DOI: 10.2478/jlecol-2026-0024 Journal of Landscape Ecology (2026), Vol: 19 / No. 3

SPATIAL VARIABILITY OF SOIL QUALITY UNDER DIVERSE LAND USE SYSTEMS IN TROPICAL COASTAL ENVIRONMENTS: A CASE STUDY FROM INDIA

SETHUMADHAVAN PARTHASARATHI AKILA AND LINGASSAMY ARUL PRAGASAN*

Environmental Ecology Lab, Department of Environmental Sciences, Bharathiar University, Coimbatore – 641 046, Tamil Nadu, India.
**Corresponding author email: arulpragasan@buc.edu.in*

Received: 11th September 2025, **Accepted:** 10th November 2025

ABSTRACT

Soil quality is a key determinant of ecosystem functions and land sustainability in rapidly changing coastal regions. This study evaluated spatial variation in soil quality across five land-use types (agriculture, urban green spaces, built-up areas, mangroves, and barren land) in the Puducherry region of India. A total of 225 surface soil samples (0-20 cm) were collected and analyzed for fifteen physicochemical parameters. Principal component analysis (PCA) identified four key indicators: electrical conductivity (EC), organic carbon (OC), available nitrogen (Av. N), and manganese (Av. Mn). A weighted linear scoring system was used to compute the Soil Quality Index (SQI), and spatial interpolation was performed using ordinary kriging. SQI values ranged from 0.45 in built-up areas to 0.60 in mangroves, showing the order: mangroves > urban green spaces > agriculture > barren > built-up areas. Mangrove soils showed higher SQI due to greater organic carbon and nutrient content, while inland and built-up areas reflected lower quality linked to soil disturbance and reduced fertility. These findings highlight spatial patterns of soil degradation and provide a practical framework for improving land management in tropical coastal environments.

Keywords: SQI, spatial variability, PCA, Ordinary kriging interpolation, Puducherry region

INTRODUCTION

Human-induced activities have transformed nearly three-quarters of the Earth's land surface over the past thousand years (IPCC, 2019). In recent decades, urban expansion driven by population growth and increasing demand for housing, infrastructure, and industry has intensified the conversion of rural landscapes into urban environments (Ansari *et al*., 2025; Mahtta *et al*., 2022). By 2036, urban growth is projected to account for more than two-thirds of the global population increase (NCP, 2019), intensifying land conversion and environmental stress. These large-scale land-use changes have become a central focus of global environmental policy because they influence carbon sequestration, exacerbate climate change, and contribute to biodiversity loss (Winkler *et al*., 2021).

Soil, as a finite resource, is fundamental to agriculture, ecosystem stability, and infrastructure development, with an estimated 95 % of food production depending directly and indirectly on it (FAO, 2015). As land conversion increases, understanding how soil quality varies across different land uses is essential for safeguarding food security and maintaining ecosystem functions (Kumar *et al*., 2025). In addition to supporting plant growth, soils play a crucial role in the global carbon cycle by sequestering carbon, thereby reducing atmospheric carbon dioxide (CO_2) concentrations and contributing to climate change mitigation (Tadese *et al*., 2023).

Soil quality, conceptually defined by the Soil Science Society of America (SSSA) as "the capacity of soil to function", encompasses physical, chemical, and biological parameters that collectively determine soil health and productivity (Maji & Mistri, 2024). Physicochemical indicators such as OC, pH, nutrient availability, and EC are widely used in soil quality assessment because they respond consistently to land-use change and management intensity and remain comparatively stable over time (Bünemann *et al*., 2018). Biological indicators such as enzyme activity or microbial biomass are ecologically important but highly variable and site-specific, which limits their use for comparing different land uses within a single framework. In coastal and mangrove-influenced soils, OC, Av. N, and EC are particularly informative because they indicate soil fertility, carbon storage, and salt stress, which together describe soil condition in these environments (Mello *et al*., 2024; Zou *et al*., 2023). Monitoring these indicators is therefore necessary for early detection of degradation and for maintaining soils that can continue to support ecological functions (Kaur *et al*., 2021).

The SQI provides an integrative measure of soil health, condensing complex datasets into a single metric that reflects the capacity of soils to sustain productivity, buffer environmental stress, and support ecosystem services (Lenka *et al*., 2022). Various approaches have been employed to develop SQI, including additive scoring models, weighted linear combinations, and non-linear scoring techniques (Nasir *et al*., 2024; Tejashvini *et al*., 2023b; Ellur *et al.,* 2024). Among these, principal component analysis PCA has been most widely applied for identifying key indicators, minimizing redundancy, and defining a minimum data set (MDS) for efficient SQI computation (Maji & Mistri, 2024; Sanad *et al*., 2024; Bel-Lahbib *et al*., 2023; Tejashvini *et al*., 2023a; Tejashvini *et al*., 2023b). Spatial representation of SQI has subsequently been achieved through geostatistical interpolation techniques such as ordinary kriging, enabling prediction of soil quality across unsampled areas and identification of zones exhibiting degradation or high fertility potential (Pirestani *et al*., 2024; Coulibaly & Sako, 2024).

Although soil quality has been widely assessed under different land-use systems in inland and semi-arid environments (Ibrahim *et al*., 2023; Sanad *et al*., 2024; Tejashvini *et al*., 2023a; Tejashvini *et al*., 2023b; Kumar *et al*., 2025), studies focusing on tropical coastal peri-urban regions remain limited. These landscapes are shaped by complex interactions among saline intrusion, heterogenous land use, and rapid urban expansion, all of which strongly influence soil properties. The Puducherry region represents one such landscape, where mangroves, croplands, urban green spaces, built-up, and barren land coexist within a small coastal area undergoing fast-paced development. Despite this unique land-use diversity, little is known about how soil quality varies spatially across these systems. Therefore, this study evaluates the spatial distribution of soil quality in the Puducherry region using the SQI, addressing a major knowledge gap in tropical coastal peri-urban ecosystems. The specific objectives are to: (1) assess the variation in soil physicochemical properties across major land use types (agriculture, urban green spaces, built-up areas, mangroves and barren lands) of the Puducherry region, (2) define a MDS for soil quality evaluation, (3) develop a linear scoring system for varied land uses, and (4) map the spatial distribution of soil quality using ordinary kriging within a GIS framework based on the computed SQI. The findings will provide baseline data for urban planners, policy makers, and scientists to support sustainable land management, maintain productivity, and preserve soil fertility in rapidly changing coastal peri-urban environments.

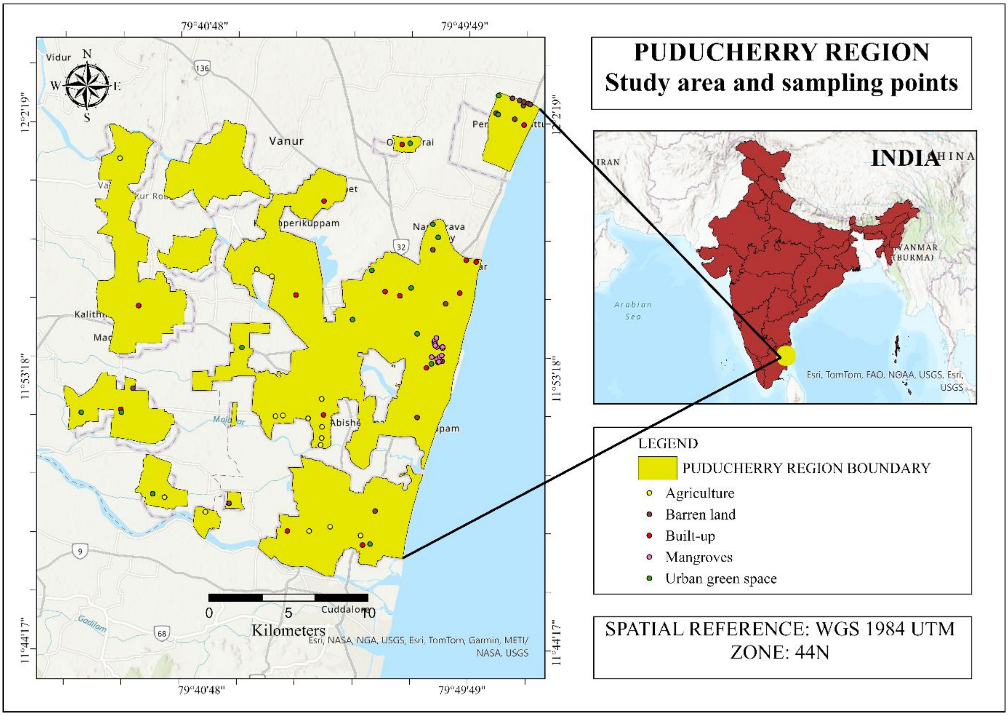
MATERIALS AND METHODS

Study area

This study examined soil quality in the Puducherry region (~294 km^2) of the Union Territory of Puducherry, India (Fig. 1). The Union Territory comprises two revenue districts: Puducherry district (encompassing the Puducherry, Yanam, and Mahe regions) and Karaikal district (encompassing the Karaikal region). Geographically, the Puducherry region lies between latitudes 11°52′56″ and 11°59′53″ N and longitudes 79°45′00″ to 79°52′43″ E. The region, predominantly a flat plain, has an average elevation of 15 m above mean sea level (MSL) and a coastline of approximately 22 km (Sangaradasse & Eswari, 2019).

The climate is tropical with mean annual temperatures between 27 °C and 37 °C and relative humidity of 60–70 %. The average rainfall is about 1527 mm, largely from the northeast monsoon (October–December) and partly from the southwest monsoon (July–September). The region has an estimated population of about 1.32 million in 2024 (Puducherry at a glance, 2024), reflecting continued urban growth and pressure on land resources. Land use in the region includes irrigated agriculture, urban settlements, mangroves, and barren lands. The soils are primarily coastal alluvial and red ferrallitic, which correspond to Fluvisols and Acrisols according to the World Reference Base for Soil Resources (WRB, 2022).

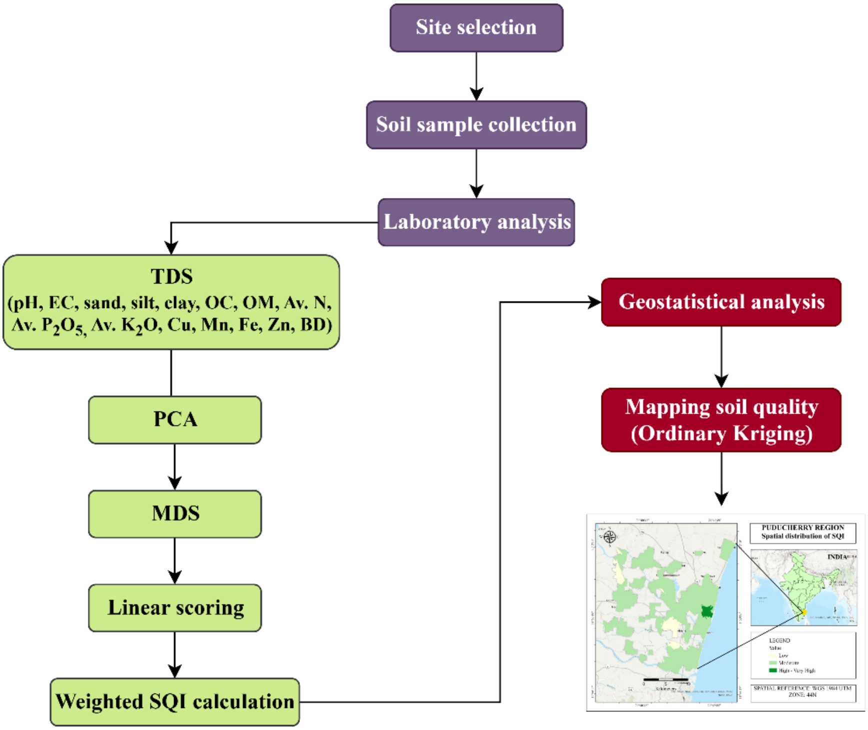
Fig. 1: Location map of the Puducherry region indicating soil sampling sites across five land-use types: agriculture, urban green spaces, built-up, mangroves, and barren land



Soil sampling and analysis

A total of 225 surface soil samples (0-20 cm) were collected in June 2024 across five representative land-use types: agriculture, urban green spaces, built-up areas, mangroves, and barren land, using a stratified random design. Prior to sampling, loose surface litter and undecomposed organic material were removed so that only the mineral topsoil was collected. For each land-use type, 15 geo-referenced locations were identified, and at each location, three replicate samples were collected within ~1 m^2, resulting in 45 samples per land use. All samples were air-dried, homogenized, and sieved (2 mm) prior to analysis.

Fig. 2: Methodological flowchart summarizing SQI computation steps including sampling, indicator selection, and kriging-based mapping.



Fifteen physicochemical parameters were quantified following standard protocols. The particle size distribution (sand, silt, and clay) was determined by the hydrometric method (Bouyoucos, 1962) after dispersion with sodium hexametaphosphate. Soil pH was measured in a 1:2.5 soil-water suspension using a digital pH meter, and EC was determined in the same extract using a Labtronics LT-23 conductivity meter (Jackson, 1973). OC content was estimated by the Walkley and Black wet oxidation method (Walkley & Black, 1934), where the soil carbon was oxidized by the presence of potassium dichromate ($K_2Cr_2O_7$) and concentrated sulphuric acid (H_2SO_4); and organic matter (OM) was calculated by multiplying OC by the factor 1.724. Av. N was determined by the alkaline permanganate method (Subbaiah & Asija, 1956), where soil N is oxidized by alkaline $KMnO_4$ and the released ammonia is distilled and quantified using a Kjeldahl apparatus. Available phosphorus (Av. P_2O_5) was quantified using Olsen's method (Olsen, 1954) with 0.5M sodium bicarbonate ($NaHCO_3$) extraction for alkaline soils and the Bray No.1 method (Bray & Kurtz, 1945) for acidic soils. Available potassium (Av. K_2O) was extracted with 1N ammonium acetate and measured using a flame photometer (Chapman, 1965). Micronutrients, including Av. Mn, available copper (Av. Cu), iron (Av. Fe), and zinc (Av. Zn), were extracted using the DTPA method (Lindsay & Norvell, 1978) and quantified using a Lab India AA8000 Atomic Absorption Spectrophotometer (AAS). Bulk density (BD) was measured using the core sampler method with a cylindrical sampler of 100 cm^3 volume, expressed as the ratio of oven-dried soil mass to the core volume (Singh, 1980).

Assessment of soil quality index

SQI was developed in three steps: (i) identification of MDS using PCA, (ii) normalization of selected indicators, (iii) determination of overall SQI using a weighted method.

Determining the minimum data set

PCA is regarded as effective and was applied to the total data set (TDS) of fifteen soil variables to reduce dimensionality and minimize redundancy (Mahajan *et al*., 2019). All variables were standardized to zero mean and unit variance prior to analysis to remove the effect of differing measurement scales. Components with eigenvalues ≥1 were retained, and high-loading variables were selected as potential indicators (Andrews *et al*., 2002). For highly correlated variables ($r > 0.80$), the parameter with the higher absolute loading was retained as the representative indicator (Chandel *et al*., 2018). Indicators selected for the MDS were required to be independent and sufficiently informative to detect changes in soil quality (Andrews *et al*., 2002).

Scoring of indicator soil properties

The chosen indicators were standardized through linear scoring functions according to their relationship with soil quality, categorized as ‘more is better,’ ‘less is better,’ or ‘optimum range’. In the ‘more is better’ case, each observation was divided by the maximum observed value, assigning the highest score of 1 to the maximum (Equation 1). For the “less is better” function, the minimum observed value was divided by each observation, such that the lowest value received a score of 1 and all others scored < 1 (Equation 2). For the “optimum is better” function, values up to a defined threshold were scored as “more is better,” whereas values exceeding the threshold were scored as “less is better.” This approach standardized all indicators to a 0-1 scale (Budak *et al*., 2018).

For the “more is better” approach, $S_i = \frac{Value}{X_{max}} \dots\dots\dots\dots\dots\dots\dots\dots\dots (eq. 1)$

For the “less is better” approach, $S_i = \frac{X_{min}}{Value} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (eq. 2)$

Calculation and classification of SQI

Indicator weights were derived by dividing the percentage variance of the corresponding PC by the cumulative variance of all retained PCs. The weighted approach ensures that indicators contributing more to overall soil quality variation exert proportionally greater influence on the final index. The SQI for each sampling location was computed using the following equation 3 outlined by Chen YuDong *et al*. (2013).

$$SQI = \sum_{i=1}^{n} W_i S_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (eq. 3)$$

where S_i is the score for variable i and W_i is the weighted factor derived from the PCA. Higher SQI values indicate better soil quality and vice versa. The calculated SQI was interpreted following the SQI classification as shown in Table 1.

Table 1: Classification of SQI values with corresponding ratings and suitability interpretations

Grade	SQI	Rating of soil quality	Description of SQIs grade
I	>0.60	Very high	Most suitable for plant growth
II	0.55-0.60	High	Suitable for plant growth
III	0.45-0.54	Moderate	Suitable with limitations
IV	0.38-0.44	Low	Serious than grade III
V	<0.38	Very low	Most severe

Spatial variability mapping of SQI

For geostatistical modelling, replicates were averaged to a single value per location (n = 75) to avoid pseudo-replication and ensure spatial independence (Webster & Oliver, 2007; Cressie, 2015). The spatial variability of SQI was modelled using the Geostatistical Analyst extension in ArcGIS Pro (v. 3.3.2). Ordinary kriging, a geostatistical interpolation method was used for the prediction of the values in the unsampled locations. The spatial autocorrelation structure was quantified using semivariograms, calculated as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(xi) - Z(xi+h)]^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (eq.4)$$

In equation 4, $\gamma(h)$ is the semivariance, h is the lag distance, and Z is the parameter of the soil property, $Z(xi)$ is the value at location xi; $Z(xi + h)$ is the value at a distance h from xi (Rosemary *et al*., 2017). Three theoretical semivariogram models - exponential, spherical, and gaussian were fitted to the empirical semivariograms. Model performance was assessed via cross-validation using mean error (ME), root mean square error (RMSE), mean standardized error (MSE), and root mean square standardized error (RMSSE). Spatial dependence was classified as strong (<25 % nugget/sill), moderate (25-75 %), or weak (>75 %) following Cambardella *et al*. (1994). The best-fitting semivariogram model was used to generate SQI maps.

Statistical analysis

A Shapiro-Wilk test was performed to test for the normality of the data. Differences in soil properties across land uses were assessed using a non-parametric Kruskal-Wallis test ($p < 0.05$), followed by Dunn's post hoc test for pairwise comparisons with Bonferroni correction. Statistical comparisons were performed in IBM SPSS Statistics 25 and RStudio. PCA with varimax rotation was applied to construct the MDS, and land use-wise SQI values were computed as the mean SQI of all sites within each category.

RESULTS

General characteristics of soil physicochemical properties

The assessment of soil physicochemical properties revealed distinct patterns across the five land use systems in the Puducherry region. Kruskal-Wallis tests indicated significant differences ($p < 0.05$) across all measured parameters, with Dunn's post hoc comparisons confirming clear pairwise separation between land uses (Table 2).

Table 2: Descriptive statistics of soil properties from five different land uses of the Puducherry region

Soil property	Land Use				
	Agriculture	Urban green spaces	Built-up areas	Mangroves	Barren land
pH	7.96±0.35^{a}	6.20±0.43^{b}	7.79±0.41^{a}	7.16±0.47^{c}	9.10±0.37^{d}
EC (dS m^{-1})	0.36±0.09^{a}	0.17±0.08^{b}	0.20±0.09^{bc}	4.52±0.37^{d}	0.20±0.06^{bc}
Sand (%)	44.02±5.20^{a}	39.27±3.23^{a}	71.27±3.02^{b}	63.63±5.75^{b}	80.61±3.08^{c}
Silt (%)	38.35±3.34^{a}	39.91±1.87^{a}	11.10±2.83^{b}	23.61±3.29^{c}	10.93±2.21^{b}
Clay (%)	17.63±2.15^{a}	20.98±2.40^{b}	17.63±2.73^{a}	7.97±3.65^{c}	8.44±1.70^{c}
OC (g kg^{-1})	6.91±1.33^{a}	7.46±0.80^{a}	4.23±0.54^{b}	17.82±3.89^{c}	2.25±0.62^{d}
OM (%)	1.19±0.23^{a}	1.29±0.14^{a}	0.73±0.09^{b}	3.07±0.67^{c}	0.39±0.11^{d}
Av. N (kg ha^{-1})	184.97±29.96^{a}	273.86±15.97^{b}	244.41±19.79^{c}	186.00±31.66^{a}	119.74±10.21^{d}
Av. P_2O_5 (kg ha^{-1})	41.85±5.98^{a}	50.69±2.61^{b}	44.40±3.16^{a}	38.38±3.02^{a}	17.61±2.45^{c}
Av. K_2O (kg ha^{-1})	223.42±15.55^{a}	261.60±8.98^{b}	197.11±14.04^{c}	507.65±90.50^{d}	158.71±11.97^{e}
Av. Cu (ppm)	2.73±0.22^{a}	1.76±0.39^{b}	1.94±0.14^{b}	2.65±0.31^{a}	1.37±0.13^{c}
Av. Mn (ppm)	9.54±0.53^{a}	17.87±2.48^{b}	19.11±1.27^{b}	16.51±1.17^{b}	5.39±0.47^{c}
Av. Fe (ppm)	24.55±1.25^{a}	18.87±0.64^{b}	15.74±1.13^{c}	24.93±3.59^{a}	10.34±1.16^{d}
Av. Zn (ppm)	1.15±0.09^{a}	0.88±0.12^{b}	0.62±0.10^{c}	2.22±0.58^{d}	0.46±0.10^{c}
BD (g cm^{-3})	1.12±0.10^{a}	1.23±0.06^{b}	1.34±0.03^{c}	0.97±0.21^{a}	1.48±0.04^{d}

EC Electrical Conductivity; OC Organic Carbon; OM Organic Matter; Av. N Available Nitrogen; Av. P_2O_5 Available Phosphorous; Av. K_2O Available Potassium; Av. Cu Available Copper; Av. Mn Available Manganese; Av. Fe Available Iron; Av. Zn Available Zinc; BD Bulk Density. Means sharing the same letter across rows are not significantly different; while differing letters indicate statistical significance at $p<0.05$.

Soil pH varied from slightly acidic in urban green spaces to strongly alkaline in barren land. EC was highest in mangroves, indicating saline influence, and remained low in other land uses. Texture also differed significantly among land use: sand dominated built-up and barren soils, while agriculture and UGS had more silt and clay. OC and OM followed the trend: mangroves > urban green spaces > agriculture > built-up areas > barren land; whereas BD showed the opposite pattern, with highest value in the barren and built-up areas and lowest in mangroves. Among macronutrients, Av. N was highest in UGS and lowest in barren land; Av. P_2O_5 was elevated in UGS and otherwise comparable across agriculture, built-up areas, and mangroves; Av. K_2O was highest in mangroves and lowest in barren. For micronutrients, Av. Mn was higher in built-up areas and urban green spaces and lowest in barren, while Av. Zn showed a declining trend from mangroves to barren. These patterns align with vegetation cover, salinity exposure, and disturbance intensity across land uses.

Soil quality index model

PCA for fifteen soil properties (TDS)

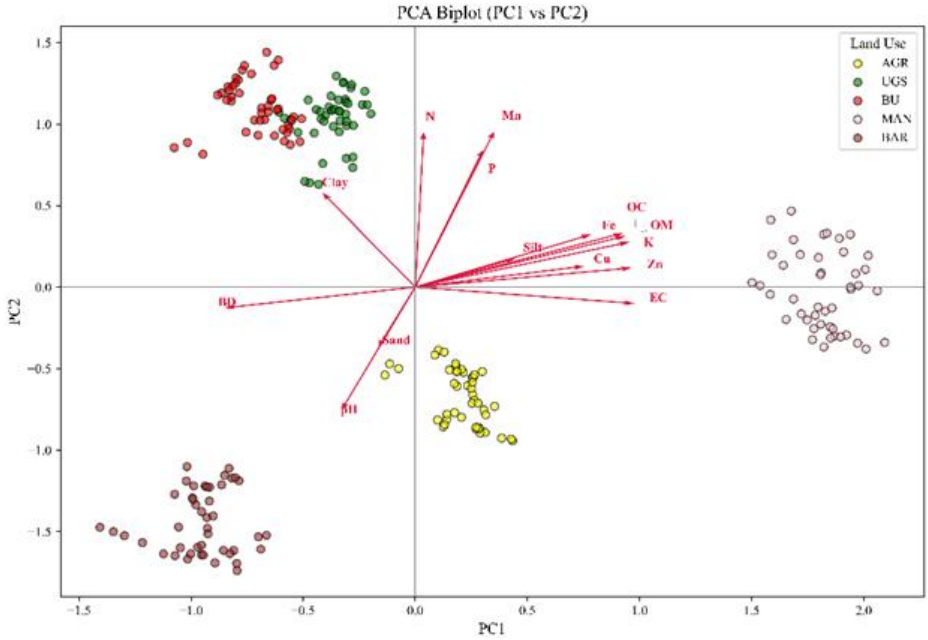
PCA of the fifteen measured soil variables retained three components with eigenvalues > 1, as determined from the varimax rotation. These three components cumulatively accounted for 87.47 % of the total variance in the dataset (Table 3; Fig. 3). PC1 with an eigenvalue of 6.548, explained the largest proportion of the variance (43.65 %) and was characterized by high positive loadings for EC (0.937), OC (0.891), OM (0.900), Av. K_2O (0.916), Av. Zn (0.925) and a strong negative loading for BD (-0.812). PC2 (eigenvalue = 3.696) contributed 24.63 % of the variance and was dominated by Av. N (0.913), Av. Mn (0.920) and Av. P_2O_5 (0.807). PC3 (eigenvalue = 2.878) accounted for 19.18 % of the variance and was associated with high positive loading for silt (0.847) and a strong negative loading for sand (-0.906).

Table 3: Eigenvalues, variance contributions and component loadings of soil properties derived from PCA

Principal components	PC1	PC2	PC3
Statistic			
Eigen-values	6.548	3.696	2.878
% of variance	43.652	24.638	19.183
Cumulative %	43.652	68.290	87.473
pH	-0.313	-0.719	-0.356
EC	**0.937**	-0.096	-0.262
Sand	-0.149	-0.333	**-0.906**
Silt	0.408	0.161	**0.847**
Clay	-0.391	0.548	0.634
OC	**0.891**	0.319	0.163
OM	**0.900**	0.301	0.147
Av. N	0.036	**0.913**	0.254
Av. P_2O_5	0.290	**0.807**	0.421
Av. K_2O	**0.916**	0.265	0.002
Av. Cu	0.714	0.122	0.336
Av. Mn	0.339	**0.920**	-0.028
Av. Fe	0.748	0.308	0.501
Av. Zn	**0.925**	0.113	0.211
BD	**-0.812**	-0.122	-0.210

Bold values under each component are highly weighted

Fig. 3: PCA biplot showing land use-wise variation in soil indicators, illustrating distinct clustering of mangrove, urban green spaces, agricultural, barren, and built-up soils.
(AGR Agriculture; UGS Urban green spaces; BU Built-up; MAN Mangroves; BAR Barren land)



Highly loaded variables within each PC were further examined for redundancy using Pearson correlation analysis (Table 4). In PC1, strong intercorrelations were observed among OC and OM, Av. K_2O and Av. Zn, EC and Av. Zn, OC and EC were retained for their ecological significance and to minimize redundancy. In PC2, although Av. N, Av. P_2O_5 and Av. Mn all exhibited high loadings, Av. N and Av. Mn were retained based on their strong contributions, lower redundancy and moderate inter-correlation. The variables associated with PC3 were excluded from the MDS after PCA, as they primarily represented textural fractions with limited influence on nutrient availability and soil functional dynamics across land uses. Consequently, four key indicators: EC, OC, Av. N and Av. Mn were selected to form the MDS for SQI computation.

Table 4: Correlation matrix of principal soil quality indicators selected from PCA

	EC	Sand	Silt	OC	OM	N	P_2O_5	K_2O	Mn	Zn	BD
EC	1										
Sand	0.126	1									
Silt	0.141	-0.923	1								
OC	0.746	-0.42	0.598	1							
OM	0.762	-0.403	0.586	0.999	1						
N	-0.115	-0.534	0.384	0.353	0.331	1					
P_2O_5	0.07	-0.656	0.574	0.575	0.555	0.833	1				
K_2O	0.848	-0.25	0.439	0.889	0.896	0.252	0.434	1			
Mn	0.223	-0.327	0.263	0.596	0.584	0.816	0.85	0.542	1		
Zn	0.798	-0.35	0.554	0.867	0.869	0.184	0.436	0.902	0.407	1	
BD	-0.67	0.321	-0.486	-0.729	-0.73	-0.253	-0.437	-0.74	-0.355	-0.799	1

Indicator scores and their corresponding weights

Indicator weights were derived from PCA, where the proportion of variance and variable loadings defined each indicator’s contribution, ensuring data-driven weighting across land uses. OC and Av. N were scored as “more is better” for their role in sustaining nutrient supply and biological activity (Ma *et al*., 2024; Mulat *et al*., 2021), whereas EC and Av. Mn were considered “less is better” as elevated values reflect salinity or metal stress that impair soil performance (Damiba *et al*., 2024; Saleh *et al*., 2021). Higher SQI values thus represent soils with balanced soil fertility, stable organic matter, and minimal chemical stress, reflecting desirable functional conditions across diverse land-use systems.

SQI values were subsequently computed for each land use category (Table 5). Mangrove soils exhibited the highest SQI (0.60; classified as very high), with OC contributing 56.15 % of the index, followed by Av. N (29.90 %), Av. Mn (13.57 %) and EC (0.37 %). Urban green spaces ranked second (0.56; high), with average scoring values of 0.16, 0.28, 0.93 and 0.27 for EC, OC, Av. N and Av. Mn, respectively. Indicator contribution to SQI followed the order Av. N (46.73 %) > OC (25.52 %) > EC (14.12 %) > Av. Mn (13.63 %). Agricultural soils recorded an SQI of 0.48 (moderate), with average values of 0.06, 0.26, 0.63 and 0.50 for EC, OC, Av. N and Av. Mn, respectively. Indicator contributions ranked EC (6.42 %) < OC (27.57 %) < Av. Mn (29.38 %) < Av. N (36.63 %). Barren land and built-up areas had the lowest SQI values at 0.46 and 0.45 (moderate), respectively. For barren land, average scoring values were 0.11, 0.09, 0.41 and 0.89 for EC, OC, Av. N and Av. Mn with contributions Av. Mn (54.12 %) > Av. N (24.80 %) > EC (11.78%) > OC (9.31 %). Built-up soils had scoring values of 0.14, 0.16, 0.83 and 0.25, with contributions EC (14.83 %) < Av. Mn (15.54 %) < OC (17.98 %) < Av. N (51.64 %). The SQI showed clear gradients across land uses, reflecting variation in vegetation cover and soil management. Although the range (0.45-0.60) appears narrow, higher SQI values (≥0.55) denote good-quality soils with balanced soil fertility and low stress, while lower values indicate compaction, salinity, or nutrient loss. These differences highlight ecological contrasts and help identify and preserve high-quality soils in the Puducherry region.

Table 5: SQI and indicator contributions across land use systems

Land use		EC	OC	Av. N	Av. Mn	SQI±SD (n=225)	SQI classification
AGR	Avg. scoring value	0.06	0.26	0.63	0.50	0.48±0.04	Moderate
	% contribution	6.42	27.57	36.63	29.38		
UGS	Avg. scoring value	0.16	0.28	0.93	0.27	0.56±0.05	High
	% contribution	14.12	25.52	46.73	13.63		
BU	Avg. scoring value	0.14	0.16	0.83	0.25	0.45±0.06	Moderate
	% contribution	14.83	17.98	51.64	15.54		
MAN	Avg. scoring value	0.00	0.68	0.63	0.29	0.60±0.05	Very high
	% contribution	0.37	56.15	29.90	13.57		
BAR	Avg. scoring value	0.11	0.09	0.41	0.89	0.46±0.03	Moderate
	% contribution	11.78	9.31	24.80	54.12		

AGR Agriculture; UGS Urban green spaces; BU Built-up; MAN Mangroves; BAR Barren land

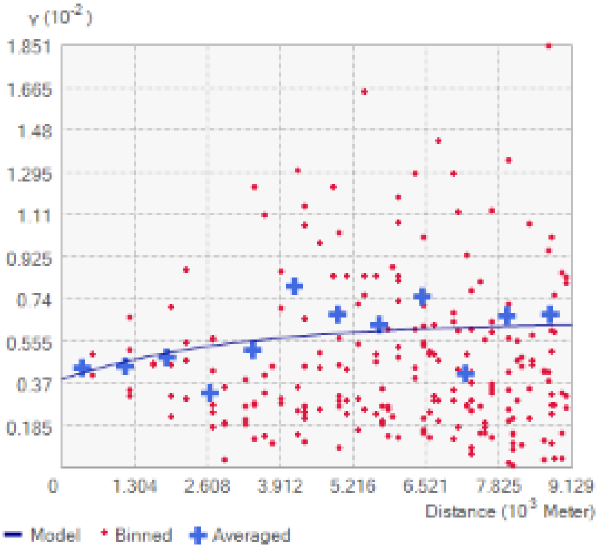
Spatial variability of SQI

The spatial distribution of SQI across the five major land use categories in the Puducherry region was modelled using the geostatistical analyst extension in ArcGIS pro (v.3.3.2). Ordinary kriging was applied to interpolate SQI values based on the selected four key indicators (EC, OC, Av. N and Av. Mn) using three theoretical semivariogram models: exponential, spherical and gaussian. Model performance was assessed based on nugget (C_0), sill ($C_0 + C$), spatial range, nugget/sill ratio, coefficient of determination (R^2), and root mean square error (RMSE) (Table 6). The semivariogram analysis indicated moderate spatial dependence across all models, with nugget-to-sill ratios between 0.612 and 0.677. Among them, the exponential model demonstrated the best predictive performance with the highest R^2 value of 0.20 and the lowest RMSE of 0.064, indicating that 20 % of the variation in SQI could be explained by spatial structure with minimal prediction error (Fig. 4). The range parameter for the exponential model was 9128.78 m, the largest among the tested models, indicating a broader spatial autocorrelation of SQI values. Consequently, the exponential model was used to generate the final SQI surface map.

Table 6: Semivariogram parameters and cross-validation metrics of geo-statistical models for SQI mapping

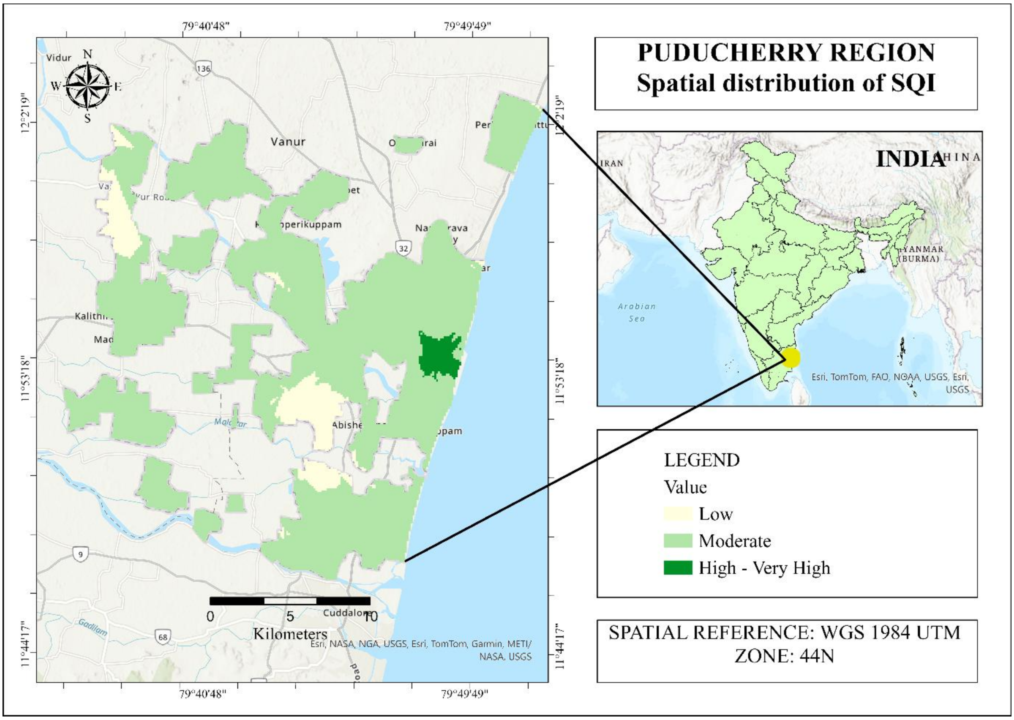
Model	Nugget (C_0)	Partial sill (C)	Sill ($C_0 + C$)	Range (m)	Nugget/Sill	R^2	RMSE
Exponential	0.0038	0.0024	0.0062	9128.78	0.612	0.20	0.0642
Spherical	0.003998	0.0021	0.0060	6524.87	0.650	0.19	0.0644
Gaussian	0.004227	0.0020	0.0062	5943.75	0.677	0.19	0.0647

Fig. 4: Exponential semivariogram model illustrating spatial dependence of SQI.



The SQI values displayed notable spatial variation in Puducherry region across the five primary land use types: mangroves, urban green spaces, agriculture, barren land, and built-up areas across the communes and municipalities (Fig. 5). The SQI values ranged from 0.455 to 0.69, indicating variation in soil quality across the region. Low-moderate SQI (0.455-0.50) occupied the largest proportion of the region, covering 173.21 km^2 (58.06 % of the total area) and was predominantly concentrated in the western and southwestern parts, including Nettapakkam, Mannadipet, and interior Bahour. Moderate SQI (0.51-0.54) accounted for 95.54 km^2 (32.03 %), occurring mainly in central Villianur and the peripheries of Oulgaret and Ariankuppam. High SQI (0.55-0.58) covered 26.05 km^2 (8.73 %), localized in parts of eastern Villianur, Ariyankuppam, and peri-urban fringes of Puducherry municipality. Very high SQI (>0.59) was the least represented, with only 3.53 km^2 (1.18 %), concentrated in coastal pockets of Puducherry municipality and central Ariankuppam, corresponding to zones of elevated OC and Av. N content. Overall, the spatial pattern revealed a distinct coastal to inland gradient with higher SQI values in eastern and coastal communes (Puducherry, Ariankuppam, Oulgaret) and lower values inland (Nettapakkam, Mannadipet, Bahour). This pattern reflects variations in soil properties and land use intensity, highlighting the need for targeted management to restore low-SQI zones and preserve coastal peri-urban soils.

Fig. 5: Spatial distribution of the SQI in the Puducherry region showing higher SQI values along the coastal mangrove zones and moderate values in urban green spaces, while inland agricultural and built-up areas exhibit relatively lower SQI levels.



DISCUSSION

Influence of land use on soil physicochemical properties

Land use alters soil properties by changing organic matter inputs, nutrient cycling, and loss pathways such as leaching and erosion (Byers *et al.,* 2024). In the Puducherry region, this influence was evident in the distinct soil characteristics observed across agriculture, urban green spaces, built-up areas, mangroves, and barren land. Each land use category reflected a unique balance between natural ecological processes and anthropogenic pressures, resulting in clear differences in soil quality.

Mangroves demonstrated the most favourable soil conditions, with elevated OC, Av. N and EC, coupled with lower BD. Such characteristics align with previous observations that tidal inundation, high litter deposition from salt-tolerant vegetation, and anaerobic conditions promote organic matter accumulation and nutrient retention in mangrove soils (Wu *et al*., 2025; Zhang *et al*., 2024). Urban green spaces maintained moderate OC and Av. N levels due to managed vegetation, periodic organic amendments, and limited soil disturbance. However, their slightly acidic pH could be linked to specific plant species, irrigation patterns, and atmospheric deposition (Polyakov *et al*., 2023). Although lower pH may enhance the solubility of certain nutrients, it can also increase the mobility of toxic metals, necessitating continued monitoring of urban soils for potential contamination risks (Magiera *et al*., 2007).

Agricultural soils presented moderate OC and Av. N values, reflecting contributions from crop residues and root biomass (Emiru & Gebrekidan, 2013). The comparatively lower Av. P_2O_5 and Av. K_2O levels, however, suggest nutrient depletion through repeated harvesting and leaching, contrasting with studies conducted by Tejashvini *et al*. (2023a), where regular manure and fertilizer applications elevated these nutrients. BD values remained within acceptable limits, indicating that tillage-induced compaction may be less severe in the present sites than in more intensively cultivated systems (Meena *et al*., 2018; Seyoum, 2016). In contrast, built-up soils were characterized by poor nutrient status, high BD, and alkaline pH likely resulting from the removal of topsoil during construction and its replacement with compacted fill materials (Nölke *et al*., 2023). These conditions reduce infiltration, hinder biological activity, and limit the capacity for carbon sequestration (Upadhyay & Raghubanshi, 2020). Barren land displayed the most degraded profile with very low OC, high BD, and nutrient depletion reflecting the cumulative effects of vegetation loss, surface exposure, and erosive forces. Our results (r = -0.73) show a negative association between OC and BD, confirming the importance of organic matter in stabilizing soil aggregates and minimizing compaction.

Similar land use effects on soil physicochemical properties have been reported in other regions of India. Forest soils in peri-urban Ghaziabad maintained higher OC, cation exchange capacity, and nutrient levels compared to agricultural soils, largely due to greater organic matter inputs and permanent vegetation cover (Chaurasia *et al*., 2024). In the Cauvery Delta, rice-pulse rotations supported greater OC stocks than sugarcane systems, emphasizing how crop type and residue management regulate soil nutrient pools (Prabakaran *et al*., 2023). In Uttarakhand, oak forest soils also exhibited significantly higher OC and nutrient retention compared to agricultural and vegetable fields, where repeated crop harvests and leaching reduced nutrient levels (Tewari *et al*., 2016). Likewise, barren soils in Delhi showed BD values as high as 2.79 g cm^{-3} and organic matter as low as 1.84 %, confirming their severely degraded condition (Singh & Sarma, 2020). These comparisons reinforce the present findings that vegetation-rich systems sustain more favourable soil conditions, while disturbed soils are more prone to nutrient depletion and compaction.

Soil quality index and indicator performance

The PCA-MDS analysis revealed four indicators: EC, OC, Av. N and Av. Mn as the most informative, for assessing soil quality. The final SQI ranking followed the order: mangroves (0.60) > urban green spaces (0.56) > agriculture (0.48) > barren land (0.46) > built-up areas (0.45), revealing a clear decline in soil quality with increasing anthropogenic disturbance. OC emerged as the dominant positive contributor in mangroves (56.15 %), reflecting the high carbon sequestration potential of waterlogged, densely vegetated coastal systems (Alongi, 2014; Pérez *et al*., 2018). In contrast, OC contributions were lowest in built-up areas and barren land soils, where vegetation removal and surface sealing severely limit organic matter inputs (Samota *et al*., 2024). Av. N was a significant contributor in both urban green spaces (46.73 %) and built-up areas (51.64 %) systems, which may be attributed to irrigation runoff, atmospheric deposition, and fertilization of landscaped areas (Yang & Zhang, 2015). Agriculture soils showed moderate Av. N contribution (36.63 %), reflecting fertilization balanced against leaching losses under tillage (Ramirez *et al*., 2022). Av. Mn is considered a “less is better” indicator due to its potential toxicity at high levels, contributed minimally in mangroves and urban green spaces, where higher OC facilitates Av. Mn immobilization (Dhaliwal *et al*., 2023). EC, also categorized as “less is better”, showed the lowest contributions overall but remains important in indicating salinity stress and ionic balance in plants (Yang *et al*., 2020).

A similar PCA-MDS approach was applied in the Bengaluru rural-peri-urban-urban transect, where the MDS comprised pH, dehydrogenase activity, Av. K_2O, and EC. Among these, dehydrogenase activity was the most influential contributor, and SQI values declined systematically from rural (0.61) to peri-urban (0.52) and urban (0.44) soils, reflecting intensifying anthropogenic disturbance (Tejashvini *et al*., 2023b). This pattern is consistent with our findings, where organic matter and nutrient-related indicators contributed to higher SQI in vegetation-rich systems, while disturbance and compaction reduced index values in urban and barren soils.

Spatial variation and land management implications

The spatial distribution of the SQI across the Puducherry region revealed gradients that closely followed land use intensity. High-SQI clusters were concentrated in mangrove-dominated areas, reflecting the combined effects of tidal inputs, dense root networks, and high litter deposition that enhance nutrient cycling and stabilize organic matter (Li *et al*., 2024; Ali *et al*., 2025). Mangrove soils show resilience to both natural stressors and localized anthropogenic disturbance (Alongi, 2008). In contrast, built-up and barren areas formed extensive low-SQI patches, confirming the severe degradation associated with surface sealing and compaction (Ferreira *et al*., 2018). Agricultural lands exhibited fragmented SQI patterns, with fields practicing residue incorporation and balanced fertilization maintaining moderate scores, while intensively tilled and nutrient-depleted soils performed poorly. Transition zones at the interface of mangroves and agricultural fields often showed intermediate SQI values, indicating a gradual decline in soil functionality from coastal to inland systems. The R^2 value (0.20) for the kriging model appears modest but is typical of heterogeneous soil systems with high local variability. Models with lower R^2 can still produce reliable spatial predictions when cross-validation statistics like mean error is near zero and root mean square standardized error is close to one (Hengl *et al*., 2004).

These spatial differences hold practical significance for land management in tropical coastal regions. Protecting the soils of mangroves and urban green spaces as ecological buffers can sustain OC stocks and mitigate salinity intrusion, while agricultural areas should prioritize residue retention, crop-rotation planning, and reduced tillage. Rehabilitation of degraded barren and built-up areas through vegetation establishment and topsoil recovery would enhance infiltration, reduce compaction, and restore nutrient cycling. Altogether, these findings highlight that targeted, land-use specific interventions are essential to maintain soil resilience and advanced land-degradation neutrality goals under sustainable development goal 15 (SDG 15).

The spatial variability patterns identified in Puducherry are in accordance with other kriging-based assessments of soil quality. Studies in Madurai and eastern India have demonstrated higher SQI in vegetated or agricultural zones than in urban-industrial or degraded lands, while similar gradients were reported in Moroccan semi-arid systems under contrasting management intensities (Anuradha, 2024; De *et al*., 2022; Sanad *et al*., 2024). Collectively, these reinforce the reliability of the present findings and highlight SQI mapping as a valuable decision-support tool for conservation, sustainable agriculture, and restoration of degraded soils in coastal regions.

Study limitations

This study provides useful information on the regional soil quality; however, there are some limitations to note. The SQI was derived from a limited set of physicochemical indicators and might not fully capture biological processes influencing soil health. Also, the results are based on a single season, limiting the ability to account for seasonal or inter-annual variability. Spatial interpolation, while robust, is constrained by the density of sampling points, which means the unsampled areas might have some uncertainty. Future work should integrate biological indicators, adopt multi-seasonal analysis, and link SQI with ecosystem services like crop yield, carbon storage, and erosion control to strengthen the utility for land management and policy planning.

CONCLUSION

This study provides the first comprehensive assessment of soil quality across five major land-use types in the Puducherry region using a PCA-based MDS (EC, OC, Av. N, Av. Mn) and geostatistical interpolation. The results revealed a distinct hierarchy in soil quality: mangroves and urban green spaces maintained the highest soil quality due to greater organic carbon and nutrient retention, whereas agricultural soils showed moderate quality influenced by management, and built-up and barren lands exhibited severe degradation from compaction and nutrient loss. SQI mapping revealed clear coastal-to-inland gradients, highlighting the influence of land use intensity and management practices. The findings highlight the potential of SQI mapping as a practical tool for guiding site-specific interventions, conserving high-quality soils, restoring degraded areas, and supporting sustainable land-use planning aligned with SDG 15.

ACKNOWLEDGEMENT

The authors would like to thank the Jawaharlal Nehru Memorial Fund for providing financial assistance for the present work.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

REFERENCES

Ali, S., Dey, G., Nuong, N. H. K., Rahman, A., Wang, L. C., Sukul, U., & Chen, C. Y. (2025). Carbon sequestration in mangrove ecosystems: Sources, transportation pathways, influencing factors, and its role in the carbon budget. *Earth-Science Reviews*, *269*, 105184. https://doi.org/10.1016/j.earscirev.2025.105184.

Alongi, D. M. (2008). Mangrove forests: resilience, protection from tsunamis, and responses to global climate change. *Estuarine, Coastal and Shelf Science*, *76*(1), 1-13. https://doi.org/10.1016/j.ecss.2007.08.024.

Alongi, D. M. (2014). Carbon cycling and storage in mangrove forests. *Annual Review of Marine Science*, *6*(1), 195-219. https://doi.org/10.1146/annurev-marine-010213-135020.

Andrews, S. S., Karlen, D. L., & Mitchell, J. P. (2002). A comparison of soil quality indexing methods for vegetable production systems in Northern California. *Agriculture, Ecosystems & Environment*, *90*(1), 25-45. https://doi.org/10.1016/S0167-8809(01)00174-8.

Ansari, T.A.A., Singh, C.K. & Albawwab, W. (2025). Urbanization and its Impact on Land Use and Land Cover in Al Buraimi City, Oman Using Remote Sensing and GIS. *Journal of*

Landscape Ecology, 18(2), 2025. 1–20. https://doi.org/10.2478/jlecol-2025-0009.

Anuradha, C. T. (2024). Soil quality analysis and mapping of various land uses using geospatial technology: a case study. *Applied Geomatics*, *16*(1), 57-66. https://doi.org/10.1007/s12518-023-00538-3.

Bel-Lahbib, S., Ibno Namr, K., Rerhou, B., Mosseddaq, F., El Bourhrami, B., & Moughli, L. (2023). Assessment of soil quality by modeling soil quality index and mapping soil parameters using IDW interpolation in Moroccan semi-arid. *Modeling Earth Systems and Environment*, *9*(4), 4135-4153. https://doi.org/10.1007/s40808-023-01718-1.

Bouyoucos, G. J. (1962). Hydrometer method improved for making particle size analyses of soils 1. *Agronomy Journal*, *54*(5), 464-465. https://doi.org/10.2134/agronj1962 .00021962005400050028x.

Bray, R. H., & Kurtz, L. T. (1945). Determination of total, organic, and available forms of phosphorus in soils. *Soil Science*, *59*(1), 39-46. http://dx.doi.org/10.1097 /00010694-194501000-00006.

Budak, M., Günal, H., Celik, I., Yıldız, H., Acir, N., & Acar, M. (2018). Soil quality assesment of upper Tigris basin. *Carpathian Journal of Earth and Environmental Sciences*, *13*(1), 301-316. https://doi.org/10.26471/cjees/2018/013/026.

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., De Goede, R., Fleskens, L., Geissen, V., Kuyper, T.W., Mäder, P., Pulleman, M., Sukkel, W., Groenigen, J.W.V., & Brussaard, L. (2018). Soil quality-A critical review. *Soil biology and biochemistry*, *120*, 105-125. https://doi.org/10.1016/j.soilbio.2018.01.030.

Byers, A. K., Condron, L., Wakelin, S. A., & Black, A. (2024). Land use intensity is a major driver of soil microbial and carbon cycling across an agricultural landscape. *Soil Biology and Biochemistry*, *196*, 109508. https://doi.org/10.1016/j.soilbio.2024.109508.

Cambardella, C. A., Moorman, T. B., Novak, J. M., Parkin, T. B., Karlen, D. L., Turco, R. F., & Konopka, A. E. (1994). Field-scale variability of soil properties in central Iowa soils. *Soil Science Society of America Journal*, *58*(5), 1501-1511. https://doi.org/10.2136/ sssaj1994.03615995005800050033x.

Chandel, S., Hadda, M. S., & Mahal, A. K. (2018). Soil quality assessment through minimum data set under different land uses of submontane Punjab. *Communications in Soil Science and Plant Analysis*, *49*(6), 658-674. https://doi.org/10.1080/00103624.2018.1425424.

Chapman, H. D. (1965). Cation-exchange capacity. *Methods of soil analysis: Part 2 Chemical and microbiological properties*, *9*, 891-901.

Chaurasia, M., Patel, K., Bhadouria, R., & Rao, K. S. (2024). Spatial variability in soil physicochemical parameters across land use classes in the peri-urban landscape. *Environment, Development and Sustainability*, *26*(10), 24791-24815. https://doi.org/10.1007/s10668-023-03653-8.

Chen YuDong, C. Y., Wang HuoYan, W. H., Zhou JianMin, Z. J., Xing Lu, X. L., Zhu BaiShu, Z. B., Zhao YongCun, Z. Y., & Chen XiaoQin, C. X. (2013). Minimum data set for assessing soil quality in farmland of northeast China. *Pedoshpere*, *23*(5), 564-576. https://doi.org/10.1016/S1002-0160(13)60050-8.

Coulibaly, K., & Sako, A. (2024). Geostatistical modelling of physico-chemical properties of soils impacted by artisanal gold mining and farming: implications for soil environmental quality assessment. *Sustainable Environment*, *10*(1), 2333631. https://doi.org/10.1080/27658511.2024.2333631.

Cressie, N. (2015). *Statistics for Spatial Data*. John Wiley & Sons.

Damiba, W. A. F., Gathenya, J. M., Raude, J. M., & Home, P. G. (2024). Soil quality index (SQI) for evaluating the sustainability status of Kakia-Esamburmbur catchment under three different land use types in Narok County, Kenya. *Heliyon*, *10*(5). https://doi.org/10.1016/j.heliyon.2024.e25611.

De, P., Deb, S., Deb, D., Chakraborty, S., Santra, P., Dutta, P., & Choudhury, A. (2022). Soil quality under different land uses in eastern India: Evaluation by using soil indicators and quality index. *PLoS One*, *17*(9), e0275062. https://doi.org/10.1371/journal.pone.0275062.

Dhaliwal, S. S., Sharma, V., Shukla, A. K., Kaur, J., Gupta, R. K., Verma, V., & Singh, P. (2023). Interactive effect of land use systems on depth-wise soil properties and micronutrients minerals in North-Western, India. *Heliyon*, *9*(2), e13591. https://doi.org/10.1016/j.heliyon.2023.e13591.

Puducherry at a glance. (2024). *Directorate of economics and statistics*. https://statistics.Py.gov.in.

Ellur, R., Ankappa, A. M., Dharumarajan, S., Puttavenkategowda, T., Nanjundegowda, T. M., Sannegowda, P. S., & Dogančić, D. (2024). Soil quality assessment and its spatial variability in an intensively cultivated area in India. *Land*, *13*(7), 970. https://doi.org/10.3390/land13070970.

Emiru, N., & Gebrekidan, H. (2013). Effect of land use changes and soil depth on soil organic matter, total nitrogen and available phosphorus contents of soils in Senbat Watershed, Western Ethiopia. *ARPN Journal of Agricultural and Biological Science*, *8*(3), 206-212.

FAO, (2015). *Healthy Soils Are the Basis for Healthy Food Production*; Food and Agriculture Organization (FAO), Rome, Italy. Retrieved June 27, 2025, from https://openknowledge.fao.org/server /api/core/bitstreams/4fb89216-b131-4809-bbed-b918 50738fa1/content

Ferreira, C. S., Walsh, R. P., & Ferreira, A. J. (2018). Degradation in urban areas. *Current Opinion in Environmental Science & Health*, *5*, 19-25. https://doi.org/10.1016/ j.coesh.2018.04.001.

Hengl, T., Heuvelink, G. B., & Stein, A. (2004). A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma*, *120*(1-2), 75-93. https://doi.org/10.1016/j.geoderma.2003.08.018.

Ibrahim, A. J., Bedadi, B., & Feyissa, S. (2023). Assessment of Selected Physicochemical Properties of Soils under Different Land Uses and Topographic Positions at Gola Wachu Subwatershed, Eastern Ethiopia. *Applied and Environmental Soil Science*, *2023*(1), 9988495. https://doi.org/10.1155/2023/9988495.

Jackson, M. L. (1973). Soil Chemical Analysis. Prentic Hall Pvt. *Ltd*. New Delhi, India.

Kaur, T., Sehgal, S. K., Singh, S., Sharma, S., Dhaliwal, S. S., & Sharma, V. (2021). Assessment of seasonal variability in soil nutrients and its impact on soil quality under different land use systems of lower Shiwalik foothills of Himalaya, India. *Sustainability*, *13*(3), 1398. https://doi.org/10.3390/su13031398.

Kumar, J., Kalita, H., Alone, R. A., Sinha, N. K., Rani, A., Kumar, D., & Orban, Z. (2025). Multivariate assessment of soil quality across different land use types in the hilly terrain of the subtropics of India. *Soil and Water Research*, *20*(3), 1-17. https://doi.org/10.17221/6/2025-SWR.

Lenka, N. K., Meena, B. P., Lal, R., Khandagle, A., Lenka, S., & Shirale, A. O. (2022).

Comparing four indexing approaches to define soil quality in an intensively cropped region of Northern India. *Frontiers in Environmental Science*, *10*, 865473. https://doi.org/10.3389/fenvs.2022.865473.

Li, X., Cheng, X., Cheng, K., Cai, Z., Feng, S., & Zhou, J. (2024). The influence of tide-brought nutrients on microbial carbon metabolic profiles of mangrove sediments. *Science of the Total Environment*, *906*, 167732. https://doi.org/10.1016/j.scitotenv.2023.167732.

Lindsay, W. L., & Norvell, W. (1978). Development of a DTPA soil test for zinc, iron, manganese, and copper. *Soil Science Society of America Journal*, *42*(3), 421-428. https://doi.org/10.2136/sssaj1978.03615995004200030009x.

Ma, L., Si, H., Li, M., Li, C., Zhu, D., Mao, Z., Yan, Y., Jiang, K., & Yu, P. (2024). Influence of land use types on soil properties and soil quality in karst regions of Southwest China. *Agronomy*, *14*(5), 882. https://doi.org/10.3390/agronomy14050882.

Magiera, T., Strzyszcz, Z., & Rachwal, M. (2007). Mapping particulate pollution loads using soil magnetometry in urban forests in the Upper Silesia Industrial Region, Poland. *Forest Ecology and Management*, *248*(1-2), 36-42. https://doi.org/10.1016/j.foreco.2007.02.034.

Mahajan, N. C., Mrunalini, K., Prasad, K. K., Naresh, R. K., & Sirisha, L. (2019). Soil quality indicators, building soil organic matter and microbial derived inputs to soil organic matter under conservation agriculture ecosystem: a review. *International Journal of Current Microbiology and Applied Sciences*, *8*(2), 1859-79. https://doi.org/10.20546/ijcmas.2019.802.218.

Mahtta, R., Fragkias, M., Güneralp, B., Mahendra, A., Reba, M., Wentz, E. A., & Seto, K. C. (2022). Urban land expansion: the role of population and economic growth for 300+ cities. *Npj Urban Sustainability*, *2*(1), 5. https://doi.org/10.1038/s42949-022-00048-y.

Maji, P., & Mistri, B. (2024). Comparative assessment of soil quality dynamics using SQI modelling approach: a study in rice bowl of West Bengal, India. *Environmental Monitoring and Assessment*, *196*(6), 567. https://doi.org/10.1007/s10661-024-12697-w.

Meena, V. S., Mondal, T., Pandey, B. M., Mukherjee, A., Yadav, R. P., Choudhary, M., & Pattanayak, A. (2018). Land use changes: Strategies to improve soil carbon and nitrogen storage pattern in the mid-Himalaya ecosystem, India. *Geoderma*, *321*, 69-78. https://doi.org/10.1016/j.geoderma.2018.02.002.

Mello, F. A., Ferreira, T. O., Bernardino, A. F., Queiroz, H. M., Mello, D. C., Menillo, R. B., & Cherubin, M. R. (2024). Soil Health and Ecosystem Services in Mangrove Forests: A Global Overview. *Water*, *16*(24), 3626. https://doi.org/10.3390/w16243626.

Mulat, Y., Kibret, K., Bedadi, B., & Mohammed, M. (2021). Soil quality evaluation under different land use types in Kersa sub-watershed, eastern Ethiopia. *Environmental Systems Research*, *10*(1), 19. https://doi.org/10.1186/s40068-021-00224-6.

Nasir, M. J., Haider, M. F., Ali, Z., Akhtar, W., & Alam, S. (2024). Evaluation of soil quality through simple additive soil quality index (SQI) of Tehsil Charsadda, Khyber Pakhtunkhwa, Pakistan. *Journal of the Saudi Society of Agricultural Sciences*, *23*(1), 42-54. https://doi.org/10.1016/j.jssas.2023.09.001.

National Commission on Population. (2019). *Population projections for India and states 2011–2036*. Ministry of Health and Family Welfare, Technical Group on Population Projectionshttps://nhm.gov.in/New_Updates_2018/Report_Population_Projection_2019.pdf

Nölke, N., Fehrmann, L., Plieninger, T., & Kleinn, C. (2023). Categorization of green and grey infrastructure complexity in the rural–urban interface of Bengaluru, India: an unsupervised volumetric approach with relevance for urban quality. *Urban Ecosystems*, *26*(1), 161-172. https://doi.org/10.21203/rs.3.rs-1155273/v1.

Olsen, S. R. (1954). *Estimation of available phosphorus in soils by extraction with sodium bicarbonate* (No. 939). US Department of Agriculture.

Pérez, A., Libardoni, B. G., & Sanders, C. J. (2018). Factors influencing organic carbon accumulation in mangrove ecosystems. *Biology Letters*, *14*(10), 20180237. https://doi.org/10.1098/rsbl.2018.0237.

Pirestani, N., Ahmadi Nadoushan, M., Abolhasani, M. H., & Zamani Ahmadmahmoudi, R. (2024). Mapping soil characteristics: Spatio-temporal comparison of land use regression and ordinary kriging in an Arid Environment. *Journal of the Indian Society of Remote Sensing*, *52*(1), 79-93. https://doi.org/10.1007/s12524-023-01804-y.

Polyakov, V., Abakumov, E., Nizamutdinov, T., Shevchenko, E., & Makarova, M. (2023). Estimation of carbon stocks and stabilization rates of organic matter in soils of the «Ladoga» carbon monitoring site. *Agronomy*, *13*(3), 807. https://doi.org/10.3390/agronomy13030807.

Prabakaran, S., Kaleeswari, R. K., Backiyavathy, M. R., Jagadeeswaran, R., Selvi, R. G., & Bama, K. S. (2023). Estimation of soil carbon pools under major cropping systems of Mayiladuthurai district of Cauvery Delta Zone, Tamil Nadu, India. *Journal of Applied & Natural Science*, *15*(2). https://doi.org/10.31018/jans.v15i2.4600.

Ramirez, M. A. J. P., Visco, R. G., Predo, C. D., & Galang, M. A. (2022). Assessment of Soil Condition Using Soil Quality Index of Different Land Use Types in Liliw, Laguna, Philippines. *Philippine Journal of Science*, *151*(3), 1157-1169.

Rosemary, F., Indraratne, S. P., Weerasooriya, R., & Mishra, U. (2017). Exploring the spatial variability of soil properties in an Alfisol soil catena. *Catena*, *150*, 53-61. https://doi.org/10.1016/j.catena.2016.10.017.

Saleh, A. M., Elsharkawy, M. M., AbdelRahman, M. A., & Arafat, S. M. (2021). Evaluation of soil quality in arid western fringes of the Nile Delta for sustainable agriculture. *Applied and Environmental Soil Science*, *2021*(1), 1434692. https://doi.org/10.1155/2021/1434692.

Samota, R., Piploda, T., Dwivedi, D. K., Umiam, M., & Kumar, I. P. (2024). Current Trends in Soil Science: Challenges and Innovations for Effective Ecosystem Management. In *Soil Degradation and Land Use Change: Challenge and Implications*. Selfypage developers Pvt. Ltd.

Sanad, H., Moussadek, R., Mouhir, L., Oueld Lhaj, M., Dakak, H., El Azhari, H., & Zouahri, A. (2024). Assessment of soil spatial variability in agricultural ecosystems using multivariate analysis, soil quality index (SQI), and geostatistical approach: A case study of the Mnasra Region, Gharb Plain, Morocco. *Agronomy*, *14*(6), 1112. https://doi.org/10.3390/agronomy14061112.

Sangaradasse, P., & Eswari, S. (2019). Impact of Urbanisation on Land Use/Land Cover in Puducherry City, India. *Journal of Transportation Technologies*, *9*(3), 331-341. https://doi.org/10.4236/jtts.2019.93021.

Seyoum, B. (2016). Assessment of soil fertility status of Vertisols under selected three land uses in Girar Jarso District of North Shoa zone, oromia national regional state, Ethiopia. *Environmental Systems Research*, *5*(1), 18. https://doi.org/10.1186/s40068-016-0069-y.

Shukla, P. R., Skeg, J., Buendia, E. C., Masson-Delmotte, V., Pörtner, H. O., Roberts, D. C., & Malley, J. (2019). Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. https://www.ipcc.ch/site/assets/uploads/sites/4/2020/02/SPM_Updated-Jan20.pdf.

Singh, R.A. 1980. Soil Physical Analysis. Kalyani Publisher, New Delhi, 163

Singh, S., & Sarma, K. (2020). Mapping surface soil characteristics of barren land by using geospatial technology in NCT of Delhi. *Society for Environment and Development (India)*, *15*, 15-27. https://doi.org/10.13140/RG.2.2.32453.06887.

Subbaiah, B. V. & Asija, G. L. (1956). A rapid procedure for the determination of available nitrogen in soil. *Current Science,* 25, 259–260.

Tadese, S., Soromessa, T., Aneseye, A. B., Gebeyehu, G., Noszczyk, T., & Kindu, M. (2023). The impact of land cover change on the carbon stock of moist afromontane forests in the Majang Forest Biosphere Reserve. *Carbon Balance and Management*, *18*(1), 24. https://doi.org/10.1186/s13021-023-00243-z.

Tejashvini, A., Ramamurthy, V., & Thimmappa Subbarayappa, C. (2023a). Soil quality assessment of different land use systems of peri-urban-rural landscape of Deccan plateau, hot semi-arid agro-ecosystem. *Archives of Agronomy and Soil Science*, *69*(14), 3060-3072. https://doi.org/10.1080/03650340.2023.2196718.

Tejashvini, A., Subbarayappa, C. T., Ramamurthy, V., & Srinivasan, R. (2023b). Urbanization Impact on Soil Quality Assessment in Semi-Arid Region: Bangalore Metropolitan City, India. *Communications in Soil Science and Plant Analysis*, *54*(22), 3122-3135. https://doi.org/10.1080/00103624.2023.2256792.

Tewari, G., Khati, D., Rana, L., Yadav, P., Pande, C., Bhatt, S., & Joshi, P. K. (2016). Assessment of physicochemical properties of soils from different land use Systems in Uttarakhand, India. *Journal of Chemical Engineering and Chemistry Research*, *3*(11), 1114-1118.

Upadhyay, S., & Raghubanshi, A. S. (2020). Determinants of soil carbon dynamics in urban ecosystems. In *Urban Ecology*. Elsevier. https://doi.org/10.1016/B978-0-12-820730-7.00016-1.

Walkley, A., & Black, I. A. (1934). An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. *Soil Science*, *37*(1), 29-38.

Webster, R., & Oliver, M. A. (2007). *Geostatistics for environmental scientists, second edition*. John Wiley & Sons.

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications*, *12*(1), 2501. https://doi.org/10.1038/s41467-021-22702-2.

WRB, 2022. World Reference Base for Soil Resources. International soil classification system for naming soils and creating legends for soil maps. 4th edition. International Union of Soil Sciences (IUSS), Vienna, Austria.

Wu, T., Guo, J., Li, G., Jin, Y., Zhao, W., Lin, G., & Wen, L. (2025). Soil organic carbon contents and their major influencing factors in mangrove tidal flats: a comparison between estuarine and non-estuarine areas. *Ecological Processes*, *14*(1), 15. https://doi.org/10.1186/s13717-025-00581-5.

Yang, J. L., & Zhang, G. L. (2015). Formation, characteristics and eco-environmental implications of urban soils–A review. *Soil Science and Plant Nutrition*, *61*(sup1), 30-46.

https://doi.org/10.1080/00380768.2015.1035622.

Yang, X., Henry, H. A., Zhong, S., Meng, B., Wang, C., Gao, Y., & Sun, W. (2020). Towards a mechanistic understanding of soil nitrogen availability responses to summer vs. winter drought in a semiarid grassland. *Science of the Total Environment*, *741*, 140272. https://doi.org/10. 1016/j.scitotenv.2020.140272.

Zhang, J., Gan, S., Yang, P., Zhou, J., Huang, X., Chen, H., & Wang, F. (2024). A global assessment of mangrove soil organic carbon sources and implications for blue carbon credit. *Nature Communications*, *15*(1), 8994. https://doi.org/10.1038/s41467-024-53413-z.

Zou, H., Li, X., Li, S., Xu, Z., Yu, Z., Cai, H., Chen. W., Ni, X, Wu, E., & Zeng, G. (2023). Soil organic carbon stocks increased across the tide-induced salinity transect in restored mangrove region. *Scientific Reports*, *13*(1), 19758. https://doi.org/10.1038/s41598-023-45411-w.