Using hyperspectral remote sensing data for the assessment of topsoil organic carbon from agricultural soils

Bastian Siegmann*[a], Thomas Jarmer[a], Thomas Selige[b], Holger Lilienthal[c], Nicole Richter[c], Bernhard Höfle[d]

[a]Institute for Geoinformatics and Remote Sensing, University of Osnabrück, D- Barbarastraße 22b, 49076 Osnabrück, Germany; [b]Institute of Soil Ecology, TU Munich, Ingolstädter Landstrasse 1, D-85764 Neuherberg, Germany; [c]Julius Kühn-Institut, Institute for Crop and Soil Science, Bundesallee 50, D-38116 Braunschweig, Germany; [d]Institute of Geography, University of Heidelberg, Berliner Straße 48, D-69120 Heidelberg, Germany

ABSTRACT

Detecting soil organic carbon (SOC) changes is important for both the estimation of carbon sequestration in soils and the development of soil quality. During a field campaign in May 2011 soil samples were collected from two agricultural fields northwest of Koethen (Saxony-Anhalt, Germany) and the SOC content of the samples was determined in the laboratory afterwards. At the same time image data of the test site was acquired by the hyperspectral airborne scanner AISA-DUAL (450-2500 nm). The image data was corrected for atmospheric and geometric effects and a spectral binning has been performed to improve the signal-to-noise ratio (SNR). For parameter prediction, an empirical model based on partial least squares regression (PLSR) was developed from AISA-DUAL image spectra extracted at the geographic location of the soil samples and analytical laboratory results. The obtained SOC concentrations from the AISA-DUAL data are in accordance with the concentration range of the chemical analysis. For this reason, the PLSR-model has been applied to the AISA-DUAL image data. The predicted SOC concentrations reflect the spatial conditions of the two investigated fields. The results indicate the potential of the used method as a quick screening tool for the spatial assessment of SOC, and therefore an appropriate alternative to time- and cost-intensive chemical analysis in the laboratory.

Keywords: Hyper spectral, AISA-DUAL, soil organic carbon, PLS regression

1. INTRODUCTION

The assessment and mapping of soil organic carbon (SOC) is very important in order to develop strategies to mitigate global warming [1]. Soil can store more than twice as much carbon compared to vegetation or atmosphere [2]. Thus, improving carbon storage as soil organic matter by the adoption of land-use and land management practices is an option to reduce the carbon dioxide content in the atmosphere [3]. Additional SOC influences aggregate stability as well as water and nutrient storage capacity of the topsoil [4]. Especially, agricultural soils suffer from SOC depletion as a result of low organic carbon input due to harvesting and/or removal of plant residues and simple crop rotations. Organic matter contents which are below a threshold of approx. 1.5-2.0 % in the topsoil bear the risks of soil erosion and physical soil degradation. Within the EC Soil Thematic Strategy the loss of organic matter is considered as a substantial risk for the resource soil [5].

Detecting SOC changes is of importance for both the estimation of carbon sequestration in soils and the development of soil quality. Change rates of SOC are very limited but show high spatial variability even on short distances. Acquiring spatial soil variability analytically in the lab is cost- and time-intensive, which is especially true for large scale applications with a necessarily high number of soil samples [6, 7]. Thus, a soil monitoring technique comprising

*bsiegmann@igf.uni-osnabrueck.de; phone 49 541 969-3930; fax 49 541 969-3939; www.igf.uos.de

both analytical speed and precision is expected to be of great implication as alternative to the cost- and time-intensive lab analysis [8]. In this context, reflectance spectroscopy has been proven as a quick, non-destructive method allowing very sound estimates of soil chemical properties of agricultural soils [e.g., 9, 10, 11]. Spectral reflectance of soils is affected by varying combinations of mineral components, organic matter and soil moisture. Many studies demonstrated the relationship between soil properties, like grain size distribution, soil moisture, iron oxides, carbonate content and organic matter and its resulting spectral reflectance. Most of the studies were performed under controlled laboratory conditions to derive soil properties [e.g., 12, 13]. Although imaging hyperspectral data have a great potential to derive soil parameters at a larger scale, studies applying soil spectroscopy on airborne or spaceborne data are limited [e.g., 14, 15, 16]. Consequently, in this study the potential of hyperspectral imagery for the spatial assessment of soil organic carbon of agricultural soils is investigated.

2. STUDY AREA AND DATA

2.1 Study area

The study area (11°54E, 51°47 ′N) is intensively used for agriculture and located in the eastern part of Germany in the federal state of Saxony-Anhalt (Fig. 1). The region is characterized by a slightly undulated tertiary plain with an altitude of 70 m above sea level that is covered by a thin Loess layer up to 1.2 m deep. The study area is situated in the rain shadow of the Harz Mountains. For that reason the region is distinctly dry with 430 mm mean annual precipitation and 9°C mean annual temperature. The two investigated fields have a size of 100 ha (Field A) and 21 ha (Field B), respectively. Chernozem in conjunction with Cambisols and Luvisols is the predominant soil type of the Loess covered Tertiary plain. The test site is characterized by highly diverse soil properties that results in fine-scale pattern of soil texture and organic matter.
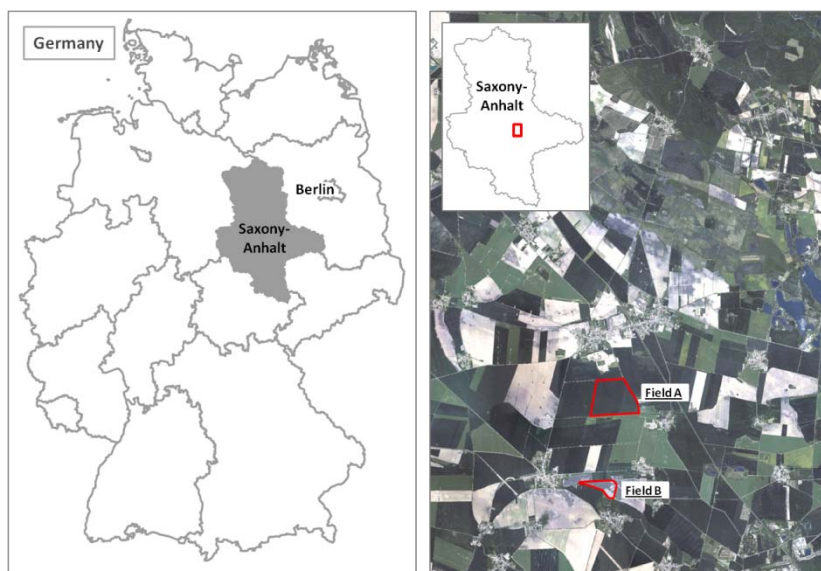

Figure 1. Location of the test site with the two investigated fields in the federal state Saxony-Anhalt in Germany

2.2 Data

For the spatial assessment of SOC hyperspectral data of the airborne system AISA-DUAL (Specim) was used. AISA-DUAL is a hyperspectral pushbroom scanner consisting of the two separate sensors, AISA-EAGLE (VIS/NIR, 400-1000 nm) and AISA-HAWK (SWIR, 1000-2500 nm). The AISA-DUAL imagery of the test site was aquired on the 10th of May 2011. The image data has a geometric resolution of 3 m in 367 spectral bands in the wavelength range of 400-2500 nm. At the beginning of the data correction the ROME destriping algorithm [17] was used to reduce

miscalibration effects of the sensors in form of deficient lines along track in the images. For the following atmospheric correction the software FLAASH (Fast Line-of-sight Atmospheric Analysis of spectral Hyper cubes) was used. Additionally, an empirical line correction was made with spectral ground measurements of different dark and bright targets collected in the test site during the time of AISA-DUAL data acquisition [18]. The geometric correction of the AISA-DUAL data was realized with the software CaliGeo and orthorectification was performed with the software ENVI.

Additionally, 32 soil samples were collected from the two test fields on May 3 and 4, 2011 (Fig. 2). Differential GPS was used to locate the exact sampling position. An integrative topsoil sample was taken from the upper 1 cm of the soil profile for each position representing an area of about 1 m². Afterwards the soil samples were air-dried, gently crushed in order to pass a 2 mm-sieve and carefully homogenized. Subsequently, the organic carbon content of the prepared samples was determined in the laboratory using an elemental analyser (Elementar Analysensysteme GmbH).
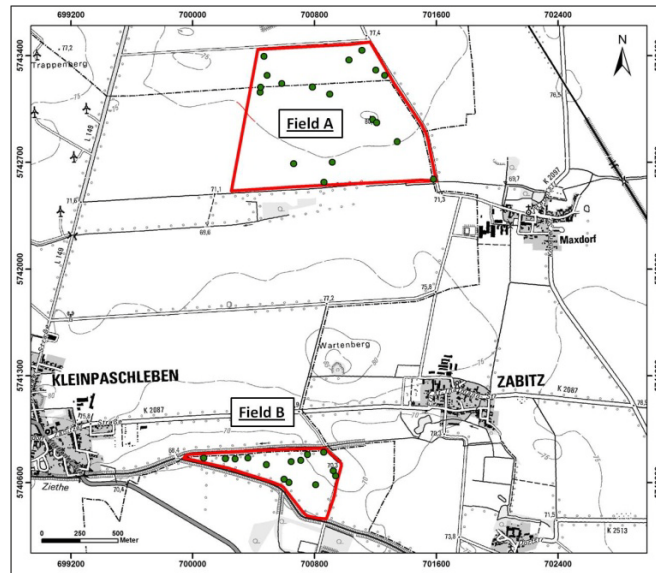

Figure 2. Investigated fields with location of the soil samples

3. METHODS

3.1 Spectral binning

The spectral signatures of the processed AISA-DUAL pixels show a high level of noise. For the reduction of the noise a spectral binning was made on the AISA-DUAL data. Spectral binning is a commonly used method to reduce noise in hyperspectral data. In this context adjacent spectral bands will be summed up to one new single binned spectral band to enhance the signal-to-noise ratio (SNR) of the data [19]. In this study in each case three adjacent spectral bands of the AISA-DUAL data were averaged to generate one new spectral band. In this way the number of spectral bands was reduced from 367 to 122 and the signal-to-noise ratio of the AISA-DUAL data could be improved. Furthermore, 22 spectral bands in the range of the water vapor absorption bands (1354-1411 nm, 1807-1996 nm) and selected bands at the beginning and at the end of the AISA-DUAL spectral range (400-418 nm, 2410-2500 nm) were deleted because of the high rates of noise in this spectral region of the AISA-DUAL system leaving 100 spectral bands for further analysis.

3.2 Partial Least Square Regression

First, the spectral signatures of the image pixels corresponding to the geographic location of the different soil samples were extracted from the AISA-DUAL data. Afterwards a Partial-Least Squares regression (PLSR) model with a

limitation of ten latent variables (LV) built from the extracted spectral signatures and the organic carbon content of the soil samples has been set up to estimate SOC from the AISA-DUAL image data. The PLSR result was cross-validated (cv) with the 'leave-one-out-method'. For accuracy assessment of the results the coefficient of determination (r^2_{cv}) and the root mean square error ($RMSE_{cv}$) were calculated for the predictions. Furthermore, the ratio between standard deviation of the measured values and the $RMSE_{cv}$ (RPD) was determined as an additional measure of the estimation accuracy [20].

4. RESULTS

The investigated soil samples covered a SOC range from 10.6 g kg^{-1} at minimum and 39.1 g kg^{-1} at maximum (Tab. 1). Substantial regional differences could be found by comparing the samples from the different fields. SOC of the samples taken from the northern Field A with a mean of 14.0 g kg^{-1} was by far lower than for the southern Field B with a mean of 31.0 g kg^{-1} respectively. However, since SOC values cover the concentration range relatively uniform without gaps, the samples from the two fields were included for further investigation.

Table 1. Descriptive statistics of the SOC [g kg^{-1}] samples

	n	Min	Max	Mean	SD
Field A	18	10.6	18.7	14.0	0.23
Field B	14	16.7	39.1	31.0	0.65
Total	32	10.6	39.1	21.5	0.97

PLSR was used to predict SOC from AISA Dual data for the reduced data set with 100 spectral bands. The results of the PLSR modeling indicate that SOC was predicted with very high accuracy (r^2_{cv}=0.933, $RMSE_{cv}$=2.478, RPD=3.90). Table 2 summarizes the final results of the PLSR for 32 soil samples. The r^2_{cv} and RPD for the PLSR model according to Malley et al. [20] indicated a successful calibration and the RPD is much higher than the value of 2 which is suggested as excellent for soil analysis by Dunn et al. [21].

Table 2. Results of the PLSR

n	r^2_{cv}	$RMSE_{cv}$	RPD	LV
32	0.933	2.478	3.90	6

Examining the scatter plot of measured versus predicted SOC values (Fig. 3) points out the achieved prediction accuracy. The linear fit between predicted and measured values is relatively close to the 1:1-line with no significant offset observed. The maximum difference between measured and predicted SOC was determined with 6.7 g kg^{-1} for a sample with high SOC. In the lower concentration range between 10-25 g kg^{-1} the maximum difference was calculated with 4.0 g kg^{-1}. This fact needs to be considered when applying the PLSR model to the AISA DUAL imagery.

In the next step the developed PLSR model was transferred to AISA DUAL imagery to assess spatial variability of SOC for the investigated fields (Fig. 4). The two maps illustrate the already existing miscalibration problem of the AISA-DUAL Sensor in form of deficient lines along track in the images which could not be removed completely during the data processing. However, the concentration range obtained from the hyperspectral image data for both fields agreed well with those of the laboratory analysis. Figure 4 (left) shows the spatial prediction of SOC for Field A. Predicted SOC for Field A exhibits limited spatial dynamics. Most of the area is characterized by low to very low SOC between 8 g kg^{-1} and 15 g kg^{-1}. Higher SOC concentrations up to 22 g kg^{-1} are found in the southern parts of the field, even going up to 25 g kg^{-1} in the south-western area. This increase in SOC at the southern fringe of the field is related to topography. While the northern and central parts of Field A are characterized by very flat terrain, the field is sloping to the south providing a higher water availability and resulting in an accumulation of SOC. Besides this general SOC distribution, local hot spots of high SOC with 25-30 g kg^{-1} are found in the south-western corner with the maximum at the western fringe where locally 30-32 g kg^{-1} are estimated.
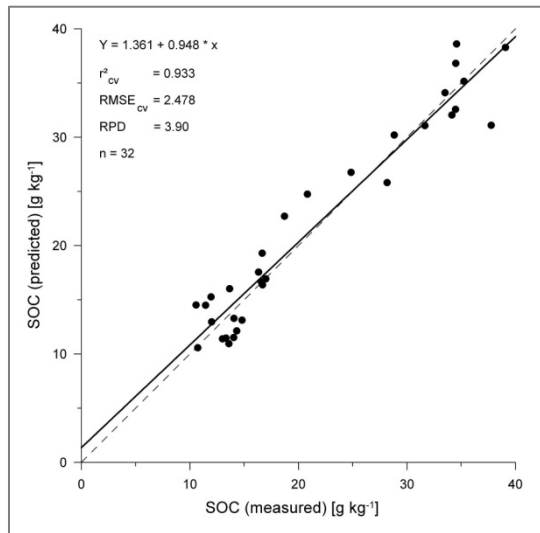
Figure 3. Scatter plot of the PLSR model (cross-validated) for predicting SOC from 100 spectral bands
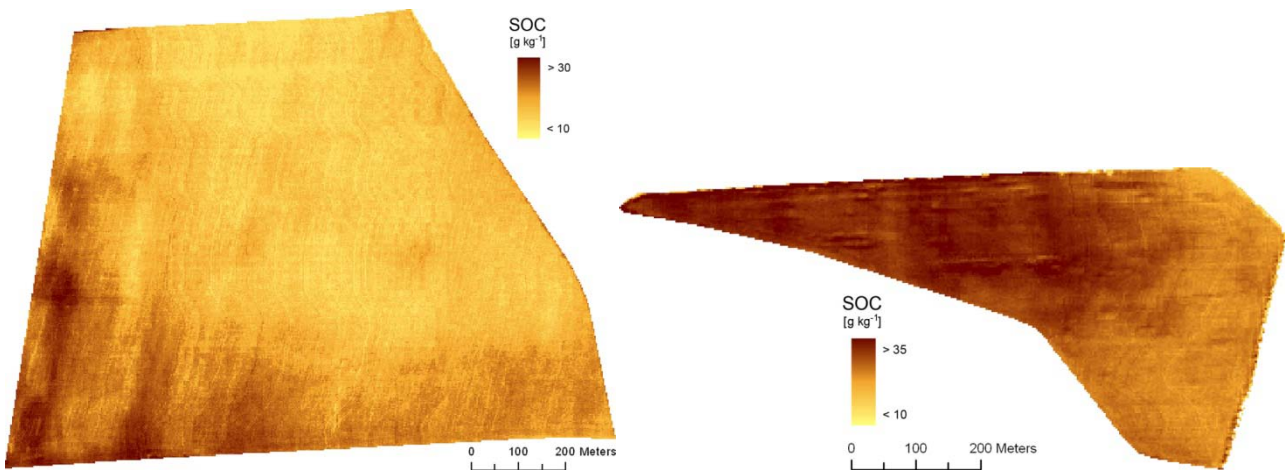

Figure 4. Spatial distribution of SOC for Field A (left) and B (right) predicted by PLS regression from 100 spectral bands (please consider different SOC concentration ranges and different scales)

Much higher SOC values were predicted for Field B (Fig. 4 right) with a general trend of decreasing SOC to the east. The eastern third of the field is characterized by SOC values of 20 to 25 g kg^{-1}. Lowest concentrations below 20 g kg^{-1} are only predicted for the north-eastern corner. The central and western part of the field show high to very high SOC between 25 g kg^{-1} and almost 40 g kg^{-1}. In small local spots SOC is even estimated with 40-45 g kg^{-1}. An explanation for this inner-field variability is currently missing.

Ecological site conditions and current management practice influence the spatial heterogeneity of soil parameters of agricultural fields. For example, management practises can have significant influence on the amount and composition of the organic matter. Differences in SOC between Field A and B may be attributed to varying soil texture influencing soil particle aggregation and soil moisture content which are both strongly related to soil reflectance characteristics. However, no analytical data on soil texture was available for this study.

5. CONCLUSIONS

The SOC prediction by PLSR from hyperspectral data was very reliable. The subsequent transfer of the PLSR model to AISA-DUAL imagery allowed to assess spatial distribution of SOC with reasonable accuracy and reflected the spatial pattern of SOC of the investigated fields very well. The concentration range obtained from the hyperspectral image data for both fields agreed well with those of laboratory analysis. For further investigations additional soil samples of the fields collected in 2012 will be used to build more robust regression models to predict SOC. Furthermore, a new destriping algorithm will be applied in the near future to correct the miscalibration effects in the AISA-DUAL data. Finally, the results of the study indicate the high potential of SOC prediction from hyperspectral data on regional scale.

ACKNOWLEDGEMENTS

REFERENCES

[1] Jones, R.J.A., Hiederer, R., Rusco, E. and Montanarella, L., "Estimating organic carbon in the soils of Europe for policy support", European Journal of Soil Science 56, 655–671 (2005).

[2] Batjes, N.H., "Total carbon and nitrogen in the soils of the world", European Journal of Soil Science 47, 151-163 (1996).

[3] Lal, R., Kimble, J.M., Follett, R.F. and Cole, C.V., [The potential of U.S. cropland to sequester carbon and mitigate the greenhouse effect.], Ann Arbor Press, Chelsea, Michigan (1998).

[4] Volk, B.G. and Loeppert, H., [Soil organic matter". In: Handbook of Soils and Climate in Agriculture (Eds.: V.J. Kilmer and A.A. Hanson)], CRCPress, Boca Raton, FL, 211–268 (1982).

[5] Van-Camp, L., Bujarrabal, B., Gentile, A.R., Jones, R.J.A., Montanarella, L., Olazabal, C. and Selvaradjou, S.K., "Organic Matter and Biodiversity", Reports of the Technical Working Groups established under the Thematic Strategy for Soil Protection. Vol. III. OOP EC, EUR 21319 EN/3, Luxembourg (2004).

[6] Viscarra-Rossel R.A. and McBratney A.B., "Soil chemical analytical accuracy and costs. Implications from precision agriculture." Australian Journal of Experimental Agriculture 7, 765-775 (1998).

[7] Plant, R.E., "Site-specific management. The application of information technology to crop production." Computers and Electronics in Agriculture 30, 9-29 (2001).

[8] Shepard K.D. and Walsh, M.G., "Development of reflectance spectral libraries for characterization of soil properties." Soil Science Society of America Journal 66, 988-998 (2002).

[9] Ben-Dor, E. and Banin, A., "Near-infrared reflectance analysis of carbonate concentration in soils." Applied Spectroscopy 44(6), 1064-1069 (1990).

[10] Brown, D.J., Shepherd, K.D., Walsh, M.G., Mays, M.D. and Reinsch, T.G., "Global soil characterization with VNIR diffuse reflectance spectroscopy." Geoderma 132, 273–290 (2006).

[11] Jarmer, T., Vohland, M., Lilienthal, H. and Schnug, E., "Estimation of some chemical properties of an agricultural soil by spectroradiometric measurements." Pedosphere 18(2), 163-170 (2008).

[12] Udelhoven, T., Emmerling, C. and Jarmer, T., "Quantitative analysis of soil chemical properties with diffuse reflectance spectrometry and partial-least-square regression: A feasibility study." Plant and Soil 251(2), 319-329 (2003).

[13] Richter, N., Jarmer, T., Chabrillat, S., Oyonarte, C., "Hostert, P and Kaufmann, H., Free iron oxide determination in Mediterranean soils using diffuse reflectance spectroscopy". Soil Science Society of America Journal73, 72-81(2009).

[14] Palacios-Orueta, A., and Ustin. S.L., "Remote sensing of soil properties in the Santa Monica Mountains I. Spectral analysis." Remote Sensing of Environment 65, 170–183 (1998).

[15] Selige, T., Böhner, J. and Schmidhalter, U., "High resolution topsoil mapping using hyperspectral image and field data in multivariate regression modeling procedures." Geoderma 136(1-2), 235-244 (2006).

[16] Bartholomeus, H., Epema, G. and Schaepman, M., "Determining iron content in Mediterranean soils in partly vegetated areas, using spectral reflectance and imaging spectroscopy." International Journal of Applied Earth Observation and Geoinformation 9, 194–203 (2007).

[17] Rogaß, C., Spengler, D., Bochow, M., Segl, K., Lausch, A., Doktor, D., Roessner, S., Behling, R., Wetzel, H.U. and Kaufmann, H., "Reduction of Radiometric Miscalibration-Application to Pushbroom Sensors." Sensors 11, 6370-6395 (2011).

[18] Smith, G.M. and Milton, E.J., "The use of the empirical line method to calibrate remotely sensed data to reflectance." International Journal of Remote Sensing 20(13), 2653-2662 (1999).

[19] Dell'Endice, F., Nieke, J., Koetz, B., Schaepman, M.E. and Itten, K., "Improving radiometry of imaging spectrometers by using programmable spectral regions of interest." ISPRS Journal of Photogrammetry and Remote Sensing 64(6), 632-639 (2009).

[20] Malley, D.F., Martin,P.D. and Ben-Dor, E., "Application in analysis of soils." Nearinfrared spectroscopy in agriculture 44, 729-783 (2004).

[21] Dunn, B.W., Beecher, H.G., Batten, G.D. and Ciavarella, S., "The potential of near-infrared reflectance spectroscopy for soil analysis-A case study from the Riverine Plain of south-eastern Australia." Australian Journal of Experimental Agriculture 42(5), 607-614 (2002).