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Spatial mapping of soil chemical properties using multivariate geostatistics. A study from cropland in eastern Croatia

Prostorno mapiranje kemijskih svojstava tla koristeći multivarijatnu geostatistiku. Studija s oraničnih tala u istočnoj Hrvatskoj

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ABSTRACT

The spatial variability of soil chemical properties is affected by factors of soil formation and human activities. Understanding their spatial variability will improve agricultural production, reduce environmental problems (e.g., soil pollution, offsite effects), and achieve sustainable agroecosystems. The main objective was to study the spatial variability of pH, soil organic matter, available phosphorus, and available potassium using univariate and multivariate methods in cropland fields in eastern Croatia. For the study, 169 (0-30 cm) soil samples were collected in a 911 ha study area. The results showed that soils had slightly acidic pH, adequate available phosphorus and potassium values for crop production, and low soil organic matter concentration. The variability was high in available phosphorus and low in pH. Soil pH, soil organic matter, available phosphorus, and potassium nugget/sill ratio was 0.00, 2.79, 18.68, and 22.08, respectively. Auxiliary variables increased the accuracy of the predictions. Soil organic matter levels were below the recommendable, and this is very likely an anthropogenic effect, even though the intrinsic process influences soil organic matter. The heterogeneous distribution of phosphorus and potassium highlighted the necessity of fertilization in some areas. For the sustainability of agroecosystems, adaptable site-specific soil management strategies need to be implemented.

Keywords: auxiliary data, Co-kriging, nutrient maps, land management, spatial variability

SAŽETAK

Prostorna varijabilnost kemijskih svojstava tla uvjetovana je pedogenetskim čimbenicima i ljudskom aktivnošću. Razumijevanje prostorne varijabilnosti poboljšati će poljoprivrednu proizvodnju, smanjiti okolišne probleme (npr. zagađenje tla, off-site učinci), i postići održivost agroekosustava. Glavni cilj rada je istraživanje prostorne varijabilnosti pH, organske tvari i biljci pristupačnog fosfora i kalija, koristeći univarijatne i multivarijatne metode na oraničnim tlima u istočnoj Hrvatskoj. Za rad je prikupljeno 169 (0-30 cm) uzoraka tla s površine od 911 ha. Rezultati pokazuju da su tla blago kisela, adekvatnog sadržaja biljci pristupačnog fosfora i kalija za biljnu proizvodnju i niskog sadržaja organske tvari tla. Varijabilnost je visoka kod biljci pristupačnog fosfora i niska kod pH tla. pH tla, organska tvar te biljci pristupačan fosfor i kalij imaju nuget/sill omjer 0.00, 2.79, 18.68, i 22.08. Pomoćni podaci povećali su preciznost predikcije. Identificiran je sadržaj organske tvari tla ispod preporučljive razine i to vrlo vjerojatno radi antropogenog utjecaja, iako i pedogenetska svojstva utječu na organsku tvar tla. Heterogena distribucija fosfora i kalija istaknula je nužnost za gnojidbom u nekim područjima. Za održivost agroekosustava potrebno je provesti prilagodljive strategije korištenja i upravljanja tlima na svakoj pojedinoj lokaciji.

Ključne riječi: pomoćni podaci, Co-kriging, karte hraniva, gospodarenje tlom, prostorna varijabilnost

INTRODUCTION

Soils are essential for life and provide many vital services to sustain humanity (Brevik et al., 2015; Pereira et al., 2018). Unsustainable soil practices decrease the soil organic matter (SOM), structure deterioration, compaction, erosion, and chemical degradation (Lorenz et al., 2019). Soil degradation is a natural process; however, human activities such as agriculture increase this process, regardless of climate and soil types. In this context, Keesstra et al. (2016) highlighted that UN Sustainable Development Goals (SDGs) should consider adopting innovative forms of precision agriculture to increase efficiency, build resilience and mitigate the impacts of agriculture. Nutrient management is vital to increase soil productivity and reduce yield variability in vulnerable environments (Bruelle et al., 2015).

Geostatistics is one of the most used tools to study soil properties' spatial variability, especially where there are a limited number of samples (Webster and Oliver, 2007). Soil nutrient maps offer a vast number of advantages, such as identifying areas with a lack of nutrients or overfertilized. This allows identifying problems associated with crop production and pollution of surface and groundwater (Fu et al., 2010; Libutti and Monteleone, 2017). Maps also allow having a deeper understanding of the soil spatial variability. Nutrients distribution is controlled by parent material, topography, climate, vegetation, time, and anthropogenic activities. Previous works highlighted that croplands' soil chemical properties have high spatial variability (e.g., Bogunovic et al., 2014; Schillachi et al., 2017). Other works investigated the spatial variability of soil pH, SOM, phosphorus, potassium, and their impacts on crop performance (e.g., Behera and Shukla, 2015; Reza et al., 2017). These works contributed to understanding the link between soil status and crop yield. Nevertheless, the accuracy of the predictions depends on data availability and the usage of auxiliary variables to estimate soil properties. The application of univariate methods may limit the precision of the soil properties estimation (Bogunovic et al., 2018). Therefore, the use of auxiliary variables (e.g., as in co-kriging analyses) is an advantage to estimate a determined soil property. Usually, if the variable of interest is related to others, it is an indication that the auxiliary variables may increase the accuracy of the spatial prediction of the estimated variable (Lipiec and Usowicz, 2018). Co-kriging (CoK) is the method that allows the incorporation of auxiliary variables and is widely used in soil science. Although several studies showed the advantages of CoK over univariate techniques (e.g., ordinary kriging) (Chen et al., 2016), the inverse was observed as well (e.g., Ceddia et al., 2015). The CoK lack of improvement is due to the absence of a correlation between the estimated and auxiliary variable(s). For correcting land management, it is crucial to have accurate maps, especially from critical variables for crop production such as soil pH, SOM, available phosphorus (AP), and potassium (AK). This work aimed to study the spatial distribution of soil pH, SOM, AP, and AK in cropland located in eastern Croatia. The specific objectives were to (1) identify the relation between the studied variables and characterize their spatial distribution, (2) Identify the most accurate method (univariate or multivariate geostatistical technique) to predict the spatial variability of the studied variables and, (3) propose the use of most accurate produced maps of soil properties for guiding sustainable site-specific management practices.

MATERIALS AND METHODS

Study area

The study area is located in eastern Croatia at 45° 46' N and 18° 30' E and 90 - 92 m a.s.l. in a rural/forest interface area (Figure 1). The topography is flat with a maximum elevation of 100 m a.s.l. The land use is cropland. The climate is moderate continental, classified as Cfwbx, according to Köppen (Kottek et al., 2006); summers are warm and sunny, and winters are cold and snowy. The average annual precipitation (1980 - 2018) is 677.9 mm, ranging from a minimum of 317.0 mm (2000) to a maximum of 1038.2 mm (2010). Rainfall is the highest from June and May and the lowest from January to March. The mean annual temperature is 11.5 °C.

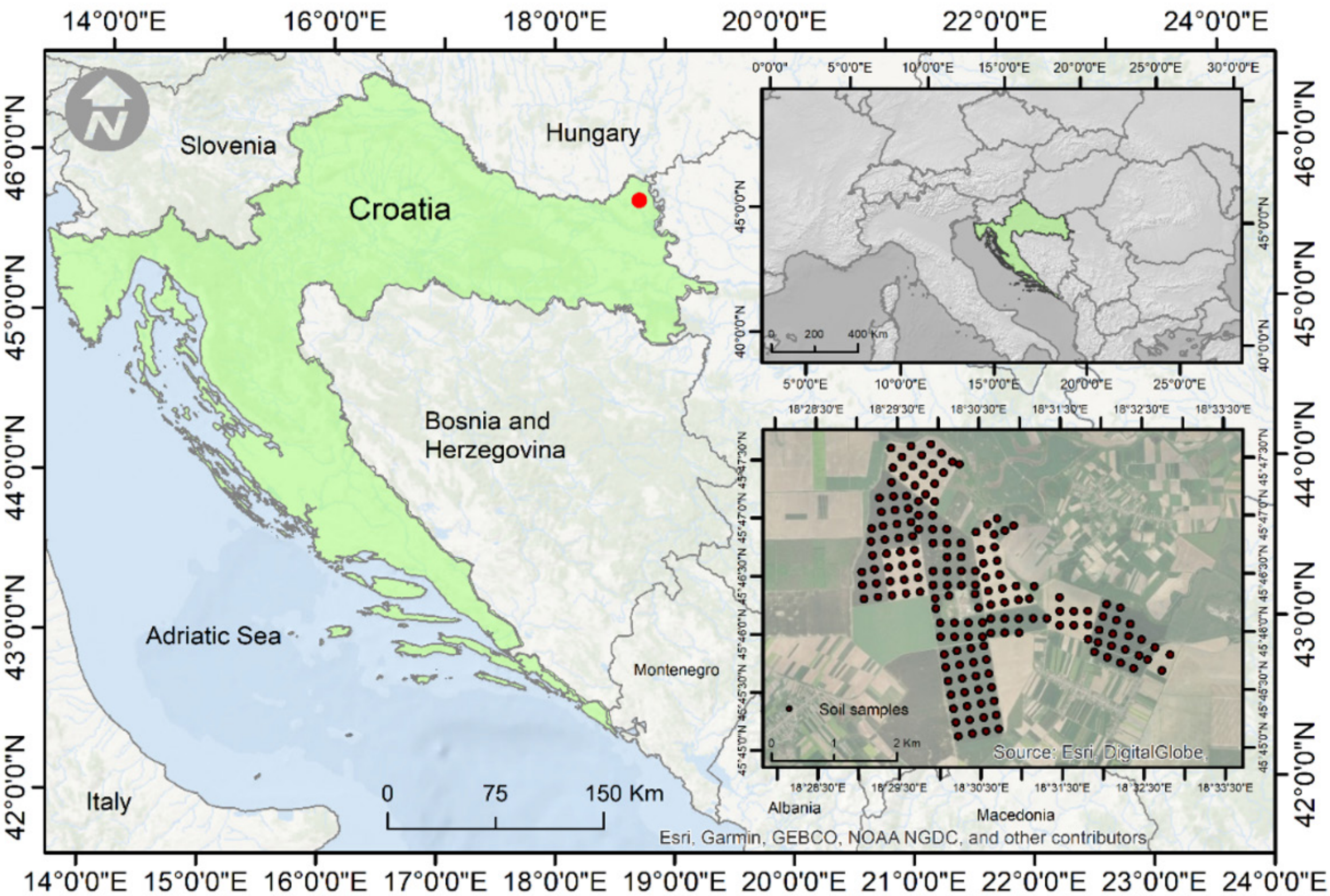

Figure 1. Study location and samples distribution
Slika 1. Mjesto istraživanja i distribucija uzoraka

January is the coldest month (0.1 °C) and July the warmest (22.2 °C). The parent material is Loess, and soils are clay loam textured, classified as Cambisols (IUSS WRB 2015).

Sampling design and laboratory analyses

Soil sampling was carried out in July 2011 in the field of 911 ha (Figure 1). Soil samples (0–30 cm) were taken (a total of 169) in a 225 m x 225 m grid. A Trimble GeoXH 6000 GPS with 10 cm accuracy was used to georeferenced the soil sampling point. Each soil sample is composed of subsamples taken from 17 to 20 points. Samples were homogenized in order to represent an area of 5 ha. Individual samples were mixed and taken to the laboratory for analysis. In the laboratory, samples were air-dried, milled, and sieved (<2 mm mesh). Soil pH was measured at a ratio of 1:5 (w/v) in a KCl suspension, following the electrometric method, using pH meter (Beckman Φ72). SOM content was determined by the method of Walkley and Black (1934). Ammonium lactate solution was used for AP and AK extraction (Egnér et al., 1960), followed by spectrophotometric and flame photometric analyses, respectively.

Statistical and geostatistical analysis

Before the analysis, data were checked for normality using the Kolmogorov–Smirnov (K–S) test. If the K–S test had a P>0.05, data was considered normal. If data was not normal, it was transformed by applying the most common transformation methods: logarithmic (log) and Box-Cox (BC). Data normalization is crucial to avoid errors in the geostatistical analysis (Pereira et al., 2015). Using the normalized data, a Pearson correlation coefficient was applied among the studied variables. Significant correlations were considered at a P<0.05. Statistical analyses were carried out with Statistica

12.0 for Windows. The geostatistical analysis starts with data error detection, local and global outliers, and the presence of non-stationary spatial data using moving window statistics and the interactive analysis of the variogram cloud. Secondly, the spatial continuity structure of soil pH, SOM, AP, and AK was characterized using experimental variograms to detect anisotropies (Hengl et al., 2004). The experimental model results were fitted with different theoretical methods to find the most appropriate. Semivariance was calculate using 12 lags and a maximum lag distance of 250 m. In this study, the modeled semivariograms are unidirectional. Variable spatial dependence was assessed by measuring the nugget/sill ratio, according to Cambardella et al. (1994): 0-25% - high spatial dependence; 25-75% - moderate spatial dependence and >75% - low spatial dependence. Ordinary kriging (OK) and co-kriging (CoK) was used to map soil pH, SOM, AP, and AK. OK is a widely used interpolation technique that estimates the values at un-sampled locations by a weighted averaging of nearby samples. CoK is a method more advanced than OK and allows incorporating auxiliary information (Goovaerts, 1998). Usually, CoK has a good estimation performance of the target variable using spatially exhaustive auxiliary information. The success of CoK depends on the correlation between modeled variables, the spatial continuity of the attributes, and the proper sampling strategy of the variables (Goovaerts, 1998). In this work, an isotopic CoK technique was used. This means that estimations on the un-sampled location are created using primary and secondary variables derived from one sampling point (in this study, correlated parameters from the same soil samples). Here the variables as auxiliary were considered significantly correlated ($P<0.05$) with the estimated variable. The interpolations' accuracy was carried out using the cross-validation method, which compares predicted values with the estimated values. The difference between the observed and the estimated represents the error of interpolation. Cross-validation calculates the mean error (ME), and the root means square error (RMSE). The determination of the most accurate technique following the approach described in Bogunovic et al. (2018), where the relative improvement (RI) is calculated to obtain the difference of percentage of prediction accuracy between CoK and OK. All the spatial analyses were carried out using ArcGIS 10.1.

RESULTS

Descriptive statistics

Mean pH and SOM contents were 5.64 and 1.72%, while mean AP and AK were 189 mg/kg and 237 mg/kg, respectively. The coefficient of variation (CV) was the highest for AP (31.4%) and the lowest for pH (15.2%). The original values of all studied properties were highly skewed (Table 1) and did not follow the Gaussian distribution. After trying different transformations, Box-Cox transformation provided the closest distributions to Gaussian with corrected skewness, and it was used for correlation and spatial modeling analysis, as in the previous works (Pereira et al. 2015). Pearson correlation coefficient results are shown in Table 2. Soil pH was significantly positively correlated with SOM and AP. SOM was also significantly positively correlated with AK. Finally, soil AP was significantly positively correlated with AK. No significant correlations were observed between soil pH and AK and between SOM and AP.

Semivariogram analysis and mapping soil properties

The exponential model was the best fitted for pH, SOM, and AK experimental variograms, while the AP experimental variogram was best fitted with the spherical model. The nugget effect in soil pH was not observed. However, it was identified in the other variables. In all cases, the spatial dependence was < 25%. It was lower in pH and SOM (0.00% and 2.79%) than AP and AK (18.68% and 22.08%). A similar pattern was identified in the spatial correlation. The range was lower in pH and SOM than in AP and AK (Fig. 2). The geostatistical techniques tested for pH, SOM, AP, and AK are shown in Table 3. The most accurate method to estimate pH was using AP as an auxiliary variable. The best predictor of SOM was AK. AK was the best predictor of AP, and AP was the best predictor for AK.

Table 1. Descriptive statistics of soil pH, organic matter (SOM), available phosphorus (AP), and available potassium (AK). Min – minimum, Max – maximum, CV – coefficient of variability, K-S p – Kolmogorov - Smirnoff p-value

Tablica 1. Deskriptivna statistika za pH, organsku tvar (SOM), pristupačan fosfor (AP) i pristupačan kalij (AK). Min – minimum, Max – maksimum, CV – koeficijent varijacije, K-S p – Kolmogorov - Smirnoff p vrijednost

		Mean	Median	Min	Max	Range	CV %	Kurtosis	Skewness	K-S p
pH	Original data	5.64	5.42	4.20	7.52	3.32	15.2	-0.94	0.42	P<0.05
	Box Cox	0.89	0.89	0.82	0.95	0.13	3.8	-1.07	0.05	P>0.20
	Log-transformed data	0.75	0.73	0.62	0.88	0.25	8.7	-1.06	0.22	P<0.20
SOM	Original data	1.72	1.65	1.29	4.65	3.36	19.8	35.96	4.82	P<0.01
	Box Cox	0.29	0.29	0.19	0.40	0.21	12.3	0.51	-0.05	P>0.20
	Log-transformed data	0.23	0.22	0.11	0.67	0.56	29.3	12.27	2.43	P<0.05
AP	Original data	189	178	84	399	315	31.4	1.77	1.08	P<0.15
	Box Cox	3.99	3.98	3.53	4.43	0.89	4.4	0.06	0.00	P>0.20
	Log-transformed data	2.26	2.25	1.92	2.60	0.68	5.8	0.09	0.10	P>0.20
AK	Original data	237	230	158	471	313	19.3	4.97	1.65	P<0.01
	Box Cox	0.99	0.99	0.99	0.99	0.004	0.07	0.73	-0.04	P<0.05
	Log-transformed data	2.37	2.36	2.20	2.67	0.47	3.3	1.74	0.73	P<0.05

Table 2. Correlations of studied soil properties. SOM - organic matter, AP - available phosphorus, and AK - available potassium

Tablica 2. Korelacijski odnosi istraživanih značajki tla. SOM – organska tvar, AP – biljci pristupačan fosfor i AK – biljci pristupačan kalij

Variable	pH	SOM	AP	AK
pH	-			
SOM	0.268*	-		
AP	0.351*	0.126n.s.	-	
AK	0.082n.s.	0.335*	0.575*	-

n.s., not significant at a P>0.05. Significant at a *P<0.05
n.s., nije signifikantno na P>0.05. Signifikantno na *P<0.05

Table 3. Summary statistics of the accuracy of the tested geostatistical techniques. SOM - organic matter, AP - available phosphorus, AK - available potassium, ME – mean error, RMSE – root mean square error, and RI – relative improvement

Tablica 3. Zbirna statistika preciznosti testiranih geostatističkih metoda. SOM – organska tvar, AP – biljci pristupačan fosfor, AK – biljci pristupačan kalij, ME – srednja pogreška, RMSE – korijen srednje kvadratne pogreške i RI – relativno poboljšanje

pH	ME	RMSE	RI (%)	SOM	ME	RMSE	RI (%)
OK	-0.0003	0.0266		OK	-0.0002	0.0288	
pH x SOM	-0.0004	0.0267	-0.21	SOM x pH	-0.0001	0.0282	2.33
pH x AP	-0.0002	0.0247	7.10	SOM x AK	-0.0002	0.0278	3.61
AP	ME	RMSE	RI (%)	AK	ME	RMSE	RI (%)
OK	0.0001	0.1077		OK	0.000002	0.000545	
AP x pH	-0.0003	0.1016	5.68	AK x SOM	0.000003	0.000538	1.37
AP x AK	-0.0007	0.0972	9.79	AK x AP	0.000006	0.000495	9.16

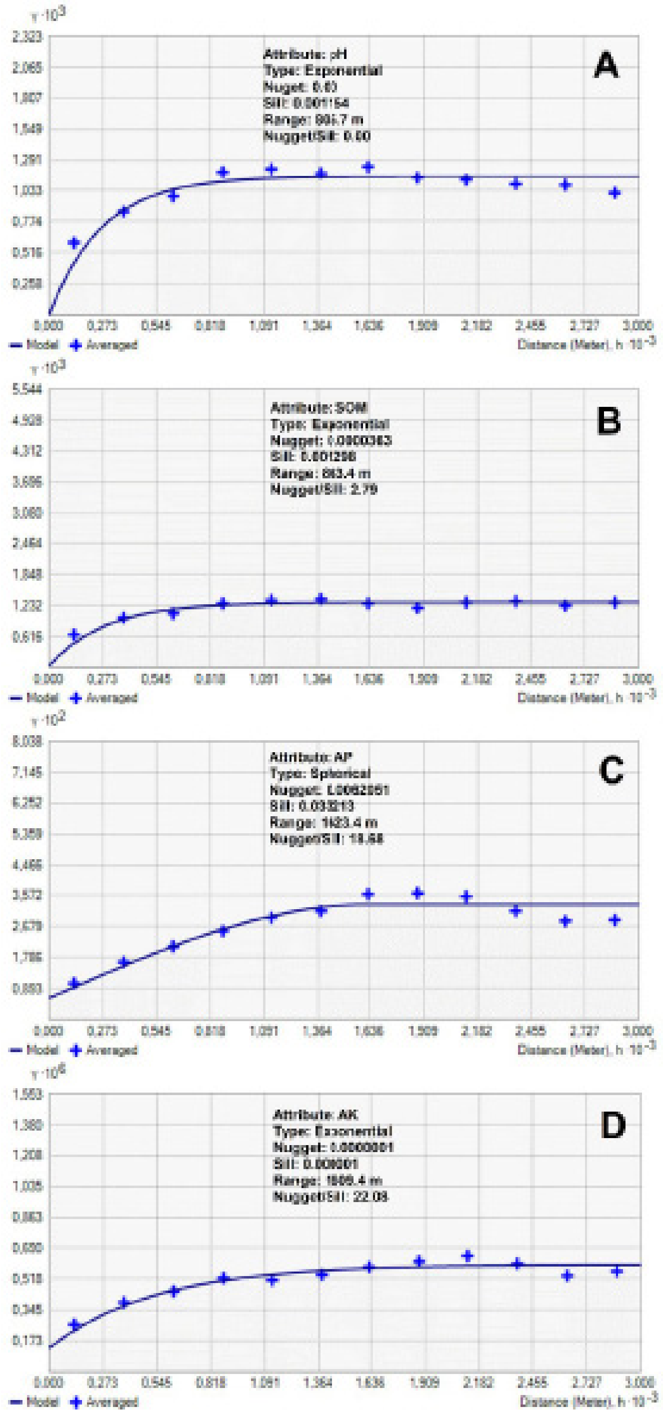

Figure 2. Semivariogram analysis and their parameters for a) pH, b) soil organic matter (SOM), c) available phosphorus (AP), and d) available potassium (AK)

Slika 1. Semivariogramska analiza i pripadajuća svojstva za a) pH, b) organska tvar (SOM), c) pristupačan fosfor (AP) i d) pristupačan kalij (AK)

The maps produced from the most accurate techniques are shown in Fig. 3. The highest values of pH and SOM were observed in the northwest part. The spatial distribution of AP and AK were similar, with the highest concentrations observed in the central and northwestern part of the study area.

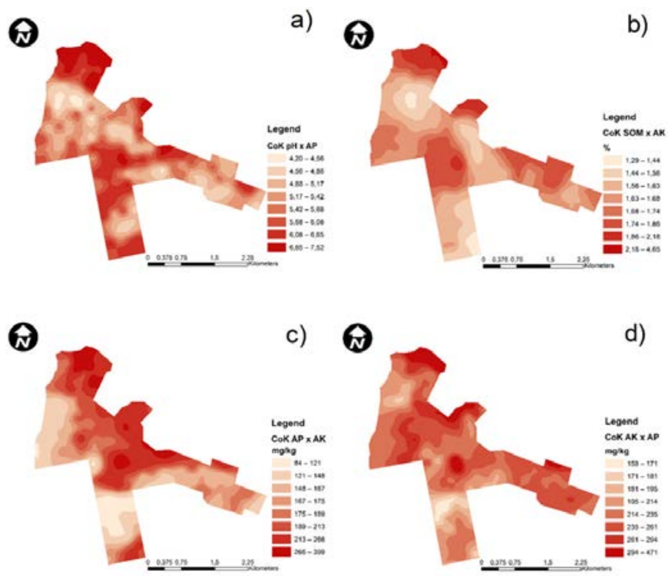

Figure 3. Spatial distribution maps according to the most accurate technique: a) pH, b) soil organic matter (SOM), c) available phosphorus (AP), and d) available potassium (AK)

Slika 3. Karte prostorne distribucije dobivene najtočnijom metodom: a) pH, b) organska tvar (SOM), c) pristupačan fosfor (AP) i d) pristupačan kalij (AK)

DISCUSSION

Following the classification proposed by Thun et al. (1955), the soils are, in average, slightly acidic. The pH value observed does not impose limitations for agricultural production since most cropland cultures' desirable pH is slightly acidic to neutral (Keesstra et al., 2016). However, spatial maps reveal several areas that should be treated with lime materials. Since the studied soils were subjected to intensive agricultural practices, soil pH should be monitored. The results showed that SOM content (1.72%) is low, which can be evidence of degradation. The threshold for soil degradation occurs where SOM is between 2.6 and 3.5% in the rhizosphere (Loveland and Webb, 2003; Lal, 2016). Future management should consider soil conservation measures to increase SOM and avoid soil degradation. According to Wunderer et al. (2003), soil AP and AK concentrations have a medium supply. This supply is higher than in the natural soils due to fertilization (Bašić, 2013). Soil pH was positively correlated with SOM, AP, and AK, which agrees with Behera and Shukla (2015), who found similar interrelations in India's cropland soils. Soil pH mean was 5.64, and an additional raise can favor AP. This element is mostly available in the pH range from 6 to 7 (Penn and Camberato, 2019). Moreover, decomposition and formation of passive forms of SOM are higher in soils with higher addition of fresh biomass, i.e., at soils with neutral soil reaction, which can explain the positive interrelations of soil pH AP and SOM. Finally, SOM is the main source of nutrients, and their positive interrelations with AP and AK are thus expectable and in agreement with other studies (Iticha and Takele, 2019). This interrelation also explains the positive correlation between AP and AK.

A CV value lower than 10% indicates a low variability, between 10% and 90% a moderate variability, and higher than 90% a high variability (Zhang, 2006). The variables studied had moderate variability. The minimum observed was 15.2% (pH) and a maximum of 31.4% (AP). Soil pH was less heterogeneous than other variables, as observed in previous works. Rarely exceeds 15% (Fu et al., 2010; Sağlam, 2015). For management purposes, the homogeneous distribution of pH is preferred. Typically, SOM content is influenced by topography and climate. However, in present case, the differences observed may be attributed to the ununiformed crop rotation and soil management that farmers apply on their land in the research area. The spatial variability of AP and AK was moderate, and this is a consequence of the unequal fertilization. Previous works for AP and AK observed a CV of 22.1% and 32.6% in Croatian (Bogunovic et al., 2014) and 68.4% and 60.6% in Ireland soils (Fu et al., 2010), respectively. Usually, forest soils near the studied area have reduced AK and AP. Loess soils are deficient in these elements (Bašić, 2013). Nowadays, the content of AP and AK was strongly changed due to intensive use and different fertilization practices. Intensive fertilization in the second part of the last century has dramatically increased the concentration of these elements in eastern Croatia's soils (Bogunovic et al., 2017). Furthermore, spatial heterogeneity of pH may have influenced the concentration of AP and AK. Low acid and neutral pH values increase these elements' bioavailability (Pereira et al., 2017).

The exponential and spherical models were the best-fitted models for the studied soil properties. Similar results were identified in previous works, where these two models dominate (e.g., Sağlam, 2015; Lipiec and Usowicz, 2018). According to the variogram parameters, analyzed soil properties showed a strong spatial dependence (nugget to sill ratio < 25%) (Cambardella et al., 1994). Their spatial dependence may be controlled by intrinsic variations of soil properties and extrinsic factors such as fertilization (Goovaerts, 1998). The reduced nugget effect suggested that intrinsic factors more influenced pH and SOM. Nevertheless, a low content of SOM was also observed, and this is evidence of degradation. Using the sampling resolution of 5 ha, the human effect did not detect. However, this can be identified at a finer resolution. On the other hand, the high nugget effect in AP and AK is an indicator of the short-range spatial variability and the impact of human activities. This is a critical aspect, mainly because fertilization is already observed at 5 ha resolution, showing a high degree of human impact. Several studies reported that low spatial dependence was attributed to the effect of extrinsic factors (e.g., Xu et al., 2013; Liu et al., 2014). Ranges derived from the best-fitted variogram model show the spatial autocorrelation extension (Behera and Shukla, 2015). The range varied from 805.7 m (pH) to 1623.4 m (AP) in the studied soils. The ranges observed are high and can serve as guidance for future sampling activities in the area. In all the cases, the ranges were higher than 250 m showing that the sampling procedure was appropriated to detect the variables' spatial variability (Kerry and Oliver, 2004).

Testing different interpolation methods comparison enable to identify the most accurate key to identify the best map. In the present case, it is crucial to identify areas where the lack of nutrients in the soil can affect crop yield and areas where a high concentration of elements can affect surface and groundwater. Likewise, numerous studies compared different interpolation techniques to describe soil properties' spatial variability (e.g., Ceddia et al., 2015; Bogunovic et al., 2017). Here, the tested methods revealed different results. However, only in one case, CoK showed the reduced prediction capacity (soil pH using SOM) auxiliary variable, while all other soil properties showed an increase of the prediction (Table 3). These results indicated that the inclusion of auxiliary variables increased the estimations' accuracy, as observed in previous works (e.g., Ceddia et al., 2015; Chen et al., 2016). Overall, it was demonstrated that spatial modeling using auxiliary variables could improve estimation at un-sampled locations and increase the predictions' accuracy. Nevertheless, this depends on the relationship between the primary and auxiliary variables. Spatial analysis can reduce sampling costs and provide accurate information for crop production firms, environmental monitoring, protection, and management purposes.

Several studies have highlighted the importance of precision maps and the application of geostatistical techniques to identify areas with a deficit of nutrients and affected by degradation (Liu et al., 2016; Iticha and Takele, 2019). On the other hand, maps with a high precision identify with accuracy areas with an excess of nutrients and induce toxicity to the crops and reduce food production and security. The excess of nutrients such as phosphorous reduce surface and groundwater quality and increase water bodies' eutrophication. Agriculture activities are one of the main responsible for water quality degradation and biodiversity decrease in rivers and lakes (Van Soesbergen et al., 2019; Withers and Haygarth, 2007). Identifying areas with low and high nutrients will facilitate the management of the farmland and reduce costs (Bongiovanni and Lowenberg-Deboer, 2004; Schimmelpfennig and Ebel, 2006). All in all, maps at different scales are an essential tool to have better sustainable land management and contribute to the achievement of global targets (Munoz-Rojas et al., 2017; Tamene et al., 2017). The study carried out was essential to verify that the soil degradation process needs to be reversed due to the reduced SOM and apply soil conservation practices to increase nutrients in some areas and reduce the losses and the consequent offsite in others. This will increase the management effectiveness and cost-saving in the studied farm.

CONCLUSION

The geostatistical modeling provide an opportunity to characterize the spatial variability and spatial patterns of soil pH, SOM, AP, and AK at the field scale. The spatial variability of AP was the highest, and pH the lowest. Final maps reveal heterogeneous spatial patterns of soil properties and indicate a need for sustainable site-specific soil management strategies. Several parts of the area reveal an acidic soil environment, and a liming application is needed. Moreover, large parts of studied soils were over-or under- fertilized, indicating possible environmental problems or inadequate soil conditions for plant production. Particular attention should be paid to SOM contents since they are below critical levels for agricultural production. Such a soil environment threat requires adopting conservation management practices to achieve the sustainability of the studied agroecosystems.

REFERENCES

Bašić, F. (2013) The soils of Croatia. Dordrecht: Springer.

Behera, S. K., Shukla, A. K. (2015) Spatial distribution of surface soil acidity, electrical conductivity, soil organic carbon content and exchangeable potassium, calcium and magnesium in some cropped acid soils of India. Land Degradation & Development, 26 (1), 71-79. DOI: https://doi.org/10.1002/ldr.2306

Bogunovic, I., Mesic, M., Zgorelec, Z., Jurisic, A., Bilandzija, D. (2014) Spatial variation of soil nutrients on sandy-loam soil. Soil and tillage research, 144, 174-183. DOI: https://doi.org/10.1016/j.still.2014.07.020

Bogunovic, I., Pereira, P., Brevik, E. C. (2017) Spatial distribution of soil chemical properties in an organic farm in Croatia. Science of the total environment, 584, 535-545. DOI: https://doi.org/10.1016/j.scitotenv.2017.01.062

Bogunovic, I., Trevisani, S., Pereira, P., Vukadinovic, V. (2018). Mapping soil organic matter in the Baranja region (Croatia): Geological and anthropic forcing parameters. Science of the total environment, 643, 335-345. DOI: https://doi.org/10.1016/j.scitotenv.2018.06.193

Bongiovanni, R., Lowenberg-Deboer, J. (2004) Precision Agriculture and Sustainability. Precision Agriculture, 5, 359-387. DOI: https://doi.org/10.1023/B:PRAG.0000040806.39604.aa

Brevik, E. C., Cerdà, A., Mataix-Solera, J., Pereg, L., Quinton, J. N., Six, J., Van Oost, K. (2015) The interdisciplinary nature of SOIL. Soil, 1 (1), 117-129. DOI: https://doi.org/10.5194/soil-1-117-2015

Bruelle, G., Naudin, K., Scopel, E., Domas, R., Rabeharisoa, L., Tittonell, P. (2015) Short-to mid-term impact of conservation agriculture on yield variability of upland rice: Evidence from farmer's fields in Madagascar. Experimental agriculture, 51 (1), 66-84. DOI: https://doi.org/10.1017/S0014479714000155

Cambardella, C. A., Moorman, T. B., Parkin, T. B., Karlen, D. L., Novak, J. M., Turco, R. F., Konopka, A. E. (1994) Field-scale variability of soil properties in central Iowa soils. Soil science society of America journal, 58 (5), 1501-1511. DOI:https://doi.org/10.2136/sssaj1994.03615995005800050033x

Ceddia, M. B., Villela, A. L. O., Pinheiro, É. F. M., Wendroth, O. (2015) Spatial variability of soil carbon stock in the Urucu river basin, Central Amazon-Brazil. Science of the Total Environment, 526, 58-69. DOI: https://doi.org/10.1016/j.scitotenv.2015.03.121

Chen, T., Chang, Q., Liu, J., Clevers, J. G. P. W., Kooistra, L. (2016) Identification of soil heavy metal sources and improvement in spatial mapping based on soil spectral information: A case study in northwest China. Science of The Total Environment, 565, 155-164. DOI: https://doi.org/10.1016/j.scitotenv.2016.04.163

Egner, H., Riehm, H., Domingo, W. R. (1960). Investigations on the chemical soil analysis as a basis for assessing the soil nutrient status. II: Chemical extraction methods for phosphorus and potassium determination. Kungliga Lantbrukshügskolans Annaler, 26, 199-215.

Fu, W., Tunney, H., Zhang, C. (2010) Spatial variation of soil nutrients in a dairy farm and its implications for site-specific fertilizer application. Soil and Tillage Research, 106 (2), 185-193. DOI: https://doi.org/10.1016/j.still.2009.12.001

Goovaerts, P. (1998) Ordinary CoKriging revisited. Mathematical Geology, 30 (1), 21-42. DOI: https://doi.org/10.1023/A:1021757104135

Hengl, T., Heuvelink, G. B., Stein, A. (2004) A generic framework for spatial prediction of soil variables based on regression-kriging. Geoderma, 120 (1-2), 75-93. DOI: https://doi.org/10.1016/j.geoderma.2003.08.018

Iticha, B., Takele, C. (2019) Digital soil mapping for site-specific management of soils. Geoderma, 351, 85-91. DOI: https://doi.org/10.1016/j.geoderma.2019.05.026

IUSS Working Group WRB World reference base for soil resources 2014 update 2015 (2015) International soil classification system for naming soils and creating legends for soil maps World Soil Resources Reports No 106. Rome: FAO.

Keesstra, S.D., Bouma, J., Wallinga, J., Tittonell, P., Smith, P., Cerdà, A., Montanarella, L., Quinton, J.N., Pachepsky, Y., van der Putten, W.H., Bardgett, R.D., Moolenaar, S., Mol, G., Jansen, B., Fresco, L.O. (2016) The significance of soils and soil science towards realization of the United Nations Sustainable Development Goals. Soil, 2, 111–128. DOI: https://doi.org/10.5194/soil-2-111-2016

Kerry, R., Oliver, M.A. (2004) Average variograms to guide soil sampling. International Journal of Applied Earth Observation and Geoinformation, 5 (4), 307-325. DOI: https://doi.org/10.1016/j.jag.2004.07.005

Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F. (2006) World map of the Köppen-Geiger climate classification updated. Meteorologische Zeitschrift, 15 (3), 259-263. DOI: https://doi.org/10.1127/0941-2948/2006/0130

Lal, R. (2016) Soil health and carbon management. Food and Energy Security, 5 (4), 212-222. DOI: https://doi.org/10.1002/fes3.96

Libutti, A., Monteleone, M. (2017) Soil vs. groundwater: The quality dilemma. Managing nitrogen leaching and salinity control under irrigated agriculture in Mediterranean conditions. Agricultural Water Management, 186, 40-50. DOI: https://doi.org/10.1016/j.agwat.2017.02.019

Lipiec, J., Usowicz, B. (2018) Spatial relationships among cereal yields and selected soil physical and chemical properties. Science of the Total Environment, 633, 1579-1590. DOI: https://doi.org/10.1016/j.scitotenv.2018.03.277

Liu, R., Xu, F., Yu, W., Shi, J., Zhang, P., Shen, Z. (2016) Analysis of field-scale spatial correlations and variations of soil nutrients using geostatistics. Environmental Monitoring and Assessment 188, 126. DOI: https://doi.org/10.1007/s10661-016-5130-9

Liu, Z., Zhou, W., Shen, J., He, P., Lei, Q., Liang, G. (2014) A simple assessment on spatial variability of rice yield and selected soil chemical properties of paddy fields in South China. Geoderma, 235, 39-47. DOI: https://doi.org/10.1016/j.geoderma.2014.06.027

Lorenz, K., Lal, R., Ehlers, K. (2019) Soil organic carbon stock as an indicator for monitoring land and soil degradation in relation to United Nations' Sustainable Development Goals. Land Degradation & Development, 30 (7), 824-838. DOI: https://doi.org/10.1002/ldr.3270

Loveland, P., Webb, J. (2003) Is there a critical level of organic matter in the agricultural soils of temperate regions: a review. Soil and Tillage research, 70 (1), 1-18. DOI: https://doi.org/10.1016/S0167-1987(02)00139-3

Munoz-Rojas, M., Pereira, P., Brevik, E., Cerda, A., Jordan, A. (2017) Soil Mapping and Processes Models for Sustainable Land Management Applied to Modern Challenges. In: Pereira, P., Brevik, E., Munoz-Rojas, M., Miller, B., eds. Soil Mapping and Process Modeling for Sustainable Land Use Management, 1st ed. London: Elsevier, pp. 151-190.

Penn, C. J., Camberato, J. J. (2019) A critical review on soil chemical processes that control how soil pH affects phosphorus availability to plants. Agriculture, 9 (6), 120. DOI: https://doi.org/10.3390/agriculture9060120

Pereira, P., Bogunovic, I., Muñoz-Rojas, M., Brevik, E. C. (2018) Soil ecosystem services, sustainability, valuation and management. Current Opinion in Environmental Science & Health, 5, 7-13. DOI: https://doi.org/10.1016/j.coesh.2017.12.003

Pereira, P., Cerda, A., Martin, D., Úbeda, X., Depellegrin, D., Novara, A., Martínez-Murillo, J.F., Brevik, E.C., Menshov, O., Rodrigo Comino, J., Miesel, J. (2017) Short-term low-severity spring grassland fire impacts on soil extractable elements and soil ratios in Lithuania. Science of the Total Environment, 578, 469-475. DOI: https://doi.org/10.1016/j.scitotenv.2016.10.210

Pereira, P., Cerdà, A., Úbeda, X., Mataix-Solera, J., Arcenegui, V., Zavala, L. M. (2015) Modelling the impacts of wildfire on ash thickness in a short-term period. Land Degradation & Development, 26 (2), 180-192. DOI: https://doi.org/10.1002/ldr.2195

Reza, S. K., Nayak, D. C., Mukhopadhyay, S., Chattopadhyay, T., Singh, S. K. (2017) Characterizing spatial variability of soil properties in alluvial soils of India using geostatistics and geographical information system. Archives of Agronomy and Soil Science, 63 (11), 1489-1498. DOI: https://doi.org/10.1080/03650340.2017.1296134

Sağlam, M. (2015) Evaluation of the physicochemical properties of alluvial and colluvial soils formed under ustic moisture regime using multivariate geostatistical techniques. Archives of Agronomy and Soil Science, 61 (7), 943-957. DOI: https://doi.org/10.1080/03650340.2014.978764

Schillaci, C., Lombardo, L., Saia, S., Fantappie, M., Märker, M., Acutis, M. (2017) Modelling the topsoil carbon stock of agricultural lands with the Stochastic Gradient Treeboost in a semi-arid Mediterranean region. Geoderma, 286, 35-45. DOI: https://doi.org/10.1016/j.geoderma.2016.10.019

Schimmelpfennig, D., Ebel, R. (2016) Sequential Adoption and Cost Savings from Precision Agriculture. Journal of Agricultural and Resource Economics 41, 97-115.

Tamene, L., Adimassu, Z., Ellison, J., Yaekob, T., Woldearegay, K., Mekonnen, K., Thorne, P., Bao Le, Q. (2017) Mapping soil erosion hotspots and assessing the potential impacts of land management practices in the highlands of Ethiopia. Geomorphology 292, 153-163. DOI: https://doi.org/10.1016/j.geomorph.2017.04.038

Thun, R., Herrmann, R., Knickmann, E. (1955) Die Untersuchung von Boden Radebeuel und Berlin. Berlin: Neumann.

Van Soesbergen, A., Sassen, M., Kimsey, S., Hill, S. (2019) Potential impacts of agricultural development on freshwater biodiversity in the Lake Victoria basin. Aquatic Conservation, 29, 1052-1062. DOI: https://doi.org/10.1002/aqc.3079

Walkley, A., Black, I. A. (1934) An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil science, 37(1), 29-38.

Webster, R., Oliver, M.A. (2007) Geostatistics for environmental scientists. Chichester: John Wiley & Sons.

Withers, P.J.A., Haygarth, P.M. (2007) Agriculture, phosphorus and eutrophication: a European perspective. Soil Use and Management, 23, 1-4.

Wunderer, W., Fardossi, A., Baumgarten, A., Bauer, K. (2003) Richtlinien für die sachgerechte Düngung im Weinbau Anleitung zur Interpretation von Boden-und Blattuntersuchungsergebnissen im Weinbau Bundesministerium für Land-und Forstwirtschaft. Umwelt und Wasserwirtschaft, Wien. Available at: https://wwwbmlrtgvat/dam/jcr:deaac27e-f1e5-4ed4-bdaf-89d4e88fb9d6/Brosch%C3%BCre_Sachgerechte_D%C3%BCngung_im_Weinbau_02052014.pdf

Xu, Y., Dong, D., Duan, G., Yu, X., Yu, Z., Huang, W. (2013) Geostatistical analysis of soil nutrients based on GIS and geostatistics in the typical plain and hilly-ground area of Zhongxiang, Hubei Province. Open Journal of Soil Science, 3, 218-224. DOI: https://doi.org/10.4236/ojss.2013.35026

Zhang, C. (2006) Using multivariate analyses and GIS to identify pollutants and their spatial patterns in urban soils in Galway, Ireland. Environmental pollution, 142 (3), 501-511. DOI: https://doi.org/10.1016/j.envpol.2005.10.028