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Spatial Patterns of Soil Organic Carbon in South Delhi District : A Multi-Land Use Baseline Assessment

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ABSTRACT

Soil organic carbon (SOC) is a fundamental component of soil health and plays a critical role in climate regulation and ecosystem functioning. In rapidly urbanizing regions, spatial variation in SOC reflects complex land use patterns, yet spatially explicit assessments across diverse urban land uses remain limited. This study characterized the spatial distribution of SOC and associated soil physicochemical properties across five major land-use and land-cover (LULC) types in South Delhi District, India. Soil samples were collected from 98 locations representing agriculture, forest, scrub forest, built-up, and wasteland areas during 2021 and 2022. At each location, samples were obtained from three depth intervals (0–10, 10–20, and 20–30 cm) and analyzed for SOC, bulk density, moisture content, pH, electrical conductivity, water holding capacity, porosity, and particle density. Spatial patterns of SOC were assessed using Empirical Bayesian Kriging (EBK). SOC concentrations varied significantly across LULC types, with forest soils highest (0.62–0.66% at 0–10 cm) and wasteland soils lowest (0.15–0.17% at 0–10 cm, dropping to 0.06–0.08% at 20–30 cm). Built-up areas had similar low levels. SOC decreased with depth across all land uses, with 60–70% in the surface layer. SOC correlated strongly with bulk density, porosity, and water retention. EBK mapping revealed SOC-rich zones in forests and depleted zones in urban and degraded lands, with good validation. This study sets a baseline for SOC in South Delhi, highlighting hotspots and depleted areas for conservation. The spatial patterns suggest stability over two years. Limitations include uneven sampling, short duration, and lack of vegetation and land management data. Future work should include long-term monitoring, vegetation, soil texture, and SOC fractionation to better understand carbon dynamics.

1 | INTRODUCTION

Soils are a major terrestrial carbon reservoir, holding nearly twice as much carbon as the atmosphere and more than above-ground vegetation (Batjes, 1996; Ontl & Schulte, 2012). Soil organic carbon (SOC) is crucial for soil health, affecting structure, nutrients, water retention, and biological activity. Because SOC links closely to atmospheric carbon dioxide through biological and chemical processes, small changes in soil carbon stocks can influence the broader carbon cycle and climate (Lal, 2021). Land use and cover (LULC) changes significantly affect SOC (Singh *et al.*, 2019); converting natural vegetation to farmland or urban areas often leads to SOC loss from reduced organic inputs, soil disturbance, and increased decomposition. Globally, deforestation, agriculture, and urbanization have led to soil carbon loss (Lal, 2021), while vegetation cover and limited soil disturbance in forests and scrublands tend to preserve or boost SOC through litter and root inputs (Lupi *et al.*, 2021). Climate variability influences SOC by affecting decomposition and organic matter turnover, with rising temperatures and altered rainfall accelerating microbial activity, especially in semi-arid regions (Wiesmeier *et al.*, 2019). Studies from India show land systems with perennial vegetation are more resilient to climate-driven SOC loss than intensive annual cropping (Paramesha *et al.*, 2025). Interactions between land use, climate, and soil make SOC dynamics complex in urban areas. To address this gap, the present study was guided to explore:

i. How does soil organic carbon (SOC) vary across major land use/cover types and soil depths in South Delhi?

ii. What are the key relationships between SOC and soil physico-chemical properties such as bulk density, porosity, water holding capacity, pH, and electrical conductivity?

iii. What is the spatial distribution pattern of SOC across the study area, and which zones represent hotspots or depleted areas under different land use/cover types?

2 | MATERIALS AND METHODS

2.1 | Study Area

South Delhi District is one of the eleven administrative divisions of the National Capital Territory (NCT) of Delhi, India (Fig.1). Geographically, it lies between 28°22'N and 28°45'N latitude and 77°00'E and 77°15'E longitude, occupying the southern segment of the city. The district spans approximately 247 square kilometres, accounting for about 16.65% of the total area of the NCT of Delhi (Government of NCT of Delhi, 2024). South Delhi presents a diverse mosaic of land uses, comprising planned residential colonies, urban villages, agricultural lands, forest patches, and major institutional zones.

Climatically, the district is in the semi-arid zone, with extreme seasonal changes: summer temperatures often go over 44°C and winter temperatures fall below 4°C. The region gets about 790 mm of average annual rainfall, mostly during the monsoon season (IMD, 2023). Due to its complex LULC patterns and increasing environmental pressures, South Delhi becomes a key area for studying urban ecological dynamics, resource management issues, and ways to achieve sustainable development within the growing urban landscape.

HIGHLIGHTS

- Significant spatial heterogeneity in SOC distribution across South Delhi (0.06–0.66%) was successfully captured using Empirical Bayesian Kriging with high accuracy.
- Land use type explained >80% of SOC variance, while soil depth accounted for an additional 12–13%.
- Forest soils maintained 2–4 times higher SOC than degraded land uses across all depth intervals.
- SOC showed consistent associations with soil properties (bulk density, porosity, pH, EC).

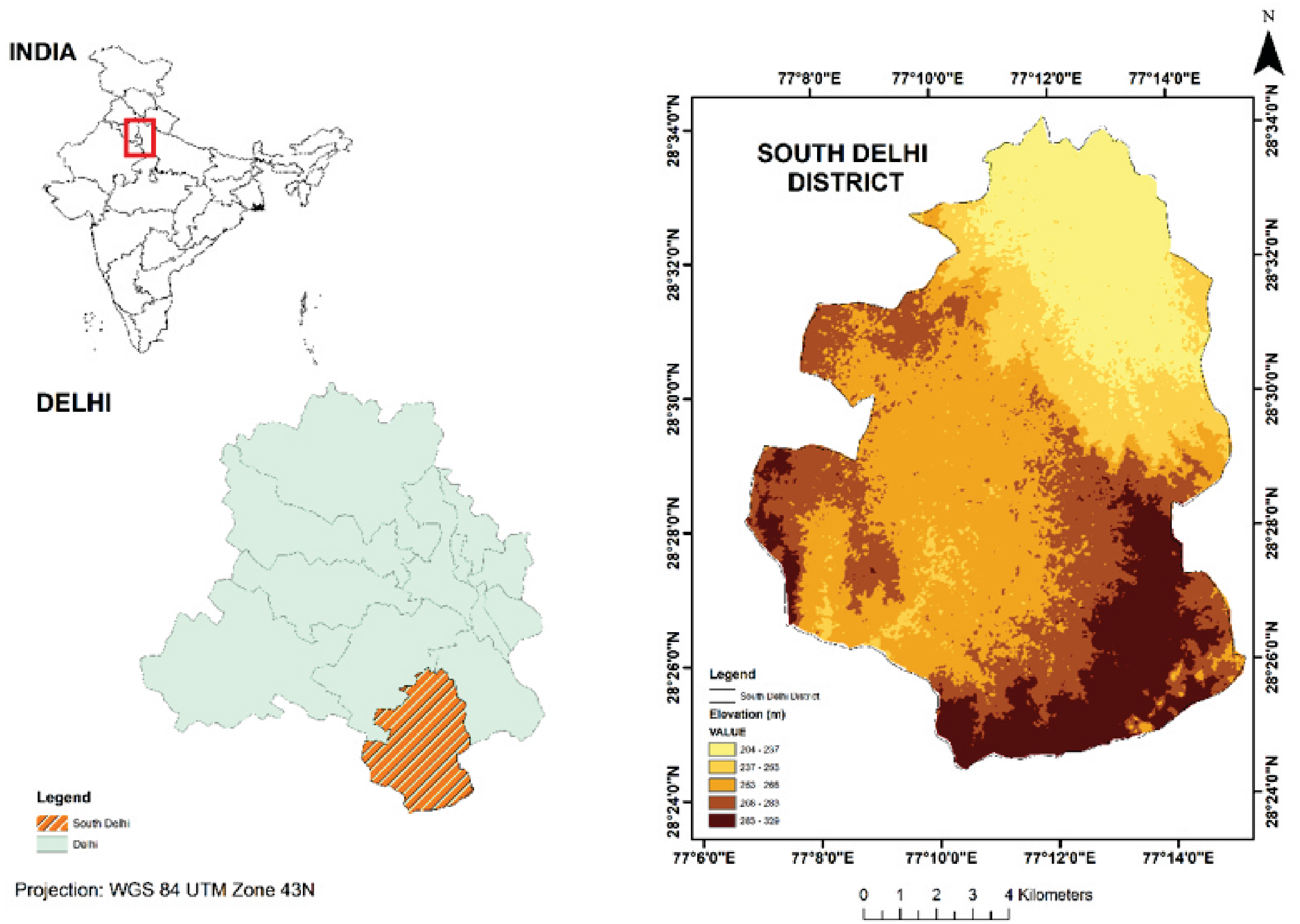

FIGURE 1 Location and topographic setting of South Delhi District showing its position within India and the National Capital Territory of Delhi

2.2 | Soil Analysis

Soil sampling was conducted across five major land use/cover (LULC) types: agriculture, forest, scrub forest, built-up, and wasteland. A total of 98 sampling locations were chosen using a stratified approach to ensure representation of each LULC category, while also considering accessibility constraints in forested and built-up areas. Forest and scrub forest sampling sites were limited to their fixed spatial extents, whereas agricultural sites were randomly selected from accessible fields. Wasteland and built-up locations were chosen based on field accessibility and land use characteristics. At each sampling site, a soil pit was dug, and samples were taken from three depth ranges: 0–10 cm, 10–20 cm, and 20–30 cm. Sampling occurred during similar periods in 2021 and 2022, with the same locations revisited using handheld GPS to ensure spatial consistency. Visible plant residues, roots, and surface litter were removed before processing the samples. The samples were georeferenced, transported to the lab, and stored at 4 °C until analysis. They were air-dried, gently ground with a mortar and pestle, and passed through a 2 mm sieve for laboratory analysis. The spatial distribution of sampling locations is shown in (Fig. 2).

Physical and chemical soil properties were analyzed using standard protocols. Bulk density was determined by collecting undisturbed samples in metal cores and calculated with the core method (Blake & Hartge, 1986). Water holding capacity (WHC) was assessed gravimetrically after saturation and drainage procedures (Piper, 1945). Soil pH and electrical conductivity (EC) were measured in a 1:2.5 soil-to-water suspension with a calibrated pH meter and EC meter, respectively (Estefan *et al.,* 2013). Particle density was determined via the pycnometer method (Bandyopadhyay, 2012), and porosity was calculated using bulk and particle density values (Estefan *et al*., 2013). Soil moisture content was measured by oven-drying soil samples at 105°C until reaching a constant weight (Estefan *et al.*, 2013). Organic carbon was estimated using the Walkley-Black wet oxidation method, with appropriate blanks and standards to ensure data quality (Walkley & Black, 1934; Lal, 2021). All laboratory analyses were performed in triplicate to enhance accuracy.

2.3 | Statistical Analysis

Data were analyzed using descriptive statistics and inferential tests to evaluate differences in soil organic carbon (SOC) and related soil properties across land use/cover types and soil depths. One-way analysis of variance (ANOVA) tested differences among LULC categories and soil depths, followed by Tukey's HSD test for pairwise comparisons at $p < 0.05$. Before conducting ANOVA, the assumptions of normality and homogeneity of variances were checked using the Shapiro–Wilk test and Levene's test, respectively. Since these assumptions were mostly met, parametric ANOVA was deemed appropriate. Pearson's correlation analysis examined relationships between SOC and soil physicochemical properties, such as bulk density, porosity, water-holding capacity, electrical conductivity, and pH. All statistical analyses were performed using R software (version 4.5.1) and PAST (version 5.1).

2.4 | Spatial Analysis

Spatial analysis was carried out to study the distribution and variability of SOC across the South Delhi District. The geographic coordinates of all sampling sites were projected into the WGS 1984 UTM Zone 43N coordinate system to ensure spatial accuracy. Empirical Bayesian Kriging (EBK) was used in ArcGIS 10.4.1 to create continuous SOC prediction surfaces for 2021 and 2022. EBK was selected for its ability to handle uncertainty in semivariogram estimation through repeated simulations, which is well-suited for the heterogeneous urban landscape. The predicted SOC surfaces and the related prediction standard error maps

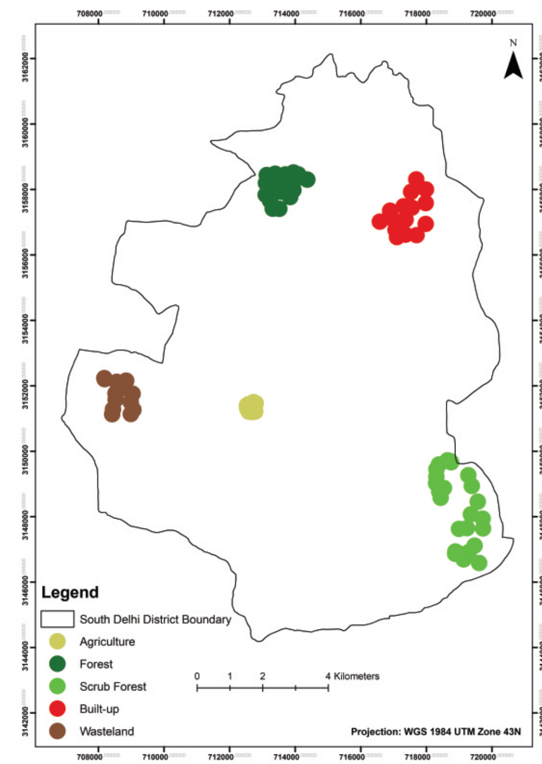

FIGURE 2 Spatial distribution of soil sampling locations across major LULC types in South Delhi District.

were clipped to the district boundary for visualization and analysis. Model performance was evaluated using cross-validation statistics, including mean error, root mean square error (RMSE), standardized RMSE, and regression slopes between observed and predicted values. The results showed that mean errors were nearly zero, regression slopes approached one, and standardized errors were close to one, indicating unbiased and reliable predictions of SOC spatial patterns.

3 | RESULTS AND DISCUSSION

3.1 | Soil Organic Carbon Distribution Across Land Use/Cover And Depths

Soil organic carbon (SOC) concentrations varied significantly across land use/cover (LULC) types and soil depths in both 2021 and 2022 (Tables 1 and 2). Forest soils consistently recorded the highest SOC values at all depths (0.62–0.66% at 0–10 cm), followed by scrub forest soils (0.54–0.58%). Agricultural soils showed moderate SOC concentrations (0.27–0.32%), whereas built-up (0.24–0.26%) and wasteland soils (0.15–0.17%) exhibited substantially lower values. Among all land uses, wasteland soils contained the lowest SOC across all depth intervals, with values declining to as low as 0.06–0.08% at 20–30 cm.

These patterns clearly demonstrate the dominant role of land use in regulating SOC distribution (Sharda et al., 2019) Higher SOC in forest and scrub forest soils can be attributed to continuous organic inputs from litter and roots, minimal disturbance, and relatively stable microclimatic conditions, which promote organic matter accumulation and stabilization. In contrast, built-up and wasteland soils showed pronounced SOC depletion, likely due to vegetation removal, soil sealing, compaction, and restricted organic matter inputs associated with urbanization. Similar relationships between vegetation cover, disturbance, and SOC storage have been reported in earlier studies (Post & Kwon, 2000; Ontl & Schulte, 2012). Agricultural soils showed moderate SOC concentrations (0.27–0.32%),

TABLE 1 Soil physico-chemical properties (mean ± SD) across five land use/cover (LULC) types and three soil depths (0–10, 10–20, and 20–30 cm) in South Delhi District during 2021.

LULC Type (2021)	Depth (cm)	SOC (%)	Bulk Density (g cm^{-3})	pH	EC (dS m^{-1})	Moisture (%)	Particle Density g cm^{-3})	Water Holding Capacity	Porosity (%)
Agriculture	0-10	0.27 ± 0.04	1.44 ± 0.04	6.67 ± 0.14	0.37 ± 0.06	18.5 ± 0.30	2.59 ± 0.02	26.92 ± 1.08	44.20 ± 1.46
	10-20	0.20 ± 0.02	1.52 ± 0.03	6.79 ± 0.31	0.35 ± 0.06	20.3 ± 4.03			
	20-30	0.15 ± 0.02	1.64 ± 0.03	7.18 ± 0.08	0.33 ± 0.05	22.2 ± 4.40			
Forest	0-10	0.62 ± 0.03	1.28 ± 0.05	6.50 ± 0.19	0.14 ± 0.02	9.7 ± 1.7	2.57 ± 0.04	30.06 ± 1.55	50.37 ± 2.01
	10-20	0.50 ± 0.02	1.37 ± 0.05	7.02 ± 0.21	0.13 ± 0.01	11.2 ± 2.0			
	20-30	0.41 ± 0.02	1.51 ± 0.05	7.52 ± 0.21	0.11 ± 0.01	12.1 ± 2.20			
Scrub Forest	0-10	0.54 ± 0.05	1.33 ± 0.04	6.25 ± 0.09	0.34 ± 0.05	4.1 ± 0.78	2.64 ± 0.02	25.20 ± 1.47	49.63 ± 1.63
	10-20	0.44 ± 0.04	1.41 ± 0.04	6.63 ± 0.23	0.30 ± 0.02	4.5 ± 0.86			
	20-30	0.36 ± 0.03	1.56 ± 0.04	7.05 ± 0.27	0.23 ± 0.02	4.9 ± 0.9			
Built-up	0-10	0.24 ± 0.05	1.48 ± 0.03	6.91 ± 0.29	0.51 ± 0.04	6.6 ± 3.2	2.66 ± 0.02	22.28 ± 0.66	44.17 ± 1.02
	10-20	0.15 ± 0.04	1.57 ± 0.03	7.51 ± 0.29	0.46 ± 0.02	7.4 ± 3.6			
	20-30	0.10 ± 0.02	1.72 ± 0.03	8.01 ± 0.29	0.39 ± 0.01	7.9 ± 3.94			
Wasteland	0-10	0.15 ± 0.02	1.51 ± 0.02	6.84 ± 0.40	1.51 ± 0.10	5.1 ± 1.87	2.67 ± 0.02	29.11 ± 0.61	43.30 ± 1.03
	10-20	0.09 ± 0.01	1.61 ± 0.03	7.31 ± 0.43	1.33 ± 0.05	5.8 ± 2.0			
	20-30	0.06 ± 0.01	1.74 ± 0.02	7.81 ± 0.43	1.19 ± 0.05	6.2 ± 2.248			

Note: Particle density, water holding capacity (WHC), and porosity were measured for surface soil (0–10 cm) only.

TABLE 2 Soil physico-chemical properties (mean ± SD) across five land use/cover (LULC) types and three soil depths (0–10, 10–20, and 20–30 cm) in South Delhi District during 2022.

LULC Type (2022)	Depth (cm)	SOC (%)	Bulk Density (g cm^{-3})	pH	EC (dS m^{-1})	Moisture (%)	Particle Density g cm^{-3})	Water Holding Capacity	Porosity (%)
Agriculture	0-10	0.32 ± 0.04	1.46 ± 0.03	7.29 ± 0.30	0.38 ± 0.06	19.48 ± 3.5	2.59 ± 0.02	27.86 ± 1.13	43.96 ± 1.42
	10-20	0.24 ± 0.03	1.54 ± 0.03	7.40 ± 0.30	0.36 ± 0.06	21.2 ± 3.5			
	20-30	0.20 ± 0.02	1.64 ± 0.03	7.58 ± 0.30	0.34 ± 0.06	23.17 ± 3.6			
Forest	0-10	0.66 ± 0.03	1.30 ± 0.03	7.49 ± 0.25	0.15 ± 0.01	11.79 ± 2.0	2.57 ± 0.04	28.77 ± 0.98	49.58 ± 1.12
	10-20	0.54 ± 0.03	1.39 ± 0.03	7.59 ± 0.25	0.13 ± 0.01	13.49 ± 2.0			
	20-30	0.43 ± 0.03	1.50 ± 0.04	7.78 ± 0.25	0.12 ± 0.01	14.65 ± 1.9			
Scrub Forest	0-10	0.58 ± 0.05	1.38 ± 0.04	7.07 ± 0.27	0.32 ± 0.05	4.48 ± 0.8	2.64 ± 0.02	25.88 ± 1.25	47.71 ± 1.55
	10-20	0.47 ± 0.04	1.47 ± 0.04	7.17 ± 0.27	0.28 ± 0.02	5.98 ± 0.8			
	20-30	0.37 ± 0.03	1.59 ± 0.04	7.89 ± 0.38	0.23 ± 0.02	7.08 ± 0.90			
Built-up	0-10	0.26 ± 0.04	1.51 ± 0.04	7.99 ± 0.38	0.55 ± 0.05	6.51 ± 2.5	2.66 ± 0.02	23.68 ± 0.69	43.20 ± 1.56
	10-20	0.18 ± 0.03	1.61 ± 0.05	8.19 ± 0.38	0.47 ± 0.03	7.71 ± 2.5			
	20-30	0.13 ± 0.02	1.72 ± 0.04	7.80 ± 0.44	0.38 ± 0.02	8.01 ± 2.17			
Wasteland	0-10	0.17 ± 0.02	1.57 ± 0.05	7.90 ± 0.44	1.53 ± 0.11	5.3 ± 1.9	2.67 ± 0.02	28.77 ± 1.20	41.76 ± 1.93
	10-20	0.11 ± 0.01	1.66 ± 0.05	8.10 ± 0.44	1.35 ± 0.06	6.53 ± 1.9			
	20-30	0.08 ± 0.01	1.76 ± 0.04		1.19 ± 0.06	7.58 ± 1.6			

Note: Particle density, water holding capacity (WHC), and porosity were measured for surface soil (0–10 cm) only.

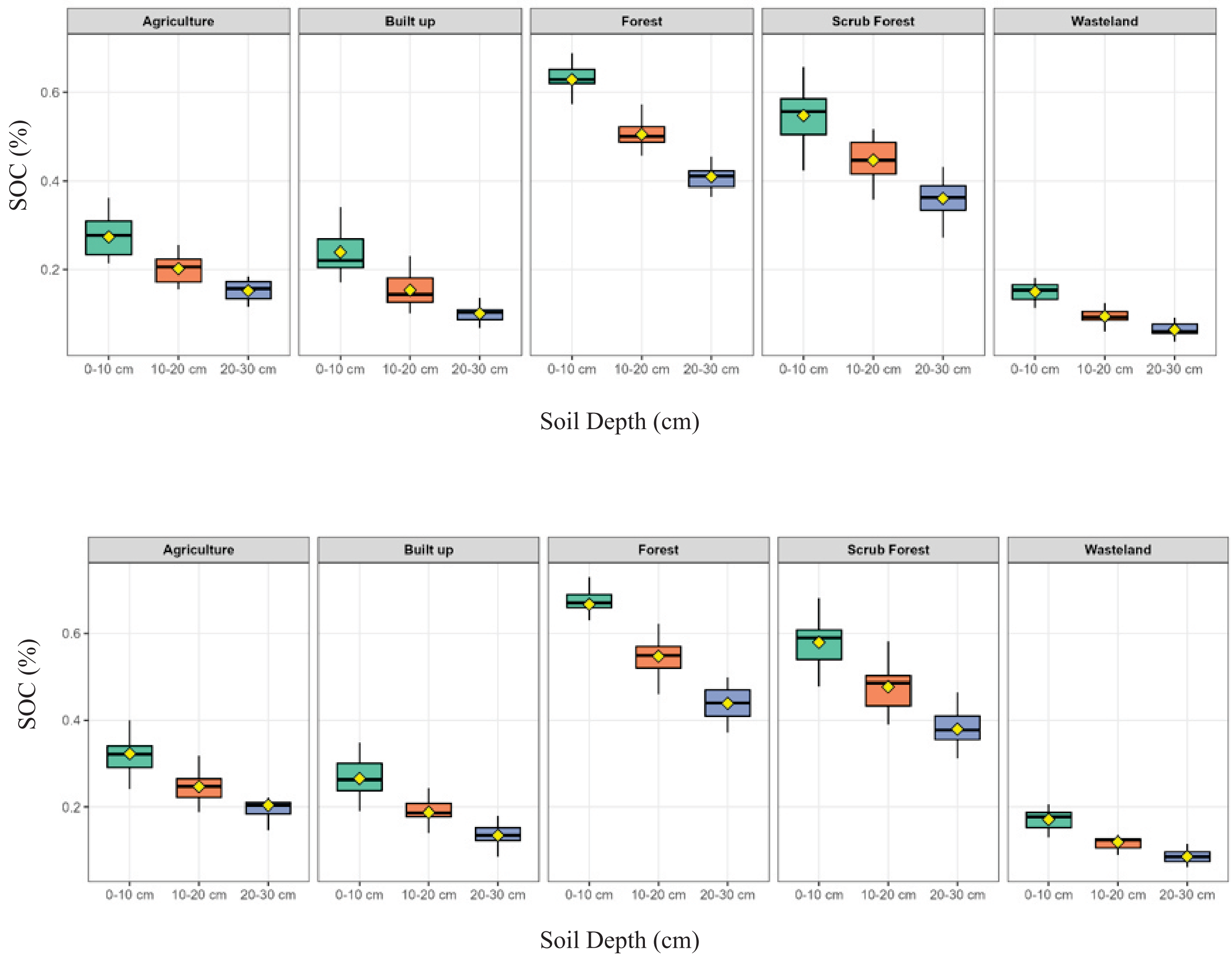

FIGURE 3 Boxplots showing the distribution of soil organic carbon (SOC %) across LULC types and soil depths (0–10 cm, 10–20 cm, 20–30 cm) in South Delhi during (A) 2021 and (B) 2022.

reflecting a balance between organic inputs from crop residues and carbon losses due to frequent tillage and limited organic amendments. Such intermediate SOC levels in agricultural systems have also been reported in semi-arid regions of India (Mandal *et al.*, 2019).

SOC decreased significantly with increasing soil depth across all LULC categories ($p < 0.001$), with approximately 60–75% of SOC concentrated in the surface layer (0–10 cm). Forest and scrub forest soils showed a more gradual reduction in SOC with depth, whereas agricultural, built-up, and wasteland soils exhibited a sharper decline. This vertical stratification reflects the concentration of organic inputs, root activity, and microbial processes near the soil surface, consistent with established soil carbon dynamics (Ontl & Schulte, 2012; Post & Kwon, 2000).

Boxplot analysis further illustrated a clear separation of SOC values across LULC types and soil depths (Fig. 3), with minimal overlap between categories. Forest and scrub forest soils consistently showed higher median SOC values and narrower variability, whereas built-up and wasteland soils exhibited lower medians and greater spread. Similar distribution patterns were observed in both 2021 and 2022, indicating that the relative differences among land use types and depth-wise trends remained stable over time, reflecting short-term temporal consistency in SOC distribution.

3.2 | Statistical Significance of SOC Variation

One-way analysis of variance (ANOVA) confirmed statistically significant differences in SOC concentrations among land use/cover types and soil depths for both study years ($p < 0.001$; Table 3). Land use explained a substantial proportion of the observed variation in SOC (>80%), while soil depth accounted for an additional 12–13% of the variance. Interaction effects between land use and depth were comparatively weak, indicating that depth-related SOC declines were broadly consistent across different land uses.

Post hoc Tukey's HSD tests showed that forest and scrub forest soils contained significantly higher SOC compared to agricultural, built-up, and wasteland soils ($p < 0.05$). Similarly, the 0–10 cm soil layer differed significantly from the 10–20 cm and 20–30 cm layers across all LULC categories, confirming the strong vertical stratification of SOC in the study area.

TABLE 3 Analysis of variance (ANOVA) results showing the effects of land use/cover (LULC) and soil depth on soil organic carbon (SOC) during 2021 and 2022.

Year	Factor	Source	df	SS	MS	F	p-value	ω^2
2021		Between groups	4	7.995	1.999	331.1	<0.001	0.82
2021		Within groups	289	1.745	0.006			
2021	LULC	Total	293	9.74				
2022		Between groups	4	8.013	2.008	311.5	<0.001	0.81
2022		Within groups	289	1.863	0.006			
2022		Total	293	9.894				
2021		Between groups	2	1.267	0.633	21.76	<0.001	0.12
2021	Depth	Within groups	291	8.473	0.029			
2021		Total	293	9.74				
2022		Between groups	2	1.327	0.663	22.53	<0.001	0.13
2022		Within groups	291	8.567	0.029			
2022		Total	293	9.894				

TABLE 4 Correlation matrix of soil organic carbon (SOC) with soil physico-chemical properties, 2021

Variable	SOC %	Moisture	EC (dS m^{-1})	pH	Bulk density (g cm^{-3})	WHC	Porosity (%)	Particle density g cm^{-3})
SOC %	1	-0.125	-0.721	-0.607	-0.919	0.302	0.879	-0.479
Moisture		1	-0.281	0.145	0.044	0.230	-0.169	-0.416
EC (dS m^{-1})			1	0.399	0.683	0.089	-0.592	0.563
pH				1	0.552	-0.085	-0.551	0.195
Bulk density (g cm^{-3})					1	-0.383	-0.969	0.478
Water holding capacity						1	0.325	-0.367
porosity (%)							1	-0.247
Particle density g cm^{-3}								1

3.3 | Relationship Between SOC And Soil Properties

Correlation analysis showed strong, consistent relationships between SOC and key soil physico-chemical properties across both years (Tables 4 and 5). SOC exhibited a strong negative correlation with bulk density ($r = -0.92$ to -0.93, $p < 0.001$), indicating reduced compaction in soils with higher organic carbon content. Moderate to strong negative correlations were also observed with pH ($r = -0.41$ to -0.61) and electrical conductivity ($r = -0.72$ to -0.77), while strong positive correlations were found with porosity ($r = 0.88$–0.91). Additionally, SOC showed a positive relationship with water holding capacity ($r = 0.30$–0.37).

These relationships highlight the fundamental role of SOC in improving soil physical structure, enhancing porosity, and increasing moisture retention capacity. The negative association with electrical conductivity further suggests that higher organic matter content may contribute to improved soil chemical conditions. These findings are consistent with earlier studies demonstrating the role of SOC in enhancing soil quality and resilience (Gol, 2009; Singh & Sharma, 2017; Zhang & Shangguan, 2016).

TABLE 5 Correlation matrix of soil organic carbon (SOC) with soil physico-chemical properties, 2022

Variable	SOC %	Moisture	EC ($dS\ m^{-1}$)	pH	Bulk density ($g\ cm^{-3}$)	WHC	Porosity (%)	Particle density $g\ cm^{-3}$)
SOC %	1	0.007	-0.766	-0.409	-0.931	0.148	0.908	-0.479
Moisture		1	-0.330	-0.084	-0.169	0.368	-0.044	-0.509
EC ($dS\ m^{-1}$)			1	0.394	0.766	0.129	-0.699	0.568
pH				1	0.335	-0.018	-0.325	0.165
Bulk density ($g\ cm^{-3}$)					1	-0.239	-0.972	0.543
Water holding capacity						1	0.191	-0.294
porosity (%)							1	-0.332
Particle density $g\ cm^{-3}$								1

3.4 | Spatial Distribution Patterns

Spatial interpolation using Empirical Bayesian Kriging (EBK) revealed pronounced heterogeneity in SOC distribution across South Delhi (Fig.4). High SOC concentrations were concentrated in forest and scrub forest patches, particularly in the northern and northeastern parts of the district associated with the Asola Bhatti Wildlife Sanctuary and ridge forest areas. These locations consistently appeared as SOC "hotspots," attributable to dense vegetation cover and minimal disturbance.

Agricultural soils displayed moderate SOC levels, with higher values observed in areas where crop residues are likely retained, while intensively managed fields showed lower SOC. Built-up and wasteland soils appeared as distinct "coldspots," reflecting vegetation removal, soil compaction, and sealing associated with urbanization.

The strong contrast between high-SOC forest zones and low-SOC urban/degraded zones demonstrates how land use transitions have reshaped soil carbon distribution across the landscape. Similar spatial patterns have been reported in other regions, where natural vegetation patches function as important carbon reservoirs within human-dominated systems (Tomar & Baishya, 2019; Olorunfemi *et al.*, 2020; Mabicka *et al.*, 2021).

The persistence of high SOC in forest and scrub forest areas underscores the need to protect remnant green spaces and ridge ecosystems from further degradation, in line with broader soil and ecosystem conservation priorities (FAO & UNEP, 2020).

3.5 | Validation Of Spatial Predictions

Cross-validation statistics indicated good agreement between observed and predicted SOC values (Table 6). Mean prediction errors were close to zero, and root mean square error (RMSE) values remained low for both years. Regression slopes between observed and predicted SOC values ranged from 0.93 to 0.94, with coefficients of determination (R^2) exceeding 0.88. Standardized errors were close to unity, indicating unbiased predictions.

These results confirm that the EBK interpolation effectively captures spatial variability in SOC and produces reliable prediction surfaces suitable for identifying SOC-rich and SOC-depleted areas within the study region.

TABLE 6 Cross-validation statistics for Empirical Bayesian Kriging (EBK) interpolation of soil organic carbon (SOC) in South Delhi during 2021 and 2022

Year	Mean Error	Root Mean Square Error (RMSE)	Root Mean Standardized Square Error	Regression Slope	R^2
2021	-0.0011	0.051	0.971	0.93	0.88
2022	-0.0011	0.048	1.01	0.94	0.90

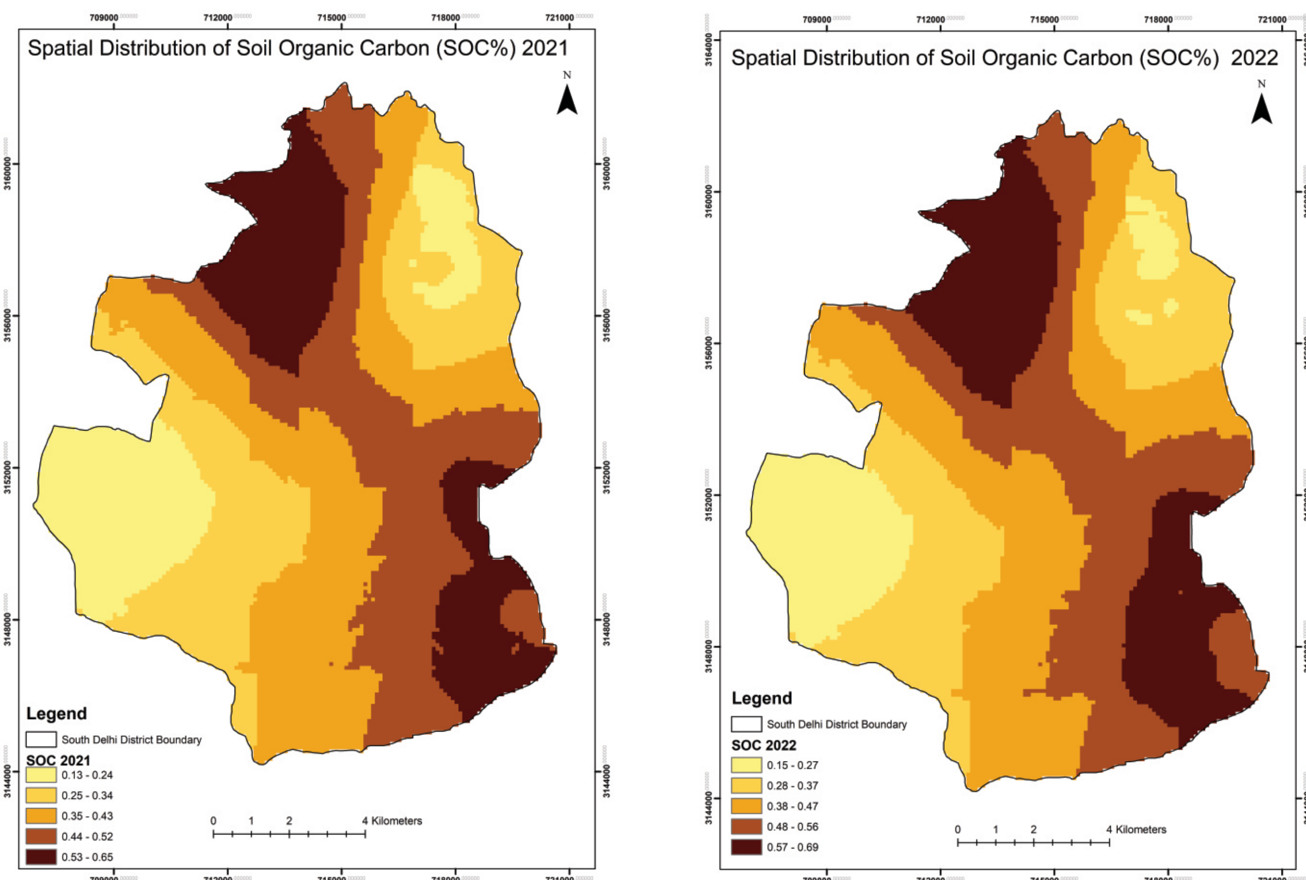

FIGURE 4 Spatial distribution of soil organic carbon (SOC, %) in South Delhi District, 2021 and 2022 (EBK interpolation)

3.6 | Key Findings

The study results show the following patterns:

1. Significant spatial variation across land uses: Forest and scrub forest soils contained the highest SOC concentrations (0.62–0.66% and 0.54–0.58% at 0–10 cm), approximately 2–4 times higher than built-up (0.24–0.26%) and wasteland soils (0.15–0.17%). Agricultural soils showed intermediate values (0.27–0.32%). These differences were highly significant ($p < 0.001$) and explained 81–82% of SOC variance.

2. Consistent depth stratification: SOC decreased significantly with soil depth across all land uses ($p < 0.001$), with 60–75% of organic carbon concentrated in the surface 0–10 cm layer. Forest and scrub forest soils showed more gradual depth-related declines (33–34%) compared to agricultural (44%), built-up (58%), and wasteland soils (60%).

3. Strong associations with soil properties: SOC exhibited strong negative correlations with bulk density ($r = -0.93$) and electrical conductivity ($r = -0.77$), and strong positive correlations with porosity ($r = +0.91$). These relationships were consistent across both study years, indicating stable associations between organic carbon and soil physical and chemical characteristics.

4. Distinct spatial patterns: Empirical Bayesian Kriging interpolation identified clear SOC hotspots in forest and scrub forest areas (particularly Asola Bhatti Wildlife Sanctuary and ridge forests) and depleted zones in built-up and wasteland areas. Cross-validation demonstrated good prediction accuracy ($R^2 > 0.88$, RMSE < 0.051%), though prediction uncertainty was higher in under-sampled urban zones.

5. Spatial consistency across years: SOC distribution patterns were remarkably similar between 2021 and 2022, suggesting spatial stability in land use–SOC relationships over the short term, though the two-year period is insufficient for assessing temporal trends.

4 | LIMITATIONS AND FUTURE SCOPE OF THE STUDY

The current study has some limitations that should be recognized. Although soil samples were collected across major land use and cover types, the sampling density was uneven due to accessibility issues in developed and forested areas. Additionally, soil organic carbon was estimated using the Walkley–Black method, which might underestimate the total carbon content. The study also did not explicitly consider vegetation biomass, litter input, or land management history, which could help explain spatial differences in SOC. Future research should include SOC fractionation, microbial indicators, assessments of vegetation biomass, and long-term monitoring to better understand carbon stabilization in urban soils. Incorporating high-resolution remote sensing data and climate projections would further improve the usefulness of SOC assessments for urban soil conservation and land use planning.

5 | CONCLUSIONS

This study offers a spatial baseline assessment of soil organic carbon (SOC) distribution across major land use and cover types in South Delhi District. Analysis of 98 locations sampled in 2021 and 2022 showed significant spatial variation in SOC concentrations, with clear differences among land uses and consistent vertical stratification with soil depth. Key findings include notable spatial variation across land uses, consistent depth stratification, and strong SOC relationships with soil properties. Forest and scrub forest soils had approximately 2–4 times higher SOC levels than built-up (0.24–0.26%) and wasteland soils. Agricultural soils exhibited intermediate values (0.27–0.32%). These differences were highly significant ($p < 0.001$) and accounted for 81–82% of SOC variance. SOC levels decreased significantly with soil depth across all land uses, with 60–75% of organic carbon found in the top 10 cm layer. Forest and scrub forest soils showed more gradual declines with depth (33–34%) compared to agricultural (44%), built-up (58%), and wasteland soils (60%). SOC had strong negative correlations with bulk density and electrical conductivity, and strong positive correlations with porosity. Empirical Bayesian Kriging interpolation identified clear SOC hotspots in forest and scrub forest areas (especially Asola Bhatti Wildlife Sanctuary and ridge forests) and depleted zones in built-up and wasteland areas. Cross-validation indicated good prediction accuracy ($R^2 > 0.88$, RMSE < 0.051%), although uncertainty was higher in under-sampled urban zones. The SOC distribution patterns were remarkably similar between 2021 and 2022, suggesting spatial stability in land-use–SOC relationships over the short term, although the two-year period is insufficient to assess long-term trends.

These findings offer spatially explicit information for prioritizing soil conservation efforts in South Delhi. Forest and scrub forest areas represent existing SOC stores that require protection from further degradation or conversion. Agricultural lands exhibit intermediate SOC levels with potential for improvement through appropriate management, though specific practices warrant further investigation. Built-up and wasteland areas show significant SOC depletion and could benefit from restoration initiatives, although their feasibility and effectiveness require experimental evaluation. Spatial maps allow identification of priority zones for different management goals—either protecting hotspots or restoring depleted areas.

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CONFLICT OF INTEREST

The authors declare that there are no competing or conflicting interests.

DATA AVAILABILITY STATEMENT

All data supporting the findings of this study are available from the author upon reasonable request. Summary datasets generated or analyzed during the current study are included in the article.

AUTHOR'S CONTRIBUTION

TP conceived and designed the study, conducted all analyses, and wrote the first draft of the manuscript. PL and TS assisted with fieldwork and provided technical inputs. All authors reviewed and approved the final manuscript.

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