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Spatial distribution of soil aggregate stability (MWD) as compared to particle size distribution (PSD) using geostatistics

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A B S T R A C T

Soil aggregate is one of the most important soil properties governing most of the physical, chemical, hydrological and biological properties of soils. Also soil particle size distribution (PSD) is one of the fundamental physical properties affecting aggregate stability. Characterizing the variation of both properties is very important in environmental research. The objective of this study was to assess effects of (PSD) on soil aggregates stability (i.e. MWD) and to compare spatial pattern these properties at agricultural field in North of Iran. From the study area 75 soil samples were sampled by a systematic sampling strategy at 0 to 30 cm depth below the surface on a regular grid spacing of 10m×10m and transported to laboratory. Soil mean weight diameter (MWD) was negatively correlated with silt (-0.424; $p < 0.01$) and positively correlated with clay (+0.454; $p < 0.01$). The semivariograms analysis showed moderate to strong spatial dependency for all soil properties. The soil properties with strong spatial correlations were clay and silt content, whereas sand and MWD were moderately correlated. The range spatial dependence for soil properties varied from 31m for MWD to 58m for silt content. The results showed that areas with higher silt and clay are always associated with the lower and higher MWD, respectively. Therefore we assume that the areas associated with the lower clay might be due to the effect of soil erosion or leaching in rainy season.

1. Introduction

Soil aggregates are formed and stabilized by means of physical, chemical and biological processes, which can vary from one location to another location within a landscape. Variation in soil aggregate stability in the field directly contributes to the variation in the hydrological properties, porosity, soil structure, soil permeability and compaction of soil layers (Baumgartl and Horn, 1991; Kjaergaard et al., 2004). Furthermore, Aggregate stability is considered to be one of the main soil properties regulating soil erodibility (Cerda, 1998). When soil aggregates break down, finer particles are produced, which are easily carried away by wind and water flow and which upon re-sedimentation tend to clog soil pores, leading to the formation of soil crusts (Kirkby and Morgan, 1980; Yan et al., 2008). While variation of some physiochemical soil process affected by aggregate stability, other such as soil texture, organic content, clay mineralogy, and the presence of chemical dispersing agents, may influence aggregate stability (Silva and Mielniczuk, 1998; Canasveras et al., 2010). For example, Soil texture especially clay content is known to have a significant relationship with aggregate formation and stabilization. This relationship could be reciprocal in the sense that soil particle size distribution is critical for aggregate formation and stabilization. Soil aggregation as influenced by higher clay content was the most important soil property influencing the soil loss by splash (Luk, 1979). Various indicators have been proposed to characterize soil aggregate stability such as the geometric mean diameter (GMD), mean weight diameter (MWD), water-stable aggregation (WSA), and aggregate stability index (ASI) (Calero et al., 2008). However, there is no universal prescription as to which of these methods should be preferred or used for specific cases.

The degree of spatial variability for each variable can be determined by geostatistical methods using semivariogram model (McBratney and Pringle, 1999). Also geostatistics is a useful tool for analyzing the structure of spatial variability, interpolating between point observations, and creating the map of interpolated values with an associated error map. Several attempts have been made to characterize the spatial dependency of soil properties and kriged maps of different soil properties are presented for scales ranging from a few meters to several kilometers (Sun et al., 2003; Lin et al., 2005; Juan et al., 2011; Tesfahunegn et al., 2011; Motaghian and Mohammadi, 2012). During the last two decades it has been widely used in various subfields of soil science such as soil reclamation, soil classification and soil pollution studies. The objectives of this paper are to: i) to analyze and describe the spatial variable pattern of aggregate stability (MWD) and particle size distribution (PSD) on the top 30cm of the soil; and, ii) to display the variability pattern of these properties through the predicted maps.

2. Materials and methods

2.1. Study design and field sampling

Research was conducted in in a near flat agricultural field (2-3% Slope) of about 1ha (90 m×90 m) located in Rasht, Guilan provenance, North of Iran. This field was covered by vegetation and this vegetation has been removed by tillage practices and the field has been remained uncultivated for nearly 3 years. The climate is temperate with a mean annual temperature of 15.5 ˚C. Mean annual precipitation is 1200 mm with bimodal maxima in October and November.

A 90m ×90m plot consisting of 10m × 10m grid cells was established in 2012 (Figure.1). Three repeat were collected randomly from 0-30 cm depth around in each of the 75 point. The particle size distribution (PSD) of soil samples i.e., sand, silt, and clay content was done with a combination of the hydrometer and the wet sieving method as described by Gee and Bauder (1986). The size distributions of particles greater than 75 µm in diameter were determined by wet sieving. Particles smaller than 75 µm were analyzed using the hydrometer test method. The soil samples for aggregate stability assessment were taken to the laboratory in such a way that minimum structural destruction occurred. Following van Bavel (1950) method, as modified by Kemper and Rosenau (1986), was used to parameterize the mean weight diameter (MWD) of wet-sieved aggregates. The MWD (mm) of water-stable aggregates was calculated using the following equation:

$$MWD = \sum_{i=1}^{n} w_i x_i \qquad (1)$$

Where xi is the mean diameter of each size-fraction i, and wi is the proportion of the total sample weight occurring in the size fraction i.

2.2.Statistical and geostatistiacal analysis

Descriptive statistics were computed with SPSS 18 (SPSS Inc., Chicago, IL, 2010). To test the hypothesis of normality, standard error of skewness for each property was conducted (Balasudram et al., 2008). Pearson correlation coefficients and T-test were calculated for all possible variable pairs to generate a correlation matrix (Bai et al., 2012). To evaluate the spatial structure of the properties, a semivariogram was used which represents the relationship between the lag or any integral multiple of the sampling interval and the semi- variance (Goovaertes, 1997). Theoretically, a variogram can be calculated as equation (2):

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

Where Z(xi) and Z(xi+h) are sample values at two point separated by the distance h, and N(h) is the number of pairs separated by lag distance, within the distance interval h. Generally, semivariogram consists of three basic parameters including the nugget effect, the sill and the range. The nugget effect is a local variance component occurring at scales finer than the shortest sampling interval. The sill represents the total variance and range determines the distance, which beyond that distance the values of the variable considered as not correlated. The theoretical models were fitted to experimental variograms. The selection of appropriate model was based on qualitative interpretation of which model best represented the overall behavior of the experimental semivariogram. The model parameters were calibrated based on a minimization of residual sum square (RSS) and highest (r2) between the fitted and computed values. We used each experimental semivariogram for constructing contour maps of the interpolated variable. In such a case, ordinary kriging was considered as the most suitable working tool (Millan et al., 2012):

$$Z^*(x_0) = \sum_{i=1}^{N} \lambda_i Z(x_i) \qquad (3)$$

Where Z* is the estimated ordinary kriged values of Z at X0 location, and λi refer to weighing factors such that:

$$\sum_{i=1}^{N} \lambda_i = 1 \qquad (4)$$

Accuracy of the kriging maps was evaluated through a cross-validation process using the using root mean square error (RMSE), The RMSE statistics are defined as (Besalatpour et al., 2013):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(P(x_i) - M(x_i) \right)^2} \qquad (5)$$

Where P(xi) denotes the predicted value of observation i, M(xi) is the measured value of observation i, and n is the total number of observations. The software packages GS+ 5.1 (Gama Design, 2001) was also used for geostatistical analysis and mapping spatial distribution.

3. Results and discussion

Table 1 shows the main descriptive statistics for each of soil properties. According to the standard error of skewness, Silt content and MWD had lower skewness and were normally distributed, clay content showed slightly deviation from normality and sand contents were abnormally therefore, sand was transformed by using natural logarithm method to a normal distribution. Based on the entire data set, coefficients of variation for soil properties ranged from 7.2% for silt content to 31.2% for MWD. In general the use of the CV is a common procedure to assess variability in soil properties since it allows comparison among properties with different units of measurement.

Among the soil properties, MWD showed a higher CV value of 31.2%. Soil texture usually shows low spatial variability. In this soil, the silt CV was low as compared to the other measured particle soil distance. It could be due to the larger amount silt content as compared to clay and silt content .According to Vanni (1998), a CV of over 35 % shows that the data set is heterogeneous and the mean is little relevant. If it is over 65 %, the data set is highly heterogeneous and the mean insignificant. However, if it is less than 35 %, the data set is homogeneous, the mean significant and it can be used as representative of the original data set.

Table 1
Summary Statistics for the original variable.

Variable	unit	Min	Max	Mean	SD	Skewness	Kurtosis	CV (%)
MWD	mm	0.6	2.3	1.3	0.47	-0.07	-0.82	31.20
Clay	%	22.0	48.0	32.0	5.29	0.58	0.47	16.91
Silt	%	51.0	70.0	59.7	4.33	0.34	-0.39	7.26
Sand	%	5.0	18.0	9.2	2.86	0.74*	0.15	31.10

*significant at the 0.05 probability level; SD: Standard deviation;
CV: Coefficient of variation.

Table 2
Liner correlation between soil properties.

Variable	Sand	Silt	Clay	MWD
Sand	1	-0.146	-0.492**	-0.148
Silt		1	-0.810**	-0.424**
Clay			1	0.454**

**significant at the 0.01 probability level.

The liner correlation coefficients between PSD and MWD were statistically significant in the case of silt and clay content. Also no-significant relationships were found between MWD and sand. Soil MWD was negatively correlated with silt (-0.424; $p < 0.01$) and positively correlated with clay (+0.454; $p < 0.01$). Similarly, Levy and Miller (1997) reported very comparable correlations between aggregate stability and clay content.

Soil variables showed differences in spatial dependence as determined by semivariance analysis (Tables 3). The spherical model was adjusted to the data of all studied variables base on minimum RSS and highest regression (Figure. 2). Semivariance increased with distance between samples (lag distance) to a constant value (sill or total variance) at a given separation distance (the range of spatial dependence) for spherical model (Isaaks and Srivastava, 1989). The parameters semivariograms of selected soil variables are shown in (Table3). To define the degree of spatial dependency, spatial class ratios similar to those presented by Cambardella et al. (1994) were adopted. That is the ratio of nugget variance (noise) to total variance (sill) multiplied by 100. If the ratio of spatial class was less than 25% then the variable is considered to be strongly spatially dependent; if the ratio was between 25% and 75%, the variable was regarded as moderately spatially dependent; and if the ratio was more than 75%, the variable was considered weakly spatially dependent. The fitted semivariograms indicated the existence of moderate to strong spatial dependency for all soil properties. Among all variables, semivariogram of silt with large and intermediate represented the strong spatial dependency, which suggested that these variables showed a considerable spatial dependence within sampling distances. However, MWD semivariogram showed high ratio of nugget variance to total variance (sill). Spatially dependent variables may be controlled by intrinsic variations in soil. therefore, in this study, soil variables for spherical models were spatially correlated at all lag distances greater than the minimum grid spacing distances, and All soil variables had a range and did not randomly distributed.

The range of influence is considered to the maximum distance up to which two sample points in the study area remain correlated. Beyond the range, the average rate of change becomes independent of the separation distance important for finding the minimum sampling distance for the evaluation of sampling design and mapping of soil properties (Utset et al., 2000; Fu et al., 2010). The range spatial dependence for soil properties varied from 31m for MWD to 58m for silt content. The different ranges of the spatial dependence among the soil properties may be attributed to differences in response to the erosion–deposition factors, land use-cover, topography, parent material and human and livestock interferences (Tesfahunegn et al., 2011). Range values of silt, and clay content were larger than that of range values of sand, and MWD. According to Ayoubi et al. (2007), a large range indicates that the measured soil parameter value is influenced by natural and anthropogenic factors over greater distances than parameters which have smaller ranges. Similar result were reported by Motaghian and Mohammadi (2012), they reported MWD variograms showed high ratio of nugget variance to total variance (sill) for the aggregate size fractions. Therefore, a definite and positive range for semivariograms showed that the most attributes were not completely random at the scale of sampling and measurement.

Table 3
Values of model parameters used to find the best semivariogram to predict soil parameter.

Variable	model	C0	C0+C	C0/(C+C0)	Class	RSS	R2	Range (m)	RMSE
MWD (mm)	spherical	0.0880	0.1660	53.0	M	2.6×10-4	0.85	31	0.442
Clay (%)	spherical	0.0013	0.0372	3.4	S	5.1×10-6	0.99	53	3.196
Silt (%)	spherical	3.3600	20.450	16.4	S	0.930	0.99	58	3.257
Sand (%)	spherical	0.0360	0.1380	26.0	M	1.2×10-4	0.97	37	2.271

C0: nugget effect; C0+C: sill; RSS: residual of some square; DSD: degree of spatial dependence (C0/C+C0);
M: moderate; S: strong; G: goodness of prediction statistics.

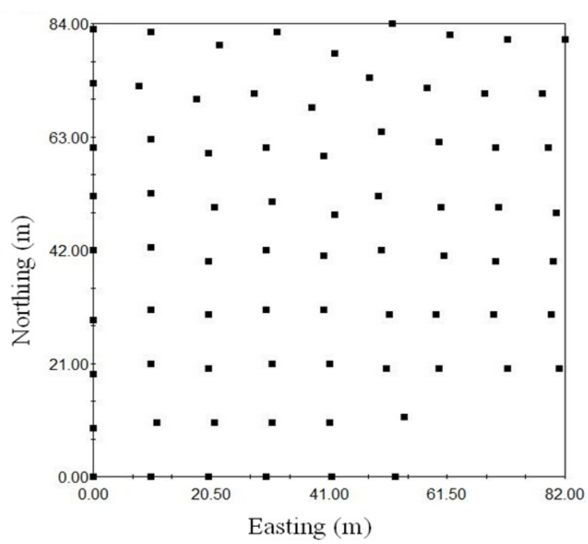

Fig.1. The distribution of representative soil sampling points in the study field.

The spatial predictions of soil properties in the study area are shown in (Figure. 3). For all soil variables, the root mean standard errors of the predictions (table 3) are less and indicating that the resulting spatial predictions obtained kriging techniques can be trusted. Measured soil properties exhibited differences in their spatial patterns in each soil properties. Furthermore, the spatial pattern MWD (Fig. 3(a)) is approximately consistent with the spatial Pattern of silt (fig. 3(c)) and clay (Fig. 3(b)) content in the field. However, spatial patterns for sand content also differed with spatial pattern MWD and sand content was distributed patchy in this study. Figures 3(b) suggest that the entire study area is characterized by a low to moderate level of clay content from east to west with only few small areas which are rich in clay. Although the spatial variability of sand content was appears in patchier. Moreover, the areas with higher silt are always associated with the lower MWD. Clay and silt content are found to be highly correlated (with a negative correlation coefficient, r = -0.81). We assume that the areas associated with the lower clay might be due to the effect of soil erosion or leaching in rainy season (which removed the easily detachable soil clay leaving behind the course grains on the surface). Kriging interpolation predicted higher values of MWD at the field (western part) which is due to the influence of higher clay and lower sand content. The estimated soil MWD had the highest values in the western. The lowest values of the soil MWD were from the eastern. The highest values of the measured soil clay content occurred mainly in the western and rarely as a point place in any other area. MWD had high values in the western side of fields, indicating that significant rates of soil clay content in this portion, whereas it had low values in the east side (fig. 3(a)). MWD values were more variable in east–west direction compared to that in north–south direction.

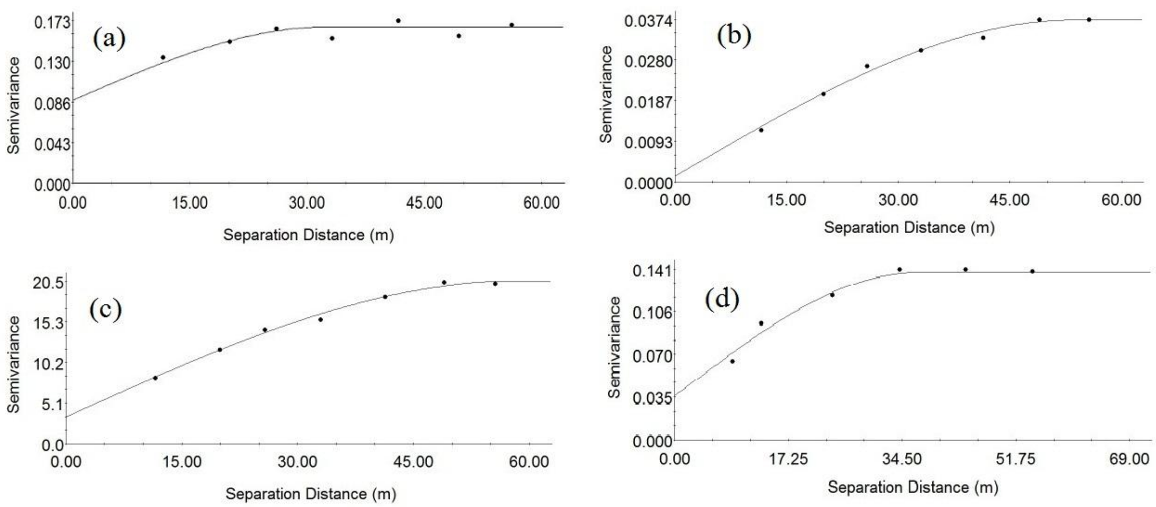

Fig.2. Experimental semivariograms of (a) MWD, (b) Clay, (c) Silt, (d) Silt.

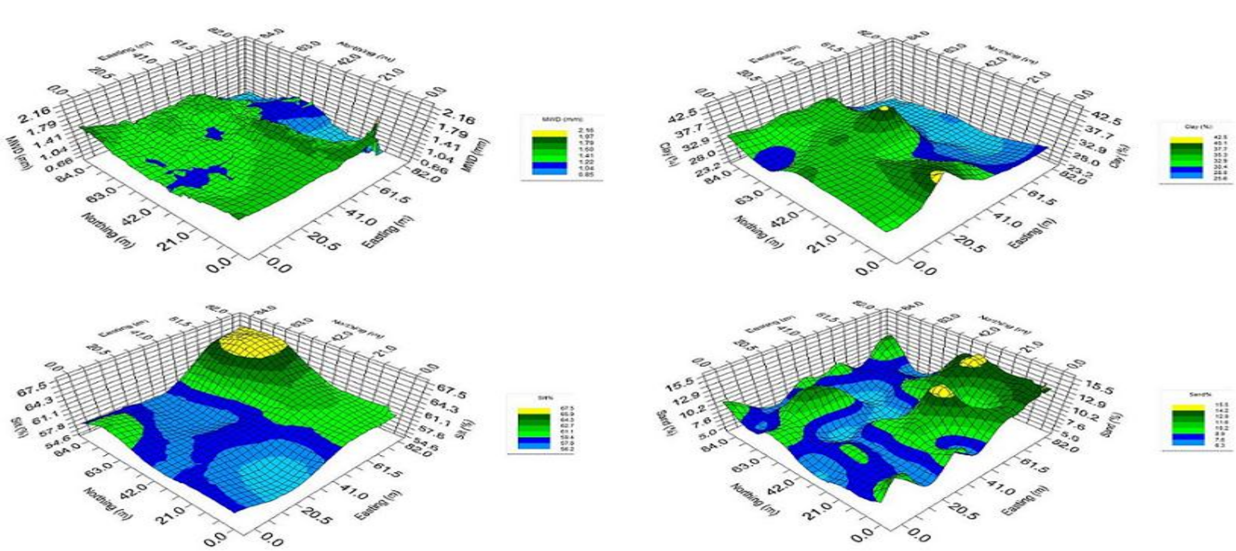

Fig.3. Spatial Patterns of (a) MWD (mm), (b) Clay (%), (c) Silt (%), (d) Sand (%).

4. Conclusions

This study has elucidated the spatial patterns and variations in soil aggregate stability related to particle size distribution. The clay and silt content has been found to be one of the main factors controlling the mean weight diameter in these soils, however no significant relationships were found between the sand content and the mean weight diameter. Range values of the above mentioned soil properties were generally greater than 31 m. Consequently, soil sampling distance of these properties for practical sampling purposes could be taken separated, as 31 m. The results of this study thus generalized that soil properties with a strong to moderate spatial structure can predict relatively accurate soil properties maps. Spatial patterns for sand content differed with spatial pattern MWD and sand content was distributed patchy in this study. Whereas the spatial pattern MWD is approximately consistent with the spatial Pattern of silt and clay content in the field. The results of the geostatistical analyses can be applied in making decisions regarding environmental monitoring, remediation, land management and planning.

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