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EFFECT OF SOIL TILLAGE ON SOIL ORGANIC MATTER IN A CLAY FIELD

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Abstract

In this study, effect of soil tillage on spatial variability of soil organic matter content (OM) in a clay field was determined by geostatistical method. The clay field was cultivated using a mouldboard plough at a depth of 15 cm. After conventional tillage, soil samples were taken from a square grid at 5 m spacing of a 30 x 30 m^2 plot selected in the clay field. Soil OM contents of the samples varied between 2.03 % and 2.98 %. Clay content (31.48 to 43.97 %), bulk density (BD) (1.12 to 1.41 g/cm^3), total porosity (F) (46.79 to 57.73 %), volumetric water content (θ) (19.64 to 43.86%), soil pH (6.47 to 7.40) and electrical conductivity (EC) (0.31 to 0.80 dS/m) values also showed variations among the soil samples. In kriging interpolation for the spatial variability of SOM, the biggest r^2 (0.766) and the smallest RSS (0.0013) values were determined with Gaussian model. Spatial dependences of the SOM was strong in the field with 6.4 of nugget/sill ratio. The semivariogram of SOM showed spatial dependence with a range of 157.61 m. SOM had significant positive correlations with clay (0.365**), F (0.287*) and significant negative correlations with BD (-0.286*), θ (-0.362*) and silt (-0.429**) content. This study showed there is a spatial variability of SOM in arable fields, it can be predicted for precision agricultural practices and monitoring organic carbon in global warming researches by geostatistically.

Keywords: Soil organic matter, tillage, soil properties, spatial variability, kriging

INTRODUCTION

Soil organic matter (OM), which is one of the most important soil properties, affects soil physical, chemical and biological quality indicators (Gülser, 2006; Candemir and Gülser, 2010; Gülser et al., 2015; Demir and Gülser, 2021). Many studies indicated that increasing soil OM content by the addition of agricultural residues in soils improved soil structural and hydraulic properties (Gülser and Candemir, 2015, Gülser et al., 2015; 2017). The loss of soil OM depends on tillage practices as well as other environmental conditions. Gülser et al. (2020) reported that soil organic matter content in the reduced tillage system was higher than the conventional tillage system under dry climate condition due to slow mineralization rate of soil OM.

Spatially variables influencing crop yields are usually soil related, anthropogenic, topographic, biological, and meteorological factors (Tanji, 1996; Corwin, 2012). Knowledge of the spatial variation of soil properties is important for crop production in precision agricultural management systems. It has been known that most soil properties are spatially variable in a field (Burrough, 1993). Iqbal et al. (2005) reported that spatial variability of soil properties in any field position is inherent in nature due to geologic and pedologic soil forming factors, but some of the variability may be induced by tillage and other management practices. Benefits from soil tillage are known as i) improvement of soil-air-water relations in seedbeds, ii) control of undesired vegetation, and iii) reduction of the mechanical impedance to root growth (Gardner et al. 1999). Soil tillage practices causes changes to soil structure and hydraulic properties dynamically in space and time (Mueller et al., 2003; Strudley et al. 2008). Selvi et al. (2019) reported that the fall tillage treatment with mouldboard had the highest corn yield (61.1 Mg/ha) while the lowest yield value (30.9 Mg/ha) was found with the direct drilling treatment in a clay soil. They found that late tillage timing at the end of May reduced corn yield due to changing soil structure with reducing penetration resistance, increasing macroporosity and nitrate leaching in the soil profile.

The ordinary kriging is one of the most common methods in spatial interpolation of soil properties after estimating semivariogram parameters of soil properties using geostatistical tools (Goovaerts, 1998; Utset and Greco, 2001; Castrignano et al., 2003; Zhao et al., 2009). Strudley et al. (2008) reviewed tillage effects on soil hydraulic properties in space and time. They have found little work on small-scale spatial variability in soil hydraulic properties resulting from tillage practices. The aim of soil cultivation is generally to form a homogeneous media to supply optimum growth conditions for seeds and plants. Therefore, the objective of this study was to determine changes in spatial variability of soil organic matter content in a cultivated field by geostatistical method.

MATERIALS AND METHODS

This study was carried out on Vertic Haplustoll in the Experimental Field of Ondokuz Mayıs University having a 4% slope north to south (41º21´ N, 36º10´ E) direction in Samsun-Turkey. Conventional tillage in 4 ha field was used with a mouldboard plough at a depth of 15 cm. Soil properties were measured in a randomly selected small-scale plot near the center of the field 20 days after soil tillage. The measurements in 49 different soil sampling points were made in a square grid at 5 m spacing in the 30 x 30 m^2 plot. After determining the bulk density (BD) by undisturbed soil core method (Demiralay, 1993), total porosity (F) was calculated using the equation; F=1-(BD/2.65). Gravimetric (W) and volumetric water (θ) contents, soil pH (1:1) and Electrical Conductivity (EC) values were determined (Tüzüner, 1990). Particle size distribution of the surface soil samples (0-15 cm depth) was determined by hydrometer method (Demiralay, 1993). Organic matter contents of the soil samples were analyzed by Walkley-Black method (Kacar, 1994).

The geostatistical analyses were performed with the GS+ version 9, and the correlations among the soil properties were calculated using SPSS program. The semivarince ($\gamma(h)$) describing degree of spatial dependence of random variable $Z(x_i)$ over a certain distance was estimated from (Trangmar et al., 1985):

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

Where γ(h) is the semivariance for the interval distance class h, N(h) is the number of pairs, $Z(x_i)$ and $Z(x_i + h)$ are the measured sample values at position i and (i + h), respectively.

RESULTS AND DISCUSSION

According to the results of soil analyses, while soil organic matter (SOM) content values varied between 2.03 and 2.98%, bulk density (1.12 to 1.41 g cm^{-3}), clay (31.48 to 43.97%), silt (14.49 to 36.38%), sand (30.11 to 47.57%), volumetric water content (15.19 to 32.56%), pH (6.47 to 7.40) and EC (0.31 to 0.80 dS m^{-1}) values showed variations among the sampling points at the cultivated field (Table 1). Ogunkunle (1993) reported that soil properties having a coefficient of variation (CV) between 0 and 15 % are considered least variable, 15 and 35%, moderately variable, and bigger than 35% highly variable. The CV values of the soil properties indicated that the most soil properties are least variable while EC values having

22.41% of CV was more variable than the other soil properties at the field.

Skewness and kurtosis values and frequency distributions for clay, BD, SOM, θ, pH and EC indicated that the soil properties usually showed normal distribution (Table 1, Figure 1). Therefore, the original values of soil properties were not transformed. Warrick and Nielsen (1980) reported that the spatial variability of the static soil physical properties is commonly fitted to normal probability distributions; whereas the dynamic properties, related to water or solute movement, are usually lognormally distributed. Veronese-Junior et al. (2006) reported that moisture content values for Brazilian Ferralsol showed normal distribution. Utset and Greco (2001) found that BD in 30 x 30 m^2 plot of Rhodic Ferralsol is normally disturbed.

Table 1. Descriptive statistics for the soil properties.

	Minimum	Maximum	Mean	Std. Dev.	CV, %	Skewness	Kurtosis
Clay, %	31.48	43.97	38.31	2.92	7.62	0.030	-0.785
Silt, %	14.49	36.38	22.54	3.42	15.17	1.266	4.907
Sand, %	30.11	47.57	39.15	3.74	9.55	0.209	-0.463
BD, g cm^{-3}	1.12	1.41	1.27	0.067	5.28	0.016	-0.109
W, %	15.19	32.56	24.32	3.24	13.32	-0.069	0.681
Θ, %	19.64	43.86	30.87	4.70	15.22	0.223	0.625
SOM, %	2.03	2.98	2.52	0.23	9.13	-0.254	-0.419
pH(1:1)	6.47	7.40	6.84	0.184	2.69	0.446	0.851
EC, dS m^{-1}	0.31	0.80	0.531	0.119	22.41	0.151	-0.476

OM: organic matter, BD: bulk density, W: gravimetric water, Θ: volumetric water.

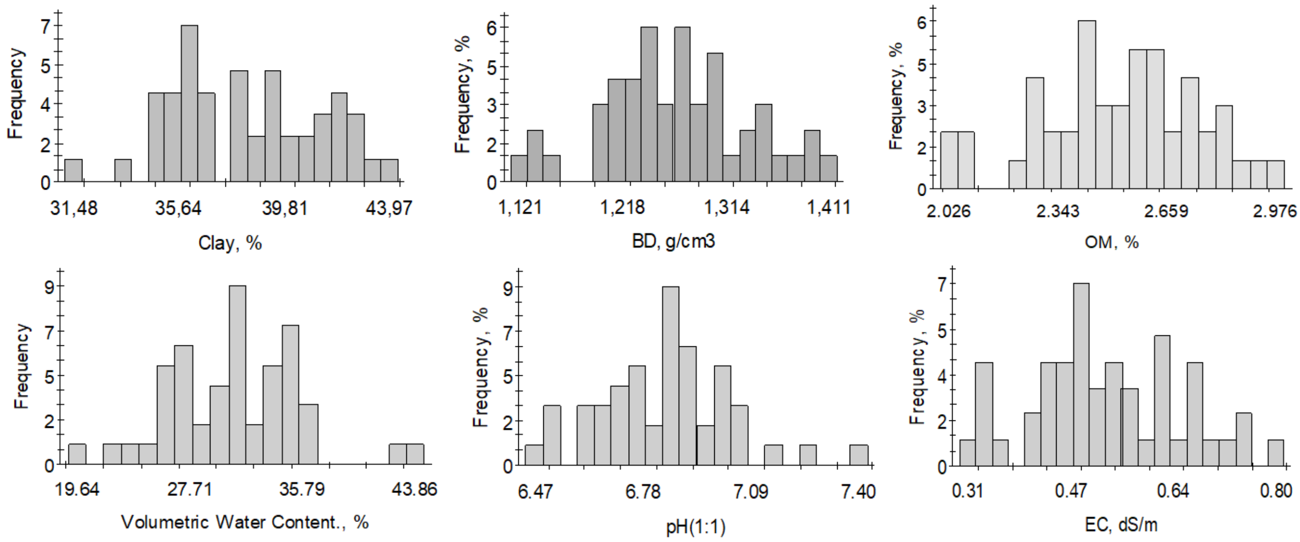

Figure 1. Frequency distribution of soil properties.

To evaluate the spatial variability of the soil properties, the exponential model for clay content and BD and the Gaussian model for SOM and θ were selected with their biggest r^2 values and the smallest residual sum of squares (RSS) values using the GS+9 package program (Table 2). The semivariograms of the soil properties indicated that the range in spatial correlation varied among soil properties. The range indicates the distance in a field where measured properties were no longer spatially correlated. Measured properties of the samples at a distance less than the range become more alike with decreasing distances between them

(Tabi and Ogunkunle, 2007). The shortest range (19.67 m) was observed for BD and the longest range (157.61 m) was observed for SOM content.

The nugget effect, which represents random variation caused mainly by the undetectable experimental error and field variation within the minimum sampling space (Cerri et al., 2004; Aşkın and Kızılkaya, 2006), was higher in θ content than in the other soil properties. Generally, the nugget values close to zero for the physical properties revealed that all variances of the soil properties were reasonably well explained at the sampling distance used in this study by the lag. A variable has strong spatial dependency if the ratio of nugget/sill is equal or less than 25%, moderate spatial dependency if the ratio is between 25 and 75%, and weak spatial dependency if the ratio is greater than 75% (Cambardella et al., 1994; Bo et al., 2003). Generally, strong spatial dependency of soil properties is related to structural intrinsic factors such as texture, parent material and mineralogy, and weak spatial dependency is related to random extrinsic factors such as plowing, fertilization and other soil management practices (Zheng et al. 2009). The ratios of nugget/sill in the soil physical properties, except BD, were less than 25% in Table 2. Therefore, spatial dependence values for SOM and the other soil properties were strong. Spatial dependence of BD was moderate due to having 44.91% nugget/sill ratio. This indicated that soil plowing as an extrinsic factor weakened spatial dependency of BD in the field. Cressie and Horton (1987) found that there was a strong spatial dependence (12 m lag distance) in infiltration rates for a silty clay loam undergoing moldboard plowing.

Table 2. Models and parameters for soil properties

	Model	Nugget, (C_0)	Sill, (C_0+C)	$C_0/(C_0+C)$	a	r^2	RSS	Cross Val. r^2
Clay	Exponential	3.750	28.490	13.16	80.19	0.723	16.20	0.541
BD	Exponential	0.00269	0.00599	44.91	19.67	0.786	7.68E-7	0.122
SOM	Gaussian	0.0320	0.4990	6.40	157.61	0.766	0.00131	0.292
θ	Gaussian	12.90	76.80	16.80	79.07	0.750	276	0.040

(SOM: soil organic matter, BD: bulk density, θ volumetric water content)

Block-kriged maps of the soil properties were created by GS+ 9 program (Gamma Design, 2010), using 0.32 x 0.32 m^2 grid system with 8836 points (Figure 2). While the SOM content values increased from the east to the west part of field, the lowest SOM content values were obtained at the northeast part of field. Similarly, clay content in soil generally increased in the east to west direction of the plot. On the contrary, high BD is found in the eastern part of the plot. It is known that the variation in bulk densities is the result of differences in soil texture, organic matter contents and management practices (Wolf and Snyder, 2003). Gülser (2006) reported that increasing macroaggregation in a clay soil due to increased organic matter content in soil and decreases in bulk density values. In another study, Gülser (2004) found that increments in soil organic matter content decreased bulk densities with increasing total porosities. Soil OM content had significant positive correlations with clay (0.365**) and total porosity (0.288*), while it gave negative correlations with BD (-0.286*), silt (-0.429**), W (-0.288*) and θ (-0.362*) contents (Table 3). Organic matter increases the soil's capacity to hold water by direct absorption of water and by enhancing the formation and stabilization of aggregates containing abundance of pores that hold water under moderate tensions (Weil and Magdoff, 2004). Volumetric water content had a significant positive correlation with BD (0.480**).

Table 3. Correlation matrix among the soil properties

	Clay	Silt	Sand	BD	F	W	θ	pH	EC
SOM	0.365**	-0.429**	0.157	-0.286*	0.288*	-0.288*	-0.362*	-0.034	0.178
Clay		-0.495**	-0.313*	-0.358*	0.362*	-0.347*	-0.431**	0.176	0.007
Silt			-0.671**	0.139	-0.127	0.211	0.232	-0.139	0.007
Sand				0.153	-0.170	0.066	0.114	0.002	-0.013
BD					-0.995**	0.159	0.480**	-0.138	0.018
F						-0.144	-0.466**	0.134	-0.015
W							0.942**	0.067	0.087
θ								0.019	0.082
pH									-0.602**

** correlation is significant at 0.01 level, *correlation is significant at 0.05 level. (SOM: soil organic matter, BD: bulk density, W: gravimetric water content, θ: volumetric water content,)

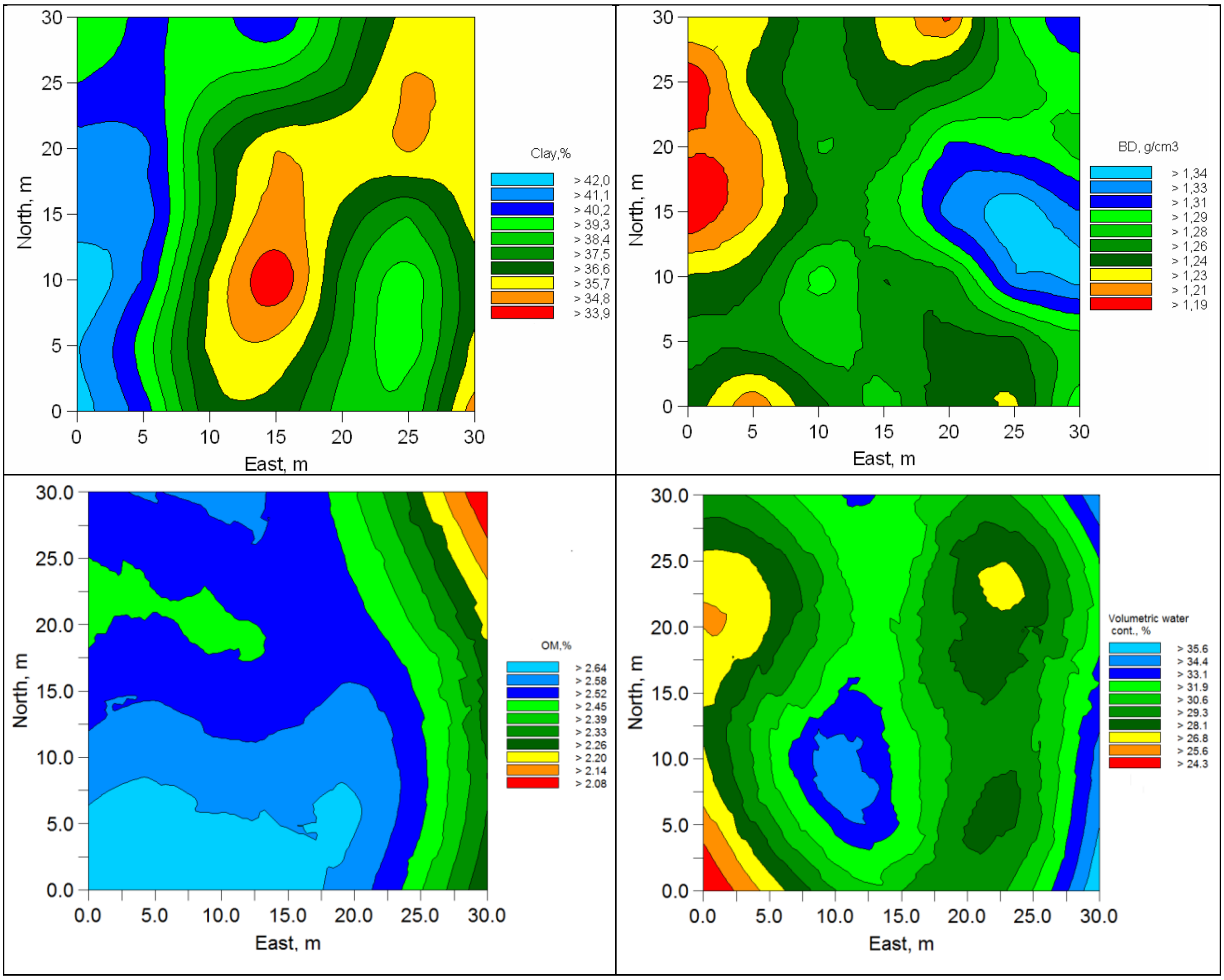

Figure 2. Block kriged maps for clay content, bulk density (BD), soil organic matter content (OM) and volumetric water content.

CONCLUSION

According to the CV values, SOM and the other soil properties, except clay content, showed less variation in the field. Generally, the range or the distance of spatial dependence for the soil physical parameters, except BD, varied between 79 m and 157 m. These are the distance between two sample-collecting points for soil properties in the field. While the BD had moderate spatial dependence, the other soil physical properties had strong spatial dependence with having lower nugget/sill ratio less than 25%. Strong spatial dependency of the soil properties may be attributed to clay content, and moderate spatial dependency of BD can be attributed to effect of soil tillage. There were strong relationships among the soil properties. Kriged maps illustrated positional similarity between the SOM content and related with other soil properties along the small scale plot of cultivated field.

As a result, SOM showed high spatial variability even if in the small-scale plot cultivated for preparing suitable seed bed and plant growth soil conditions. Therefore, in precision agricultural, heterogeneity and variation of soil properties such as, SOM, BD and water content in a field due to soil plowing should be taken into consideration for a successful site specific management. The spatial variability of SOM in cultivated fields can also be predicted for monitoring organic carbon in global warming researches.

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