Spatial Variability of Penetration Resistance on Pseudogley

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Summary

Usually large numbers of measurements are required to describe spatial variability of soil resistance but GIS technology with interpolations methods make it possible to estimate data from unsampled locations. In this paper cone index (CI) measurements were made in two occasions in 2.88 ha field in central Croatia to present soil condition. A commonly used tillage operation consists of ploughing (about 30 cm depth) and disc harrowing (12 - 15 cm), and they are practiced on annual basis. Measurements (240) were taken according sample grid in 48 different 24 x 25 m^2 fields. Cone index (CI) data were interpolated using geostatistical techniques (ordinary kriging) to produce the maps of soil resistance. These maps combined with expert knowledge can provide good direction for applying appropriate soil management. Our results demonstrate that the investigated layers had variable spatial structures in terms of their linear trends. This suggests that each layer has a unique spatial structure possibly as consequence of pedogenetic processes, tillage operations and changes influenced by drainage and leveling operations. The results presented here describe spatial variability of soil resistance of a drained Pseudogley of Central Croatia, measured as CI in a field conditions. Tillage practices caused the formation of a plow pan at a depth 30 – 40 cm where the maximum CI values were obtained. According to the values of penetration resistance the tillage practices should be changed if we consider improved conditions for plant roots development.

Key words

mapping, soil variability, penetration resistance, cone index

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Introduction

Soil resistance is usually measured with a cone penetrometer and values are reported as cone index (CI) values in MPa. It is widely used method because it provides an accurate measurement of soil resistance at particular location. However, it is a very variable parameter, because it depends on such factors as are soil morphology, the geometry and physics associated with tillage operation under consideration, and temporal variation (Cassel, 1982). For proper meaning of CI, these variable data should be accompanied with corresponding soil water content and bulk density data collected near CI measurement points. At the present time in Croatia the conventional tillage systems dominates and usually consists of two or more operations, the first of which involves plowing and others finer treatments for the seedbed preparation (Bogunovic et al., 2014a). This kind of repeated tillage to the same soil depth often led to an increased compaction in a subploughing layer, especially at the ploughing depth (Birkás, 2008). In order to avoid possible confusion Birkás (2008) states that various tillage implements produce a compact tillage pan, while loosen the top layer, between the cultivated and the undisturbed layer. Inadequate soil management without proper organic matter cycling, repeated tillage operations at similar depth, narrow crop rotation and machinery traffic on moist soil accelerates degradation of arable layer, which influences the decrease of soil fertility. Nowadays, this kind of improper land use dominates in Croatia, which results in a degradation of soil by tillage induced compaction. Unfortunately, of all agricultural land in Croatia almost 35% was detected degradation by compaction (Birkás et al, 2011).

Today, GIS presents powerful tool used for cartography, mapping and modeling soil properties. With this tool, understanding and assessing the spatial variability of soil characteristics (in present case soil compaction) and their effect on yield is a crucial step towards the appropriate application of precision agriculture technology. GIS with geostatistics provide possibility for determination of soil properties at unsampled location. Also, geostatistic based on principles of regionalized variable theory (Clark, 1979; Matheron, 1963) allows us to find the necessary dependence between two sampling points in space. For quality prediction mapping it is necessary to collect enough number of samples in proper scheme on a way that semivariogram analysis provides spatial dependency of this information. Papers with spatial variability analyses are mainly oriented to the soil nutrients and yield variability, and relatively rarely on the soil physical properties (Castrignano et al., 2002). In the context of precision agriculture, the knowledge of soil resistance variability at the field scale may be useful for improving site-specific tillage. Therefore, within the context of precision farming, the knowledge of soil physical and mechanical properties, as well as the spatial variability of these properties, could be useful for possible modifications of tillage operations.

Materials and methods

Study site and soil sampling

Experimental site was a 2.88 ha field located near Popovaca in Croatia (45° 34'45.03 N; 16°34'18.28 E, 98 m.a.s.l.), used by the company Moslavka d.d. Investigated location has temperate continental climate, with 10.7°C mean temperature and 865 mm of annual precipitation (multiyear average 1961-1990). Smallholdings that dominate within agricultural land from one side, and hydro-ameliorated area with organized agricultural production within larger agricultural holdings are characteristic for this region. Terrain is flat with average altitude of 97.2 m. Soil type is Pseudogley on plain (Škorić, 1986) or Stagnosols (FAO, 2006), with unfavorable water regime and high level of ground water. It is plain, distric, with implemented drainage system of canals and drain pipes. Despite of drainage, sufficient moisture is present in upper part of soil profile especially after heavy precipitation. Precipitation water periodically stagnates on illuvial horizon. The content of the main chemical soil characteristics was: total nitrogen - 0.086 g kg^{-1}, total carbon - 0.902 g kg^{-1}, available phosphorus (measured as P_2O_5) 214 mg kg^{-1}, plant available potassium (K_2O) 270 mg kg^{-1}, humus - 1.55% and pH - 3.9.

In accordance with practiced tillage operations trial field was ploughed to the depth of 30 cm, and disc-harrowed to 12 cm depth. Ploughing was performed on November 16 (2012) while disking and finer seedbed preparation was performed prior to sowing on May 2 (2013).

Soil resistance was measured on 25 May 2013 to a depth of 80 cm using the penetrometer Eijkelkamp Penetrologger. In the area of 2.88 ha there were 240 measurements of soil resistance. The location and scheme of measurement are presented in Fig 1. Precise positioning in space was conducted by GIS device GeoExplorer GeoXH 6000, with an accuracy of positioning ± 10 cm (Fig 1). Penetrometer conical point was 1 cm^2 in area and the point angle was 60^0. The measurement range was from 0 to 9 MPa. Soil resistance data were grouped as means at soil layers 0 - 10 cm, 10 - 20 cm, 20 - 30 cm, 30 - 40 cm, 0 - 20 cm, 20 - 40 cm, 40 - 60 cm and 60 - 80 cm, respectively. Average soil water content (SWC) was estimated by moisture meter (Theta probe instrument – Eijkelkamp) in three replicates in the central point of each plot, from two sampling depths: 0 - 20 and 20 - 40 cm. Data were analyzed using descriptive statistics in Microsoft Excel for Windows.

Geostatistical analysis

The skewness and kurtosis evaluate data normality and asymmetry that have important implications on interpretation of methods performance (Bogunovic et al., 2014b). For achieving a correct interpretation of the spatial interpolation, it is desirable to have data as close to normal distribution as possible (Goovaerts et al., 2005) because presence of extreme values and high skewness can have negative consequences on the semivariogram interpretation. For a population that follows the normal frequency distribution, skewness and kurtosis should have values between 0 and 3, respectively (PazGonzales et al., 2000).

Geostatistics is based on the spatial correlation between the observed samples, and this correlation can be mathematically expressed through a model called the semivariance. The semivariance is a function that describes the spatial variations of a observed parameter in nature. It can be expressed as:

$$y(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(xi) - Z(xi+h) \right]^2$$

where $\gamma(h)$ is the semivariance at a given distance h; $Z(xi)$ is the value of a variable Z at the xi location and $N(h)$ is the

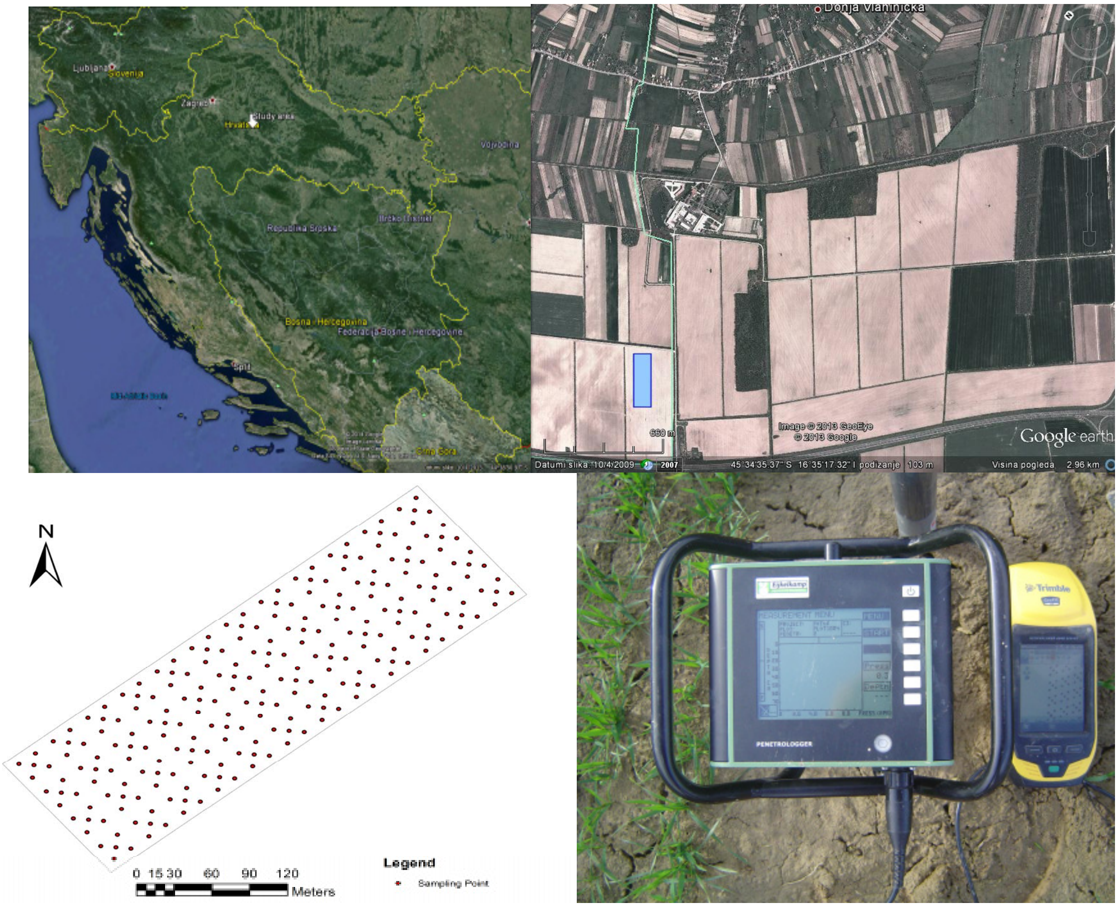

Figure 1. Sampling location, scheme of investigated area and tools that were used

number of pairs of sample points separated by the *lag* distance *h*. Graphical representation of semivariance $\gamma(h)$ as a function is semivariogram. There are some frequently used models to describe experimental semivariograms: spherical, exponential, Gaussian and linear (Isaaks and Srivastava, 2011). Size of semivariance depends on the sampling distance where sampling over shorter distances results in a smaller semivariance and *vice versa*. Semivariance in space increases with the distances that are correlated and if the variogram stabilizes it reaches the sill, showing that at distance *x* the samples are considered spatially independent. The variance observed at a shorter scale than the field sampling is identified at 0 lag distance, known as the nugget effect. This nugget effect makes the short-scale variability and/or sampling errors evident (Burgos et al., 2006). Variable spatial dependency was calculated by the nug/sill ratio. If the ratio is lower than 25%, the variable has strong spatial dependence; if it is between 25% and 75%, the variable has moderate spatial dependence; and if it is higher than 75% the variable shows only weak spatial dependence (Chien et al., 1997).

The ordinary kriging method was used with isotropic semivariogram models in preparation of interpolation maps for the soil properties investigated (Isaaks and Srivastava, 2011). For ordinary kriging procedure, at least 12 neighboring points were considered. The maps of soil properties were drawn with Geostatistical extension of ArcGIS 10.1 (ESRI) using the semivariogram parameters (nugget, sill, nugget ratio, range).

Results and discussion

Descriptive parameters

Basic statistical properties of the CI, made within the field are presented in Table 1. The soil strength varied spatially from a minimum of 0.93 MPa in upper 10 cm to 3.27 MPa in layer from 60 to 80 cm. Mean CI values were greatly affected by the tillage depth. They were less in the upper 30 cm, reaching mean values of 2.15 MPa at the depth of 20 - 30 cm. In addition to that, mean CI values were continuously increasing with depth, as a consequence of higher compaction of deeper layers. Measured CI values exceeded limit of 2 MPa in layers below 20 cm (Figure 2). These values may severely inhibit root growth. According to the previous research (Taylor and Gardner, 1963) value of 2 MPa is the border for normal root growth, while at 2.5 MPa roots stop penetrate the soil (Taylor, 1971), while others (Håkansson and Lipiec, 2000; Hamza and Anderson, 2005) move that limit to the 2.5-3 MPa.

Mean values of soil penetration resistance were greatly affected by the SWC (Table 1), they were lower in a surface layer (27.39% SWC) compared to subsurface layer (28.62% SWC). Also, the spatial variance followed the same depth pattern (Figure 2). Coefficient of variation (C.V.) showed a continuous decrease from surface to the depth of 80 cm, with exception of layer 20 - 30 cm. In a deeper layers coefficient of variation is lower, which indicates that layers below 40 cm have higher spatial homogeneity.

Table 1. Descriptive statistics for CI (MPa) and soil water content (%), Potok, May 25, 2013

Depth (cm)	Mean	S.D.[a]	Kurtosis	Skewness	Range	Minimum	Maximum	Confidence Level (95%)	C.V.[b]
					CI (MPa)				
0-10	0.93	0.42	-0.31	0.42	1.96	0.13	2.09	0.0533	45.11
10-20	1.62	0.54	2.65	0.86	3.96	0.38	4.34	0.0683	33.10
0-20 (mean)	1.26	0.40	-0.05	0.33	2.24	0.32	2.55	0.0513	32.01
20-30	2.15	0.83	0.33	0.82	4.03	0.83	4.86	0.1055	38.65
30-40	3.00	0.81	0.52	0.28	5.26	0.84	6.10	0.1027	26.95
20-40 (mean)	2.54	0.70	0.49	0.59	3.98	0.88	4.86	0.0896	27.77
40-60	3.25	0.80	2.23	1.03	5.59	1.53	7.12	0.1012	24.48
60-80	3.27	0.89	0.69	0.88	4.72	1.71	6.43	0.1134	27.29
					SWC (%)				
0-20	27.39	3.25	0.72	-0.23	17.64	18.56	36.19	0.9432	1.71
20-40	28.62	3.82	0.60	-0.63	17.95	18.48	36.43	1.1092	1.93

[a]standard deviation; [b]coefficient of variation (%)

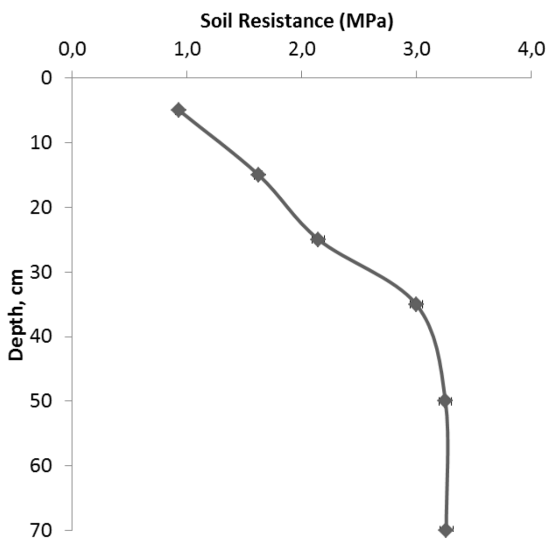

Figure 2. Average values of soil penetration resistance (MPa) at each soil depth

Heterogeneity of surface layer and whole plough layer is influenced by ploughing. Highest spatial heterogeneity (C.V.) was recorded at the plowing layer (0 - 10, 10 - 20, 20 - 30 cm) seven months after primary tillage. This indicates that soil settling is highly variable in these layers.

However, some layers have close to normal distributions of soil strength over the investigated area, as it is illustrated by skewness near zero. Shape parameter (kurtosis) showed shifting from normality in layers 10 - 20 cm and 40 - 60 cm. These statistical informations assume that all CI measurements are not spatially correlated. It was common to monitor and compare the CI values as mean values of the individual layers (Cassel et al., 1978, Bogunovic et al., 2014a), but most of these papers provide additional support informations as organic matter content, texture classes, bulk density values and soil structure. Therefore, in future research some support data may be required to equalize variances between depths.

Spatial characteristics

The parameters for semivariogram models and fitted semivariogram plots of CI are shown in Fig. 3(a-h). The CI values of soil had spatially dependent structures that are described by semivariograms with a defined rank fitting to the stable, exponential and spherical models. Although Guedes Filho et al. (2010) stated that spherical mathematical is predominantly fitted model in soil science research, the exponential and stable semivariograms were mostly the best fitting models to the experimental semivariances of CI at surface and subsurface layers. The best-fit models used for SWC in layers 0-20 cm and 20-40 cm are exponential (Table 1).

The measurement error or micro-variability of a property, which can't be detected with current scale of sampling, causes the nugget variance (Isaaks and Srivastava, 2011). Nugget variance values of CI were present in all layers except in layer 60 - 80 cm (Fig 3.a-h). This occurrence of nugget indicates small-scale variance. Moreover, CI is a point measurement and then it is highly variable in space. Compared to CI, SWC does not record nugget effect (Table 2) that indicates that sampling errors are negligible.

The range is another important parameter of interpretation of semivariograms and spatial variations in general, indicating the limit distance at which a sample point has influence over another point, i.e., the maximum distance up to which sample points are correlated. In present study sample scheme is representative for the studied plot. Ranges of all investigated parameters (Fig 3.a-h) were much wider than the sampling interval of 12 m as longest distance in present study. Ranges of CI are between 23.84 m and 162.97 m, and from 150.80 m to 174.75 m for SWC, depending of observed soil layer. This indicates that in the future research sampling interval for observing SWC in

Table 2. Best fitted variogram models for SWC and corresponding parameters.

Type	Nugget	Partial Sill	Sill	Nugget/ Sill	Spatial dependence	Range (m)
Exponential	0.00	13.61	13.61	0.00	Strong	150.80
Exponential	0.00	17.94	17.94	0.00	Strong	174.75

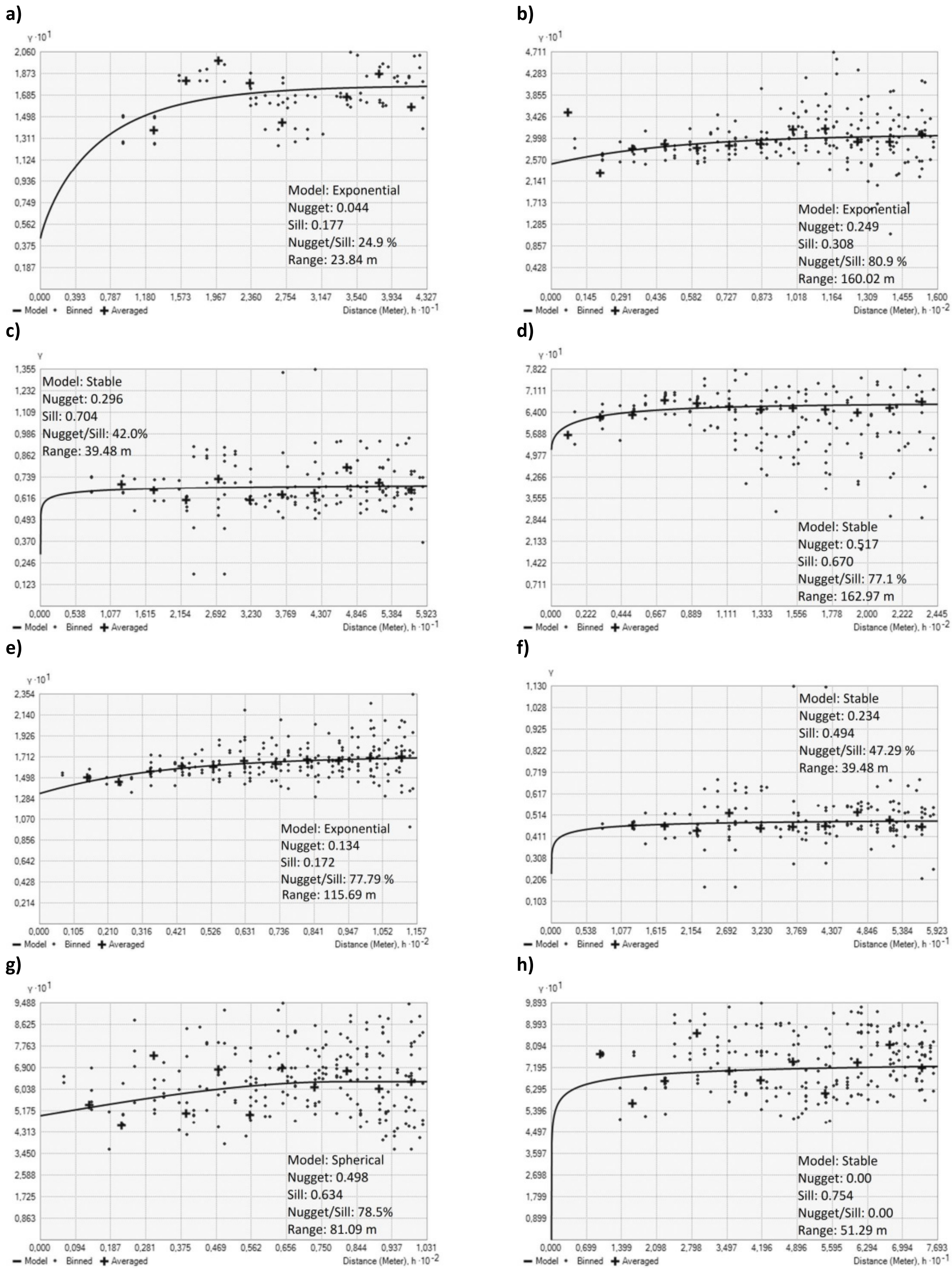

Figure 3. Semivariogram calculated for CI at layers: a) 0-10 cm, b) 10-20 cm; c) 20-30 cm; d) 30-40 cm; e) 0-20 cm; f) 20-40 cm; g) 40-60 cm; h) 60-80 cm. Bold line represents the best fit model

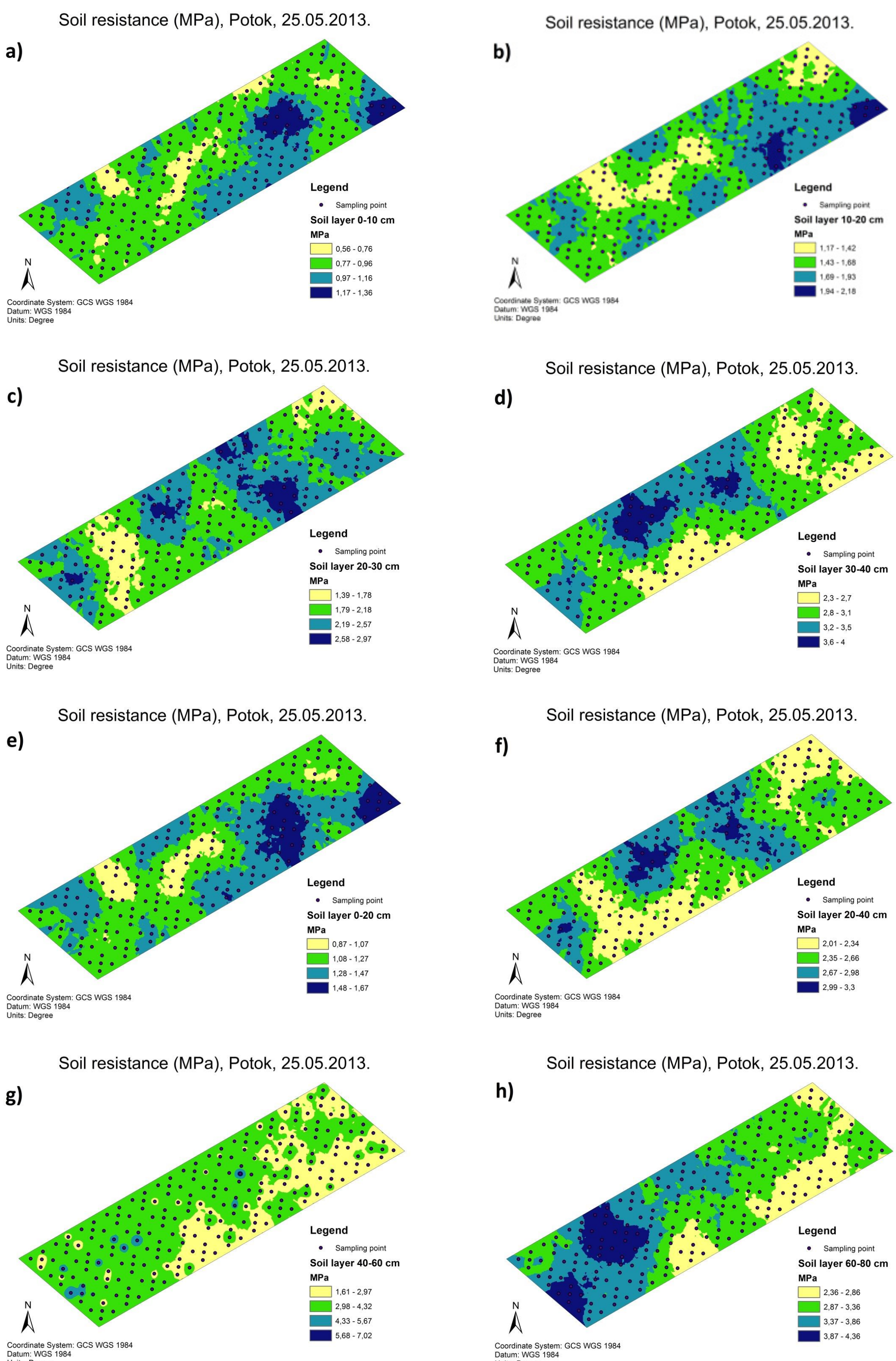

Figure 4. Spatial variability maps made by ordinary kriging: a) CI at 0-10 cm; b) CI at 10-20 cm; c) CI at 20-30 cm; d) CI at 30-40 cm; e) CI at 0-20 cm; f) CI at 20-40 cm; g) CI at 40-60 cm; h) CI at 60-80 cm

investigated field could be at least 75 m, because rough guide for choosing sampling interval should be less than half of the semivariogram range (Kerry and Oliver, 2004).

CI variable in layers 0-10 cm and 60-80 cm with nugget/sill ratio of 24.9 and 0.00, respectively, showed strong spatial dependence. Layers 20-30 cm and 20-40 cm with 42.00 and 47.29 nugget/sill ratio, respectively, showed moderate spatial dependence. The rest of the layers recorded weak spatial dependence of CI measurements (Fig.3 a-h). When we observe SWC (Table 2), both investigated layers recorded strong spatial dependence. Özgöz et al. (2012) found CI ranges between 234 m and 257 m, while Guedes Filho et al. (2010) found CI ranges between 50 m and 60 m. Suitable sampling intervals in others studies are variable and depend on the distance between sampling points and on the data transformations.

Figure 4a-h presents interpolated soil resistance values on maps, separated by soil layers. Figures show high heterogeneity of surface layer. Presence of higher CI values at layer 20-30 cm, characterized by CI greater than 2 MPa is also shown. This is directly influenced by SWC and by soil settling from previous ploughing.

Conclusion

Based on presented results we can assume that CI is highly variable soil property. Nevertheless, it can be very useful for observing compacted areas and layers, and position of compacted layer in soil profile. Presented data show greater CI values in a settled soil with lower SWC. Highest spatial heterogeneity (C.V.) was recorded at the plowing layer (0 - 10, 10 - 20, 20 - 30 cm) seven months after tillage. This indicates that soil settling is highly variable in these layers. Increased soil compaction is observed at a depth of 20–30 cm. This zone had a penetration resistance of 2.15 MPa. Although CI values of soil resistance up to 2 MPa probably do not inhibit root development, obtained values are directly influenced by SWC at the time of measurement, and by previous tillage operations. Collection of other supporting data, as bulk density and organic matter content, should be useful in the future investigation. Deeper layers (> 40 cm) are highly compacted with CI values above 3 MPa. Also, these layers have better homogeneity. Based on literature data root development can be severely reduced in such conditions. The skewness and kurtosis of evaluate data showed normality and asymmetry, and collected values followed normal distribution. Semivariogram analysis indicates proper sampling strategy for current soil. When we observed penetration resistance, for most soil layers best semivariogram fitted model was exponential or stable. Variable spatial dependency showed strong spatial dependency in layers 0-10 cm and 60-80 cm, while other layers recorded moderate and low spatial dependence. Presence of nugget effect makes the short-scale variability and/or sampling errors evident and for that reason future sampling request support data. Soil water content showed strong spatial dependency for all investigated layers with ranges of semivariogram above present sampling interval. Tillage practices should be changed if we consider improved conditions for plant roots development. Produced prediction maps could be useful for possible modifications of tillage operations. Interpolation methods with geostatistical techniques (kriging) are powerful tool to produce soil resistance maps, and to provide fast and enough accurate data. Based on these conclusions we can re-think our soil tillage and generally soil management systems.

References

Birkás, M. (2008). Environmentally-sound adaptable tillage. Akadémiai Kiado, Hungary, p. 354.

Birkás, M., Kisić, I., Jug, D., Jolánkai, M., Kakuszi, Z. (2011). Tillage induced soil compaction consequences in the Pannonian region. In: International Scientific Symposium of Agriculture "Agrosym Jahorina 2011", p. 9 – 16.

Bogunovic, I., Kisic, I., Jurisic, A. (2014a). Soil Compaction under Different Tillage System on Stagnic Luvisols. Agriculturae Conspectus Scientificus (ACS), 79(1), 57-63.

Bogunovic, I., Mesic, M., Zgorelec, Z., Jurisic, A., Bilandzija, D. (2014b). Spatial variation of soil nutrients on sandy-loam soil. Soil and Tillage Research, 144, 174-183.

Burgos, P., Madejón, E., Pérez-de-Mora, A., Cabrera, F. (2006). Spatial variability of the chemical characteristics of a trace-element-contaminated soil before and after remediation. Geoderma, 130(1), 157-175.

Cassel, D. K., Bowen, H. D., Nelson, L. A. (1978). An evaluation of mechanical impedance for three tillage treatments on Norfolk sandy loam. Soil Science Society of America Journal, 42(1), 116-120.

Cassel, D. K. (1982). Tillage effects on soil bulk density and mechanical impedance. In Predicting tillage effects on soil physical properties and processes, P.W. Unger, D.M. Van Doren Jr. (ed.), ASA Special Publication Number 44, 45-67.

Castrignano, A., Maiorana, M., Fornaro, F., Lopez, N. (2002). 3D spatial variability of soil strength and its change over time in a durum wheat field in Southern Italy. Soil and Tillage Research 65(1), 95-108.

Chien, Y. J., Lee, D. Y., Guo, H. Y., Houng, K. H. (1997). Geostatistical analysis of soil properties of mid-west Taiwan soils. Soil Science, 162(4), 291-298.

Clark, I. (1979). Practical geostatistics. Applied Science Publishers, London, Vol. 3, p. 129.

FAO. 2006. World reference base for soil resources 2006. A framework for international classification, correlation and communication. FAO, Rome, 128.

Goovaerts, P., AvRuskin, G., Meliker, J., Slotnick, M., Jacquez, G., Nriagu, J. (2005). Geostatistical modeling of the spatial variability of arsenic in groundwater of southeast Michigan. Water Resources Research, 41(7).

Guedes Filho, O.G., Vieira, S.R., Chiba, M.K., Nagumo, H., Dechen, S.C.F (2010). Spatial and temporal variability of crop yield and some rhodic hapludox properties under no-tillage. Revista Brasileira de Ciência do Solo 34: 1-14.

Hamza, M. A., Anderson, W. K. (2005). Soil compaction in cropping systems: A review of the nature, causes and possible solutions. Soil and Tillage research, 82(2), 121-145.

Håkansson, I., Lipiec, J. (2000). A review of the usefulness of relative bulk density values in studies of soil structure and compaction. Soil and Tillage Research, 53(2), 71-85.

Isaaks, E.H., Srivastava, R.M. (2011). Applied Geostatistics. Vol 2, p. 561. Oxford University, London, p. 561.

Kerry, R., Oliver, M. A. (2004). Average variograms to guide soil sampling. International Journal of Applied Earth Observation and Geoinformation, 5(4), 307-325.

Matheron, G. (1963). Principles of geostatistics. Econ. Geol. 58(8), 1246-1266.

Özgöz, E., Günal, H., Önen, H., Bayram, M., Acir, N. (2012). Effect of management on spatial and temporal distribution of soil physical properties. Journal of Agricultural Sciences, 18, 70-91.

Paz-Gonzalez, A., Vieira, S. R., Taboada Castro, M. T. (2000). The effect of cultivation on the spatial variability of selected properties of an umbric horizon. Geoderma, 97(3), 273-292.

Škorić, A. (1986): Postanak, razvoj i sistematika tla. FPZ Sveučilišta u Zagrebu, str. 172, Zagreb

Taylor, H. M., Gardner, H. R. (1963). Penetration of Cotton Seedling Taproots As Influenced By Bulk Density, Moisture Content, and Strength of Soil. Soil Science, 96(3), 153-156.

Taylor, H.M. (1971). Effect of soil strength on seedling emergence, root growth and crop yield. Compaction of Agricultural Soils, American Society of Agricultural Engineering, pp. 292-305

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