# Spatial Variability of Soil Chemical Properties within a KVK Farm of Budgam in Lesser Himalayas

**Abstract**

Assessing the spatial variability of soil chemical properties is essential for optimizing crop productivity and ensuring sustainable land management. This study evaluated the spatial distribution of key soil fertility indicators at KVK Farm, Budgam, in the Lesser Himalayas. A total of 21 soil samples were collected from a 0–30 cm depth across different land uses and analyzed for organic carbon (OC),nitrogen (N), phosphorus (P) and potassium (K). Results revealed moderate variability for OC, N and K, while P showed high variability (>50%). Spatial variability maps generated using geostatistical techniques and GIS tools indicated that land use significantly influences soil fertility. All the studied soil properties (OC, N, K, P) exhibited patchy distribution, with excess accumulation in some areas and deficiencies in others. These findings highlight the need for site-specific nutrient management to optimize fertilizer use and enhance soil fertility. Precision agriculture approaches can improve resource utilization and promote sustainable agricultural practices in similar agroecosystems.

**Keywords**: Spatial variability; GIS; Kriging; organic carbon; nitrogen, phosphorus, potassium.

**Introduction**

In nature, soil is inherently variable due to the variations in soil-forming processes at different spatial scales. Additionally, anthropogenic influences such as land use, cultivation, and erosion further contribute to soil variability. As a result, soil properties change across both space and time due to **geochemical processes** and **soil management practices** such as fertilization and irrigation (Buol et al., 2011; Davatgar et al., 2012; Arunkumar et al., 2023). This variability has significant implications for soil management, particularly in optimizing agricultural input requirements to enhance productivity, profitability, and environmental sustainability.

Soil fertility properties must be analyzed to understand the impact of **land use and management systems** on soil functions (Denton et al., 2017; Mansour et al., 2019). Recognizing and quantifying this variation is crucial, as it helps determine the extent to which soil characteristics reflect **long-range environmental and anthropogenic influences.** Consequently, soil management recommendations should ideally differ between farms and even between fields within the same farm. A site-specific approach allows for **more efficient, cost-effective, and environmentally sustainable** use of agricultural inputs (Brevik et al., 2016; Bogunovic et al., 2017; Shukla et al., 2017; Abd-Elmabod et al., 2019). A better understanding of soil fertility variation can thus assist farmers in enhancing soil productivity while advancing the principles of **sustainable agriculture** (Abd-Elmabod et al., 2017; Buttafuoco et al., 2017).

A study by Franzluebbers and Hons (1996) compared the distribution of available soil nutrients in fields under different farming systems and recommended the importance of soil information as a foundation for effective soil management. Farming decisions should be guided by soil management zones to support precision agriculture ([Kathumo, 2007](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/%22%20%5Cl%20%22bib34); [Ali et al., 2022](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/#bib4)). These management zones delineate farms on the basis of soil attributes, helping to optimize fertilizer application ([Fridgen et al., 2004](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/%22%20%5Cl%20%22bib27); [Bao-wei et al., 2018](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/#bib8); [Ali et al., 2019](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/#bib3); [McEntee et al., 2020](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/#bib50); [Ali et al., 2022](https://pmc.ncbi.nlm.nih.gov/articles/PMC9424958/#bib4)). Consequently, an estimation of geographical variability of soil parameters is vital for management of crop and assessment of field research studies (Ramzan et al., 2017).

One of the well-established techniques for categorizing the **spatial variability** of soil properties is **spatial interpolation of soil parameters** based on point measurements using geostatistics (Liu et al., 2006). In regions such as **Kashmir,** inappropriate land management practices, including the indiscriminate application of **blanket fertilizers**, remain a challenge. **Site-specific crop management** requires detailed mapping of essential **macronutrients** (Mazur et al., 2022) to optimize soil fertilization and ensure balanced nutrient application. Consequently, assessing the **spatial variability** of key nutrients is essential for identifying and delineating **critical nutrient-deficient zones.** Thus, the objectives of this study were:

1) To determine trends and long-range variations in soil fertility those justify differentiated soil management recommendations across the study area.

2) To map soil fertility properties exhibiting spatial dependence using geostatistics and Geographic Information System (GIS) tools.

# Materials and methods

***Study Area:***The study was carried out in the month of October 2024 during the autumn season at the KVK Farm (34.0619, 74.7092), located in Budgam district of Kashmir division. The farm covers a total area of 20 ha and consists of diverse land uses, including apple and walnut orchards, cereal crops, and vegetable cultivation. The climate of the study area is temperate, characterized by an average annual rainfall of approximately 585 mm and an average temperature of 14°C. Figure 1 shows the location of the study area in the Google Earth alongwith the illustration of different land uses on the farm. The farm is divided into distinct sections, including apple and walnut orchards, cereal crops, vegetable blocks, and various research plots. Additionally, infrastructure such as chain-link fencing, vermicompost units, a meteorological station, and nursery blocks are marked, providing a detailed spatial representation of the farm layout. This visual representation aids in understanding the spatial distribution of land use types and their relevance to the study.



**Figure 1: Google Earth view of the KVK Farm, Budgam, showing different land use zones.**

***Soil Sampling and Analysis:***

The primary goal of soil sampling was to accurately characterize the spatial variability of nutrients in the soil. Sample locations in KVK Field were geo**-**referenced using a GPS to facilitate the correlation of soil test results with spatial details of the soil sample (Figure 2).

Samples were collected at a depth of 0 to 30 cm from 21 sampling points across the farm ensuring representation based on different land uses. Areas with non-typical features, such as field edges, were excluded from sampling. At each site, a composite soil sample was obtained by thoroughly mixing multiple subsamples. From this mixture, 500 grams of soil was retained, properly labeled, and transported to the laboratory for preparation, which included air-drying and sieving. The soil samples were analyzed using Near-Infrared (NIR) Spectroscopy with the Bhu Parikshak rapid soil testing device, allowing for the rapid and precise assessment of soil fertility parameters.



**Figure 2: Location map of study area with the soil sampling points.**

***Exploratory Statistical Analysis:***Descriptive statistical parameters, including mean, minimum, maximum values, standard deviation, coefficient of variation (CV), skewness, and kurtosis, were computed using SPSS 20.0 (2011). Additionally, Pearson’s correlation coefficients were calculated to determine relationships between soil properties at 1% and 5% significance levels.

***Geostatistical Analysis:***To assess the spatial variability of soil properties, geostatistical method was applied using ArcGIS 10.2. The analysis involved generating variograms to evaluate the spatial distribution of soil properties and determine the necessary parameters for kriging interpolation, which was used to estimate soil properties in unsampled areas and create spatial variability maps.

# Results and discussion

Table 1 summarizes descriptive statistics of soil physicochemical properties for the soil samples collected from KVK Budgam farm. Organic Carbon varies from 0.32 to 1.93 % with a mean value of 1.07%. The available nitrogen (N) ranged from 180.3 to 442.5 kg/ha, with a mean value of 296.02 kg/ha. Available phosphorus (P) ranged from 8.4 to 76.6 kg/ha, with a mean value of 128.7 kg/ha, while exchangeable potassion (K) ranged from 135.4 to 590.9 kg/ha, with mean value of 248.54 kg/ha. The extent of spatial variability of the properties was assessed using the coefficient of variation (CV) based on the guideline of Warrick (1998) who classified <15% as low, 15**-**50% as medium and >50% as high.

**Table 1: Descriptive statistics for the measured soil parameters.**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Soil Parameter** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** | **CV (%)** | **Skewnes** | **Kurtosis** |
| OC (%) | 0.32 | 1.93 | 1.070 | 0.64 | 60.69 | 0.38 | -1.88 |
| N (kg/ha) | 180.30 | 442.50 | 296.02 | 110.32 | 37.27 | 0.38 | -1.94 |
| P (kg/ha) | 8.40 | 76.60 | 39.91 | 23.62 | 59.18 | -0.16 | -1.87 |
| K (kg/ha) | 135.40 | 590.90 | 248.54 | 128.70 | 51.78 | 1.09 | 0.67 |

In this study, soil nitrogen showed moderate variation (37.27%), while organic carbon (60.967%), phosphorus (59.181%) and potassium (51.783%) showed high variability (Table 1). The high variation of soil organic matter (SOM), P and K observed in this study aligns with findings from other agricultural regions, such as Croatia (Bogunovic et al., 2017) and Sri Lanka (Rosemary et al., 2017). These variations can be attributed to long-term interactions between soil-forming factors and soil management practices.

**Spatial Variability of Soil Parameters**

**Organic Carbon**

The spatial distribution map (Figure 3) generated through **ordinary kriging** indicate that the organic carbon (OC) levels across the study site were generally high (>0.75%), with only small patches of low levels (<0.5%) observed in certain areas of KVK Budgam farm. A medium range of organic carbon (0.5–0.75%) was found towards the northeastern end of the study site. Organic carbon is generally considered a stable parameter. However, the medium to high variability observed in this study can be attributed to pedogenic processes influenced by micro-topography over different time scales (Ajayi and Okonokhua, 2024). Additionally, variations in land use contribute significantly to differences in soil organic carbon (SOC) content (Xiong et al., 2016; Lei *et al*., 2019; Guillaume *et al*., 2021).



**Figure 3: Spatial variability of Organic Carbon across the study area.**

The lowest SOC levels recorded in the **northeastern** region of the study area may be due to the **depletion of organic matter** caused by continuous cultivation, removal of crop residues, and limited organic input applications. Continuous cultivation has been shown to deplete soil organic matter and reduce SOC content, leading to diminished soil fertility and biological activity (van Beek *et al.*, 2018; Kartini *et al*., 2024). Consequently, a reduction in soil organic matter impacts **nutrient retention, water-holding capacity, and soil biological activity,** all of which are essential for maintaining soil health (Corsi *et al*., 2012).

In contrast, higher SOC levels in the central and southeastern parts of the study area could be attributed to greater inputs of organic residues, possibly due to differences in crop management practices. This suggests that land use and soil management practices significantly influence organic carbon distribution across the farm.

**Major Nutrients**

**Nitrogen (N)**

The spatial distribution map (Figure 4) of available nitrogen across the KVK farm showed medium to high concentrations (>250 kg/ha), with isolated patches of low nitrogen content (<250 kg/ha) in the northeastern parts of the farm. Nitrogen deficiency in these areas may be linked to the long-term cultivation of heavy feeder crops, such as maize, coupled with the insufficient application of nitrogenous fertilizers.



**Figure 4: Spatial variability of Nitrogen across the study area.**

**Phosphorus**

The spatial distribution map (Figure 5) of available phosphorus exhibited a **patchy distribution** across the farm. The **northeastern** region showed **high phosphorus content (50–60 kg/ha),** which may be attributed to the **excessive application of phosphatic fertilizers.** However, approximately one-third of the study area (particularly in the southeastern region and a small portion of the southwestern region) had phosphorus levels below the critical limit of 23 kg/ha, which is considered insufficient for optimal agricultural production. These findings indicate the need for targeted phosphorus management strategies to correct deficiencies and enhance soil fertility.



**Figure 5: Spatial variability of Phosphorus across the study area.**

**Potassium**

Potassium concentrations across the study area were generally in the **medium to high range (>130 kg/ha) as depicted in Figure 6.** The highest K values were recorded near the **northwestern boundary** of the farm. The spatial variability of potassium content is influenced by **land use practices, soil type, and environmental factors,** aligning with findings from Zhang et al. (2022). Similar studies in various agricultural ecosystems have demonstrated that soil nutrient distribution is controlled by a combination of **the** climate (Li et al., 2020), topography (Karchegani et al., 2012), soil type (Tajik et al., 2020), fertilization practices (Tang et al., 2020), cropping system (Xie et al., 2021) and tillage method (Shahriari et al., 2011).



**Figure 6: Spatial variability of Potassium across the study area.**

**Conclusion**

This study assessed the spatial variability of key soil chemical properties at KVK Farm, Budgam, and highlighted the impact of land use on soil fertility. The results revealed significant spatial heterogeneity in organic carbon, nitrogen, phosphorus, and potassium levels across the farm. Organic carbon and phosphorus showed the highest variability. Nitrogen indicated moderate variability, with deficiencies linked to long-term cultivation and inadequate fertilization. Potassium levels were found to be mostly adequate, with variations influenced by cropping systems and soil management practices. The geostatistical analysis demonstrated that land use and management practices significantly influence soil fertility patterns, even within a relatively small agricultural area. These findings underscore the necessity for precision agriculture approaches, including site-specific nutrient management and targeted fertilizer application, to enhance soil productivity while minimizing environmental impacts. Future research should focus on integrating long-term monitoring and remote sensing techniques to further refine soil fertility assessments and enhance decision-making in soil management.

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