Spatial modelling for describing spatial variability of soil physical properties in eastern Croatia

Prostorno modeliranje radi opisivanja prostorne varijabilnosti fizikalnih svojstava tla u istočnoj Hrvatskoj

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SPATIAL MODELLING FOR DESCRIBING SPATIAL VARIABILITY OF SOIL PHYSICAL PROPERTIES IN EASTERN CROATIA

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SUMMARY

The objectives of this study were to characterize the field-scale spatial variability and test several interpolation methods to identify the best spatial predictor of penetration resistance (PR), bulk density (BD) and gravimetric water content (GWC) in the silty loam soil in Eastern Croatia. The measurements were made on a 25 x 25-m grid which created 40 individual grid cells. Soil properties were measured at the center of the grid cell deep 0-10 cm and 10-20 cm. Results demonstrated that PR and GWC displayed strong spatial dependence at 0-10 cm BD, while there was moderate and weak spatial dependence of PR, BD and GWC at depth of 10-20 cm. Semi-variogram analysis suggests that future sampling intervals for investigated parameters can be increased to 35 m in order to reduce research costs. Additionally, interpolation models recorded similar root mean square values with high predictive accuracy. Results suggest that investigated properties do not have uniform interpolation method implying the need for spatial modelling in the evaluation of these soil properties in Eastern Croatia.

Key-words: soil physical properties, GIS, mapping, Chernozem, interpolation models

INTRODUCTION

Soil physical properties are typically related to variability in crop yields and therefore important to monitor and model. One important property is soil compaction, characterized by reduction of macrospores, available water and thus productivity (Birkas et al., 2008). Current intensive agricultural production practices often employ intensive tillage that use heavy machinery for tillage, planting, pest management and harvest which can lead to unfavourable physical soil conditions. Moreover, soil properties can vary from different tillage implements, factors such as depth and speed of tillage, as well as soil factors (e.g. water content, texture, residue cover etc.). Therefore, it is difficult to monitor and predict the soil conditions or/and compaction resulting from a given operation (Unger and Cassel, 1991). Excluding management factors such as tillage and machinery traffic, soil physical characteristics showed spatial variability as a direct result from soil forming factors variations: climate, organisms, relief, parent material, and time (Jenny, 1994). Thus, assessing the spatial variability of soil physical properties is crucial for efforts in transitioning to sustainable crop production as well as for intensive production. Precision agricultural practices or site specific management is aimed at managing soil spatial variability by applying inputs in accordance with the site-specific requirements of a specific soil and crop (Fraisse et al., 1999). GIS, together with geostatistics, present powerful tool used for mapping and modelling soil properties. Mapping spatial distribution of soil variables is important to be able to understand how processes change in space and time (Pereira and Ubeda, 2010). Spatial variability

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of soil physical properties has been well documented. Penetration resistance and bulk density have been documented as varying significantly within single fields (Bogunović et al., 2014; Barik et al., 2014) as well as soil moisture content (Iqbal et al., 2005; Brocca et al., 2007; Tokumoto et al., 2014). Spatial distribution of soil physical properties, however, requires better interpolations methods. Recent studies compared different interpolation methods (Pereira et al., 2013a,b; Bogunovic et al., 2014; Xie et al., 2011) but there is no specific interpolator that can provide an accurate prediction of soil properties. Therefore, the purpose of this study was to investigate statistical methods to describe observed spatial patterns of bulk density (BD), penetration resistance (PR) and gravimetric water content (GWC), according to tillage and spatial distribution patterns using several interpolation methods.

MATERIAL AND METHODS

The study was located near Vukovar (Eastern Croatia) at 45° 24′ N, 18° 56′ E. The climate is temperate continental with an annual precipitation average of 654±208 mm (2009 – 2014). The soil is classified as Chernozem by the Croatian classification (Škorić et al., 1985). Based on its texture, the soil on the experimental field is a silty loam through the whole profile (Table 1). Soil samples were collected on 17 March 2015 on soils ploughed in autumn. Undisturbed soil samples (metal cylinders with volume of 100 cm^3) were taken in a 25 x 25 m grid from 0 to 10 cm and 10 to 20 cm. At each soil layer 40 undisturbed soil samples were taken, 80 in total. The samples were oven dried at 105 °C for 48 h to determine GWC and BD following standard core method (Grossman and Reinsch, 2002). At the same time when undisturbed samples were taken, PR was determined by an electronic hand-pushed cone penetrometer (Eijkelkamp Penetrologger, Netherland) with 1 cm^2 base area. At each sampling point, three penetration repetitions were made and presented as an average, 120 in total. PR data were grouped in soil layers 0-10 cm and 10-20 cm, respectively.

Statistical analyses of BD, PR and GWC include descriptive statistics such as mean, standard deviation (SD), coefficient of variation (CV%), minimum (Min), maximum (Max), skewness (skew) and kurtosis (kur) to analyze data distribution. Prior to modelling, normal distribution was assessed with Kolmogorov-Smirnov test (K-S). Comparisons among depths were analyzed with One-way ANOVA using the original data for GWC and BD, and log-transformed data for PR. Data were transformed for spatial modelling to minimize the effects of the outliers and back-transformed in order to observe spatial distribution of the real values.

Table 1. Soil physical and chemical properties

Tablica 1. Fizikalna i kemijska svojstva tla

Depth (cm) Horizons	0 - 40 Ap	40 -88 Btg	88 - 170 Cg	170 - 250 Cg2
Organic matter (g kg^{-1})	23	13	-	-
pH in H_2O (w w^{-1} 1:5)	7.5	8.0	8.1	8.1
$CaCO_3$ (g kg^{-1})	60	304	298	240
P_2O_5 (g kg^{-1})	417	-	-	-
K_2O (g kg^{-1})	415	-	-	-
Clay (g kg^{-1})	252	257	143	138
Fine silt (g kg^{-1})	322	332	347	315
Coarse silt (g kg^{-1})	369	361	432	500
Fine sand (g kg^{-1})	54	44	73	43
Coarse sand (g kg^{-1})	3	6	5	4

Spatial patterns of soil physical properties were analyzed with the experimental semi-variogram modelling using the data developed to identify the spatial continuity of BD, PR and GWC among sampling points. Semi-variogram can be expressed as:

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

where γ(h) is the semi-variance at a given distance *h*; *Z(xi)* is the value of the variable *Z* at the *xi* location and *N(h)* is the number of pairs of sample points separated by the lag distance *h*. In the present study the omni-directional semi-variogram was assessed assuming that the variability of the variable is equal in all directions. The variable spatial dependency was calculated by the nugget/sill ratio (Chien et al., 1997). Tested interpolation methods are a part of ArcGIS software and they are described in the literature (Pereira et al. 2010): local polynomial with the power of 1 and 2 (LP), radial basic functions - inverse multiquadratic (IMTQ), completely regularized spline (CRS), multiquadratic (MTQ), spline with tension (SPT) and thin plate spline (TPS) - and two geostatistical methods, ordinary kriging (OK) and simple kriging (SK). The cross-validation method is commonly used for comparing the interpolation methods. Cross-validation involves consecutively removing a data point, interpolating the value from the remaining observations and comparing the predicted value with the measured value (Mueller et al., 2004). The mean error (ME) and the root mean square error (RMSE) calculated from the measured and interpolated values at each sample site were used to compare the accuracy of predictions:

$$ME = \frac{1}{N}\sum_{i=1}^{n}\{Z(Xi) - \hat{Z}(Xi)\},\ RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\{Z(Xi) - \hat{Z}(Xi)\}^{2}},$$

where: $Z(Xi)$ is the observed value, $\hat{Z}(Xi)$ is the predicted value and N is the number of samples. The best method was the one which had the lowest RMSE. Statistical analyses were carried out with SAS software (Version 9.3) and the semi-variogram and interpolation methods analysis with ArcGIS 10.0 (ESRI) for Windows.

RESULTS AND DISCUSSION

In this study, BD and GWC data respected Gaussian distribution while PR respected normal distribution only after logarithm transformation. The results show significant differences in soil depth for GWC (F=19.55, $P<0.0001$) and PR (F=21.47, $P<0.0001$), while differences between depths for BD (F=0.02, $P=0.9002$) were not found. PR was significantly higher at 10-20 cm, yet GWC was significantly lower at 0-10 cm. BD values were 1.45 Mg m^{-3} at 0-10 cm and 1.46 Mg m^{-3} at 10-20 cm (Table 2). Among the presented statistical data in Table 2, CV value is the most discriminating factor for describing variability. A CV value lower than 10% indicates low variability while a CV value above 90% shows extensive variability (Zhang et al., 2007).

Table 2. Univariate statistics for bulk density (Mg m^{-3}), soil water content (% vol) and penetration resistance (MPa)

Tablica 2. Univarijantna statistika za volumnu gustoću (Mg m-3), trenutačnu vlažnost tla (% vol) i otpore tla (MPa)

	Mean	SD	Kurt	Skew	Range	Min	Max	CV (%)
GWC 0-10	37.6^{b}	2.02	1.45	-0.96	9.9	31.3	41.2	5.4
GWC 10-20	39.5^{a}	1.85	0.12	-0.22	8.3	35.0	43.3	4.4
BD 0-10	1.45^{a}	0.07	0.76	-0.10	0.3	1.28	1.59	3.2
BD 10-20	1.46^{a}	0.05	0.28	-0.01	0.2	1.34	1.57	4.9
PR 0-10	0.54^{b}	0.16	2.02	1.11	0.8	0.27	1.07	30.0
PR 10-20	0.76^{a}	0.25	2.92	1.59	1.2	0.43	1.62	33.3

Bulk density and GWC values at all depths had low variability, while the PR recorded moderate variability with CV from 30.0% at 0-10 cm to 33.3% at 10-20 cm. Both investigated depths for BD showed low spatial heterogeneity in contrast to PR. Bulk density can typically show a low spatial variability (Kılıç et al., 2004; Jabro et al., 2006; Barik et al., 2014) and normal distribution (Kılıç et al., 2004). In contrast to BD, PR is a variable that is measured at one point and usually records high heterogeneity in space and time. PR is a variable that is highly dependent on BD, GWC, texture, structure and organic matter content (Cassel, 1982), and therefore is more variable than BD which is mostly related to only soil porosity (Hamza and Anderson, 2005). The PR values presented in this study, however, are different from the heterogeneity presented in papers by Barik et al. (2014), Özgöz et al. (2012) and Duffera et al. (2007) with CV values between 37 - 70%. The results are probably related to soil tillage, soil texture and weather conditions.

The parameters for the variogram models are listed in Table 3. Among other models, the exponential model gave the best fit for the experimental variograms calculated for GWC, BD 0-10 cm and PR 10-20 cm. Gaussian model was best for BD 10-20 cm whereas Spherical was for PR 0-10 cm. Nugget effect was not recorded for BD 0-10 cm and PR 0-10 cm, while the recorded nugget for BD 10-20 cm and PR 10-20 cm was 0.001 and 0.007, respectively. GWC recorded higher nugget values with 0.068 and 2.255 depending on the depth. Compared to sill, small nugget values at depth 0-10 cm in all studied variables indicate that sampling errors are negligible. Usually, the nugget effect occurs as a consequence of limited samples, small-scale variance and the existence of outliers (McGrath and Zhang, 2003). Ranges of variogram models for all investigated parameters were much wider than the sampling interval of 25 m. By the geostatistical theory, this sampling design is sufficient for the investigation of spatial dependence and distribution of investigated parameters in the investigated soil. Therefore, the number of samples was representative of the studied plot and nugget effect can be attributed to the small-scale variance observed in some areas of the plot in the study sampling density. BD 0-10 cm, GWC 0-10 cm and PR 0-10 cm variable with nugget/sill ratio of 0.0, 1.4 and 0.0, respectively, showed strong spatial dependence, while PR 10-20 cm and BD 10-20 cm with a 38.8 and 74.4 nugget/sill ratio showed moderate spatial dependence. The nugget/sill ratio (84.3) showed that GWC 10-20 cm had a weak spatial dependence.

Table 3. The best-fitted varigram models of bulk density, soil water content and penetration resistance and corresponding parameters

Tablica 3. Najbolje odgovarajući variogramski modeli s pripadajućim čimbenicima za trenutačnu vlažnost, gustoću volumnu i otpore tla

	Model	Nugget	Sill	Nugget/Sill	Range (meters)
BD 0-10	Exponential	0.000	0.004	0.0	112
BD 10-20	Gaussian	0.001	0.002	74.7	68
GWC 0-10	Exponential	0.068	4.806	1.4	186
GWC 10-20	Exponential	2.255	2.675	84.3	323
PR 0-10	Spherical	0.000	0.019	0.0	226
PR 10-20	Exponential	0.007	0.019	38.8	172

The results of the tested interpolation methods for all parameters are shown in Table 4. The test of the different interpolation methods provides an accurate insight in the spatial distribution of BD, PR, and GWC on silty loam soil. MTQ method was the most accurate for interpolating the GWC 0-10 cm (RMSE, 1.4091) and the least precise method was LP1 (RMSE, 1.7741). The most precise method for GWC 10-20 cm was SK (RMSE 1.5553) and the least accurate method was TPS (RMSE 2.1206). IMTQ proved to be the most accurate method for BD 0-10 cm (RMSE 0.0625) and the least precise method was TPS (RMSE, 0.0722), while for BD 10-20 cm the most accurate method was IMTQ (RMSE, 0.0298) and the least precise method was LP1 (RMSE, 0.0401). On the contrary, LP1 method was the most accurate for PR at both depths (RMSE, 0.0992 at 0-10 cm and 0.2317 at 10-20 cm). Visualizations of most accurate techniques are depicted in Figure 1. The interpolation comparisons and the most precise model identified describe more precisely the spatial variability of BD, PR and GWC. Normally, accuracy of mapping depends on number of samples, the distance between sampling locations and the choice of interpolation method (Kravchenko, 2003). The tested methods showed that the ME was very close to 0 in all parameters (according to Pereira et al., 2013a) suggesting that predictions are unbiased. Also, there is a very small difference between observed and predicted values on the all investigated parameters. According the small RMSE and ME we can conclude that the predictions do not deviate much from the measured values. Generally, a larger number of samples will produce more accurate spatial map (Mueller et al., 2001) and the results are likely a consequence of sufficient number of samples in this study confirmed by the corresponding parameters of the best-fitted variogram models.

Table 4. Summary statistics of the accuracy (MIN – the lowest error, Max – the highest error, ME - mean error, RMSE - root mean square error) of interpolations models. Number in bold indicates the most accurate model

Tablica 4. Sumarna statistika preciznosti (MIN - najmanja pogreška, MAX - najveća pogreška, ME - srednja vrijednost pogreške, RMSE - korijen srednje kvadratne pogreške) interpolacijskih modela. Podebljana slova označavaju najprecizniji model

Model	GWC 0-10cm				Model	GWC 10-20cm			
	MIN	MAX	ME	RMSE		MIN	MAX	ME	RMSE
LP1	-3.605	3.772	-0.2009	1.7741	LP1	-3.037	3.811	-0.1268	1.5910
LP2	-2.551	3.358	0.0079	1.5483	LP2	-2.835	4.129	-0.0241	1.6313
SPT	-2.748	3.488	-0.0230	1.5654	SPT	-3.063	3.874	0.0531	1.6358
CRS	-2.773	3.092	-0.0127	1.4192	CRS	-3.062	4.029	0.0411	1.6714
MTQ	**-2.838**	**3.028**	**-0.0369**	**1.4091**	MTQ	-3.260	4.419	-0.0197	1.7974
IMTQ	-2.861	3.033	-0.0195	1.4136	IMTQ	-2.761	3.517	0.1627	1.5818
TPS	-2.685	3.474	-0.0591	1.5570	TPS	-3.990	5.235	-0.0767	2.1206
OK	-2.522	4.096	0.0476	1.6794	OK	-2.721	3.627	0.0631	1.5741
SK	-2.653	5.057	0.0649	1.6966	**SK**	**-2.649**	**3.521**	**0.0718**	**1.5553**
	BD 0-10cm					BD 10-20cm			
LP1	-0.139	0.145	-0.0032	0.0638	LP1	-0.073	0.067	0.0002	0.0401
LP2	-0.113	0.144	-0.0004	0.0657	LP2	-0.062	0.080	-0.0004	0.0322
SPT	-0.139	0.162	-0.0006	0.0639	SPT	-0.070	0.074	0.0002	0.0304
CRS	-0.143	0.163	-0.0006	0.0645	CRS	-0.073	0.076	0.0002	0.0309
MTQ	-0.151	0.164	-0.0007	0.0681	MTQ	-0.079	0.080	-0.0002	0.0328

Model	GWC 0-10cm				Model	GWC 10-20cm			
	MIN	MAX	ME	RMSE		MIN	MAX	ME	RMSE
IMTQ	**-0.128**	**0.162**	**-0.0008**	**0.0625**	**IMTQ**	**-0.079**	**0.064**	**0.0004**	**0.0298**
TPS	-0.159	0.176	-0.0018	0.0722	TPS	-0.094	0.082	-0.0002	0.0378
OK	-0.135	0.162	0.0005	0.0631	OK	-0.079	0.061	0.0012	0.0400
SK	-0.141	0.167	-0.0002	0.0626	SK	-0.070	0.060	0.0000	0.0367
	PR 0-10cm					**PR 10-20cm**			
LP1	**-0.179**	**0.238**	**-0.0009**	**0.0992**	**LP1**	**-0.710**	**0.411**	**-0.0013**	**0.2317**
LP2	-0.160	0.248	-0.0008	0.1052	LP2	-0.635	0.434	-0.0026	0.2354
SPT	-0.187	0.252	-0.0012	0.1021	SPT	-0.738	0.377	-0.0040	0.2403
CRS	-0.177	0.252	-0.0013	0.1024	CRS	-0.733	0.399	-0.0045	0.2455
MTQ	-0.166	0.267	-0.0015	0.1070	MTQ	-0.780	0.466	-0.0052	0.2657
IMTQ	-0.194	0.252	-0.0022	0.1028	IMTQ	-0.802	0.315	-0.0109	0.2377
TPS	-0.217	0.292	-0.0036	0.1136	TPS	-0.842	0.622	-0.0134	0.3115
OK	-0.192	0.243	-0.0010	0.1014	OK	-0.772	0.339	-0.0014	0.2366
SK	-0.195	0.252	-0.0013	0.1023	SK	-0.776	0.338	-0.0035	0.2363

*local polynomial with the power of 1 and 2 (LP), inverse multiquadratic (IMTQ), completely regularized spline (CRS), multiquadratic (MTQ), spline with tension (SPT), thin plate spline (TPS), ordinary kriging (OK), simple kriging (SK)

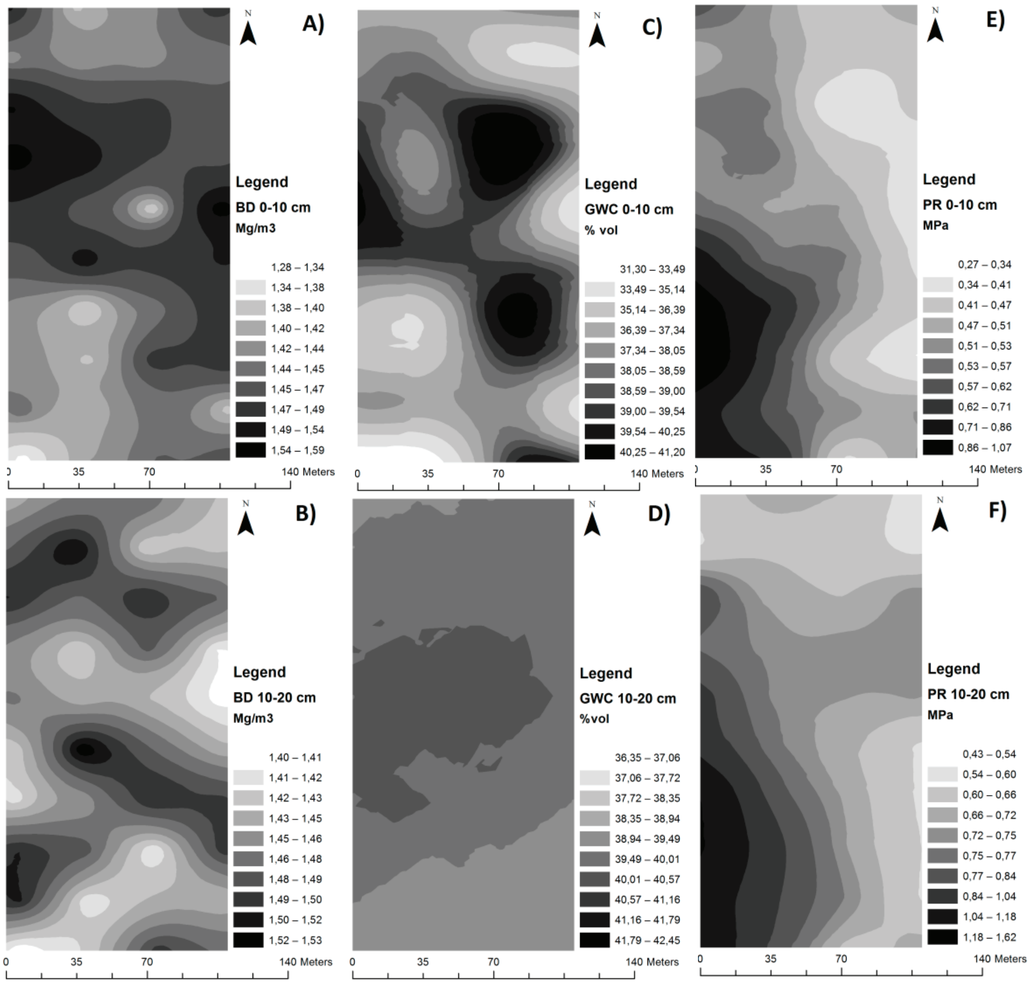

Figure 1. Interpolation mapping by the most accurate technique. A) BD in layer 0-10 cm; B) BD in layer 10-20 cm; C) GWC in layer 0-10 cm; D) GWC in layer 10-20 cm; E) PR in layer 0-10 cm; E) PR in layer 10-20 cm

Slika 1. Interpolacijski prikaz prema najtočnijoj metodi. A) BD na dubini 0-10 cm; B) BD na dubini 10-20 cm; C) GWC na dubini 0-10 cm; D) GWC na dubini 10-20 cm; E) PR na dubini 0-10 cm; F) PR na dubini 10-20 cm

CONCLUSION

This study shows that BD and PR were favorable for crop production in the sampling time. Variability of GWC and BD were much lower compared to higher heterogeneity of PR at all depths. At depth 0-10 cm, BD and PR recorded lower variability compared to 10-20 cm depth. These are directly affected climatic conditions on the different soil layers which led to the settling of the soil surface, causing a greater homogenization of the BD and PR. The range of values for the investigated properties were generally greater than 68 m, which according to Kerry and Oliver (2004) indicates that future sampling intervals could be at distance of 34 m. All the investigated properties at 0-10 cm showed strong spatial dependence, while 10-20 cm showed moderate to weak spatial dependence. Interpolation comparisons demonstrated that no interpolator could be chosen as the best one for mapping soil properties. It is necessary, therefore, to use geostatistical models in order to provide the most accurate information for site specific management.

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PROSTORNO MODELIRANJE RADI OPISIVANJA PROSTORNE VARIJABILNOSTI FIZIKALNIH SVOJSTAVA TLA U ISTOČNOJ HRVATSKOJ

SAŽETAK

Ciljevi ovoga istraživanja su opisati prostornu varijabilnost na opsegu proizvodne table i testirati interpolacijske modele radi odabira najboljega prostornoga pokazatelja otpora tla (PR), gustoće volumne (BD) i trenutačne vlažnosti (GWC) na praškasto ilovastome tlu u istočnoj Hrvatskoj. Mjerenja su obavljena na sjecištima mreže 25 x 25-m, gdje je stvoreno 40 pojedinih mjesta uzorkovanja. Svojstva tla mjerena su u središtu svakoga sjecišta, na dubinama 0-10 cm i 10-20 cm. Rezultati prikazuju da na dubini 0-10 cm BD, PR i GWC pokazuju snažnu prostornu zavisnost, dok je na dubini 10-20 cm zabilježena umjerena i slaba prostorna zavisnost PR, BD i GWC. Semi-variogramska analiza pretkazuje da se budući razmaci uzorkovanja istraživanih čimbenika mogu povećati na razmake od 34 m, u svrhu smanjenja troškova istraživanja. Osim toga, interpolacijski modeli bilježe podjednake vrijednosti korijena srednje kvadratne pogreške s visokom točnošću predikcije. Rezultati navode da istraživana svojstva nemaju jedinstvenu interpolacijsku metodu, što podrazumijeva potrebu za prostorno modeliranje, radi točnije procjene tih svojstava tla u istočnoj Hrvatskoj.

Ključne riječi: fizikalna svojstva tla, GIS, mapiranje, černozem, interpolacijski modeli

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