Soil quality assessment for conservation planning: insights from PCA-based SQI

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Abstract. Soil quality assessment is essential for the sustainable management of fragile hill ecosystems in Northeast India. This study evaluated soil quality under natural fallow, cultivated fallow, and degraded land uses at two depths (0–15 cm and 15–30 cm) in Mokokchung District, Nagaland. A comprehensive set of soil physico-chemical and textural properties was analyzed and reduced to a Minimum Data Set (MDS) using Principal Component Analysis, retaining silt, nitrogen (N), zinc (Zn), and phosphorus (P) as key indicators. The Soil Quality Index (SQI) was computed using linear and nonlinear scoring functions with additive and weighted aggregation methods. Results showed that natural fallow topsoil (0-15cm) exhibited the highest soil quality, whereas degraded subsoil (15-30cm) recorded the lowest. Nonlinear methods demonstrated greater sensitivity to site variability (CV up to 46.36%) compared to linear methods, while weighted indices produced more conservative estimates by emphasizing critical variables. Overall, the study demonstrates the value of PCA-based SQI as a comparative assessment tool for identifying soil quality gradients in shifting cultivation landscapes and provides baseline information for site-specific conservation and land management planning.

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1 Introduction

Soil quality monitoring is central to both agricultural sustainability and environmental conservation. Globally, soils are increasingly threatened by land-use change, intensive cultivation and food demand, and climate variability, which accelerate degradation, diminish productivity, and undermine ecosystem services [1]. Beyond such critical agricultural roles, soils perform essential ecological functions, namely: nutrient cycling, carbon sequestration, and water regulation, thereby contributing to ecosystem resilience and climate mitigation [2]. In the Northeast regions of India, shifting cultivation, land degradation, and deforestation exert strong pressure on fragile hill ecosystems [3, 4]. These landscapes are highly susceptible to erosion, nutrient depletion, and fertility loss, posing serious risks to food security, biodiversity conservation, and water resource stability [5]. Under such conditions, systematic soil quality assessment becomes essential for sustainable land management.

The Soil Quality Index (SQI) provides an inclusive structure for measuring soil health by incorporating various soil parameters into a single metric [6,7]. By linking soil properties with ecological functions, SQI facilitates comparison across land-use systems and supports identification of degraded areas and management priorities. Its ability to capture subtle variations across soil depths and land-use types makes it particularly suitable for heterogeneous landscapes such as shifting cultivation systems. In Mokokchung District, where shifting cultivation remains a dominant livelihood practice, SQI-based assessment can support community-based resource management and sustainable agricultural transitions [8]. Although SQI approaches have been applied in various agroecosystems, evidence from fragile hill landscapes of Northeast India remains limited [8, 9]. Most regional studies have primarily focused on soil fertility and nutrient dynamics, with limited integration of multiple soil indicators into a unified soil quality framework or comparison of alternative SQI computation approaches, and have largely relied on linear SQI methods [8-10]. Hence, the present study contributes primarily in a contextual and comparative manner by (i) generating baseline SQI estimates for natural fallow, cultivated fallow, and degraded land-use systems in Mokokchung District (ii) evaluating the influence of scoring (linear vs nonlinear) and aggregation (additive vs PCA-weighted) methods on SQI sensitivity and ranking.

By positioning SQI as a decision-support tool rather than a novel methodology, this study aims to strengthen locally relevant evidence for soil management and conservation planning in shifting cultivation landscapes. Accordingly, the study was guided by the following research questions:(i) How does soil quality vary across natural fallow, cultivated fallow, and degraded land-use systems and soil depths in Mokokchung District? (ii) How do linear and nonlinear scoring approaches differ in capturing soil quality variability? (iii) How do additive and weighted SQI models influence soil quality ranking? We hypothesized that soil quality would decline significantly with increasing land degradation and soil depth, and that nonlinear and weighted SQI approaches would exhibit greater sensitivity in discriminating soil quality across heterogeneous land-use systems.

2 Materials and methodology

2.1 Study site and soil sampling

Soil samples were collected from Mokockhung district (**Figure 1**), Nagaland (26.4896° N, 94.5212°E). A subtropical climate prevails in the district, with yearly rainfall averaging nearly 2500 mm [3]. Soils were categorized into three land-use systems: natural fallow (NF), cultivated fallow land (FAL), and degraded land (DEG). From each land-use system, samples were collected at two soil depths: topsoil (0–15 cm) and subsoil (15–30 cm), resulting in six soil categories: NF_T, NF_S, FAL_T, FAL_S, DEG_T, and DEG_S. The 0–15 cm layer corresponds to the plough layer and zone of highest organic matter input, microbial activity, and nutrient cycling, while the 15–30 cm layer represents the subsoil zone influencing root penetration, moisture storage, and nutrient reserve dynamics. These depth intervals are commonly used in soil quality and land-use studies to capture vertical variation in soil properties relevant to agricultural productivity and ecosystem functioning [3, 9]. For each soil category, three independent composite samples were collected, giving a total of 18 soil samples. Each composite sample was prepared by thoroughly mixing subsamples collected from multiple points within a 10 m × 10 m area to minimize microscale spatial heterogeneity. Sampling was carried out during the post-monsoon season of 2024 to reduce the influence of short-term moisture variability. Physico-chemical and textural soil parameters, including pH, electrical conductivity (EC), soil organic carbon (SOC), available nitrogen (N), available phosphorus (P), available potassium (K), sulphur (S), boron (B), zinc (Zn), iron (Fe), magnesium (Mg), copper (Cu), and particle size distribution were obtained from the Department of Soil and Water Conservation, Mokokchung District. These measurements were generated as part of routine soil testing activities conducted by the department. Although the authors did not directly conduct the laboratory analyses, the data were obtained from an established government soil testing facility. All soil parameters are presented as mean ± standard deviation (SD) based on three independent composite samples (n = 3). Prior to statistical analysis, all datasets were screened for unit consistency and outliers to ensure comparability. The use of secondary laboratory data is therefore recognized as a methodological limitation of the present study. All statistical analyses were performed using SPSS software (version 26.0). Soil data were tested for normality and homogeneity of variance prior to analysis using the Shapiro–Wilk test and Levene's test, respectively.

2.2 Generation of Minimum data set

Using SPSS (version 26.0), PCA was implemented with Varimax rotation to extract principal components having eigenvalues above 1 and contributing no less than 5% of the total variance [11]. To minimize redundancy among highly correlated variables, Pearson's correlation analysis was further employed [4, 10]. From each principal component, the variable with the highest loading was retained to form the MDS (Minimum data set). The SQI is typically expressed on a scale of 0 to 1, with values approaching 1 indicating better soil quality [9]. Construction of the SQI involves three main steps: establishing the MDS), applying appropriate scoring functions (linear or nonlinear), and integrating the scores to generate the index [12]. Based on these procedures, both additive (SQIA) and weighted (SQIW) SQI models were developed.

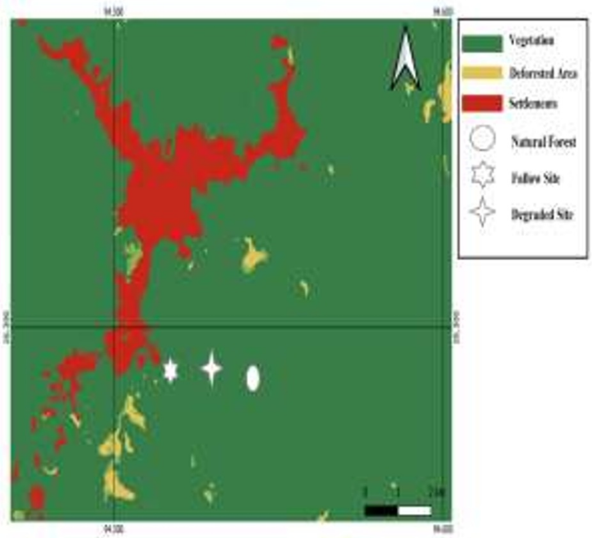

Fig.1. Location of the study area in Mokokchung District, Nagaland, showing vegetation cover, settlements, and sampling sites representing natural fallow (NF), cultivated fallow land (FAL), and degraded land (DEG). White symbols indicate soil sampling locations.

2.3 Indicator Scoring

Linear scoring assumes a proportional relationship between soil indicator values and soil quality, meaning that improvements or declines in indicator levels directly translate into proportional changes in soil quality scores. In contrast, nonlinear scoring is designed to capture threshold-type responses commonly observed in soil processes, where soil quality may change rapidly beyond certain critical limits. Therefore, nonlinear scoring is considered more suitable for representing complex soil responses in heterogeneous landscapes such as shifting cultivation systems [6, 12]. For linear scoring (LS) of individual soil variables, the equations [7] were applied:

$$LS = \frac{Amin}{A} \quad (1)$$

$$LS = \frac{A}{Amax} \quad (2)$$

Where LS denotes the linear score, A is the observed value of the soil property, and Amax and Amin represent the maximum and minimum values of that parameter, respectively.
For non-linear scoring (NLS), a sigmoid function was used following [7]:

$$NLS = \frac{P}{1+\left(\frac{L}{Lmean}\right)O} \quad (3)$$

Where, NLS- Non Linear score; L_{mean} denotes the mean value of the selected soil variable; P denotes the highest score achieved by the function which is equal to 1; O denotes the scope of the equation which Is 2.5 for "less is better" and -2.5 for "more is better". The final values obtained from the different scoring methods were converted into their respective additive [13] and the weighted index [7].

a. Additive quality index:

$$SQI(a) = \sum_{i=1}^{K} \frac{Sr}{n} \quad (4)$$

b. Weighted quality index:

$$SQI(w) = \sum_{i=1}^{K} WSr \quad (5)$$

Where K is the number of soil indicators selected in MDS screening, Sr is the score of the individual soil parameters, and W represents its assigned weight. A higher SQI value denotes healthier soil, with improved nutrient cycling, fertility, and productivity. The schematic workflow is presented in **Figure 2**.

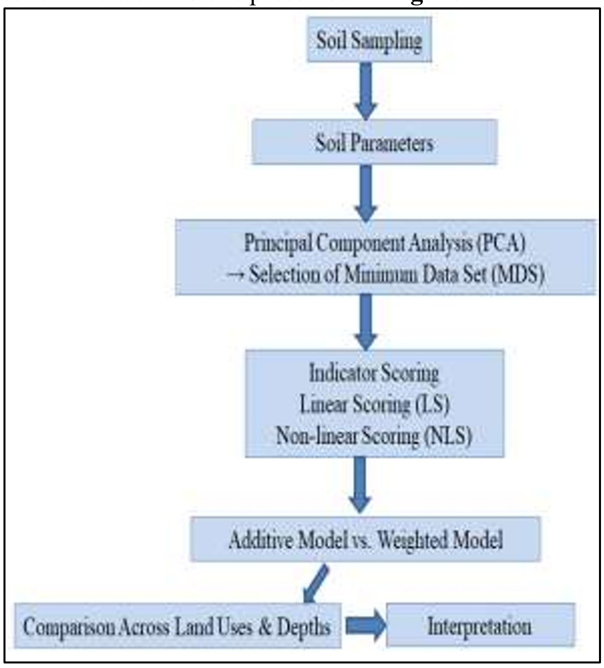

Fig. 2. Schematic diagrams of workflow

Differences among SQI of the different land-use systems and soil depths were evaluated using one-way analysis of variance (ANOVA), considering three independent replicates for each soil category (n = 3). Mean comparisons were performed using Duncan's Multiple Range Test (DMRT) at a significance level of $p < 0.05$.

3 Results and discussion

3.1 Soil physico-chemical properties

The results of the soil properties (**Table 1**) display that land use and soil depth strongly influence the physico-chemical and textural properties of soils, consistent with prior studies [11, 14]. Soil pH remained acidic across all categories (4.80–5.65), reflecting high rainfall, base-cation leaching, and organic acid accumulation typical of humid hill environments [15]. The consistent increase in pH with depth suggests downward translocation of bases and reduced organic acid input in subsoils. EC remained uniformly low (<0.1 dS m^{-1}), confirming the leaching-dominated nature of these soils and indicating minimal salinity constraints [8]. However, relatively higher variability in EC among surface soils highlights the influence of organic inputs and micro-scale heterogeneity. SOC content was highest in NF_T (2.49±0.37%) and declined progressively in subsoils and degraded lands, with the lowest value observed in DEG_S (0.70±0.50%). The topsoil of fallow lands recorded intermediate SOC values (1.57±0.04% in FAL_T), while a marked drop was evident in FAL_S (0.95±0.19%). SOC contents were highest in natural fallow topsoil and declined with increasing land degradation and soil depth, a trend well documented in Nagaland and neighbouring areas [8, 11]. This decline correlates positively with N availability, as both decrease with increased soil disturbance and organic matter loss. N followed a trend similar to SOC, with maximum levels in NF_T (556.67±5.77 kg/ha) and minimum in DEG_S (288.50±17.53 kg/ha). This pattern highlights the strong relationship between organic matter and N. Macronutrients (P and K) also declined with increasing degradation and depth. The comparatively high variability of P, particularly in surface soils, reflects the combined influence of fertilizer history, fixation by Fe and Al oxides, and erosion losses under acidic conditions [16]. The persistence of moderate K levels in DEG_T suggests partial mineral weathering contribution, although overall depletion was evident in subsoils. Micronutrients (S, B, Zn, Fe, Mg, and Cu) exhibited consistent declines with depth and degradation intensity. Their strong association with SOC highlights the role of organic matter in micronutrient retention. The contrasting Fe trend, with higher concentrations in DEG_T, likely reflects parent material influence and redox-controlled mobilization rather than biological accumulation [8, 15, 17]. Textural analysis showed progressive coarsening of soils with degradation, as reflected by declining clay and silt contents and increasing sand fractions. This structural deterioration was further supported by the increase in bulk density from NF_T to DEG_S, indicating compaction, reduced porosity, and impaired root penetration [11, 14, 17]. Collectively, these patterns demonstrate that land degradation in Mokokchung not only reduces nutrient reserves but also weakens physical soil structure, thereby compounding long-term productivity risks. Although consistent trends were observed, variability within categories indicates that micro-topography, local management history, and erosion intensity may introduce site-specific uncertainty, which should be considered when extrapolating results beyond the sampled locations.

Table 1. Soil physicochemical properties under different land-use systems and soil depths

Site	pH	EC (dS/m)	SOC (%)	N (Kg/ha)	P (Kg/ha)	K (Kg/ha)	S (ppm)	B (ppm)
NF_T	4.80±0.15	0.05±0.13	2.49±0.37	556.67±5.77	60.43±18.07	286.80±23.20	41.70±5.94	2.74±0.81
NF_S	5.35±0.21	0.03±0.02	1.66±0.11	432.50±26.18	36.38±36.38	143.45±25.09	20.63±2.83	0.95±0.65
FAL_T	4.88±.0.07	0.08±0.04	1.57±0.04	435.00±25.00	39.32±2.61	132.77±40.96	26.30±5.47	1.51±0.10
FAL_S	5.15±0.39	0.05±0.02	0.95±0.19	396.80±13.3	22.03±4.97	130.48±26.14	18.16±1.88	1.88±1.02
DEG_T	5.39±0.024	0.05±0.01	1.00±0.09	314.67±15.01	36.27±2.10	235.42±34.01	32.20±1.42	1.42±0.37
DEG_S	5.65±0.12	0.05±0.02	0.70±0.50	288.50±17.53	20.17±2.99	124.43±5.66	17.43±1.43	1.43±0.92
Site	**Zn (ppm)**	**Fe (ppm)**	**Mg (ppm)**	**Cu (ppm)**	**Clay (%)**	**Silt (%)**	**Sand (%)**	**BD (g/cm3)**
NF_T	3.81±0.81	16.21±3.93	15.41±3.07	0.60±0.16	20.33±0.58	50.67±2.58	29.00±1.00	1.08±0.01
NF_S	2.74±1.11	7.03±1.47	12.94±3.99	0.55±0.13	18.18±1.67	36.68±2.36	43.21±1.92	1.12±0.01
FAL_T	2.34±0.10	11.68±0.36	15.07±3.08	0.40±0.02	18.59±0.56	40.62±2.18	40.79±0.70	1.23±0.02
FAL_S	1.51±0.66	5.40±1.54	13.65±5.45	0.15±0.03	18.25±0.41	38.15±3.94	42.31±3.00	1.23±0.02
DEG_T	1.42±0.67	21.62±1.49	13.46±2.47	0.20±0.04	17.52±0.76	40.59±1.53	45.50±1.80	1.49±0.02
DEG_S	0.61±0.15	3.37±1.27	5.48±1.21	0.16±0.04	17.17±1.89	37.33±1.72	41.83±1.56	1.52±0.01

Values are expressed as mean ± standard deviation.NF_T = natural fallow topsoil; NF_S = natural fallow subsoil; FAL_T = cultivated fallow land topsoil; FAL_S = cultivated fallow land subsoil; DEG_T = degraded land topsoil; DEG_S = degraded land subsoil.

3.2 Creation of MDS

The resulting PCA analysis produced four principal components (PCs) with eigenvalues greater than 1, accounting for 82.246 % of the total variance. The results of the Varimax rotation revealed that at PC1, high values were observed for silt (0.945), K (0.882), S (0.816), clay (0.807), B (0.667), SOC (0.621), P (0.509), and sand (-0.939). At PC2, high loadings were recorded for N (0.849), Mg (0.791), BD (-0.836) and pH (-0.710). At PC3, Zn (0.894), Cu (0.861), Fe (0.699), and EC (0.639) were retained. At PC4, P (0.707), B (0.326), and EC (0.495) showed high loadings. Amongst these, silt (PC1), N (PC2), Zn (PC3), and P (PC4) were selected as the MDS. Silt was retained in the MDS (PC1) as it exhibited the highest absolute loading while also showing comparatively lower redundancy with other texture and nutrient variables after correlation screening [9, 10]. Soils rich in silt have good water-holding capacity, moderate drainage, and are generally fertile, making them highly productive for crops. Silt also helps in providing a balance of aeration and retention, which is optimal for plant growth [18]. Clay, SOC, K, and S, although highly loaded, showed stronger inter-correlations and therefore were excluded to minimize multicollinearity within the MDS. Similarly, N (PC2), Zn (PC3), and P (PC4) were selected based on their high loadings and relatively independent contributions to soil variability. N is vital for vegetative growth, photosynthesis, and crop productivity. Its presence in soil is directly linked to plant health, yield, and microbial activity, making it an essential indicator in soil quality monitoring [19]. Zn is vital for optimum plant growth, normal leaf development, yield, and grain nutritional quality [20]. Lastly, P is vital for seed germination and establishment, and fundamental to multiple plant processes [21]. The retained MDS variables therefore represent complementary soil quality dimensions, including physical structure (silt), macronutrient availability (N and P), and micronutrient status (Zn). This approach ensured that the MDS captured maximum information with minimal redundancy, consistent with established PCA-based SQI methodologies [9, 10, 18].

3.3 Soil quality index creation across sites

On screening of the MDS, selected indicators were normalized and integrated to calculate the SQI (**Figure 3, Table 2**). Across all scoring methods, SQI values consistently declined from natural fallow to degraded systems and from topsoil to subsoil, indicating a strong degradation gradient. Under the additive approach, the highest SQI values were observed in NF_T (0.893), followed by NF_S (0.603) and FAL_T (0.573), whereas DEG_S recorded the lowest value (0.387). Weighted SQI showed the same ranking pattern, although with lower absolute values (NF_T = 0.759; DEG_S = 0.335), reflecting the more conservative nature of weighted aggregation. When SQI was computed using the weighted method, absolute values were further reduced, but the relative ranking of sites remained unchanged, confirming the stability of the observed soil quality pattern [12]. Across all approaches, NF_T consistently recorded the highest SQI values, indicating superior soil quality, while DEG_S showed the lowest values. Intermediate values were observed in NF_S and FAL_T, whereas FAL_S and DEG_T clustered together, reflecting progressive soil quality deterioration with increasing land-use intensity and depth. The SQI trends observed in the present study are consistent with earlier reports from hill ecosystems of Nagaland. Temjen et al. [3] documented increasing SQI with longer fallow duration and declining soil quality with depth under shifting cultivation, which agrees with the degradation gradients observed in this study. Similarly, Mishra et al. [10] reported strong influences of organic carbon, and nutrient availability on SQI under shifting cultivation and forest systems in the North Eastern Himalaya, supporting the ecological relevance of the selected MDS indicators. Semy et al. [9] also reported lower SQI in disturbed forest soils and progressive decline with depth, confirming that land-use disturbance and organic matter loss are dominant drivers of soil quality deterioration in Northeast Indian hill landscapes. The additive methods (NLS Additive and LS Additive) generally resulted in higher SQI values than their weighted counterparts (NLS Weighted and LS Weighted), suggesting that equal-weight aggregation may overestimate soil quality by masking weaker indicators, whereas weighted methods emphasize critical variables [12].

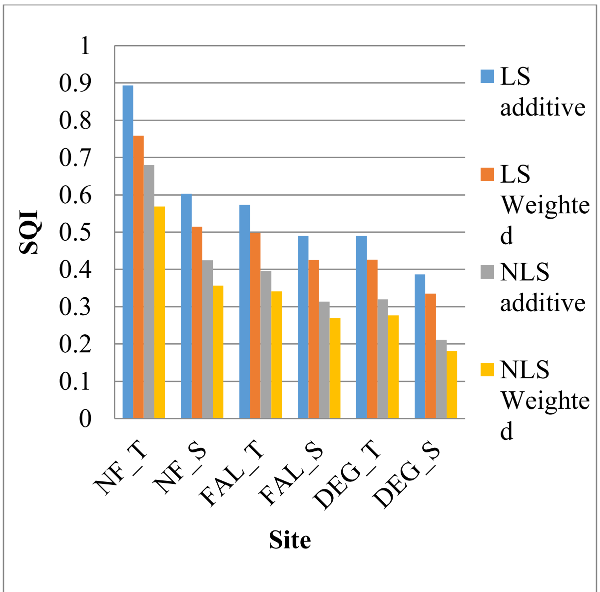

Fig. 3. Comparison of Soil Quality Index (SQI) values across land-use systems and soil depths using linear scoring (LS) and nonlinear scoring (NLS) under additive and weighted aggregation approaches. NF_T = natural fallow topsoil; NF_S = natural fallow subsoil; FAL_T = cultivated fallow land topsoil; FAL_S = cultivated fallow land subsoil; DEG_T = degraded land topsoil; DEG_S = degraded land subsoil.

Table 2. Soil Quality Index (SQI) values under different land uses and depths

Site	LSA	LSW	NLSA	NLSW
NF_T	0.893^{1a}	0.759^{1a}	0.680^{1a}	0.568^{1a}
NF_S	0.603^{1b}	0.515^{1b}	0.424^{1b}	0.356^{1b}
FAL_T	0.573^{1b}	0.498^{1b}	0.396^{1b}	0.341^{1b}
FAL_S	0.490^{1c}	0.426^{1c}	0.314^{1c}	0.270^{1c}
DEG_T	0.490^{1c}	0.427^{1c}	0.320^{1c}	0.277^{1c}
DEG_S	0.387^{1d}	0.335^{1d}	0.211^{1d}	0.181^{1d}

*Additive (LSA, NLSA) and weighted (LSW, NLSW) approaches. Different superscript letters within each column indicate significant differences at $p \leq 0.05$ (Duncan's test). NF_T = natural fallow topsoil; NF_S = natural fallow subsoil; FAL_T = cultivated fallow land topsoil; FAL_S = cultivated fallow land subsoil; DEG_T = degraded land topsoil; DEG_S = degraded land subsoil.

3.4 Soil quality model comparison

Comparison of SQI computation methods revealed systematic differences between linear and nonlinear scoring as well as between additive and weighted aggregation approaches (**Table 3**). Nonlinear scoring methods (NLS_A and NLS_W) exhibited higher coefficients of variation (32.24% and 46.36%) than linear methods (24.10% and 33.87%), indicating greater sensitivity to spatial heterogeneity across land-use systems. This enhanced variability suggests that nonlinear transformations are more responsive to site-specific differences in soil conditions, particularly under heterogeneous shifting cultivation landscapes [12]. However, nonlinear methods also produced lower mean SQI values, reflecting their tendency to penalize low-performing indicators more strongly under nutrient-poor and acidic conditions. Additive approaches consistently yielded higher mean SQI values than weighted approaches (0.3908 vs. 0.3322 for nonlinear; 0.5726 vs. 0.4930 for linear), confirming that equal-weight aggregation may overestimate soil quality by masking the influence of weaker indicators. Weighted approaches, guided by PCA-derived loadings, generated more restrained SQI estimates and lower variability, indicating improved balance between indicator contribution and redundancy control. Although the nonlinear weighted SQI (NLS_W) demonstrated comparatively higher discrimination capacity among land-use systems, its apparent superiority should be interpreted cautiously due to the limited spatial scale of the study and the absence of formal sensitivity analysis. Overall, the results indicate that nonlinear scoring enhances sensitivity to heterogeneity, while weighted aggregation improves realism in SQI construction. Their combined application therefore offers a useful and context-dependent framework for soil quality assessment in shifting cultivation landscapes rather than a universally superior model. Similar trends have been reported in recent SQI studies, where nonlinear weighted models exhibited greater sensitivity to site-level variability, particularly under heterogeneous soil conditions, while linear additive approaches produced higher but less responsive index values due to uniform weighting of indicators [12,13].

Table 3. Soil quality model comparison.

Variable	Mean	Std. Dev.	CV
NLS_A	0.3908	0.126	32.24
NLS_W	0.3322	0.154	46.35
LS_A	0.5726	0.138	24.1
LS_W	0.4930	0.167	33.87

LS = linear scoring; NLS = non-linear scoring; A = additive model; W = weighted model; CV = coefficient of variation.

4 Conclusion

This study evaluated soil quality across contrasting land-use systems and soil depths in Mokokchung District, Nagaland using linear and nonlinear SQI computation approaches within an MDS framework. Soil quality consistently declined from natural fallow to degraded systems and from topsoil to subsoil, confirming the strong influence of land degradation and management intensity on soil health in shifting cultivation landscapes. Nonlinear scoring approaches demonstrated greater sensitivity to spatial heterogeneity, while weighted aggregation methods produced more conservative and balanced SQI estimates. Although the nonlinear weighted SQI showed comparatively higher discrimination capacity under the present dataset, its performance should be interpreted cautiously due to the limited spatial scale, reliance on secondary laboratory data, absence of soil biological indicators, and lack of formal sensitivity analysis. Formal uncertainty and sensitivity analyses of the SQI models were therefore not performed due to the limited sample size and reliance on secondary data. Therefore, the results should be considered site-specific rather than universally applicable. Nevertheless, the study demonstrates the practical utility of SQI as a comparative assessment tool for identifying soil quality gradients within fragile hill agroecosystems. The findings provide locally relevant baseline information that can support future, more comprehensive soil monitoring programs and guide site-specific land management and restoration strategies in Mokokchung District. Future studies incorporating larger spatial coverage, soil biological indicators, and sensitivity testing of SQI models would further strengthen the reliability and applicability of soil quality assessment frameworks in Northeast Indian hill ecosystems.

Wati Temjen conceived and designed the study, coordinated field sampling, performed data analysis, interpreted the results, and prepared the original manuscript. Maibam Romeo Singh contributed to study design and reviewed the manuscript. Chubaienla Imchen assisted in data compilation and reviewed the manuscript. Mum Tatung supported statistical analysis and data interpretation. Seyievino Catherine Chasie contributed to literature review and manuscript editing. All authors read and approved the final manuscript.

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