Utilization of VNIR diffuse reflectance spectroscopy to map soil erosion study on two arable fields

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Abstract

The study focuses on erosion mapping approach at filed scale by VNIR spectroscopy and digital soil mapping technique. 950 samples in total from two arable fields were collected, while 292 were used for PLSR models calibration and validation, and 658 samples for spectroscopic soil properties prediction. In general, the results confirmed that the soil organic carbon prediction by soil spectral characteristics (PLSR R^2 = 0.58 and 0.88) is a good tool, which together with digital soil mapping techniques provides basis for detailed field scale mapping. Soil organic carbon distribution is mapped to indicate potential erosion and accumulation areas.

Keywords: soil reflectance, VNIR spectroscopy, PLSR, digital soil mapping.

Introduction

Soils originating from loess are highly susceptible to erosion and re-deposition due to their physical character (high silt content). The low density (e.g. soil organic matter) and fine particles (clay and silt) are removed preferentially from the profile due to a selective process of soil erosion. Erosion re-deposition cycle can be correlated with the organic carbon content in topsoil. The organic mass, as a matter of low density concentrated in the topsoil, is removed from soil exposed to erosion and accumulated in depression sites. Role of topography in distribution of organic carbon and erosion processes was proved by large number of studies (Florisky et al. 2002, Zádorová et al. 2011).
VNIR diffuse reflectance spectroscopy (Viscarra Rossel et al. 2006) is here used as fast and accurate technique for principal soil property estimation and consequent digital soil mapping technique is employed to provide spatial distribution of the phenomena.

Materials and methods

The study was performed on two arable fields with area of about 10 and 100 ha located in the Central Bohemia (Chrastany cadaster) and South Moravia (Brumovice cadaster). Soil samples were extensively collected from both fields. There were 65 samples taken for model training, 10 samples for independent validation and 72 for VNIR prediction in the first field; while 181 samples were taken for model training, 36 samples for independent validation and 586 for prediction, in the second field. Training samples were measured in laboratory for soil organic carbon (SOC). Partial-Least Square Regression – PLSR (Viscarra Rossel, 2007) was employed to model relationship between the spectra and soil properties. Consequently SOC predictions were done by the inference model. Geostatistical mapping from point samples provided information on spatial distribution of the SOC.

<u>Instrumentation</u>
Soil spectra were collected by FieldSpec ® 3 (350 – 2500 nm) under laboratory conditions. General GPS receiver was used to collect sample coordinates. A DGPS receiver (Magellan ProMark 2) was used in areas of high density soil sampling (20m grid).

Results

PLSR with leave-one-out cross-validation was used to calibrate the spectral data with the reference laboratory SOC data. Statistical results of the cross-validation and independent validation are summarized in the table 1. Median filter was applied on raw spectra as a pre-processing step. Data set from the first filed required more preprocessing, outlier rejection and histogram normalization by square root.

Table 1. Statistical description of the PLSR cross-validation and independent validation

	Chrastany field	Brumovice field
Cross-validation	*#65*	*#181*
R^2	0.58	0.88
RMSE	0.19	0.13
RPD	1.55	2.66
No. factors	6	14
Independent validation	*#10*	*#36*
R^2	0.60	0.89
RMSE	0.18	0.14
ME	-0.04	0.03

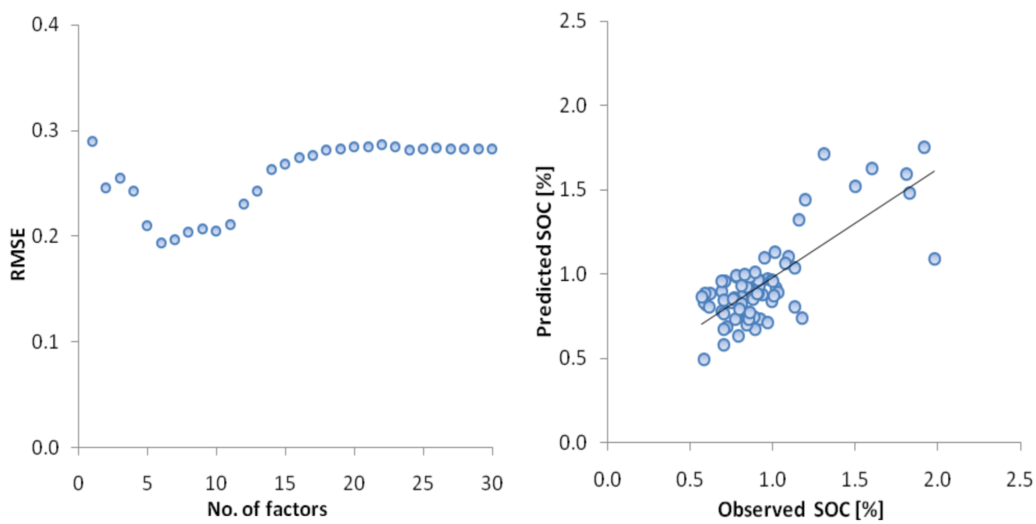

Figure 1. PLSR cross-validation results for soil organic carbon at Chrastany field.

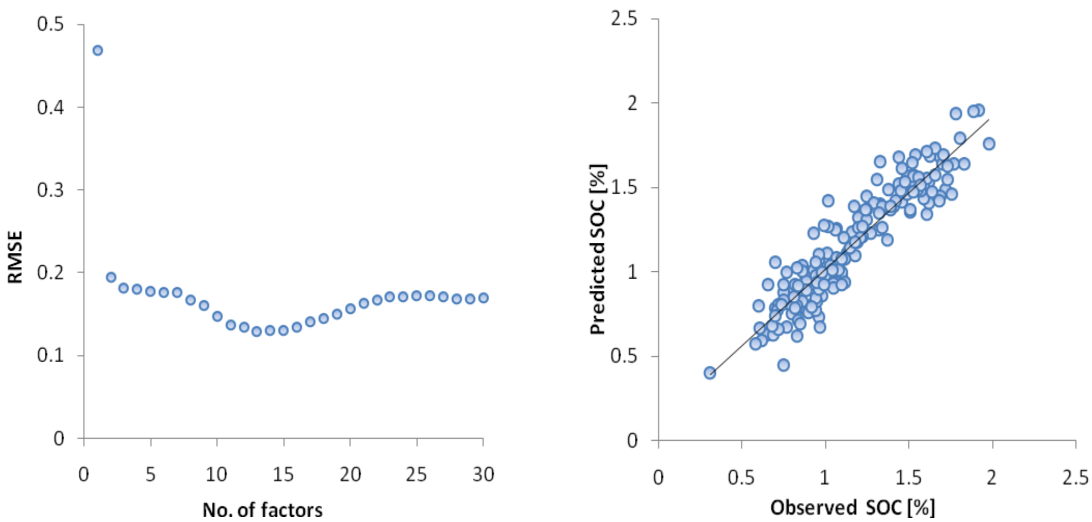

Figure 2. PLSR cross-validation results for soil organic carbon at Brumovice field.

Figure 1 and 2 present graphically the PLSR modeling results from Chrastany and Brumovice fields. Left is shown the cross-validated root mean square error (RMSE) of prediction against the number of factors. Right is shown the observed against the cross-validated PLSR predictions of soil organic carbon. Independent validation proved high quality of the PLSR models; hence SOC prediction by the model was applied.

Next, map of SOC (Figure 3) was created from the point sampling using ordinary kriging as input to erosion analysis. Tests on using environmental co-variable as slope and curvature were done by universal kriging but did not prove initially useful as artifacts from low quality DEM negatively influenced the mapping results.

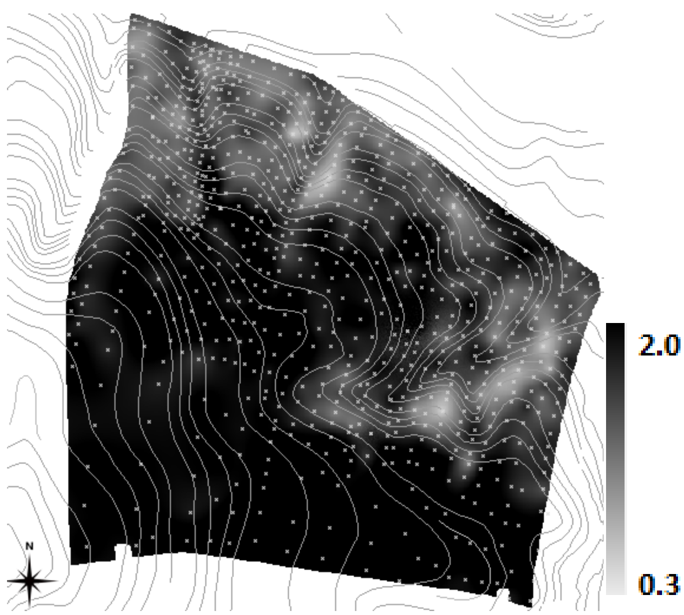

Figure 3. Soil organic carbon [%] distribution at Brumovice field (100 ha) with gray crosses of soil samples and elevation contours with 2 m spacing (elevation levels: 184m - 254m)

Discussion

PLSR analysis of soil organic carbon proved high correlation of the spectra and reference laboratory analysis. The inference model for the larger field showed better correlation of the spectra with reference measurements. One possible explanation is that there were more, 181, samples in training compare to only 65. The other argument is that the larger filed is geologically homogenous, while the other is highly diversified. The resulting map of SOC distribution shows areas with different affection by erosion and deposition processes. Bright parts indicating low organic matter content correspond to the back-slope segments with high slope and convex curvature covered mainly by Regosols and eroded Chernozems. The SW flat upper part of the plot shows high organic matter content corresponding to low erosional activity. Most of this area is covered by Haplic Chernozem. The concave side valleys and the toe slope is defined by 0.6 – 1.5 SOC content. Values represent the accumulation of both humic and mineral material from the neighboring slopes. The mixture of humus and loessic materials implicates that SOC content does not reach the values from the upper part of the plot (Zádorová et al 2011). Combination with DEM should help delineation of the areas with different erosion phases.

Conclusions

In general, the results confirmed that the soil properties prediction by soil spectral characteristics is a good tool, which together with digital soil mapping techniques provides basis for detailed field scale soil erosion mapping. Geologically homogenous filed showed higher correlation between soil spectra and reference laboratory data. The SOC map indicates actual soil organic carbon distribution, while combination with DEM should provide delineation of accumulation parts with variable SOC content.

Acknowledgements

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