



RESEARCH ARTICLE

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

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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 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 (2). Another study highlighted that forest restoration protects soil in semi-arid environments while trees mitigate salinization (3). 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" N latitude 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 km². 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 features were thoroughly documented (8). Horizon-wise soil samples were collected 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 (9). 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 K and subsequently quantified through distillation (9). Bulk density (BD) was assessed using the core method (13), and OC was quantified which involves oxidation with potassium dichromate (14).

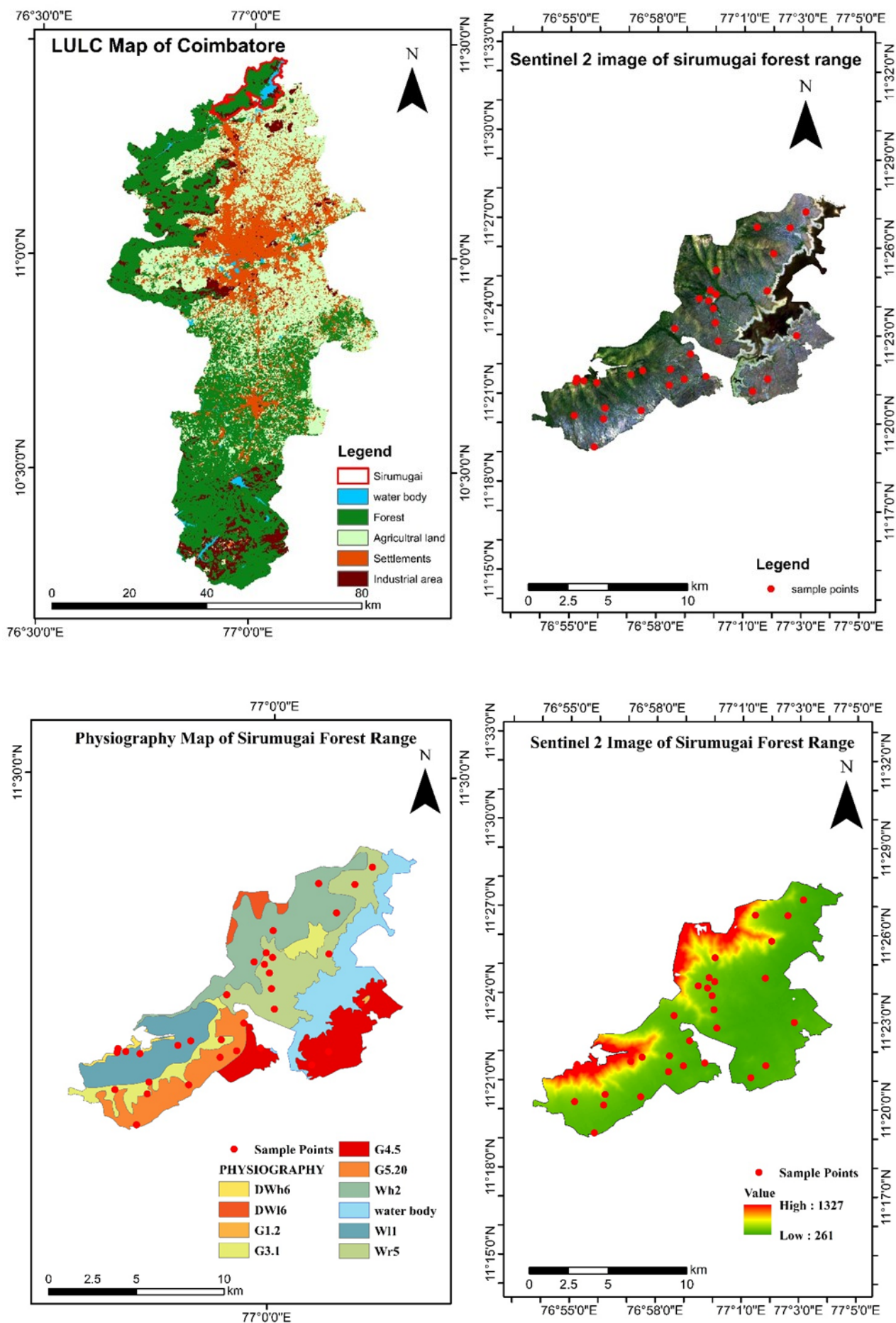


Fig. 1. Study area map.

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 (Geographic Information System) 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).

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

where $\gamma(h)$ represents the semivariance at a given distance h ; $z(X_i)$ is the value of the variable Z at location X_i , 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.

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

where, N represents the number of observations, $z(x_i)$ denotes the observed value at location or instance i , and the second $\hat{z}(x_i)$ 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: EC at 0.05 dS/m, pH at 8.80, available phosphorus (P_2O_5 (phosphorus pentoxide)) at 72.5 kg ha⁻¹, and 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). K concentration also varied, though to a moderate

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

extent (CV = 0.48), with values ranging between 14.37 and 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. Na 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 Na, contributed to the high kurtosis value (27.10), suggesting the presence of potential outlier in the dataset. BD 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 (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 (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, Na concentration was shown to decrease in more acidic soils, as evidenced by the negative correlation between Na and pH (r

$= -0.33$). Elevation exhibited a weak negative correlation with Na ($r = -0.12$), 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 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 Table 3. 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, Mg, OC, and 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, K and BD exhibited lesser spatial dependence, with respective N ratios of 0.69 and 0.85. Among all variables studied, Ca exhibited the least spatial 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.

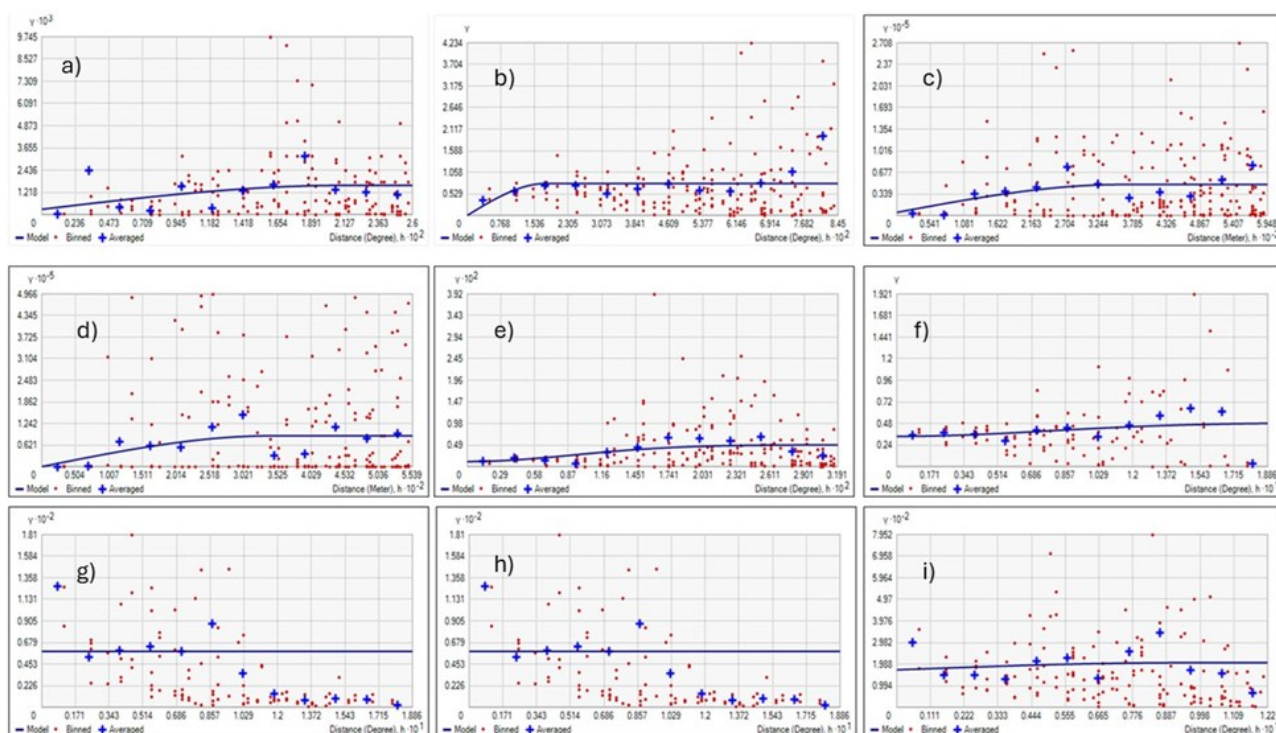
Models cross-validation

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 spherical model demonstrating the highest predictive accuracy for most soil parameters, indicating its suitability for spatial interpolation in this study.

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

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 r2 values.

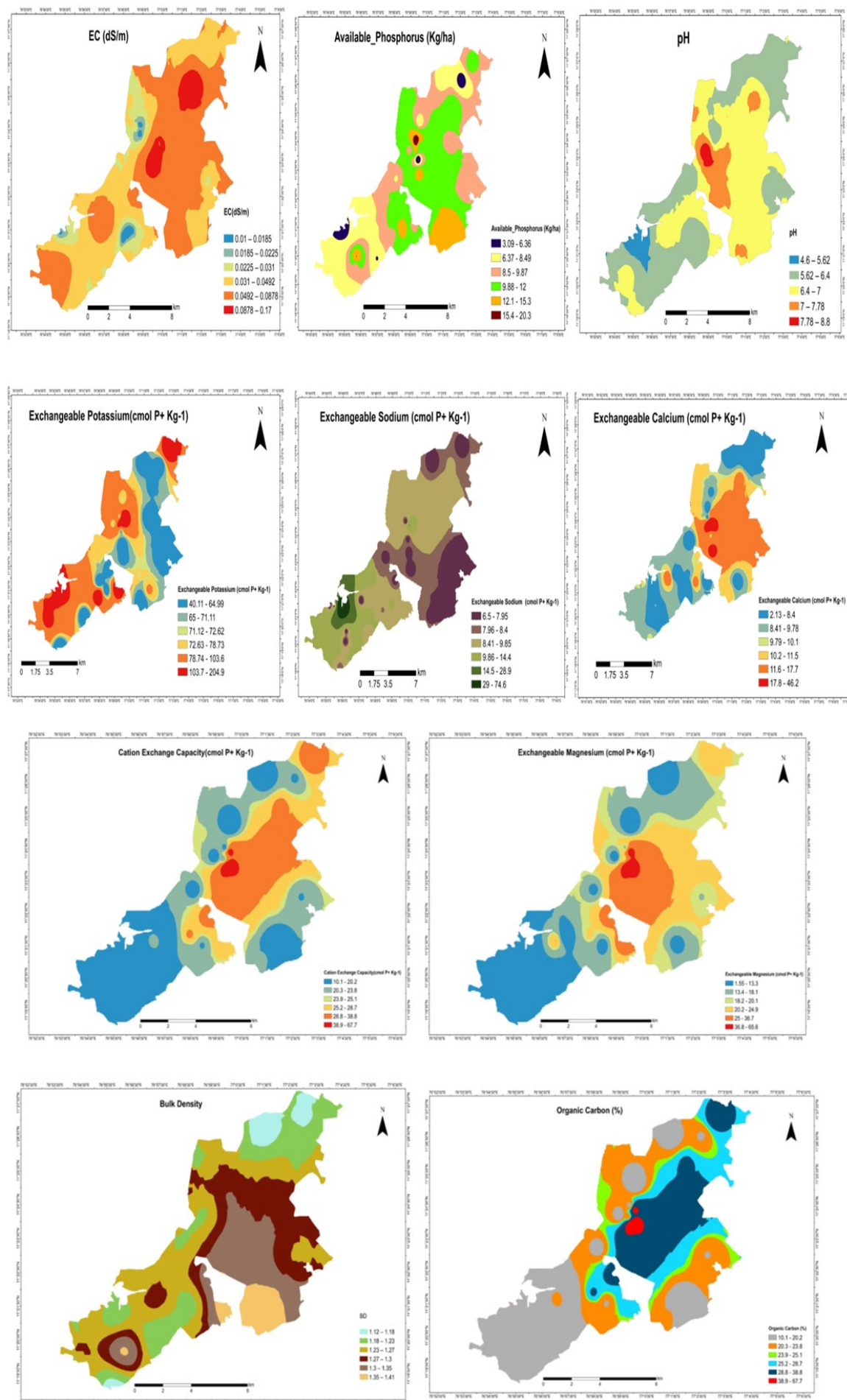


Fig.3. Spatial maps showing soil property variability map of pH, EC, available phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), CEC (cation exchange capacity) organic carbon (OC) and bulk density (BD) across the study area. Hotspots distribution.

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 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 EC ($R^2 = 0.70$, RMSE = 0.670) and the circular model for CEC ($R^2 = 0.82$, RMSE = 10.719). These models performed well in capturing the spatial variability of these parameters. The stable model for P also demonstrated good accuracy. In contrast, the performance of models for K (tetra-spherical), Mg and Na (rational quadratic), and 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. EC and OC displayed low standard deviations, indicating that data points were closely clustered around the mean. In contrast, P and K exhibited high heterogeneity, likely influenced by localized nutrient cycling and vegetation patterns. 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 OC were moderate, likely due to differences in plant litter decomposition and microbial activity, as similarly observed in a study (22). The significant variability of Ca and Mg (23) suggests the importance of weathering and parent material in nutrient cycling. The notable kurtosis of Na indicates the presence of extreme outliers, which may negatively impact soil structure and warrant management intervention. CEC showed moderate heterogeneity, reflecting changes in the soil's ability to retain nutrients, which is critical for forest

productivity. BD 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 in a study (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, EC, OC, and CEC. As altitude 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 in a study (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; it is reported higher EC values at lower elevations due to the accumulation of basic cations (27), 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 Mg 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 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 Na, 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 K (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 (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 another study (35), which highlighted the importance of elevation gradients in structuring forest ecosystems and influencing species diversity and persistence across tropical rainforests. Similarly, another study 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 (36).

K and Ca, 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, K is rapidly cycled due to its mobility and its essential role in plant metabolism, whereas Ca tends to accumulate through the decomposition of leaf litter and woody debris (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 Na corresponds with previous studies indicating the dynamic nature of Na 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 OC, reflecting improved soil health, minimal disturbance, and dense vegetation cover. Moderate OC 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 OC 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 OC content. A clear geographical trend is

evident, with OC 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. Study (41) show considerable variation in the distribution of Ca concentrations. The western and northeastern regions, which feature higher green and blue Ca zones, might be affected by leaching, acidic soils, and Ca-poor bedrock material. The Ca 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, Mg in nitrophilous vegetation contributes to nutrient fluxes due to mineral weathering (42, 43). The map illustrates the regional distribution of accessible Mg in the Sirumugai Reserve Forest. Significantly elevated areas (3.4 to 4.1 $\text{cmol P}^+ \text{kg}^{-1}$) 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 $\text{cmol P}^+ \text{kg}^{-1}$), which function as buffer zones with diverse soil compositions. The lowest concentration regions (0.8 to 2.0 $\text{cmol P}^+ \text{kg}^{-1}$), 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 Mg-deficient areas to improve Mg levels.

Regional evaporation and associated acidity values (purple/brown) are high in the northeast and central-east regions (44). High Na 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 Na levels prevail, soil quality is likely to be high, and vegetation is presumably healthier. This may be attributed to geography or water flow, as Na levels seem to increase from the west towards the east.

Regions with high Na 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 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 CEC were found to be linked to phosphorus availability, showing moderate correlations.

The statistical analysis revealed high variability in P and K, while electrical conductivity and OC 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.

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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. KR carried out the investigation, provided software support, conducted the geostatistical analysis and contributed to data visualization. BK and RM reviewed and corrected grammatical errors and provided guidance and support in the writing of the research paper. All authors read and approved the final manuscript.

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

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