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Testing the Performance of Different Models to Analyze Spatial Variability of Soil Physical Properties

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ABSTRACT

Spatial variability and its importance were kept in view and this research was designed to compare the accuracy of different experimental variograms models (exponential, spherical, Gaussian and linear models) based on cross-validation procedure (MSE, ASE, RMSE, RMSSE) for interpolating soil physical properties (bulk density and particle density) at research farm of SKUAST-K, Shalimar, Srinagar. The model with the smallest residual sum of squares (RSS) was further interrogated to find the number of neighbors that returned the best cross-validation result. Soil sampling was done on a grid system using Global Positioning System (GPS). On this research field, soil bulk density was best fitted to spherical model with a range of 112.53 m. There was no preferential model for soil particle density and all the models tested have same precision. Both bulk density and particle density were moderately spatially dependent. It was concluded from the present study that the moderate spatial dependency along with small range of soil physical properties would be the result of soil disturbances caused by recent cut and fill for lazer levelling.

Keywords: ***Spatial variability* ⁎ *Geostatistics* ⁎ *Soil physical properties* ⁎ *GIS***

I. INTRODUCTION

Spatial variability of soil physical properties within or among agricultural fields is inherent in nature due to geologic and pedologic soil forming factors, but tillage and other management practices may induce some of the variability. Consequently, the physical properties of the soil are also affected by many factors that change laterally across fields, vertically with depth, and temporally in response to climate and human activity [1]. Since this variability affects plant growth, nutrient dynamics, and other soil processes, knowledge of the spatial variability of soil physical properties is therefore necessary.

Many studies have focused on studying variability at large and medium scales [2]. For instance, studies on soil texture by Warrick and Gardner (1983) [3] and Tanji (1996) [4] found that soil texture variability has a significant influence on the moisture, availability of nutrient and yield potential of any soil of any site. Similarly, Zhang et al

(2010) [5] assessed variability of surface soil moisture in Karst regions using a 20m interval grid sampling technique and found that variability was explained by the exponential and Gaussian models with a weak to moderate spatial dependence and a mosaic pattern exhibited in the kriged maps. Soil moisture is also known to exhibit moderate variability spatially at a field scale [6, 7]. These studies are in tandem with the farming systems in the developed world.

Although the level of spatial soil variability is scale dependent, assessing spatial soil variability is vital before conducting site specific crop and soil management practices [8]. Typically, spatial variability of soil depends on the specific soil studied but, such information for soil of Kashmir Himalayas is lacking and hence, need to be assessed. So, the objective of this study was therefore to assess the spatial variability of soil physical properties in a research farm of SKUAST-K, Shalimar cropped to cereals, vegetables and horticultural crops.

II MATERIALS AND METHODS

Study Area

The present investigation was carried out in a research farm of SKUAST-K, Shalimar (34º 8'42" and 34º 9'3" N latitudes and 74º 39' 5" and 74º 53'5.6"E longitude), Srinagar (Fig. 1). It has 1615 m average altitude above sea surface and covers an area of 23.8 ha. The climate is temperate and characterized by mild summers and chilling winters having normal annual maximum temperature of 19.5°C and minimum of 6.8°C with normal annual rainfall of 786.2 mm.

Soil Sampling

Soil samples were collected from research farm of SKUAST-K, Shalimar in the spring, 2013. A total of seventy seven (Table 1; Fig. 1) samples were selected in a systematic grid design using Arc.GIS (10.2). Each grid was specified at a fixed distance of 50 × 50 m^2 grid from 0-22.5 cm depth. The cylinders of 12.5cm height were used for soil samples collection and the collected samples were taken to the laboratory where they were weighed (fresh weight of sample; FWS) then oven dried at 105^{o}C for 72 hrs. The weight was taken after oven drying (dry weight of soil; DWS). The samples were analyzed for bulk density and particle density. Particle density was determined by pycnometer method [9]. Bulk density of soil was determined by core sampler method as described by Black (1965) [10].

III STATISTICAL ANALYSIS

Descriptive statistics of collected data

The data were first tested for frequency distribution and then their normality was analyzed. Using SPSS (2011) [11], data were analyzed for the statistical parameters, viz. mean, median, standard deviation, coefficient of variation, skewness and kurtosis. The coefficient of variation (CV) was mainly used to assess the variability of the different data sets.

Geostatistical analysis

The Krigging interpolation and semivariogram analysis were performed using Arc.GIS (10.2). The semivariogram analyses were conducted before the application of ordinary Krigging interpolation on the soil physical properties. A semivariogram is defined by the following equation [12] as**:**

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

where γ(h) is the experimental semivariogram value at a distance interval h, m(h) is number of sample value pairs within the distance interval h, Z(Xi), Z(Xi + h) are sample values at two points separated by the distance h. Several standard models were compared to determine the best fit experimental semivariogram, e.g., spherical, exponential, Gaussian and stable. These models are defined in the following equations respectively [13]:

$\gamma(h) = Co + C_1 [1 - \exp(-h^2/a^2)]$

$\gamma(h) = Co + C_1 [1 - \exp(-h/a)]$

$\gamma(h) = C_o + C_1 [l.5 (h / a)^3]$ for $h \leq a$

where C_0 is the nugget variance (h = 0), C is the structural variance and a is the spatial range. Nugget variance represents the experimental error and field variation within the minimum sampling spacing. The nugget/sill ratio can be regarded as a criterion to classify the spatial dependence of soil properties. If the ratio is less than 25%, the variable has strong spatial dependence; between 25 and 75%, the variable has moderate spatial dependence; and greater than 75%, the variable shows only weak spatial dependence [14].

Criteria for comparison of different interpolation models

To compare different interpolation techniques, we examined the difference between the known data and the predicted data using the mean square error (MSE), average standard error (ASE), the root-mean-square error (RMSE) and the standardized root mean square error (RMSSE).

Thus, if for every one of the locations where we have a measured value, $Z(x_i)$, we estimate a value $Z'(x_i)$ then standard value of them were $Z_1(xi)$ and $Z_2(x_i)$, then the expression of their error's are**:**

$$MSE = \frac{1}{N} \sum_{i=1}^{N} [Z1(xi) - Z2(xi)]$$

$$ASE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left[Z'(xi) - \left[\sum_{i=1}^{N} Z'(xi)\right] / N\right]^2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [Z(xi) - Z'(xi)]^2}$$

$$\mathrm{RMSSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Z1(xi) - Z2(xi)]^2}$$

If MSE (Mean standard error) approaches 0, ASE (Average standard error) approaches RMSE (Root-mean-square error), RMSSE (Root-mean-square standardized error) approaches 1, it verifies the goodness of the fitted semivariogram models [15, 16].

As the semivariogram models of the soil data were evaluated, they were used in the development of maps by ordinary kriging interpolation [13].

IV STATISTICAL ANALYSIS

Descriptive statistics for soil Physical parameters

Table 2 presents the summary statistics of the datasets for soil physical properties in the study area. The coefficient of variation values (CV) indicates low variability for particle density and bulk density, based on classification proposed by Gomes and Garcia (2002) [17]**:** low (CV<10%), medium (CV=10–20%); high (CV = 20-30%) and very high (CV>30%) variabilities. Nevertheless, CV is the most discriminating factor for describing variability of a soil property than the other parameters such as SD, mean, median, etc. [18], since it allows comparison among properties with different units of measurement.

Probability distributions of the soil properties were evaluated using skewness and kurtosis. Minimum and maximum values of kurtosis are particle density and bulk density, respectively (Table 2). In spite of skewness and kurtosis of the distribution of some soil properties, the mean and median values were similar with means being equal to or almost equal to the median (Table 2).

The normal distribution of data was examined by Quantile-Quantile (QQ) plot. The quantile-quantile plot (QQ plot) is a simple graphical method for comparing two sets of sample quantiles. The normal Q–Q plots for the raw data were produced (Fig. 2). All the soil physical parameters followed a straight diagonal line except for few samples that deviated from the majority slightly at both ends, indicating normal distribution. The reason for normally or non-normal distribution may be due to differences in management practices, land use, vegetation cover, and topographic effects [19].

A wide range of variability was found for soil physical properties (Table 2). For the mean data values it can be noted that soil bulk density ranged from 0.97 to 1.71 gcm^{-3} and particle density from 2.05 to 2.98 gcm^{-3}. The bulk density was found higher in the sites where the upper layer was removed and subsurface layer was exposed which are highly compacted due to the intensive use of heavy implements [31].

V. SPATIAL VARIABILITY OF SOIL PROPERTIES

After computing summaries of simple statistics with SPSS, data on soil physical properties was transferred to Arc.GIS (10.2) for semivariogram analysis. Semivariogram model fit was determined by cross-validation procedure. If MSE (Mean standard error) approaches 0, ASE (Average standard error) approaches RMSE (Root-mean-square error), RMSSE (Root-mean-square standardized error) approaches 1, it verifies the goodness of the fitted semivariogram models [20, 21].

Table 3 shows that among soil physical properties, best fit model for bulk density is spherical and the poor one was Gaussian model. There was no preferential model for soil particle density and all the models tested have same precision.

When the distribution of soil properties is strongly or moderately spatially correlated, the average extent of these patches is given by the range of the semivariogram. For bulk density range value was 112.53 m (Table 3). There were big differences between ranges of the soil bulk densities as 900 to 1200 m by Santra et al. (2008) [31], 21 m by Rabbi (2014) [40] and 23 m by Yogita et al. (2012) [37]. Range value for soil particle density was 73.33m. The spatial variability is also an indication of the variable precision and hence its applicability. Based on the ratio of nugget and sill, the spatial dependency of the data was assessed. Cambardella et al. (1994) [15] defined this ratio of < 25, 25 to 75, and > 75 as categories of strong, moderate, and weak spatial dependence, respectively. According to this classification, sand, clay, bulk density and particle density showed moderate and weak degree of spatial dependence are exhibited by silt and soil porosity (Table 3). The strong spatial dependence may be controlled by intrinsic variations in soil characteristics such as texture and mineralogy whereas extrinsic variations such as fertilizer application, tillage, soil and other management practices may control the variability of the moderately spatial dependent [19].

VI. SPATIAL DEPENDENCE OF PHYSICAL VARIABILITY

From the spatial distribution of soil bulk density as presented in fig. 3, it is clear that there is increased abundance of higher bulk density values (1.35-1.51 g/cm^3) in the central part of south west direction and lowest value of bulk density (0.97-1.27 g/cm^3) was found in northeastern, northwestern and in small area of southern direction of research farm. The clusters of high and low particle density in topsoil were located over the study area. Lower particle density (2.05 to 2.44 gcm^{-3}) were observed in south and south west part of the study area and, higher values of particle density (2.59 to 2.98 gcm^{-3}) appeared in northwestern and north eastern part of the study area. Distribution of soil porosity shows that there is certainly higher soil porosity (52.38 to 58.36%) at north eastern direction and comparatively homogenous pattern were obtained in the southwestern and northwestern part of area (Fig. 3).

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VII. TABLES AND FIGURES

Table 1 Description of georeferenced sampling sites of research farm of SKUAST-K, Shalimar

Map ID	Latitude	Longitude	Map ID	Latitude	Longitude
2	34.1457	74.8796	50	34.1480	74.8828
3	34.1458	74.8801	51	34.1480	74.8834
5	34.1457	74.8812	54	34.1484	74.8796
6	34.1462	74.8790	55	34.1484	74.8801
7	34.1461	74.8797	56	34.1484	74.8807
9	34.1461	74.8807	57	34.1485	74.8812
10	34.1462	74.8812	58	34.1484	74.8818
21	34.1470	74.8791	59	34.1484	74.8823
22	34.1471	74.8796	60	34.1484	74.8829
23	34.1471	74.8800	61	34.1484	74.8834
24	34.1470	74.8806	65	34.1489	74.8801
25	34.1471	74.8812	66	34.1489	74.8806
26	34.1471	74.8817	67	34.1489	74.8813
27	34.1471	74.8823	68	34.1490	74.8817
28	34.1471	74.8828	69	34.1489	74.8823
30	34.1475	74.8780	70	34.1488	74.8824
31	34.1475	74.8785	71	34.1488	74.8834
32	34.1478	74.8793	72	34.1489	74.8839
33	34.1474	74.8799	75	34.1493	74.8801
34	34.1475	74.8802	76	34.1494	74.8807
35	34.1475	74.8808	77	34.1493	74.8812
36	34.1473	74.8812	78	34.1493	74.8818
37	34.1475	74.8819	79	34.1493	74.8823
38	34.1475	74.8823	80	34.1493	74.8828
39	34.1475	74.8828	81	34.1493	74.8834
42	34.1479	74.8785	82	34.1493	74.8839
43	34.1479	74.8791	84	34.1498	74.8812
44	34.1480	74.8796	85	34.1498	74.8818
45	34.1479	74.8801	86	34.1498	74.8823
46	34.1479	74.8807	87	34.1498	74.8828
47	34.1479	74.8811	88	34.1498	74.8834
48	34.1480	74.8818	89	34.1498	74.8839
49	34.1479	74.8823	91	34.1502	74.8817

Table 2 Descriptive statistics for soil physical properties in a research farm of SKUAST-K farm

Soil Parameter	Mean	Median	Mode	Min	Max	Range	SD	CV	Skewness	Kurtosis
Bulk Density	1.29	1.28	1.29	0.97	1.71	0.74	0.12	9.14	0.53	2.13
Particle Density	2.54	2.56	2.56	2.05	2.98	0.93	0.19	7.33	-0.31	0.25

Table 3 Values of model parameters used to find the best semivariogram

Soil Parameter	Model	Nugget	Partial sill	Sill	Range	DSD (%)	SD	Estimated error			
		C_0	C_1	C_O+C_1				MSE	ASE	RMSE	RMSSE
Bulk density	Stable	0.01	0.006	0.016	94.94	62.50	Moderate	-0.01	0.13	0.12	0.98
	Gaussian	0.01	0.006	0.016	94.94	62.50	Moderate	-0.01	0.14	0.12	0.99
	Exponential	0.004	0.01	0.014	94.94	28.57	Moderate	-0.01	0.13	0.12	0.97
	Spherical	0.009	0.007	0.016	112.53	56.25	Moderate	0.002	0.12	0.12	0.96
Particle density	Stable	0.022	0.008	0.03	100	73.33	Moderate	-0.05	0.18	0.17	0.97
	Gaussian	0.026	0.003	0.029	100	89.66	Weak	-0.05	0.18	0.17	0.97
	Exponential	0.022	0.008	0.03	100	73.33	Moderate	-0.05	0.18	0.17	0.97
	Spherical	0.025	0.005	0.03	100	83.33	Weak	-0.05	0.18	0.17	0.97

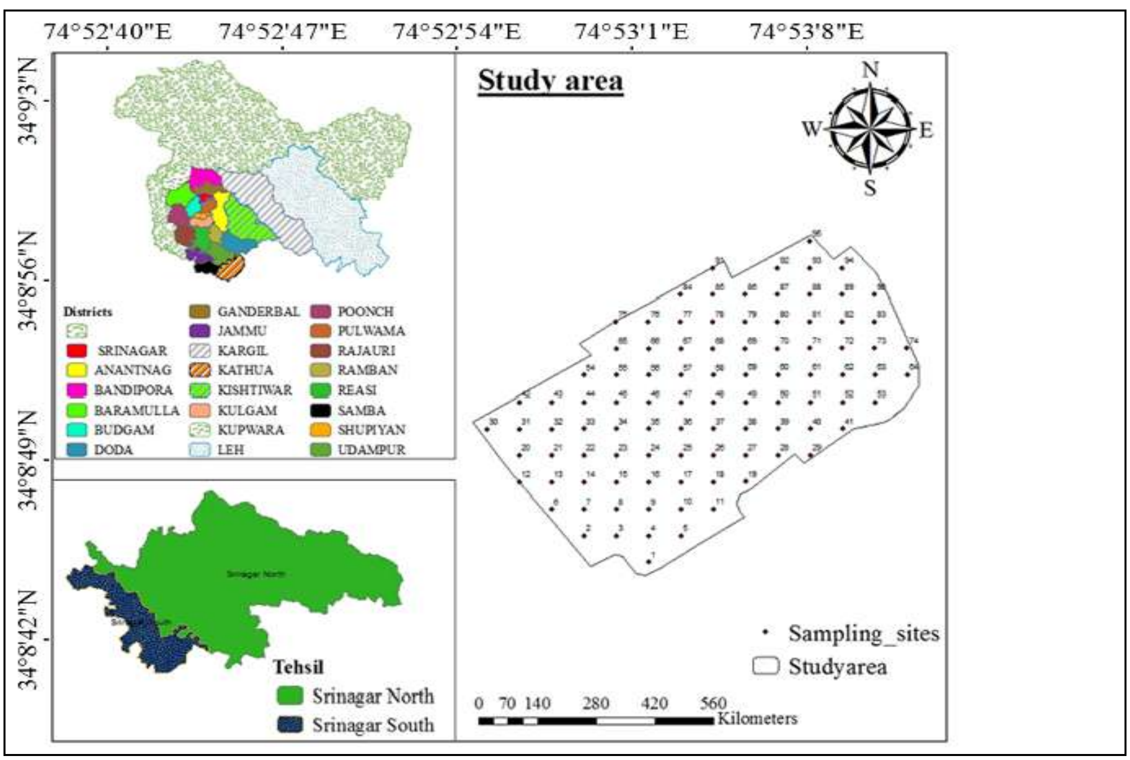

Fig. 1 Georeferenced sampling sites of research farm of SKUAST-K, Shalimar

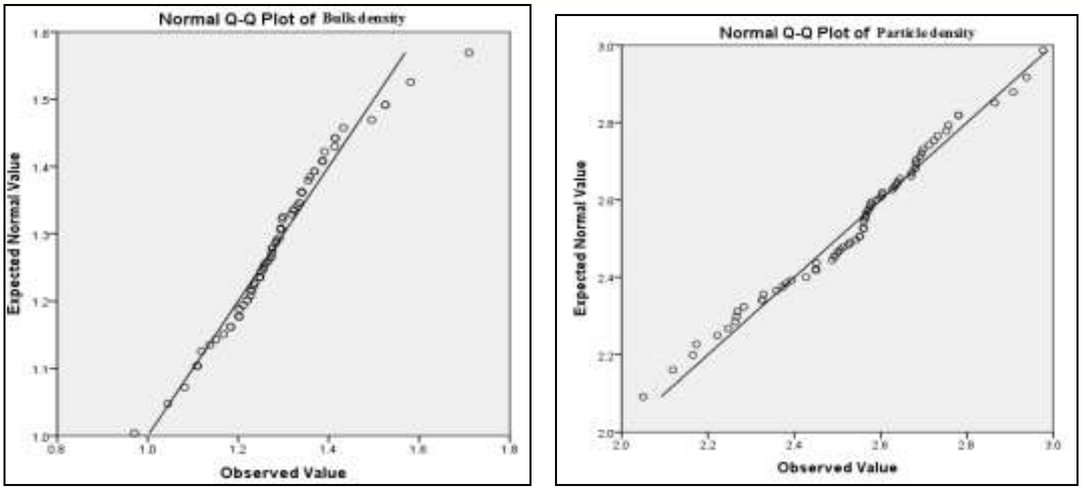

Fig. 2 Normal Q–Q plot for selected soil physical properties.

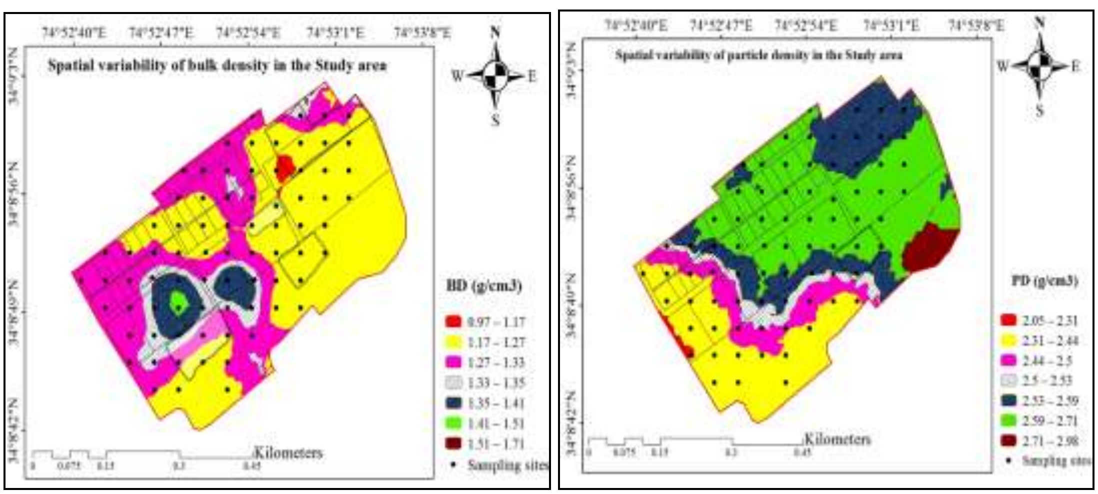

Fig. 3 Spatial distribution map of bulk densityand particle density interpolated by ordinary krigging

IX. CONCLUSION

Soil physical properties were analyzed for their spatial variability in a research farm of SKUAST-K, Shalimar. Results showed that disturbances in the soil by cut and fill resulted in variability of soil physical properties, which either decreased or increased sharply in different sites. In addition, depending on soil physical property, maps produced by kriging showed either good or poor spatial distribution. The semivariogram analysis showed the presence of a moderate spatial dependence of soil physical properties. Our understanding of the behavior of soil properties in this study provides new insights for soil site-specific management in addressing issues like identification of sites which needs immediate attention.

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