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RESEARCH

# Geospatial Approach to Soil Fertility Mapping in Dailekh District, Nepal: A GIS Perspective

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## Abstract
Spatial mapping of the soil gives the distribution patterns of the nutrients, which is crucial for integrated nutrient management, site-specific crop selection, water resource management, and adaptation to climate change for optimizing productivity. This research aims to identify the spatial variability of soil chemical properties in the Dailekh district of Karnali Province, Nepal, by preparing a map in a raster setting. A total of 204 samples were collected using stratified random sampling techniques using Google Earth Pro and were analyzed using IBM SPSS 27.0 and Arc Map 10.2 software. The classical statistical method was used for the descriptive analysis of sampled data. The Quantile Quantile (QQ) plot was made to visualize the distribution pattern, and non-normal data were log-transformed to match the straight line. Before making a map, sampled datasets were examined using the trend analysis feature of Arc Map using second-order polynomials in 3D scattered plots. The widely used interpolation technique, Ordinary kriging of two Exponential and Circular models, was applied to data and cross-validated with minimum estimated errors. Fertility mapping of parameters results in more than 81%, 56 %, and 57% of the areas covered by nitrogen, phosphorus, and potassium, with medium in status. Similarly, organic matter has low content shades in 65% of areas and moderately acidic pH in 49% of areas. This research supports decision-making for nutrient distribution across agricultural fields and sustainable land management for precision farming.

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**Statement of Sustainability:** Spatial soil fertility mapping plays a crucial role in achieving multiple Sustainable Development Goals (SDGs) by providing a detailed assessment of soil nutrient levels, enabling farmers to apply fertilizer efficiently and enhance soil health. This directly supports SDG 2 (Zero Hunger) by improving crop yields and food security. Healthier soil stores more carbon, aiding SDG 13 (Climate Action) by mitigating greenhouse gas emissions. Additionally, sustainable soil management helps combat desertification and land degradation, aligning with SDG 15 (Life on Land) to protect terrestrial ecosystems.

## 1. Introduction

Soil fertility mapping plays a vital role in precision farming by enabling farmers to optimize fertilizer use, enhance productivity, and minimize soil degradation (Malla et al., 2020; Chalise et al., 2019). However, natural calamities such as floods, droughts, and landslides can damage the soil by causing erosion, nutrient depletion, compaction, and contamination. Soil mapping creates detailed maps of soil properties and can help to identify the most vulnerable areas to such disasters (Oli et al., 2020). Mapping also allows farmers to apply fertilizer in the right amount in the right place based on the demand for crops, the selection of suitable crops for a specific soil, and site-specific management for long-term soil health (Chakraborty et al., 2024; Jena et al., 2024b). Geographic Information Systems (GIS) have widely adopted geostatistical tools for spatial interpolation and visualization of soil properties across diverse landscapes by reflecting the exact ground condition into a single analysis (Ghimire et al., 2024). Different geostatistical interpolation methods such as kriging, Inverse Distance Weighted (IDW), and deterministic interpolation techniques such as Local Polynomial Interpolation (LPI), Radial Basis Function (RBF), and Empirical Bayes kriging (EBK) have been used for analysis (Bhunia et al., 2016; Kaur et al., 2020). For highly accurate spatial prediction, ordinary kriging is the best model due to its ability to account for irregular data and features like spatial autocorrelation using a semivariogram model for well-distributed samples (Eldeiry and Garcia, 2012). However, one major challenge is creating an even distribution of sample data due to erratic topographical conditions in the mid-hills, leading to low spatial resolution (Zhang et al., 2015). Many traditional mapping methods fail to consider spatial dependencies and autocorrelation features, leading to interpolation errors, biased prediction, and misleading spatial patterns. Due to anthropogenic activities and land use patterns, soil properties such as organic matter, pH, and nitrogen vary considerably over short distances. That is why some models may struggle to capture small-scale heterogeneity (Ghimire et al., 2018; Trangmar et al., 1986).

This study aims to map the spatial variability of soil chemical properties using a stable geostatistical model that has been cross-validated by calculating estimated errors. This information can be used to optimize productivity, crop suitability analysis, sustainable land use planning, environmental protection, and climate change adaptation.

## 2. Materials and Methods

### 2.1. Study Area

The study was conducted in the Dailekh district of Karnali province, Nepal (Figure 1), located between 28° 35′ 00″ N to 29° 08′ 00″ N latitude and 81° 25′ 00″ E to 81° 53′ 00″ E longitude. The district comprises four municipalities and seven rural municipalities scattered across the 148.350 ha area. The elevation of the study area ranges from 539 to 4009 meters (m), and it is present in the hilly zone, with slope ranging from 0° to 75.58°. Due to elevation differences, three types of climate patterns were found: tropical up to 1000 m elevation covers 16% of the area, subtropical 1000 to 2000 m covers 69%, and temperate >2000 m covers 15% of the area (Karki et al., 2015). The study region gets 1500 mm of precipitation annually and 4°c to 34°c of temperature. The major crops, like maize, paddy, and millet, produced a good harvest in the study region.

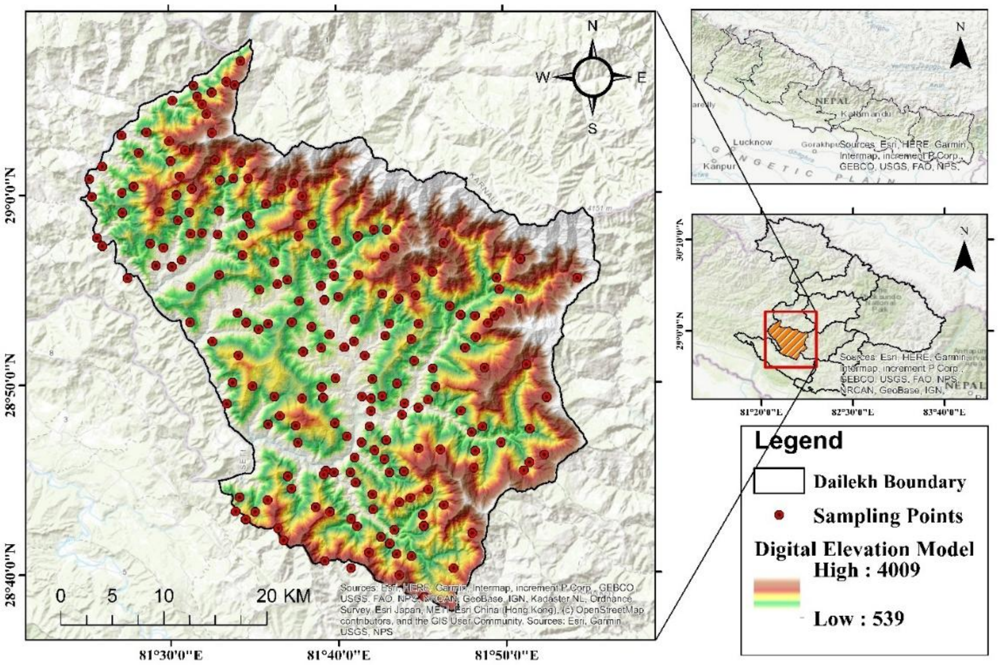


Figure 1. Map of Nepal showing the study area.

### 2.2. Soil Sampling Techniques

A total of 204 soil samples were collected using stratified random sampled locations within 11 municipalities of the study area based on altitude variation, slope, and land unit types. A digital elevation model downloaded from the USGS Earth Explore (https://earthexplorer.usgs.gov/) was used to calculate the slope and aspect to locate the soil point on the map. In field conditions, the soil pit was identified using Google Earth Pro, and a georeferenced soil auger was driven to collect the soil from the required depth of 10- 20 cm. The many-core samples were bulked into composite samples by removing and mixing each quadrate. The collected samples were brought to the Regional Laboratory of Karnali province, Nepal, to characterize chemical properties.

### 2.3. Soil Analysis

The soil's chemical properties, like pH, organic matter, total nitrogen, phosphorus, and potassium, were analyzed in a laboratory. The potentiometric method was used to determine the pH value (Jackson, 1967). The organic carbon was determined using the Walkley and Black wet digestion method (Walkley and Black, 1934), and the obtained value was multiplied by the constant number of 1.72 to calculate the organic matter content (Malla et al., 2020). The total nitrogen was determined by using wet digestion in a Kjeldahl distillation unit (Bremner and Mulvaney, 1982). The available phosphorus and potassium were measured using Olsen's bicarbonate and ammonium acetate method in a flame photometer, respectively (Olsen et al., 1954; Jackson, 1967).

### 2.4. Analytic Statistical Analysis

Explorative analysis of the data was done in IBM SPSS 27.0 released Software. For each of the soil properties, the statistical attributes such as minimum, maximum, mean, standard deviation, coefficient of variation, skewness, kurtosis, and median were subjected to analysis. The simple graphical Quantile Quantile (QQ) plot was produced to visualize the mostly deviated data and normal distribution pattern of the datasets. The non-normal data were brought to log transformation to stabilize the variance within data and recalculated the normality test.

### 2.5. Geostatistical Analysis

The spatial analysis was carried out in ArcGIS 10.2 software. The geospatial interpolation technique called Ordinary kriging was used to calculate the spatial variability (Panday et al., 2019). Ordinary kriging uses the spatial auto-correction feature by considering the distance and degree of variation of known data attributes by using a semivariogram model (Goovaerts, 1997). The formula of semivariogram is:

$$\mathrm{Y(h)} = \frac{1}{2\mathrm{N(h)}} \sum_{\alpha=1}^{\mathrm{N(h)}} [\mathrm{z}(\mathrm{u}_\alpha) - \mathrm{z}(\mathrm{u}_\alpha + \mathrm{h})]^2 \tag{1}$$

Where Y(h) is the semivariogram value at distance h, N (h) is the number of data pairs located by the distance h, $\mathrm{z}(\mathrm{u}_\alpha)$ is the value of the variable at the location $(\mathrm{u}_\alpha)$, and $\mathrm{z}(\mathrm{u}_\alpha + \mathrm{h})$ is the value of a variable at another location separated by distance h. Different semivariogram models that best fit with data were used for interpolation. Two empirical models, named Circular and Exponential, were fit with data, which were explained in the following equations (Mokarram and Sathyamoorthy, 2016).

$$\mathrm{Y(h)} = \mathrm{c_0} + \mathrm{c}\left(1 - \frac{2}{\pi}\cos^{-1}\left(\frac{\mathrm{h}}{\mathrm{a}}\right)\right) + \sqrt{1 - \frac{\mathrm{h}^2}{\mathrm{a}^2}} \tag{2}$$

$$\mathrm{Y(h)} = \mathrm{c_0} + \mathrm{c}\left(1 - \exp\left(\frac{-\mathrm{h}}{\mathrm{a}}\right)\right) \tag{3}$$

Where $C_0$ is the nugget variance, C is the partial sill, and a is the spatial dependency range to reach the sill ($C_0$+C). Nugget represents the variance at a small distance and accounts for the measurement of spatial changes at a distance smaller than the sampling resolution (Tesfahunegn et al., 2011). Sill represents the total variance in the data, indicating that beyond this range, there is no further correlation. Partial sill is the lag distance at which one variable does not influence the neighboring value, i.e., variability that can be explained by spatial autocorrelation (Ramzan et al., 2017).

## 3. Results and Discussion

### 3.1. Descriptive Statistics of Soil Properties

The summary of the descriptive statistics of nitrogen, phosphorus, potassium, organic matter, and soil pH status is presented in Table 1. The coefficient of variation (CV) was used to interpret the heterogeneity of the data. The greatest and least CV was obtained from the phosphorus (123.99%) and pH (11.95%), respectively. Similar research on fertility mapping in Gulmi figured out a 100.09% variation in phosphorus and 6.30% in pH (Ghimire et al., 2024). In the study region, the concentration of nitrogen varied from 0.01% to 0.38%, with a mean value of 0.12 (Table 1). Out of the total area of the district, 81.15% of the area is medium (0.10-0.20), and 18.85% is low (0.05-0.10) in the status (Table 2 and Figure 5). Similarly, the mapping of nitrogen in Dhanusha revealed that 68.91% of the area is medium in range (Yadav et al., 2022). The potassium content varied from 0.39 to 619.21, with a mean value of 72.62 (Table 1). More than 56% of the area is medium (30-55 kg/ha), and only 0.85% is very high (>110 kg/ha) in the available potassium (Table 2). The concentration of potassium ranges from 2.16 to 2426.10, with a mean value of 339.11 (Table 1). Soil fertility mapping for the potassium reveals that 57.40% of the area is medium (110-280 kg/ha), and 41.62% is high (280-504 kg/ha) (Table 2 and Figure 5). Statistics of organic matter show that OM ranges from 0.10 to 6.51 with a mean value of 2.38. This indicates that 65.05% of the area is low (1-2.5%), and 34.78% is medium in organic matter (Table 2 and Figure 5). The least variable parameter pH ranges from 4.34 to 7.80 with a mean of 5.86 (Table 1). More than 49% of the area is moderately acidic (4.5 -5.5), 27% is strongly acidic (<4.5), and only 9.51% is neutral in the pH content (Table 2 and Figure 5).

Table 1. Descriptive statistics of soil chemical properties of Dailekh district, Nepal.

| Parameters | Minimum | Maximum | Mean | SD | CV | Skewness | Kurtosis | Median |
|---|---|---|---|---|---|---|---|---|
| N | 0.01 | 0.38 | 0.12 | 0.07 | 60.00 | 0.82 | 3.65 | 0.11 |
| $P_2O_5$ | 0.39 | 619.21 | 72.62 | 90.04 | 123.99 | 2.83 | 13.68 | 38.65 |
| $P_2O_5^*$ | -0.94 | 6.42 | 3.69 | 1.14 | 30.89 | -0.30 | 3.69 | 4.54 |
| $K_2O$ | 2.16 | 2426.10 | 339.11 | 339.46 | 100.10 | 2.58 | 12.27 | 238.80 |
| $K_2O^*$ | 0.77 | 7.79 | 5.40 | 1.00 | 18.52 | -0.84 | 5.49 | 5.47 |
| OM | 0.10 | 6.51 | 2.38 | 1.42 | 59.66 | 0.64 | 2.95 | 2.17 |
| pH | 4.34 | 7.80 | 5.86 | 0.70 | 11.95 | 0.45 | 2.66 | 5.80 |
| $pH^*$ | 1.46 | 2.05 | 1.76 | 0.11 | 6.25 | 0.19 | 2.53 | 1.75 |

N = Nitrogen, $P_2O_5$ = Phosphorus, $K_2O$ = Potassium, OM = Organic matter, SD = Standard deviation, CV = Coefficient of variation (%), and * = Log transformed.

The Simple Quantile-Quantile (QQ) graphical method was used to examine the normal distribution of the data by comparing the expected normal value with the observed value (Augustin et al., 2012). Q-Q plots of the laboratory data are presented in Figure 2. The variable that matches the normal distribution lies in a straight diagonal line. Most nitrogen and organic matter data follow a straight line, except a few samples deviated.

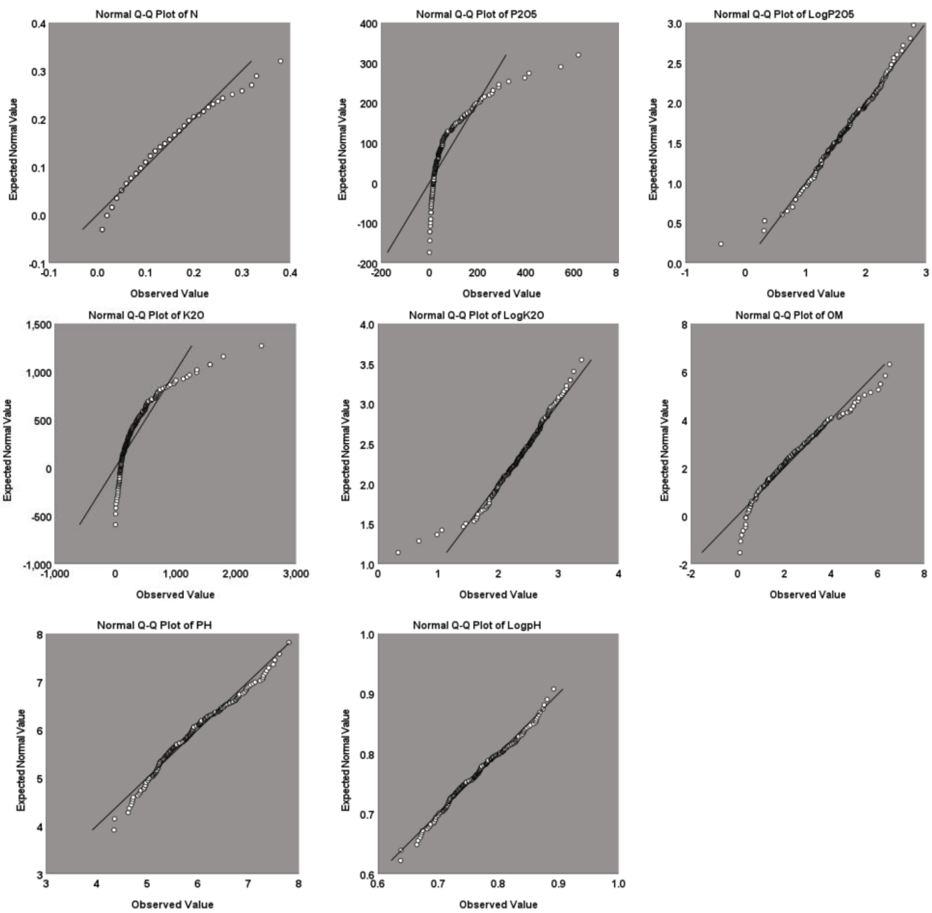


Figure 2. Normal Q-Q plot of the selected parameters.

### 3.2. Trend analysis

The trend analysis of the data was done in the geostatistical tool of ArcGIS10.2 software. The trend represents the three-dimensional perspectives of the data in which polynomials are fit through scatter plots. In Figure 3, the X and Y planes represent the soil sample, and the Z plane represents the chemical properties of the soil. The green and blue lines represent the trend in X, Z, and Y, Z planes. The global trend exists when curved lines fit with the data. The U-shaped curve in the trend shows the second-order polynomial that fits with the data. The analysis results show that parameters such as nitrogen, phosphorus, organic matter, and pH have a strong direction trend effect. This effect can be due to vegetation cover, land uses land cover, and topographic conditions. But, the potassium shows no direction trend. Before applying the normalization, data must be fitted with a second-order polynomial to create an accurate map (Tesfahunegn et al., 2011).

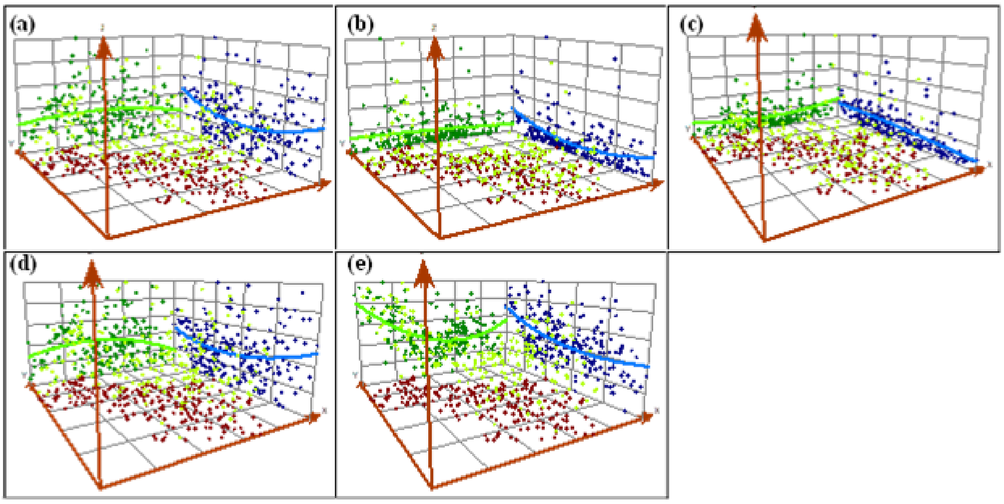


Figure 3. Trend analysis of the sampled data (a) Nitrogen, (b) Phosphorus, (c) Potassium, (d) Organic matter, and (e) soil pH.

Table 2. Areas covered by soil parameters in different ranks given by the Soil Management Directorate, Department of Agriculture for Hills.

| Parameters | Unit | Rank | Description | Area (ha) | Area (%) |
|---|---|---|---|---|---|
| N | % | <0.05 | Very low | - | - |
| | | 0.05-0.10 | Low | 27958.61 | 18.85 |
| | | 0.10-0.20 | Medium | 120391.02 | 81.15 |
| | | 0.20-0.40 | High | - | - |
| | | >0.40 | Very high | - | - |
| $P_2O_5$ | Kg/ha | <10 | Very Low | - | - |
| | | 10-30 | Low | 35150.85 | 23.69 |
| | | 30-55 | Medium | 83167.99 | 56.06 |
| | | 55-110 | High | 28767.13 | 19.39 |
| | | >110 | Very high | 1263.31 | 0.85 |
| $K_2O$ | Kg/ha | <55 | Very low | - | - |
| | | 55-110 | Low | 1386.62 | 0.93 |
| | | 110-280 | Medium | 85149.78 | 57.40 |
| | | 280-504 | High | 61740.49 | 41.62 |
| | | >504 | Very high | 72.77 | 0.05 |
| OM | % | <1 | Very low | 262.44 | 0.18 |
| | | 1-2.5 | Low | 96497.51 | 65.05 |
| | | 2.5-5.0 | Medium | 51589.29 | 34.78 |
| | | 5.0-10.0 | High | - | - |
| | | >10.0 | Very high | - | - |
| pH | | <4.5 | Strongly acidic | 40470.91 | 27.28 |
| | | 4.5-5.5 | Moderately acidic | 72949.26 | 49.17 |
| | | 5.5-6.5 | Slightly acidic | 20824.92 | 14.04 |
| | | 6.5-7.5 | Neutral | 14104.89 | 9.51 |
| | | >7.5 | Strongly alkaline | - | - |

### 3.3. Spatial Dependency and Estimated Error

The geospatial semivariogram models named Exponential and Circular were best fit with the data. The parameters phosphorus, potassium, and organic matter fit with the circular model, while nitrogen and soil pH fit with the Exponential model (Figure 4). Cross-validation of the experimental model was done by calculating and comparing the estimated errors, such as root mean square error (RMSE), mean square error (MSE), root mean square standardized error (RMSSE), and average standard error (ASE) (Table 3). The spatial dependence represents the similarity and dissimilarity of soil properties with distance. The nugget-to-silt ratio was used to identify the spatial dependency (Ramzan et al., 2017). The ratio >25 represents strong, 25 to 75 is moderate, and >75 is weak, according to Cambardella et al (1994). The parameters phosphorus, potassium, and organic matter show weak dependency (i.e., dissimilar data with distance), and nitrogen and pH exhibit moderate spatial dependency, which means similar data with the distance (Table 3).

Table 3. Values of model parameters for best-fit semivariogram.

| Parameters | Model | Nugget | Partial sill | Sill | Nugget/sill | Spatial dependency | Estimated error | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | RMSE | MSE | RMSSE | ASE |
| N | Exponential | 0.199 | 0.259 | 0.457 | 43.42 | Moderate | 0.564 | -0.003 | 1.010 | 0.557 |
| $P_2O_5^*$ | Circular | 1.086 | 0.145 | 1.231 | 88.23 | Weak | 88.510 | -0.034 | 0.863 | 127.270 |
| $K_2O^*$ | Circular | 0.965 | 0.106 | 1.072 | 90.09 | Weak | 338.070 | 0.034 | 0.631 | 562.660 |
| OM | Circular | 1.769 | 0.354 | 2.123 | 83.34 | Weak | 1.433 | 0.004 | 1.022 | 1.404 |
| $pH^*$ | Exponential | 0.006 | 0.007 | 0.013 | 43.76 | Moderate | 0.563 | -0.007 | 1.023 | 0.561 |

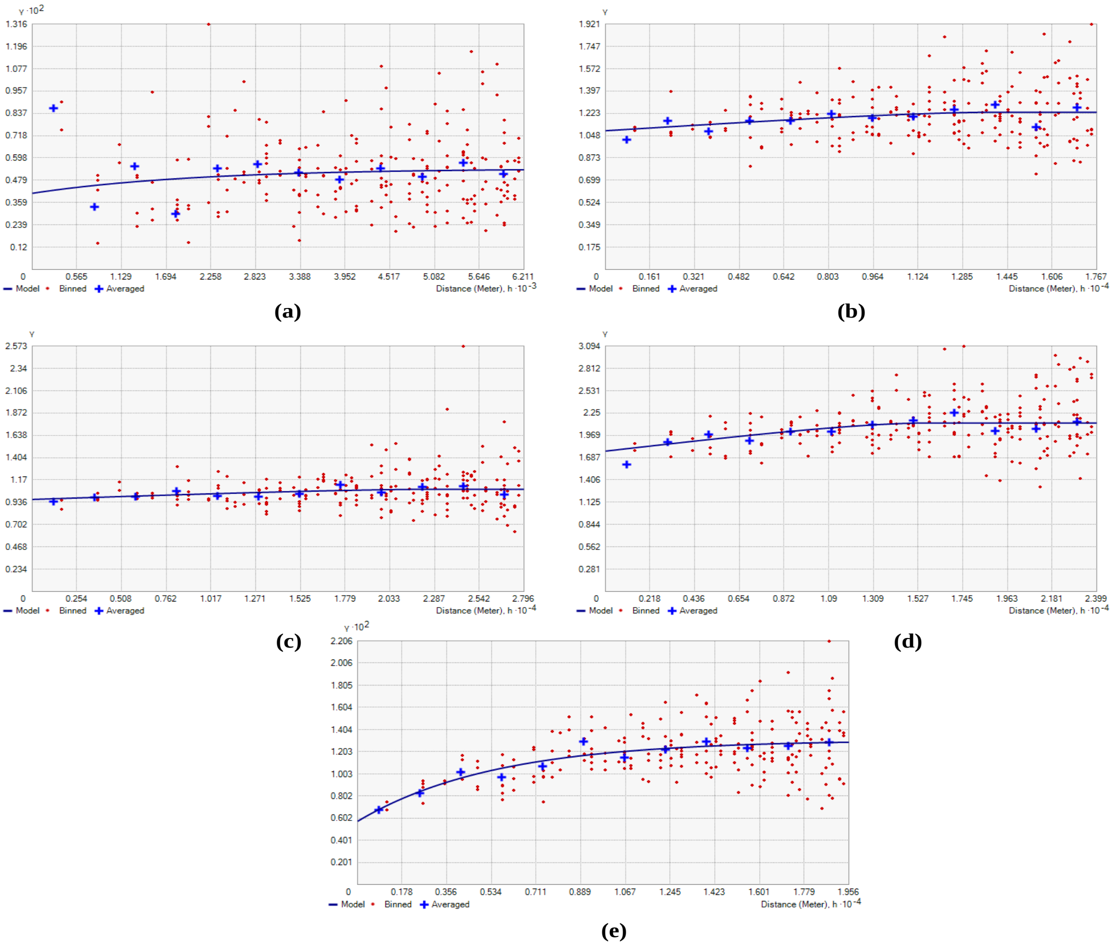

Figure 4. semivariogram model for different soil parameters: (a) Nitrogen, (b) Phosphorus, (C) Potassium, (d) Organic matter, and (e) Soil pH.

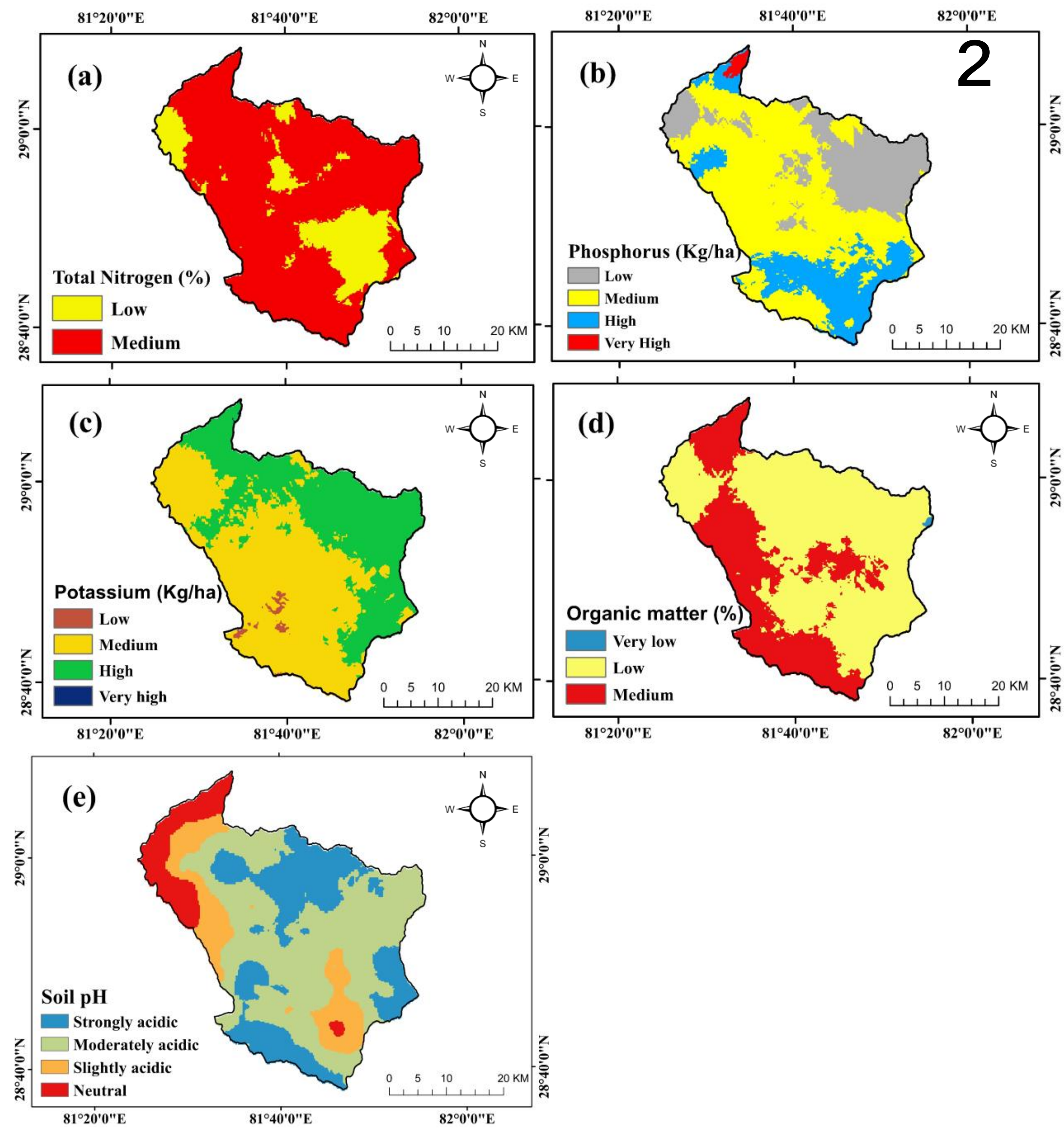


Figure 5. Spatial map of soil properties (a) Nitrogen, (b) Phosphorus, (c) Potassium, (d) Organic matter, and (e) Soil pH.

## 4. Conclusion

This research demonstrates the spatial variability of the soil properties using a stable semivariogram model that best fits with sample data. Traditional classical statistical methods only tell about the variation in data by analyzing minimum and maximum values but lack in identifying the source of variability. However, by applying the exponential and circular models, the present research shows that soil pH and nitrogen were the spatially least varying parameters than phosphorus, potassium, and organic matter. The reason behind the variation within a small distance is due to land management and cultivation practices. Fertility mapping shows that the parameters nitrogen, phosphorus, and potassium were medium in status at 81%, 56%, and 57% of areas, respectively. Likewise, 65% of the area is low in organic matter content, and 49% of the area is covered by moderately acidic pH soil. Acidic soil in most of the area needs to be reclaimed by using farmyard manure, green manuring, and reducing the use of acid-forming fertilizers. Furthermore, this research would be the backbone for integrated nutrient management, cropland suitability analysis, land use planning, and sustainable land management in the future.

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