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# Assessing the Spatial Variability of Soil Physical Properties of the Lesser Himalayas in India

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**ABSTRACT**

Understanding the spatial variability of soil properties is crucial for assessing the impact of measures taken to address land surface processes such as soil erosion and water pollution. It is also vital for recommending effective land management strategies. The present study was conducted to assess the spatial variations in soil textural fractions (sand, silt, and clay), bulk density and porosity. Soil samples were collected from 115 randomly selected locations using the Global Positioning System (GPS). The samples were taken at an average depth of 0-20 cm. A thorough examination was carried out in the laboratory to assess the physical properties of the soil. Afterwards, there was an analysis conducted to characterise the physical properties of soil and understand how they vary across different locations. The measured soil properties showed low to very high variability (6.26- 37.2%) for the Coefficient of variation (CV). The spatial dependence of soil properties was observed through the weak to strong nugget-to-sill ratios. Mapping the spatial variability of soil parameters involved using the Ordinary Kriging (OK) approach of Geostatistical analysis. This method helped identify the best-fit models for different soil parameters, such as Spherical for Silt, bulk density and porosity. Exponential for clay; and Gaussian for sand these spatial interpolation maps can be a valuable tool for pinpointing areas of land degradation in the study region and recommending specific land management strategies.

***Key words :*** *Geostatistics, Ordinary Kriging, Global Positioning system*

## Introduction

Hydrology, geology, geomorphology, climate, and biosphere interact to generate soils. Understanding soil patterns and their spatial distribution was important for environmental change reconstruction and earth system research. Land resource information relies on soil maps and reports. Wang *et al*. (2013), Mondal *et al*. (2017), and Xu *et al.* (2018) have extensively researched soil property spatial distribu-

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tion. Climate, organic matter, relief, and formation affect soil depth and length. According to Bockheim (2014), human activities can disturb soil up to 25 cm deep, depending on texture. Soils vary in space and time due to natural and human influences (Cruz *et al*., 2011). Accurate collection and data interpretation require knowing and mapping soil property differences. This lets us examine the geographical correlations of various traits and parameters and approximate values where measurements have not been made. Kriging, a geostatistical method that uses the semivariogram model to minimize interpolation errors, provides the most accurate and unbiased estimation for unmeasured locations, according to Elleithy *et al*. (2015). Different methods for mapping qualitative variable spatial distribution involve technical expertise and specialized knowledge (Fabiy *et al*., 2013; Wang *et al.,* 2017). Kriging has become a popular method for forecasting continuous soil characteristics at unsampled areas. Studying soils with GIS and geostatistical methods is promising. GIS technology has improved soil property distribution and inconsistency studies, minimizing evaluation and implementation errors (Ramzan and Wani, 2018). Geostatistics uses mathematical and statistical functions to interpolate data based on statistical properties. Based on autocorrelation and spatial structure of sampled points, the geostatistical approach can estimate un-sampled points. This permits soil property maps to show spatial diversity. Geostatistical methods map well with little samples Reza *et al.* (2017). Several researchers have evaluated geostatistical methods to find the best way to assess soil property spatial variability (Bhunia *et al*., 2018; Sahabiev *et al*., 2018). These studies found kriging to be the most accurate geostatistical method.

Numerous studies have been done on spatial variation of soil physical qualities, generally within a single land use class and a few with multiple land use classes at numerous locations globally, but few in the lesser Himalayas. This study maps soil physical characteristics and examines spatial variability.

## Materials and Methods

The research was conducted in the Baramulla district of Jammu and Kashmir, from 2021 through 2023. The objective was to analyze the spatial distribution of certain soil properties, including bulk density (ρb), porosity (η), and the contents of Sand, Silt, and Clay. Soil samples were gathered using randomized grid sampling from the top layer of soil (0-20 cm depth) in 115 different locations of the study area. The soil samples were accurately located in the field using GPS. Soil samples were collected using a hand auger and prepared for analysis by air-drying, crushing, and passing them through a 2 mm sieve. The sampling units were chosen randomly and independently, without any consideration for previous selections. The analysis of Bulk density and porosity and clay followed the methods outlined by Blake and Hartge (1986) and Bouyoucos (1962).

## Results and Discussion

Understanding the connection between the standard deviation and the arithmetic mean allows us to calculate the coefficient of variation (CV), which measures the extent of variability in the variables. As Kalil (1977) points out, one of the key advantages of using the coefficient of variation (CV) as a measure of dispersion is its ability to compare different results that involve the same response variable. This was also highlighted by Cortés-D *et al.* (2016) and can be seen in Table 1, where it allows for quantifying an initial behaviour.

Table 1 shows the basic statistical values of the research area soil physical property data. The average textural component values show that silt (43.08%) and clay (30.21%) dominate the soil, followed by sand (26.66%). Variable heterogeneity was assessed using the coefficient of variation (CV). As per Zhang *et al.* (2007), a Coefficient of Variation (CV) below 10% indicates a low level of variability, while a CV exceeding 30% indicates a high degree of variability. Table 1 shows that silt had the most spatial variability (CV = 37.2%) compared to sand (35.45%) and clay (27.6%). With CVs greater than 20%, sand, silt, and clay textural fractions are highly variable. Different soil textures and micro-topographical changes may alter pedogenic processes in the research area (Vasu *et al.,* 2016). Saleh (2018) and Delbari *et al*. (2019) also found high soil textural fraction variation bulk density and porosity exhibit low variability, having CV values of 6.26% and 6.9%, respectively. The observed CV value for ñ in this study aligns with earlier research conducted by Usowicz and Lipiec (2021) and Javed *et al.* (2021). Increased CV values for soil properties follow the order of bulk density, porosity Clay, Sand, and Silt.

To determine the geographic dependency of soil parameters, an experimental semivariogram was

**Table 1.** Descriptive statistical analysis of soil physical parameters of the study area

| Soil Properties | Units | Mean | Skewness | Kurtosis | CV% |
|---|---|---|---|---|---|
| Bulk Density | g $cm^{-3}$ | 1.26 | 0.49 | -0.56 | 6.26 |
| Porosity | % | 51.74 | 0.35 | -0.240 | 6.9 |
| Sand | % | 26.66 | -0.18 | -0.82 | 35.45 |
| Silt | % | 43.08 | 0.73 | -0.09 | 37.2 |
| Clay | % | 30.21 | -1.08 | 0.70 | 27.6 |

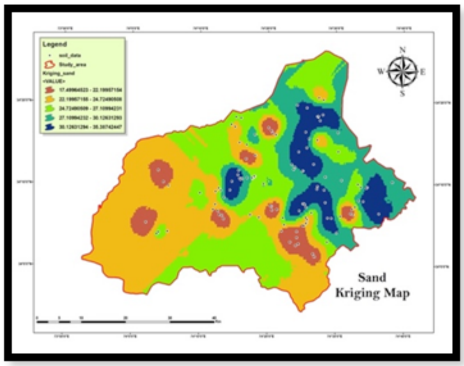
calculated. The semivariogram parameters for soil qualities in the research region are listed in Table 2. The optimal geostatistical model was chosen based on the lowest MSE, ASE, RMSE, and RMSSE values for certain parameters. The spherical model best fits the semivariogram of silt, bulk density, and porosity. while the Exponential model fits clay. The Gaussian model is best for sand fractions. The range is the stretch of spatial dependency and can be used to estimate sampling methods and map soil attributes (Zhang *et al*., 2010). Table 2 shows the range of soil qualities from 1426.1 m (Sand) to 9955.2 m (Clay). Soil characteristics vary widely due to variability due to pedogenic processes, erosion rates under different land cover conditions, eluvial translocation, and runoff detachment (Jaiyeoba, 2003). Compaction from heavy machinery for site preparation and land levelling, ongoing farming operations like ploughing and disking, etc. may also affect soil qualities. From the preceding findings, environmental influences may affect soil physical property spatial variation. The nugget-to-sill ratio $C_0/(C_0 + C)$ (DSD) was used to allocate spatial dependency (Cambardella *et al*., 1994). In this investigation, porosity was strongly spatially dependent, while sand, silt, and clay textural fractions were moderately dependent (Table 2) (Figure 1). Bogunovic *et al.* (2017) and Rasool *et al.* (2020) found comparable findings. The spatial and temporal interaction of topographical, soil-forming, and land-use factors causes intrinsic variation in soil traits including texture and parent material, which govern soil physical attributes. Our findings showed weak to strong spatial dependence of soil physical parameters, especially topsoil, which contradicts (Wang *et al*., 2021).

## Conclusion

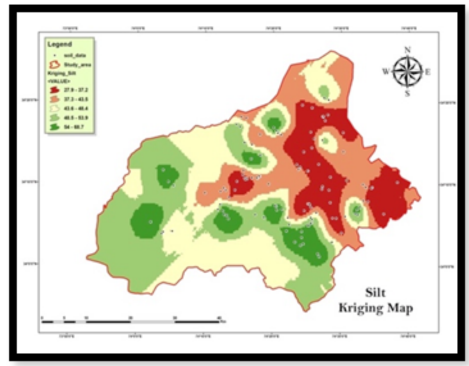
Having an in-depth knowledge of the spatial distribution and mapping accuracy of soil properties for large-scale areas is crucial for precision farming, environmental monitoring, and modelling.For this study, we aimed to analyze the soil physical properties of the lesser Himalayas using a combination of classical and geostatistical techniques. Our goal was to understand the spatial pattern of these properties. Based on the analysis of soil properties, it was observed that there was a considerable variation in soil physical properties across the study area. The CV values indicate moderate to strong variability in all measured soil properties, except for bulk density, which exhibited a weak variability. The semivariogram revealed a noticeable spatial dependence of soil properties. Overall, the porosity exhibited a significant spatial pattern, while the other assessed soil properties showed a moderate to strong spatial pattern. By utilizing data on soil physical properties, one can gain valuable insights into determining sampling distance and taking independent samples. This can greatly enhance the accuracy of the analysis. Conducting such an investigation will not only be cost-effective and time-saving, but it will

**Table 2.** Computed semivariogram soil parameter characteristics

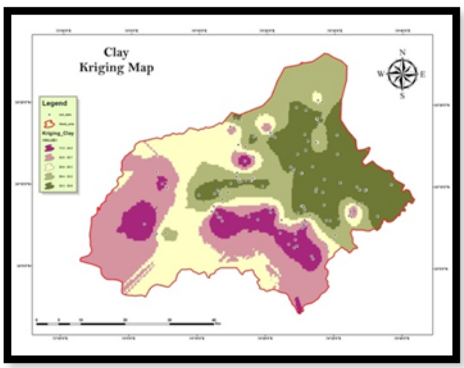
| Variable | Model | Nugget (C0) | Partial sill (C1) | Sill (C0+ C1) | Range (m) | DSD (%) (Nugget/ sill) | SD | MSE | ASE | RMSE | RMSSE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bulk Density (g $cm^{-3}$) | Spherical | 0.004 | 0.001 | 0.005 | 1426.1 | 80.0 | Weak | 0.0087 | 0.075 | 0.075 | 1.0 |
| Porosity (%) | Spherical | 12.18 | 0 | 12.18 | 3929.3 | 1 | Strong | 0.0084 | 3.505 | 3.5 | 1.002 |
| Sand (%) | Gaussian | 53.23 | 34.47 | 87.7 | 7070.2 | 60.6 | Moderate | 0.0064 | 8.58 | 8.54 | 0.99 |
| Silt (%) | Spherical | 98.68 | 145.49 | 244.17 | 7070.2 | 40.41 | Moderate | -0.004 | 13.166 | 1.06 | 1.06 |
| Clay (%) | Exponential | 31.16 | 37.23 | 68.39 | 9955.2 | 45.56 | Moderate | 0.0036 | 7.22 | 7.72 | 1.06 |



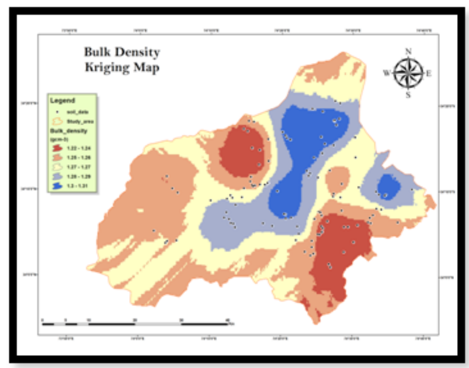

a. Sand



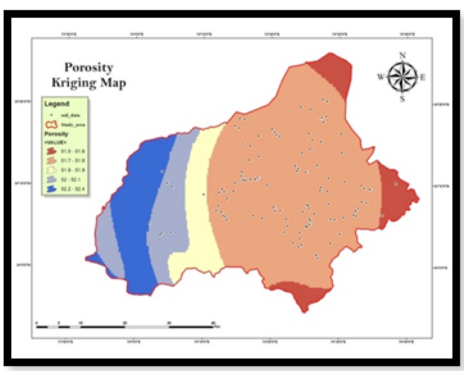

b. Silt




c. Clay




d. Bulk Density




e. Porosity

**Fig. 1.** Ordinary kriging maps of a) Sand b) Silt c) Clay d) bulk density e) porosity

also provide highly accurate and adaptable statistical results. Additionally, the kriged maps produced in this study have the potential to serve as valuable reference maps for the researchers, thereby making it possible to recommend soil management strategies and conservation measures to reduce the potential for erosion and land degradation in the study area.

**Conflict of Interest:** None

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