SPATIAL ASSESSMENT OF SOIL DEPTH FROM LABORATORY REFLECTANCE MEASUREMENTS AND HYPERSPECTRAL IMAGERY

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ABSTRACT:

Knowledge on soil depth is important to evaluate the potential and appropriate utilization of the soil for crop growing because the depth of a soil and its capacity for water and nutrients often determine the crop yield. But especially soil depth data retrieval with reasonable spatial resolution is work-intensive and time-consuming. Therefore, an approach to predict soil depth at plot level is presented. This approach is based on spectral information of soil inherent characteristics and canopy water content. The relationship of soils developed on carbonatic bedrock material between inorganic carbon concentrations and soil depth was utilized to estimate soil depths with reliable accuracy. Since soil depth is known to have substantial influence on water available for plant communities an index sensitive to canopy water content was introduced into the regression model. A multivariate regression based on both water index and inorganic carbon enhanced soil depths prediction accuracy substantially. This methodology has been successfully applied to an agricultural plot in Rhineland-Palatinate (Germany). Results confirm that the approach is predicting very similar depths to those observed in the field descriptions. The use of this combined approach will facilitate the implementation of digital soil mapping.

1. INTRODUCTION

Knowledge on soil depth is important to evaluate the potentials for plant growth and to allow for an appropriate soil management. Existing barriers in the soil may hinder roots to extend and crops will often suffer from water shortage and limited nutrient availability. Deep soils are able to hold more water and plant nutrients than shallow soils with similar textures.
Soil depth estimation is commonly carried out coring or digging pits. But necessary efforts for coring are relatively high. Especially soil depth data retrieval with reasonable spatial resolution is work-intensive and time-consuming. Therefore, when spatial information on soil depth is required, new techniques need to be developed and implemented.
Laboratory reflectance spectrometry is accepted as a fast and non-destructive tool to assess soil properties (e.g. Couillard et al. 1997, Chang et al. 2001; Shepard & Walsh 2002). Varying combinations of mineral components, soil organic matter and the soil moisture affect the reflectance of soils by inherent spectral characteristics (Baumgardner et al. 1985).

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Thereby carbonate content is one of the major driving forces in soil reflectance since soil brightness is substantially influenced by the relative amount of carbonate in soils. Hence, several authors established statistical models between soil reflectance and carbonate content (e.g. Ben-Dor and Banin, 1990, 1995; Udelhoven et al. 2003; Jarmer et al. 2009).

Since optical remote sensing is limited to soil surface, an assessment of soil depth is only feasible based on indicators which are related to soil depth and predictable from remote sensing data. For soils developed on carbonate bedrocks the inorganic carbon content (C_{inorg}) is such an indicator; during soil development C_{inorg} of the soil is reduced by weathering. Well developed soils in this case tend to lower C_{inorg} while shallow soils incline to higher concentrations due to their nearness to the carbonate bedrock.

Further on, the growing vegetation canopy can give important hints on soil depth. As soil depth is related to the soils' capacity for water supply, canopy water content may change with varying soil depth. The canopy water content can be determined by empirical approaches which generate a statistical relationship between spectral indices derived from spectral measurement and water content (e.g. Peñuelas et al. 1997; Gao 1996).

Generally a data set in soil mapping is limited to only a few locations. Although laboratory and field spectroscopy allows increasing the number of sampled locations substantially, the spatial assessment exclusively based on terrestrial inquiry for broader areas is rarely feasible. High spatial and spectral resolution of airborne hyperspectral sensors may provide more detailed pattern recognition of the soil's and vegetation's heterogeneity and are in particular suitable for monitoring required parameters (e.g., Selige et al. 2006; Vohland 2008).

Consequently, this case study focuses on practical implication of reflectance spectrometry for the assessment of C_{inorg} and soil depth of an agricultural soil. Specific aims were to develop a two-step empirical approach for predicting C_{inorg} from reflectance measurements. In a first step C_{inorg} was estimated from soil reflectance spectra while in the second step soil depth was linked to the soil C_{inorg}. Subsequently, the potential of integrating hyperspectral imaging spectrometer data into the model approach was investigated. Finally, the obtained regression model was implemented to predict soil depth for the entire plot from values of interpolated C_{inorg} and HyMap-derived vegetation index.

2. DATA AND METHODS

The study site is located in the Trier region, Rhineland-Palatinate, Germany. A plot of approximately five hectares in size was investigated which was cropped with summer barley during growing season. Soil types are eutric cambisols and haplic to mollic stagnosols with sitly texture derived from loess over limestone. In the area the long-term mean annual precipitation is around 750 mm y^{-1}.

Field survey and soil sampling were performed during dry weather conditions in March 2005 before the crop season. A sampling raster of 30×30 m was realized for investigation to consider spatial variability of soil properties ($n = 52$). Differential GPS was employed to locate exact sampling position. An integrative sample was taken from the upper 5 cm of the soil profile for each position representing an area of about 1 m². At every second sampling position a Pürckhauer probe was conducted to assess soil-profile data ($n = 29$).

The soil samples were air-dried in the laboratory, gently crushed in order to pass a 2 mm-sieve and carefully homogenized. The total amount of inorganic carbon (C_{inorg}) was analysed by elemental analyser (Elementar Analysensysteme GmbH).

Bi-directional reflectance measurements of the homogenized soil samples were acquired in the laboratory with an ASD FieldSpec-II spectroradiometer in the wavelength range 350 – 2500 nm using a reflectance standard of known reflectivity (Spectralon). The optical head of the spectroradiometer was mounted on a tripod in nadir position with 10 cm distance to the sample. A 1000 W quartz-halogen lamp set in a distance of approx. 30 cm and an

illumination angle of 30 degrees was used to illuminate reference panel and samples.
Multiplying the raw reflectance spectra by the certified reflectivity of the Spectralon panel absolute bi-directional reflectance spectra were obtained. For further analysis spectra were resampled to HyMAP spectra resolution.
The hyperspectral image data were acquired by a HyMap airborne imaging sensor on May 28, 2005 between 11.00 h and 11.30 h local time. The sensor recorded spectra in the wavelength range from 420 to 2480 nm in 126 spectral bands with a ground resolution at nadir of approximately 5 m. Image pre-processing was performed including across-track illumination correction and both atmospheric and geometric correction steps. For the latter, ENVI's atmospheric correction module FLAASH and the PARGE™ software (Schläpfer & Richter, 2002) were used.
Estimation of C_{inorg} of the investigated soil samples was performed by Partial least-squares regression (PLS). PLSR results were cross-validated (cv) according to the 'leave-one-out-method'. The coefficient of determination (r^2) and the root mean squared error (RMSE) were calculated to assess the prediction accuracy. In addition, the RPD was determined by dividing the standard deviation of the measured values by the RMSE (Malley et al., 2004).
A linear regression model was performed to predict soil depth based on C_{inorg} estimates. In a multiple regression analysis, an index related to vegetation was integrated as additional predictor variable. For the adequacy of the implemented regression model the residuals were tested for normal distribution and exclusion of auto-correlation.
To benefit from most likely significant influence of soil depth on plant growth and canopy water content, a spectral vegetation index was applied. Here, results from former local studies (Sonnenschein et al., 2006; Vohland, 2008) suggest applying the water index (WI), originally introduced by Peñuelas et al. (1997).
For WI calculation from the HyMap data, a modification of the original WI formula was necessary selecting those HyMap channels closest to the original WI wavelengths:

$$WI_{HyMap} = \frac{\rho_{895nm}}{\rho_{975nm}} \tag{1}$$

GPS coordinates measured in the field were applied to assign one WI_{HyMap} value to each sampling position. A 3x3 window of pixels centred on the coordinates of each field sample location was considered to compensate for inevitable position errors enclosed in image geocoding and GPS measurements, and from the nine WI values the median was extracted.

3. RESULTS AND DISCUSSION

C_{inorg} of samples varied between 2.53 g kg^{-1} as minimum and more than 64 g kg^{-1} as maximum. Soil depths measured in the field ranged from 19 cm indicating a very shallow soil to more than 90 cm representing a deep soil. Only one soil showed a profile depth less than 30 cm, at eleven sampling positions depths were estimated to be between 30 and 60 cm while almost sixty percent of the investigated soils (n = 17) were characterized by depths of more than 60 cm. Based on these measured data, a negative correlation of 0.86 can be found between soil depth and C_{inorg}.
Soil samples' C_{inorg} have been predicted by PLS regression. Since two samples were found to be outliers they were excluded from further analysis. One with the highest C_{inorg} of about 64.1 g kg^{-1} which is almost 10 g kg^{-1} above the sample with the next highest concentration, for the other excluded soil sample C_{inorg} slightly above zero was measured in laboratory. To allow a reliable estimation of C_{inorg} in soil samples at least a concentration of 3 g kg^{-1} was required. The result of the PLS prediction for the remaining 50 samples with an r^2_{cv} of 0.957 ($RMSE_{cv}$ = 2.689; RPD = 5.58; eight latent variables) was very high and proves that estimation of C_{inorg} from reflectance data at HyMap spectral resolution to be absolutely reliable (Figure 1).
In the next step, the potential of predicting soil depth from C_{inorg} estimates was explored. Here, the soil sample with the extremely high C_{inorg} concentration of 6.41 percent was again

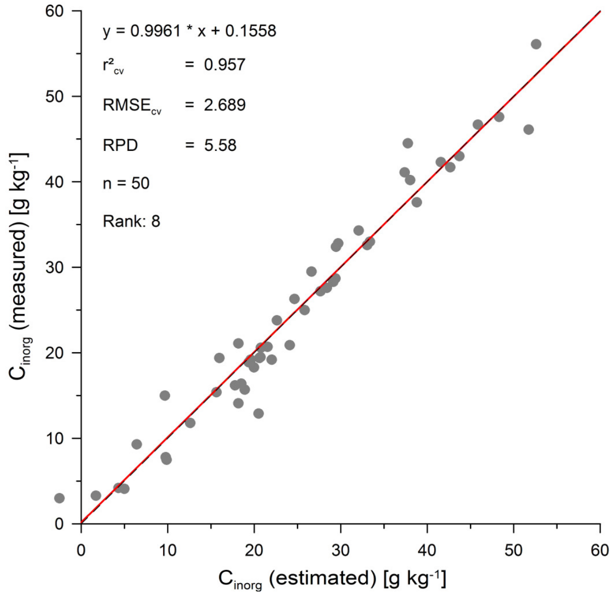

Figure 1. Scatterplot of PLS regression results (cross-validated) for C_{inorg} .

excluded. Based on the remaining samples, a linear regression model was found for the prediction of soil depth from C_{inorg} estimates. The predictions prove to be reliable (r^2_{cv} = 0.687, $RMSE_{cv}$ = 10.88, RPD = 1.755), and the linear fit between estimates and measured values is close to the 1:1-line with an offset less than 2 cm. For more than two thirds of the samples the prediction error of soil depth is less than ten centimeters, and only for one sample that represents a shallow soil with a profile depth of 34 cm, soil depth is overestimated by more than 20 cm (20.9 cm).

Considering a link between soil depth and soil water holding capacity on the one hand, and water supply and plant water content on the other hand, the WI, as a measure for canopy water content, was explored as another predictor variable for soil depth. WI values, calculated from the HyMap data, vary between 1.1206 in the minimum and 1.2735 in the maximum with a mean of 1.2295 (standard deviation: 0.03). Lowest WI values are found at the south-eastern fringe and in the central part of the plot, whereas highest WIs – indicating high water contents – are widely spread over the plot with one well-pronounced accumulation in the south-western part of the field. WI values were extracted from the image data for those positions where soil depths had been measured; here, a positive correlation of 0.714 was found.

Based on this finding, WI was integrated as second predictor variable - in addition to C_{inorg} - in a linear multiple regression model for the prediction of soil depth:

$$
\begin{aligned}
&\textit{soil depth}\,[cm] = \\
&\quad -419.20 + 412.13 * WI \\
&\quad -9.94 * C_{inorg}\,[g\ kg^{-1}]
\end{aligned}
\tag{2}
$$

Compared to the regression model using solely C_{inorg} as predictor, the multiple regression allows a clearly more reliable assessment of soil depth (r^2 = 0.826, $RMSE_{cv}$ = 7.927, RPD = 2.407). The linear fit between estimates and measurements is again close to the 1:1-line with an offset less than 1 cm (Figure 2). Prediction errors are only for two samples beyond 15 cm (16.8 cm and 16.7 cm for two samples with measured depths of 36 cm and 41 cm respectively); another five samples are over-/underestimated by 10 to 13 cm, while more than seventy-five percent of the samples exhibit prediction errors below an absolute value of 10 cm.

The final goal of this study was the implementation of the obtained regression model to predict soil depth in the spatial

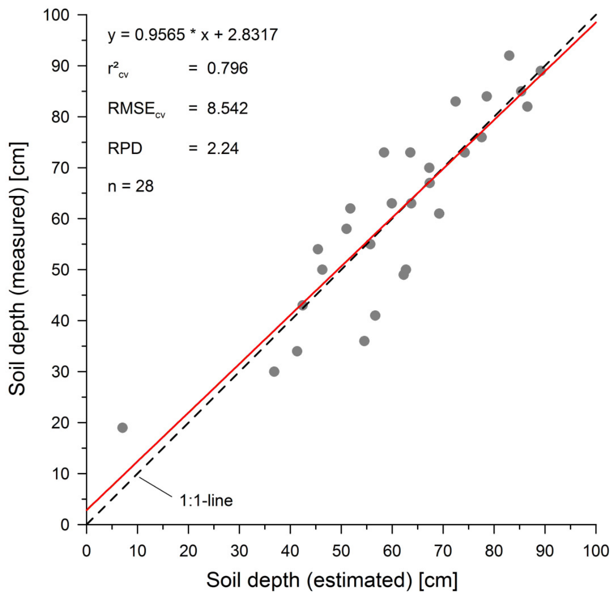

Figure 2. Scatterplot of multiple regression model estimates for soil depth.

domain. However, spatial soil depth estimates for the entire plot required an additional modeling step. While WI was calculated from HyMap data at 5 m resolution, C_{inorg} was predicted according to 30 x 30 m sampling raster. Hence, estimated C_{inorg} were interpolated with 5 m resolution from point data to match resolution of HyMap-derived WI. Interpolation results were compared for both measured and predicted values of C_{inorg} to prove the prediction power beyond point data. The pattern produced by estimated C_{inorg} from PLS coincides with the pattern resulting from the measurements of the laboratory chemical analysis. Hence, comparing interpolation results clearly reveals, that PLS predictions allowed an excellent reproduction of C_{inorg} spatial pattern. Consequently, the interpolated C_{inorg} predictions and the WI were used to estimate soil depths at 5 m resolution. The result is illustrated in Figure 3.

Deep soils (> 70 cm) primarily occur in the western and eastern part of the field with the deepest on the eastern edge where a brook limits the field. Shallow soils (< 40 cm) were largely predicted for the central part (figure 3). This spatial heterogeneity is mainly attributed to topography since the central part of the plot is characterized by a slight rim with gentle slopes to the west and east.

The range of predicted depths predicted by multiple regression at 5 m resolution was quite close to depth estimates during field survey (Table 1). While the mean and maximum depth are quite similar, the minimum depth differs by more than 10 cm. In the field a very shallow soil (19 cm) was sampled which is limited to a very small area. This local "spot" was not detectable at HyMap resolution.

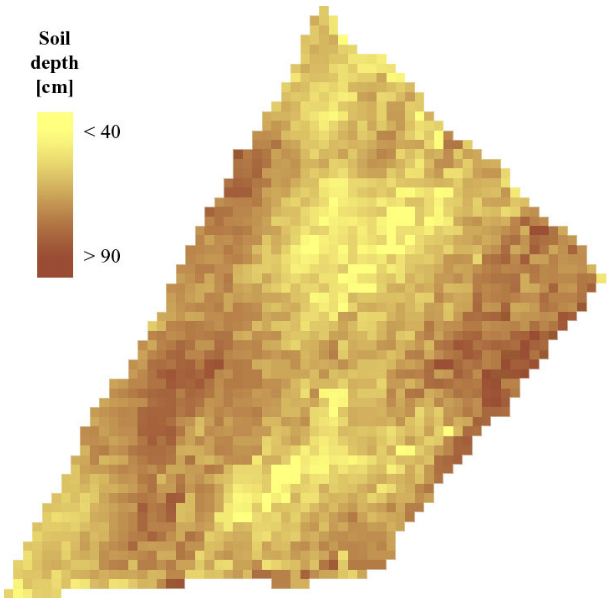

Figure 3. Soil depth estimates at plot level.

Soil depth [cm]	min	max	mean	std.-dev.
Field	19.0	92.0	59.9	20.2
"Image"	29.8	97.2	63.8	11.7

Table 1. Descriptive statistics of soil depths field-estimated and predicted "image"-based

4. CONCLUSIONS

Soil depths of soils developed on carbonatic bedrock material were estimated with reliable accuracy by partial least squares regression from inorganic carbon concentrations. A multivariate regression based on both water index and inorganic carbon enhanced soil depths prediction accuracy substantially. This methodology has been successfully applied to an agricultural plot. Results confirm that the approach is predicting very similar depths to those observed in the field descriptions. The use of this combined approach will facilitate the implementation of digital soil mapping.

Nevertheless, the approach presented here suffers from some limitations, e.g., intensities of weathering and leaching of carbonates are controlled by the local climatic conditions, management practices like deep ploughing weaken the correlation of C_{inorg} with soil depth, and plant growth can substantially be modified by fertilizer application. In either case, local calibration seems to be mandatory.

In this study, a mixture of non-imaging and imaging spectroradiometer data was used to derive both variables for the prediction of soil depth. For an operational use, the acquisition of two hyperspectral datasets, one covering vegetation status and another one covering the status of bare soils, is advised.

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