PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol 11(sp4): 01–12
https://doi.org/10.14719/pst.5678

HORIZON
e-Publishing Group
HePG

RESEARCH ARTICLE

Geostatistical assessment and mapping of soil spatial variability in Sirumugai, Western Ghats

Jayasuriya J[1], Jagadeeswaran R[1*], Kumaraperumal R[1], Balaji Kannan[2] and Raju M[3]

[1]Department of Remote Sensing and Geographic Information System, Tamil Nadu Agricultural University, Coimbatore,641 003, Tamil Nadu, India
[2] Department of Physical Sciences and Information Technology, Tamil Nadu Agricultural University, Coimbatore, 641 003, Tamil Nadu, India
[3]Cotton Research Station, Tamil Nadu Agricultural University, Srivilliputhur, 626 125, Tamil Nadu, India

*Email: jagawaran@tnau.ac.in

OPEN ACCESS

ARTICLE HISTORY
Received: 09 October 2024
Accepted: 06 November 2024
Available online
Version 1.0 : 27 December 2024

Check for updates

Additional information
Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

Copyright: © The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution and reproduction in any medium, provided the original author and source are credited (https://creativecommons.org/licenses/by/4.0/)

CITE THIS ARTICLE
Jayasuriya J, Jagadeeswaran R, Kumaraperumal R, Balaji K, Raju M. Geostatistical assessment and mapping of soil spatial variability in sirumugai, western ghats. Plant Science Today.2024;11(sp4):01-12. https://doi.org/10.14719/pst.5678

Abstract

This study examines the spatial variability of soil properties and classifies the soil in the Sirumugai Reserved Forest range, located in the Western Ghats, India. A systematic soil survey and profile studies were conducted, using landforms as the basis for investigation within the study area. Horizon-wise soil samples were analysed for key soil parameters, including pH, electrical conductivity (EC), soil organic carbon, phosphorus, and potassium. The results revealed significant variations in soil properties across different locations, primarily influenced by elevation. The coefficient of variation for phosphorus was 0.87, while for potassium, it was 0.48. The analysis also encompassed assessments of skewness and kurtosis. pH (0.15) and phosphorus (0.75) exhibited kurtosis values close to 1, indicating relatively normal and flatter distributions. Conversely, sodium (27.10), elevation (3.91), and calcium demonstrated high kurtosis. Most soil properties were found to be right-skewed, while bulk density (0.09) was left-skewed.. Geostatistical analysis in the Sirumugai Reserved Forest revealed considerable spatial variability in soil properties, particularly in EC and organic carbon. Elevation emerged as a strong influencing factor for soil properties, coupled with soil depth and nutrient leaching, which were prominent at higher altitudes. Ordinary kriging provided accurate spatial predictions, offering valuable insights for land management and conservation strategies tailored to the region.

Keywords

forest soils; geostatistical; spatial variability; Western Ghats

Introduction

Soil quality along the Western Ghats exhibits significant variability due to differential pedogenic processes influenced by geology, elevation, and climate. Forest soils from the foundation of the forest ecosystem, where complex and long-term interactions between trees, soil animals, and microbial populations results in soil development that is markedly distinct from agricultural soils. In most forest ecosystems, rainfall plays a pivotal role in promoting plant growth, which subsequently enhanced soil organic carbon content levels through the incorporation of plant residues. However, monoculture vegetation such as Malapari (Pongamia pinnata), rubber plantation (Hevea brasiliensis), and teak (Tectona grandis) adversely impact organic carbon content (OC) (1). Natural forest soils are nutrient-rich due to the breakdown of plant litter, leading to highly productive and sustainable soils in mountainous regions.

Scientists studying forested areas often utilize altitude to examine how climatic factors influence soil organic matter dynamics. Studies (2) identified key factors such as summer precipitation, forest stand age, parent material alkalinity, and edaphically dry conditions as critical drivers of organic humus accumulation in mountainous regions. Another study (3) highlighted that forest restoration protects soil in semi-arid environments while trees mitigate salinization. Forests play a vital role in minimizing soil degradation in mountainous areas; however, challenges such as steep slopes and shallow soils persist. Additionally, forests are crucial for watershed management, clean water supply,, and the sustainable preservation of sensitive soil ecosystems (4).

Geostatistical approaches have been widely employed to analyze the spatial distribution and variability of soil data, considering factors such as the scale of the study region, the distance between sampling locations, and spatial patterns utilized to generate semivariograms. These methods effectively assess correlations and geographic variability of soil properties', including physical, chemical, and biological attributes (5). Cross-validation of variogram models using Ordinary Kriging (OK) indicated that spatial prediction of soil attributes is more accurate than relying on mean observed values at unmeasured locations.

Variogram modelling enables the examination and quantification of spatial autocorrelation, a process referred to as spatial modelling, structural analysis, or variography in geostatistics (6). Most natural phenomena exhibit variability across both space and time, as evidenced by the high variability observed within short distances on a topographic surface. This variability is deterministic, resulting from natural processes, although the exact conditions under which these processes occur are not always fully understood (7).

The ArcGIS Geostatistical Analyst tool provides a user-friendly interface for performing advanced geostatistical analyses, including variogram modelling, kriging, inverse distance weighting (IDW), and cross-validation.

The objective of this study is to evaluate the factors influencing soil quality in forest ecosystems by analyzing the spatial variability of soil properties in the Sirumugai Reserved Forest. This investigation focuses on soil nutrients, soil depth, and other critical soil attributes, while examining how factors such as elevation, soil structure, and leaching interact. Geostatistical methods will be applied to model and predict soil characteristics across different physiographic units, providing valuable insights for improved land management and conservation strategies.

Materials and Methods

Study area

The study area, Sirumugai Reserved Forest range, is located in the Coimbatore district of Tamil Nadu, India, and forms parts of the Western Ghats. Geographically, it lies between 11° 27'46.06" and 11°20'1.06" Nlatitude and 77°3'42.56" and 76° 54'12.92" E longitude, approximately 40 km north of Coimbatore city. The forest spans an area of 128 km^2. According to the India Meteorological Department, the region receives an average annual rainfall of 689 mm and experiences a semiarid climate with temperature ranging from 14° to 40 °C during summer and winter.

Geomorphologically, the research area features a piedmont slope and a weathered pediplain with a regional slope predominantly oriented southward. Over time, the west-to-east regional slope has influenced the shifting channels and courses of rivers. The area is categorized into six basic physiographic units based on a regional slope:

i) Western Ghats hills top 2 (Wh2),

ii) Western Ghats hills 6 (DWh6),

iii) Western Ghats side slopes 1(Wl1),

iv) Western Ghats foothills (Wr5),

v) Rolling lands (G 3.1) and,

vi) Undulating lands.

The elevation within the study area varies significantly, ranging from 300 to 1000 meters above mean sea level. The soils in this region are primarily derived from unconsolidated sediments of the Quaternary epoch, reflecting the area's complex geomorphic and pedogenic history.

Soil sampling

A comprehensive survey was conducted to achieve the research objectives. Thirty-three soil profiles were chosen based on soil morphological observations, with sample site distribution tailored to align with the physiographic units of the study area. The locations of soil samples were recorded in the field using GPS and subsequently mapped (Fig. 1). The profile studies were undertaken as per the soil survey manual guidelines. Relevant site characteristics and morphological featured were throughly documented (8). Horizon-wise soil samples werecollected from all profile points, transported to the laboratory, processed, and conserved for further laboratory examination.

Laboratory analysis

Soil pH was measured in a 1:2.5 soil-water suspension using a digital pH meter at 25 °C, as outlined by (9). Electrical conductivity (EC), representing soil salinity, was determined in the same suspension using a conductivity meter (9). Available phosphorus (10) was extracted using the Bray 1 technique and analysed calorimetrically. Potassium (K) was extracted with 1 N ammonium acetate (pH 7.0) and quantified by flame photometry (11). Exchangeable calcium (Ca) and magnesium (Mg) were extracted with ammonium acetate and analysed using atomic absorption spectrophotometry (12), while sodium (Na) was quantified using a flame photometer. Cation exchange capacity (CEC) was determined via the ammonium acetate method, where ammonium was replaced with potassium and subsequently quantified through distillation, as described in (9). Bulk density was assessed using the core method described in (13), and organic carbon (OC) was quantified using the Walkley-Black method, which involves oxidation with potassium dichromate (14).

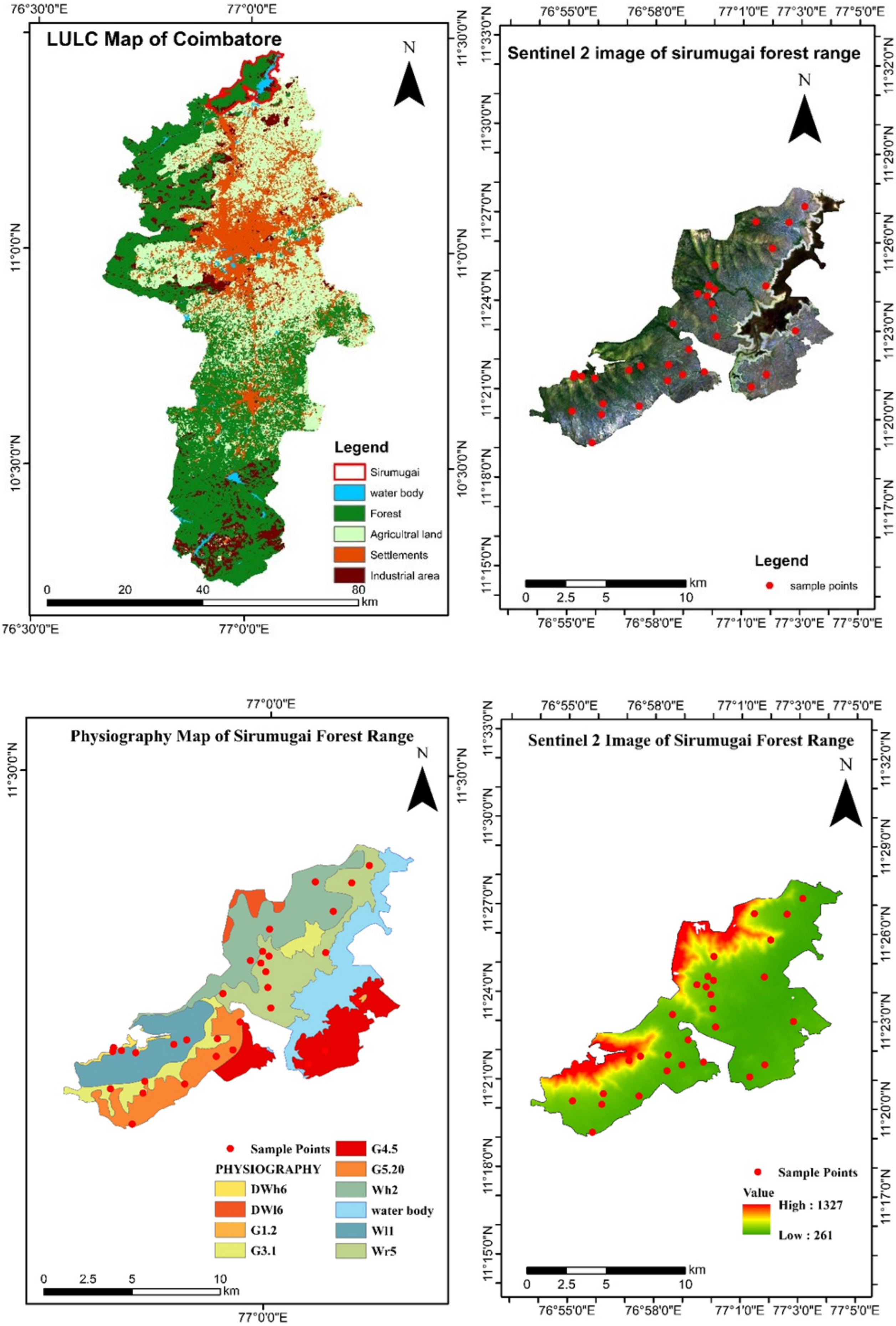

Fig. 1. Study area map

Statistical Analysis

Descriptive statistics of the analysed soil data, including minimum, maximum, mean, standard deviation, coefficient of variation, and skewness, were computed. Pearson correlation coefficients were utilized to determine the relationships among the variables. A matrix of correlation coefficients was created by estimating these coefficients for all possible pairing of the response variables.

Geostatistical Analysis

Geostatistics methods were employed to assess the spatial variability patterns of soil properties in the study area. Spatial interpolation and GIS mapping techniques were applied to create spatial distribution maps of the analyzed soil properties. Kriging in ArcGIS was utilized to minimize prediction errors while effectively representing spatial variability and enabling the generation of various map outputs (15). Since the semi-variogram model dictates the interpolation function, semi-variogram analysis was conducted prior to applying ordinary kriging interpolation. The semi-variogram was calculated using the equation provided in (7) to evaluate the structure of spatial variability (Eqn. 1).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(Xi) - Z(Xi + h)]^2 \quad \text{(Eqn. 1)}$$

where γ(h) represents the semivariance at a given distance h; z(Xi) is the value of the variable Z at location Xi, and N(h) is the number of sample points pairs separated by the lag distance h. (6) Semi-variogram models, including spherical and circular models, were evaluated based on multiple criteria in the present study. For each soil property dataset, the semi-variogram models were verified.

The method of cross-validation was used to determine which model provides the most accurate predictions. Cross-validation was used to evaluate the accuracy of prediction performance through a comparative analysis of the likely error values associated with each model. Equations from (Eqn. 2) were used to compute prediction errors, which included the root mean square error (RMSE). The RMSE evaluates a model's ability to predict observed values and provides an estimate of the residuals' standard deviation. Smaller RMSE values indicate more accurate predictions and lower degrees of error (16).

To characterize various forms of spatial dependence for the soil properties, the nugget variance was applied. The spatial dependence was classified as highly spatially dependent (S) if the nugget-to-sill ratio (N:S) was less than or equal to 0.25, moderately spatially dependent (M) if the ratio ranged between 0.25 and 0.75, and weakly spatially dependent (W) if the ratio exceeded 0.75 (17). Regardless of the nugget ratio, a variable was considered randomly distributed (R) if the slope of the semi-variograms was close to zero.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \{z(xi) - z(xi)\}^2} \quad \text{(Eqn. 2)}$$

In the equation, N represents the number of observations, z (xi) denotes the observed value at location or instance i, and the second $z(xi)$ indicates the predicted value at the same location.

Results

Descriptive statistics of soil parameters

Table 1 presents the descriptive statistics of soil parameters, with variability assessed using the coefficient of variation (CV). Parameters were classified into different variability levels: least variable (CV < 15%), moderately variable (CV 15–35%), and most variable (CV > 35%)(18). The mean values of the soil properties were as follows: electrical conductivity (EC) at 0.05 dS/m, pH at 8.80, available phosphorus (P_2O_5) at 72.5 kg ha^{-1}, and organic carbon (OC) at 0.81 %. The standard deviation ranged from 0.04 for EC to 39.78 for phosphorus (P_2O_5), indicating notable variability in the dataset.

Soil depth varied between 7 and 42 cm, with an average depth of 18 cm. Electrical conductivity ranged from 0.01 to 0.178 dS/m, while pH values ranged from 4.5 to 8.8, with a mean of 6.3. The concentration of phosphorus exhibited a high range, varying from 5.38 to 72.58 kg ha^{-1} (CV = 0.87). Potassium concentration also varied, though to a moderate extent (CV = 0.48), with values ranging between 14.37 and

Table 1. Descriptive statistics of soil characteristics in the study region (n = 33)

S. No	Parameter	Minimum	Maximum	Mean	Standard Deviation	CV	Skewness	Kurtosis
1	Soil depth	7	42	18.91	7.65	0.40	0.79	0.66
2	Elevation	283	1080	419.91	213.58	0.50	2.27	3.91
3	EC	0.01	0.17	0.05	0.04	0.78	1.32	1.42
4	pH	4.60	8.80	6.39	0.89	0.14	0.33	0.15
5	P	5.38	72.58	22.04	19.11	0.87	1.34	0.75
6	k	40.00	205.00	82.82	39.78	0.48	1.20	1.04
7	ca	2.00	46.50	10.05	7.66	0.76	3.41	13.85
8	Mg	1.50	66.00	17.03	13.56	0.80	1.67	3.40
9	Na	6.50	75.00	10.31	11.70	1.14	5.35	27.10
10	CEC	10.05	68.05	22.06	12.12	0.55	1.83	4.40
11	OC	0.14	2.44	0.81	0.62	0.77	1.19	0.53
12	BD	1.12	1.41	1.26	0.08	0.06	0.09	-0.61

298.47 kg ha^{-1}. OC content ranged from 0 to 14%, with a standard deviation of 0.62, and was further classified into broader ranges from 2 to 44%.

Cation exchange capacity (CEC) ranged from 10.05 to 68.05 cmol/kg, showing low variability. Sodium content exhibited significant variability (CV = 1.14). Most soil parameters displayed positive skewness, with minimum and maximum values ranging from 0 to 5 and the kurtosis values varying from -0 to 27. The variability in soil depth, ranged from 7 to 42 cm on average (Table 1).

Skewness and Kurtosis

The skewness values of the soil properties were positive, indicating an asymmetric distribution of data. Outliers, especially for sodium, contributed to the high kurtosis value (27.10), suggesting the presence of potential outlier in the dataset. Bulk density exhibited low variability (CV = 0.06), reflecting a relatively consistent soil structure.

The correlation coefficients matrix of soil attributes

A negative correlation (r = -0.41) was observed between elevation and soil depth. Table 2 shows the correlation coefficients relating soil qualities to elevation. These findings align with previous research by (19), which reported that higher elevation soils tends to have shallower textures due to increased runoff and erosion.

Phosphorus availability demonstrated a strong association with soil salinity and acidity, as evidenced by its positive correlations with pH (r = 0.37) and electrical conductivity (r = 0.46). Table 2 also highlights a positive correlation (r = 0.39) between soil organic carbon and elevation. However, contrary findings by (20) indicated that organic content decreases with increasing elevation.

A significant negative correlation (r = -0.41) was noted between soil pH and elevation, suggesting that soils at higher altitudes are generally more acidic. Furthermore, sodium concentration was shown to decrease in more acidic soils, as evidenced by the negative correlation between sodium (Na) and pH (r = -0.33). Elevation exhibited a weak negative correlation with sodium (r = -0.12), likely due to nutrient erosion and leaching being more pronounced at higher altitudes. .

Additionally, there was a modest positive correlation (r = 0.39) between soil depth and magnesium (Mg), and a stronger positive correlation (r = 0.50) was also observed between these two parameters. These correlations underline the intricate interactions between soil properties and topographical factors.

Semi variogram of soil parameters

Fig.2 exhibits the spatial variability of soil parameters, evaluated using semi-variograms, which revealed varying levels of spatial dependence across different soil characteristics. The spatial structure for each parameter was defined by calculating the values of the nugget effect, partial sill, and sill, as shown in . EC demonstrated significant spatial dependence with a nugget-to-sill ratio N = 0.26, indicating that EC variations have a strong spatial correlation and exhibit a clearly defined spatial structure across the landscape. Similarly, P also showed significant spatial dependence with an N ratio of 0.28, and CEC displayed significant spatial dependence (N = 0.29). These results suggest that EC, P, and CEC are strongly influenced by landscape features and follow similar spatial patterns.

Nugget-to-sill ratios for other soil properties, such as pH, magnesium (Mg), organic carbon (OC), and sodium (Na), ranged from 0.34 to 0.69, indicating moderate spatial dependence. This suggests that the distribution of these parameters is controlled by both intrinsic soil properties and external factors such as vegetation and topography. The N ratio for pH was 0.35, indicating that the variability in pH is influenced by both soil characteristics and environmental conditions. .

On the contrary, potassium and bulk density exhibited lesser spatial dependence, with respective N ratios of 0.69 and 0.85. Among all variables studied, Ca exhibited the least spatially dependence, with an N ratio of 0.81. This trend suggests that Ca distribution is more erratic, likely influenced by localized processes such as litter decomposition and uptake by plants.

Table 2. The correlation coefficients matrix of the studied soil attributes

	Soil depth	Elevation	EC	pH	P	k	ca	Mg	Na	CEC	OC	BD
Soil depth	1.00											
Elevation	-0.41	1.00										
EC	0.25	-0.29	1.00									
pH	0.28	-0.41	0.58	1.00								
P	0.04	-0.26	0.46	0.37	1.00							
k	0.03	0.12	-0.09	-0.21	-0.28	1.00						
ca	0.17	-0.02	0.36	0.43	0.36	-0.16	1.00					
Mg	0.50	-0.31	0.43	0.43	0.50	0.08	0.70	1.00				
Na	0.04	-0.12	-0.11	-0.33	-0.15	0.39	-0.13	-0.13	1.00			
CEC	0.39	-0.18	0.43	0.41	0.51	0.04	0.76	0.93	-0.15	1.00		
OC	-0.21	0.39	0.08	0.06	0.16	0.11	0.33	0.06	-0.06	0.15	1.00	
BD	0.15	-0.16	0.35	0.30	0.34	0.03	0.15	0.37	-0.17	0.18	0.01	1.00

Table 3. Semi variogram parameters of soil parameters

Soil Parameters	Nugget (Co)	Partial sill (C)	Sill Co + C	N:S ratio	Spatial dependence
EC	0.039	0.11	0.149	0.26	Strong
pH	0.096	0.176	0.272	0.35	Moderate
P	0.352	0.89	1.242	0.28	Strong
k	0.467	0.21	0.677	0.69	Moderate
ca	0.289	0.067	0.356	0.81	Weak
Mg	0.172	0.33	0.502	0.34	Moderate
Na	0.369	0.193	0.562	0.66	Moderate
CEC	0.14	0.35	0.49	0.29	Strong
OC	0.277	0.536	0.813	0.34	Moderate
BD	0.282	0.049	0.331	0.85	Weak

Understanding these differences in spatial dependence is crucial for a better understanding of the distribution of soil characteristics across the landscape. These insights can inform more effective management practices in forestry and land-use planning, contributing to sustainable land management..

Models cross-validation

This study evaluates the effectiveness of numerous semi-variogram models—including exponential, tetra-spherical, circular, and spherical models—applied to various soil parameters. Through cross-validation, the performance of these models was assessed, with the

Root Mean Square Error (RMSE) being considered a key performance metric. No single model provided the best fit for all soil factors under investigation, as evidenced by the differences between the best-fitting models for each parameter. Table 4 presents the best-fit models for each specific soil property, showing that different models yield better results for different soil attributes. The table further

Table 4. Calculated semi variograms of soil properties with the lines indicating the selected best-fit model based on RMSE and r2 values.

Parameters	Best fit model	R^2	RMSE
EC	Circular	0.70	0.670
pH	Spherical	0.56	0.437
P	Stable	0.59	0.346
k	Tetra spherical	0.48	7.860
ca	Exponential	0.49	2.85
Mg	Rational Quadratic	0.31	4.365
Na	Rational Quadratic	0.32	1.000
CEC	Circular	0.82	10.719
OC	Hole Effect	0.53	3.856
BD	J-Bessel	0.56	0.644

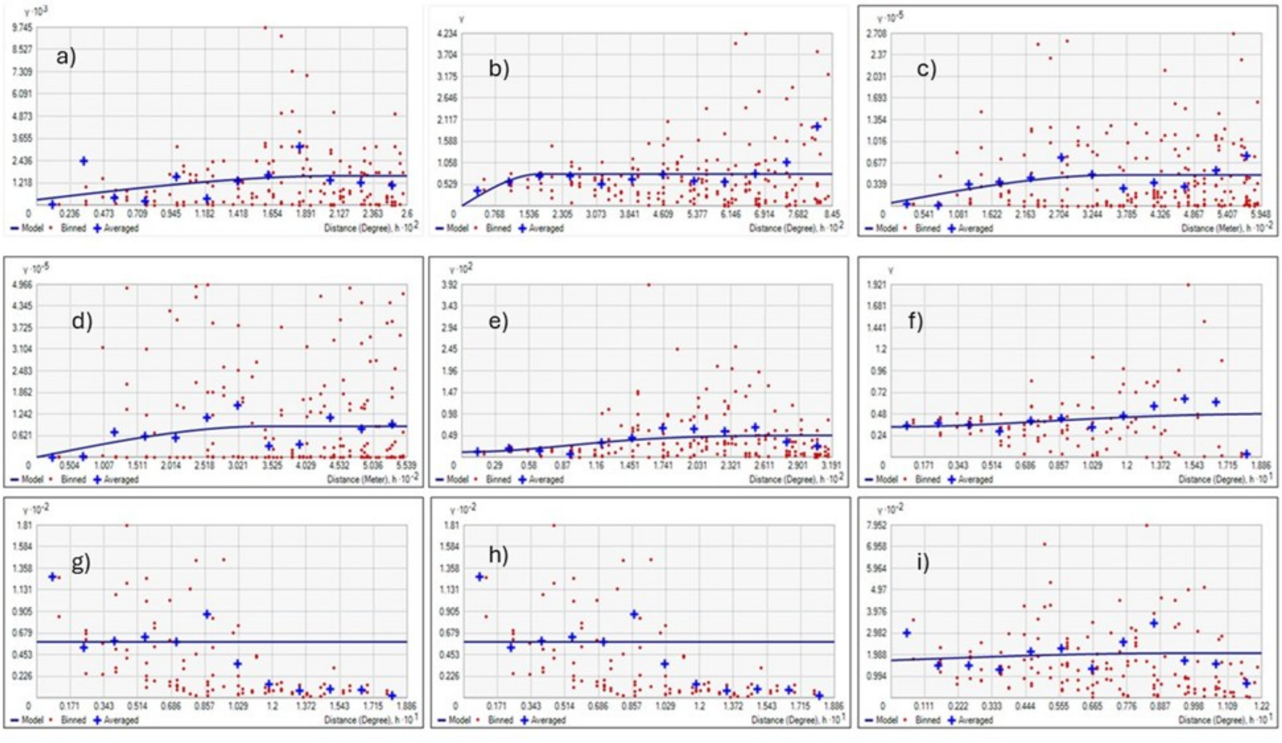

Fig. 2 a)- EC, b)-pH, c)-K, d)-P, e)- BD, f)-OC, g)-ca, h)-mg, i)- Na, calculated semi variograms of soil properties with the lines indicating selected best fit model based on RMSE and r2values.

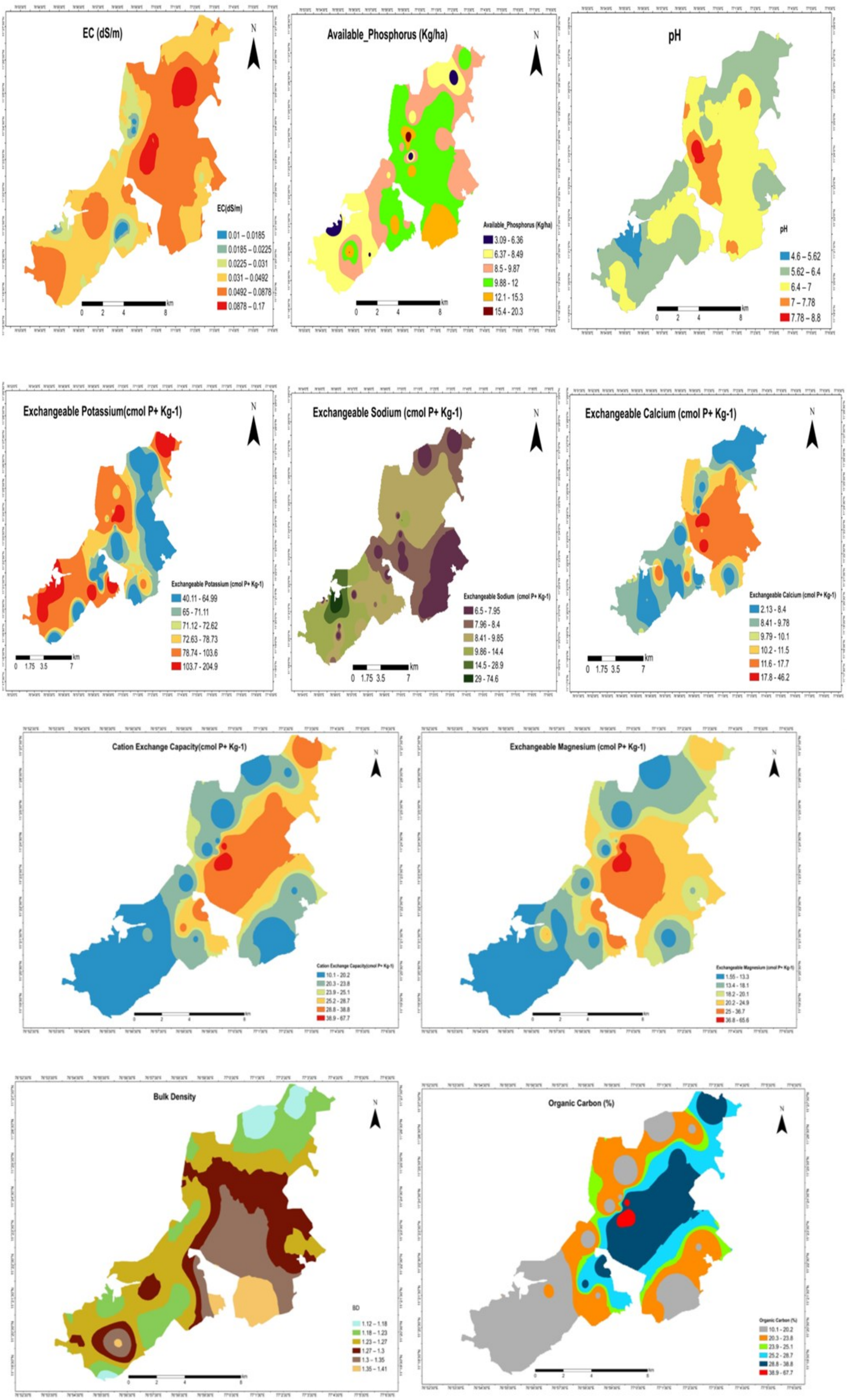

Fig.3. Spatial maps showing soil property variability map of pH, EC, available phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na),CEC (Cation exchange capacity) organic carbon (OC) and Bulk density (BD) across the study area. Hotspots distribution emphasizes the importance of selecting the appropriate model to ensure accurate spatial prediction and mapping of soil characteristics.

Additionally, Table 4 includes the R^2 and RMSE values for each soil parameter, providing a quantitative assessment of the performance of the semi-variogram models. Models that explain a significant proportion of variation with relatively low errors include the circular model for electrical conductivity (EC) (R^2 = 0.70, RMSE = 0.670) and the circular model for cation exchange capacity (CEC) (R^2 = 0.82, RMSE = 10.719). These models performed well in capturing the spatial variability of these parameters. The stable model for phosphorus (P) also demonstrated good accuracy. In contrast, the performance of models for potassium (K) (tetra-spherical), magnesium (Mg) and sodium (Na) (rational quadratic), and bulk density (BD) (J-Bessel) was poorer, as evidenced by their higher R^2 and RMSE values. This suggests that further refinement or the use of alternative models may be necessary to improve their predictive accuracy.

Discussion

Descriptive statistics and distribution of soil parameters

As illustrated in Table 1, soil characteristics exhibited significant variability across various factors. Electrical conductivity (EC) and organic carbon (OC) displayed low standard deviations, indicating that data points were closely clustered around the mean. In contrast, phosphorus (P) and potassium (K) exhibited high heterogeneity, likely influenced by localized nutrient cycling and vegetation patterns. Sodium (Na) showed substantial variability (CV = 1.14), suggesting that localized factors, such as proximity to water bodies, contribute to soil salinity in forest ecosystems. The average soil depth was 18 cm, which is consistent with previous studies (21). The broad pH range (4.5–8.8) reflects the diversity in soil chemistry, driven by parent material and plant influence. Soil pH plays a critical role in regulating the populations of soil organisms. Certain microorganisms, such as nitrifying bacteria, can only function within specific pH ranges. Consequently, their activity and the associated material transformations occur only under suitable pH conditions. Moreover, the structure and solubility of many chemical compounds in forest soils are pH-dependent. For example, in acidic soils, elements such as manganese, copper, and zinc become more mobile, and the solubility of phosphorus is significantly affected by pH. In the rooting zone, soil pH can influence the availability of essential nutrients.

While variations in EC were linked to elevation changes across the landscape, fluctuations in organic carbon were moderate, likely due to differences in plant litter decomposition and microbial activity, as similarly observed by (22). The significant variability of calcium and magnesium (23) suggests the importance of weathering and parent material in nutrient cycling. The notable kurtosis of sodium indicates the presence of extreme outliers, which may negatively impact soil structure and warrant management intervention. Cation exchange capacity (CEC) showed moderate heterogeneity, reflecting changes in the soil's ability to retain nutrients, which is critical for forest productivity. Bulk density exhibited low variability, indicating a homogeneous soil structure conducive to root growth and water movement, which supports overall forest health. These findings underscore the diversity of soil properties and their implications for the nitrogen cycle and forest management (24).

Forest environments are largely shaped by litter fall and root decomposition, which provide a continuous influx of organic matter to the soil. Additionally, the tree canopy and shading enhance moisture retention and maintain cooler soil temperatures, thereby promoting decomposition and nutrient availability. Trees participate in nutrient cycling by absorbing soil nutrients, which are then returned to the soil through the decomposition of fallen leaves and branches, thereby sustaining soil fertility as discussed by (25). Forest ecosystems are inherently sustainable and capable of withstanding global changes. However, increasing pressures from cultural, nutritional, and climatic factors pose significant risks to chemical fertility. Many forest soils are becoming more acidic, and atmospheric deposition of nutritional cations has decreased over the past few decades. Both clay minerals and organic compounds, particularly those of a colloidal nature, carry a net negative charge.

The relationship among soil properties with elevation

The study demonstrates the intricate connections between soil characteristics and elevation in forest ecosystems, demonstrating how elevation influences pH, electrical conductivity, organic carbon, and cation exchange capacity. Asaltitude increases, precipitation and leaching also increase, leading to lower pH values due to the loss of base cations (Ca^{2+}, Mg^{2+}, K^{+}), as reported by (25).. Additionally, higher elevations are associated with higher OC levels, owing to increased organic matter accumulation and slower decomposition rates, while lower elevations tends to have lower OC levels due to disturbances such as grazing, erosion, and changes in vegetation (26). EC values show variation along the elevation gradient; (27) reported higher EC values at lower elevations due to the accumulation of basic cations, while soils at medium elevations exhibit lower EC value due to the erosion and leaching of these nutrients. Similarly, the increase in CEC at higher elevations is connected with the buildup of clay and organic matter, which act as a reservoir for important cations. In contrast, sandy soils at lower elevations, with less organic matter, tend to have lower CEC (28). Phosphorus availability showed moderate associations with EC, pH, and CEC, suggesting that soil salinity and acidity influence P retention, with higher salinity reducing P solubilisation (29).

Soil depth and elevation are negatively association, with flatter soils occurring at higher elevations due to greater erosion and runoff (19).Mineral weathering at higher elevations contributes to increased magnesium concentration, while the positive correlation between soil depth and CEC suggests that deeper soils have a greater nutrient storage capacity, which is essential for forest productivity. Acidic soils at higher elevations, which are more leached, lead to greater nutrient depletion, and as acidity increases, sodium (Na) concentration decreases (30, 31). In tropical forests such as those in the southern Western Ghats, higher elevations receive more rainfall than plain area; consequently, as the slope descends towards the west, salts and other compounds may leach from the soil, especially sodium, resulting in nutrient depletion and accelerated soil acidification (32). It was found that less leaching at lower elevations can lead to the accumulation of soluble ions, including potassium (33).

Spatial pattern of soil properties

The soil parameters exhibit geographical variability, reflecting both the inherent soil qualities and external environmental influences, such as vegetation, topography, and hydrological processes.. Consistent with the findings of (34), the substantial spatial dependence observed for EC, P, and CEC implies that topographical features and water movement play a significant role in shaping these parameters. This aligns with the work of (35), which highlighted the importance of elevation gradients in structuring forest ecosystems and influencing species diversity and persistence across tropical rainforests.. Similarly, (36) emphasized the role of elevation as both a regional and local environmental factor, serving as a key predictor for the spatial distribution of plant litter in certain areas.

Potassium and calcium, which exhibit shorter spatial ranges and weaker spatial dependence, are likely influenced by localized biological processes such as plant uptake and decomposition. In forest ecosystems, potassium is rapidly cycled due to its mobility and its essential role in plant metabolism, whereas calcium tends to accumulate through the decomposition of leaf litter and woody debris, as defined by (37). These processes contribute to the formation of localized spatial patterns within forest soils, where nutrient recycling is closely linked with vegetation distribution. The lower phosphorus availability in forest systems compared to coffee systems indicates that the soils in this region are phosphorus-deficient (35).

The variations in pH were influenced by factors such as vegetation type and organic matter decomposition, as reflected in their moderate association with geographical patterns. Similarly, the modest geographical dependence of sodium corresponds with previous studies indicating the dynamic nature of sodium concentration in response to variations in soil pH and salinity (38).

Spatial variability mapping

Fig. 3 illustrates the northeastern and central regions of Sirumugai (39). The results show that the soil organic carbon (SOC) level in the 0–5 cm soil depth was highest in mixed forests, while the chemical stability of SOC was highest in forests. The areas showed in red and dark blue exhibit the highest concentrations of organic carbon, reflecting improved soil health, minimal disturbance, and dense vegetation cover. Moderate organic carbon levels, represented by blue and green hues, are observed in the outlying areas, particularly in the northeast and south. In contrast, the southern and northern regions, depicted in orange and yellow, show reduced organic carbon levels, likely due to soil erosion, degradation, or sparse vegetation, which severely impacts soil structure and nutrient cycling. The grey areas, mainly in the southwest, may represent barren land or excluded zones, such as stony terrains or urbanized regions with negligible organic carbon content. A clear geographical trend is evident, with organic carbon levels decreasing from the forest core towards the outer edges, indicating a healthier ecosystem at the center.

Conservation and restoration strategies such as erosion control, reforestation, and the addition of organic supplements are necessary to preserve or improve soil health in low-carbon areas. A similar observation of pH was made in a Quercus frainetto woodland in Turkey (40), where significant changes in soil pH, particularly under high-intensity conditions, were attributed to the addition of base cations from the decomposition of organic materials and the breakdown of organic groups from organic matter. The pH and EC maps of the Sirumugai Range highlight critical soil variables impacting plant development. The pH map shows sections in the west and central regions that are neutral to slightly alkaline (light yellow/green), which are favorable for microbial activity and nutrient availability. The very acidic zones (red) in the central and northeastern regions signal potential nutritional deficits. Meanwhile, the southwest's somewhat acidic soils (light blue) may indicate leaching or organic matter accumulation.

The EC map reveals excessive salinity (red) in the center and northeastern areas, which could be detrimental to plants due to salt stress. Given the considerable prevalence of EC (orange), continuous monitoring is recommended. Lower EC readings (yellow/blue) in the southwest suggest healthier soils. The spatial trends in the center and northeastern regions point to compounded issues of acidity and salinity. Studies by (41) show considerable variation in the distribution of calcium concentrations. The western and northeastern regions, which feature higher green and blue calcium zones, might be affected by leaching, acidic soils, and calcium-poor bedrock material. The calcium levels are medium to high (yellow/orange/red) in the central and southern sections, where retention is influenced by terrain, parent material, and drainage.

In forest trees, magnesium (Mg) in nitrophilous vegetation contributes to nutrient fluxes due to mineral weathering (42, 43). The map illustrates the regional distribution of accessible magnesium in the Sirumugai Reserve Forest. Significantly elevated areas (3.4 to 4.1 cmol P+ kg–1) are found in the center (43), indicating fertile soils high in nutrients, which are suitable for plant growth. These are surrounded by regions with low concentrations (2.7 to 3.3 cmol P+ kg–1), which function as buffer zones with diverse soil compositions. The lowest concentration regions (0.8 to 2.0 cmol P+ kg^{-1}), primarily in the western and northeastern parts, could be due to leaching from significant rainfall, limiting plant growth. Management practices such as selective cutting or organic matter amendments can be implemented in magnesium-deficient areas to improve magnesium levels.

According to (44), regional evaporation and associated acidity values (purple/brown) are high in the northeast and central-east regions. High sodium levels are prevalent in most of the region, with areas marked in yellow and light brown requiring observation to prevent deterioration. In the southwest and northwestern areas, where very low sodium levels prevail, soil quality is likely to be high, and vegetation is presumably healthier. This may be attributed to geography or water flow, as sodium levels seem to increase from the west towards the east. Regions with high sodium levels should be closely monitored. The application of forest ecosystem management should consider discouraging monoculture and promoting mixed forests instead.

Although individual forest soils have shown significant variation in cation exchange capacity (CEC), the map displays classifications of CEC, with fertile soils found in the eastern regions characterized by elevated trees (45). Higher CEC values are absent in soils in the yellow and brown regions to the south and west, suggesting that these soils are less fertile and require increased management practices. The central regions show moderate levels of fertility, which can be attributed to the types of soils found in these areas (46). Depths, in g/cc, indicate CEC levels in high-density dark brown soils in the southeast and central regions, which could impede root growth and drainage. In the northern region, low -density blue/green soils are found, which encourage better infiltration. Moderate densities in the yellow/brown areas provide adequate conditions for a variety of land uses.

Conclusion

The identification of soil properties was aimed at similar objectives but resulted in different prediction accuracies due to characteristics of the landscape. Specifically, land uses, primarily bedrock and rock outcrops, are key factors that impede terrain formation. In light of these findings, the research on the spatial variability of soils within the Sirumugai Reserve Forest plays a crucial role in understanding the dynamics between elevation, soil properties, and other environmental drivers. The results indicated that elevation gradients significantly affect soil properties, with shallower soils found at higher elevations, which experienced greater nutrient leaching. Additionally, the role of soil salinity, pH, and cation exchange capacity were found to be linked to phosphorus availability, showing moderate correlations.

The statistical analysis revealed high variability in phosphorus and potassium, while electrical conductivity and organic carbon exhibited low variability. Further details were provided by the examination of skewness and kurtosis. Considerable focus was also placed on semivariograms modeling in conjunction with ordinary kriging, which was employed to perform geostatistical analysis. Results from the analysis of variance indicated that spatial variability in predictions was dependent on the elevation range. Cross-validation demonstrated that the mean within the study area was less robust than spatial predictions.

These findings are valuable for understanding soil nutrient availability, thereby promoting sustainable land use and management practices in tropical forest ecosystems. The approach and model presented here may also be applied to the reconverted terrain of the scarp lands of the Western Ghats, given the usability of feature space covariates in various landscapes. For further research, conducting comparative geostatistical analyses across the Western Ghats is recommended to identify broader soil variability patterns. Additionally, assessing microbial communities, organic matter decomposition, and other biological indicators alongside physical and chemical properties would provide a more comprehensive understanding of soil fertility, particularly in biodiversity-rich regions. The integration of biological factors can offer deeper insights. Advanced machine learning techniques, such as random forests or deep learning, should be employed to develop high-resolution predictive models for soil properties based on geostatistical data.

Acknowledgements

The authors wish to thank the Department of remote sensing and GIS, Tamil Nadu Agricultural University, for providing the necessary facilities and support to write this paper. We also extend our gratitude to our colleagues and reviewers who provided valuable feedback and suggestions to improve the manuscript.

Authors' Contributions

JJ was responsible for conceptualizing the study, coordinating fieldwork, curating data, conducting formal analysis, and preparing the original draft of the manuscript. JR provided supervision, developed the methodology, and contributed to the review and editing of the manuscript. K R carried out the investigation, provided software support, conducted the geostatistical analysis, and contributed to data visualization. All authors read and approved the final manuscript.

Compliance with Ethical Standards

Conflict of interest: The authors declare that they have no conflict of interest regarding the publication of this paper.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT to enhance language clarity and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

1. Surendran U, Raja P, Liu K, Bilotto F, Sridevi G. Comparative analysis of soil organic carbon and soil properties in landscapes of Kerala: insights from the Western Ghats of India. Environmental Monitoring and Assessment. 2024;196(9):838.
2. Prietzel J, Christophel D, Traub C, Kolb E, Schubert A. Regional and site-related patterns of soil nitrogen, phosphorus and potassium stocks and Norway spruce nutrition in mountain forests of the Bavarian Alps. Plant and Soil. 2015;386:151-69. https://doi.org/10.1007/s11104-014-2248-9

3. Bhattacharyya T, Pal D, Chandran P, Ray S. Landuse, clay mineral type and organic carbon content in two millisols-alfisols -vertisols catenary sequences of tropical India. Clay Research. 2005;24(2):105-22.

4. Lathrop Jr RG, Aber JD, Bognar JA. Spatial variability of digital soil maps and its impact on regional ecosystem modeling. Ecological Modelling. 1995;82(1):1-10. https://doi.org/10.1016/0304-3800(94)00068-S

5. John K, Afu S, Isong I, Aki E, Kebonye N, Ayito E, et al. Mapping soil properties with soil-environmental covariates using geostatistics and multivariate statistics. International Journal of Environmental Science and Technology. 2021;1-16. https://doi.org/10.1007/s13762-020-03089-x

6. Maliva RG, Maliva RG. Geostatistical methods and applications. Aquifer Characterization Techniques: Schlumberger Methods in Water Resources Evaluation Series No 4. 2016;595-617. https://doi.org/10.1007/978-3-319-32137-0_20

7. Curran PJ. The semivariogram in remote sensing: an introduction. Remote Sensing of Environment. 1988;24(3):493-507. https://doi.org/10.1016/0034-4257(88)90021-1

8. Staff SS. Keys to soil taxonomy. 13th Edition ed 2022.

9. Jackson W, Flesher D, Hageman R. Nitrate uptake by dark-grown corn seedlings: some characteristics of apparent induction. Plant Physiology. 1973;51(1):120-27. https://doi.org/10.1104/pp.51.1.120

10. Olsen SR. Estimation of available phosphorus in soils by extraction with sodium bicarbonate: US Department of Agriculture; 1954.

11. Stanford G, English L. Use of the flame photometer in rapid soil tests for K and Ca. 1949. https://doi.org/10.2134/agronj1949.00021962004100090012x

12. Chapman C. Exact and approximate generalized ray theory in vertically inhomogeneous media. Geophysical Journal International. 1976;46(2):201-33. https://doi.org/10.1111/j.1365-246X.1976.tb04154.x

13. Dakshinamurti CaG. Practicals in soil physics. I. A. R. I. New Delhi1; 968.

14. Black Wa. An examination of the different methods for determining soil organic matter and the proposed modification of the chromic acid wet titration method. Soil Science of America Journal. 1934;37:29-38. https://doi.org/10.1097/00010694-193401000-00003

15. Vasu D, Singh S, Sahu N, Tiwary P, Chandran P, Duraisami V, et al. Assessment of spatial variability of soil properties using geospatial techniques for farm level nutrient management. Soil and Tillage Research. 2017;169:25-34. https://doi.org/10.1016/j.still.2017.01.006

16. Khan M, Islam M, Amin MS, Bhuiyan M. Spatial variability and geostatistical analysis of selected soil. Bangladesh Journal of Scientific and Industrial Research. 2019;54(1):55-66. https://doi.org/10.3329/bjsir.v54i1.40731

17. Cambardella C, Karlen D. Spatial analysis of soil fertility parameters. Precision Agriculture. 1999;1(1):5-14. https://doi.org/10.1023/A:1009925919134

18. Wilding L, Flach K. Micropedology and soil taxonomy. Soil Micromorphology and Soil Classification. 1985;15:1-16. https://doi.org/10.2136/sssaspecpub15.c1

19. Schulte A, Ruhiyat D. Soils of tropical forest ecosystems: characteristics, ecology and management. Springer Science and Business Media; 2013.

20. Bhunia GS, Shit PK, Chattopadhyay R. Assessment of spatial variability of soil properties using geostatistical approach of lateritic soil (West Bengal, India). Annals of Agrarian Science. 2018;16(4):436-43. https://doi.org/10.1016/j.aasci.2018.06.003

21. Kannan P, Natarajan S, Sivasamy R, Kumaraperumal R. Soil resource information and alternative crop planning for Cauvery delta region of Tiruvarur district, Tamil Nadu. Journal of the Indian Society of Soil Science. 2011;59(2):109-20.

22. Hazelton P, Murphy B. Interpreting soil test results: What do all the numbers mean?. CSIRO Publishing; 2016. https://doi.org/10.1071/9781486303977

23. Vishnu P, Sandeep S, Kumar KA. Taxonomy and genesis of soils in contrasting ecosystems of Southern Western Ghats, India. Catena. 2023;231:107325. https://doi.org/10.1016/j.catena.2023.107325

24. Bel J, Legout A, Saint-André L, Hall SJ, Löfgren S, Laclau J-P, et al. Conventional analysis methods underestimate the plant-available pools of calcium, magnesium and potassium in forest soils. Scientific Reports. 2020;10(1):15703. https://doi.org/10.1038/s41598-020-72741-w

25. Yimer F, Ledin S, Abdelkadir A. Soil property variations in relation to topographic aspect and vegetation community in the south-eastern highlands of Ethiopia. Forest Ecology and Management. 2006;232(1-3):90-99. https://doi.org/10.1016/j.foreco.2006.05.055

26. Moser G, Röderstein M, Soethe N, Hertel D, Leuschner C. Altitudinal changes in stand structure and biomass allocation of tropical mountain forests in relation to microclimate and soil chemistry. Gradients in a Tropical Mountain Ecosystem of Ecuador. 2008;229-42. https://doi.org/10.1007/978-3-540-73526-7_22

27. Nketia K, Asabere S, Ramcharan A, Herbold S, Erasmi S, Sauer D. Spatio-temporal mapping of soil water storage in a semi-arid landscape of northern Ghana–A multi-tasked ensemble machine-learning approach. Geoderma. 2022;410:115691. https://doi.org/10.1016/j.geoderma.2021.115691

28. Chinevu NC, Unanaonwi EO, Amonum IJ. Physical and chemical characteristics of forest soil in southern Guinea savanna of Nigeria. Agriculture, Forestry and Fisheries. 2013;2(6):229-34. https://doi.org/10.11648/j.aff.20130206.15

29. Bueis T, Bravo F, Pando V, Turrión M-B. Relationship between environmental parameters and *Pinus sylvestris* L. site index in forest plantations in northern Spain acidic plateau. iForest-Biogeosciences and Forestry. 2016;9(3):394. https://doi.org/10.3832/ifor1600-008

30. He X, Yang L, Li A, Zhang L, Shen F, Cai Y, et al. Soil organic carbon prediction using phenological parameters and remote sensing variables generated from Sentinel-2 images. Catena. 2021;205:105442. https://doi.org/10.1016/j.catena.2021.105442

31. Dharumarajan S, Kalaiselvi B, Lalitha M, Vasundhara R, Kumar K, Hegde R. Predictive soil mapping of key soil properties in Western Ghats, India. Journal of the Indian Society of Soil Science. 2022;70(3):266-78. https://doi.org/10.5958/0974-0228.2022.00032.9

32. James J, Harrison R. The effect of harvest on forest soil carbon: A meta-analysis. Forests. 2016;7(12):308. https://doi.org/10.3390/f7120308

33. Tsui C-C, Chen Z-S, Hsieh C-F. Relationships between soil properties and slope position in a lowland rain forest of southern Taiwan. Geoderma. 2004;123(1-2):131-42. https://doi.org/10.1016/j.geoderma.2004.01.031

34. Verma S, Singh D, Singh AK, Jayakumar S. Post-fire soil nutrient dynamics in a tropical dry deciduous forest of Western Ghats, India. Forest Ecosystems. 2019;6(1):6. https://doi.org/10.1186/s40663-019-0168-0

35. Bhatt H, Gopakumar S, Bhindhu P, Vishnu B, Jugran HP. Woody vegetation and soil composition of tropical forest along an altitudinal gradient in Western Ghats, India. Asian Journal of Forestry. 2024;8(1).

36. Bacaro G, Rocchini D, Bonini I, Marignani M, Maccherini S, Chiarucci A. The role of regional and local scale predictors for plant species richness in Mediterranean forests. Plant Biosystems-An International Journal Dealing with all Aspects of Plant Biology. 2008;142(3):630-34.https://doi.org/10.1080/11263500802411064

37. Binkley D, Fisher RF. Ecology and management of forest soils. John Wiley and Sons; 2019.https://doi.org/10.1002/9781119455745

38. Nayak R, Karanth KK, Dutta T, Defries R, Karanth KU, Vaidyanathan S. Bits and pieces: Forest fragmentation by linear intrusions in India. Land Use Policy. 2020;99:104619. https://doi.org/10.1016/j.landusepol.2020.104619

39. Xu S, Yang Y, Sun G, Zhang Q, Wang Y, Zeng H, et al. Aridity affects soil organic carbon concentration and chemical stability by different forest types and soil processes across Chinese natural forests. Science of The Total Environment. 2024;944:174002. https://doi.org/10.1016/j.scitotenv.2024.174002

40. Akburak S, Son Y, Makineci E, Çakir M. Impacts of low-intensity prescribed fire on microbial and chemical soil properties in a Quercus frainetto forest. Journal of Forestry Research. 2018;29:687-96. https://doi.org/10.1007/s11676-017-0486-4

41. Drápelová PG. The figure of Tyche on coins of Antioch in early Byzantium (337–ca 530): 1. Byzantinoslavica-Revue internationale des Etudes Byzantines. 2021;79(1-2):144-73.

42. Cleveland D, Hinck JE, Lankton JS. Elemental and radionuclide exposures and uptakes by small rodents, invertebrates and vegetation at active and post-production uranium mines in the Grand Canyon watershed. Chemosphere. 2021;263:127908. https://doi.org/10.1016/j.chemosphere.2020.127908

43. Uhlig D, Amelung W, Von Blanckenburg F. Mineral nutrients sourced in deep regolith sustain long term nutrition of mountainous temperate forest ecosystems. Global Biogeochemical Cycles. 2020;34(9):e2019GB006513. https://doi.org/10.1029/2019GB006513

44. Erdem R, Çetin M, Arıcak B, Sevik H. The change of the concentrations of boron and sodium in some forest soils depending on plant species. Forestist. 2023;73(2). https://doi.org/10.5152/forestist.2022.22061

45. Solly EF, Weber V, Zimmermann S, Walthert L, Hagedorn F, Schmidt MW. A critical evaluation of the relationship between the effective cation exchange capacity and soil organic carbon content in Swiss forest soils. Frontiers in Forests and Global Change. 2020;3:98. https://doi.org/10.3389/ffgc.2020.00098

46. Katuwal S, Knadel M, Norgaard T, Moldrup P, Greve MH, de Jonge LW. Predicting the dry bulk density of soils across Denmark: Comparison of single-parameter, multi-parameter and vis–NIR based models. Geoderma. 2020;361:114080. https://doi.org/10.1016/j.geoderma.2019.114080