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Evaluating the Spatial Variability of Soil Physicochemical Characteristics in an Indian Lesser-Himalayan Region

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ABSTRACT: The utilisation of digital soil mapping has gained significant traction in the scientific community to construct statistical models that elucidate the intricate connections between environmental factors and soil characteristics. A comprehensive understanding of the inherent spatial variability of soil physical and chemical properties is imperative to enhance the precision and effectiveness of site-specific soil nutrient management strategies. In this research endeavour, we explored the multifaceted domain of spatial variability of a wide range of soil physical and chemical properties, including pH levels, organic carbon content, and available nitrogen, phosphorus, potassium, and sulphur across diverse geographical locations within the Baramulla district. Soil samples were carefully collected from a depth of 0-15 cm, employing a randomized sampling technique with the aid of GPS technology, ensuring precise geospatial coordinates were recorded for each of the 120 sampling locations. The statistical analysis conducted on soil properties revealed that the pH levels exhibit a relatively low coefficient of variation (CV), measuring less than 15%. On the other hand, organic carbon, nitrogen, phosphorus, potassium, and sulphur display a substantial coefficient of variation, surpassing 20%. Although there has been a rise in the use of probabilistic and statistical analysis, there are still several obstacles to overcome when it comes to integrating the spatial variability inherent in soil parameters into prediction analysis. The geostatistical interpolation technique has successfully revealed a moderate spatial variability in the levels of pH, organic carbon, phosphorus, potassium, and sulphur. Additionally, it has indicated a weaker spatial variability in the levels of nitrogen. The soil variables were subjected to fitting models such as Exponential (N and K), Spherical (OC), and Gaussian (pH, P_2O_5, Sulphur) to analyse their semivariograms. This study demonstrates the versatility of the framework in analysing soil parameters throughout a wide range of variability, from low to high. These cartographic representations enable agricultural practitioners to evaluate the prevailing soil conditions on their farms, facilitating streamlined and optimised decision-making processes. This, in turn, contributes to the preservation of productivity sustainability while ensuring enhanced operational efficiency.

Keywords: Soil mapping, Geostatistics, Interpolation, Semivariogram, site-specific soil nutrient management.

INTRODUCTION

The significance of soil as the fundamental basis for life and biodiversity cannot be overstated, as its overall quality has a direct impact on crucial processes such as nutrient cycling and the well-being of human populations (Fitter *et al.*, 2005; Bogunović *et al.*, 2017). Sustainable soil management, when coupled with a comprehensive comprehension of soil properties, has the potential to enhance both food quality and security (Brevik and Sauer 2015). Additionally, it plays a crucial role in preserving or enhancing soil fertility levels and mitigating the widespread issue of soil degradation, which has global implications (Thapa and Yila 2012; Zhao *et al.*, 2013). In recent decades, the agricultural sector has witnessed the implementation of soil management practices that are deemed unsustainable. These practices have resulted in a range of detrimental effects on soil quality, leading to significant soil degradation. The consequences of such degradation are far-reaching, particularly in terms of soil productivity.

This issue has been extensively studied and documented by researchers such as Nawaz *et al.* (2013) and Keesstra *et al.* (2016). Soil degradation processes primarily arise from the synergistic effects of various factors, including parent material, climate, physical, chemical, and biological processes occurring within the soil, as well as human and animal activities (Goovaerts 1998; Ji *et al.*, 2006). Moreover, it is important to note that soil degradation can significantly influence the capacity of soil to sustain its crop cultivation capabilities. Hence, it is imperative to acquire knowledge about the existing state of soil properties and the precise measurements of the impact of different factors on soil properties. This knowledge serves as a fundamental requirement for making informed decisions regarding soil management, with the ultimate goal of ensuring the sustainable utilisation of soil resources (Plant 2001; McBratney *et al.*, 2014). In order to effectively implement sustainable soil management practices, it is imperative to possess a comprehensive understanding of the spatial distribution of soil properties. This knowledge allows for the identification of specific areas that necessitate intervention, as well as the determination of the appropriate level of intervention required (Behera *et al.*, 2018).

The spatial characterization of soil properties necessitates the examination of numerous interconnected field data, which can be acquired through a range of direct and indirect techniques. These methods encompass sampling and chemical analysis, proximal and remote sensing, as well as geophysical approaches (Bogunović *et al.*, 2017). The field data that is gathered frequently yields intricate multivariate data sets in terms of both spatial and temporal dimensions. These data sets often exhibit varying coverage rates and spatial densities. To enhance the comprehensiveness and perceptibility of the data sets, it is imperative to employ resilient spatial statistical techniques (Trevisani and Fabbri 2010; Vasu *et al.*, 2017; Behera *et al.*, 2018). The application of geostatistical methodologies in the field of soil sciences has a rich and extensive history. The geostatistical methodology, utilising the family of best linear unbiased interpolators commonly referred to as "kriging", presents a diverse range of mapping techniques. The assessment of spatial and temporal variations of soil properties can be effectively conducted by employing tools that take into account autocorrelation and random variation components. This approach enables the generation of maps depicting the spatial distribution of the studied soil property, while also providing an assessment of the associated uncertainty. Notable studies in this field include those conducted by Bogunović *et al.* (2014), Pereira *et al.* (2015), and Rosemary *et al.* (2017) Geostatistical techniques have been employed in numerous investigations to examine the spatial heterogeneity of soil properties such as pH (Bogunović *et al.*, 2014; Zhang *et al.*, 2018), organic matter content (Byrne and Yang 2016), phosphorus levels (Behera *et al.*, 2016; Wilson *et al.*, 2016), and potassium concentrations (Bogunović *et al.*, 2014; Behera and Shukla 2015). Furthermore, it is worth noting that geostatistical methods have been utilised in the context of site-specific management of plant nutrients (Fraisse *et al.*, 2001; Moshia *et al.*, 2014) as well as in the realm of process-based land use planning and environmental modelling (Oliver 2010). By employing geostatistical techniques, researchers can generate estimations that exhibit enhanced accuracy while simultaneously minimising the associated error. Geo-statistics is a field of study that focuses on the examination of variables that exhibit spatial structure or possess a continuous spatial distribution. One of the fundamental principles in the field of geo-statistics is that the degree of similarity between samples tends to decrease as the distance between them increases (Isaaks and Srivastava 1989; Goovaerts 1997). According to Kresic (1997) findings, the geostatistics technique emerges as the most reliable, robust, and comprehensive approach for interpolation. Kresic (1997) acknowledged that geostatistics is a strategic method that takes into account the spatial variability, location, and distribution of samples. Based on recent scientific investigations and the establishment of a spatial connection between soil characteristics and plant distribution in various ecosystems, it has been determined that understanding the spatial variability of soil properties is crucial for practical applications and the advancement of modelling techniques (Sovik and Aagaard 2003). The present study aimed to examine the spatial variability of soil physicochemical characteristics within the Baramulla agroecosystem, located in the lesser Himalayas.

MATERIALS AND METHODS

A. Study Area

The focused region under investigation encompasses the Baramulla district, situated within the esteemed union territory of Jammu and Kashmir. The geographical coordinates of the specified area correspond to a latitude of 34.1595°N and a longitude of 74.3587°E. Baramulla, situated at an elevation of 1593 metres above mean sea level, encompasses a land area spanning 2398 hectares. The climatic conditions prevailing in the region are characterised by a temperate climate, exhibiting mild summers and cold winters. The average annual maximum temperature recorded stands at 30°C, while the minimum temperature hovers around 18°C. Furthermore, the area experiences an average yearly precipitation of approximately 710 mm.

B. Sampling

The samples were collected in a systematic manner utilising the Randomised Grid Sampling technique from diverse locations situated within the Baramulla district. The selection of sampling points was conducted strategically, employing the use of a Geographical Positioning System (GPS) to augment the accuracy and precision of the sampling process in field studies. To ensure a comprehensive and unbiased sampling approach, a systematic randomised grid design was implemented in the selection process of 120 sites. The widely recognised Geographic Information System (GIS) software, ArcGIS, was utilised to facilitate this procedure. The selection of these sites was conducted with meticulous care, taking into consideration a depth range spanning from 0 to 20 centimetres. This deliberate approach was employed to guarantee a comprehensive and all-encompassing representation of the study area. The UTM coordinates of the soil samples were carefully recorded to facilitate their utilisation in the spatial analysis of soil characteristics.

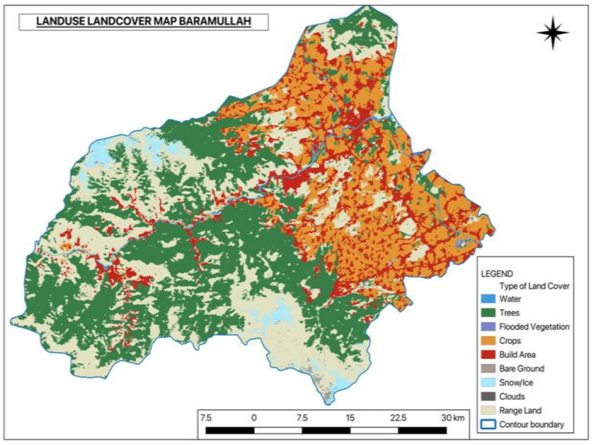


Fig. 1. Land-use land cover map of the Study Area.

C. Laboratory Analysis

The samples underwent a process of air-drying and subsequent passage through a 2 mm sieve to adequately prepare them for subsequent analysis. The pH measurement was conducted using a pH meter with a soil-to-water ratio of 1:2.5. The quantification of soil organic matter (OM) was conducted using the modified Walkley–Black method (Nelson and Sommers 1983). The determination of available phosphorus (AP) was conducted using Olsen's method (Olsen and Sommers,1982). The extraction of available potassium (AK) was conducted using a solution of 1 mol/L NH_4Ac (International Soil Science and Conservation Agricultural Society (ISSCAS) in 1978). Subsequently, the concentration of potassium was determined using an atomic absorption spectrometer. The measurement of available nitrogen (AN) was conducted using the Alkaline $KMnO_4$ method (Subbiah and Asija 1956). The determination of available sulphur was conducted using the turbidimetric method (Chesnin and Yien 1951). The methodology employed in this study is visually depicted in the subsequent flowchart.

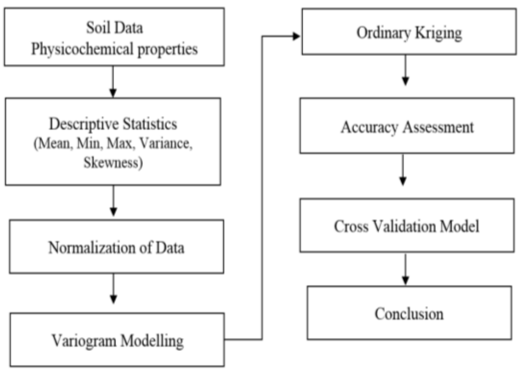


Fig. 2. Methodology employed in this study

D. Geostatistical Analysis

The investigation of soil properties involved the examination of their spatial and temporal variation, which was regarded as a stochastic process. The efficacy of geostatistics as a means of investigating the spatial variability and patterns of soil properties has been demonstrated by Wang (1999). Geostatistics is a scientific discipline that revolves around the analysis of spatial correlation among samples. This correlation is quantitatively represented by a mathematical construct known as a "variogram". The variogram, in the context of spatial analysis, is a mathematical function that characterises the spatial variability of a given variable. It is commonly defined using the following formula:

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

The variable N(h) represents the count of sample pairs that exhibit a specific spatial separation distance, denoted as h. Z (xi) and Z (xi+ h) represent the values of a regionalized variable at two distinct locations, namely xi and xi+ h, respectively.

The semivariogram, denoted as γ(h), is a measure that characterises the spatial dependence of attribute values within a given dataset. It is mathematically defined as one-half of the variance of the differences between attribute values at all pairs of points that are separated by a distance h. The semivariograms were analysed using four variogram models, namely spherical, exponential, linear, and Gaussian. The model that provided the best fit was determined based on the criteria of minimising the residual sum of squares (RSS) and maximising the coefficient of determination (R^2) between the predicted variances and the observed variances.

Following the computation of the variogram, it becomes imperative to proceed with the fitting of a theoretical model. This step is crucial to facilitate the process of generalising deductions and estimating variables from unsampled points. The Kriging method was employed for spatial interpolation and spatial mapping of soil characteristics. The Kriging method, in essence, is a statistical estimator that assigns statistical weights to individual observations. This weighting process aims to ensure that the resulting linear structure is unbiased and possesses the minimum possible estimation variance. The estimator under consideration exhibits a notable degree of applicability owing to its ability to minimise error variance while simultaneously providing unbiased estimation, as highlighted by Pohlmann in 1993.

$$Z^*(X_o) = \sum_{i=0}^{N} \lambda i Z(X_i)$$

The estimated variable at location Xo, denoted as Z*(Xo), represents the values of the investigated variable at location Xi. The statistical weight, λi, is assigned to the sample Z(Xi) which is located near Xo. The variable N represents the total count of observations within the vicinity of the estimated point. The accuracy assessment of interpolation was conducted through the utilisation of cross-validation methods, as outlined by Goovaerts in 1997. The geo-statistical analysis in this study was conducted using the software package ArcGIS version 10.5.

RESULTS AND DISCUSSION

The summary statistics of soil characteristics are presented in Table 1. The coefficient of variation is a statistical measure utilised to express the relative magnitude of variability in a dataset. It is commonly employed to assess the degree of dispersion or spread to the mean value. Among the variables that were examined, it was found that organic carbon had the highest coefficient of variation, which amounted to 46.69%. The obtained outcome aligns with the findings reported by Delbari *et al.* (2019) in their research study. The coefficient of variation for pH was observed to be the lowest at 5.05%. This finding suggests that the pH values in the region exhibited a high degree of uniformity. This uniformity may be attributed to the consistent conditions prevailing in the area, including minimal variations in slope and direction, which likely contributed to the homogeneity of the soil in this particular region. Similar findings were also reported by Cambardella *et al.* (1994), Tagore *et al.* (2014).

Table 2 and Fig. 3 presents the semivariogram model and a selection of geostatistical parameters of soil chemical properties. The selection of theoretical semivariogram models for achieving a significant fit of soil chemical properties is determined by the lowest root mean square error (RMSE) (Robertson 1998). The semivariogram analysis of nitrogen and potassium revealed that an exponential model exhibited the most optimal fit. The utilisation of the spherical model yielded the most optimal alignment with the semivariogram to the organic carbon (OC%), while the Gaussian model exhibited the most favourable conformity with the semivariogram associated with pH, phosphorus and sulphur. Numerous research studies have indicated that the exponential model exhibits the highest suitability in evaluating the spatial heterogeneity of soil chemical properties (Reza *et al.* 2010; Venteris *et al.,* 2014). This preference is primarily attributed to its ability to effectively account for the maximum variability observed within the spatial dataset (Lark 2000; Tripathi *et al.,* 2015). Plotted variograms on 0°, 45°, and 135° directions for all soil variables and found uniform effective range and sill, no anisotropy, and isotropic soil features (Fig. 3 and Fig. 4). This illustrates that variables vary equally in both directions and fluctuate with sample distance (Mohammadzamani and Auubi 2007). The nugget-sill ratio (C_0/C_0+C) shows spatial autocorrelation. The geographical dependency of the variable is strong if the ratio is below 25%, moderate if it is 25–75%, and weak if it is >75% (Cambardella *et al.*, 1994). In the designated study area, it was observed that the spatial dependence of soil characteristics exhibited variations. The spatial dependence of nitrogen was found to be weak, as indicated by the R^2 value of <0.50 (Vasu *et al.,* 2017). The pH, organic carbon, nitrogen, phosphorus, potassium and sulphur, levels exhibited a moderate range, aligning with the findings presented in the research conducted by Cambardella *et al.* (1994).

Table 1: Study area soil property statistics.

Soil Properties	Units	Mean	SD	Skewness	Kurtosis	CV %
pH	-log [H^+]	6.94	0.35	-0.22	-0.58	5.05
Organic Carbon	%	1.25	0.58	0.77	-0.63	46.69
Av. Nitrogen	kg ha^{-1}	325.28	64.09	0.55	-0.82	19.70
Av. Phosphorus	kg ha^{-1}	19.21	4.70	0.56	-0.64	24.45
Av. Potassium	kg ha^{-1}	194.33	47.63	0.21	-0.82	24.51
Av. Sulphur	mg kg^{-1}	11.48	2.63	-0.18	-0.49	22.9

Table 2: Computed semivariogram soil parameter characteristics.

Variable	Model	Nugget (C_0)	Partial sill (C_1)	Sill (C_0+C_1)	Range (m)	DSD (%) (Nugget / sill)	SD	RMSE	RMSSE
pH (1:2.5)	Gaussian	0.066	0.042	0.108	8025.1	61.11	Moderate	0.29	1.014
Organic Carbon (%)	Spherical	0.098	0.153	0.251	1972.4	39.04	Moderate	0.51	1.070
Av. Nitrogen (kgha^{-1})	Exponential	1183.0	334.8	1517.8	1036.7	77.9	Weak	58.3	1.492
Av. Phosphorus (kgha^{-1})	Gaussian	11.43	12.36	23.79	14973.3	48.04	Moderate	3.81	1.019
Av. Potassium (kgha^{-1})	Exponential	742.3	909.3	1651.6	5541	44.9	Moderate	38.03	1.021
Av. Sulphur (mg kg^{-1})	Gaussian	2.30	1.61	3.92	3306	58.6	Moderate	1.99	1.072

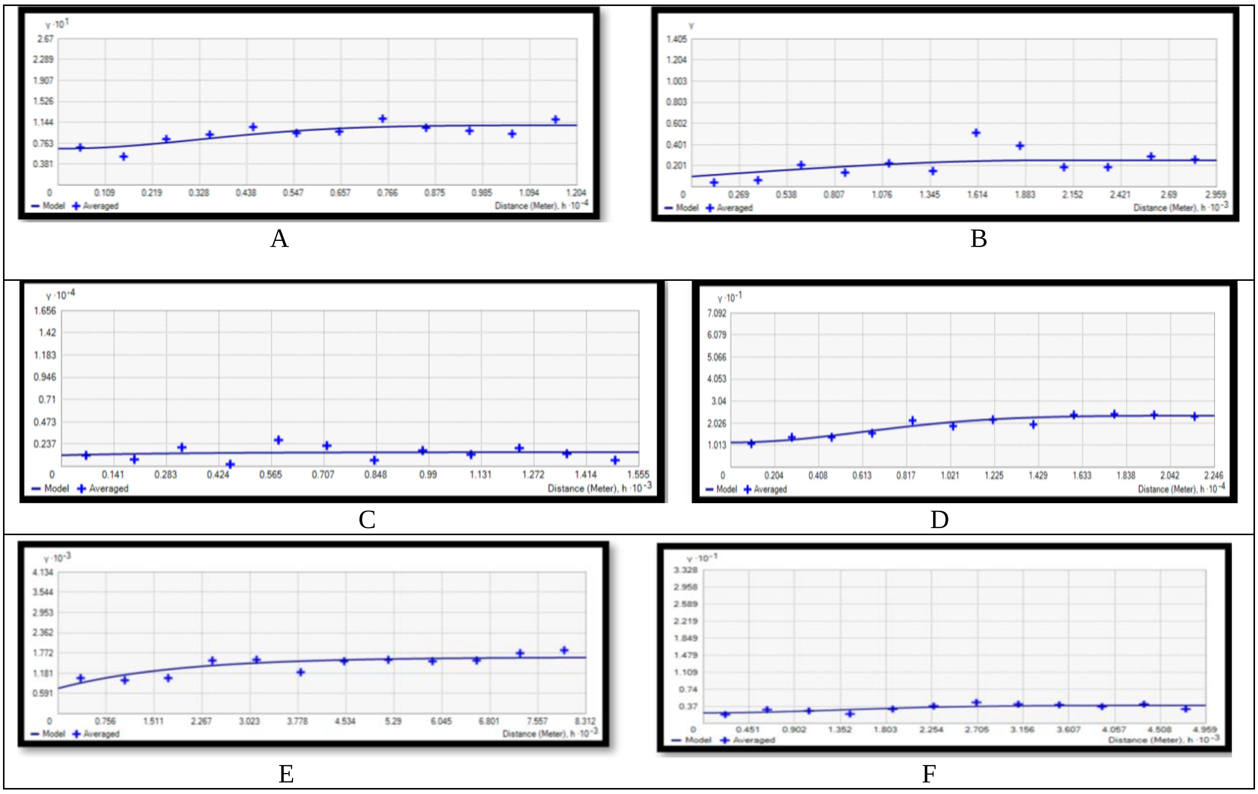
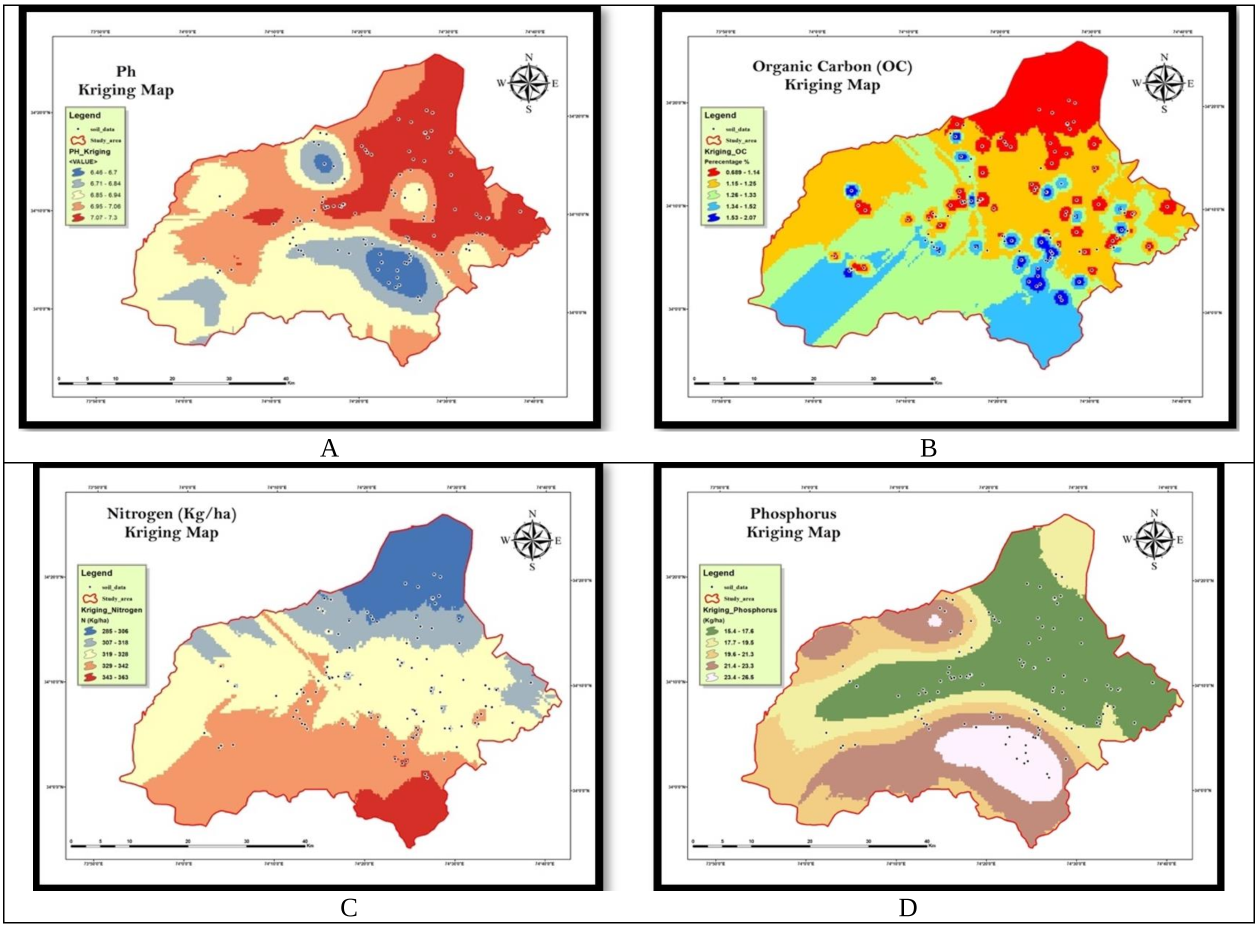


Fig. 3. Semivariograms of a) pH b) Organic Carbon c) Nitrogen d) phosphorus e) potassium f) Sulphur.



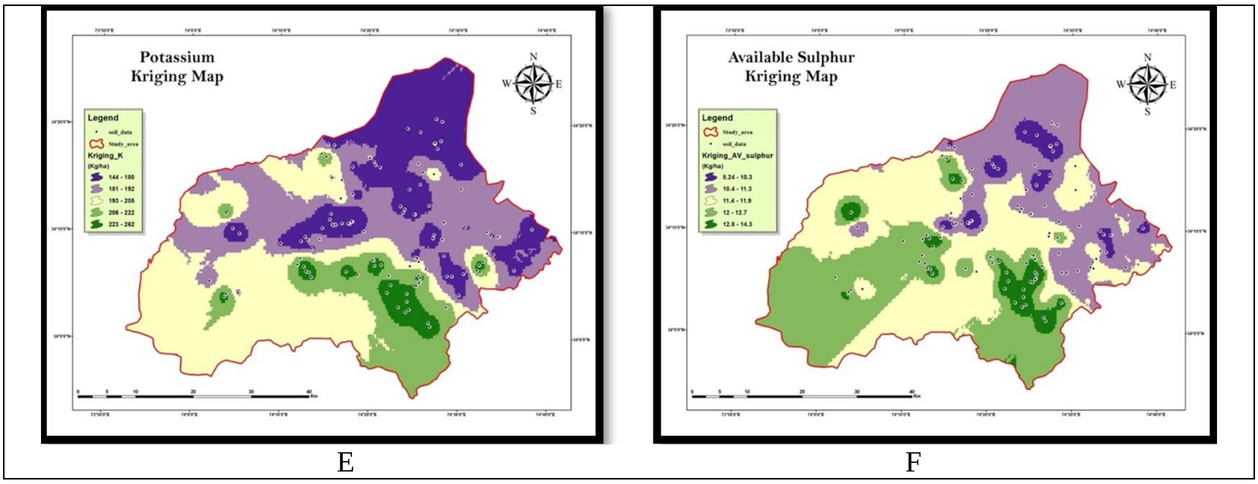


Fig. 4. Ordinary kriging maps of a) pH b) Organic Carbon c) Nitrogen d) phosphorus e) potassium f) Sulphur.

The observed moderate spatial dependence of soil characteristics suggests that the distribution of soil pH, organic carbon, phosphorus, potassium and sulphur in the study area is primarily influenced by a combination of structural and random factors. Yan *et al.* (2019) reported comparable findings in their study. The spatial dependencies exhibited notable variability, with a range spanning from 1036.7 metres for available nitrogen to 14973 metres for available phosphorus (P_2O_5). This suggests that the ideal sampling interval can differ significantly depending on the specific soil properties being assessed. The determination of range values allows for the assessment of the correlation between various sampling locations, as well as the identification of the maximum distance of spatial dependence between them (Akpa *et al*., 2014). The observation of fluctuations in the range, varying with different lag sizes, suggests that the spatial structure cannot be adequately captured by a single model for the semivariogram (Silva *et al*., 2018). The disparity in question may not hold significant relevance when conducting semivariance calculations; however, it may hold significance when the objective is to comprehend the inherent spatial patterns within the dataset (Chung *et al.*, 2014). The obtained outcomes can be utilised to formulate suggestions concerning optimal agricultural practices and the development of soil-plant interaction models for forthcoming research endeavours.

CONCLUSIONS

The geostatistical interpolation technique effectively determined that the exponential, spherical, and Gaussian models exhibited optimal conformity with the semivariograms, contingent upon the specific soil chemical variable. In a broader sense, these models demonstrated a relatively weak to moderate degree of spatial dependency across all variables. The utilisation of kriging maps for soil chemical properties has proven to be highly effective in elucidating the spatial distribution patterns of soil properties in areas where no samples were taken, solely relying on the available sampled data. The assessment of spatial heterogeneity in soil physical and chemical attributes is an essential step in implementing targeted soil and crop management strategies. The soil property maps, along with their corresponding spatial structures, have successfully delineated the priority management zones that should be addressed in the future to enhance soil quality. These maps can also be utilised to develop more effective sampling designs for making informed management decisions.

FUTURE SCOPE

The utilization of spatial distribution of soil properties holds great promise in enhancing soil sampling procedures and implementing site-specific management strategies in the designated study area, taking into account the specific needs of management and reclamation efforts.

Conflict of interest. None

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