Digital Soil Mapping from Conventional Field Soil Observations

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Abstract

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We tested the performance of a formalized digital soil mapping (DSM) approach comprising fuzzy *k*-means (FKM) classification and regression-kriging to produce soil type maps from a fine-scale soil observation network in Rišňovce, Slovakia. We examine whether the soil profile descriptions collected merely by field methods fit into the statistical DSM tools and if they provide pedologically meaningful results for an erosion-affected area. Soil texture, colour, carbonates, stoniness and genetic qualifiers were estimated for a total of 111 soil profiles using conventional field methods. The data were digitized along semi-quantitative scales in 10-cm depth intervals to express the relative differences, and afterwards classified by the FKM method into four classes A–D: (*i*) Luvic Phaeozems (Anthric), (*ii*) Haplic Phaeozems (Anthric, Calcaric, Pachic), (*iii*) Calcic Cutanic Luvisols, and (*iv*) Haplic Regosols (Calcaric). To parameterize regression-kriging, membership values (MVs) to the above A–D class centroids were regressed against PCA-transformed terrain variables using the multiple linear regression method (MLR). MLR yielded significant relationships with R^2 ranging from 23% to 47% ($P < 0.001$) for classes A, B and D, but only marginally significant for Luvisols of class C (R^2 = 14%, $P < 0.05$). Given the results, Luvisols were then mapped by ordinary kriging and the rest by regression-kriging. A "leave-one-out" cross-validation was calculated for the output maps yielding R^2 of 33%, 56%, 22% and 42% for Luvic Phaeozems, Haplic Phaeozems, Luvisols and also Regosols, respectively (all $P < 0.001$). Additionally, the pixel-mixture visualization technique was used to draw a synthetic digital soil map. We conclude that the DSM model represents a fully formalized alternative to classical soil mapping at very fine scales, even when soil profile descriptions were collected merely by field estimation methods. Additionally to conventional soil maps it allows to address the diffuse character in soil cover, both in taxonomic and geographical interpretations.

Keywords: field soil description; fuzzy *k*-means; pedometrics; regression-kriging; terrain

Digital soil mapping (DSM) has become popular for producing maps of soil classes and properties from spatially explicit soil inventories and from auxiliary landscape data (McBratney *et al.* 2003), bridging gaps between discrete soil maps and the continuous nature of soil cover (Burrough *et* *al.* 1997). DSM integrates many statistical and geo-information tools and concepts, including supervised and unsupervised classifications (De Gruijter & McBratney 1988; Burrough *et al.* 1997; Carré & Girard 2002; Hengl *et al.* 2004b; Lagacherie 2005; Zádorová *et al.* 2011), geostatistics (Webster & Oliver 2007), environmental correlations and *scorpan*-based models (McKenzie & Ryan 1999; McBratney *et al.* 2003). A thorough review of DSM methods and their applications in soil science was published by McBratney *et al.* (2003).

The DSM techniques can represent a formalized alternative to the conventional soil mapping, where both the soil classification and mapping are handled numerically. The soil profiles are classified in terms of taxonomic distance or membership to centroids of soil classes, enabling more soil variables to be addressed simultaneously (McBratney & De Gruijter 1992; Zhu *et al.* 2001; Carré & Girard 2002). The fuzzy *k*-means method (FKM, Bezdek *et al.* 1984) has recently become especially popular for classification purposes as it enables to represent a continuous character and uncertainty in mapped soils. Once classified, the soil profile partitions are then interpolated into membership maps, which are used instead of conventional soil maps. Increased availability of remote sensing and GIS data has promoted the regression-kriging method (Odeh *et al.* 1994, 1995) as a generic interpolation tool for the mapping purposes (Hengl *et al.* 2004b). That is the reason why we chose regression-kriging and FKM as major components in our DSM model. Some authors emphasize co-kriging as a superior method for mapping undersampled soil properties when auxiliary covariates are available (Kalivas *et al.* 2002; Penížek & Borůvka 2006). However, this method is more cumbersome and yields only a small benefit when soil and auxiliary variables are weakly correlated (Ahmed & De Marsily 1987).

Soil profile surveys have always been the basic strategy for soil type mapping regardless of whether or not the maps were produced with the use of DSM. Although a lot of attention has been paid to coupling of DSM with various soil information systems (McBratney *et al.* 2003), only few applications used soil profile descriptions gathered solely by empirical field observation methods (e.g. Carré & Girard 2002). This approach involves several implications compared to measured analytical data. Firstly, the horizon properties are usually described using various qualitative or semi-quantitative scales (e.g. Schoeneberger *et al.* 2002), where the continuous soil variables are ranked along discrete empirical categories. This ranking may negatively affect numerical classification if the attribute space is not correctly designed. Secondly, the resultant numerical partition may not be fuzzy enough to provide meaningful soil-terrain relationships.

In this article we add to the above context by testing the performance of a simple DSM approach to produce soil type maps from a network of common field profile descriptions from the study area in Rišňovce, Slovakia. We also examine whether the standard morphological descriptions comprising the qualitative and semi-quantitative horizon properties collected in the field fit adequately into the statistical DSM tools. Additionally, we evaluate if this approach provides pedologically meaningful outputs for very fine scales in erosion-affected landscape – both in taxonomical and geographical interpretations.

MATERIAL AND METHODS

Model description. The presented DSM model (Figure 1) integrates (*i*) digitizing of soil profile properties, (*ii*) unsupervised FKM classification of soil profiles, (*iii*) auxiliary terrain data preparation, and (*iv*) kriging of soil membership maps.

As concluded by Burrough *et al.* (1997) and De Gruijter *et al.* (1997), the FKM classification can produce meaningful soil typological results. It partitions soil profiles into the given *k* classes, where profile properties in the class centre are represented by centroids. The centroid membership values MV(m_{ij}) follow the criteria given by Eq. (1):

$$\left\{m_{ij} \in [0.1]; \sum_{j=1}^{k} m_{ij} = 1, i = 1,...,n; \sum_{i=1}^{n} m_{ij} > 0, j = 1,...,k\right\} \quad (1)$$

where:

n – total number of profiles

k – number of classes

Several authors have suggested hybrid interpolations combining kriging and linear regression with terrain variables as powerful methods for mapping soil classes when soil distribution was closely correlated with terrain (e.g. Odeh *et al.* 1994, 1995; Goovaerts 1999; Hengl *et al.* 2004a). Among the hybrid interpolation techniques, regression-kriging (Odeh *et al.* 1994, 1995) was identified as the most superior method by Knotters *et al.* (1995) and Bourennane *et al.* (2000). It couples Multiple Linear Regression (MLR) with kriging, as given by Eq. (2):

$$\hat{m}_j(s_0) = \sum_{l=1}^{p} \beta_1 \times q_l(s_0) + \sum_{i=1}^{n} w_i(s_0) \times \varepsilon_j(s_i) \quad (2)$$

where:
$\hat{m}_j(s_0)$ – MV of class j at a non-sampled location s_0
$q_l(s_0)$ – l-*th* predictor at location s_0
β_l – parameter of predictor l in MLR
p – number of predictors used for soil class j
$\varepsilon_j(s_i)$ – MLR residual at a sampled location s_i
w_i – weight of the kriging operator

The weights, w_i, depend on the distances between the observations and the predicted location s_0 and spatial relationships between sampled data around the predicted location. While geographic distances are here determined by X and Y coordinates as Euclidean distance, spatial relationships are described by the experimental semivariogram from values of Eq. (3) as stated in Burgess & Webster (1980):

$$\hat{\gamma}(h) = \frac{1}{2d(h)} \sum_{i=1}^{d} \left[\varepsilon(s_i) - \varepsilon(s_i + h)\right]^2 \quad (3)$$

where:
$\hat{\gamma}(h)$ – semivariance
h – separation lag-distance between locations s_i and s_{i+h}
$\varepsilon(s_i)$, $\varepsilon(s_{i+h})$ – MLR residuals at locations s_i and s_{i+h}
$d(h)$ – number of pairs at any separation distance h

The semivariogram is a quantitative measure of how the semivariance between the sampled points is reduced as separation distance decreases, and it can be modelled by some of the authorised semivariogram equations (cf. Webster & Oliver 2007). The weighting factors of Eq. (2) are estimated by solving the kriging equations (Burgess & Webster 1980). Regression-kriging is a powerful method when the correlation between soil and terrain variables is high and the MLR residuals are spatially correlated (cf. Hengl *et al.* 2004a). When MVs do not yield any significant linear relationship with terrain predictors, the regression-kriging interpolation can then be

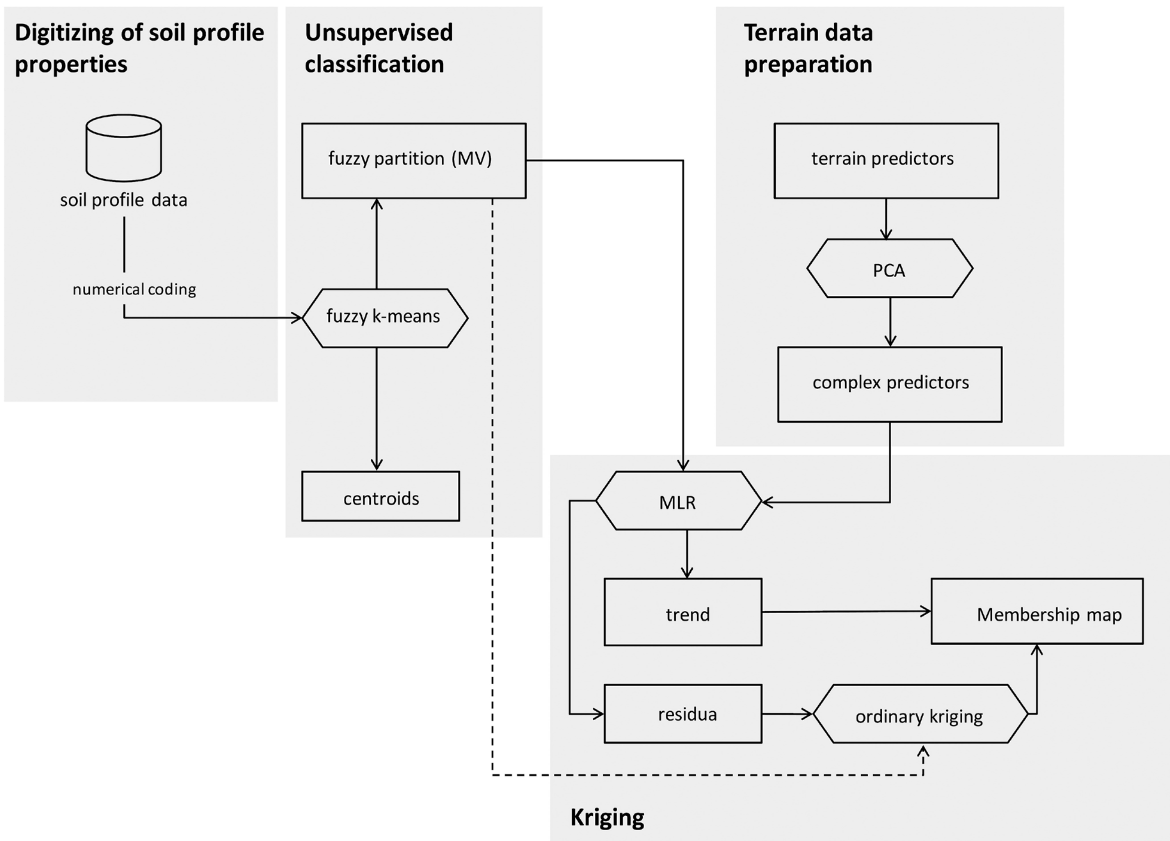


Figure 1. Scheme of the digital soil mapping algorithm, including the fuzzy *k*-mean classification of soil profiles, PCA transformation of terrain predictors and regression-kriging of soil membership maps

replaced by ordinary kriging by omitting the MLR component from Eq. (2).

The transformation of terrain predictors by Principal Component Analysis (PCA) was suggested by Hengl *et al*. (2004a) to reduce multicollinearity in MLR. Therefore the Principal Components (PCs) are here considered as complex terrain variables which are uncorrelated and standardised and can therefore be used instead of the original terrain predictors (e.g. Gobin *et al.* 2001; Hengl *et al*. 2004a).

Study area and soil sampling. The study area covers approximately 37 ha of arable land in the cadastral area of Rišňovce in Slovakia (Figure 2). The soils here are mainly Haplic Phaeozems (Anthric, Calcaric), Luvic Phaeozems (Anthric), Calcic, Cutanic Luvisols and Haplic Regosols (Calcaric), which are significantly affected by erosion.

The soil cover was studied using a grid sampling layout composed of parallel downslope transects, trying to ensure that all soil elements are represented in the grid (Figure 2). The between-sample distances in transects were slightly shorter than distances between transects: the inter-sample distance was 70 m on average. A total of 111 soil profiles were sampled using the hand auger equipment. This study was performed by the same researchers to minimize the inter-observer variability. The following profile properties were estimated using the field handbook by Schoeneberger *et al*. (2002): (*i*) horizon nomenclature, comprising master horizons and other modifiers, and horizon thickness (in cm), (*ii*) soil matrix colour in the moist state using the Munsell notation, (*iii*) texture class by the field hand test, (*iv*) carbonates by the effervescence field test, and (*v*) stoniness in vol. %. All genetic horizons were sampled up to a maximum of 100 cm depth.

Digitizing of soil profile properties. The soil horizon data were digitized using the following rules: (*i*) Munsell colours were converted into the CIELab coordinates (COLX, COLY, and COLZ) using the method published by Melville and Atkinson (1985), (*ii*) soil texture estimates were converted into central sand and clay contents (SAND, CLAY in %) of the respective texture classes of the USDA triangle, (*iii*) carbonate estimates (CARB) were placed along a 1 to 5 ordinal scale; the numbers stand for non-effervescent, very slightly effervescent, slightly effervescent, strongly effervescent, and violently effervescent soils, (*iv*) stoniness remained in the percentage (SKEL), and (*v*) soil horizons were rated by the intensity of illuvial silica clay accumulation (LUV) and mollic properties (MOL), which are two main processes in the studied soils, using the following ordinals: 1 – not applicable; here the layer does not constitute a part of either A or B horizon, 2 – weak; here the layer constitutes a part of A or

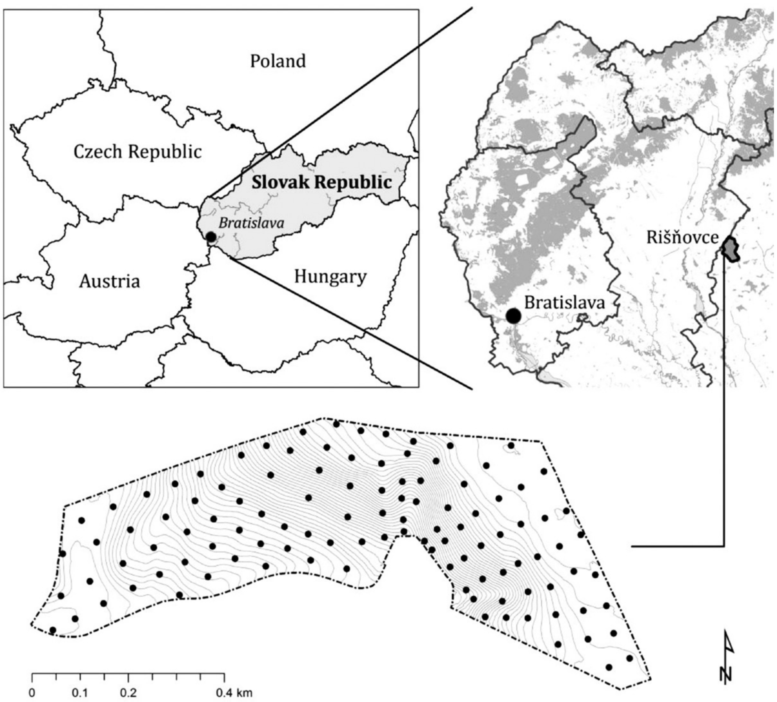


Figure 2. Sketch map of the study area (Rišňovce, Slovakia) and location of soil profiles of the experiment

B horizon, but the horizon does not meet all the criteria for mollic Am or luvic Bt horizon, and 3 – intense; here the layer constitutes a part of the Am or Bt horizon. The above variables were digitized by 10-cm depth intervals to gather the vertical profile stratification. The soil variables were distinguished by a depth interval and a property name: e.g. 10_SAND stands for sand content in the 0–10 cm layer. As a result, 89 variables were constructed for each soil profile (luvic properties were omitted for the topmost soil layers). The above digitizing avoids too many zero values in the input data, which could cause deviations in the FKM classification.

Auxiliary terrain variables. The digital elevation model (DEM) was constructed in 5-m resolution from detailed altimetry measurements using the RBF technique in Geostatistical Analyst for ArcGIS software (Johnston *et al*. 2001). The altimetry data were measured by Leica ATX900 GG GNSS receiver with real-time correction for sub-cm precise positioning provided by the Slovak Space Observing Service. The DEM resolution reflects both positional accuracy and density of measurements. The following terrain variables were calculated from DEM: (*i*) slope steepness in degrees (SLP), (*ii*) planar and profile curvature (PLANCURV, PROFCURV; cf. Moore *et al*. 1991), (*iii*) overland flow accumulation in metres calculated from filled DEM (FLW, 3 × 3 kernel, cf. Maidment 2002), and (*iv*) topographic wetness index (TWI, cf. Wilson & Gallant 2000). Detailed information concerning the above terrain variables is presented in Table 1.

PCA was calculated for the terrain variables in STATISTICA software (StatSoft Inc. 2003), thus aiming to reduce collinearity and to extract composite terrain gradients as mapping predictors. FLW and SLP variables were log-transformed prior to PCA. Hereafter, the PCA factor coordinates of cases for PC1–6 were considered as DSM predictors (cf. Hengl *et al*. 2004a).

Fuzzy k-means classification. The FKM classification was calculated in FuzME software (Minasny & McBratney 2002) using diagonal distance, number of classes $k = 4$, and fuzziness coefficient $\phi = 1.5$. The fuzziness coefficient was optimized as suggested by McBratney and Moore (1985). The number of classes respects the number of soil typological units recognised in the study area during the soil survey. Centroids were interpreted according to WRB nomenclature (FAO-ISRIC-ISSS 2006).

In addition, PCA and Detrended Correspondence Analysis (DCA) were calculated for soil profile data in STATISTICA and CANOCO (ter Braak & Šmilauer 2002) software to explore inner variability in the profile data matrix.

Kriging interpolation. The fuzzy MVs were interpolated using the regression-kriging Eq. (2). However, ordinary kriging (Burgess & Webster 1980) was used when no significant linear relationships were observed between MVs and terrain predictors. Parameterization of regression-kriging included (*i*) MLR analysis between MVs and PC1–6 terrain predictors at sampled locations independently for each soil centroid; where β coefficients and ε residuals were calculated, and (*ii*) semivariance analysis and semivariogram model estimation with the ε residuals. We used 5 × 5 neighbourhood averaging for PC1-6 rasters in order to obtain "balanced" predictor values at the sampled locations, and a conventional semivariogram analysis was performed with MVs when ordinary kriging was used. Kriging weighting factors for both ordinary and regression kriging were estimated by solving the kriging equations. All the analyses were calculated in R programme (www.R-project.org) using the following choices: Ordinary Least Squares (OLS) for MLR and punc-

Table 1. Descriptive statistics of terrain variables

	Mean	Median	Min.	Max.	SD	Skewness	Kurtosis
DEM (m)	195	198	160	223	21.5	–0.18	–1.47
SLP (°)	5.02	4.47	0.13	15.03	3.39	0.46	–0.73
PLANCURV (m^{-1})	–0.0005	0.0073	–1.664	0.785	0.171	–1.37	8.15
PROFCURV (m^{-1})	–0.0010	–0.0106	–1.081	2.277	0.183	2.08	18.06
FLW (m)	18.7	8.0	0.0	100	27.1	2.10	3.42
TWI	6.44	6.38	4.24	10.14	0.96	0.37	0.01

SD – standard deviation

tual technique for kriging. The exponential model of Eq. (4) was used to calculate the semivariogram (Webster & Oliver 2007):

$$\gamma(h) = c_0 + c_1\left(1 - \exp(-3|h|/r)\right) \qquad (4)$$

where:

c_0 – error (nugget) variance

c_1 – so-called "partial sill" variance

r – "lag" distance

The DSM algorithms were run over PC1-6 terrain predictors independently for each soil type to render the membership maps with 5m cell resolution. Given the averaging-to-the-mean effects of interpolation, the assumption of composite variables given by Eq. (1) was violated in the output MV maps. This error was corrected by the equalizing variance transformation with respect to the original MV matrix, and each voxel of the transformed MV rasters was afterwards rescaled so that the sum of its MVs was equal to one.

A cross-validation "leave-one-out" approach was used to validate the DSM model. It uses a loop function over observation data leaving a profile out of the mapping analysis when a prediction is calculated for that particular profile. Pearson's correlation coefficients (r) and the linear regression model with R^2 and F-test P values were used to test the significance of such predictions.

We used the pixel-mixture technique (De Gruijter *et al.* 1997) to visualize the soil type distribution using the algorithm published for R programme at http://spatial-analyst.net/wiki/index.php?title=Uncertainty_visualization.

RESULTS AND DISCUSSION

Fuzzy k-means classification

The ordinations of soil profiles (n = 111) and their properties (m = 89) in attribute space were analysed using PCA (Figure 3). An attribute space of linear ordinations is appropriately configured when profile attributes are linearly related to principal components. We examined this assumption by DCA as introduced by ter Braak and Šmilauer (2002), who suggested the maximum length of gradient expressed in SD of the attribute turnover along the ordination axis to be a measure of data heterogeneity. Given this measure, an input data matrix is suitable for linear ordinations when the DCA gradient length is less than 4 SD. The value of 0.95 SD in our analysis indicates that the input matrix is properly shaped for both PCA and FKM analyses. Additionally, we do not expect any severe deviations in PCA and FKM calculations caused by too many zero values in the input matrix since this was avoided with data digitizing.

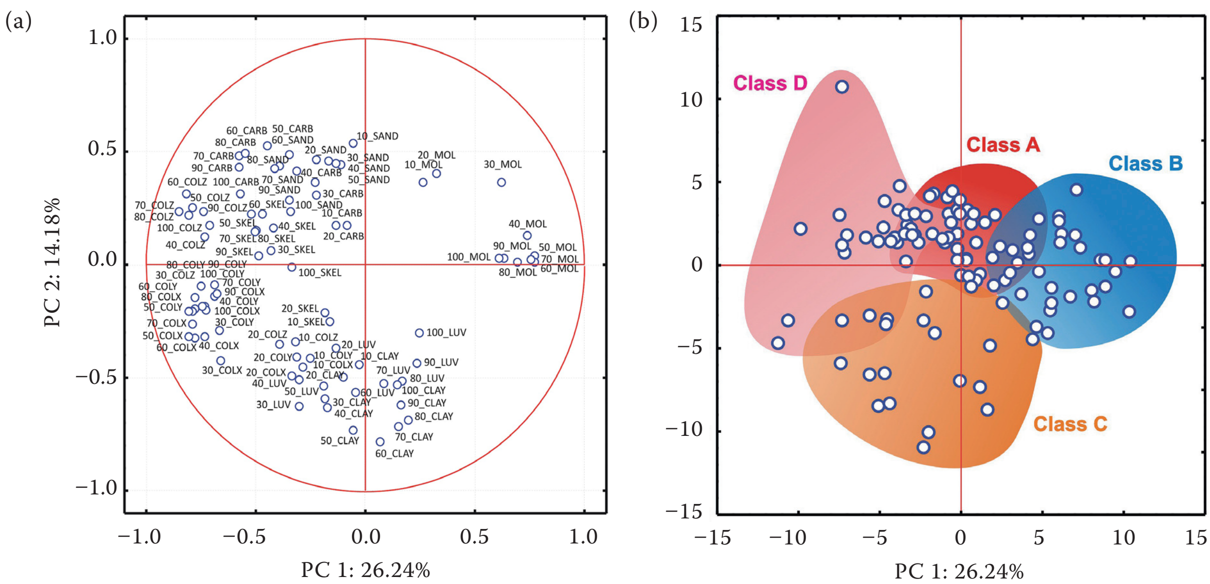


Figure 3. Principal Component Analysis (PCA) scatter plot of the soil profile data projected at the first two principal components (40.4% of the total eigenvalue): (a) factor coordinates of attributes, and (b) factor coordinates of profiles; shaded areas outline where the fuzzy *k*-means (FKM) class maxima are plotted; PCA analysis was based on correlation; notation of soil variables: "Depth_property"

Following the resultant ordination in the PC1-2 quadrate (Figure 3) we judge that semi-quantitative and ordinal profile data demonstrate quite a continuous ordination pattern which conditions proper FKM classification. Shaded areas in Figure 3b outline profiles which have their MV maxima in the particular FKM classes. It is quite clear that profiles with their MV maxima in class A constitute the most homogeneous sample, whereas the other classes, and especially classes C and D, are internally more heterogeneous.

The FKM analysis yields four class centroids (A–D), which were interpreted as Luvic Phaeozems (Anthric), Haplic Phaeozems (Anthric, Cal-

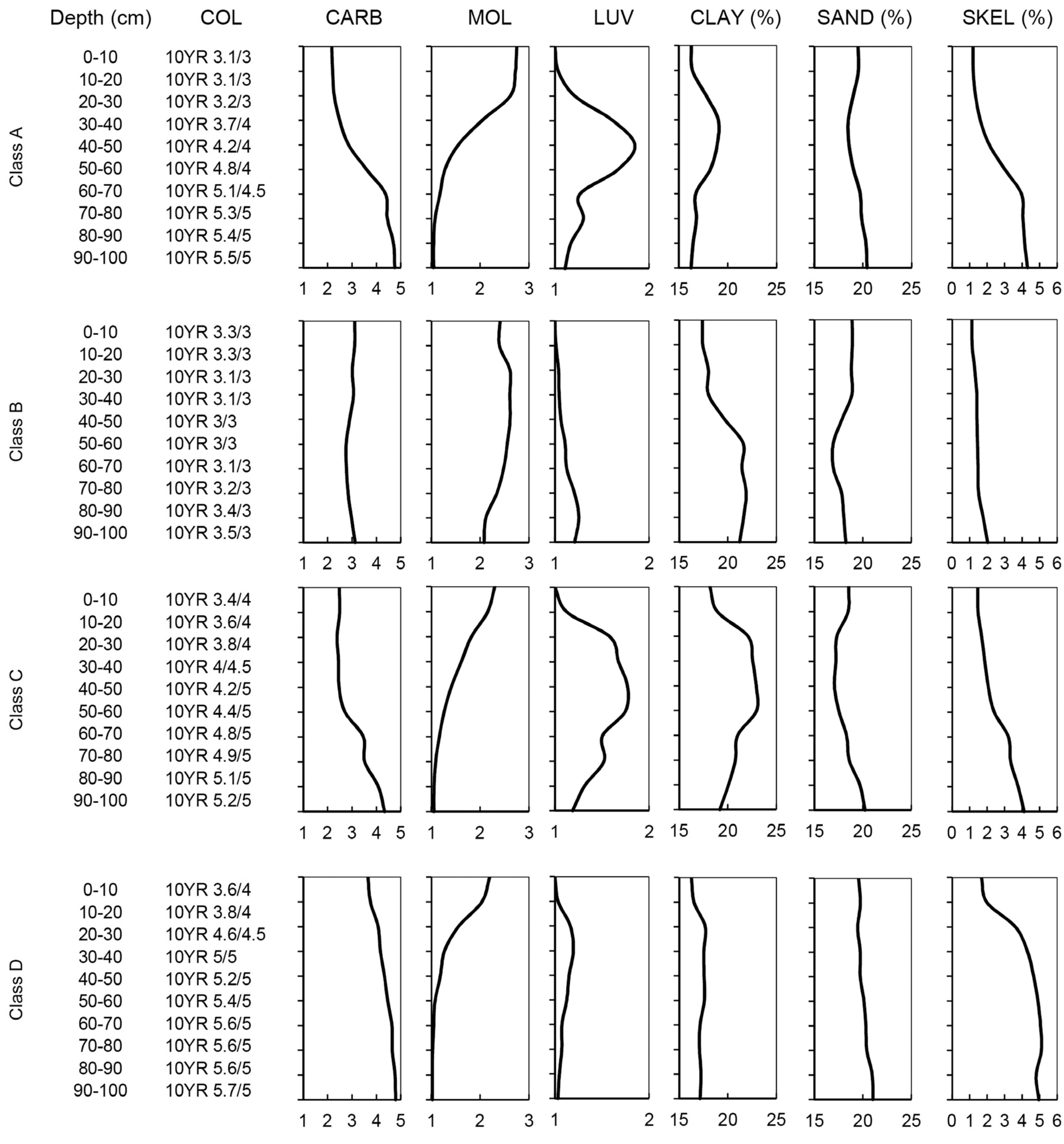


Figure 4. Class centroid details; carbonate content (CARB): 1 – non-effervescent, 2 – very slightly effervescent, 3 – slightly effervescent, 4 – strongly effervescent, 5 – violently effervescent; mollic horizon features (MOL): 1 – without, 2 – weak (A, not Am), 3 – intense (Am); luvic horizon features (LUV): 1 – without, 2 – weak (B(t), not Bt), 3 – intense (Bt); clay content estimate from textural class (CLAY) in %; sand content estimate from textural class (SAND) in %; stoniness estimate (SKEL) in %

Table 2. Principal Component Analysis (PCA) outputs; correlation coefficients between PC1–6 and the original terrain variables

	Transf.	PC1	PC2	PC3	PC4	PC5	PC6
DEM (m)	no	–0.22	0.41	–0.75	–0.34	0.32	–0.03
FLW (m)	log	0.50	–0.53	–0.42	0.45	0.27	0.12
PLANCURV (m^{-1})	no	–0.69	0.19	0.36	0.36	0.47	–0.07
PROFCURV (m^{-1})	no	0.56	–0.34	0.43	–0.47	0.40	0.00
SLP (°)	log	–0.38	–0.87	–0.20	–0.06	–0.06	–0.22
TWI	no	0.85	0.41	–0.03	0.22	0.02	–0.24
Eigenvalue		1.960	1.523	1.095	0.724	0.568	0.131
Total eigenvalue (%)		32.7	25.4	18.2	12.1	9.5	2.1

caric, Pachic), Calcic Cutanic Luvisols, and Haplic Regosols (Calcaric), respectively. Additional information needed to support the classification was provided by the Soil Science and Conservation Research Institute in Bratislava, Slovakia, from auxiliary data sources. Vertical distributions of the studied profile properties in particular centroids are illustrated in Figure 4. Whereas class A and C centroids represent more or less climax soils, the class B centroid depicts colluvic soils with topsoil material accumulated via tillage-induced erosion, and the class D centroid comprises strongly eroded soils with only shallow remnants of mollic and luvic horizons. Apparently, the soil erosion and accumulation are fundamental forces affecting the taxonomical variety of soils in this study area.

The MVs contain a significant portion of fuzziness and the overall confusion index (Burrough *et al.* 1997) averaged 0.62. When aggregated by class maxima, the average confusion index values were 0.66, 0.47, 0.79 and 0.62 for A to D classes, respectively. The highest confusion was calculated for Luvisols, which represent a minority soil type in the study area since only 14 out of 111 soil profiles were classified as Luvisols during the field survey. In contrast, Phaeozems of class B are clearly determined by its centroid as they show the lowest confusion index.

Composite terrain gradients

To a certain extent, the terrain gradients were collinear since they were all derived from DEM. In particular, DEM yields significant Pearson's correlations with FLW, PROFCURV, SLP and TWI (r = –0.08, –0.30, –0.11 and –0.07, respectively, all $P < 0.01$). The overland flow accumulation (FLW) significantly correlates with all the other variables: r = –0.32, 0.18, 0.28 and 0.30 for PLANCURV, PROFCURV, SLP and TWI, respectively. Finally, PLANCURV significantly correlates with PROFCURV (r = –0.28) and TWI (r = –0.41), and TWI

Table 3. Results of multiple linear regression method (MLR) between PC1-6 terrain predictors and log-transformed MVs of classes A to D

Regression coefficient	Class A	P	Class B	P	Class C	P	Class D	P
β_0 (intercept)	–1.441	< 0.001	–2.109	< 0.001	–1.836	< 0.001	–1.890	< 0.001
β_1 (PC1)	–0.071	< 0.172	0.365	< 0.001	–0.127	< 0.015	–0.375	< 0.001
β_2 (PC2)	0.243	< 0.001	–0.201	< 0.017	–0.088	< 0.159	–0.164	< 0.017
β_3 (PC3)	–0.019	< 0.805	0.472	< 0.001	–0.144	< 0.057	–0.229	< 0.006
β_4 (PC4)	–0.149	< 0.170	0.052	< 0.717	–0.063	< 0.554	0.118	< 0.307
β_5 (PC5)	0.148	< 0.164	–0.559	< 0.001	0.118	< 0.264	0.373	< 0.001
β_6 (PC6)	0.364	< 0.255	–0.568	< 0.182	0.030	< 0.925	0.176	< 0.606
R^2	0.233	< 0.001	0.466	< 0.001	0.136	<0.017	0.455	< 0.001

β_0–β_6 – MLR coefficients; P – probability for F-test values; R^2 – coefficient of determination of MLR yields significant correlations with PROFCURV at r = 0.23 and SLP at r = –0.63.

Because of the established collinearity, PCA was used to calculate new, uncorrelated terrain variables. The factor coordinates for PC1 to 6, which are linear combinations of the original terrain variables (Table 2), are considered new composite and uncorrelated terrain variables inputting the DSM model. A contribution of PC1-6 to the total PCA matrix eigenvalue is also shown in Table 2.

Kriging of membership maps

The β coefficients and residuals ε of MLR between log-transformed MVs and PC1-6 predictors of Eq. (2) were calculated using the OLS method. All the MLR models were statistically significant at P < 0.05 (Table 3), however, the explained variance strongly varied with soil classes: R^2 was between 14% and 47%. Haplic Phaeozems of class B and Haplic Regosols of class D, which are essentially affected by erosion and accumulation processes, respond to terrain variables better than the others (R^2 = 0.47 and 0.46 for class B and D, respectively). In contrast, Cutanic Luvisols of class C show only a weak, although still significant response (R^2 = 0.14). The spatial distribution of Luvisols is explained rather by local outcrops of clay sediments than by terrain forces in the study area.

The class A–D residuals ε had almost normal distributions, although they were not all perfectly

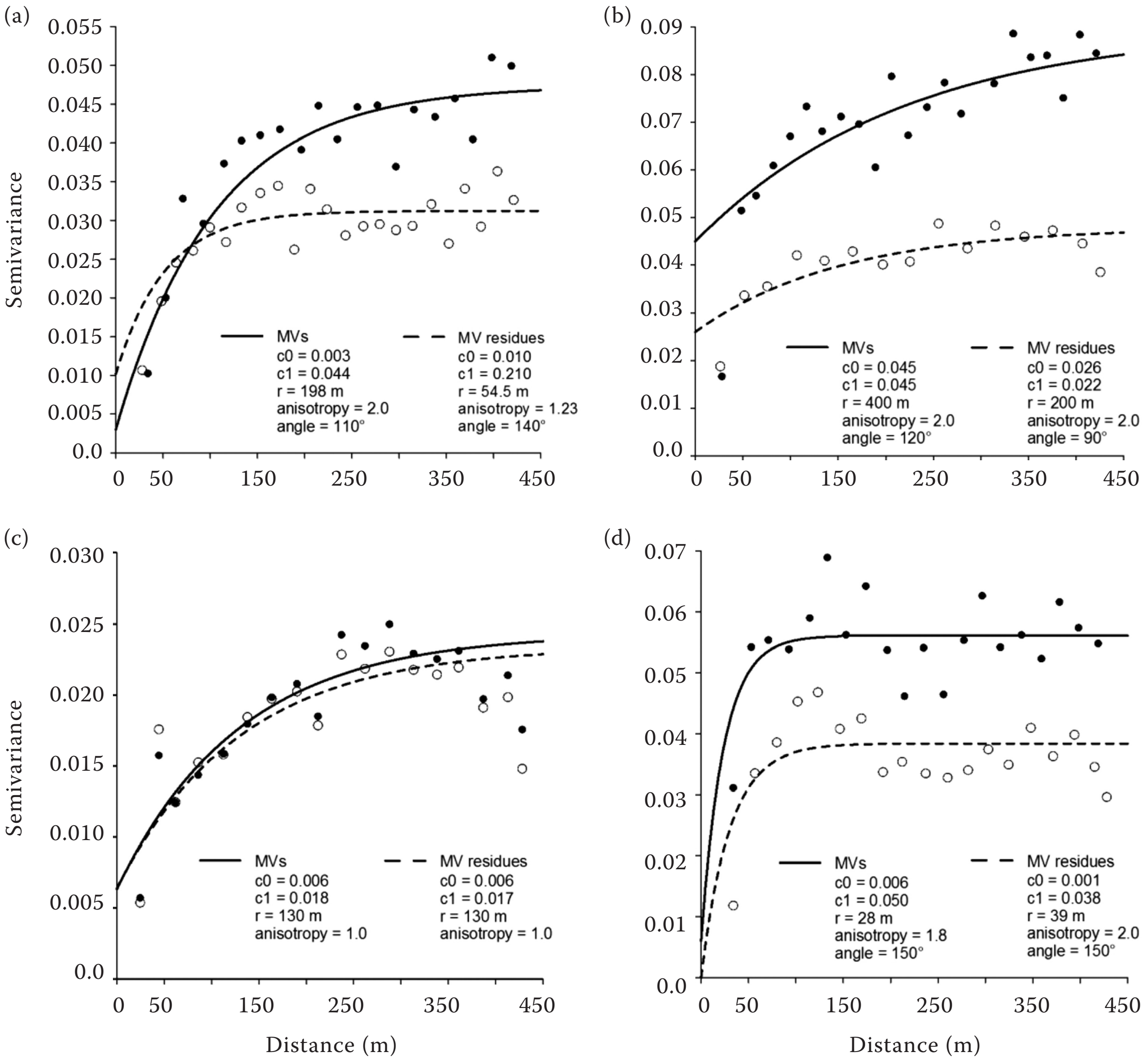
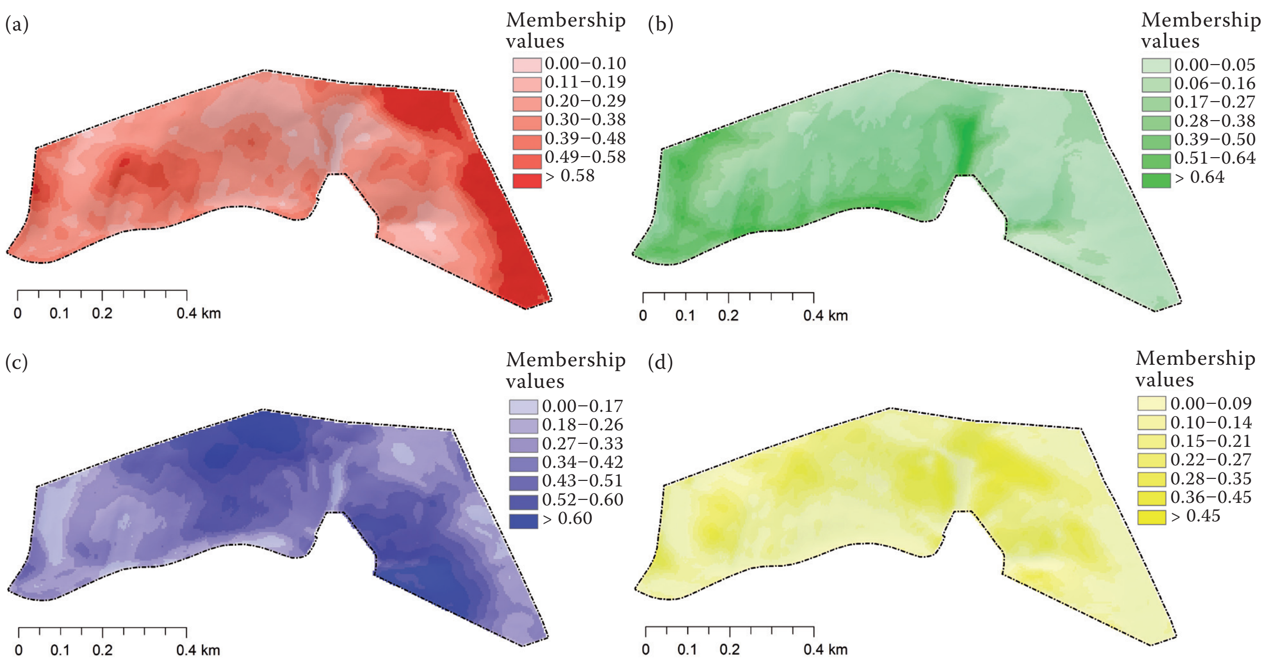


Figure 5. Exponential semivariogram models of MV (solid line) and their residuals (dashed line): (a) class A – Luvic Phaeozems, (b) class B – Haplic Phaeozems, (c) class C – Cutanic Luvisols, and (d) class D – Haplic Regosols

Gaussian. The Kolmogorov-Smirnov D test was 0.127 ($P < 0.15$), 0.222 ($P < 0.01$), 0.101 ($P < 0.2$) and 0.204 ($P < 0.01$) for classes A to D respectively. Spatial distribution of MVs and their MLR residuals was analysed using semivariograms and exponential semivariogram models of Eq. (4). All the studied soil classes demonstrate a slightly different spatial distribution. Firstly, the B class MVs (black circles in Figure 5b) yield an almost unbounded semivariogram indicating a spatial trend, which was effectively removed when terrain variables were included as indicated by the residual semivariogram (empty circles in Figure 5b). Both partial sill (c_1) and range (r) values decreased when the residuals alone were analysed. Secondly, although the D class MVs correspond quite closely with the terrain variables, they show only a very short range of spatial autocorrelation, which is also visible in its residuals (Figure 5d). This is because Regosols create only small and scattered patches rather than solid soilscapes. Thirdly, the A class MVs yield an obvious semivariogram (Figure 5a, solid line), which again has a shorter range and lower sill when residuals alone were analysed (Figure 5a, dashed line). Luvic Phaeozems, as typical climax soils in this region, create wider zones where soil profiles were strongly autocorrelated, but were less bounded by terrain dynamics. Finally, the C class MVs demonstrate a semivariogram similar to the latter one. However, there is no significant difference between MVs and their residuals (Figure 5c) since the terrain variables do not capture enough of the MV spatial variation. This is also why we used ordinary kriging instead of regression-kriging for C class MV mapping.

The classes A–D were interpolated into gridded membership maps with 5-m cell size. The four membership maps (Figures 6a–d) were rescaled as described in the methodology section to restore the assumption of composite variables. The resultant pictures concur with field experiences. Luvic Phaeozems (class A) and Cutanic Luvisols (class C) occur especially at plateau parts of the study area where they represent the remnants of



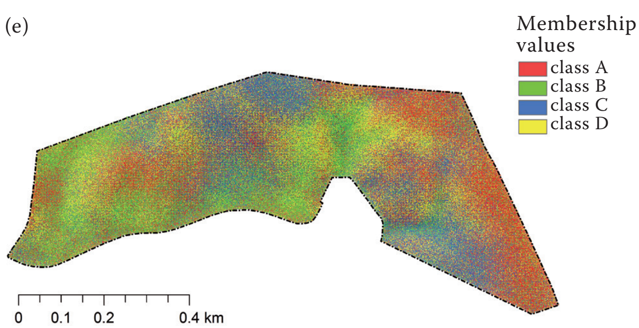


Figure 6. Digital membership maps of fuzzy k-means (FKM) classes: (a) class A – Luvic Phaeozems (Anthric), (b) class B – Haplic Phaeozems (Anthric, Calcaric, Pachic), (c) class C – Calcic Cutanic Luvisols, (d) class D – Haplic Regosols (Calcaric), (e) synthetic digital soil map constructed by a pixel-mixture technique

Table 4. Cross-validation results; the relationships between original and modelled MVs were tested using linear regression (N = 111)

Class	STU	Model	r	R^2	P
A	Luvic Phaeozems (Anthric)	Regression-Kriging	0.58	0.33	< 0.001
B	Haplic Phaeozems (Anthric, Calcaric, Pachic)	Regression-Kriging	0.75	0.56	< 0.001
C	Calcic Cutanic Luvisols	Ordinary Kriging	0.46	0.22	< 0.001
D	Haplic Regosols (Calcaric)	Regression-Kriging	0.65	0.42	< 0.001

R^2 – coefficient of determination; P – probability for F-test value; r – Pearson's correlation coefficient

a climax soil cover. Haplic Phaeozems of class B represent colluvial soils spreading along valleys, whereas Haplic Regosols of class D comprise erosive remnants of the former class A or C soils. Diffuse transitions between the four soil classes are visualized via the pixel-mixture method highlighted in Figure 6e. This kind of synthetic map can substitute for conventional soil maps and, moreover, it provides an intuitive picture of diffuse soil cover.

The four class membership maps were validated against the original MVs using the cross-validation approach (Table 4). The DSM model performed most effectively with class B and D MVs (R^2 = 56% and 42%, respectively, both P < 0.001). It performed less effectively, although still significantly with class A and C MVs (with R^2 = 33% and 22%, respectively, both P < 0.001).

CONCLUSIONS

The presented DSM model comprises FKM classification and kriging of membership maps with the use of terrain predictors. The FKM method represents a formalized approach to soil classification which addresses the continuous character of soil objects. As shown above, the digitization of soil horizon properties gathered by way of conventional field observations provided reliable soil classes and MVs continuous enough to be spatially interpolated into membership maps. Resultant digital soil maps demonstrate a rational picture of the soil type distribution, which concur with expert field experience.

The DSM method was especially powerful for erosion-affected soil B and D classes where terrain variables significantly improved mapping performance. With a decreasing correlation between MVs and terrain variables, there was accompanying deterioration in DSM model performance. The kriging component became more important for the spatial mapping of classes A and C, which were here located at plateau landscapes. Moreover, Cutanic Luvisols of class C are locally conditioned by the presence of clay stratum rather than the terrain alone, which was not considered by the DSM model. This is why the regression-kriging interpolation performed no better than the ordinary kriging method in this case.

Although the DSM model validity between 22 and 56% (P < 0.001) is not too high, it is worth noting that this study area is extremely heterogeneous due to the changes in erosion and accumulation processes over small distances. This is not fully captured even by this fine-scale sampling.

The spatial interpolation of MVs violates the compositional character of the fuzzy partition assumed by Eq. (1). Although this condition was formally restored by two-step rescaling of the resultant membership maps, this remains a methodically suboptimal solution which could potentially benefit from the compositional kriging component introduced by Walvoort and De Gruijter (2001), once it is implemented to regression-kriging.

We conclude that the DSM model represents a completely formalized alternative to classical soil mapping at very small scales, even when the soil profile descriptions were collected merely by field estimation methods. Additionally to conventional soil maps, this model enables us to address the diffuse characteristics in soil cover, both in the taxonomic and geographical meanings. Here we must stress that the fine-scale soil inventories quickly emerge as a result of precise farming support or environmental assessments at a municipal level. Increasing demands for soil information can be satisfied by local soil inventories supplying a significant and ever growing pool of soil information. Given that perspective, the coupling of such field surveys with remote sensing and GIS information at fine scales will support the generation of important soil maps for farmers and executives.

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