes (Kalivas et al. 2002, Borůvka et al. 2003, Wu et al. 2003). Another limitation, when data from conventional soil survey are used, can be their availability and exploitability due to a specific density and distribution of sampling sites over the space. The sampling design, where the soil pits are not randomly distributed over the area, but subjectively selected by the surveyors, make data less applicable for geostatistical investigation. This issue is discussed in detail by Penížek and Borůvka (2004).

Improved estimation of soil properties can be achieved by incorporating secondary spatial information into prediction (Mueller and Pierce 2003). That terrain attributes (e.g. elevation, slope, aspect, curvature) may aid spatial estimation of soil properties, because the relief has a great influence on soil formation, as it was first stated by Jenny in 1941 (McBratney et al. 2003). The exploitation of terrain attributes as secondary information for the prediction of different soil properties is presented by many authors. For example Mueller and Pierce (2003) used slope, aspect, elevation and profile curvature for improving the prediction of soil carbon. Kalivas et al. (2002) used the distance from a river for estimating the content of sand and clay. Different terrain attributes for improvement of soil depth prediction were used for example by Gessler et al. (1995), Odeh et al. (1995), McKenzie and Ryan (1999), or Hengl et al. (2003). The incorporation of the auxiliary terrain information can be made by different techniques. The most often used are co-kriging and regression-kriging (Kalivas et al. 2002, McBratney et al. 2003, Mueller and Pierce 2003).

The objective of this study is to investigate benefits of the methods that incorporate the terrain

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attributes as covariates into the prediction of soil depth. Three primary terrain attributes – elevation, slope and aspect – were used to improve the prediction from a conventional soil survey dataset.

MATERIAL AND METHODS

Studied area. The district of Tábor that was chosen for this study is located in Southern Bohemia. Its total area is 1327 km^2, 59% of which is agricultural land. Altitude in the region ranges from 354 to 722 m. Geology of the area is formed by granites, syenites, gneisses, amphibolites, tertiary sediments, loesses, clays and alluvial sediments. Annual precipitation ranges from 560 to 660 mm, average temperature is 6.4 to 7.3°C. Cambisols represent prevailing soil unit (49.5%), the rest of the area is covered mainly by Luvisols (26.9%), Gleysols (17.2%), Stagnosols and Planosols (4.4%), and Fluvisols (1.8%). Small areas are covered by Regosols, Histosols and Lithosols.

Soil survey and terrain data. Data about the soil depth from 603 profiles of agricultural soils resulting from the Systematic Soil Survey from 1960's were used (Němeček et al. 1964). Data about terrain were obtained from the Fundamental Base of Geographic Data of the Czech Republic at the scale 1:10 000 (ZABAGED, LSO 2001). The altitude, slope and aspect were generated from contour lines (2 meters density) using Spatial Analyst ArcView 3.2 software (ESRI, Inc.). The angle of aspect was transformed by cosine mathematic function to distinguish northern and southern orientation of the slopes. These three properties were generated as a raster with 100 × 100 meter pixels and consequently assigned to the 603 profiles and to a regular squared grid with cell size 1 × 1 km (1325 points) (Figure 1).

Prediction methods. The data about soil profile depth and the terrain data were used in prediction of the soil depth on unobserved places by the following methods: 1) ordinary kriging (OK), 2) co-kriging (COK), 3) regression-kriging (REK), and 4) multiple linear regression (RE).

Ordinary kriging (OK)

Ordinary kriging is one of the most basic methods of kriging (Oliver and Webster 1991). It provides estimate at unobserved location of the variable Z, based on the weighted average of adjacent observed sites within a given area. The theory is derived from that of regionalized variables and

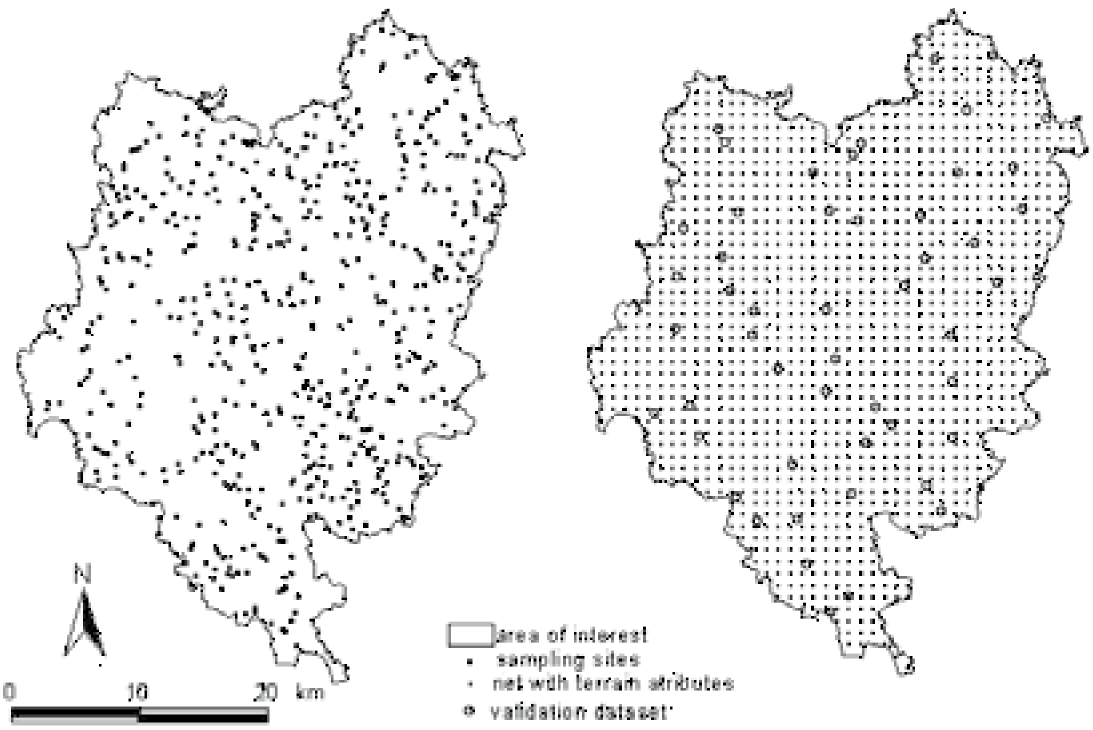

Figure 1. Area of interest: sampling sites (left), regular grids with cell size 1 × 1 km and validation dataset (right)

can be briefly described by considering an intrinsic random function denoted by $Z(s_i)$, where s_i represents all sample locations, $i = 1, ..., n$. An estimate of the weighted average given by the ordinary kriging predictor at an unsampled site $z(s_0)$ is defined by:

$$z(s_0) = \sum_{i=1}^{n} \lambda_i z(s_i) \quad (1)$$

where: λ_i are the weights assigned to each of the observed sample sites. These weights sum to unit so that the predictor provides an unbiased estimation:

$$\sum_{j=1}^{n} \lambda_i = 1 \quad (2)$$

The weights are calculated from the matrix equation:

$$c = \mathbf{A}^{-1}\mathbf{b} \quad (3)$$

where: $\mathbf{A}$ – a matrix of semivariances between the data points; $\mathbf{b}$ – a vector of estimated semivariances between the data points and the point at which the variable Z is to be predicted; and c stands for the resulting weights and the Lagrange Multipliers ψ (Triantafilis et al. 2001).

Co-kriging (COK)

Co-kriging is a geostatistical technique developed to improve the estimation of a variable using the information on other spatially correlated variables that are more densely sampled. This is very useful if the primary variable is difficult or expensive to measure and it is correlated with a more available covariate. The variables are called co-regionalized and they are spatially dependent. With one secondary variable, COK estimator for the primary variable is written:

$$z_1(s_0) = \sum_{i=1}^{n_1} \lambda_{z_1(s_i)} z_1(s_i) + \sum_{j=1}^{n_2} \lambda_{z_2(s_j)} z_2(s_j)$$

$$\sum_{i=1}^{n_1} \lambda_{z_1(s_i)} = 1 \quad \text{and} \quad \sum_{j=1}^{n_2} \lambda_{z_2(s_j)} = 0 \quad (4)$$

where: Z_1 is the primary variable and Z_2 is the secondary variable; $z_1(s_0)$ is the value of Z_1 to be estimated at location s_0; $\lambda_{Z1}(s_i)$ is the weight associated with the measured value of Z_1 at location s_i; $\lambda_{Z2}(s_j)$ is the weight associated with the measured value of Z_2 at location s_j; n_1 is the neighborhood of Z_1; and n_2 is the neighborhood of Z_2 used in estimation (Wu et al. 2003).

Regression-kriging (REK)

Regression kriging methods involve various combinations of linear regressions and kriging. The REK belongs to non-stationary geostatistical methods. It is a suitable technique for prediction of a primary variable when the auxiliary variables are available at all grid-nodes and correlated with the target variable (Hengl et al. 2003). The simplest model is based on normal regression followed by ordinary kriging with regression residuals. The prediction is based on separate prediction of drift and residuals and then adding them back together:

$$z(s_0) = m(s_0) + e(s_0)$$

$$z(s_0) = \sum_{k=0}^{p} \beta_k \cdot q_k(s_0) + \sum_{i=1}^{n} w_i(s_0) \cdot e(s_i) \quad q_0(s_0) = 1 \quad (5)$$

where: β_k are estimated drift model coefficients; w_i are weights determined by the semivariance function; e are the regression residuals; and $q_1(s_0)$ ... $q_2(s_0)$ are values of auxiliary variables at location s_0 (Hengl et al. 2003).

Regression

The general purpose of multiple regression is to find a relationship between several independent or predictor variables and a dependent or criterion variable. It is possible to construct a linear equation containing all those variables. In general, multiple regression procedures will estimate a linear equation of the form:

$$Z = b_0 + b_1 \cdot Q_1 + b_2 . Q_2 + ... + b_p \cdot Q_p \quad (6)$$

where: b_1, b_2, ..., b_p are the regression coefficients which represent the independent contributions of each independent variable (Q_1, Q_2, Q_3) to the prediction of the dependent variable (Z). The equation corresponds to the first part of equation (5):

$$z(s_0) = \sum_{k=0}^{p} \beta_k \cdot q_k(s_0) \qquad q_0(s_0) = 1$$

Spatial prediction. The spatial variation of the soil depth and terrain properties was described by semivariograms. The program used for interpolation was GS+ (Robertson 2000). The type of the theoretical model that fitted best the variogram was chosen by weighted least square method (Table 1).

Validation of models. Validation of the results was done by two comparisons. First, the sets of

Table 1. Characteristics of variograms

	Method*	Model	Nugget	Sill	Range (m)	r^2	RSS
DEPTH	OK	exponential	1.000	539.1	510	0.660	108929
SLOPE	OK	exponential	0.001	1.995	490	0.883	0.4
ALTITUDE	OK	linear	1.000	2112	6340	0.982	98908
ASPECT**	OK	exponential	0.001	0.499	490	0.798	0.1
RES_DEPTH***	REK	exponential	1.000	535	510	0.658	104647
D × SLOPE	COK	exponential	–0.010	–3.751	420	0.186	52
D × ASPECT	COK	exponential	0.000	–0.001	21100	0.246	20
D × ALTITUDE	COK	exponential	–0.010	–12.7	2870	0.102	22382

*OK – kriging, REK – regression-kriging, COK – co-kriging; **ASPECT = cos(aspect); ***variogram of regression residuals of soil profile depth

predicted values at the terrain regular grid were compared with the original set of data used for the prediction. Properties of these sets were evaluated by ANOVA multiple range test to compare the means, and F-test to compare the variance. Second, a group of 50 samples at locations other than those used for prediction of the soil depth by the models was compared. The validation set was chosen to cover the whole studied area and to describe all soil units at the studied area with regard to their proportion. Paired t-test was used to compare the values at individual locations.

RESULTS AND DISCUSSION

All models for terrain attributes showed a very small portion of nugget effect (Table 1). Slope and aspect were fitted by the exponential model with the same range of 490 meters. Altitude was described by a linear model and the range was not reached at the observed distance. Variogram describing the spatial variability of soil depth showed a similar range and proportion of the nugget variance as slope and aspect, which can indicate spatial dependence of these characteristics. The variogram of regression residuals of the depth (RES_DEPTH) used in REK analysis showed very similar results, which is not typical because the variogram of residuals has usually smaller range and sill (Hengl et al. 2003). Cross-variograms that characterize the spatial relationship of the soil depth and the terrain properties were calculated for COK analysis. Only the range for cross-variogram of soil depth and slope (D × SLOPE) showed similar value as the individual semivariograms, which indicates spatial correlation of these properties, and therefore it was used for the prediction. An overview of all variograms and cross-variograms is presented in Table 1. The prediction by multiple regression equation used for prediction in RE and REK was calculated as follows:

$$\text{DEPTH} = 88.8 + 1.020 \times \text{ASPECT} + 0.0573 \times \text{ALTITUDE} - 2.491 \times \text{SLOPE}$$

Even though the P-value of 0.0009 indicates a statistically significant relationship, only 3% of

Table 2. Summary statistics of source dataset and results of performed methods for the whole dataset

	Count	Mean (cm)	Variance	Min. (cm)	Max. (cm)	Range (cm)
DEPTH	553	111	594.0	40	160	120
OK	1325	110	142.4	70	144	74
COK	1325	110	245.2	60	153	93
REK	1325	79	169.7	40	124	84
RE	1325	108	41.5	55	127	72

Table 3. ANOVA Multiple range tests for comparison of means of performed methods with source dataset (method 95% LSD)

	Count	Mean (cm)	Homogeneous group		
DEPTH	553	111.0			X
OK	1325	110.0			X
COK	1325	110.3			X
REK	1325	79.0	X		
RE	1325	108.4		X	

Table 4. F-ratios of variance of results for comparison of performed methods with source dataset

	Variance	Df	F-ratio		P-value
DEPTH	594.0	553			
OK	142.4	1325	4.582	*	< 0.001
COK	245.2	1325	2.662	*	< 0.001
REK	169.7	1325	3.702	*	< 0.001
RE	41.5	1325	14.314	*	< 0.001

*significant difference at 95% confidence interval

the variability of the DEPTH was explained by this model (R^2 = 2.94%).

The first evaluation of predicted results by ordinary kriging (OK), co-kriging (COK), regression kriging (REK) and regression (RE) is based on comparison of mean, variance and range of values for the four prediction methods and the real data (Table 2). This comparison shows how well the parameters of the original dataset are reconstructed in the predicted datasets. With respect to means the OK and COK provided the best prediction, because the ANOVA multiple range test placed them to the same class as the original dataset (Table 3). RE and REK gave the worst results, theirs means were statistically significantly lower in both cases (Table 3). The variances analyzed by F-test show statistically significant differences between the results of prediction methods and the original dataset (Table 4). It indicates flattening in the prediction and diminishing of the local extremes. Even though, COK provides the best result. Third evaluating aspect was the range that indicates flattening of the prediction as well as of the variance. The results confirm the previous statement based on the evaluation of variance. The lowest flattening was obtained by COK (Table 2). OK, RE and REK provided worst results. The decrease of the range in OK corresponds to the results presented by Wu et al. (2003). Such a poor success of prediction by REK and RE was caused by weak relationship between the soil depth and used terrain attributes. Another possible reason why REK failed in prediction can be the fact that if areas of very steep slopes are overlooked during the sampling, in the prediction by REK they will appear as extreme biased values. This does not need to be evident in a shift (increase or decrease) of the mean, if these areas have not a large extent, but it is evident in an increase of range of the predicted values. It might be the case of this study, because the input dataset originated only from agricultural land, while the steepest areas are usually covered by forests; it shifts the predicted mean to a lower value (the relationship between slope and soil depth is inverse). This hypothesis is supported by the fact that the minimum value from REK is the lowest among the prediction methods.

Table 5 presents how precise is the prediction on individual sites. This evaluation is done by paired t-test that is focused on comparisons of predicted and real values at 50 validation sites.

Table 5. Summary statistics and t-test of paired differences between predicted values and validation dataset

	Count	Mean (cm)	Variance	Min. (cm)	Max. (cm)	Range (cm)	t-value	P-value
DEPTH	50	112	592.2	50	150	100		
OK	50	110	160.7	86	136	50	0.527	0.601
COK	50	108	236.0	67	140	73	1.073	0.289
REK	50	79	155.1	52	106	54	7.684	< 0.001*
RE	50	109	9.7	103	116	13	0.793	0.431

*significant difference at 95% confidence interval

The worst result was provided, as in the previous comparison, by REK. It is caused by high regression residuals used for kriging that are a result of weak correlation between the soil depth and used terrain covariates (Triantafilis et al. 2001). The other methods (OK, COK and RE) provided good estimation with similar results according to the *t*-test. The reason why COK did not provide significantly better results than OK can be the location of validation dataset close to the input data, while the improvement by covariates is expressed on larger distances (Wu et al. 2003). The values predicted by RE, thought not statistically different from the observed data, were in a very narrow range compared not only to the real data but also to the other prediction methods.

Generally, RE gave the worst results in prediction over the space, because no spatial correlation was taken into account. REK failed in prediction as well. One reason can be a very low correlation of soil depth and primary terrain attributes, which is apparent in this case. This result corresponds to the conclusions of Kalivas et al. (2002) and Mueller and Pierce (2003) that REK does not provide better results than COK when correlation coefficients are low. For that reason it is important to know the strength of the relationship between the target variables and the auxiliary ones (Kalivas et al. 2002). The absence or presence of a spatial structure of the regression residuals of the relation is also important for choosing among interpolation methods using auxiliary variables (Kalivas et al. 2002). Another reason can be overlooking of areas with very steep slopes during the sampling; they will appear as underestimated values in the prediction by REK. COK with slope as covariate gave slightly better results of prediction over the space than other methods.

The use of auxiliary terrain data slightly improved the prediction of soil depth. The best results were obtained using co-kriging method with slope as covariate. In prediction on validation individual sites it succeeded similarly as OK and RE. Moreover, it reproduced best the parameters of the original dataset, compared to the other three methods. The methods based on regression performed the worst. Regression-kriging reproduced better the variation in the dataset, compared to regression alone. The reason why the improvement of the prediction was not more significant is a relatively low correlation of the predicted soil property with used terrain attributes. Further research should focus on three problems: 1) how much the size of the pixel, from which the terrain parameters were generated, influences the correlation, 2) the extent of deformation of prediction given by used sampling scheme (density of sampling, non-sampled areas), and 3) exploitation of other terrain attributes (e.g. profile curvature, flow path length, topographic wetness indices) for soil depth prediction, that may be more spatially correlated.

REFERENCES

Borůvka L., Kozák J., Němeček J., Penížek V. (2003): New approaches to the exploitation of former soil survey data. Pap. No. 1692. 17th World Congr. Soil Sci., Bangkok.

Gessler P.E., Moore I.D., McKenzie N.J., Ryan P.J. (1995): Soil-landscape modeling and spatial prediction of soil attributes. Int. J. Geogr. Inf. Sci., *9*: 421–432.

Hengl T., Heuvelink G.B.M., Stein A. (2003): Comparison of kriging with external drift and regression-kriging. Technical note, ITC. <http://www.itc.nl/library/Academic_output/> [cit. 2004-11-10].

Kalivas D.P., Triantakonstantis D.P., Kollias V.J. (2002): Spatial prediction of two soil properties using topographic information. Global Nest: Int. J., *4*: 41–49.

LSO (2001): Fundamental Base of Geographic Data of the Czech Republic (ZABAGED). Land Survey Office, Czech Republic.

McBratney A.B., Mendonca Santos M.L., Minasny B. (2003): On digital soil mapping. Geoderma, *117*: 3–52.

McKenzie N.J., Ryan P.J. (1999): Spatial prediction of soil properties using environmental correlation. Geoderma, *89*: 67–94.

Mueller T.G., Pierce F.J. (2003): Soil carbon maps: Enhancing spatial estimates with simple terrain attributes at multiple scales. Soil Sci. Soc. Am. J., *67*: 258–267.

Němeček J., Mašát K., Kalenda M. (1964): Report of Soil Survey of Agricultural Lands in the district of Tábor. MZV, Praha. (In Czech)

Odeh I.O.A., McBratney A.B., Chittleborough D.J. (1995): Further results on prediction of soil properties from terrain attributes: heterotropic cokriging and regression-kriging. Geoderma, *67*: 215–225.

Oliver M.A., Webster R. (1991): How geostatistics can help you. Soil Use Manage., *7*: 206–217.

Penížek V., Borůvka L. (2004): Processing of conventional soil survey data using geostatistical methods. Plant Soil Environ., *50*: 352–357.

Robertson G.P. (2000): GS+: Geostatistics for the Environmental Sciences. Gamma Design Software, Plainwell, Michigan, USA.

Triantafilis J., Odeh I.O.A., McBratney A.B. (2001): Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. Soil Sci. Soc. Am. J., *65*: 869–878.
Utset A., López T., Díaz M. (2000): A comparison of soil maps, kriging and combined method for spatially predicting bulk density and field capacity of ferralsols in the Havana-Matanzas Plain. Geoderma, *96*: 199–213.
Wu J., Norvell W.A., Hopkins D.G., Smith D.B., Ulmer M.G., Welch R.M. (2003): Improved prediction and mapping of soil copper by kriging with auxiliary data for cation-exchange capacity. Soil Sci. Soc. Am. J., *67*: 919–927.

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