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Prediction of Soil Properties with Field Geo-electrical Probes

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Abstract: The need for more precisely located and measured soil data is increasing because of the importance of plant production and environmental threats affecting lands. There is a wide selection of field instruments available for fast assessment of soil properties. Our objectives were to test different instruments measuring soil electrical properties and to study their ability to predict soil physical and chemical properties. For predictions, multiple regression analyses were used. Prediction certainty was estimated using a jackknifing procedure. According to the results, soil electrical conductivity (EC) could be used as predictor of both soil physical and chemical properties, whereas bulk soil dielectric permittivity or soil water content could predict soil texture only. The determination coefficients between the estimated and measured values were 0.87–0.97 for EC and pH, 0.54–0.62 for humus and water contents, and 0.60–0.88 for texture. We concluded that the contemporary technical achievements provide remarkable opportunity for fast and reliable assessment of soil properties.

Keywords: Jackknifing, multiple regression, salinity, soil electrical conductivity, texture

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INTRODUCTION

Simultaneously as the need for more detailed soil information is rapidly increasing, more interest is shown in utilizing different instrumental techniques for mapping soil properties indirectly. The need for more precisely located and measured soil data is increasing either because of the importance of plant production or because of the environmental threats affecting soils. The aim in choosing indirect measurements is to overcome the costs of detailed soil mapping based on samples and to expand the spatial resolution of the information gathered. The measurement of apparent soil electrical conductivity (EC_a) has shown most promise in mapping of soil properties, because of the ease of measurement and good correlations with soil properties affecting yield potential and environmental factors. Often EC_a has been shown to correlate with salinity and soil water content, whereas in nonsaline soils EC_a has been reported to depend on soil texture, especially the clay content, organic-material content, and plant-available nutrients (Corwin and Lesch 2003). A large variety of sensors based on different measuring principles are readily available to measure soil EC_a, including electromagnetic methods (EM) with EM induction (McNeill 1980), four electrode resistivity/conductivity sensors (Rhoades, Chanduvi, and Lesch 1999), and capacitive probes. Also soil dielectric permittivity (ε), dependant on soil volumetric water content (θ), can be measured rapidly and accurately. Despite the fact that the relationship between θ and soil textural features is well studied (Hillel 1982), the measurement of ε/θ has seldom been used in the context of soil mapping. In this study, a series of near-surface geophysical measurements were made as a joint research of RISSAC, Hungary, and MTT, Finland, with the objective to test a range of instruments in different land use-patterns to estimate their ability for predicting soil properties.

MATERIALS AND METHODS

Experimental Area

Field surveys were carried out to evaluate differences between the instrument specifications and their ability to map soil type changes in Apaj region, Hungary, 50 km to the southwest of Budapest. Three 70-m-long experimental transects were established representative of different land uses in arable fields and a wide range of salinity conditions. Within each transect, soil apparent electrical conductivity (EC_a), dielectric permittivity (ε), and volumetric water content (θ) measurements were carried out in 1-m intervals. Disturbed soil samples for soil physical and chemical properties were taken from every fifth measuring point. The sampling strategy resulted in altogether 210 field-measured points and 45 points with a sampling depth of 0–0.20 m.

The aim in choosing individual transects was to cover soil type changes in the area with contrasting environmental settings. The first transect was located along an agricultural field area with different cultivation practices and crops. It was set along a pasture moderately grazed by sheep, a harvested maize (*Zea mays* L.) subfield area, a narrow headland area with native grasses, and a field sown with winter wheat (*Triticum aestivum* L.). The second transect was located nearby in salt-affected grassland crossing areas with no crop cover because of excessive soil salinity, small vegetation typical of soils moderate in salt, and some salt-affected grassland. The third transect was an example of the effect of textural changes in sandy soil compared to the two others. The third transect included areas covered by planted black locust (*Robinia pseudo-acacia* L.) trees and agricultural field sown with winter wheat (*Triticum aestivum* L.).

Field and Laboratory Measurements

Five different instruments with different sensing depths and three measurement principles were used to measure apparent soil electrical conductivity (EC_a), soil dielectric permittivity ($\varepsilon - P_{per}$, dependant on soil water content), and soil volumetric water content (θ_{BR30}) directly at the 210 measuring points of the three transects. Instrument specifications are presented in Table 1. Elevation measurements were carried out at all measuring points, using a precise leveling instrument.

From the disturbed soil samples, taken from 45 locations, soil texture (pipette method), pH, organic matter content (OM), electrical conductivity (EC of 1:2.5 soil–water suspension), and soil gravimetric water content were determined.

Data Analyses

Means, minimum, maximum values, standard deviations (SDs), and coefficients of variation (CV) were calculated for all soil properties for the whole dataset (n = 45) using the STATISTICA software (StatSoft 2003). The Kolmogorov–Smirnov normality test was performed. Pearson's correlation coefficients were calculated for all pairs of field and laboratory measured data. Linear, quadratic, and multiple models of EC_a, P_{per}, θ_{BR30}, and elevation (E) were evaluated to find the best-fitting models for predicting soil properties from field measured parameters.

Table 1. Specifications of instruments used in the study

Parameter	EMRC-120	Martek	Conductivity fork	Plak percometer	BR-30
Abbreviation	EC_{a_EM}	EC_{a_M}	EC_{a_CF}	EC_{a_PER}, P_{PER}	Θ_{BR30}
Operation principle	Electromagnetic induction	Resistivity/conductivity		Capacitance	
Operation frequency	Aprox. 10 kHz	10–1000 Hz	500 Hz	75 kHz for EC, 50 MHz for water content	Na
Specifications	Coil spacing 1 m	Dipole configuration 0.90 m electrode spacing	Wenner array, 0.48 m electrode spacing		
Operation depth	1–1.5 m with vertical coils	~0.45 m	~0.25 m	0.10–0.50 m (taken at the depth of 0.20m)	0.10 m

The jackknifing technique was used to validate the soil property regression models by taking repeated subsamples of the original sample of n = 45 observations by omitting a single observation at a time. Thus, each subsample consisted of n − 1 observations formed by deleting a different observation from the sample. The jackknife estimate ($mean_{JN}$), the standard error (SE), and the determination coefficient (R^2_{val}) between the measured and estimated values were calculated from these truncated subsamples.

A variogram model was used (GS+, Gamma Software, USA) to evaluate the distance of spatial dependence. Variograms represent variance classified according to distance between sample sites. They consist of three parts: nugget, range, and sill. Nugget characterizes the variation over short distances, whereas sill is the level where variogram model reaches the maximum and levels out. Sill values are the prior variances of the variable. Range is referred as the maximum distance where spatial dependence occurs.

RESULTS AND DISCUSSION

The descriptive statistics of direct and laboratory-measured soil properties are given in Table 2. Coefficients of variation of direct measurement readings ranged from 22 to 182%, indicating substantial spatial variation.

Pearson's correlation coefficients between the seven soil properties and results of direct measurements and elevation were significant in many instances (Table 3). In general, both EC_a and P_{PER}/θ_{BR30} (ε/θ) correlated positively with clay and silt fractions located more on low-lying soil areas, and the correlation with the sand fraction was clearly negative. These results are in good agreement with those reported by Mueller et al. (2003) and Domsch and Giebel (2004). For EC_a and P_{PER}/θ_{BR30}, the correlation was at the same level between soil textural classes and field measurements. Poor correlation, however, was found between P_{PER}/θ_{BR30} and soil chemical properties.

The differences between instruments measuring EC_a were only minor. Also both tested capacitive soil moisture content instruments produced comparable results and good correlation with soil gravimetric moisture content determined from soil samples. Compared to field-measured EC_a values, most evident was the effect of soil salinity and texture (Table 3, Figures 1 and 2). Because mineral soil particles are resistive in dry conditions and electrical conductivity in soil is mainly electrolytic, that is, through ions in soil water fractions (Friedman 2005), significant correlations with soil particle-size classes are likely due to higher soil water retention capacity typical for soils with high clay and

Table 2. Descriptive statistics of direct measurements, elevation, and soil properties (n = 45)

Parameter	Unit	Mean	Min.	Max.	SD	CV (%)
				Predictors		
E	m	97.6	95.7	101.2	1.8	1.8
EC_{a_EM}	$mS\,m^{-1}$	56.8	2.2	457.6	99.4	175.1
EC_{a_M}	$mS\,m^{-1}$	27.6	5.7	93.4	26.2	95.3
EC_{a_PER}	$mS\,m^{-1}$	24.1	13.5	30.5	4.5	18.6
EC_{a_CF}	$mS\,m^{-1}$	63.4	4.9	500.0	115.2	181.7
P_{PER}		30.2	15.7	39.0	6.6	21.8
Θ_{BR30}	$m^3\ 100\,m^{-3}$	10.2	7.8	16.9	2.4	24.1
				Predictants		
pH		8.5	7.0	10.5	0.9	10
EC	mS	0.5	0.1	4.1	0.8	148
Humus	$g\,g^{-1}$	1.7	0.2	2.7	0.7	43
Water content	$g\,g^{-1}$	17.3	10.8	21.7	2.7	15
Sand	>0.05 mm, %	57.8	29.8	84.7	15.8	27
Silt	0.002–0.05 mm, %	22.2	7.2	32.8	7.7	35
Clay	<0.002 mm; %	18.9	4.5	37.8	9.4	50

Notes. E is elevation, EC_a is apparent soil electrical conductivity measured by the four different instruments (Table 1), P_{PER} is permittivity, θ_{BR30} is the field measured soil water content, and EC is electrical conductivity measured in 1:2.5 soil–water in $mS\,10^{-2}m^{-1}$ suspension.

fine material content (Table 2). In transects 1 and 3, the increase of clay and silt content was reflected by both higher EC_a values and soil water contents.

Table 3. Correlation coefficients among soil properties and direct measurements for the 45 sampling points

Parameter	E	EC_{a_EM}	EC_{a_M}	EC_{a_PER}	EC_{a_CF}	P_{PER}	Θ_{BR30}
pH	−0.62 **	0.94 **	0.90 **	0.94 **	0.87 **	0.21	0.23
EC (mS)	−0.39 *	0.82 **	0.98 **	0.87 **	0.96 **	−0.10	−0.11
Humus ($g\,g^{-1}$)	0.31 *	−0.76 **	−0.78 **	−0.78 **	−0.76 **	0.21	0.02
Water content ($g\,g^{-1}$)	−0.49 **	−0.07	−0.23	−0.12	−0.25	0.77 **	0.61 **
Sand (>0.05 mm, %)	0.87 **	−0.75 **	−0.68 **	−0.79 **	−0.68 **	−0.63 **	−0.62 **
Silt (0.002–0.05 mm, %)	−0.90 **	0.63 **	0.52 **	0.63 **	0.51 **	0.75 **	0.69 **
Clay (<0.002 mm; %)	−0.83 **	0.81 **	0.76 **	0.86 **	0.76 **	0.53 **	0.57 **

*, ** Significance at 0.05 and 0.01 probability levels, respectively.

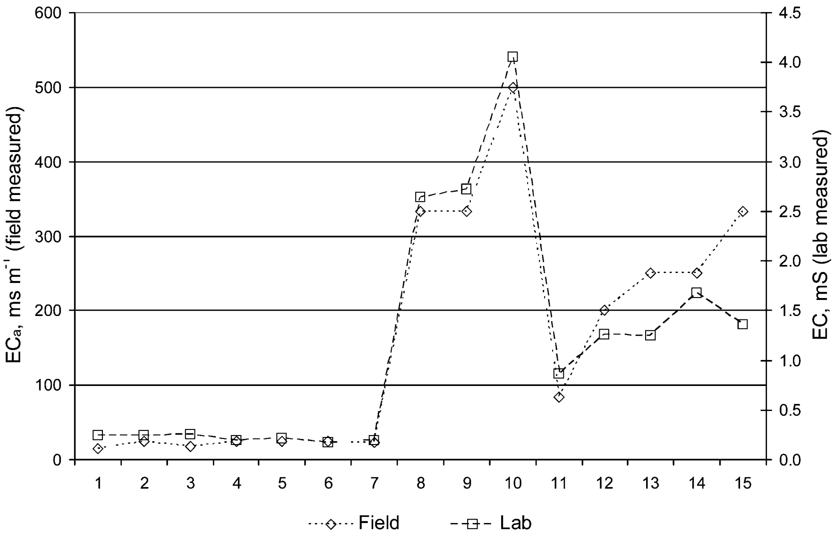

Figure 1. Variation of field measured ECa_CF (depth response 0–0.25 m) and laboratory measured (0–0.20 m) EC (1:2.5) within transect 2 located in salt affected grassland ($r = 0.97$, $p < 0.01$).

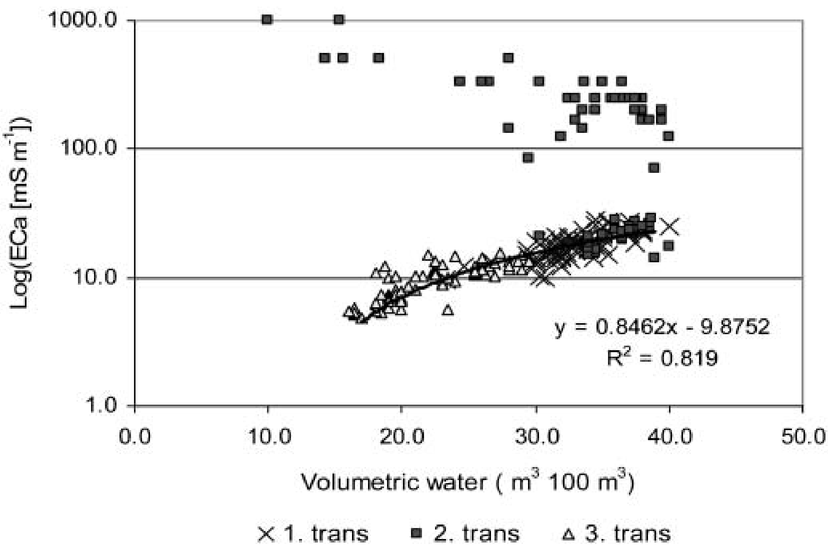

Figure 2. Relationship between soil electrical conductivity ($mS\,m^{-1}$, response from 0–0.25 m) and soil volumetric water content (m^3 $100m^3$, taken at the depth of 0.10 m) along three transects. Linear regression line represents relationship between θ and EC_a in points where the effect of salt was not dominant ($EC_a >$ $90\,mS\,m^{-1}$).

On saline plots within second transect variation of field-measured soil, EC_a followed closely that of laboratory-measured soil-suspension EC values (Figure 1). Because soil volume measured with EC_a probes is somewhat larger than that used for soil sampling (200 cm^3), small deviations within soil blocks are most likely averaged, and the method is not as susceptible to errors as sampling based on small point samples. In the other two transects, despite the correlation between field and laboratory-measured soil EC being positive, the results were more scattered and contribution of soil water content to field measured EC_a was of more importance than soil paste EC, representing the amount of ions dissolved in pore water and absorbed on colloids (Figure 2).

As field methods of measuring soil EC_a show close correlation with soil salinity as expressed by laboratory-determined soil suspension EC (1:2.5) (Table 2, Figure 1), the variation of soil EC_a could be used to estimate scales of variation of soil salinity (e.g., for sampling and measurement scheme design). The mosaic-like structure of soil formation caused by repetitive river flooding and aerial transport combined is clearly shown in the scale of spatial dependence being only about 20 m (Figure 3), which in turn could hardly be described with traditional sampling schemes, because considerably larger amounts of samples would be needed.

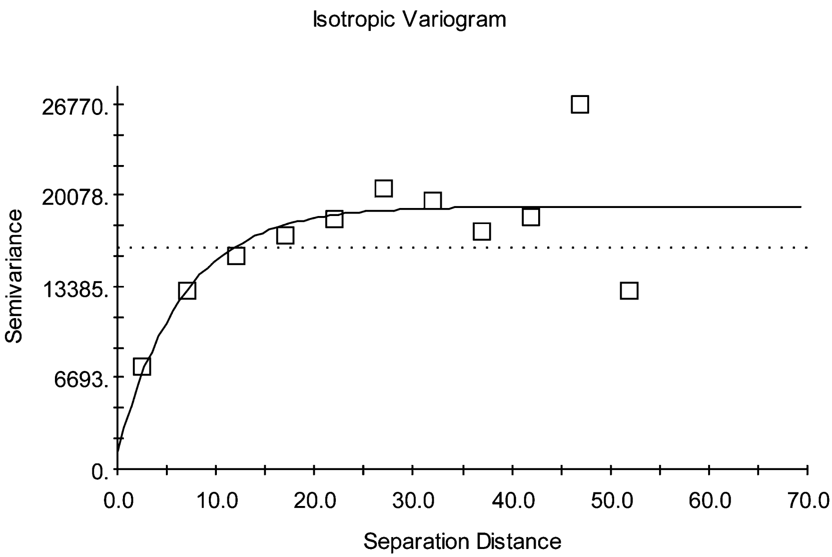

Figure 3. Exponential variogram model for soil EC_a measured with EC_m_dp (depth response 0–0.45 m) over transect 2 representing semivariance ($mS^2 m^{-2}$) over separation distances (m).

Based on multiple regression analyses, best-fit models representing soil properties with field-measured EC_a or/and P_{PER}/θ_{BR30} and local elevation parameters (E) as predictors were selected (Table 4). The first of the selected models shows the simpler predictive algorithm. Models selected were significant ($P < 0.05$).

Ristolainen, Tóth, and Farkas (2006) previously demonstrated that the differences between different instruments in measuring EC_a or P_{PER}/θ_{BR30} were minor, and therefore a single instrument was not proven to give clearly higher coefficients of determination than others, but the results demonstrated that in many cases the optimum instrument selection would depend on soil properties studied.

Table 4. Selected regression models to predict soil properties and their validation based on jackknifing ($n = 45$; $p < 0.05$)

Soil property	Selected models	R^2	Measured data		Validaton		
			Mean	SD	$Mean_{JN}$	SE	R^2_{val}
pH	$5.13 + 0.331EC_{a\_EM}$	0.88	8.50	0.87	8.50	0.47	0.87
	$7.642 + 0.031EC_{a\_PER}$	0.89			8.50	0.45	0.88
EC (mS)	$0.092 + 0.008EC_{a\_M}$	0.96	0.54	0.80	0.54	0.26	0.95
	$0.150 + 0.005EC_{a\_M} + 0.00001EC_{a\_M}^2$	0.97			0.54	0.22	0.97
Humus ($g\ g^{-1}$)	$2.25 - 0.021EC_{a\_PER}$	0.61	1.67	0.71	1.67	0.68	0.58
	$2.128 - 0.009EC_{a\_M} + 0.00001EC_{a\_M}^2$	0.66			1.68	0.65	0.62
Water content ($g\ g^{-1}$)	$6.12 + 0.470P_{PER}$	0.59	17.35	2.67	17.46	2.80	0.55
	$45.66 - 0.010EC_{a\_CF} + 0.346P_{PER} - 0.370E$	0.63			17.44	2.84	0.54
Sand (>0.05 mm, %)	$70.95 - 0.476EC_{a\_PER}$	0.62	57.85	15.84	57.76	14.85	0.60
	$103.02\ E - 0.410EC_{a\_PERR} - 1.123\Theta_{BR30}$	0.83			57.98	11.17	0.77
	$-336.53 - 0.280EC_{a\_PERR} - 0.392\Theta_{BR30} + 4.24E$	0.88			57.98	9.24	0.84
Silt (0.002–0.05 mm, %)	$382.64 + 0.010EC_{a\_M} - 3.700E$	0.82	22.20	7.70	22.20	5.11	0.80
	$161.15 + 0.047EC_{a\_M} + 0.803P_{PER} - 1.643E$	0.86			21.57	4.82	0.83
Clay (<0.002 mm; %)	$269.62 + 0.203EC_{a\_PER} - 2.627E$	0.90	18.92	9.41	18.91	4.73	0.88
	$127.88 + 0.103EC_{a\_M} + 0.672P_{PER} - 1.330E$	0.90			17.73	4.59	0.88

For the best prediction models, the determination coefficients between the estimated and measured values (R^2_{val}) were 0.97, 0.88, 0.62, and 0.55 for EC, pH, humus, and gravimetric water contents, respectively. The reason for a strong relationship between pH of soil and field measured EC_a lies in the causal connection of salinity and pH in areas dominated with sodium bicarbonate ($NaHCO_3$) and sodium carbonate ($NaCO_3$) salts, as described in more detail by Tóth and Jozefaciuk (2002) for a similar region in Hungary. Regarding texture, the highest values of R^2_{val} were 0.84, 0.83, and 0.88 for sand, silt, and clay fractions.

In this validation dataset, the average of measured soil properties was very similar to the average obtained from the models. Quality of the prediction, as indicated by the standard error (SE) and coefficient of determination (R^2_{val}), calculated for the observed and predicted soil properties are shown for these selected models. In all the cases, the SE was less than the SD of measured soil properties. We concluded that the selected models could provide reasonable estimates for the soil properties studied.

CONCLUSIONS

In conclusion, our results indicate the potential of using measurements of soil electrical properties for assessing the value of some soil properties in both subfield and aerial scale. Near-surface methods of measuring soil electrical properties showed close correlation between field measurements and laboratory-determined values and therefore could be suitable for rapid and low-cost determination of soil variation over large areas. With measurements of soil electrical properties soil salinity, pH, textural differences, soil organic matter, and water content could be predicted but with decreasing statistical significance. The prediction certainty increased to some extent when using combined EC_a, P_{PER}/θ_{BR30}, and local elevation measurements as predictors. The small scale of variation observed in the area results in high demands for detailed soil mapping and emphasizes the need for indirect measurement techniques.

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