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# TOPSOIL TEXTURE MAPS BASED ON CALIBRATION OF SOIL ELECTRICAL CONDUCTIVITY WITH SOIL DATASETS VARYING IN SIZE

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*Abstract.* The purpose of the study was to verify the possibility of creation of reliable soil texture class (STC) maps of a topsoil based on calibration of shallow (0–30 cm) soil electrical conductivity (ECsh) with small datasets of soil samples with laboratory determined STC. The study was performed in three fields located in different regions of Poland: Pomerania (glacial soils), Mazovia (alluvial soils) and Lower Silesia (soils formed from loess-derived sediments over glacial materials). ECsh values were calibrated against four datasets of soil samples. The smallest datasets (5–6 soil samples per field) were selected: 1) in an arbitrary way; or 2) based on the quartiles of ECsh values. A dataset of an intermediate size (11–17 points) and a full dataset of data available (33–38 points) were also tested. The equations used for calibration of ECsh values with fine soil fractions contents were most frequently non-linear. For the fields with smaller ST variation to a depth of 90 cm, such calibration produced STC maps with agreement of more than 90% of area with respective calibration of all data available. The ECsh values depended on the content of fine soil (<2 mm) fractions to a depth of 90 cm, so ECsh measurements can be efficient in mapping the topsoil texture of fields with relatively small texture changes in subsoil. The areas with the same STC obtained using the greatest reference dataset and the smallest dataset are a better indicator of STC assessment quality than the values of assessment errors.

**Keywords:** electrical conductivity, soil texture, calibration, linear regression, topsoil

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## INTRODUCTION

Soil texture (ST) is an important property to be considered in precision agriculture (Mzuku *et al*. 2005) in variable application of inputs: fertilizers, lime, manure (Ruckamp *et al.* 2013) seeds or water. Commonly accepted methods of ST determination (pipette and hydrometer) are expensive and time-consuming (Coates and Hulse 1985). The laser diffraction method is quick, but frequently underestimates the clay content in the soil (Ferro and Mirabile 2009, Orzechowski *et al*. 2014). A high number of soil samples (>100) is required to characterize a large field (Webster and Oliver 1992), but Florinsky (2012) suggested to reduce this number to 40. Due to high costs, the collection and analysis of such number of soil samples to characterize production fields is rather unacceptable in commercial precision agriculture. Thus, it is important to reduce the number of soil samples and detect the areas of the field differing in ST, using other methods, for example, measurements of soil electrical conductivity (EC) or apparent electrical conductivity (ECa). A strong and positive correlation between EC/ECa and a clay content in soil was observed in many studies (Sudduth *et al*. 2005, Machado *et al*. 2006, Kuhn *et al*. 2009, Landrum *et al*. 2015, Serrano *et al*. 2014). Ambiguous results refer to the relationships between EC/ECa and sand and silt content. Positive and significant correlation of EC/ECa with soil silt content was obtained by Serrano *et al*. (2014) and by Kuhn *et al*. (2009). Negative, insignificant or positive correlations between silt content and EC/ECa were observed by Sudduth *et al*. (2005) for different fields. Landrum *et al*. (2015) reported positive correlation of EC/ECa with sand content, contrary to Serrano *et al*. (2014). Insignificant, positive or negative relationships between EC/ECa and a sand content, depending on field and other factors, were obtained by Sudduth *et al*. (2005).

The aim of the present study was: 1) the evaluation of accuracy of shallow EC (ECsh) calibration for assessment of ST using a small number of soil samples 2) the assessment of ST prediction quality in topsoil (0–30 cm) using a small number of soil samples collected across a full range of soil ECsh values and best-fitted regression models; 3) comparison of quality of soil texture class (STC) maps obtained from different ST datasets of soil samples used for the calibration of the ECsh values.

## MATERIALS AND METHODS

The study considered three fields (Table 1) in northern (field A, Damno), central (field B, Imielin) and southern (field C, Górzec) Poland. Field A with soils of glacial origin is most representative for Poland, comparable with about 40% of arable land (Pondel *et al*. 1979). The soils of fields B are of alluvial origin and the soils of field C are originated from shallow loess-derived sediments (Jary *et al.* 2002) over glacial till.

TABLE 1. BASIC INFORMATION ON SITES OF THE STUDY AND SOIL ELECTRICAL CONDUCTIVITY (EC) MEASUREMENTS AND SOIL SAMPLING

| Geographic coordinates Area (ha) | Soil WRB 2007* **dominant** and associated | Texture class **dominant** (associated) | Data collection | | |
|---|---|---|---|---|---|
| | | | Type of data | Date | n |
| Field A | | | | | |
| 54°31'N, 17°18'E 22 ha | **Luvisols (about 85%),** Regosols (10%), Cambisols and Arenosols | **Sandy loam** (loamy sand) | EC | 16 Sep 14 | 4714 |
| | | | $N_{min}$ sampling (N) | 18 Aug 13 | 22 |
| | | | Soil pits (P) | 16 Nov 13 | 5 |
| | | | Additional deep soil samples (D) | 24Mar 11** (1 pit) | 9 |
| Field B | | | | | |
| 52º4'N 21º10' 20.5 ha | Fluvisols | **Silt loam** (loam, sandy loam) | EC | 8 Nov 13 | 5118 |
| | | | $N_{min}$ sampling (N) | 20 Aug 13 | 22 |
| | | | Soil pits (P) | 19 Nov 13 | 6 |
| | | | Additional deep soil samples (D) | | 5 |
| Field C | | | | | |
| 50º48'N, 17º5'E 20.5 ha | Phaeozems | **Silt loam** (loam, sandy loam) | EC | 18 Sep 14 | 5169 |
| | | | $N_{min}$ sampling (N) | 7 Mar 13 | 22 |
| | | | Soil pits (P) | 21Nov13, | 6 |
| | | | Additional deep soil samples (D) | 18Sep14 (1 pit and 1 other point) | 10 |

* – IUSS Working Group WRB 2014

** – data obtained during research project NN 310 089036 supported by the Polish Ministry of Science and Higher Education in years 2009–2012

Soil sampling comprised (Table 1): deep soil samples (N) collected separately from the approximated layers 0–30, 30–60 and 60–90 cm for a mineral nitrogen ($N_{min}$) content determination and ST analyses, soil pits (P) and additional deep soil samples (D). The points of soil sampling were selected to represent different delineations of agricultural soil map and different positions in relief. Air dried soil samples were passed through a 2 mm sieve and subjected to texture analysis using a hydrometric (areometric) method widely used in Poland (Orzechowski *et al*. 2014). Soil EC measurements were done using Veris Mobile Sensor Platform 3 (Veris Technologies, Inc. Salina, KS, USA) carried by a tractor along tramlines every 15 m.

The results of shallow EC measurements (ECsh, corresponding to a depth of about 30 cm, Kweon *et al*. 2012) were calibrated with laboratory determined ST of a topsoil layer (0–30 cm). However, the results of ST determination of subsoil layers (to a depth of 90 cm) were considered to assess the variability of sand, silt and clay content with soil depth and their correlation with ECsh readings. The median value of all ECsh measurements registered within a diameter of 10 m around each soil sampling point was calculated and treated further in calculations as the ECsh value in this point.

ECsh calibration was carried out using ST values derived from 4 soil sampling datasets for each field: R treated as reference dataset, i.e. all soil samples (sum of N, P and D, Table 1), PD (sum of data from soil pits and additional deep soil samples), P (data from soil pits only) and Q (quartiles of all ECsh values corresponding to all soil sampling points in each field). The Q datasets comprised 5 soil sampling points for fields B and C and 6 for field A, because the ECsh median was 7.32 ($mS \cdot m^{-1}$) and there were two soil sampling points close to this value (7.31 and 7.33 $mS \cdot m^{-1}$), thus both were included in the Q dataset for site A. The ST assessment was carried out in the same way for each field and dataset. The best-fitted regressions for the relationships between ECsh values and the content of each soil fine fraction were calculated for sampling points included in each dataset. The contents of 2 fine soil fractions for the remaining soil sampling points of each field (i.e. not included in a statistical analysis for each dataset), were calculated using regression equations with greater determination coefficient – $r^2$ – value from three linear equations (for sand, silt and clay). The content of a third fraction was calculated by subtracting the contents of the two already calculated fractions from 100.

The results of ECsh calibration using each dataset (R, PD, P and Q) were compared to the results of the laboratory determination of soil fractions in validation dataset. This dataset comprised sampling points not included in PA, P and Q datasets. The validation dataset comprised 12 soils sampling points in field A and 17 points both in field B and field C. Root mean square errors (RMSE) and mean absolute errors (MAE) based on analysis of a linear regression were calculated according to the following formulas:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n}$$

Where: $y_i$ is the content of the particular soil fraction, as determined in the laboratory, and $\hat{y}_i$ is the predicted soil fraction, as determined using ECsh.

MAEs values were compared between different datasets using ANOVA and a Tukey method of multiple comparisons (at 0.05 probability level). Absolute errors for each point were treated as replications. The analyses were performed for each soil fraction separately. The regression functions for relationship between fine soil fractions and ECsh and statistical analyses were carried out in a Statgraphics Plus 4.1 software (Statistica Graphics Corp. Rockville, USA). The predictive ability of ECsh at reference sampling points was assessed by comparing the predicted STC with the STC determined by laboratory analysis. If the predicted and the actual values were the same, the prediction quality was considered as a good one.

Maps of STCs for each field were made for all calibration datasets using the following procedure: 1) calculation of fine soil fraction contents for each point of ECsh measurement in .xls files containing data; 2) import of these files to a QGIS 2.0 software (Quantum GIS Development Team 2013) and preparation of .shp files; 3) interpolation using ordinary kriging (spherical function) of calculated sand and clay contents with the use of ArcGIS 9.3 software (ESRI, Redlands, USA); 4) generation of STC maps using the QGIS 2.0 software and the “soil texture” plugin. The reference ST map based only on laboratory ST analysis of all soil samples available for a field were prepared using QGIS 2.0 software, IDW interpolation with default settings and the “soil texture” plugin.

The quality of STC maps prepared using different ECsh vs. ST calibration datasets were assessed by 1) comparison of detection of particular STCs by considered datasets and laboratory results, and 2) calculation of common (overlying) areas with the same STC on a map calibrated using R-dataset and on the map prepared on the base of remaining PD, P and Q datasets.

## RESULTS AND DISCUSSION

On average, field A was characterized by sandy loam with a small area of loamy sand in a plough layer (Table 2). The topsoil of B and C fields was characterized generally by higher clay content than the topsoil of field A and the mean STC of these two fields was mainly silt loam with some areas characterized by loam and sandy loam STC. The variability of sand and silt content with depth was much greater in fields B and C than in field A, but variability of a clay content with depth was greater in field A than in the other two fields. The ECsh values were strongly correlated with fine soil fractions content even to a depth of 90 cm on all fields (Table 2).

TABLE 2. THE CONTENT OF FINE SOIL FRACTIONS IN A TOPSOIL LAYER, COEFFICIENT OF VARIABILITY OF RESPECTIVE ST FRACTIONS WITHIN A 0–90 CM LAYER AND PEARSON'S CORRELATION COEFFICIENTS BETWEEN ECSH VALUES (mS·m$^{-1}$) AND WEIGHTED CONTENT OF SAND, SILT AND CLAY (ALL DATA)

| Fraction | Fine soil fractions content (%) in topsoil | | | Coefficient of variability of the content of fine soil fractions with a depth in a layer of 0–90 cm | | | Correlation coefficients between ECsh values and weighted content of fine soil fractions to a depth of: | | |
|---|---|---|---|---|---|---|---|---|---|
| | Range | Mean | Median | Range | Mean | Median | 30 cm | 60 cm | 90 cm |
| Field A | | | | | | | | | |
| Sand | 51-78 | 65.1 | 64 | 0.007–0.15 | 0.05 | 0.06 | -0.524 | -0.495 | <u>-0.429</u> |
| Silt | 17-43 | 28.6 | 30 | 0.04–0.70 | 0.10 | 0.15 | 0.318 | 0.254 | 0.230 |
| Clay | 2-15 | 6.3 | 6 | 0.07–0.90 | 0.36 | 0.41 | 0.581 | 0.636 | <u>0.556</u> |
| Field B | | | | | | | | | |
| Sand | 20-62 | 37.8 | 37 | 0.08–0.60 | 0.30 | 0.31 | -0.684 | -0.831 | <u>-0.833</u> |
| Silt | 29-67 | 50.4 | 51.5 | 0.05–0.95 | 0.32 | 0.36 | 0.670 | 0.828 | <u>0.833</u> |
| Clay | 6-16 | 11.8 | 12.5 | 0.12–1.09 | 0.25 | 0.34 | 0.373 | 0.625 | <u>0.684</u> |
| Field C | | | | | | | | | |
| Sand | 19-65 | 34.1 | 33 | 0.06–0.67 | 0.29 | 0.31 | -0.534 | -0.727 | <u>-0.789</u> |
| Silt | 25-74 | 56.4 | 58 | 0.04–0.98 | 0.20 | 0.31 | 0.504 | 0.664 | <u>0.752</u> |
| Clay | 2-16 | 9.5 | 9 | 0.00–1.20 | 0.24 | 0.32 | 0.251 | 0.540 | <u>0.500</u> |

<u>Underlined</u> – Pearson's correlation significant, at 0.05 significance level

When considering the whole ST dataset available (dataset R), the ECsh values were positively and significantly correlated with clay, but negatively with sand content (Tables 2 and 3, Fig. 1) for each field. This was previously found by Serrano *et al*. (2014) and Kuhn *et al*. (2009). The positive relationship of ECsh with a clay content was observed in many studies (Sudduth *et al*. 2005, Machado *et al*. 2006, Kuhn *et al*. 2009, Landrum *et al*. 2015, Serrano *et al*. 2014). In fields B and C, significant and positive relationship was also found between silt content and ECsh values, as it was observed by Serrano *et al.* (2014) and Landrum *et al.* (2015).

The relationship between ECsh and soil fractions was most frequently curvilinear (Fig. 1 and Table 3). In 4 cases out of 12, a linear function was also the best-fitted model (clay content with ECsh values on field A for datasets R and Q, and silt and sand content with ECsh values on field B for dataset Q). This suggests that use of linear functions for ST prediction might diminish the quality of such prediction.

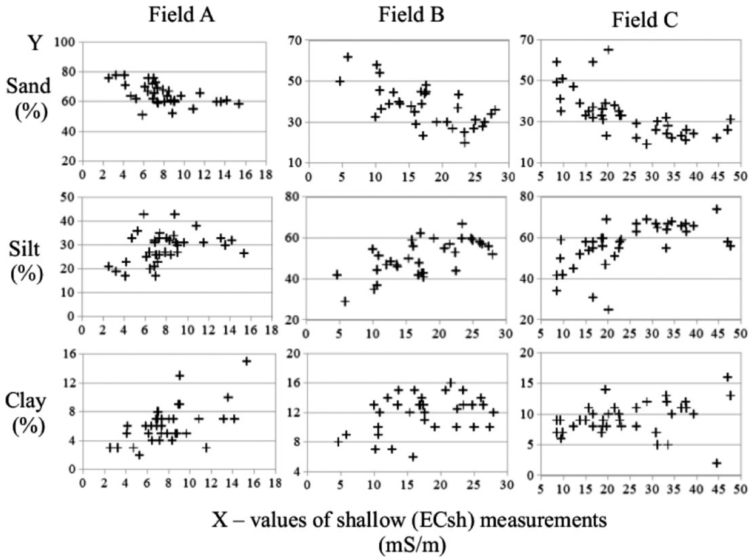


Fig. 1. The plots of dependence between the content of soil fractions and ECsh

The analysis of ANOVA (Table 4) indicated significant differences only in prediction of sand and silt in field C, where the Q dataset was a significantly worst predictor of these fractions in comparison with other datasets. The lowest RMSEs values of ST assessment (Table 4) were obtained for a complete dataset R. However, the next dataset in size – PD – was second in terms of RMSEs values only in three cases of prediction (sand and clay in field B and sand in field C), and produced the highest RMSEs in prediction in two cases (silt and clay in field A). The analysis of MAE values produced, in most cases, similar rankings (from the lowest to highest value) as RMSE ranking and, thus, brings to similar conclusions. However, in one case (prediction of silt content on field A), the greatest dataset in size R – did not produce the smallest MAE values in the reference dataset. In this case, small dataset Q was first in ranking and produced smallest MAE of all datasets. The second dataset in size – PD – was second in ranking only in three cases (prediction of sand in field A and B, and prediction of clay in field B). The PD dataset was last in ranking (produced the highest values of MAE) in two cases – prediction of silt and clay content in field A. These results indicated, that in some cases, the simple increase of the size of dataset used for ECsh calibration with fine soil fractions content might not result in improvement of prediction quality.

Overall, the smallest values of both kinds of errors (RMSEs and MAEs) were obtained for field A, and the greatest for field B. However, the use of Q dataset for calibration of ECsh results in field B with sand and silt fractions produced the highest values of errors across all fields and datasets.

TABLE 3. REGRESSION EQUATIONS BETWEEN CHOSEN FINE SOIL FRACTIONS AND ECSH VALUES USED TO PREDICT THE CONTENS OF SOIL TEXTURE FRACTIONS

| Dataset | | | | | | | |
|---|---|---|---|---|---|---|---|
| R* | | PD | | P | | Q | |
| Equation | $r^2$ | Equation | $r^2$ | Equation | $r^2$ | Equation | $r^2$ |
| Field A | | | | | | | |
| sand=55.8+61.8/ECsh | $\underline{0.35}$ | sand=88.9-12.04*ln(ECsh) | $\underline{0.48}$ | sand=57.0+48.0/ECsh | $\underline{0.95}$ | sand=89.8-8.46*sqrt(ECsh) | 0.60 |
| clay=2.12+0.526*ECsh **(L)** | $\underline{0.33}$ | silt=12.8*ECsh^0.403 | $\underline{0.48}$ | clay=1/(0.0798+0.617/ECsh) | $\underline{0.91}$ | clay=-0.858+1.01*ECsh **(L)** | $\underline{0.92}$ |
| Field B | | | | | | | |
| sand=81.4-15.7*ln(ECsh) | $\underline{0.46}$ | sand=70.6-12.7*ln(ECsh) | $\underline{0.58}$ | sand=68.3-11.8*ln(ECsh) | 0.62 | sand=53.2-0.593*ECsh **(L)** | $\underline{0.81}$ |
| silt=22.4*ECsh^0.286 | $\underline{0.44}$ | silt=1/(0.0160+0.0399/ECsh) | $\underline{0.58}$ | silt=1/(0.0159+0.0376/ECsh) | $\underline{0.66}$ | silt=39.6+0.422*Ecsh **(L)** | 0.41 |
| Field C | | | | | | | |
| sand=127.8*ECsh^-0.446 | $\underline{0.51}$ | sand=166*ECsh^-0.523 | $\underline{0.53}$ | sand=1/(0.0157+0.000381*ECsh) | $\underline{0.75}$ | sand=13.7+370/ECsh | $\underline{0.68}$ |
| silt=15.4+13.3*ln(ECsh) | $\underline{0.36}$ | silt=-0.614+18.3*ln(ECsh) | $\underline{0.43}$ | clay=5.35*ECsh^0.237 | $\underline{0.94}$ | silt=1/(0.0109+0.126/ECsh) | $\underline{0.75}$ |

* – R, P, PA and Q are various datasets used for spatial ST interpolation; R – all data, P – pits, PA – pits and augerings, Q – quartiles.

(**L**) – a linear regression function was the best-fitted

Underlined – significant, at 0.05 significance level

TABLE 4. ERRORS OF ASSESSMENT (RMSE – ROOT MEAN SQUARE ERROR AND MAE – MEAN ABSOLUTE ERROR, R, PD, P, Q – SOIL SAMPLINGS DATASETS) OF ST FRACTIONS BASED ON REGRESSION WITH ECSH VALUES AS A PREDICTOR IN THE VALIDATION DATASET. THE NUMBERS IN PARENTHESIS INDICATE THE PLACE OF PARTICULAR DATASET IN RANK, WHERE THE NUMBER 1 WAS ATTRIBUTED TO THE SMALLEST VALUE OF RMSE OR MAE

| Fraction | RMSE | | | | MAE | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R* | PD | P | Q | R | PD | P | Q | P-value** |
| Field A | | | | | | | | | |
| Sand | 5.38 (1) | 5.82 (3) | 5.40 (2) | 6.34 (4) | 3.80 (1) | 4.13 (2) | 4.19 (4) | 4.15 (3) | 0.999 |
| Silt | 5.50 (1) | 6.54 (4) | 5.60 (2) | 6.27 (3) | 3.98 (2) | 4.52 (4) | 4.47 (3) | 3.81 (1) | 0.993 |
| Clay | 2.30 (1) | 2.69 (4) | 2.37 (2) | 2.39 (3) | 1.73 (1) | 1.99 (4) | 1.81 (2) | 1.98 (3) | 0.991 |
| Field B | | | | | | | | | |
| Sand | 5.38 (1) | 8.50 (2) | 8.54 (3) | 9.21 (4) | 6.20 (1) | 6.63 (2) | 6.66 (3) | 8.38 (4) | 0.733 |
| Silt | 5.50 (1) | 8.59 (3) | 9.06 (4) | 7.26 (2) | 5.13 (1) | 6.74 (3) | 7.04 (4) | 6.47 (2) | 0.792 |
| Clay | 2.31 (1) | 2.70 (2) | 3.27 (4) | 3.07 (3) | 1.38 (1) | 2.11 (2) | 2.71 (4) | 2.65 (3) | 0.100 |
| Field C | | | | | | | | | |
| Sand | 4.84 (1) | 6.20 (2) | 6.36 (3) | 11.08 (4) | 3.69a (1) | 4.58a (3) | 4.50a (2) | 10.42b (4) | 0.000 |
| Silt | 5.75 (1) | 7.42 (3) | 7.08 (2) | 12.94 (4) | 4.70a (1) | 5.85a (3) | 5.23a (2) | 12.23b (4) | 0.000 |
| Clay | 2.58 (1) | 2.90 (3) | 3.67 (4) | 2.75 (2) | 1.90 (1) | 2.25 (3) | 2.54 (4) | 2.15 (2) | 0.853 |

* – R, PA, P and Q and O are various datasets used for spatial ST interpolation; R – all data, P – pits, PD – pits and augerings, Q – quartiles

** – the ANOVA was performed to compare datasets of R, P, PA, Q and O for each ST fraction and separately for MAEs within each field the ANOVA was performed to compare datasets of R, P, PA, Q and O for each ST fraction and separately for MAEs and MREs within each field.

The ability of ECsh to predict proper STC in validation dataset (12 points, Figure 2) was very good in field A, where only one dataset (P) failed to predict loamy sand (LS) in one point. As a result, in field A, the percentage of validation points with correctly predicted STC was 100% for datasets R, PD and Q and 91.7% for dataset P. The worst results of ECsh calibration were obtained in field B, where the percentage of validation points (total 17) with correctly predicted STC varied between 35 and 58%. Moreover, the prediction ability of ECsh calibration in validation points was better for small datasets Q (58%) and P (41%), than for an intermediate dataset PD (41%) and a complete dataset R (47%). Field B with alluvial soils (Table 1) built up of various layers with different STC was characterized by greater variation of silt and clay content to a depth of 90 cm in comparison with other fields (Table 2). As a result, ST of subsoil layers (depth greater than 30 cm) probably affected the values of ECsh. The ability of ECsh to predict topsoil STC in validation dataset (17 points) in field C varied between 53% (dataset Q) and 94% (dataset R). Other datasets (P and PD) permitted the correct prediction of STC in 82% of validation points.

The maps of STCs (Fig. 2) prepared after calibration of fine soil fractions content vs. ECsh showed the presence of small and dispersed areas of silty clay loam, clay loam, silty clay and clay areas in field A (Fig. 2). These areas were not subjected to soil sampling and their texture could not be confirmed by laboratory analysis.

The calibration of all datasets with ECsh managed to detect areas of most important (according to laboratory results) STCs in field A – sandy loam and loamy sand (Fig. 2 and Table 5).

In field B, areas of sandy loam were delineated only by calibration of ECsh with the complete dataset R. The use of other, smaller, datasets failed to delineate this STC in the fields and give inconsistent results regarding an area of most extensive STCs: loam and silt loam. The areas of loam seem to be clearly underestimated by datasets PD and P, and overestimated by dataset Q. Consequently, the calibration of ECsh with small datasets of soil data did not manage to produce maps of acceptable similarity to the map produced by IDW interpolation of soil data or based on dataset R. Such a situation probably results from the alluvial origin of soil of this field and greater variation of dominating soil fractions to a depth of 90 cm, in comparison with field A.

In field C, all datasets managed to delineate approximately the sandy loam areas. Moreover, the maps produced by calibration of ECsh and soil data from datasets PD and P were similar to the map based on dataset R calibrated with ECsh. Only the map prepared from dataset Q showed unacceptable dissimilarity, due to extensive overestimation of loam, and underestimation of silt loam area.

The agreement in ST assessment between R dataset and other datasets for sandy loam in field A was always more than 95% of the whole field area (Table 5). All datasets, even the smallest, detected not only the presence of sandy loam, the STC prevailing in the field, but also loamy sand. On the other hand, the extent of loamy sand areas delineated on the basis of various datasets was different. It should be noted that very small dataset Q delineated the area of loamy sand with almost full agreement with dataset of all available data (R), contrary to other datasets P and PD. In field B, the portion of common areas with the same STC for R and the smaller datasets did not exceed 65% for PD and Q datasets, and was smaller than 60% for P dataset. In field C, the datasets PD and P produced the maps of about 90–95% of area agreement with the map produced by R dataset, while this agreement for Q dataset was smaller than 50%. These results clearly confirm the simple, visual assessment of these maps. On the other hand, the criterion of area agreement between maps produced by ECsh calibration with R dataset with the respective map produced by other datasets led to different conclusions than the assessment of prediction errors (RMSE and MAE). For example, the best maps of field B was produced by PD dataset according to area agreement, by P dataset according to RMSE and by Q

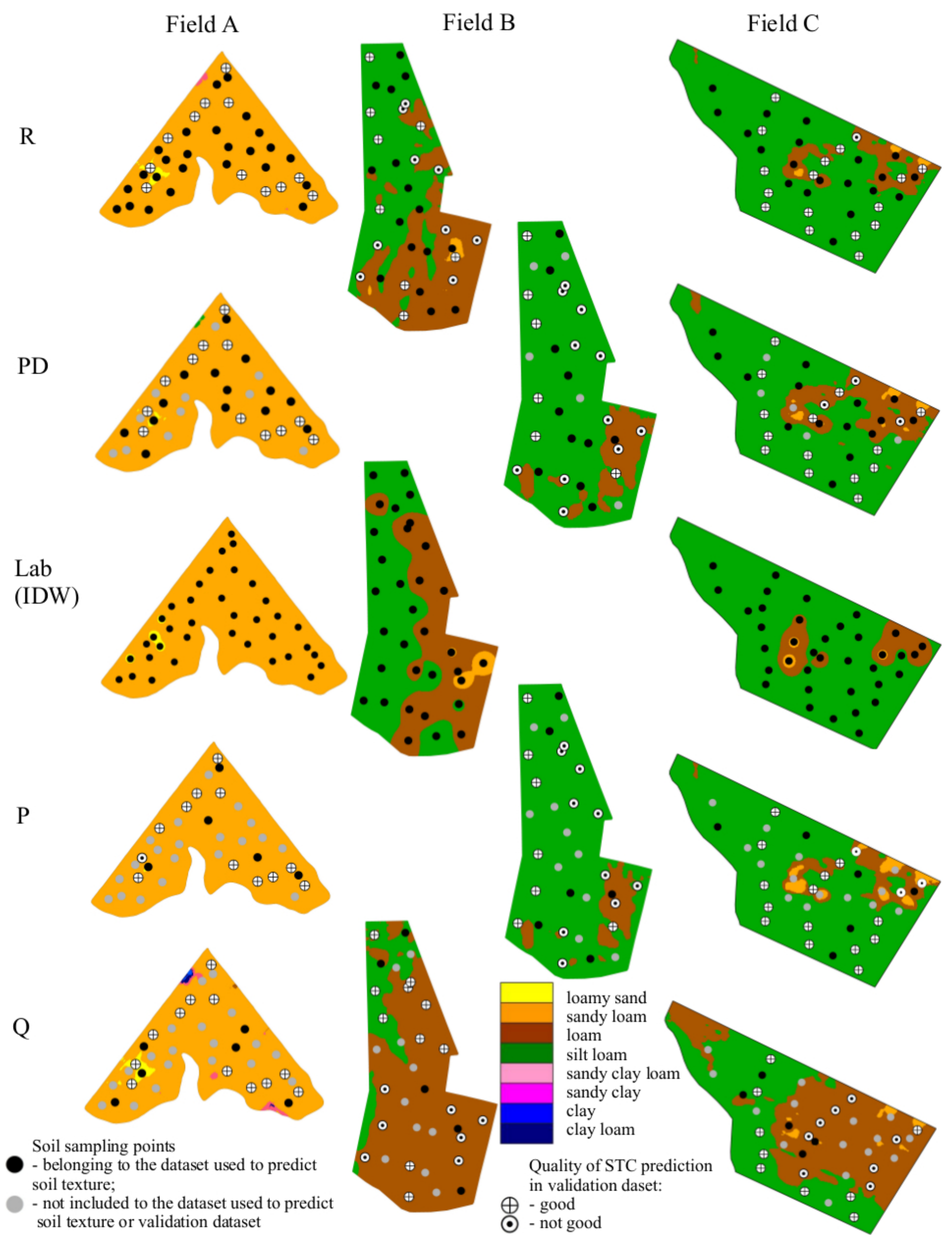


Fig. 2. Maps of soil texture classes predicted on the base of ECsh calibration using the R, PD, P and Q datasets and obtained on laboratory data only ("Lab")

dataset according to MAE. However, the resulting map and agreement of areas is probably a better criterion of prediction quality than the errors calculated for each prediction.

TABLE 5. DETECTION OF PARTICULAR STC OF A TOPSOIL LAYER, AS COMPARED TO THE LABORATORY RESULTS AND AGREEMENT BETWEEN AREAS OF PARTICULAR STCs INDICATED BY DATASET R AND THE SMALLER DATASETS

| Aspect of quality | | Detection of STC of topsoil | | | | Area with the same STC as on the map based on R dataset ha (% of field area) | | | |
|---|---|---|---|---|---|---|---|---|---|
| Dataset | | R | PD | P | Q | R | PD | P | Q |
| Field A | | | | | | | | | |
| Topsoil STC | LS | + | + | + | + | 0.26 | 0.10 (0.5) | 0.02 (0.1) | 0.26 (1.2) |
| | SL | + | + | + | + | 21.53 | 21.53 (98.8) | 21.53 (98.8) | 20.97 (97.4) |
| Whole field | | 2/2 | 2/2 | 2/2 | 2/2 | 21.79 | 21.63 (99.3) | 21.55 (98.9) | 21.23 (98.6) |
| Field B | | | | | | | | | |
| Topsoil STC | SL | + | - | - | - | 0.26 | 0.00 (0.00) | 0.00 (0.00) | 0.00 (0.00) |
| | L | + | + | + | + | 10.25 | 2.80 (13.00) | 1.81 (8.4) | 10.25 (47.6) |
| | SiL | + | + | + | + | 11.04 | 11.03 (51.2) | 11.03 (51.2) | 3.60 (16.7) |
| Whole field | | 3/3 | 2/3 | 2/3 | 2/3 | 21.55 | 13.83 (64.2) | 12.84 (59.6) | 13.85 (64.3) |
| Field C | | | | | | | | | |
| Topsoil STC | SL | + | + | + | + | 0.15 | 0.15 (0.73) | 0.15 (0.73) | 0.15 (0.7) |
| | L | + | + | + | + | 2.34 | 2.21 (11.0) | 1.70 (8.5) | 2.17 (10.8) |
| | SiL | + | + | + | + | 17.64 | 16.03 (79.6) | 17.25 (85.9) | 9.25 (45.9) |
| Whole field | | 3/3 | 3/3 | 3/3 | 3/3 | 20.13 | 18.39 (91.3) | 19.1 (94.4) | 11.57 (57.4) |

The detection of particular STC on a field by ECsh calibration with a particular dataset is indicated with d, while non-detection – with n.d.

* For the whole field, the fractions indicate a number of STCs properly detected (numerator) by a particular dataset used for ECsh calibration and the number of STCs detected in the field by the laboratory analysis (denominator).

Major problems with detection and correct assessment of the area of particular STCs of a topsoil layer were observed in fields C and especially B, both characterized by greater variation of sand and silt contents to a depth of 90 cm (Table 2). This resulted from the fact that the measured values of ECsh depended not only on the ST of a plough layer, but also on the ST of the deeper layers. Heil and Schmidhalter (2012) observed, that clay materials underlying sand at a depth of about 40 cm affected ECa readings measured by EM 38 (Geonics, Kanada) causing the overestimation of clay and underestimation of sand content.

## CONCLUSIONS

In fields with relatively homogeneous soil texture in soil profile to a depth of about 90 cm, the calibration of ECsh measurements with small soil sampling datasets led to creation of reliable STC maps of topsoil. Such datasets used for calibration were as small as 5–6 soil samples per 20 ha, and comprised STCs prevailing in the field. This calibration was more efficient in fields A and C with smaller variation of dominating fine soil fractions (sand and silt in this case) to a depth of 90 cm. The calibration of ECsh against fine soil fraction was much less efficient especially on alluvial soils of field B built up of layers differing in ST. In such soils, the results of shallow EC measurements were significantly affected by ST of all layers to a depth of about 90 cm. The lowest values of RMSE and MAE obtained after calibration of ECsh for ST mapping did not always allow to produce better quality STC maps. The areas with the same STC obtained using considered dataset and the greatest reference dataset are a better indicator of STC assessment than the values of the assessment errors.

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