Evaluation of soil sensor fusion for mapping macronutrients and soil pH

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Abstract

The effect of fusion of data from three proximal soil sensors on the prediction of macronutrients (N, P, K, Mg, Ca, Fe) and pH was studied. The commercial sensor platform Veris Technologies Inc. (Salina, KS, USA) used in the study included a soil resistivity/conductivity meter, a pH meter and two spectrophotometers for the visible (vis) and near-infrared (NIR) range. Bagging partial least squares regression was used for modeling. Adding pH and electrical conductivity readings to those of the vis-NIR sensors did only improve the prediction results for soil pH. High model quality among all target variables was achieved for soil pH and for total magnesium.

Keywords: soil electrical conductivity, soil pH, soil spectroscopy, bagging PLSR

Introduction

Information on spatial variability of soil nutrients within fields is a key factor for meeting site-specific requirements of crops. However, in most cases, soil nutrients vary strongly on field-scale, which makes adequate assessment by soil sampling and laboratory analysis laborious, time-consuming and expensive. Proximal soil sensing might offer an alternative to conventional methods for high resolution mapping of soil nutrients. While there are several proximal soil sensors in development (Adamchuk et al., 2004) mainly geo-electrical sensors (Gebbers et al., 2009) are used in praxis. In particular, there is still a lacking of soil chemical sensors. The first soil chemical sensor for automated mobile mapping successfully commercialized was the Veris pH Manager (Veris Technologies Inc., Salina, KS, USA) which is based on research by Adamchuk et al. (1999). Another approach which is gaining popularity is to record soil reflectance with a spectrometer for the determination of soil nutrients (Stenberg et al. 2010). However, soil nutrient determination is still challenging using proximal soil sensors individually. Thus, the aim was to test whether the fusion of data from sensors for measuring soil apparent electrical conductivity (ECa), soil pH and soil reflectance in the visible to near infrared (vis-NIR) spectrum can improve the prediction of soil pH and macro nutrients.

Materials and methods

Test sites

Tests were conducted on two fields in Northeast Germany: Kings Field (52° 44’ N, 13° 02’ E, ~ 3 ha) mapped in April 2010 and Red Sea (53° 06’ N, 13° 54’ E, ~ 25 ha) mapped in July 2010.

Proximal soil sensors

Soil electrical conductivity, soil pH and soil reflectance in the visible and near infrared range were measured with the Veris Mobile Sensor Platform (MSP). The Veris MSP is basically assembled with a geo-electrical sensor but can be extra-mounted with either a pH on-the-go sensor or soil reflectance sensor. The geo-electrical sensor allowed for sensing electrical conductivity in two soil depths using six coulter electrodes in Wenner configuration. While ECa mapping of Kings Field produced reasonable results, data from Red Sea were rather noisy due to a system failure. Thus, we were forced to fall back on ECa data mapped by another Veris system in 2008. The soil pH on-the-go sensor (Soil pH Manager) used a hydraulic system to grab soil material from 0.10 m depth and to bring it in direct contact with two antimony pH electrodes. Measurement time depended on the response of both electrodes and ranged between 7 and 25 s. After each measurement, the electrodes were rinsed by two wash nozzles using tap water. The spectrometer unit (vis-NIR) consisted of a fiber optic spectrometers from Ocean Optics (OFLV4-350-1000) for vis-NIR (350 – 1000 nm) and a HAMAMATSU (C9914GB) for NIR (1100 – 2200 nm) (Ocean Optics Inc., Dunedin, FL, USA, HAMAMATSU PHOTONICS K.K., Hamamatsu-City, Fukuoka, Japan). Reflectance measurements were taken continuously by a shank at approximately 10 cm soil depth. At the bottom of the shank was an outlet (18 mm in diameter, covered by a sapphire glass) for soil illumination by an integrated lamp and collection of reflected light which was led to the spectrometers via glass fibers. The shank included a shutter with a white surface to obtain calibration data from full reflection and dark current.

Data pre-processing

Spectral data were grouped into 9 classes by k-means clustering in order to detect erroneous measurements. Errors often occurred when illumination was disturbed by sunlight due to poor soil contact of the shank. Faulty spectra were removed after visual inspection. Spectral data were pruned by excluding noisy regions from 350 nm to 450 nm and 950 nm to 1050 nm.

Because soil pH and ECa values can vary due to environmental conditions from field to field, they were calibrated using linear regression. Veris pH values were calibrated against pH-CaCl values based on 5 soil samples from each field. Similarly, ECa values were calibrated against organic matter content (96 samples).

ECa data and pH data were interpolated using ordinary block Kriging (5 x 5 m) and spectral data were averaged using a buffer (5 x 5 m) onto the soil sample locations.

Chemical reference data

In total, 96 soil samples were collected within 30 cm depth. The samples were analyzed for plant available nutrients using double lactate or calcium chloride as extractants (P-DL, K-DL and Mg-CaCl) according to the German standards (VDLUFA, 2004). Total nitrogen (N_t) was determined by a Leco CNS-2000 Elemental Analyzer. Total content of the other nutrients (P_t, K_t, Mg_t, Fe_t) was measured by an ICP after *aqua regia* extraction. Soil acidity (pH-CaCl) was measured in a solution of 10 g of soil in 25 mL of 0.01 M $CaCl_2$ with a conventional glass electrode.

Data modeling

Soil sensor data were fitted to the chemical reference data by means of partial least squares regression (PLSR) with the orthogonal scores algorithm (NIPALS). The number of PLS components for the model calibration was selected by leave-one-out cross validation. Model validation was carried out with independent data obtained by splitting the complete data set into training and test data (70 and 30 %) before model calibration. Only training data were used for model calibration. After each run, the ratio of percent deviation (RPD) was calculated from the ratio of the standard deviation of the test data and the root mean squared error between model predictions and test data. To obtain a more robust estimate of model quality, RPD values were averaged from 100 PLSR model runs with different sets of training and test data (bagging). RPD values were classified according to Viscarra Rossel et al. (2006). PLSR modeling was done with the function plsr from the pls package (Mevik & Wehrens, 2007) in R (R Development Core Team, 2008).

Results and Discussion

Table 1. PLSR modelling results. Only sensor combinations that yielded the best result for each target variable are shown.

Soil parameter	Sensors	RPD value	Model quality
Soil pH	VisNIR, pH	2.38	very good model
Mg_t	VisNIR, pH	1.98	good model
P-DL	VisNIR, pH	1.67	fair model
Fe_t	VisNIR, ECa	1.52	fair model
C_t	VisNIR, ECa	1.50	fair model
Ca_t	VisNIR, pH	1.46	fair model
K_t	VisNIR, ECa	1.43	fair model
N_t	VisNIR, ECa, pH	1.40	poor model
Mg-DL	VisNIR, pH	1.35	poor model
K-DL	VisNIR, ECa	1.16	poor model
P_t	VisNIR, ECa, pH	1.12	poor model

Best model quality was achieved for soil pH. The RPD value was raised significantly with pH and vis-NIR sensor data used in combination. However, also vis-NIR sensor data alone reached an RPD value of 2.15. Mg_t models also achieved good prediction quality. Mg_t was well correlated with soil pH (r = 0.77). Probably similar soil forming factors contributed to the spatial dispersion of soil pH and Mg_t. While the inclusion of the soil pH and ECa sensor data did not improve the Mg_t model significantly it could be assumed most of the common influential factors were captured by the spectrophotometer. Fair model quality was obtained for P-DL, Fe_t, C_t, Ca_t and K_t. These models should only be used for assessment and correlation while the pH and Mg_t models are suitable for quantitative prediction (Viscarra Rossel et al., 2006). The models of the remaining soil parameter had poor model quality. Even though P-DL and P_t were well correlated with each other (r = 0.76), model quality differed substantially between those two.

One-way ANOVA using each sensor as a factor followed by a Tukey HSD test with p=0.05 showed that there was no general improvement of model quality by sensor fusion. Only with specific soil parameters improvement by fusion of sensors could be shown, e.g., in the case of soil pH addition of the pH sensor data did significantly improve the PLSR model. The prediction of the other soil parameters gained no significant improvement as when the vis-NIR sensor data were modeled individually. Noise present in the sensor data influenced the PLSR strongly and led to inferior model quality. Thus, considerable care should be taken in reducing erroneous measurements in the sensor data prior to PLSR modeling, e.g., deleting and/or filtering noisy spectral information.

Conclusions

The fusion of soil ECa and pH-on-the-go sensor data with soil reflectance data did not improve the prediction of macronutrients using the straightforward PLSR modeling approach in this case study. Only for soil pH, a significant gain in model quality was achieved by adding information from the pH on-the-go sensor. In the future, other, potentially more robust modeling approaches should be tested, e.g., robust PLSR, artificial neural networks and regression trees. It is likely that there was not enough variation in the target variables, which also led to a poor signal to noise ratio. For example, using only the sensor information from Kings Field for calibrating a full PLSR model, model predictions for soil pH and Mg_t were only weakly correlated with the reference data on Red Sea. However, in our opinion the integration of sample data with a larger variance into the models will lead to more solid and transferable models and, in this respect, the benefits of sensor fusion will become clearer. It will then be of interest to build models that are well adapted to a specific soil environment or soil landscape.

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