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Geostatistical modelling of soil properties towards long-term ecological sustainability of agroecosystems

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ABSTRACT

A profound grasp of the quantitative spatial heterogeneity and distribution of the soil physicochemical attributes is crucial in understanding agricultural landscapes for ensuring the provisioning of soil ecosystem services. However, the analysis of data from remote sensing, like NDVI, can be of help in analysing the capacity of the landscape to provide supporting ecosystem services such as primary productivity. The research investigated and addressed the dispersion of important soil physico-chemical attributes in agricultural lands of the temperate Himalayan region of India using a geostatistical method and combining normalized difference vegetation index (NDVI) time-series data and the regression Kriging method. A 206 soil samples were gathered and assessed for soil parameters like pH, EC, OC, and available N, P, K, Ca, and Mg from Kishtwar district of Jammu. The coefficient of variation (CV) for pH and electrical conductivity (EC) ranged notably from 8.75 % to 118.98 %, highlighting diverse soil characteristics critical for local management practices. Mean elevation averaged 2743.32 m (m), with a moderate NDVI of 0.15, indicating dynamics in vegetation cover. Soil pH ranged from intensely acidic to marginally alkaline, with varying EC levels. Seemingly high organic carbon (OC), nitrogen (N), and potassium (K) levels, accompanied by medium phosphorus (P), calcium (Ca), and magnesium (Mg) levels were found in the region. The study employed ordinary kriging (OK) to map the spatial distribution of soil parameters, utilizing mean square error (MSE), root mean square error (RMSE), and the Moran's I index. Exponential models were the best fit models for OC, while spherical models were fit for pH, EC, N, P, and Ca. Mathematical models were best fit for K and Mg. Spatial analysis using spherical and exponential models revealed distinct distribution patterns for pH, N, P, Ca, and Mg. The results of the degree of spatial dependence from the semi-variogram analyses indicated a strong (0.06 %) to moderate (0.51 %) to weak (2.81 %) dependence. The interpolated maps showed a distinct gradient in elevation (1053–4413 m), OC (0.13–2.80 %), NDVI (−0.16–0.54), pH (4.80–8.00), EC (0.03–9.80 dS m^{-1}), N (201.15–993.19 kg ha^{-1}), P (3.00–96.00 kg ha^{-1}), K (124.88–1110.71 kg ha^{-1}), Ca (7.00–46.00 meq 100 g $soil^{-1}$), and Mg (2.30–21.50 meq 100 g $soil^{-1}$) at the regional scale, indicating a wide range of spatial soil heterogeneity. The heterogeneity maps of soil parameters generated by this research can be effectively used by land planners and farm managers at a regional scale for crop nutrient management to reduce soil contamination risk. These maps serve as baseline materials and effective tools for suitable land management strategies such as conservation-effective tillage, integrated nutrient management, and organic farming based on the spatial distribution of soil properties and they can significantly enhance the long-term ecological sustainability of agro-ecosystems' management.

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1. Introduction

The Himalayan region in India spans eleven Indian states and territories and comprises ~16 % of the entire landmass of the nation, and it is home to ~51 million people. Majority of hill populace is engaged in farming practices amid fragile and complex ecosystems, including high species-rich forests (Yadav et al., 2020). The valley land has substantial hydropower potential and supplies multiple perennial rivers that are dependent on the ongoing survival of glaciers (Nie et al., 2021). The temperate Himalayas are rich in biodiversity (Dar and Khuroo, 2020). The region stands out as one of the earth's most diverse ecosystems. It is among one of biological hotspots due to its high levels of endemism, and outstanding biological and sociocultural diversity (Tripathi et al., 2015). This remarkable diversity arises from the region's broad altitudinal range, intricate topography, diverse soil types and climatic conditions, and its distinctive spatial position (Maletha et al., 2022). This highlights the region's unique ecological richness and cultural heritage compared to other global regions. Biodiversity hotspots represent regions that have an abundantly rich number of endemic organisms and are subject to substantial threats from human activities (Bellard et al., 2014). The Himalayan region's distinction as a hotspot underscores its critical role in preserving numerous rare and endemic species, as well as maintaining the cultural traditions and practices of the diverse human populations that inhabit the area. Compared to other regions, the Himalayas face intense pressures from habitat destruction, climate change, and socio-economic challenges, making conservation efforts in this region particularly crucial for both biological and cultural preservation (Yadav et al., 2020; Dhyani, 2023). In general, half of the native plant species in India and a tenth of recognized elevated plant and animal species in the world are found in this region (Padma, 2014). The temperate forests of the Himalayas are the utmost diverse, dynamic, fertile, and wealthy ecosystems upon the globe., due to the variety of climate, slope inclination, land use, and topography; they are characterized by the presence of coniferous and oak woodlands stretching at altitudes between 1500 and 3500 m (Salick et al., 2009; Kumar et al., 2022).

It is now widely recognized that the survival, health, and prosperity of humans also depend on the functioning of mountain ecosystems and on their capacity to supply a lot of essential ecosystem services; in fact, mountain areas provide numerous ecosystem services (ES), like biodiversity conservation, tourism, climate regulation, freshwater and raw material supply, etc (Daily, 1997; Costanza et al., 1997; Zhang et al., 2024). So it is of particular concern, the degeneration of the Himalayan ecosystem and its fragile landscapes that are particularly prone to natural disasters (Ives and Messerli, 2003), and recurring worry exists regarding the effects of climate change, which may include unusual flood events, dry spells, landslides, loss of biodiversity, and menaces to food production (Upadhyay, 2016). In particular, mountain locations around the world are highly susceptible because of the many hazards to which they are particularly exposed (IPCC, 2022; Wang et al., 2022). In addition, the ecological and economic costs could be high if the region declines or stops providing vital ecosystem services. In this context, the Himalayas are a symbol area of the threats formulated by the IPCC (Rusk et al., 2022) in its Sixth Assessment Report on the rise of landslides, floods, and other associated with climate change (IPCC, 2021), as it is among the most fragile areas susceptible to major incidents. Included in this report are 127 crucial global hazards that could cause severe and adverse situations for ecological and social systems.

The forest-community structure vary in proportion to both natural and anthropogenic factors (Sanjay, 2008). Geographical position, production, genetic competition, and interaction among species are all closely linked with changes in plant communities, richness, diversity, and distribution (Sharma and Sood, 2020). Events that cause disturbances capable of disrupting the ecosystem can radically affect the composition, spatial arrangement, and functioning of forest landscape (He et al., 2021). In this context, sustainable maintenance and security of the mountain ecosystem and its biodiversity are crucial for highland communities to safeguard their sustenance.

In this specific case, dramatic elevation fluctuations in India's temperate Himalayas have led to a particularly distinct pattern of flora types, including temperate forests and grazing lands, moist temperate conifers, and subalpine and alpine meadows. The establishment of sustainable agricultural systems requires the assessment of soil restoration strategies (Singh et al., 2023). Precise predictive evaluation of the spatial distribution of soil heterogeneity is essential for mitigating the effects of intensive agriculture, for enhancing environmental sustainability and, more specifically, the sustainable resource management (Huang et al., 2021). The potential advantages of improving input utilization efficiency, enhancing the financial edges of agricultural production, and lowering environmental hazards have drawn a great deal of attention to tailored management of pH, OC, accessible N, accessible P, and accessible K (Safari et al., 2013; Luthra et al., 2023; Samant et al., 2023). Hence, the understanding of the quantifiable regional spatial fluctuation in these soil attributes is essential for maintaining soil fertility through appropriate soil–plant-environment management methods, efficient land-use management, and interpreting ecosystem functioning. The intricate interplay between land use, geography, topography, and climate are the leading causes of variation in soil characteristics (Reza et al., 2016; Thakur et al., 2023). Land use management practices may also result in unpredictability in their consequences (Safari et al., 2013), with soils that can display noticeable spatial diversity across macro- and micro-levels (Wang et al., 2017). In this perspective, this investigation strives to ascertain the spatial heterogeneity of particular soil attributes, namely OC, pH, EC, N, P, K, Ca, and Mg, for a Jammu region of Indian Himalayas, using classical statistics and geostatistical analysis. By employing both classical statistical methods and advanced geostatistical analysis, the study seeks to comprehensively understand how these soil attributes are distributed across the landscape. Utilization of spatial analysis methods, like variogram modelling and kriging, allows for the creation of detailed spatial heterogeneity maps, which not only reveal the spatial patterns of these soil attributes but also provide insights into the underlying processes driving their spatial distribution. Furthermore, by integrating classical statistical analyses with geostatistical methods the research endeavours to improve the precision and robustness of the spatial predictions, thereby facilitating more informed decision-making in soil management and farming methods. Overall, the investigation aids in a profound comprehension of soil kinetics in the temperate Himalayan region, offering valuable implications for sustainable land use planning, environmental conservation, and agricultural productivity enhancement in this ecologically sensitive area.

1.1. *The utility of geostatistics to implement the sustainable management of agroecosystems*

To successfully implement the sustainable management of agroecosystems the precision agricultural technologies, and the correct application maps for site-specific fertilization must be developed. Soil parameters like pH, OC, accessible N, P, and K can be shown on a regional heterogeneity map, and this spatial information can be useful to reduce fertilizer consumption, costs, and environmental pressure (Wani, 2016). On the other side, geostatistics offers the tools for describing and quantifying spatial variation, using field data for logical interpolation, where variance assessment offers useful details to setup the sampling frequency to gauge a soil characteristic with accuracy. The geostatistical method is employed to estimate the values of soil attributes in areas that have not been studied or have had few taken samples (Yao et al., 2004). Geostatistical approaches by incorporating spatial data into forecasts can enhance maps' prediction and clarity (Lopez-Granados et al., 2002). Therefore, spatial-interpolation-based geostatistical tools can produce heterogeneity maps of soil attributes (Putthividhya and Tanaka, 2012) and, compared to more conventional methods, the geostatistical methods are an useful and affordable tool for mapping soil quality characteristics (Kumar et al., 2016; Saleh, 2018).

In recent years, there has been a substantial escalation in the use of different interpolation methods and geostatistical tools for the conception of spatial heterogeneity maps of soil attributes like pH (Shahbazi et al., 2013), EC (Tripathi et al., 2015), texture (Poggio and Gimona, 2017), macro-and micronutrients (Fonseca et al., 2018), and carbon dynamics (Hounkpatin et al., 2018). Geostatistics provides powerful tools for understanding and modelling the spatial heterogeneity of soil attributes. Geostatistics provide us with statistical estimation of spatial heterogeneity. The process begins with collecting soil samples from various locations within a study area, followed by an exploratory data analysis (EDA) to outline the primary features of the data (Chipres et al., 2009). A key step is variogram analysis, which quantifies the extent of spatial correlation among samples and models the spatial structure of the data. This involves fitting a conceptual framework, like spherical, exponential, or Gaussian, to the empirical variogram. The chosen model is crucial for accurate spatial predictions (Legendre and Legendre, 2012). Kriging, an advanced geostatistical interpolation technique, uses the variogram model to anticipate soil characteristics at untested sites, incorporating both the distance between known points and the spatial correlation structure (Abdel-Rahman et al., 2020). This process generates continuous surfaces that estimate soil property values across the study area, visualized as spatial heterogeneity maps. These maps reveal patterns and trends in soil attributes that are essential for precision agriculture, environmental monitoring, and land management. The accuracy of the maps is validated through cross-validation methods, comparing predicted values with actual measurements to ensure the reliability of the predictions.

2. Materials and methods

2.1. Study area

The study area spans from 32°53′ to 34°21′ N latitude and 75°1′ to 76°47′ E longitude within Kishtwar District, situated in the Indian state of Jammu and Kashmir (J&K UT) (Fig. 1).

The temperate Himalayan region of India has been selected as study area for its unique environmental characteristics and distinct soil properties compared to other regions in the country. This region spans a diverse range of elevations, from low-lying valleys to towering peaks exceeding 7000 m, creating varied topographic and climatic conditions that profoundly influence soil formation and nutrient distribution (Sati and Kumar, 2004). Unlike the tropical climates prevalent in much of India, the temperate climate of the Himalayas affects soil moisture regimes, organic matter decomposition rates, and nutrient availability, shaping distinct soil profiles (Rawat et al., 2020). Moreover, the rich biodiversity of the Himalayan region contributes to unique soil biota and ecosystem functions, further influencing soil health and fertility (Khan et al., 2020). Agricultural practices in the Himalayas are tailored to these environmental conditions and include terraced farming, elevation-specific crop cultivation, and traditional soil management techniques that have evolved over centuries (Amrith and Yu, 2022). Studying soil properties and agricultural practices in this region is crucial for developing strategies to enhance agricultural productivity, promote sustainable land management, and preserve soil health amidst the challenges posed by its rugged terrain and diverse climate.

The area's altitude varies from 900 to 6575 m above typical sea level (m amsl), having a mean altitude of 1107 m (equivalent to 3361 feet), encompassing an area of approximately 773,700 ha. The region of Kishtwar is recognized as the 'Area of Saffron and Sapphire' and boasts abundant forest resources. Kishtwar is encircled by the Anantnag and Doda districts of J&K and also shares its borders with Himachal Pradesh. The mean yearly precipitation in the locality is ~887 mm and the rainfall fluctuates across different areas within the district according to the diverse topography. The area of Kishtwar falls within the temperate climate zone, with a range of minimum and maximum temperatures from −10 °C to 30 °C and an average yearly precipitation of 887.8 mm. The chilliest month is January, having an average high temperature of approximately 6 °C and an average low temperature of about −10 °C. The lowest temperature can occasionally dip below −10 °C, and in the extremely mountainous areas of the region, the minimum temperature can plummet to around −30° to −40 °C. The Kishtwar district has

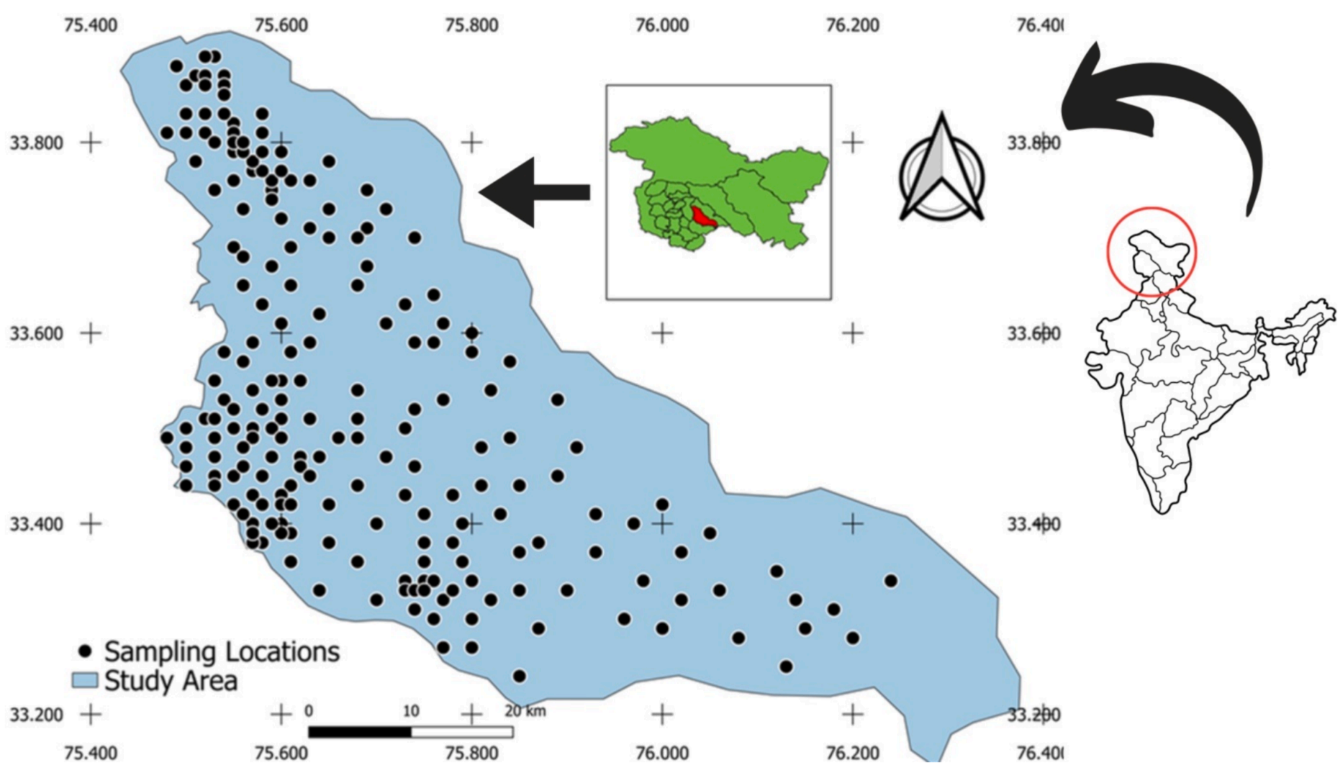

Fig. 1. Study area.

mainly Inceptisols and Entisol soil orders with soil groups like granite, gneiss, and schist and has a sandy clay loam predominant texture. Agriculture is the primary industry and income source within the area. The main agronomic crops are vegetables, pulses, wheat, maize, barley, paddy, and other grains. The major plantation crops in Kishtwar are apple, apricot, plum, pear, peach, and walnut. The region's resources, particularly its forests, soil, and water, are experiencing considerable strain from the growth in the human and cattle populations. Due to the area's mountainous terrain, undulating terrain, fragile ecosystems, weather patterns, and depletion of plant cover owing to extensive grazing, tree cutting, unauthorized logging, and intrusions, land degradation due to soil erosion emerges as a critical concern.

2.2. Collection of soil samples and analysis

A total of two hundred-six (206) soil samples up to a depth of 0–30 cm representing soil attributes and nutrient dynamics were collected. The geo-coordinates were recorded using global positioning system (GPS) across the Kishtwar district of Jammu. The soil samples were gathered during the fall of 2020 using a stratified random sampling approach. Each chosen sampling location was subdivided into smaller sub-sections using a stratified random sampling technique. To accurately depict each location, a systematic sampling system was employed. Soil samples were combined, resulting in a total of three replicates, with each duplicate being comprised of six randomly gathered, combined, and sifted subsamples. After following the designated laboratory procedures, the gathered soil samples underwent air-drying, grinding in a wooden pestle and mortar, and filtering through a 0.5 mm sieve before being examined for the specified soil characteristics. The organic carbon (OC) content of the soil was determined using the wet digestion method (Walkley and Black, 1934). pH levels were measured with a glass electrode pH meter while employing a 1:2.5 soil–water ratio, and the electrical conductivity (EC) was gauged using a conductivity meter (Jackson, 1973) in a 1:2.5 soil–water suspension. Additionally, the available nitrogen (N) was ascertained through the alkaline $KMnO4$ method (Subbaiah, 1956), available phosphorus (P) using 0.5 N $NaHCO3$ (Olsen, 1954), available potassium (K) through neutral 1 N $NH4OAC$ (Schollenberger and Simon, 1945), and available calcium (Ca) and magnesium (Mg) using the versenate method with EDTA (Heald, 1965).

2.3. Classical statistical and geostatistical analysis

R software was utilized to conduct a range of descriptive statistical analyses, encompassing minimum, maximum, mean, median, standard deviation (SD), coefficient of variation (CV), skewness, normality test, and geostatistical analysis for assessing spatial heterogeneity. Shapiro-Wilk test with probability $p \leq 0.05$ was employed to evaluate the normal distribution of the data. The soil parameters' skewness was employed to look for deviations from normality. Positively skewed soil parameters imply that the variances are less reliable because the variograms' confidence limits are broader than they would alternatively exist, whereas negatively skewed soil parameters imply the opposite. No data treatment was favoured because skewness was smaller than 1 for several soil factors (elevation, OC, NDVI, pH, N, P, and K) where, normalized difference vegetation index (NDVI) is among the most ancient remote sensing analytical index, frequently utilized as a metric for appraising vegetation and streamlining the complexity of multi-spectral images (Huang et al., 2021). NDVI acts as a valuable tool for understanding soil-vegetation relationships and assessing the ecological factors influencing soil heterogeneity, as well as the possible combined effects of land-use change and primary productivity (Petrosillo et al., 2013; Petrosillo et al., 2022). NDVI provides information about vegetation health and biomass, acting as a proxy for landscape ecological conditions, which influence soil heterogeneity (Shoshany et al., 2013). In this study, NDVI data are utilized alongside analyses of soil attributes, including pH, EC, OC, and the availability of key nutrients like N, P, K, Ca, and Mg. The NDVI data serve as an indicator of vegetation health and biomass, reflecting the interaction between vegetation cover and soil conditions. By analysing NDVI in conjunction with soil property measurements, the study aims to elucidate the relationship between vegetation dynamics and soil characteristics. Specifically, NDVI may provide insights into areas of vegetation stress or health, which can be correlated with variations in soil attributes like pH, nutrient levels, and organic matter content. This integrated approach between remote sensing techniques and field monitoring allows for a comprehensive assessment of soil-vegetation interactions and provides valuable information for understanding ecosystem dynamics and guiding land management decisions towards the maintenance of ecological functioning and supporting ecosystem services (Fadl et al., 2024). Several studies have shown the relevance of the interplay among soil properties and vegetation traits, which involve plant variety, spatial distribution, and tree dimensions (Chen et al., 2020). Great plant variety boosts soil organic carbon (SOC) accumulation by growing carbon inputs (Lange et al., 2015). Forest diversity can grow productiveness and enhance soil health (Houlahan et al., 2018). Forest structure is linked to earth and atmospheric circumstances (Quesada et al., 2012). For example, varying types of N have important effects on the N cycle of woodland ecosystems, and flora features are strongly linked to soil N and its abundance (Wieder et al., 2015). Soil N is a fundamental nutrient crucial for every existence upon the planet. N is an essential control of organic productivity, soil richness, and additional ecosystem services in forest environments (Stueken et al., 2016). Data transformation was performed in soil parameters like EC, Ca, and Mg where skewness was greater than 1 (Webster and Oliver, 2007). The results of Q-Q plots were used to further analyse the normality of the data distribution. However, due to variations in agricultural land-use patterns, the various soil parameters were not normally distributed. Additionally, a considerable divergence from normalcy was seen in the Shapiro-Wilk test.

The soil parameters under investigation were spatially interpolated using a geostatistical approach termed Ordinary Kriging (OK). By averaging the weights of nearby samples, the widely used geostatistical interpolation approach known as OK forecasts the values of unsurvey locations. OK assumes a stationary mean and calculates weights for neighbouring sample points based on their spatial proximity and similarity in soil properties (Webster and Oliver, 2007). The spatial self-correlation of recorded points is a technique used by OK to interpolate values in the spatial field with distance as a function that is specified by the variogram modelling. Experimental semi-variogram modelling was employed to evaluate the spatial dependence of the investigated soil parameters, as shown below:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(xi) - Z(xi + h)]^2$$

Where γ(h) stands for the experimental semi variance at a specified distance h, and N(h) represents the count of potential pairs of observed points at a designated distance (h), known as the "lag". Z(xi) and Z(xi + h) denote sample values of the variable Z that are spaced apart by distance h (Bohling, 2005).

The nugget effect and nugget (n)/sill ratio were used to estimate the spatial dependence of specific soil parameters. When the n/s ratio is smaller than 0.25, there is a significant dependence. 0.25–0.75 and greater than 0.75, respectively, indicate a moderate and weak dependence (Cambardella et al., 1994).

The data set was randomly and uniformly divided into 10 subsamples of equal size, and the 10-fold cross-validation was used to assess how well the model performed in terms of spatial predictions of soil attributes. Each of the 10 subsamples is used as validation data exactly once during the ten validation cycles. We calculated the MSE for evaluating prediction accuracy (Utset et al. 2002) as shown below:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}[\{Z(xi) - \widehat{Z}(xi)\}]^2$$

N represents the number of samples, Z(xi) denotes the observed value, and Z ̂(xi) signifies the predicted value. The model harbouring the smallest MSE yields the highest accuracy. The spatial distribution of soil properties such as OC, pH, EC and nutrient content (N, P, K, Ca, Mg) was modelled. Consequently, the spherical model was employed for pH, EC, N, P, and Ca, the mathematical model for K, and Mg, and the exponential model for OC. These models were selected on the basis of their ability to fit the variogram structures observed in the dataset, ensuring robust predictions across the study area (Hengl et al., 2004). Parameters such as MSE, RMSE, and the Moran's I index were utilized to assess model accuracy and spatial dependence of interpolated maps. Cross-validation techniques were employed to validate the predictive accuracy of kriging models, ensuring reliable estimation of soil properties at unsampled locations (Goovaerts, 1997).

3. Results

3.1. Classical statistics of soil attributes

The descriptive statistics of soil physicochemical attributes are depicted in Table 1. The elevation of the soil ranged from 1,053 to 4.413 m, OC from 0.13 to 2.80 %, while NDVI ranged from −0.16 to 0.54. The mean values for elevation, OC, and NDVI were 2743.32 m, 1.19 %, and 0.15, with SD values of 667.22, 0.63, and 0.10, respectively. The soil pH in the region had a mean of 6.74, with values for SD and CV being 0.59 and 8.75 %, respectively. The study area's mean EC value was 1.37 dS $m^{-1,}$ with SD and CV being 1.63 and 118.98 %. The lowest and highest measurements for pH and EC were 4.80 and 8.00, 0.03 and 9.80 dS m^{-1}, with the mean EC value being more than 1 dS m^{-1} and having greater than 35 % CV. The minimum and maximum content of N, P, and K were 201.15 and 993.19, 3.00 and 96.00, 124.88 and 1110.71 kg ha^{-1}, whereas Ca and Mg ranged from 7.00 to 46.00 and 2.30 to 21.50 meq 100 g $soil^{-1}$, correspondingly. The average values for N, P, and K, were 414.81, 30.97, and 526.30 kg ha^{-1}, while for Ca and Mg, values were 17.64 and 7.54 meq 100 g $soil^{-1}$ (Table 1). The N, P, K, Ca, and Mg values in the study area had SD and CVs of more than 130 and 30 %, 18 and 59 %, 250 and 45 %, 6 and 38 %, and 2 and 35 %, respectively. The skewness of soil attributes fluctuated from marginally adversely skewed (skewness; −0.37) to highly positively skewed (skewness; 2.57).

3.2. Geostatistical analysis of soil attributes

The spatial diversity of essential soil characteristics in the surveyed region. Geostatistical semi-variogram analysis of the examined soil parameters reveals the spatial arrangement of chosen soil attributes following adjustment to various models (Tables 2, Fig. 2).

The spherical model better-described soil parameters: pH, N, P, and Ca. In contrast, the mathematical model described Ca and Mg, and the exponential model best explained the OC based on the lowest MSE. The nugget, representing the small-scale heterogeneity was found to increase in the order; pH<K<N<Mg < Ca < OC<P<EC. The K recorded the highest (0.24) partial sill, followed by OC (0.18), while the lowest was in EC (−0.65). The spatial dependence expressed through the spectrum of the chosen soil parameters fluctuated greatly from 1,906.96 m (OC) to 34,199.40 m (EC) and surpassing this spectrum showed no evidence of any spatial autocorrelation. Except for EC, N, P, and K, the estimated range values closely matched the sampling range values (1,500–6,500 m). This structure hints at surface similarity or heterogeneity in the soil parameters. The semi-variogram analysis for the soil parameters reflected strong to weak spatial dependence. The level of spatial interdependence (LSI) that indicates the intensity of soil characteristics' spatial reliance varied from 0.06 to 2.81 % (Table 2). The semi-variogram analysis showed that K had a strong spatial dependence (DSD; 25 %), OC, N, P, and Mg had a moderate spatial dependence (DSD; 25 to 75 %), while pH, EC, and Ca had a weak spatial dependence (DSD; > 75 %). The kriging cross-validation method was utilized to assess the predictive precision of the semi-variogram models by considering the minimal MSE, the RMSE and Moran I value. After running the data through several models, the lowest MSE model was chosen (Table 2).

3.3. Spatial distribution of soil attributes

The spatial heterogeneity of cultivated areas was represented through a geostatistical analysis of the soil attributes. The semi-variogram's model parameters were utilized in kriging to produce maps for specific soil attributes (Fig. 3). The north-western area displays elevated spatial distribution, while the southern regions exhibit lower elevation (Fig. 3a). Conversely, the SOC demonstrates an opposite pattern in spatial distribution compared to elevation. The lowest OC values were predicted along the north-western region, whereas the highest ones were found in the southwestern and south-eastern regions (Fig. 3b).

The NDVI was comparably observed to be higher in the north western and southwestern regions than in the north-eastern and south-eastern regions (Fig. 3c). The soil pH was recorded to be near neutral in the north-western and south-eastern regions, while it was slightly acidic in the south-western and north-eastern regions (Fig. 3d). The soil EC was higher in the north-western and south-western regions than in the eastern region of the study zone (Fig. 3e).

Comparatively, higher N content spatial distribution occurred in the northern part, which decreased in content towards the southern terrain (i.e., southwest and southeast) (Fig. 3f). The study area's north-eastern

Table 1
Descriptive statistics of selected soil attributes.

Parameters	Min	Max	Mean	Med.	Std. Dev.	CV (%)	Skew.	Kurt.	Std. Error	Shapiro (P-value)
Elev. (m)	1,053.00	4,413.00	2,743.32	2,790.00	667.22	24.32	−0.28	−0.32	46.38	0.11
OC (%)	0.13	2.80	1.19	1.20	0.63	52.94	0.58	0.00	0.04	0.00
NDVI	−0.16	0.54	0.15	0.14	0.10	66.67	0.33	0.20	0.01	0.03
pH	4.80	8.00	6.74	6.80	0.59	8.75	−0.37	−0.02	0.04	0.02
EC (dS m^{-1})	0.03	9.80	1.37	0.80	1.63	118.98	2.57	7.88	0.11	0.00
N (kg ha^{-1})	201.15	993.19	414.81	396.02	134.65	32.46	0.65	0.50	9.36	0.01
P (kg ha^{-1})	3.00	96.00	30.97	31.00	18.57	59.96	0.75	0.38	1.29	0.02
K (kg ha^{-1})	124.88	1110.71	526.30	512.30	254.58	48.37	0.45	−0.63	17.69	0.00
Ca (meq 100 g $soil^{-1}$)	7.00	46.00	17.64	16.50	6.84	38.78	1.23	1.92	0.48	0.03
Mg (meq 100 g $soil^{-1}$)	2.30	21.50	7.54	7.19	2.90	38.46	1.02	2.53	0.20	0.02

Elev. (m): elevation (meters); OC (%): organic carbon (percentage); NDVI: normalized difference vegetation index; pH: soil pH level; EC (dS m^{-1}): electrical conductivity (deciSiemens per meter); N (kg ha^{-1}): nitrogen (kilograms per hectare); P (kg ha^{-1}): phosphorus (kilograms per hectare); K (kg ha^{-1}): potassium (kilograms per hectare); Ca (meq 100 g $soil^{-1}$): calcium (milliequivalents per 100 g of soil); Mg (meq 100 g $soil^{-1}$): magnesium (milliequivalents per 100 g of soil); Min: minimum; Max: maximum; Mean: mean (average); Med.: median; Std. Dev.: standard deviation; CV (%): coefficient of variation (percentage); Skew.: skewness; Kurt.: kurtosis; Std. Error: standard error; Shapiro (P-value): shapiro–wilk test probability value.

Table 2
Semi-variogram parameters of selected soil attributes.

Parameters	Model	Nugget	Partial Sill	Range	Ratio	Spatial Dependence	MSE	RMSE	Moran I	P-value
OC (%)	Exp	0.09	0.18	1906.96	0.33	Moderate	0.27	0.52	0.33	0.00
pH	Sph	0.01	0.00	5115.07	1.63	Weak	0.38	0.61	−0.03	0.70
EC (dS m^{-1})	Sph	1.00	−0.65	34199.40	2.81	Weak	2.28	1.51	0.18	0.00
N (kg ha^{-1})	Sph	0.03	0.06	18063.09	0.32	Moderate	11227.80	105.96	0.40	0.00
P (kg ha^{-1})	Sph	0.17	0.16	24296.21	0.51	Moderate	226.93	15.06	0.37	0.00
K (kg ha^{-1})	Mat	0.02	0.24	7259.36	0.06	Strong	34422.70	185.53	0.50	0.00
Ca (meq 100 g soil^{-1})	Sph	0.06	0.00	4420.16	1.05	Weak	44.62	6.68	−0.02	0.68
Mg (meq 100 g soil^{-1})	Mat	0.04	0.06	6231.39	0.38	Moderate	4.92	2.21	0.41	0.00

OC (%): organic carbon (percentage); pH: soil pH level; EC (dS m^{-1}): electrical conductivity (deciSiemens per meter); N (kg ha^{-1}): nitrogen (kilograms per hectare); P (kg ha^{-1}): phosphorus (kilograms per hectare); K (kg ha^{-1}): potassium (kilograms per hectare); Ca (meq 100 g soil^{-1}): calcium (milliequivalents per 100 g of soil); Mg (meq 100 g soil^{-1}): magnesium (milliequivalents per 100 g of soil); Exp: exponential model; Sph: spherical model; Mat: matérn model (mathematical); Model: model; Nugget: nugget effect; Partial Sill: partial sill; Range: range; Ratio: nugget to sill ratio; Spatial Dependence: spatial dependence; MSE: mean square error; RMSE: root mean square error; Moran I: Moran's I index; P-value: probability value.

part is relatively higher in P than the north-western. However, the southwestern part has more P content than the south-eastern (Fig. 3g), and a similar trend in the spatial pattern of K was observed (Fig. 3h). Ca was found to be higher in the northeast and southwest part of the study area (Fig. 3i), whereas Mg was higher north-western area (Fig. 3l).

4. Discussion

Spatial variability of elevation reveals lower altitude on southern side and highest elevation on western side, and across the study area elevation varied randomly with high variability within the study area. Soil organic carbon (SOC) resulted lowest from northern side, while higher amount of SOC was recorded in the western side of study area. Alkaline pH was recorded in the northern side of study area, while acidic pH was recorded in the southern side of study area. EC was highest on western side of study area. Nitrogen varied across the study area, while P and K was highest in the western side and in the southern side varying randomly. Relative to the average OC content of cultivated soils in Jammu and Kashmir, respectively, which is 0.69 % and 0.85 %, the soils in the present study is relatively rich in OC within the region as demonstrated also in other studies (Bangroo et al., 2021; Tagore et al., 2014). The majority of the studied region showed significant levels of OC, with the average being greater than 0.5 % and 1.0 %, considering it as the medium range. In particular, the study area showed a mean OC content of 1.19 %, which indicates richer organic matter in the Himalayan soils, similar to findings by Sharma and Sood (2020), who noted higher OC levels in mountainous regions. As a result, they continue to be able to provide important nutrients through organically bound mediums. Because of the region's mountainous geography, maintaining the status of organic matter proves challenging; consequently, it is essential to utilize organic fertilizers frequently to make up for the topsoil erosion that the area frequently experiences (Babu et al., 2020a; Singh et al., 2021, Das et al., 2022). The soil within the examined region was strongly acidic to slightly alkaline with slightly saline EC. Studies in similar regions by Suri et al. (2013) and Sharma et al. (2023) found that the soil pH were similar in range that affected crop suitability and nutrient availability. Our findings suggest that soil pH is advantageous for planting different agricultural commodities because multi-diverse agronomical crops thrive in different environments that are acidic to slightly alkaline. Numerous studies have found that agricultural practices profoundly impact the changes in soil attributes in agroecosystems (Tong et al., 2017; Wang et al., 2019; Xiao et al., 2020; Babu et al., 2020b; Kousalya et al., 2024). Sustainable agricultural management could have a higher impact on soil organic matter than natural drivers, like climate and soil, soil texture, pH, etc. (Guo et al., 2017; Yadav et al., 2021, 2023; Babu et al., 2023).

The area's mean EC value was considerably higher than 1 dS m^{-1}, which must be below 0.8 dS m^{-1} for all crops to be within safer limits (Richards, 1954). The mean EC value of 1.37 dS m^{-1} in our study, indicates slightly saline conditions, aligns with findings in other mountainous regions where EC levels influence soil salinity management practices (Gupta et al., 2018; Yadav et al., 2021). The EC>1 dS m^{-1} demonstrates an inconsistent balance of the soil status that promotes both plant growth and microbial niche. Saline conditions in the study area can impact crucial microbial processes like N cycling, the production of nitrous and other N oxide gases, breathing, and breakdown. Communities of roundworms that parasitize vegetation may also rise, and N losses may increase (Smith and Doran, 1996). The N in the soils ranged from medium to high, and in some areas, it was highest; this could be attributed to higher levels of OC. Our findings concurred well with those of Wani (2016). The soil P ranged from low to high, with most of the area having medium P levels. This might be related to beneficial soil reactions, the production of organo-phosphate complexes, and the encapsulation of iron and aluminium particles by humus (Rao et al., 2008). The soil K had high availability levels. Our findings are consistent with nutrient distribution patterns observed in other temperate regions influenced by topography and agricultural practices (Li et al., 2021; Su et al., 2024). The illitic nature of these soils, further corroborated by the predominance of illitic clay in these soils, could cause increased K values across the region (Thangasamy et al., 2005). The median of a few soil attributes (NDVI, EC, N, K, Ca, and Mg) was lower than its mean, showing anomalous data did not significantly impact the sample value. The most frequent type of deviation from normalcy is skewness. Positive skewness causes the confidence bounds on the variogram to be wider than they otherwise would be, making the variances less dependable. When the skewness coefficient surpasses 1, necessitating a logarithmic conversion (Webster and Oliver, 2007). According to Hillel's (2003) standards, the CV collectively shows the range of soil attributes, from low to high values. The lowest findings were for soil pH (8.75 %), and the largest CV variation was recorded in EC (118.98 %). The undulating nature of the topography and inconsistent land management practices with deteriorated soil organic matter is to blame for this changeability, which results in observable differences in soil (Tesfaye et al., 2022). Based on a study of Wilding (1985) classification of heterogeneity, which places least, moderate, and most as having a CV of < 15 %, 15–35 %, and > 35 %, respectively, the CV was selected to test the data for heterogeneity. The lowest heterogeneity was exhibited by soil pH, with moderate heterogeneity by elevation, N, while the remaining soil characteristics had greater heterogeneity. Comparable CV figures were revealed by Kalambukattu et al., (2018) and Sharma and Sood (2020).

Knowledge of the spatial heterogeneity of soil attributes and the spatial distribution of those attributes is essential for conserving natural resources, fostering input efficiency, and environmental stewardship for the cultivation areas in the Kishtwar district (Carrow et al., 2010). The spherical model provided the greatest fit to the current investigation's semi-variograms of most soil parameters. This model is among the common models employed in the investigation of soil attributes (Bhatti et al., 1991; Goovaerts, 1998). Typically, nugget represents

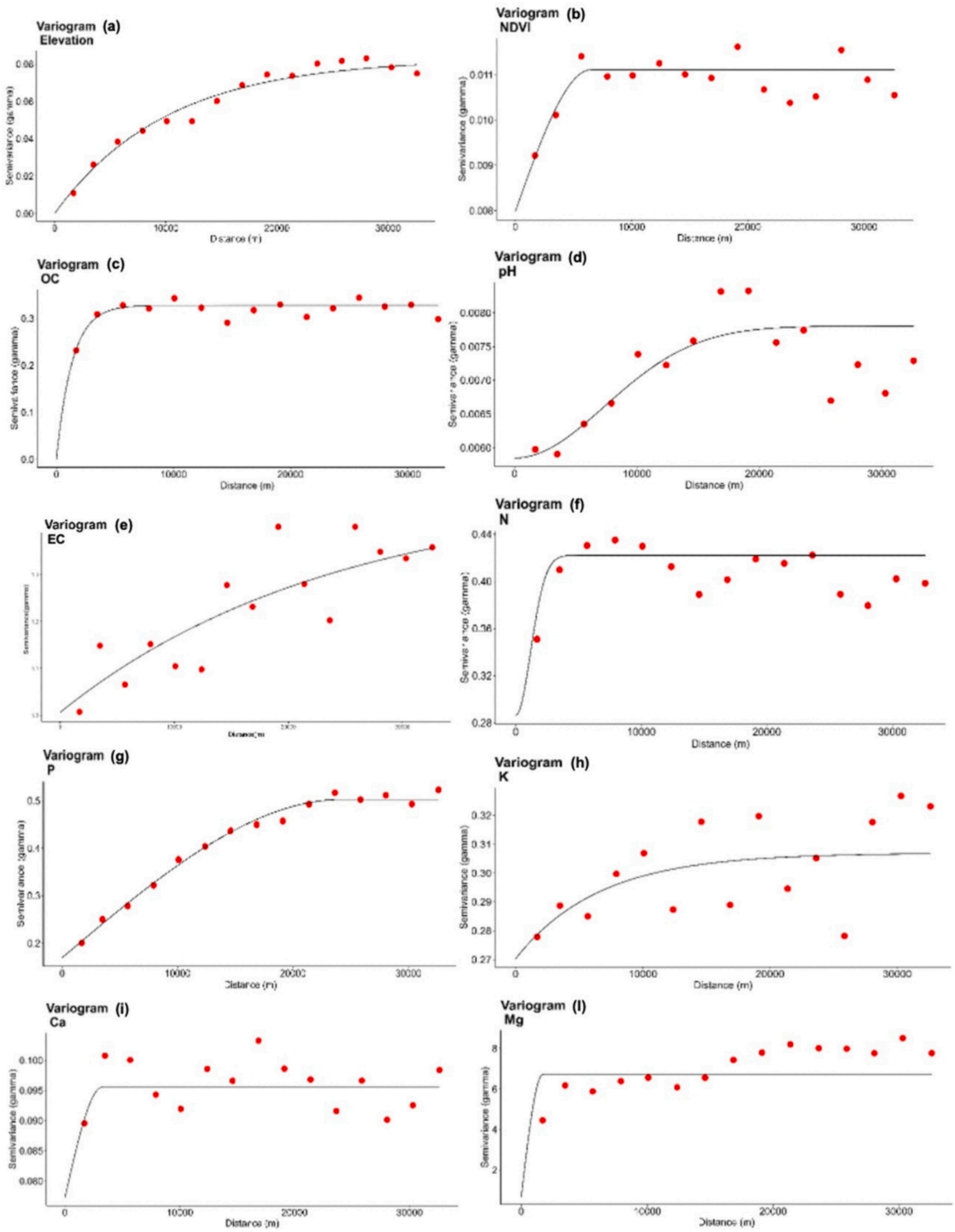

Fig. 2. Semi-variograms and fitted models for the Elevation (a), NDVI (b), Organic Carbon (OC) (c), pH level (d), Soil Electrical Conductivity (EC) (e), Nitrogen (N) (f), Phosphorus (P) (g), Potassium K (h), Calcium (Ca) (i), and Magnesium (Mg) (l).

heterogeneity brought on by experimental error or a smaller sampling scale. A greater nugget value indicates that a particular lower-scale process cannot be disregarded. The overall marginally positive nugget effects OC=0.09, pH=0.01, N=0.03, P=0.17, K=0.02, Ca = 0.06, and Mg = 0.04 could be a result of the intrinsic unpredictability and sampling error brought on by the differences in topography, slope, and aspect. In contrast to the other attributes, the lowest nugget value for soil pH implies that the chosen sampling distance performed well in capturing spatial dependence. It was observed that EC had the highest nugget value. This suggests that EC had significant spatial variation over a wider range. The sampling interval ought to be shorter than half the semi-variogram span, according to (Bogunovic et al., 2017). The partial sill represents the spatial correlation structure that depicts the amount of variation. Partial sill in the semi-variogram model is the distinction between the nugget and the sill. The term "range" in modelling pertains to the maximum distance at which measured values are associated in a semi-variogram. When determining the sampling frequency and design for mapping soil parameters, the range could be a useful tool (Awal et al., 2019). When compared to soil attributes with larger ranges, a small range means that the observed soil characteristic is further influenced by environmental and land management variables across small distances (Zhang et al., 2014). A study by Lal (2010), highlights that soil attributes, like pH, OC, and nutrient content, are highly responsive to variations in environmental conditions, including climate, vegetation cover, and land use practices. These factors influence soil processes, like nutrient cycling, soil organic matter decomposition, and soil erosion,

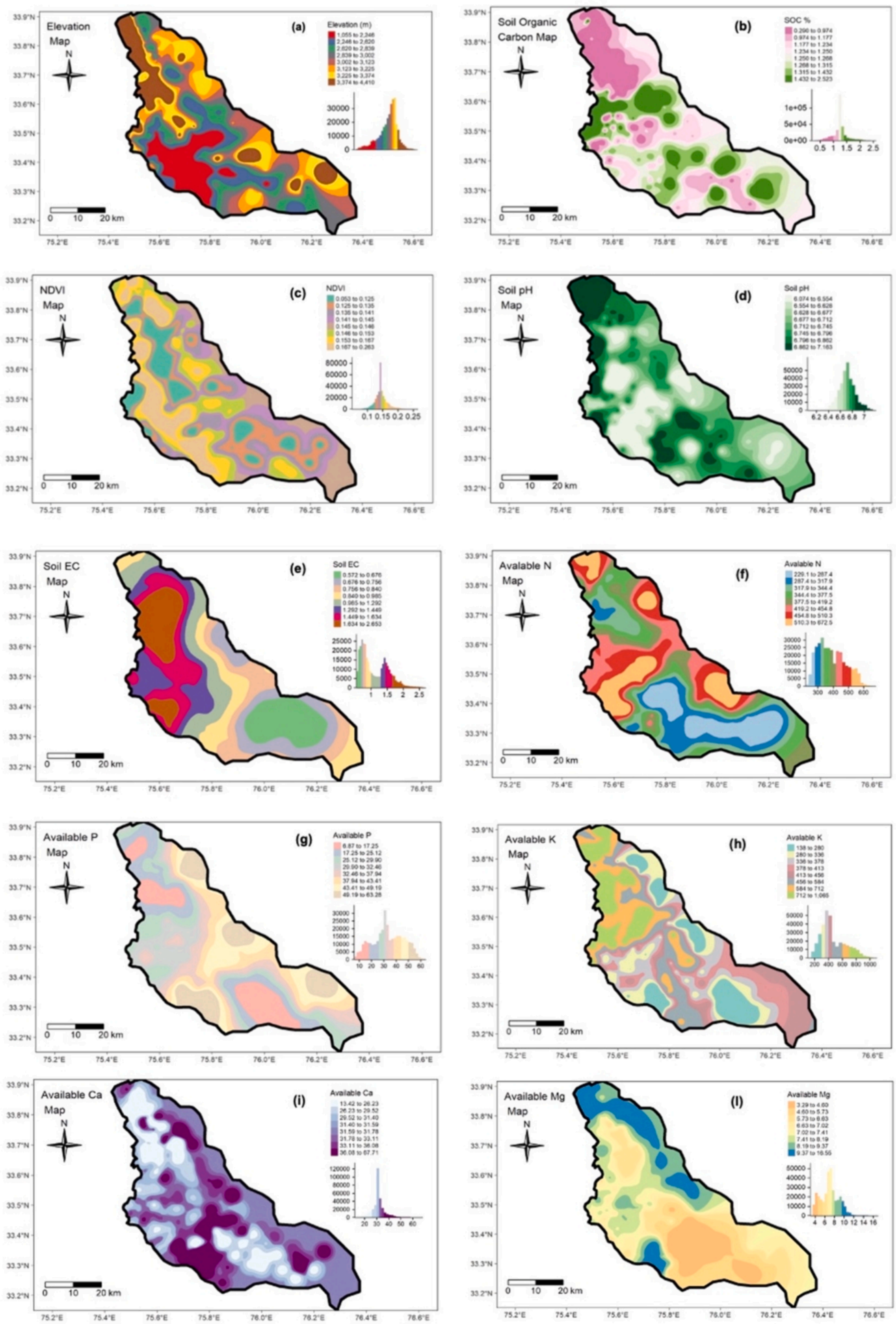

Fig. 3. Prediction map of Elevation in m (a), Soil Organic Carbon (SOC) in percentage (b), NDVI (c), Soil pH level (d), Soil Electrical Conductivity (EC) in deci-Siemens per meter (e), Nitrogen (N) in kg ha^{-1} (f), Phosphorus (P) in kg ha^{-1} (g), Potassium (K) in kg ha^{-1} (h), Calcium (Ca) in meq 100 g soil^{-1} (i), and Magnesium (Mg) in meq 100 g soil^{-1} (l).

which ultimately shape soil attributes over small spatial scales. Similarly, Viscarra Rossel et al. (2006) and Arrouays et al. (2006) demonstrate that soil attributes exhibit significant spatial heterogeneity at fine spatial scales due to the heterogeneity of environmental factors and land management practices. Variations in soil attributes over short distances reflect the intricate interactions between soil formation processes, landscape characteristics, and anthropogenic activities. The work of Guo and Gifford (2002) and Lal (2004) emphasizes that land management practices, like tillage, irrigation, fertilization, and land use changes, can have localized effects on soil attributes. These practices alter soil structure, nutrient availability, and microbial activity, leading to spatially heterogeneous soil attributes, particularly in agricultural landscapes.

This suggests that in contrast to soil Ca and Mg, which have smaller ranges, measured values for soil N and P, which have larger ranges of roughly 18,063.09 m and 24,296.21 m, respectively, are influenced by nearby values over larger distances. Thus, soils having smaller ranges are considered to vary widely. Compared to soil attributes with lower ranges, large-range values show that measured soil attributes are affected by natural and anthropogenic causes over larger distances (Lopez-Granados et al., 2002). Also, the discrepancies in the ranges could be brought on by variations in the parent material's impedance, slope and aspect, cation exchange capacity, and fluctuation in topography, erodibility, land management practices, and particle size distribution (Opolot et al., 2015; Rabia et al., 2022; Yadav et al., 2023). Comparable outcomes reflecting significant discrepancies in soil ranges attributes were also reported. For instance, Behera et al. (2018) found the ranges of 11,129 and 10,727 m for available P and K. DSD larger than 75 % indicates a lack of spatial dependence, and the sampling strategy is inappropriate for determining the variance in the process. Weak dependency implies that data heterogeneity comprises random, limited distance variation and that the measurement technique is consequently unsuitable for describing soil heterogeneity. The soil attributes revealing moderate DSD could be governed by external factors differential fertilizer rates, land-management methods, and tillage operations. In contrast, soil parameters like K showing strong DSD may be managed by intrinsic soil factors like clay minerology and soil separate sizes. The weak DSD in Ca may be due to external variables like fertilization and the redistribution of rainfall caused by the canopy differences with topography (Liu et al., 2015). Our findings are in line with those of Sharma and Sood (2020). The low MSE values suggest that kriging soil property predictions align with actual values. Therefore, by producing prediction maps, the interpolation procedure could be useful for site-specific and soil-crop management (Shaddad et al., 2016; Kersebaum and Wallor, 2023).

The northwest and southwest regions of the research zone possessed the highest levels of soil attributes, which fell in levels toward the eastern side, according to the predicted maps. The difference in the elevation is due to pedogenic processes along with weathering of rock and heterogeneity in parent material present in the region (Brimhall et al., 1991). Low values of OC in the north-western region may be due to more significant erosion loss due to intensive tillage practices, less retained soil organic matter, and crop removal during harvesting season (Jin et al., 2021). High NDVI in the north-western and south-western regions may be due to greater plant, crop, and tree densities compared to the eastern part as an incidence of different wave-length reflectance. The differences in soil pH may be ascribed to variations in the added matter to the cultivated soil, like different chemical fertilizers and the addition of organics in different localities (Ozlu and Kumar, 2018). The variation in EC across the region could be due to crop type, rainfall intensity, land-use pattern, and chemical fertilizers (Assefa et al., 2020). It may also differ due to intrinsic factors like unalterable soil minerals, climate, and soil texture. When determining the spatial visual trend and measuring the heterogeneity rate at the farm-scale level for sustainable management, such knowledge about the spatial structure and distribution of soil attributes is essential. The heterogeneity of soil attributes spatially might be ascribed to various factors (Iqbal et al., 2005). In addition to intrinsic soil attributes, agricultural practices with less input (Metwally et al., 2019; Kundu et al., 2023), tillage systems (Xue et al., 2015), organic incorporation and cropping systems (McCormack et al., 2013) could be the sources of heterogeneity. Nevertheless, more research is necessary to clarify the governing variables for spatial heterogeneity in this study area in the future. The spatial investigation of important soil attributes, which may in the future be contrasted on a time scale for enhancing decision support and management strategies, is one of the study's significant advantages. This makes it possible to locate problem areas quickly and set priorities for site-specific management. Therefore, the spatial heterogeneity of surface soil attributes may be used as a land management indicator for cultivated areas in the north-eastern part of Jammu.

5. Conclusions

Effective land use, management and environmental policies increasingly rely on comprehensive soil data to improve understanding and management of landscapes (Grealish et al., 2015; Brungard et al., 2015). The analysis of soil spatial characteristics integrated with data from remote sensing (NDVI) can help in assessing the agricultural landscape capacity to provide ecosystem services (ES) from global to local (Zurlini et al., 2014), therefore these data are essential for informed landscape management (Gogoi et al., 2021; Jones et al., 2013) and to foster their adaptive capacity and sustainability (Zurlini et al., 2013). Soil maps play a crucial role in implementing this knowledge, highlighting spatial distribution patterns and contributing to soil conservation and sustainable environmental modelling (Yaalon, 1989). Accurate mapping of soil attributes at different scales is crucial for effective resource management and long-term sustainability efforts. Precise nutrient management and variable fertilisation rates are essential to optimise agricultural productivity, including crops such as vegetables, pulses and maize. The study identified significant variability in soil parameters in the region, therefore, sustainable nutrient management practices are essential to maintain soil fertility and crop productivity. The spatial analysis revealed different patterns of soil distribution, emphasising the need for site-specific management approaches to optimise resource use efficiency and minimise environmental impacts. Spherical and exponential models for pH, N, P, Ca and Mg highlight the different spatial relationships, guiding precision farming practices for sustainable crop production. The study emphasises the crucial need for tailored soil management strategies to achieve sustainable agriculture in the Himalayan region. It revealed substantial variability in soil parameters, such as nutrient content, pH levels and spatial distribution patterns, which are critical for optimising agricultural productivity and ensuring long-term soil health and sustainability. This study demonstrates the ability of remote sensing and GIS techniques integrated with geospatial statistics to improve sustainable land use in the Himalayan region, emphasising their utility for monitoring and spatially explicit assessment of soil properties at the landscape scale, with a focus on the ecological characteristics of the ecosystems under study. GIS technologies allow for integrated and spatially comprehensive processing of multiple variables simultaneously, which enables the identification and analysis of spatial inhomogeneity and key factors in the ecosystems under study.

Despite these insights, the study recognises the limitations inherent in studying heterogeneous natural systems and the complexities associated with scaling results to larger regional contexts. Future research should prioritise the study of temporal variations in soil properties, the integration of holistic soil management practices, and the resolution of scalability issues to improve the resilience of soils and ecosystems by adding geospatial tools to support accurate soil management. By addressing these challenges, future studies can provide more robust recommendations for effective soil conservation and sustainable agricultural practices in different environmental contexts. The spatial variability maps produced using ordinary kriging will serve as a basis for future research. Hilly areas are very difficult to assess and the estimation of soil nutrients is difficult. Predictions based on gesostatistical modelling will further improve site-specific nutrient management and drastically reduce crop production costs and environmental impacts.

CRediT authorship contribution statement

Owais Ali Wani: Writing – original draft, Methodology, Investigation, Data curation. **Vikas Sharma:** Software, Resources, Project administration. **Shamal Shasang Kumar:** Writing – review & editing, Software. **Ab. Raouf Malik:** Writing – review & editing. **Aastika Pandey:** Writing – review & editing, Software. **Khushboo Devi:** Writing – review & editing, Software. **Vipin Kumar:** Writing – review & editing, Resources. **Ananya Gairola:** Writing – review & editing. **Devideen Yadav:** Writing – review & editing. **Donatella Valente:** Writing – review & editing. **Irene Petrosillo:** Writing – review & editing, Writing – original draft. **Subhash Babu:** Writing – review & editing, Writing – original draft, Resources, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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