Geophysical Research Abstracts
Vol. 15, EGU2013-7885-1, 2013
EGU General Assembly 2013

Optimal sampling and sample preparation for NIR-based prediction of field scale soil properties

Maria Knadel, Yi Peng, Kirsten Schelde, Anton Thomsen, Fan Deng, and Mogens Humlekrog Greve

University of Aarhus, Dept. of Agroecology , Faculty of Science and Technology, Blichers Allé 20, PO box 50, DK-8830 Tjele, Denmark (maria.knadel@agrsci.dk)

The representation of local soil variability with acceptable accuracy and precision is dependent on the spatial sampling strategy and can vary with a soil property. Therefore, soil mapping can be expensive when conventional soil analyses are involved. Visible near infrared spectroscopy (vis-NIR) is considered a cost-effective method due to labour savings and relative accuracy. However, savings may be offset by the costs associated with number of samples and sample preparation. The objective of this study was to find the most optimal way to predict field scale total organic carbon (TOC) and texture. To optimize the vis-NIR calibrations the effects of sample preparation and number of samples on the predictive ability of models with regard to the spatial distribution of TOC and texture were investigated. Conditioned Latin hypercube sampling (cLHs) method was used to select 125 sampling locations from an agricultural field in Denmark, using electromagnetic induction (EMI) and digital elevation model (DEM) data. The soil samples were scanned in three states (field moist, air dried and sieved to 2 mm) with a vis-NIR spectrophotometer (LabSpec 5100, ASD Inc., USA). The Kennard-Stone algorithm was applied to select 50 representative soil spectra for the laboratory analysis of TOC and texture. In order to investigate how to minimize the costs of reference analysis, additional smaller subsets (15, 30 and 40) of samples were selected for calibration. The performance of field calibrations using spectra of soils at the three states as well as using different numbers of calibration samples was compared. Final models were then used to predict the remaining 75 samples. Maps of predicted soil properties where generated with Empirical Bayesian Kriging. The results demonstrated that regardless the state of the scanned soil, the regression models and the final prediction maps were similar for most of the soil properties. Nevertheless, as expected, models based on spectra from field moist soils showed the lowest predictive ability with root mean square error of cross-validation (RMSECV): 0.62%, 1.51%, 1.08%, 2.4% for TOC, clay, silt and sand respectively, resulting also in less detailed maps. The best calibration models for TOC, clay and silt were obtained from air dried soils (RMSECV: 0.43%, 1.18%, 0.99%, 2.55%, respectively). Sieving improved the results of sand calibration only (RMSECV=2.13%). Despite the positive effect of drying the soils, very little improvement was gained and on average accounted for a 19% decrease in RMSECV, with the highest decrease in RMSECV reported for TOC (30%). In general, no substantial effect of sampling intensity on the predictive ability of calibration models was found. The only significant differences were recorded for sand calibrations between models based on 50 and 15 moist soil samples and for silt between models based on 50 and 15 sieved soil samples. The results from this study show that one can produce acceptable vis-NIR predictions without the necessity of sieving or even drying the soils and using as few as 15 samples for field calibrations. Nevertheless, the selection of sample preparation and number of samples is dependent on soil properties and should be adjusted to the precision needed.