Sensor data fusion for topsoil clay mapping of an agricultural field

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Abstract

Data from proximal sensors for gamma (γ) radiation and apparent electrical conductivity (ECa) was combined with elevation, radiance and drainage data. Predictions of clay content were made with different combinations of predictor variables. Predictions from ECa were improved by using multitemporal measurements or multiple measurements with different depth responses. They were also improved by addition of radiance data. Predictions from γ radiation were found to be accurate and was not much improved by adding ECa or any other ancillary data. Predictions by a k Nearest Neighbor algorithm were somewhat better than predictions by Partial Least Squares regression.

Keywords: Clay, electrical conductivity, gamma radiation, proximal sensing, soil mapping.

Introduction

Clay content is an important factor for soil fertility, as it affects the structural and hydrological properties as well as the nutrient availability. High resolution maps of clay content are therefore a requirement for some precision agriculture applications. Proximal sensors for apparent electrical conductivity (ECa) or gamma (γ) radiation can be used for cost effective high-resolution digital soil mapping. There are several studies in the literature that use either ECa or γ radiation sensors individually for this purpose. There are also a few recent studies of multi sensor approaches to map clay content of agricultural soils. For example, Taylor et al (2010) found that a multivariate model based on two different sensors was superior to univariate models based on either of the two sensors. The combination of ECa and γ radiation data has also been used to predict topsoil soil type by a rule-based method (Wong et al, 2010).

The aim of the present study was to evaluate and compare the ability of different combinations of spatial data (ECa, γ radiation, radiance, drainage and elevation) to predict topsoil clay content of an agricultural field. The hypotheses were:

1) Multiple ECa measurements from different occasions would perform better than one ECa measurement alone.
2) Multiple ECa measurements with different measurement depths would perform better than one single-depth ECa measurement.
3) Using the ECa and the γ radiation sensor together would improve predictions compared to using one sensor alone.
4) Introducing information on variation patterns by adding other relevant ancillary data would improve the predictions of either sensor.

In addition, the predictive powers of two different prediction methods (Partial Least Squares Regression, PLS-R, and k Nearest Neighbour prediction, kNN) were compared.

Materials and methods

Study field

The study field is situated in Västra Götaland County in Sweden (N 58º 15' 38"; E 13º 7' 58"). Clay content was analyzed for four topsoil samples per hectare (n = 98) and ranged between 4 and 30 %.

Study design

Seventy samples were chosen as a training dataset, which was used for calibration of the PLS-R models and as reference values in the kNN predictions. The remaining 28 samples were used for validation.

Data collection and preparation

Spatial data were collected with proximal sensors for γ radiation (The Mole, The Soil Company, the Netherlands; ^{232}Th, ^{40}K, ^{238}U and total counts) and ECa (EM38 Mk 2 2, Geonics Ltd., Canada; 4 depths x 1 occasion + 2 depths x 3 occasions). Panchromatic radiance data was obtained from a bare-ground airial photography (Swedish Land Survey, Gävle, Sweden). Slope, aspect and measures of concave and convex terrain features were calculated from elevation data collected with RTK-GPS and distances to the drainage system were derived from a tile drainage map. Values of all predictor variables were calculated for a 10×10 m^2 grid and extracted for the 98 sampling points using ArcGIS 9.3 (ESRI Inc. CA, USA). In order to transform the values of the different entities to a common scale, data were centred by the mean and scaled by the standard deviation.

Predictions

PLS-R models were parameterized and deployed using the Unscrambler X 10.0.1 (Camo Software AS, Oslo, Norway). The kNN predictions with distance weighting were performed with an algorithm analogous to the inverse distance weighting algortithm commonly used for spatial interpolation, see e.g. Burrough & McDonnell (1998).

Validation

The predictive power of the different predictor sets were quantified by the mean absolute error (MAE) and the modelling efficiency (ME), see Janssen & Heuberger (1995).

Results

Prediction quality tended to be improved (lower MAE and higher ME) by increasing the number of ECa measurement occasions or the number of measurement depths (Figure 1 a-b). The trend was somewhat stronger for PLS-R predictions than for predictions by kNN.

The clay content predictions based on γ radiation was better than those based on ECa (Figure 2 a-b). Using the two sensors together yielded predictions of about the same quality as using the γ radiation sensor alone. Clay content predictions based on ECa were improved by the addition of surface radiance data from the aerial photo but addition of elevation or drainage data had no obvious effect (Figure 2 a-b). The kNN method was most often better than the PLS-R method (Figure 1-2).

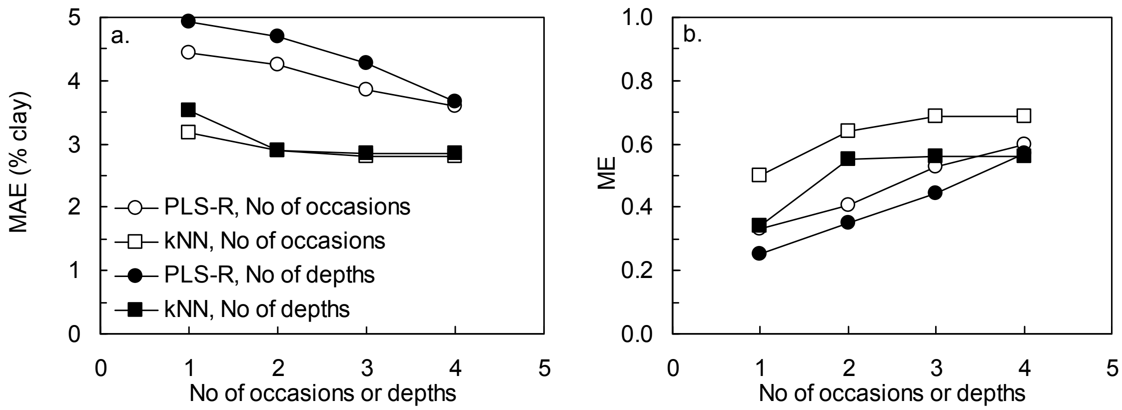

Figure 1. Validation of clay content predictions based on multiple measurements of bulk electrical conductivity. Predictions were made for all possible combinations of 1-4 measurement occasions (vertical mode only) or measurement depths (one occasion only). a) mean absolute error (MAE) and b) modelling efficiency (ME). The legend is valid for both a and b.

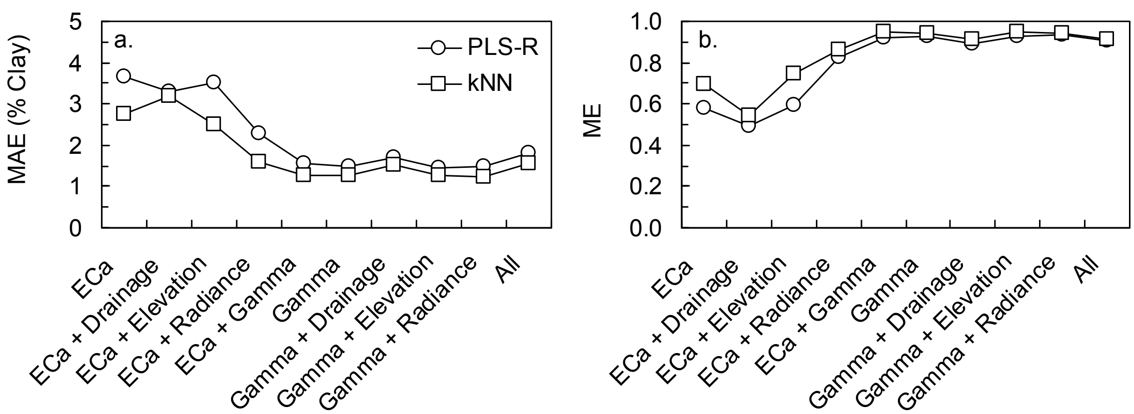

Figure 2. Validation of clay content predictions based on different predictor sets. a) mean absolute error (MAE) and b) modelling efficiency (ME). The legend is valid for both a and b.

Discussion

As ECa is affected by soil temperature and soil moisture, ECa readings vary over time. The magnitudes of temporal moisture and temperature variations are related to soil type and the present results indicate that the temporal variation in ECa may be useful as input for clay content predictions.

The reason for the relatively low prediction quality for predictions based on one single ECa measurement may be that the clay content depth profiles differs considerably across the study field (data not shown). The ECa sensor is affected by both the topsoil and the subsoil and the present results indicate that using multiple ECa measurements with different depth responses might be helpful to account for the subsoil impact.

Both in the present study and in the study by Taylor *et al.* (2010) it was found that γ radiation alone was a better predictor of topsoil clay content than if only ECa was used. However, Taylor *et al.* (2010) found that the dual sensor approach was superior to using either sensor individually. In the present study, the dual sensor approach was superior to using the ECa sensor alone but the γ radiation sensor did more or less as good on its own.

Conclusions

The following results were summarized from the study.

1) Clay content mapping was improved by using ECa measurements from multiple occasions, probably because the temporal variation was related to clay content.
2) Predictions based on ECa data were somewhat improved by using measurements over multiple depths. A likely explanation to the observed improvement is that the impact from deeper layers could be accounted for, by using a combination of measurements with different depth responses.
3) Predictions based on ECa data were improved by adding radiance data, while addition of drainage or elevation data had no noticable effect.
4) Predictions from γ radiation were found to be rather accurate (MAE < 1.5% clay) and was not much improved by adding ECa or any other independent data.
5) The kNN method often performed better than the PLS-R method

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