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Multivariate assessment of soil quality across different land use types in the hilly terrain of the subtropics of India

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Abstract: The unsustainable conversion of forest areas into agricultural land poses a serious danger to the soil eminence of Arunachal Pradesh's environmentally delicate hilly topography. Understanding the impacts of this land-use change is crucial for preventing further degradation. This study aimed to develop soil quality indices (SQIs) for different land use types: natural forest (NF), current jhum cultivation (JC), fallow jhum land (FJC), and pineapple cultivation (PA). Samples of soil were taken at a depth of 0 to 15 cm and examined for 22 potential soil quality indicators, with 19 showing significant ($P < 0.05$) influence from land use, constituting the total dataset (TDS). Principal component analysis (PCA) was employed on TDS to identify the minimum data set (MDS), comprising dehydrogenase activity, diethylenetriaminpentahacetic acid (DTPA)-extractable iron, and bulk density, contributing 73%, 19%, and 8% to the overall SQI, respectively. Subsequently, different SQIs were estimated using linear/nonlinear and additive/weighted scoring functions. The results revealed substantial alterations in SQIs among the land use types, through NF exhibiting the highest soil quality. Notably, the nonlinear SQIs exhibited greater sensitivity to land use conversion compared to their linear counterparts, indicating their potential as a more robust tool for assessing soil quality changes. This study concludes that the transformation of land use in the hilly regions of subtropics of Arunachal Pradesh has led to the deterioration of soil quality. The proposed indexing framework, leveraging the sensitivity and clarity of nonlinear SQIs, can effectively evaluate and compare soil quality across different land use scenarios, thereby informing sustainable land management strategies.

Keywords: Arunachal Pradesh; fallow land; jhum cultivation; multivariate analysis; natural forest; soil quality index

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Soil constitutes an essential element of the Earth's ecosystem, playing an indispensable role in sustaining life. Its significance in supporting human existence cannot be overstated. In addition to being the main basis of key nutrients required for plant growth, soil supports a wide range of metabolic activities that are critical for the growth of roots, leaves, flowers, and fruits. Moreover, soil contributes to the delivery of ecosystem services through intricate interactions among its physical, chemical, and biological components, thus underscoring its pivotal role in maintaining ecological balance and fostering biodiversity (Karlen et al. 1997). Assessing soil quality includes the comprehensive assessment of soil properties and developments, which directly influence its capacity to function effectively within a thriving ecosystem. This encompasses an analysis of various factors, including nutrient content, physical structure, and biological activity, all of which contribute to the soil's ability to support and sustain ecological health (Bünemann et al. 2018). Depending on a wide range of soil chemical, biological, and physical characteristics as well as their individual roles, soil's role and the value it subsequently contributes to ecosystems are intrinsically varied. These factors exhibit variability across spatial and temporal scales, further emphasising the dynamic nature of soil-ecosystem interactions (Doran 2002; Nannipieri et al. 2003; Van Diepeningen et al. 2006; Spiegel et al. 2015). Hence, the assortment of a standardised set of soil properties for assessing the soil quality proves to be a multifaceted task as it varies across different agricultural classifications and organization objectives. According to Islam and Weil (2000), the evaluation of soil quality primarily revolves around the soil properties that exhibit high variability and sensitivity to various management practices. Since the introduction of the land capability classification system by the USDA Soil Conservation Service in 1961 (Klingebiel & Montgomery 1961), numerous soil quality assessment methodologies have emerged to address this dynamic aspect. These procedures include soil test kits and soil quality cards (Ditzler & Tugel 2002), soil quality index (SQI) methods (Doran & Parkin 1994; Andrews et al. 2002), fuzzy association rules (Yue et al. 2010), dynamic models of soil quality (Larson & Pierce 1994), and soil management assessment frameworks (Andrews et al. 2004; Masto et al. 2007; Karlen et al. 2008; Wienhold et al. 2009). Among these methodologies, the SQI method stands out as possibly the most prevalent (Andrews et al. 2002), owing to its simplicity and computational flexibility. Soil quality indices serve as valuable tools for adaptive soil resource management, enabling farmers and other stakeholders to monitor soil health trends and to identify requisite adjustments in soil management practices (Karlen et al. 2001).

Soil quality assessment has been predominantly focused on agricultural lands, with limited attention given to traditional land use systems like jhum (slash-and-burn or shifting cultivation), pineapple-based cultivation, and fallow jhum lands. The present study aims to address this breach by investigating SQIs across these land-use systems prevalent in the mid-hill regions, where jhuming is considered a leading cause of physical soil degradation, especially in the states of Arunachal Pradesh, Nagaland, and Meghalaya. Alarmingly, 67.6% of Arunachal Pradesh's total geographical area has exceeded the soil loss tolerance limit (Bandypadhyay et al. 2014), resulting in a massive annual loss of soil nutrients. The traditional practices of clearing natural forests for agricultural land through shifting cultivation have been a significant driver of ecosystem degradation due to declining soil productivity and fertility. Imprudent deforestation, coupled with unsustainable jhum cultivation practices, has led to severe soil loss and the deterioration of the soil physical environment. This problem is further exacerbated by reduced jhum cycles, which impede the natural rejuvenation of vegetation and the restoration of soil fertility. Deterioration of soil fertility, organic matter, biomass carbon, microbial diversity, and microbial activities, along with an increase in soil erodibility, acidity, and exposure of compact subsoils with poor physicochemical properties, are some of the factors contributing to the retrogression of soil quality and health. Despite its reputation as a location with heavy rainfall, the study area has a distinct mix of edaphic difficulties, such as high soil acidity, aluminium toxicity, significant soil carbon loss, and severe water shortages for most of the year. Soil acidity emerges as a significant concern for chemical degradation in the northeastern states of the country. The pervasive soil acidity in this area is attributed to multiple factors, including the elevated levels of exchangeable aluminium resulting from the weathering of acidic parent materials and the significant leaching of bases due to the region's abundant rainfall (Bandypadhyay et al. 2018).

Given the limited prospects for industrialisation in mountainous regions and the predominant reliance

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on agriculture for rural livelihoods, the agricultural sector stands as a cornerstone for economic growth in the northeastern states of India. Hill agriculture faces inherent constraints, yet opportunities exist to harness the region's agricultural potential. This requires a focus on soil health and quality, allowing for the cultivation of a diverse range of crops, including fruits, vegetables, and commercial crops. To achieve sustainable soil management, identifying a minimal set of key soil parameters is crucial. These parameters will guide informed decision-making regarding soil health and its ability to support agricultural production. Understanding the complex interplay between traditional land-use practices and their influence on these soil quality pointers is essential. This knowledge will pave the way for the development of effective and sustainable soil management strategies in these ecologically vulnerable regions. The present study addresses this critical need. This study has two primary objectives. The first is to identify a minimal set of key soil parameters that exert a significant influence on soil quality within the agricultural and forestry ecosystems of the mid-hill region. The second objective is to develop a robust methodology for constructing an SQI precise to this region.

MATERIAL AND METHODS

Studied site. The experimental farm of ICAR Research Complex for North East Hill Region, along with farmers' fields in the Leparada and West Siang districts of Arunachal Pradesh, was selected for the present investigation (Figure 1). This region lies between longitudes 93.57°E to 95.23°E and latitude 27.69°N to 29.20°N. It extends over an area of 7 643 km^2 and shares its border with East Siang and Upper Siang districts to the east, Upper Subansiri district to the west, China to the north, and Assam to the south (Table 1). The soil of this region is under Ultisols and Inceptisol soil orders, with kaolinite as the dominating clay mineral. As per the World Reference Base soil classification, this region has red soil type, and subtype is Acrisols.

Soil handlings. Georeferenced surface samples collected from eight different land use locations *viz.* natural forest (NF), current jhum cultivation (JC), fallow jhum land (FJC), and pineapple cultivation (PA) on a 50 × 50 m grid and divided into three parts. Four land uses, sixteen sampling sites, and three replications made up the 192 composite samples that were collected. To analyse chemical properties like soil pH,

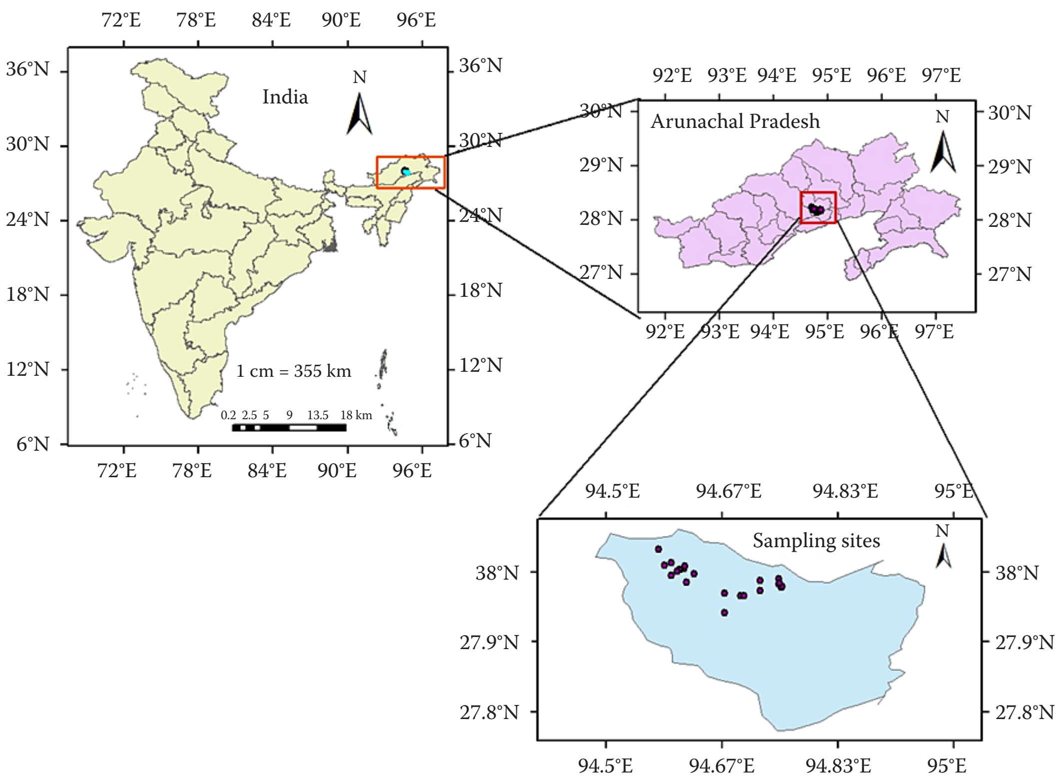

Figure 1. Location of the study sites in Arunachal Pradesh, India

This map was prepared by the first author, Jitendra Kumar, with the help of ArcGIS 10.4 (http://www.esri.com/software/arcgis)

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Table 1. Site history and characteristic features of different land use systems in our study

Land use system	Background information	Latitude	Longitude	Altitude (m)
Jhum cultivation (JC)	current year of jhum, the jhum cultivation is a traditional shifting cultivation practice that entails burning forests to make way for agricultural land	27.9664	94.6931	646
Fallow jhum cultivation (FJC)	fallow from last two years after two-year jhum	27.9661	94.6978	647
Pineapple (PA)	jhum land settle for pineapple cultivation in the last seven-year	27.5703	94.6708	711
Natural forest (NF)	naturally grown forest of unknown history	27.9422	94.7006	743

soil organic carbon (SOC), carbon fractions, available nitrogen (N), available phosphorus (P), exchangeable potassium (K), diethylenetriaminpentahacetic acid (DTPA)-extractable zinc (Zn), iron (Fe), manganese (Mn), and copper (Cu), a portion of the soil sample was air-dried, ground, and sieved through a 2.00-mm sieve. In order to ascertain the biological characteristics of soil microbial biomass carbon (SMBC) and soil dehydrogenase activity (DHA), the second portion was placed in a deep freezer after passing through a 0.5 mm screen. Reduction of 2, 3, 5-triphenyl tetrazolium chloride was used

Table 2. Laboratory protocol for estimating soil parameters

		Parameters	Abbreviation (unit)	Analytical method	Reference
1	Physical parameters	available water content	AWC (%)	gravimetric with oven drying method	Gong et al. (2015)
2		water holding capacity	WHC (%)	Keen boxes	Richard (1954)
3		clay content (texture)	CC (%)	international pipette method	Page et al. (1982)
4		bulk density	BD (mg/m^3)	core method	Blake and Hartge (1986)
5		porosity	PORE (%)	indirect method	Blake and Hartge (1986)
6	Chemical parameters	available nitrogen	AN (kg/ha)	alkaline $KMnO_4$ method	Subbiah and Asija (1956)
7		available phosphorous	AP (kg/ha)	Olsen method	Olsen et al. (1954)
8		available potassium	AK (kg/ha)	flame photometer	Jackson (1973)
9		DTPA extractable zinc	Zn (mg/kg)	atomic absorption spectroscopy	Lindsay and Norvell (1978)
10		DTPA extractable mangnease	Mn (mg/kg)		
11		DTPA extractable iron	Fe (mg/kg)		
12		DTPA extractable copper	Cu (mg/kg)		
13		pH	pH (–)	1 : 2 soil/water	Thomas (1996)
14		soil organic carbon	SOC (%)	wet digestion method	Walkley and Black (1934)
15		very labile	VL (mg/g)	modified Walkley-Black method	Chan et al. (2001)
16		labile	L (mg/g)		
17		less labile	LL (mg/g)		
18		non-labile	NL (mg/g)		
19		active pool	AP (mg/g)		
20		passive pool	PP (mg/g)		
21	Biological parameters	soil microbial carbon biomass	SMBC (μg/dry soil)	chloroform fumigation-extraction method	Vance et al. (1987)
22		dehydrogenase activity	DHA (μg TPF/g soil h)	2, 3, 5-triphenyl tetrazolium chloride method	Casida et al. (1964)

DTPA – diethylenetriaminpentahacetic acid

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to measure dehydrogenase activity (Casida et al. 1964). Using a standard curve of triphenyl formazan (TPF) in methanol, DHA activity was computed and reported as µg TPF/g soil h. The chloroform fumigation-extraction method (Vance et al. 1987) was utilised to determine SMBC, which was expressed in µg/dry soil. Physical characteristics of the soil, including bulk density, particle size distribution, water-holding capacity (AWC), porosity, and plant-available water capacity, were analysed in the third section. The characteristics of the soil and the analytical techniques employed are listed in Table 2. The wet digestion method was used to determine the Walkley and Black oxidizable carbon (WBC) content (Walkley & Black 1934). The other soil nutrient, *viz*., potassium permanganate oxidizable soil N ($KMnO_4$-N) (Subbiah & Asija 1956), available phosphorus (Olsen et al. 1954). Available K (Hanway & Heidal 1952) in the soil was estimated using a standard technique.

Soil quality assessment. Using the corresponding conventional laboratory procedures, twenty-two soil quality parameters – physical, chemical, and biological – were investigated for each sampling plot (Table 2). To investigate the impact of different land uses on soil properties, an ANOVA was performed on all twenty-two parameters. To estimate the SQI, only indicators that demonstrated a significant difference ($P < 0.05$) among the four land uses were included in the total data set (TDS). Utilizing the scoring function analysis framework, the SQI was computed through three distinct steps: (1) identification of the minimum data set (MDS) of indicators from the complete dataset; (2) application of the standard scoring function to assign scores to the identified minimum dataset of indicators, and (3) integration of the individual indicator scores to derive a unified relative SQI value (Andrews et al. 2004; Raiesi 2017).

To determine the MDS of soil metrics that represent important facets of soil quality, the principal component analysis (PCA) technique was utilised. A standardised data matrix that included the complete dataset was used for the analysis. For additional examination, principal components (PCs) whose eigenvalues could account for at least 5% of the overall variability in the data were chosen. Parameters that had loading values within 5% of the maximum absolute loading for each PC were taken into consideration for the MDS. To address potential redundancy within the MDS, Pearson's correlation analysis (Andrews et al. 2002) was applied to highly loaded parameters. If these parameters exhibited low correlation coefficients, indicating distinct information content, both were retained in the MDS. Conversely, only the parameter with the highest absolute loading was included when highly loaded parameters were highly correlated. Following the selection of the MDS, each soil parameter was transformed into a unitless score ranging from 0 to 1. This conversion employed linear or non-linear scoring functions adapted from established methods (Andrews et al. 2002, 2004; Askari & Holden 2015; Raiesi 2017). The most appropriate scoring method was selected and interpreted based on the intended purpose of soil sustainability and productivity. Scoring curves such as "Less is better" and "More is better" were applied for parameters depending on whether a soil parameter was deemed favourable for soil quality in descending order (less is better) or ascending order (more is better), as outlined in Table 3. For linear scoring, "less is better' (Equation 1), or "more is better (Equation 2). The following functions are used:

$$S_L = \frac{Y_{min}}{Y} \tag{1}$$

$$S_L = \frac{Y}{Y_{max}} \tag{2}$$

where:

S_L – the linear score of the soil parameter;

Y – the soil parameter value;

Y_{max}, Y_{min} – the maximum and minimum values of each soil parameter studied among the four-land use (Askari & Holden 2014; Raiesi 2017).

Table 3. Soil scoring curves for linear and non-linear equations based on critical and optimum limit

Parameters	Scoring curve	Linear		Non-linear		Optimum	Weight
		Y_{Max}	Y_{Min}	mean Y_m	slope (b)		
DHA	more is better	62	41	49.68	–2.5		0.73
DTPA-Fe	optimum is better	33.88	13.5	23.00	2.5	4.5	0.19
BD	less is better	1.41	0.98	1.19	2.5		0.08

DHA – dehydrogenase activity; DTPA-Fe – diethylenetriaminpentahacetic acid extractable iron; BD – bulk density

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For nonlinear scoring, the following sigmoidal function (Equation 3), was employed:

$$S_{LN} = \frac{a}{1+\left(\frac{Y}{Y_m}\right)b} \quad (3)$$

where:

S_{LN} – the non-linear score of the soil parameter;

Y_m – the mean value of each soil parameter;

a – the highest score achieved by the function which is equal to 1 in this study;

b – the inclination or slope of the equation and is fixed as 2.5 for a "less is better" curve and –2.5 for "more is better" curve (Bastida et al. 2006; Raiesi 2017).

The converted parameter scores were combined into a relative SQI using an additive (Equation 4), and weighted additive (Equation 5) methods as follows:

$$SQI_A = \sum_{i=1}^{n}\left(\frac{S_i}{n}\right) \quad (4)$$

$$SQI_W = \sum_{i=1}^{n} W_i \times S_i \quad (5)$$

where:

SQI_A, SQI_W – the additive and weighted additive soil quality indices, respectively;

S_i – the parameter score (linear or non-linear);

n – is the number of soil parameters in the MDS;

W_i – the value of the weighted soil parameters estimated from the variation of each respective PC in percentage and normalized to one (Andrews et al. 2002; Askari & Holden 2014).

Four SQIs – the linear scoring-additive integration method (SQLAI), the linear scoring-weighted additive integration method (SQLWAI), the nonlinear scoring-additive integration method (SQNLAI), and the nonlinear scoring-weighted additive integration method (SQNLWAI) – were compared in this study based on the combination of integration methods and parameter scoring functions. Greater SQI values indicate healthier soil and reflect the beneficial effect of land-use changes on soil processes such as cycling of nutrients, enhanced soil resistance and resilience to change, improved soil fertility and productivity, and greater tenability of the soil (Raiesi 2017).

Sensitivity index (SI). Each soil parameter's SI Raiesi (2017) was calculated by dividing the values found in natural forests by the comparable values found in jhum land. When land use changes from natural forest to jhum farming, a movement in soil characteristics toward deterioration is indicated by an SI value larger than one. For instance, an SI value of 1.3 signifies a 30% reduction, while an SI value lower than one suggests a change in soil parameters toward improvement. For example, an SI value of 0.7 indicates a 30% increase in soil parameters due to the transition from natural forest to jhum cultivation. A 30% deviation in the SI value in either direction implies that the parameter is highly sensitive to land use transformation.

Analysis of statistics. The SAS statistical software (Ver. 9.3, 2011) tool was used to statistically evaluate all of the soil parameter data. Normality and equal variance tests were performed in order to satisfy the statistical analysis's presumptions. The impacts of land use on all soil characteristics and SQIs were assessed using a one-way analysis of variance (ANOVA) in a completely randomised manner. The mean difference between land uses was estimated using the least significant difference test (LSD). The analysis's significance level was set at 5% ($P < 0.05$). Soil characteristics and SQI coefficients were correlated using Pearson correlation matrices, with significance values set at 5% ($Pb < 0.05$) and 1% ($Pb < 0.01$) levels. The coefficient of variance (CV) was used to calculate each SQI's difference and dispersion. Figure 2 shows the percentage contribution of each chosen indicator for the various land use types.

RESULTS

Land use *viz-a-viz* on soil parameters and sensitivity index. In the West Siang region of Arunachal Pradesh, India, the impact of land use on soil quality measures was examined. As promising markers of the soil quality of the chosen land use categories, a total of 22 soil metrics were examined (Table 3). 19 of the 22 characteristics were found to be substantially ($Pb < 0.05$) influenced by land use, according to the ANOVA results; as a result, these parameters were retained as part of the entire dataset for the PCA. The 19 soil parameters included were AWC, WHC, BD, PORE, AN, AP, AK, Zn, Mn, Fe, Cu, pH, SOC, VL, L, NL, AP, SMBC, and DHA. Different land uses exert varying influences on soil characteristics. However, some soil parameters, such as BD, CC, AK, Fe, Cu, LL, PA, and AP, showed similar trends for different land use types. Specifically, the lowest values for all other indicators were observed under jhum land use,

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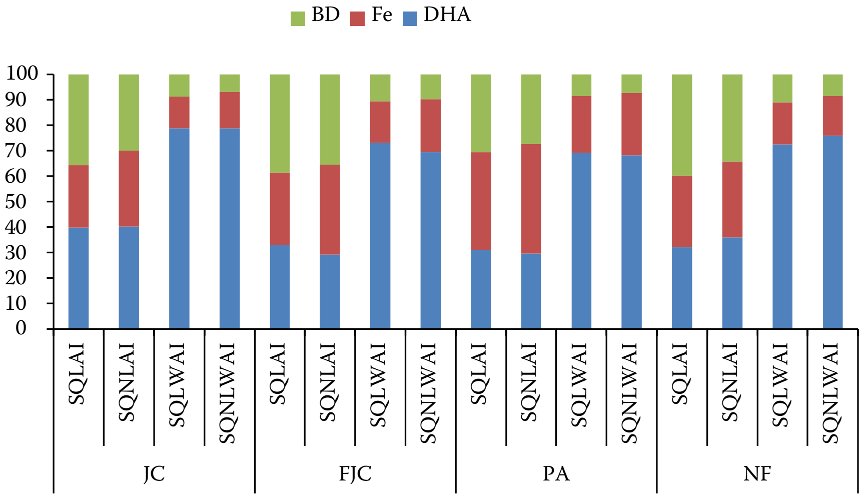

Figure 2. Percentage contribution of selected soil indicators of the minimum data set in various soil quality indices
SQLAI – the linear scoring-additive integration method; SQLWAI – the linear scoring-weighted additive integration method; SQNLAI – the nonlinear scoring-additive integration method; SQNLWAI – the nonlinear scoring-weighted additive integration method; JC – jhum cultivation; FJC – fallow jhum land; PA – pineapple cultivation; NF – natural forest; BD – bulk density; DHA– dehydrogenase activity

Table 4. Measured potential soil quality indicator as affected by the land use

S. No.	Parameters	JC	FJC	PA	NF	LSD	SD	SI
1	AWC	20.6[c]	24.8[b]	23.8[b]	28.6[a]	1.92	4.66	1.39
2	WHC	38[b]	40[b]	41[b]	44[a]	2.21	2.55	1.07
3	CC	46	44	44	49	7.66[NS]	2.48	1.06
4	BD	1.40[a]	1.07[a]	1.27[a]	1.01[b]	0.21	0.22	0.72
5	PORE	43[b]	44[b]	44[b]	49[a]	1.44	2.26	1.14
6	AN	219[c]	237[b]	221[c]	283[a]	5.85	29.07	1.29
7	AP	11.8[b]	15.1[a]	17.5[a]	16.5[a]	2.86	3.78	1.40
8	AK	260[a]	207[b]	209[b]	266[a]	13.6	29.72	1.02
9	Zn	0.46[a]	0.36[b]	0.41[a]	0.29[b]	0.12	0.48	0.63
10	Mn	3.53[c]	7.32[b]	7.29[b]	11.69[a]	2.08	3.16	3.31
11	Fe	22.15[b]	22.56[b]	31.62[a]	15.67[c]	2.77	6.09	0.71
12	Cu	0.13[a]	0.12[a]	0.05[a]	0.11[a]	0.11	0.26	0.85
13	pH	4.50[d]	4.95[b]	4.70[c]	5.07[a]	0.12	0.24	1.13
14	SOC	1.19[c]	1.24[c]	1.79[b]	2.43[a]	0.18	5.15	2.04
15	VL	5.48[b]	4.70[b]	6.25[b]	13.09[a]	5.02	2.98	2.39
16	L	2.42	3.25	4.32	5.07	2.55	1.11	2.10
17	LL	5.22	2.66	1.77	4.89	3.95[NS]	1.68	0.94
18	NL	10.10[c]	12.57[b]	15.11[a]	16.67[a]	4.01	2.01	1.65
19	PA	7.90[a]	7.95[b]	10.57[b]	18.16[a]	5.82	3.78	2.30
20	PP	15.32	15.23	16.88	21.56	6.58[NS]	2.97	1.41
21	SMBC	309[d]	355[c]	439[b]	516[a]	33.9	73.75	1.67
22	DHA	43.7[c]	44[c]	49.7[b]	61.7[a]	5.13	7.76	1.41

JC – jhum cultivation; FJC – fallow jhum land; PA – pineapple cultivation; NF – natural forest; LSD – least significant difference; SD – standard deviation; SI – sensitivity index; NS – non significant; at $P < 0.05$, values that share lowercase letters across rows (land uses) do not differ significantly; see Table 2 for explanation of parameter abbreviations

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while the highest values were recorded in natural forest areas. Notably, the highest copper (Cu) content was observed in jhum land use, whereas iron (Fe) content was highest in pineapple cultivation areas (Table 4). The SI varied from 0.62 to 3.31. The SI was found more than 1 in some soil parameters such as Mn content (3.31), very labile carbon (2.39), passive pool (2.30), labile pool (2.10), SOC (2.04), SBMC (1.67), and DHA (1.41), which indicates a decrease of these parameters from the transformation of natural forest to jhum system. These reductions highlight the detrimental effects of jhum practices on soil organic matter content, microbial activity, and overall soil health. Conversely, some soil parameters exhibited SI values less than 1, such as bulk density (0.72), Zn (0.63), Fe (0.71), and less labile carbon (0.94), indicating an increase in the value of these soil parameters during the transition from natural forests to jhum systems.

Minimum data set and SQI calculation. In PC1, the highest weighted parameters were found with DHA 0.268 (Table 5), which was significantly ($P < 0.05$) correlated with each other (Table 5); therefore, it was chosen for MDS in PC1. Among PC2, Fe showed the highest loading factor of 0.48, whereas in PC3, the bulk density of 0.463 showed the highest loading factor, and all three were significantly ($P < 0.05$) correlated with each other (Table 6). Therefore, DHA, Fe, and BD were chosen as the MDS.

In PC1, the highest weighted parameter was DHA 0.268 (Table 5, Figure 3), and they were significantly ($P < 0.05$) correlated with other soil parameters (Table 5); therefore, this parameter was chosen for MDS in PC1. Among PC2, Fe showed the highest loading factor of 0.48, whereas in PC3, the bulk density of 0.463 showed the highest loading factor, and all three showed a significant ($P < 0.05$) correlation with

Table 5. Loading coefficients (eigenvectors) of soil quality parameters of the total data set, their eigenvalues, and the percentage of total variance explained by each factor

	PC1	PC2	PC3	PC4	PC5
AWC	0.2605	–0.06	–0.18	–0.07	–0.06
WHC	0.1797	0.39	0.003	–0.066	–0.09
BD	–0.22	0.039	0.463	0.058	0.038
PORE	0.2637	0.092	0.056	–0.077	–0.09
AN	0.2555	0.149	–0.1	–0.077	–0.08
AP	0.2563	0.053	0.229	–0.074	–0.09
AK	0.0866	0.448	0.333	–0.043	–0.08
Zn	–0.252	0.002	0.278	0.0692	0.061
Mn	0.2631	–0.09	–0.09	–0.069	–0.07
Fe	–0.11	0.48	0.001	0.0113	–0.01
Cu	–0.026	0.473	–0.35	–0.011	–0.02
pH	0.2289	–0.05	–0.42	–0.06	–0.04
SOC	0.2645	0.084	0.05	–0.077	0.956
VL	0.2483	0.128	0.237	–0.075	–0.1
L	0.2417	–0.2	0.163	–0.06	–0.06
NL	0.2373	–0.23	0.126	–0.057	–0.06
AP	0.2563	0.053	0.229	–0.074	–0.09
SMBC	0.2483	–0.15	0.206	–0.064	–0.07
DHA	0.268	0.039	0.003	0.9627	0
Eigenvalue	13.87	3.6224	1.5078	0	0
Difference	10.247	2.1146	1.5078	0	0
Proportion	0.73	0.1907	0.0794	0	0
Cumulative	0.73	0.9206	1	1	1

Boldface factor loadings are considered highly weighted; the first three principal components (PC) are considered highly weighted and included in the minimum data set; see Table 2 for explanation of parameter abbreviations

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Table 6. Pearson correlation matrix of the total data set

	AWC	WHC	BD	PORE	AN	AP	AK	Zn	Mn	Fe	Cu	pH	SOC	VL	L	NL	AP	SMBC	DHA
AWC	1																		
WHC	0.64*	1																	
BD	0.93**	–0.73**	1																
PORE	0.91**	0.48	–0.91**	1															
AN	0.91**	0.75**	–0.99*	0.9**	1														
AP	0.92**	0.64*	–0.97**	0.93**	0.97**	1													
AK	0.31	0.71**	–0.59*	0.39	0.62*	0.51	1												
Zn	–0.1	–0.08	0.22	–0.18	–0.23	–0.35	–0.34	1											
Mn	0.89**	0.4	–0.81**	0.88**	0.8**	0.87**	0.1	–0.09	1										
Fe	–0.33	0.29	0.14	–0.27	–0.09	–0.27	0.6	0.22	–0.54	1									
Cu	–0.53	0.08	0.35	–0.45	–0.29	–0.47	0.37	0.42	–0.62*	0.93**	1								
pH	0.43	0	–0.19	0.26	0.15	0.14	–0.46	0.7	0.48	–0.86**	–0.28	1							
SOC	0.91**	0.58*	–0.95**	0.91**	0.93**	0.98**	0.44	–0.44	0.85**	–0.37	–0.58*	0.1	1						
VL	0.91**	0.68*	–0.98**	0.89**	0.96**	0.97**	0.56	–0.31	0.79**	–0.16	–0.38	0.11	0.96**	1					
L	0.71**	0.33	–0.69*	0.75**	0.73**	0.79**	0.22	–0.38	0.83**	–0.49	–0.58*	0.17	0.79**	0.63*	1				
NL	0.64*	0.07	–0.57*	0.61*	0.52	0.63**	–0.03	–0.47	0.64*	–0.72**	–0.87**	0.19	0.74**	0.58*	0.59*	1			
AP	0.92**	0.64*	–0.97**	0.93**	0.97**	1	0.51	–0.35	0.87**	–0.27	–0.47	0.14	0.98**	0.97**	0.79**	0.63*	1		
SMBC	0.85**	0.34	–0.81**	0.85**	0.78**	0.89**	0.15	–0.46	0.87**	–0.64*	–0.8**	0.2	0.94**	0.84**	0.8**	0.86**	0.89**	1	
DHA	0.87**	0.5	–0.88**	0.9**	0.87**	0.94**	0.38	–0.51	0.83**	–0.62*	–0.67*	0.08	0.97**	0.87**	0.86**	0.78**	0.94**	0.95**	1

*,**Pearson correlation significant at 5% and 1% level (two-tailed test); see Table 2 for explanation of parameter abbreviations

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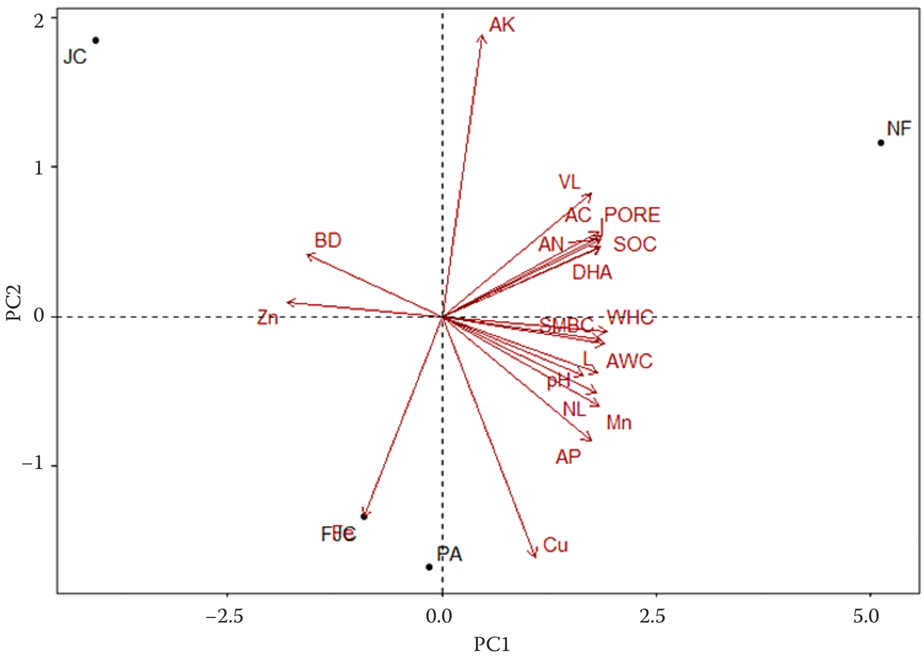

Figure 3. Biplot diagram of different soil quality parameters

See Table 2 for explanation of parameter abbreviations

each other (Table 6). Therefore, these three DHAs, Fe, and BD, were chosen for the MDS.

Equations (1), (2), and (3) were used to convert all soil characteristics in the MDS using linear and nonlinear scoring functions. A "more is better" curve was applied to the DHA indicators, while a "less is better" curve was applied to the Fe content parameters, taking into account the role that MDS parameters have on soil function. Since the concentration of micronutrients over the critical limit was deemed sufficient (i.e., optimal) and that below the critical limit was deemed insufficient, the availability of iron in this study was higher than the optimal value (4.5 mg/kg). Deficit and sufficiency of accessible Fe (4.5 mg/kg) (Lindsay & Norvell 1978) were deemed optimal based on this rationale. The "more is better" scoring approach is employed; wherein higher values are considered favourable up to an optimum level. However, beyond the optimum level, higher values are scored as "less is better" (Liebig et al. 2001; Mandal et al. 2011; Singh et al. 2014). Based on the percentage of variation to total variance, each PC's weight varied between 0.08 and 0.78. The trend of the MDS weighted factor is PC1 (0.73) > PC2

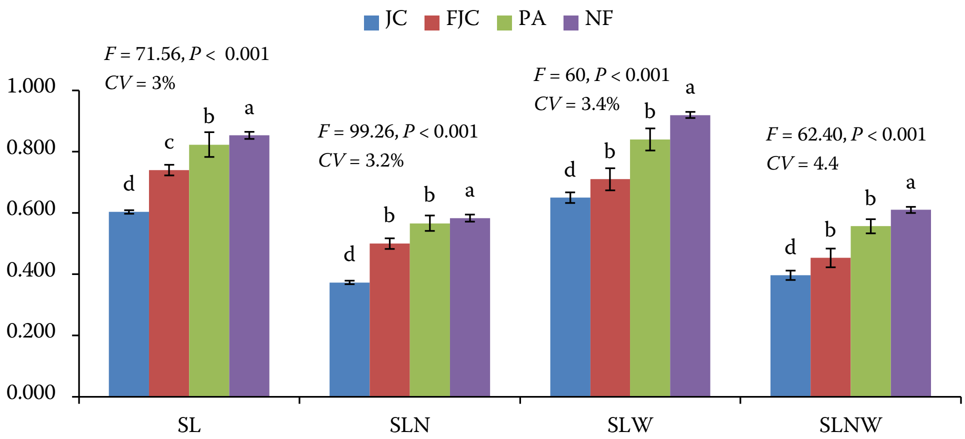

Figure 4. Comparing the soil quality of the indices created for this study across various land uses

JC – jhum cultivation; FJC – fallow jhum land; PA – pineapple cultivation; NF – natural forest; SL – simple linear; SLN – simple non linear; SLW – simple linear weighting; SLNW – simple nonlinear weighting; at $P < 0.05$, there is no significant difference between values with the same lowercase letters among land uses

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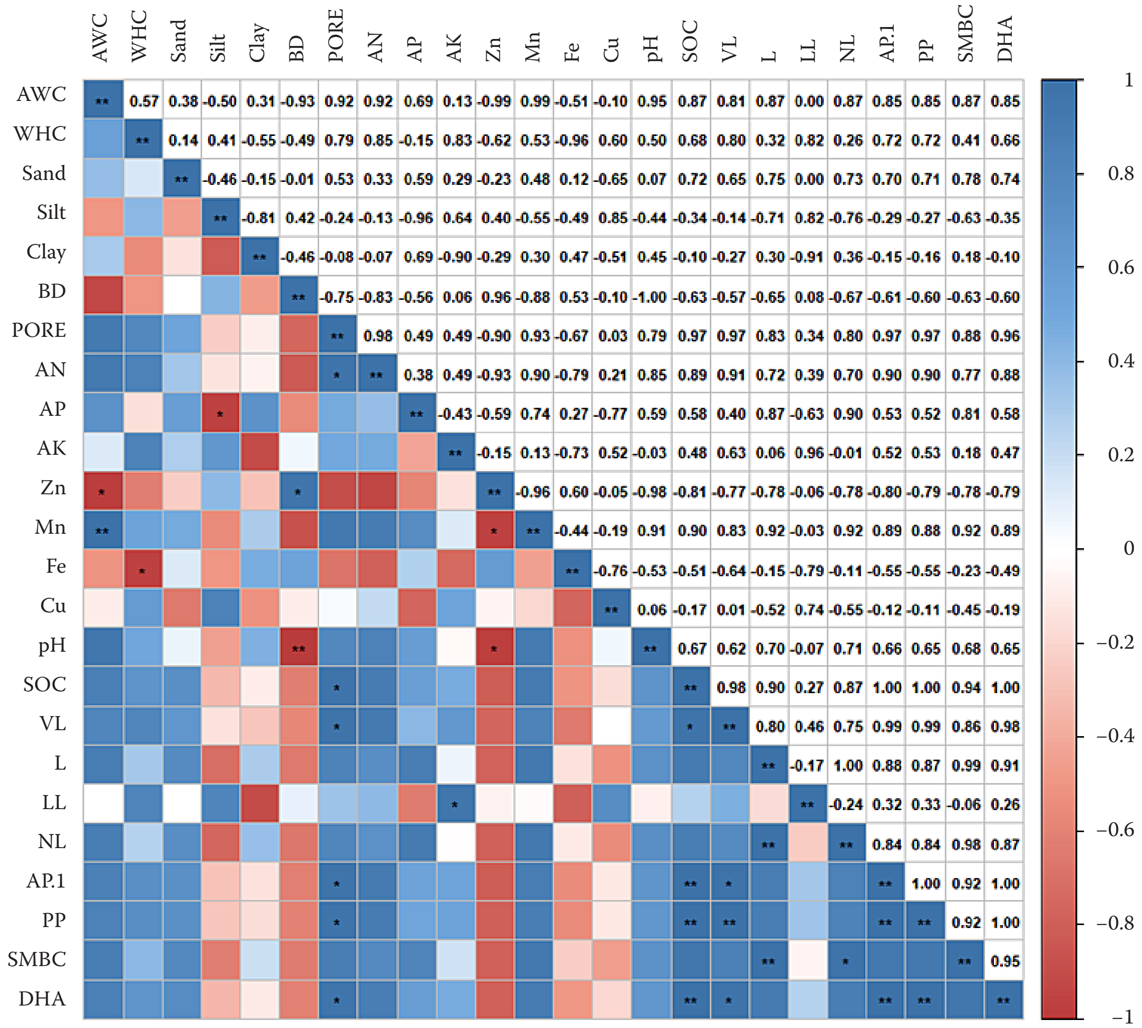

Figure 5. Pearson correlation matrix of the total data set
See Table 2 for explanation of parameter abbreviations

(0.19) > PC3 (0.08). The variance in each PC was used to determine the weights of the soil indicators (Table 6 and Figure 5). Due to its highest weighting, DHA contributed the most to SQI, followed by Fe and BD. Finally, a comparative SQI was computed using an additive (Equation 4), and the weighted additive (Equation 5) methods as given below:

$$\text{SLA and SNLA} = (S_{DHA}+S_{Fe}+S_{BD})/3 \quad (6)$$

$$\text{SLWA and SNLWA} = (0.73 \times S_{DHA}) + (0.19 \times S_{Fe}) + + (0.08 \times S_{BD}) \quad (7)$$

where:
SLA – simple linear additive;
SNLA – simple nonlinear additive;
SLWA – simple linear weighting additive;
SNLWA – simple nonlinear weighting additive.

Influence of land use on various SQIs. The value of the SQI is significantly ($P < 0.05$) influenced by the various land uses, and it varied from 0.60 to 0.85, 0.37 to 0.58, 0.65 to 0.92, and 0.40 to 0.62, for SQLAI, SQNLAI, SQLWAI, and SQNLWAI, respectively (Table 7). In both the weighted additive and additive methods, the linear SQI had a wider range of values than the nonlinear SQI. Additionally, the coefficient of variation (*CV*) and *F*-values associated with the non-linear SQNLAI and SQNLWAI were higher than those of the linear SQLAI and SQLWAI (Figure 4). This suggests that the nonlinear SQI methods demonstrate greater sensitivity to land

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Table 7. Pearson correlation matrix of different soil quality index methods

	SQLAI	SQNLAI	SQLWAI	SQNLWAI
JC	0.60	0.37	0.65	0.40
FJC	0.74	0.50	0.71	0.45
PA	0.82	0.57	0.84	0.56
NF	0.85	0.58	0.92	0.61

SQLAI – the linear scoring-additive integration method; SQLWAI – the linear scoring-weighted additive integration method; SQNLAI – the nonlinear scoring-additive integration method; SQNLWAI – the nonlinear scoring-weighted additive integration method; JC – jhum cultivation; FJC – fallow jhum land; PA – pineapple cultivation; NF – natural forest

Table 8. Various soil quality indices (SQI) of different land use

	SQLAI	SQNLAI	SQLWAI	SQNLWAI
SQLAI	1.000			
SQNLAI	0.997***	1.000		
SQLWAI	0.94***	0.91***	1.000	
SQNLWAI	0.95***	0.93***	0.997***	1.000

SQLAI – the linear scoring-additive integration method; SQLWAI – the linear scoring-weighted additive integration method; SQNLAI – the nonlinear scoring-additive integration method; SQNLWAI – the nonlinear scoring-weighted additive integration method

use management practices. Conversely, the *F*-values of the linear methods were lower than those of their nonlinear counterparts.

In this study, the highest SQI range with the largest *F*-value (Figure 3) was found for the SQNLAI. This suggests that the weighted-additive strategy is less susceptible than the nonlinear approach. The four SQIs showed a substantial positive link with one another, according to the Pearson correlation matrices among the SQIs (Table 8). Among the various land use types, all of the SQIs showed significant differences (Figure 3, $P < 0.001$). The analysis of the four SQIs revealed that there were notable differences in the soil quality across the four land uses. However, compared to jhum, fallow jhum, and pineapple land usage, the natural forest's soil quality was noticeably superior.

DISCUSSION

Different land uses *viz-a-viz* soil quality indicators. Conversion of NF to JC, FJC, and PA cultivation had significantly decreased SOC, AN, and AP in the study area. The observed patterns can be attributed to the decline in organic matter input and the removal of vegetation cover, which contribute to erosion loss (Kumar et al. 2017). Natural forests have very high litterfall that covers the soil surface and behaves like mulch along with increasing soil organic matter (Kumar et al. 2021). Consequently, SOC content in natural forest areas tends to be high. However, when such land is converted to shifting cultivation practices like jhum, SOC content experiences a significant decrease due to forest burning. The process of forest burning leads to the oxidation of organic matter, resulting in a reduction in SOC content (Jitendra et al. 2017). The AK remains at par with natural forest soils. This is because of the addition of K minerals due to the burning of forests (Kumar et al. 2017). A significantly higher AP (16.5 kg/ha) was found in the pineapple land use system, followed by natural forest and fallow jhum land, and the lowest was recorded in jhum cultivation (11.5 kg/ha). The extensive root systems and greater exudates from the various vegetation species in the natural forest may have contributed to the natural forest's noticeably higher pH, which in turn affected soil fertility (Chen et al. 2017). The lowest pH was found in the Jhum land-use system, followed by the pineapple land-use. Similar to this study, Kumar et al. (2020) reported that the pH of horticulture-based land use improved over jhum land use. Owing to the acidic pH, the micronutrient content was recorded beyond the optimum level. The highest DTPA-Fe (4.5 mg/kg optimum) was recorded in pineapple land, whereas the lowest was found in natural forests. The Mn content was also recorded beyond the optimum level; however, Zn and Cu are found at the optimum level. Variations in soil pH due to continuous jhum cultivation on the same land and their management practices following various land-use types have also been reported by other researchers (Parras-Alcantara et al. 2016; Orgill et al. 2018). The natural forest land use had the lowest bulk density, jhum had the highest, and SOC displayed the reverse tendency when compared to the other land-use systems in our study. These results are consistent with those of Sharma et al. (2010), who discovered a negative correlation between bulk density and soil organic carbon in the western Himalayan soils. The AWC values ranged from 20% to 28.6%. The maximum AWC was observed

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in the natural forest (28.6%), and the lowest AWC was recorded in the jhum cultivation, while in the fallow jhum (24.8%), it was significantly at par with that of pineapple (23.8%). The AWC followed a similar trend to that found in the case of the BD, indicating that the BD is highly positively correlated between the AWC and WHC. However, it is well established that BD and SOC are negatively proportional (Post & Kwon 2000; Pulido-Fernández et al. 2013).

Soil microbial carbon biomass and dehydrogenase were also highest in the natural forest and lowest in the jhum land use, owing to the biological activities caused by the presence of the highest amount of soil organic carbon. Furthermore, jhum had deleterious impacts on the land's preparation for cultivation, which may have led to a greater loss of the soil's AC pool (Yao et al. 2010). Very labile (VL) and labile (L) showed a similar trend and were found to be highest in the natural forest, whereas the lowest was found in the jhum land use. However, the less labile (LL) and non-labile (NL) fractions showed no trend, even though the natural forest had the highest non-labile fraction of soil carbon.

Due to the substantial input of plant litter and protection of additional carbon, which raised microbial activity and thus enhanced very labile carbon, natural forest and pineapple land-use systems have significantly greater very labile carbon percentages than fallow land. Because of its adsorption on tiny particles, the non-labile carbon fraction is resistant to soil management practices and the breakdown of soil microorganisms (Sherrod et al. 2005; Sainepo et al. 2018). The current analysis found that land use had a significant impact on MBC and DHA operations. Jhum and fallow jhum had the lowest MBC, while the natural forest had the highest, followed by pineapple land use. Numerous studies have documented a decrease in microbial biomass following a fire, which is consistent with our findings (Holden & Treseder 2013; Girona-García et al. 2018). The loss of plant cover and SOC from the soil surface causes the soil microbial biomass content to drop in deforested areas.

Selection of MDS and soil quality evaluation. The PCA results indicate that in PC1, AWC, SOC, SMBC, and DHA showed high loading and explained 73% of the variation among these parameters; DHA found the highest loading with a significant correlation coefficient with the remaining total data set parameters; therefore, from PC1, DHA was chosen as the MDS. Similar to our study, Salazar et al. (2011) widely studied DHA with other soil parameters and reported that soil dehydrogenases are sensitive and useful indicators of changes in soil quality. Bandick and Dick (1999) also reported that the DHA is a potential indicator of soil quality due to its sensitivity towards the alteration in soil management as compared to other soil biological properties. Alef (1995), Garcia et al. (1997) and Skujins (1973) reported that DHA activity is a viable index of the oxidising processes occurring within the soil. Therefore, it may be a good indicator of microbial reactions in soil (Skujins 1976). Soil DHA activity acts as a sensor of soil degradation because it is strongly associated with the microbial status, soil physicochemical conditions (Aon & Colaneri 2001), nutrient cycling, fertiliser management, carbon cycles, and soil organic matter (SOM) (Błońska et al. 2016). In PC2, nutrient content, such as Fe and Cu, and Available Potash showed high loading and explained 19% of the variation; however, the Fe content was the highest among them. Therefore, in PC2, only the Fe content was retained for the MDS. The pH and redox conditions are the two important factors that govern the dynamics of Fe availability in soil. Due to the lower pH in our study, the concentration of iron was more than the critical level, and in PCA analysis, it was represented in PC2. Similar to our study, Zhou et al. (2022a) assigned DTPA–Fe in a minimal dataset based on PCA. However, contrary to what our study represented in PC1, this was found in PC2. In PC3, the highest bulk density was recorded, explaining 8% of the variation. Therefore, the bulk density was maintained in the MDS. Soil bulk density is a crucial physical parameter that indicates the status of soil fertility and crop productivity. Similar to our study, Zhou et al. (2022b) also included bulk density in MDS in PC3, while Askari and Holden (2014) included BD in PC2. This is also an indicator of soil mechanical resistance to root growth, and hence, soil compaction (Castellini et al. 2015). SOC and bulk density are negatively correlated (Wang et al. 2011). A lower bulk density indicates a higher amount of SOC, and vice versa, and plays a decisive role in many soil functions, including soil aggregation, nutrient cycling, nutrient storage, and as a source of food for soil microorganisms (Nieder & Benbi 2008). Bulk density differed significantly with the land-use system. Under natural forest, it was significantly lower than that under cultivated land, which might be the result of the accumulation of higher organic matter from litterfall. This results in better aggregation and lower compaction of the soil owing to the reduction

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in SOC concentration (Abbasi & Tahir 2012). The selected soil parameters indicate that they are very important for enhancing soil sustainability. The remaining soil parameters had less factor loading or were less correlated, indicating that these were relatively less important and, therefore, not chosen for the MDS. The computed SQIs of different land uses were compared with the mean SQI values under the NF. These values were significantly higher than those in JC, FJC, and PA, indicating that the conversion of perennial natural forests to shifting cultivation degraded the soil quality. However, comparing the soil quality of PA and FJC, the soil quality was improved compared to that of JC, indicating that if the shifting land was left for rejuvenation or used for horticulture-based cultivation, their soil quality improved considerably. The higher SQI values under NF, PA, and FJC might be due to the increase in above- and below-ground biomass, which regularly added organic matter into the soil and decreased the rate of soil nutrient loss by reducing soil erosion in horticulture and forestry-based land use systems. The differences in SQI are contributed by the MDS (DHA, Fe content, and BD), as these three soil indicators are affected by the land-use system. Improved DHA, a reduction in bulk density, and preservation of the soil's iron content are the outcomes of the forest land use system's favourable conditions for microbial activity. NF had a substantially higher SQI than JC, FJC, and PA. The optimum land use pattern to preserve soil quality, based on the SQI values in the current study, was NF land use, which had the highest SQI value. The quality of the soil varied significantly between JC and FJC (Figure 3). FJC improved the SQI by increasing the DHA and decreasing the bulk density. The enhancement in SQI observed in the FJC was minimal, primarily due to the short fallow period of just two years following the initiation of farming after jhuming.

The development of a SQI that utilizes the entire dataset may yield more comprehensive outcomes. However, reducing the number of indicators by employing a Minimum Data Set (MDS) approach is less time-consuming and cost-effective (Qi et al. 2009). The linear approach for calculating SQI, as suggested by Masto et al. (2008) due to its simplicity and ease of partitioning, contrasts with the nonlinear method recommended by Sinha et al. (2009), Zhang et al. (2011), and Li et al. (2013) as a suitable method for indexing soil quality SQI. The estimation of SQI using linear equations resulted in greater variation (Table 7) among the SQIs of different land uses compared to the nonlinear approach. This suggests that nonlinear indices may better represent the system functions than linear indices (Andrews et al. 2002).

CONCLUSION

Our analysis revealed that 19 out of the 22 soil parameters measured were significantly impacted by land-use conversion in the mid-hill region of Arunachal Pradesh. The PCA technique identified DHA, DTPA-Fe content, and bulk density as the most potent and persistent indicators of land-use change on soil quality. Furthermore, the development of four SQIs employing both linear and non-linear scoring functions, alongside additive and weighted additive methods, yielded valuable insights. Non-linear SQIs (SQNLAI and SQNLWAI) exhibited higher *CV* and *F*-values than their linear counterparts (SQLAI and SQLWAI). This suggests a greater sensitivity of non-linear SQIs to land-use management practices. As a result, non-linear methods might offer a more useful instrument for evaluating the soil quality in this area. All four land-use types (natural forest, jhum, pineapple, and fallow jhum) had significantly different SQI values ($P < 0.001$), according to our analysis of the relationship between land use and soil quality. Furthermore, the gradual deterioration of soil quality from natural forest to jhum cultivation was evident from the calculated SQI. These findings highlight the urgency of establishing a critical SQI threshold for the mid-hill region of Arunachal Pradesh. Once established, this threshold can serve as a crucial reference point for implementing comprehensive strategies to prevent further soil quality degradation. Based on this result, we can recommend that the forest is best maintained to maintain the soil quality. Further, if jhum cultivation is adopted, we should give sufficient time to regain the soil quality status. I also recommend that the local policymakers facilitate the horticulture-based land use system rather than going again and again and shifting agriculture and Sustainable land management plans can be ensured by the efficient evaluation and comparison of soil quality across various land use scenarios by nonlinear SQIs.

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REFERENCES

Abbasi M.K., Tahir M.M. (2012): Economizing nitrogen fertilizer in wheat through combinations with organic manures in Kashmir, Pakistan. Agronomy Journal, 104: 169–177.

Alef K. (1995): Dehydrogenase activity. In: Methods in Applied Soil Microbiology and Biochemistry. London, Academic Press: 228–231.

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: 25–45.

Andrews S.S., Karlen D.L., Cambardella C.A. (2004): The soil management assessment framework: A quantitative soil quality evaluation method. Soil Science Society of America Journal, 68: 1945–1962.

Aon M.A., Colaneri A.C. (2001): II. Temporal and spatial evolution of enzymatic activities and physico-chemical properties in an agricultural soil. Applied Soil Ecology, 18: 255–270.

Askari M.S., Holden N.M. (2014): Indices for quantitative evaluation of soil quality under grassland management. Geoderma, 230: 131–142.

Askari M.S., Holden N.M. (2015): Quantitative soil quality indexing of temperate arable management systems. Soil and Tillage Research, 150: 57–67.

Bandick A.K., Dick R.P. (1999): Field management effects on soil enzyme activities. Soil Biology and Biochemistry, 31: 1471–1479.

Bandyopadhyay S., Baruah U., Das T., Dutta D., Reza S.K., Padua S., Sarkar D., Sah K., Singh S. (2014): Soil Nutrient Mapping of Nagaland: Assessment and Mapping of Some Important Soil Parameters Including Macro and Micronutrients for the State of Nagaland Towards Optimum Utilization of Land Resources for Integrated and Sustainable Development. NBSS Publ. 1080, Nagpur, ICAR-NBSS&LUP.

Bandyopadhyay S., Ray P., Padua S., Ramachandran S., Jena R.K., Roy P.D., Dutta D.P., Singh S.K., Ray S.K. (2018): Priority zoning of available micronutrients in the soils of agro-ecological sub-regions of North-East India using geo-spatial techniques. Agricultural Research, 7: 200–214.

Bastida F., Moreno J.L., Hernández T., García C. (2006): Microbiological degradation index of soils in a semiarid climate. Soil Biology and Biochemistry, 38: 3463–3473.

Blake G.R., Hartge K.H. (1986): Bulk density. In: Klute A. (ed.): Methods of Soil Analysis, Part 1: Physical and Mineralogical Methods. 2nd Ed., Agronomy Monograph No. 9, Madison, American Society of Agronomy, Soil Science Society of America: 363–382.

Błońska E., Lasota J., Gruba P. (2016): Effect of temperate forest tree species on soil dehydrogenase and urease activities in relation to other properties of soil derived from loess and glaciofluvial sand. Ecological Research, 31: 655–664.

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., Brussaard L. (2018): Soil quality – A critical review. Soil Biology and Biochemistry, 120: 105–125.

Casida Jr L.E., Klein D.A., Santoro T. (1964): Soil dehydrogenase activity. Soil Science, 98: 371–376.

Castellini M., Giglio L., Niedda M., Palumbo AD., Ventrella D. (2015): Impact of biochar addition on the physical and hydraulic properties of a clay soil. Soil and Tillage Research, 154: 1–13.

Chan K.Y., Bowman A., Oates A. (2001): Oxidizible organic carbon fractions and soil quality changes in an oxic paleustalf under different pasture leys. Soil Science, 166: 61–67.

Chen C., Liu W., Jiang X., Wu J. (2017): Effects of rubber-based agroforestry systems on soil aggregation and associated soil organic carbon: Implications for land use. Geoderma, 299: 13–24.

Ditzler C.A., Tugel A.J. (2002): Soil quality field tools: Experiences of USDA-NRCS soil quality institute. Agronomy Journal, 94: 33–38.

Doran J.W. (2002): Soil health and global sustainability: Translating science into practice. Agriculture, Ecosystems & Environment, 88: 119–127.

Doran J.W., Parkin T.B. (1994): Defining and assessing soil quality. In: Doran J.W., Coleman D.C., Bezdicek D.F., Stewart B.A. (eds.): Defining Soil Quality for a Sustainable Environment, Vol. 35, SSSA Special Publications: 1–21.

García C., Hernandez T., Costa F. (1997): Potential use of dehydrogenase activity as an index of microbial activity in degraded soils. Communications in Soil Science and Plant Analysis, 28: 123–134.

Girona-García A., Badía-Villas D., Martí-Dalmau C., Ortiz-Perpiñá O., Mora J.L. Armas-Herrera C.M. (2018): Effects of prescribed fire for pasture management on soil organic matter and biological properties: A 1-year study case in the Central Pyrenees. Science of the Total Environment, 618: 1079–1087.

Gong L., Ran Q., He G., Tiyip T. (2015): A soil quality assessment under different land use types in Keriya river basin, Southern Xinjiang, China. Soil and Tillage Research, 146: 223–229.

Hanway J.J., Heidal H. (1952): Soil analyses methods as used in Iowa state college soil testing laboratory. Iowa Agriculture, 57: 1–31.

https://doi.org/10.17221/6/2025-SWR

Holden S.R., Treseder K.K. (2013): A meta-analysis of soil microbial biomass responses to forest disturbances. Frontiers in Microbiology, 4: 163.

Islam K., Weil R.R. (2000): Soil quality indicator properties in mid-Atlantic soils as influenced by conservation management. Journal of Soil and Water Conservation, 55: 69–78.

Jackson M.L. (1973): Soil Chemical Analysis. New Delhi, Prentice Hall of Indian Private Ltd.

Jitendra K., Kscitiz S., Amit S., Anup C., Rupankar B., Wangnem R. (2017): Effect of different processes of jhuming on soil properties in mid hills of Arunachal Pradesh. Environment and Ecology, 35: 999–1003.

Karlen D.L., Mausbach M.J., Doran J.W., Cline R.G., Harris R.F., Schuman G.E. (1997): Soil quality: A concept, definition, and framework for evaluation (a guest editorial). Soil Science Society of America Journal, 61: 4–10.

Karlen D.L., Andrews S.S., Doran J.W. (2001): Soil quality: Current concepts and applications. Advances in Agronomy, 74: 1–40.

Karlen D.L., Tomer M.D., Neppel J., Cambardella C.A. (2008): A preliminary watershed scale soil quality assessment in north central Iowa, USA. Soil and Tillage Research, 99: 291–299.

Klingebiel A.A., Montgomery P.H. (1961): Land-Capability Classification. Agriculture Handbook No. 210. Washington, Soil Conservation Service, US Department of Agriculture.

Kumar J., Chandra A., Alone R.A., Bhagawati R., Rekhung W., Borah M.C. (2017): Effect of different land use systems on selected soil parameters in mid hill of West Siang district, Arunachal Pradesh. In: Arora S., Bhan S. (eds.): Sustainable Farming and Soil Health Management. New Delhi, A Soil Conservation Society of India: 1–13.

Kumar J., Kalita H., Angami T., Ramajayam D., Sen A., Shukla K. (2020): Impact of application of fertilizer and lime on yield of banana (Grand Naine) and soil parameters in acidic soil of Arunachal Pradesh. International Journal of Plant & Soil Science, 32: 9–17.

Kumar J., Kalita H., Angami T., Ramajayam D., Chandra A., Kumar D., Sinha N.K., Mohanty M. (2021): Effect of mulching on growth and quality of tissue culture banana (var. Grand Naine) and soil properties in mid hill jhum lands of Arunachal Pradesh. Indian Journal of Agroforestry, 22: 86–89.

Larson W.E., Pierce F.J. (1994): The dynamics of soil quality as a measure of sustainable management. In: Doran J.W., Coleman D.C., Bezdicek D.F., Stewart B.A. (eds.): Defining Soil Quality for a Sustainable Environment. Vol. 35, SSSA Special Publications: 37–51.

Li Y., Dong S., Wen L., Wang X., Wu Y. (2013): Assessing the soil quality of alpine grasslands in the Qinghai-Tibetan Plateau using a modified soil quality index. Environmental Monitoring and Assessment, 185: 8011–8022.

Liebig M.A., Varvel G., Doran J. (2001): A simple performance-based index for assessing multiple agroecosystem functions. Agronomy Journal, 93: 313–318.

Lindsay W.L., Norvell W.A. (1978): Development of a DTPA soil test for zinc, iron, manganese and copper. Soil Science Society of America Journal, 42: 421–428.

Mandal U.K., Ramachandran K., Sharma K.L., Satyam B., Venkanna K., Udaya Bhanu M., Mandal M., Masane R.N., Narsimlu B., Rao K.V., Srinivasarao Ch., Korwar G.R., Venkateswarlu B. (2011): Assessing soil quality in a semiarid tropical watershed using a geographic information system. Soil Science Society of America Journal, 75: 1144–1160.

Masto R.E., Chhonkar P.K., Singh D., Patra A.K. (2007): Soil quality response to long-term nutrient and crop management on a semi-arid Inceptisol. Agriculture, Ecosystems & Environment, 118: 130–142.

Masto R.E., Chhonkar P.K., Singh D., Patra A.K. (2008): Alternative soil quality indices for evaluating the effect of intensive cropping, fertilisation and manuring for 31 years in the semi-arid soils of India. Environmental Monitoring and Assessment, 136: 419–435.

Nannipieri P., Ascher J., Ceccherini M., Landi L., Pietramellara G., Renella G. (2003): Microbial diversity and soil functions. European Journal of Soil Science, 54: 655–670.

Nieder R., Benbi D.K. (2008): Organic matter and soil quality. In: Nieder R., Benbi D.K. (eds.): Carbon and Nitrogen in the Terrestrial Environment. Dordrecht, Springer: 113–135.

Olsen S.R., Cole C.V., Watanabe F.S. (1954): Estimation of Available Phosphorus in Soils by Extraction with Sodium Bicarbonate. USDA Circular No. 939. Washington, US Department of Agriculture.

Orgill S.E., Condon J.R., Conyers M.K., Morris S.G., Alcock D.J., Murphy B.W., Greene R.S.B. (2018): Removing grazing pressure from a native pasture decreases soil organic carbon in southern New South Wales, Australia. Land Degradation & Development, 29: 274–283.

Page A.L., Miller R.H., Keeney D.R. (1982): Methods of Soil Analysis, Part 2: Chemical and Microbiological Properties. Madison, American Society of Agronomy, Soil Science Society of America.

Parras-Alcántara L., Lozano-García B., Keesstra S., Cerdà A., Brevik E.C. (2016): Long-term effects of soil management on ecosystem services and soil loss estimation in olive grove top soils. Science of the Total Environment, 571: 498–506.

Post W.M., Kwon K.C. (2000): Soil carbon sequestration and land-use change: processes and potential. Global Change Biology, 6: 317–327.

Pulido-Fernández M., Schnabel S., Lavado-Contador J.F., Mellado I.M., Pérez R.O. (2013): Soil organic matter of Ibe-

https://doi.org/10.17221/6/2025-SWR

rian open woodland rangelands as influenced by vegetation cover and land management. Catena, 109: 13–24.

Qi Y., Darilek J.L., Huang B., Zhao Y., Sun W., Gu Z. (2009): Evaluating soil quality indices in an agricultural region of Jiangsu Province, China. Geoderma, 149: 325–334.

Raiesi F. (2017): A minimum data set and soil quality index to quantify the effect of land use conversion on soil quality and degradation in native rangelands of upland arid and semiarid regions. Ecological Indicators, 75: 307–320.

Richard L.A. (ed.) (1954): Diagnosis and improvement of saline and Alkali soils. Agriculture Handbook No. 60, Washington, United States Salinity Laboratory Staff, USDA.

Sainepo B.M., Gachene C.K., Karuma A. (2018): Assessment of soil organic carbon fractions and carbon management index under different land use types in Olesharo Catchment, Narok County, Kenya. Carbon Balance Management, 13: 1–9.

Salazar S., Sánchez L.E., Alvarez J., Valverde A., Galindo P., Igual J.M., Peix A., Santa-Regina I. (2011): Correlation among soil enzyme activities under different forest system management practices. Ecological Engineering, 37: 1123–1131.

Sharma C.M., Gairola S., Ghildiyal S.K., Suyal S. (2010): Physical properties of soils in relation to forest composition in moist temperate valley slopes of the Central Western Himalaya. Journal of Forest and Environmental Science, 26: 117–129.

Sherrod L.A., Peterson G.A., Westfall D.G., Ahuja L.R. (2005): Soil organic carbon pools after 12 years in no-till dryland agroecosystems. Soil Science Society of America Journal, 69: 1600–1608.

Singh A.K., Bordoloi L.J., Kumar M., Hazarika S., Parmar B. (2014): Land use impact on soil quality in eastern Himalayan region of India. Environmental Monitoring and Assessment, 186: 2013–2024.

Sinha S., Masto R.E., Ram L.C., Selvi V.A., Srivastava N.K., Tripathi R.C., George J. (2009): Rhizosphere soil microbial index of tree species in a coal mining ecosystem. Soil Biology and Biochemistry, 41: 1824–1832.

Skujins J. (1973): Dehydrogenase: An indicator of biological activities in arid soils. Bulletins from the Ecological Research Committee No. 17, JSTOR: 235–241.

Skujins J. (1976): Enzymes in soil. In: Mc Laren A.D., Peterson G.H. (eds.): Soil Biochemistry. New York, Marcel Dekker. Inc.: 371–414.

Spiegel H., Zavattaro L., Guzmán G., D'Hose T., Pecio A., Lehtinen T., Schlatter N., ten Berge H., Grignani C. (2015): Compatibility of Agricultural Management Practices and Mitigation and Soil Health: Impacts of Soil Management Practices on Crop Productivity, on Indicators for Climate Change Mitigation, and on the Chemical, Physical and Biological Quality of Soil. Deliverable Reference Number: D3.371, CATCH-C Project, CORDIS EU Research Results, Wageningen, European Commission.

Subbiah B.V., Asija G.L. (1956): A rapid procedure for the determination of available nitrogen in soils. Current Science, 25: 259–260.

Thomas G.W. (1996): Soil pH and soil acidity. In: Sparks D.L., Page A.L., Helmke P.A., Loeppert R.H., Soltanpour P.N., Tabatabai M.A., Johnston C.T., Sumner M.E. (eds.): Methods of Soil Analysis: Part 3 Chemical Methods. Agronomy Monograph No. 5, Madison, American Society of Agronomy, Soil Science Society of America: 475–490.

Van Diepeningen A.D., de Vos O.J., Korthals G.W., van Bruggen A.H. (2006): Effects of organic versus conventional management on chemical and biological parameters in agricultural soils. Applied Soil Ecology, 31: 120–135.

Vance E.D., Brookes P.C., Jenkinson D.S. (1987): An extraction method for measuring soil microbial biomass C. Soil Biology and Biochemistry, 19: 703–707.

Walkley A., Black I.A. (1934): An examination of the Degtjareff method for determining organic carbon in soils: Effect of variations in digestion conditions and of inorganic soil constituents. Soil Science, 63: 251–263.

Wang W.J., Qiu L., Zu Y.G., Su D.X., An J., Wang H.Y., Zheng G.Y., Sun W., Chen X.Q. (2011): Changes in soil organic carbon, nitrogen, pH and bulk density with the development of larch (*Larix gmelinii*) plantations in China. Global Change Biology, 17: 2657–2676.

Wienhold B.J., Karlen D.L., Andrews S.S., Stott D.E. (2009): Protocol for indicator scoring in the soil management assessment framework (SMAF). Renewable Agriculture and Food Systems, 24: 260–266.

Yao M.K., Angui P.K., Konaté S., Tondoh J.E., Tano Y., Abbadie L., Benest D. (2010): Effects of land use types on soil organic carbon and nitrogen dynamics in Mid-West Cote d'Ivoire. European Journal of Scientific Research, 40: 211–222.

Yue-Ju X., Shu-Guang L., Yue-Ming H., Jing-Feng Y. (2010): Soil quality assessment using weighted fuzzy association rules. Pedosphere, 20: 334–341.

Zhang C., Xue S., Liu G.B., Song Z.L. (2011): A comparison of soil qualities of different revegetation types in the Loess Plateau, China. Plant and Soil, 347: 163–178.

Zhou M., Xiao Y., Li Y., Zhang X., Wang G., Jin J., Ding G., Liu X. (2022a): Soil quality index evaluation model in responses to six-year fertilization practices in Mollisols. Archives of Agronomy and Soil Science, 682: 180–194.

Zhou Y., Fan Y., Lu G., Zhang A., Zhao T., Sun G., Yu Q., Ren X. (2022b): Assessment of soil quality for guided fertilization in 7 barley agro-ecological areas of China. PLoS ONE, 17: e0261638.

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