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Research article

Soil quality index (SQI) for evaluating the sustainability status of Kakia-Esamburmbur catchment under three different land use types in Narok County, Kenya

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A R T I C L E I N F O

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A B S T R A C T

Land and water degradation caused by soil erosion and climate change pose major environmental threats, particularly in agricultural watersheds. Soil erosion in a catchment leads to low crop yields due to declining soil quality (SQ), productivity and sustainability. However, very few studies have been done to assess soil health in Kenya, and none in Narok County. Thus, the aim of this study was to evaluate the soil sustainability status in Kakia-Esamburmbur catchment, based on the identification of key indicators (IKI) from a large dataset (LDS) of 23 indicators, across three land use types designated as grass land (GL), crop land (CL) and forest land (FL). To achieve the stated objective, two soil quality indexing methods were employed: the Additive Soil Quality Index (A-SQI) using the LDS; and the Weighted Soil Quality Index (W-SQI) using Principal Component Analysis (PCA) as a reduction tool to obtain the IKI set. The results show that at a depth of 20 cm, the catchment's soils characteristics did not differ significantly. The two methods (A-SQI and W-SQI) resulted in FL having the highest SQI mean values (0.61, 0.57), followed by CL (0.59, 0.55), while the lowest SQI mean value was recorded in GL (0.58, 0.53). Additionally, the sensitivity analysis showed W-SQI as the most sensitive and superior method in the evaluation of SQI changes due to its high sensitivity and coefficient of variation (CV), at 2.25 and >12 %, respectively. Among the ten IKI, CEC made the greatest contribution to SQ (18.68 %), followed by BD (15.61 %), BIR (14.71 %), Mg (14.26 %), MBN (8.30 %), MBC (8.26 %), Sand (6.77 %), Moisture (5.75 %), TOC (5.16 %), and PMN (2.63 %). The findings show that the catchment belongs to the "medium" category of SQ. The IKI can help save time and reduce the cost of intensive lab works for temporal assessment and monitoring of the effects of different land use on SQ.

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1. Introduction

Land degradation poses a significant threat to the livelihood of residents in Narok county. This is further exacerbated by poor land use planning and management, under growing demands and decreasing resources. Soil water erosion has been reported as the leading cause of environmental degradation, and the main challenge for hydropower plants [1–4]. It has also been associated with reduced yields, as the fertile top soil is washed away, forcing farmers to turn to chemical fertilizers to compensate for the lost nutrients. For example, maize yield declined from 1.688 tons/ha to 0.07 tons/ha/decade, while 0.6 tons per hectare per decade is the global average [5]. The study attributed the reduction in yield to loss of soil nutrients due soil erosion. Additionally, the farmers lack skills for proper land use management, further accelerating the rate of land degradation [6].

In Kenya, land degradation has been reported to have significant impact on the livelihood of the population. Loss of soil fertility has consequently resulted to lower yields thus threatening food security in the country. Likewise, in Narok county, land degradation is resulting in biomass reduction and increase in the frequency of flash floods [6–10]. The Kakia-Esamburmbur watershed within Narok county has been facing deteriorating watershed health in recent years. This has been attributed to land and water degradation caused by soil erosion and climate change, and further exacerbated by anthropogenic activities. This has led to the destruction of the watershed associated with increased flash floods causing accelerated soil losses, as water erosion has been identified as the primary source of soil erosion. Consequently, there has been a decline in agricultural yield and an increase in sediment yield. Decline in agricultural yield can be attributed to decreased soil quality (SQ) and soil productivity (SP), caused by accelerated loss of soil nutrients and changes in the soil physical indicators. Moreover, the decline in SP can be attributed to the changes in the spatial and temporal distribution of rainfall, undulating topography, changes in land use/land cover (LULC), lack of resources and awareness among farmers, depletion of the water table, poor soil structure, emergence of crops deadly illnesses like Maize Lethal Necrosis Disease (MLND) and damage to farms by wild animals such as baboons, and elephants, from the Masai Mara National Reserve [6,8,10].

Maize and wheat are the two major cash crops in Narok County, forming main source of income for the farmers there. About 135,000 million tons (MT) of wheat and 200,000 MT of maize is produced annually, from 116,605 ha in 2012 to 110,079 ha in 2016. In 2015, the total production dropped from 271,158 tons, valued at 7.5 billion shillings, compared to 2013, when the production was 462,981 tons, and cost 9.6 billion shillings. Similarly, the production of wheat declined from 2.8 tons/ha in 2014 to 1.9 tons/ha in 2016. As a result, the major livestocks (1.4 million cattle, 1.2 million sheep, and 0.8 million goats) have been impacted negatively by the decline in SP [6]. Soil quality is its ability to carry out specified tasks/functions, whereas a soil's SP is its ability to support plant growth and development in a natural setting while utilizing a particular management strategy, and it is expressed in terms of crop yields. SQ and SP have been reported as key factors for sustainable agriculture [11–13]. The two are related in that soil quality is the integrated result of key soil characteristics management that influence crop productivity [14,15]. Thus, in recent years, great interest has been given to SQ evaluation in order to quantify land degradation of different types of land use and different land management strategies.

A number of methods have been developed for quantifying and monitoring SQ using a unified single index, namely SQ index (SQI), soil health index (SHI) or soil sustainability index (SSI) as a decision support tool [15–19]. However, none of them has been widely used/accepted to assess SQ due to the complexity and variability of soil systems, and existing gaps depending on the methods used. In fact, there is no single SQI model, even with regard to the steps involved (data selection, scoring functions). For data selection, three datasets have been reported: the large set (LDS), "expert" dataset (EDS) and the smaller dataset (MDS), also referred to as identified key indicators (IKI). For scoring functions (SF), non-linear methods (NL) such as Glover's method (GNLSF) and another method using a sigmoidal curve (SNSF), and linear methods (L) such as Liebig's and Glover's homothetic methods (GLSF and LLSF) have been reported. For SQ indexing formulas, additive, weighted and Nemoro SQI have been used [14,17,20]. This multiplicity has therefore led to different results for the same terrain [14].

Additionally, for better representativeness of SQ, no limitations or restrictions should be made, a combination of all three types of soil indicators must be selected for SQ indexing because of the interactions between these individual attributes. However, most of the above stated methods have done so using individual physical, chemical and biological indicators separately and ignoring biological indicators or did exclusions [17,20]. Another limitation is that its usage by people with less knowledge in this field is complicated by the fact that the selection of indicators that best represent certain soil functions is based on the subjective judgment of the "expert" [21]. Finally, due to the intensive field and laboratory work, costs and time constraints involved in processing a large set of indicators, it is essential to reduce it to a smaller set of key indicators [14,17,21,22]. Furthermore, there is a massive lack of awareness on land quality indicators (LQIs) and SQI, compared to economic and social indicators and indices, which are widely known and used [23–25]. To our knowledge, no study using SQI has been carried out to date to assess the effects of land use on SQ in Narok County.

The aim of this study was to investigate the impact of different types of land use on individual soil indicators, and to evaluate the SQ to establish the sustainability status of this agricultural watershed through the development and application of a linear scoring function, and two SQ indexing methods. The first for a large dataset of 23 indicators, and the second to condense the dataset dimension into a limited number of most important indicators referred to as key indicators to help farmers, land managers and decision-makers with a simple, rapid and affordable approach to assess/predict land degradation.

2. Material and methods

2.1. Study area

The study was undertaken in Kakia-Esamburmbur catchment in Narok County, Kenya. The county is situated in the Great Rift

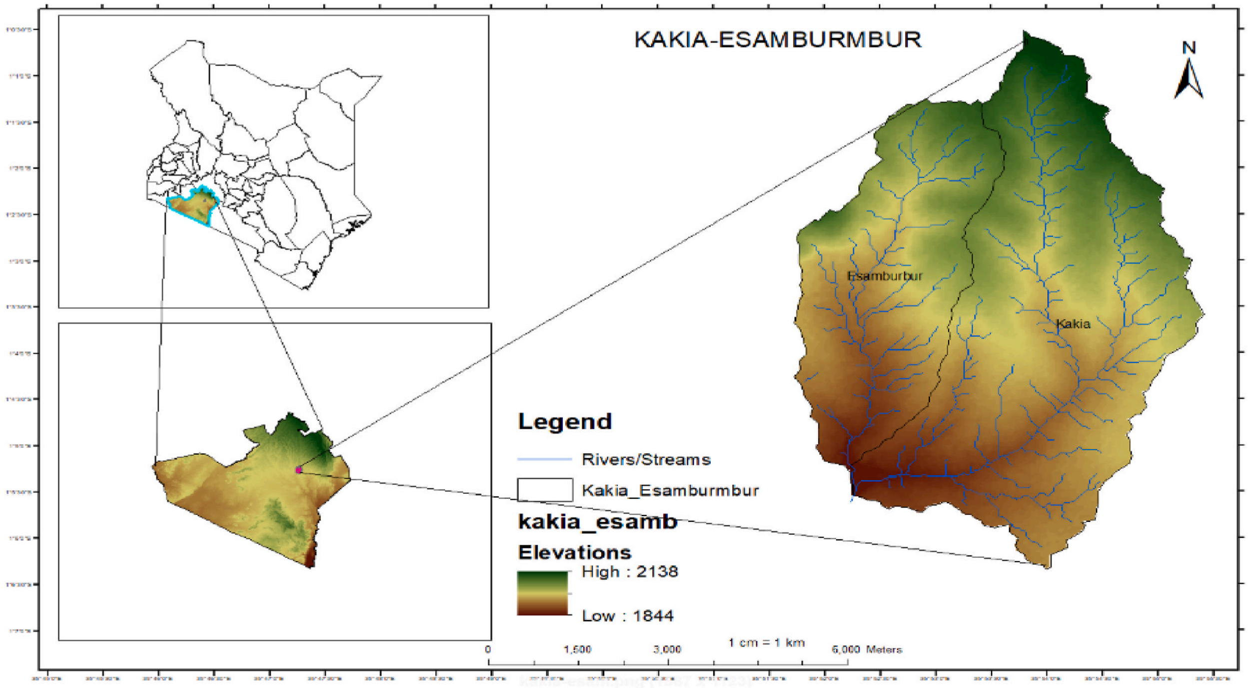

Fig. 1. Locations Maps of Narok County and the Catchment (Source: USGS DEM data, mapped using QGIS).

Valley, and covers an estimated area of 17,933 Km^2. It lies between latitudes 0° 50′ and 1° 50′ South, and longitudes 35° 28' and 36° 25 East. Bomet, Kisii, Migori, and Nyamira Counties lie to the West of Narok County, while Nakuru and Kajiado County lie to the North and East, respectively. The Republic of Tanzania lies to the South (Fig. 1).

Hydrologically, the catchment (46.2 km^2) is made up of two sub-watersheds (Esamburmbur (15.7 km^2) and Kakia (30.5 km^2))

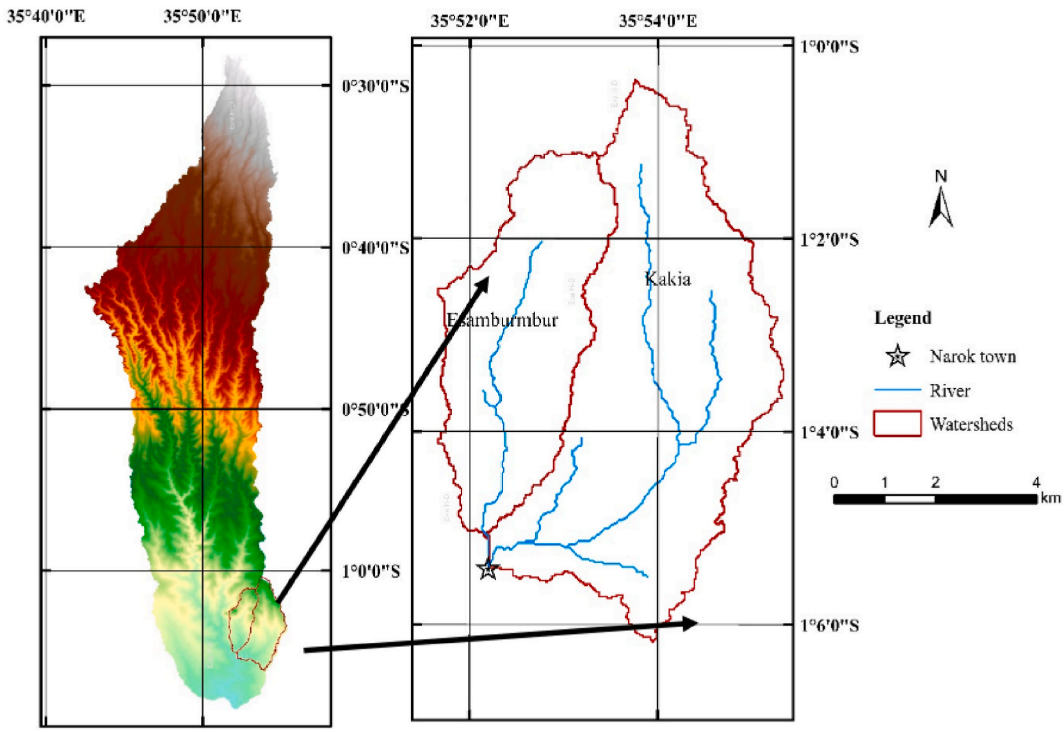

Fig. 2. Enkare Narok catchment, and Kakia - Esamburmbur sub-watersheds.

Table 1
Soil sampling sites distribution according to land use types.

Zones LULC Types	Lower Zone (A)	Medium Zone (B)	Top Zone (C)
Forest Land (FL)	2	4	2
Grass Land (GL)	2	4	2
Crop Land (CL)	2	4	2

LULC: Land Use/Land Cover.

within the Enkare watershed (971.8 km^2). River Esamburmbur and Kakia are seasonal streams meandering through Narok town, eventually forming a confluence and flowing into River Enkare as shown in Fig. 2. The two sub-watersheds make up the drainage area contributing to Narok town's flooding.

In regard to the climatic condition, the area experiences two rainy seasons, first one being from March to June, and the second lasts from September to November. Besides, the area receives annual rainfall ranging between 500 mm during sunny season, to 2,500 mm during the rainy season. The average temperature is 18 °C; however, it can range from 20 °C between January and March to 10 °C between June and September [6]. Geologically, the county has numerous volcanic formations, and a lot of geothermal activity resulting in deep volcanic soils. In terms of land use, there are about 150 land owners within this catchment practicing mixed farming: livestock and crop production with barley, maize and wheat as the main cash crops (as detailed in Table 1). The population of Narok town was estimated to be 58,239 people in 2022 [6].

2.2. Sampling, storing, preparing

Georeferenced soil samples were taken from 24 different sampling points (8-cropland, 8-grassland and 8-forest) on the basis of a 10 m × 10 m square sampling area/plot at each site, from which, five (05) sub-samples were taken at a depth of 20 cm, one at the center of the plot, and four at the corners. The sub-samples were then mixed to form a composite sample in triplicate. A total of 72 composite samples from the 3 land use types (cropland, grassland, forest) were collected from 8 sites with 3 replicates. The watershed was delimited and subdivided into three altitude-based agro-ecological zones using Google Earth (upper, middle and lower zones), away from the urban area over which the samples were geo-referenced and collected. The composition of samples and the subdivision of the watershed aimed to ensure that the size and number of samples accurately reflected the soil studied in terms of heterogeneity and spatial variability as shown in Table 1 and Fig. 3.

The study employed a cluster sampling method, which involved sampling at an average soil depth of 20 cm using a soil auger to achieve the adequate root depth of most crops. Fan et al. (2016) investigated the root distribution of 11 temperate agricultural crops and determined the estimated depth (d_{50}) at which 50 % of the total root was deposited [26]. Their findings show that the depth ranged

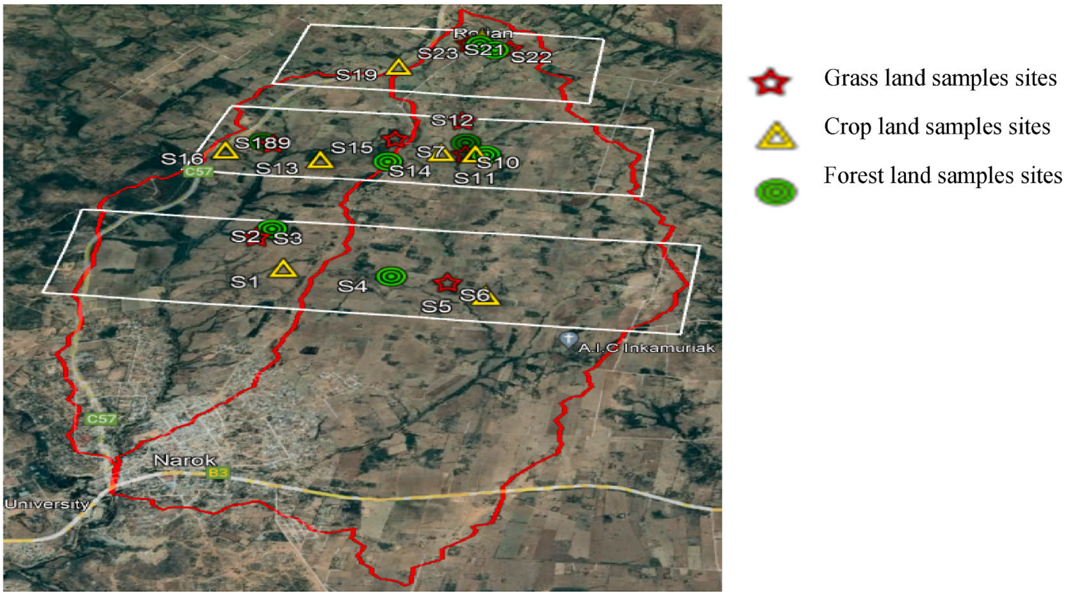

Fig. 3. Locations of the different sampling sites within the catchment.

Table 2
Topographical and landscape characteristics of the 24 selected sample sites in the catchment.

Land Use Types	Sites Nº	Latitude/Longitude	Elevation (m)	Topographic Position	Soil and Lands Characteristics
Grassland (GL)	**2**	−1.052550° S, 35.899620° E	2002	Hill (LZ)	Small weeds, subsoil rock, crusted and degraded soil
	5	−1.060090° S, 35.89959° E	1970	Plain (LZ)	Small weeds cover, stagnant water, near wheat farm
	9	−1.037845° S, 35.900452° E	2028	Plain (MZ)	Small weeds cover
	12	−1.031242° S, 35.898578° E	2045	Plain (MZ)	Small weeds cover, near water reservoir
	15	−1.039045° S, 35.891507° E	2055	Plain (MZ)	Low weeds cover, orange compacted subsoil rock, sloppy land
	18	−1.017417° S, 35.902538° E	2022	Plain (MZ)	Dry weeds, sloppy land
	22	−1.017417° S, 35.902538° E	2111	Plain (UZ)	Small weeds cover
	24	−1.016323° S, 35.897957° E	2099	Plain (UZ)	High weeds, fenced land
Cropland (CL)	**1**	−1.57708° S, 35.882932° E	1998	Plain (LZ)	Maize, sloppy land
	7	−1.037200° S, 35.896888° E	2036	Plain (MZ)	Maize, huge gulley
	16	−1.036685° S, 35.874173° E	2021	Plain (MZ)	Maize, sloppy and permeable land
	20	−1.015373° S, 35.899358° E	2114	Plain (UZ)	Maize, sloppy and permeable land
	6	−1.062293° S, 35.903622° E	1972	Plain (MZ)	Wheat, huge gulley and a dam around
	10	−1.037413° S, 35.900452° E	2029	Middle-hill (MZ)	Wheat, sloppy land
	13	−1.038475° S, 35.884383° E	2032	Plain (MZ)	Wheat, sloppy land, near a forest
	19	−1.020910° S, 35.890810° E	2093	Plain (UZ)	Wheat, near the tarmac
Forest land (FL)	**3**	−1.052316° S, 35.879464° E	2011	Shallow (LZ)	Trees of middle size, litter, not degraded land
	4	−1.059243° S, 35.893943° E	2003	Hill (LZ)	Shrubs, white subsoil rock, presence of charcoal, degraded land
	8	−1.035498° S, 35.899272° E	2032	Shallow (MZ)	Shrubs and big trees, huge gulley
	11	−1.037712° S, 35.901582° E	2041	Middle-hill (MZ)	Shrubs and trees of middle size, dam, orange subsoil rock
	14	−1.039045° S, 35.891507° E	2057	Plain (MZ)	Shrubs and trees of middle size, presence of charcoal
	17	−1.035170° S, 35.877848° E	2020	Shallow (MZ)	Shrubs and big trees, huge gulley, dry and degraded soil
	21	−1.017745° S, 35.900955° E	2106	Hill (UZ)	High weeds, shrubs and few big trees, huge gulley, white subsoil rock, dry and degraded soil
	23	−1.016625° S, 35.899205° E	2108	Hill (UZ)	Shrubs and trees of middle size, huge gulley, washed top soil

LZ: Lower Zone; MZ: Middle Zone; UZ: Upper Zone.

from 8 cm to 20 cm; summarily cereals d_{50} was 14.1 cm (exactly 16.8 cm and 14.4 cm for wheat and maize), and 50 % of root biomass for all crops was found within a soil depth of 20 cm (between 15 and 30 cm). A depth of 20 cm represents the average tillage and ploughing layer in the area. Moreover, the maximum concentrations of numerous soil components are present at this depth [27]. Accordingly, this depth has the most robust response to land-use changes, making it the most vulnerable to soil degradation. Table 2 shows the characteristics of the topographical and landscape of the sampling locations.

2.3. Soil analysis

The sample preparations were conducted in the Department of Land Resource Management and Agricultural Technology (LARMAT) laboratory, University of Nairobi before analysis. The soil reaction was measured using a glass electrode pH meter as described by Anderson and Ingram (1993) [28], and Weligama et al. (2022) [29]. The electrical conductivity (EC) was done using the EC meter, using same sample as pH meter [30]. The Walkley-Black method, Molybdenum Blue technique, and Kjeldahl steam distillation were used to determine total organic carbon (TOC), available phosphorus (P), and total nitrogen (N), respectively, following the procedures outlined by Nelson and Grossman (1996) [31], Anderson and Ingram (1993) [28], and Black et al. (1965) [32]. Soil organic matter (SOM) computed from TOC as 1.72 * TOC (%). Exchangeable potassium (K) and exchangeable sodium (Na) were measured using a flame photometer, while exchangeable calcium (Ca) and exchangeable magnesium (Mg) were analyzed using the Atomic Absorption Spectrophotometer (AAS, Model AA500F) with element-specific spectral signatures (Landon, 2014) [30]. The cation exchange capacity (CEC) was determined according to Refs. [30,33], which involves leaching with ammonium acetate (1 N NH_4OAc) and potassium chloride (1 N KCl) solution then analysing the leachates.

To determine soil reaction, the samples were weighed and shaken in a solution with a soil: distilled water ratio of 1:2.5. The pH meter was calibrated using buffer 4 and 7, and the samples were read. For carbon analysis, the samples were oxidized with potassium dichromate ($K_2Cr_2O_7$) in the presence of concentrated sulfuric acid (H_2SO_4), and titration was done using 0.5 N of FeSO4. The Molybdenum Blue technique was part of the Mehlich 1 protocol, which involved extracting phosphorus from the soil using double acid: hydrochloric acid (HCl) and sulfuric acid (H_2SO_4), shaking, developing colour, and quantifying absorbance using ultra violet (UV) light. Kjeldahl method involved digesting the sample using concentrated H2SO4 in the presence of mixed catalyst, steam distillation to obtain ammonia in 2 % boric acid, and titration using 0.01 N H_2SO_4. Exchangeable K and Na were measured in a flame photometer after activating the element. The Atomic Absorption Spectrophotometer (AAS) measured absorbance of Ca and Mg, at element-specific wavelengths.

Soil textural components (Sand, Silt and Clay) were determined using the hydrometer (Bouyoucos) method according to Refs. [34,35]. The hydrometer model used was ASTM (E100) 152H. Saturated hydraulic conductivity (Ksat) was determined according to Reynolds and Elrick (2002) [36], and the same sample used for determining bulk density (mass/volume) according to Grossman and Reinsch (2002) [37]. Other physical indicators derived from the basic indicators can be calculated, such as total porosity (TP) computed easily from particle density (PD), which is 2.65 gcm^{-3} as mean value and BD as 100 * (1-BD/PD) [14]. The basic infiltration followed the guidelines elucidated in Landon (2014). The soil moisture was determined gravimetrically [30]. Microbial Biomass Carbon (MBC), Microbial Biomass Nitrogen (MBN), Potentially Mineralizable Nitrogen (PMN), and Soil Respiration Microbial activity

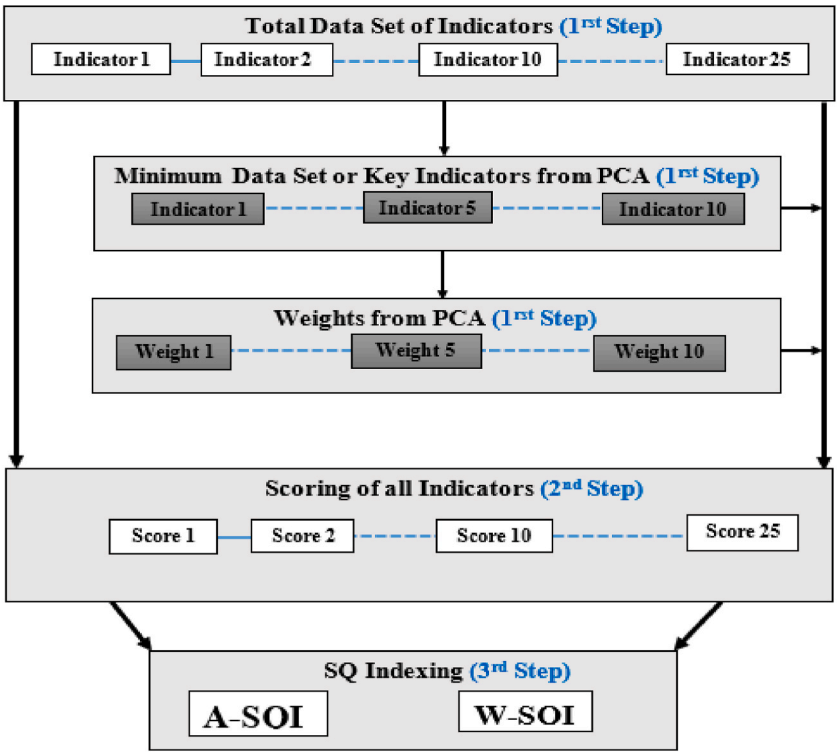

Fig. 4. Conceptual diagram for computing SQI according to the 2 models.

(SRM activity) values were determined using the procedure outlined by Ref. [28], and [33]. Fumigation-extraction using chloroform and Kjeldahl methods were used for MBN and MBC; hot potassium chloride (KCL)- ammonium-N (NH 4 –N) method for PMN and the use of Erlenmeyer flasks for SRM activity.

2.4. Soil quality index evaluation

The evaluation of the Soil Quality Index (SQI) consists of three stages: selection of relevant indicators, calculating the scores of the chosen indicators, and integrating the indicator scores into an integrating SQI formula [17,18] as detailed in the following research methodology diagram (Fig. 4). In-depth explanations of each step are given in sections 2.4.1, 2.4.2, 2.4.3 below.

2.4.1. Selection of soil indicators (1st step)

Several methods and approaches have been used to select soil indicators, but the overall criteria used by experts encompassed the different roles and importance of the indicators in terms of soil functions i.e. their influence on soil fertility/productivity, and their sensitivity to management practices and ecosystem changes [38]. This method produced a large number of indicators called the "total data set". Then, based on this method of "expert opinion", statistical and mathematical models were applied to reduce the number of the dataset into key indicators called "minimum set of data." In this study, a combination of statistical and mathematical models was used [14,20,38–40]. The two models used in this study are the "Additive Soil Quality Index model", and the "Weighted Additive Soil Quality Index".

2.4.2. Soil indicators scoring functions (2nd step)

The measured indicators are in various scales and units; however, it is necessary to normalize their values to a score that ranges from 0 to 1. The normalization/scoring gives the capacity to combine and average the indicators scores into a single value that is not limited to the relevant soil functions and processes. It also brings out information that could otherwise go unnoticed when evaluating the observed values [41]. To achieve this, linear and nonlinear scoring systems are used to convert indicators into dimensionless units with a range of 0–1. Preference is often given to linear scoring method because of the weakness of non-linear scoring method as reported by Refs. [14,17]. Homothetic Linear Scoring Transformation (HLSF) was used in this study, as detailed in Equations (1)–(3) below.

$$HLSF_1(x) = \begin{cases} 0.1, \; x \le L \\ 0.1 + \dfrac{0.9\,(x-L)}{U-L}, \; L \le x \le U \\ 1.0, \; x \ge U \end{cases} \tag{1}$$

$$HLSF_2(x) = \begin{cases} 1.0, \; x \le L \\ 1 - \dfrac{0.9\,(x-L)}{U-L}, \; L \le x \le U \\ 0.1, \; x \ge U \end{cases} \tag{2}$$

$$HLSF_3(x) = \begin{cases} 0.1, \; x < L, \; x > U \\ 0.1 + \dfrac{0.9\,(x-L)}{U-L}, \; L \le x < L_1 \\ 1 - \dfrac{0.9\,(x-L)}{U-L}, \; U_1 < x \le U \\ 1.0, \; L_1 < x < U_1 \end{cases} \tag{3}$$

Where: *F(x)* is the scoring function, x the soil indicator value, L and U are respectively the lower and the upper thresholds. L_1 and U_1 are for bell-shaped relationship i.e. when the indicator should be considered "optimum is better": L_1 the upper threshold of the first range ($L \le x < L_1$) where the indicator is considered "more is better" and U_1 is the lower threshold of the second range ($U_1 < x \le U$) where the indicator is considered "less is better".

Depending on whether a higher number is considered "good", i.e. "more is better", or "bad", i.e. "less is better", in terms of soil function, the indicators were rated in ascending or descending order. The $HLSF_2$ method was used for ascending order, while the $HLSF_1$, which is an inverse rating, was used for descending order. However, for indicators such as pH, TOC and PMN, for which an "optimum" threshold was considered because they had an increasing order up to a critical value where they became decreasing, the $HLSF_3$, a parabola was applied. The indicator thresholds are mainly determined based on literature review, and the author's experience in order to accurately match the biophysical and climatic conditions of the study area as detailed in Table 3.

Table 3
Selected soil indicators thresholds and scoring functions.

Parameters	Units	Lower	Upper	Reference Values	Function	Sources
Physical						
Moisture	%	15	105	60	More is better	[42,43]
BD	g/cm^3	1.2	1.8	1.6	Less is better	[43]
Ksat	cm/hr	0.083	36	3.6	Less is better	[30,44]
Sand	%	0	60	–	Less is better	[14]
Clay	%	0	30	–	More is better	[14]
Silt	%	0	25	–	More is better	[14]
BIR	cm/hr	1	4	2	Less is better	[16]
Chemical						
pH	1:2.5	4.5	6	6–7	More is better	[20,45]
		7	8		Less is better	
EC	dS/cm	0.2	2	1	Less is better	[20]
N	%	0.05	0.54	0.3	More is better	[14,38,43,46]
PO4–P	mg/kg	4.55	54.5	29.55	More is better	[39,47]
Exch. K	meq/100g	0.2	2	2	More is better	[38,46,47]
Exch. Na	meq/100g	0.3	0.7	–	More is better	[43]
Exch. Ca	meq/100g	4	10	–	More is better	[43]
Exch. Mg	meq/100g	3	8	–	More is better	[43]
CEC	meq/100g	15	25	15	More is better	[16,38,39,46,47]
TOC	%	2	8	5	Optimum	[38,40,46]
SOM	%	3.44	13.76	–	More is better	[38,40,46]
Biological						
MBN	ppm	0	45.5	–	More is better	[43]
MBC	ppm	0	170.5	–	More is better	[43]
PMN	ppm	0	100	90.9	Optimum	[43]
SRM activity	mg/CO2/g	0	1.25	–	More is better	[48]

2.4.3. Soil Quality Index Computation (3rd Step)

2.4.3.1. Additive Soil Quality Index (A-SQI). For the total dataset of 23 indicators, the SQI was computed as an average score, using the additive method by making the sum of concerned indicators scores, divided by the total number of the indicators as defined in Equation (4) [15,31,38]. Four (4) different types of SQIs were computed for each site using the same formula: the global SQI integrating all the indicators, and the three (03) partial ones according to the nature (physical, chemical or biological) of concerned indicators used to develop them. The partial indices include: Soil Physical Quality Index (SPQI), Soil Chemical Quality Index (SCQI), and Soil Biological Quality Index (SBQI). These were used to make comparison between SQI values, and to explain their differences better. Computation was done for each site and the average/mean taken for each land use type (compound of 8 sites). Finally, a comparison was made to know the degree of sustainability between the three land use types.

$$A - SQI = \frac{\sum_{i=1}^{n} S_i}{n} \tag{4}$$

Where: S_i is the linear score of the ith indicator and n is the total number of concerned indicators (for this study, $n = 22$ for the global SQI, 7 for SPQI, 11 for SCQI and 4 for SBQI).

2.4.3.2. Weighted Soil Quality Index (W-SQI). Principal Component Analysis (PCA) was employed in the determination of key indicators, which significantly influence soil quality in the watershed. PCA allows for the reduction of the number of indicators without altering the overall representativeness through the univariate statistical analysis (grouping the all data set into factors called PCs), and the orthogonal correlation matrix of indicators [14,39,41]. Additionally, PCA is performed to transform a large dataset of indicators that are correlated into a subset of uncorrelated indicators, which account for greatest variation within the large set by describing vectors of closest fit to the n observations in p-dimensional space [49]. PCA involves the following steps: (i) indicators standardization, (ii) correlation matrix establishment, (iii) determination of vectors called PCs with their eigenvalues, percentages of variance and weights, (iv) disqualification of PCs with smaller (eigenvalues <1), and (v) PCs matrix establishment with loading factors affected to all indicators [49,50]. The process and criteria used in this study for PCA is described below.

To avoid biasness, the data should be preprocessed to a variance of 0 and a mean of 1. This is because PCA tends to maximize data with higher variance giving a false overestimate influence to such variables. This process is called standardization instead of normalization, which does not give the same variance to variables. Accordingly, data was standardized using Equation (5):

$$x_i = \frac{X_i - \sigma}{SD} \tag{5}$$

Where: x_i is the standardized value/score of the ith indicator with its value X_i, σ the mean/average of the ith indicator values and its standard deviation *SD*.

Communalities calculated the percentage of each soil indicator's variance that accounted for the PC. A high community for a certain soil indicator denoted that a component accounted for a sizable share of the variance. Then, among PCs, only PCs with eigenvalues >1 and justifying at least 5 % of the data variation were considered for indicators selection [17]. Under PC, indicators having higher loading factors (lf $\geq \pm 0.75$), meaning it has a high correlation with the PC, were selected to be among the key indicators. But where many indicators were chosen under the same single PC, multivariate correlation matrix was used to verify how significantly ($p < 0.05$) these indicators are correlated to reduce redundancy. Among well-correlated indicators under a single PC ($r \geq 0.5$ and $p < 0.05$), the indicator with the highest loading factor and the highest coefficient of correlation, whether positive or negative (absolute value) with other highly loaded indicators (lf $\geq \pm 0.75$) was selected. If the indicators are not well-correlated ($r < 0.5$), all of them were considered.

After selection, Identified Key Indicators (IKI) were normalized using the Homothetic Linear Scoring Transformation as detailed above, then the W-SQI was computed by multiplying each score by the corresponding indicator weight and summed as shown in Equation (6):

$$\boldsymbol{W - SQI} = \sum_{i=1}^{n} \boldsymbol{W_i * S_i} \tag{6}$$

Where: S_i is still the linear score of the ith indicator, n is the total number of concerned indicators, and W_i is the ratio of the percentage of variance of each key indicator from the PC to the maximum cumulative variance of considered PCs.

2.5. Assessment of soil quality index computation methods

The level of sensitivity of the SQI for the different land use types, and the whole catchment was assessed using Equation (7) [16]:

$$\boldsymbol{Sensitivity(S)} = \frac{\boldsymbol{SQI_{max}}}{\boldsymbol{SQI_{min}}} \tag{7}$$

Where: S is the dimensionless sensitivity value, SQI_{max} and SQI_{min} are respectively the SQI maximum and minimum values of each land use type as for the overall catchment.

2.6. Statistical analysis

Microsoft Excel was used to conduct descriptive analysis of data such as min, max, mean, standard deviation, and coefficient of variation. After which, the Statistical Package for the Social Sciences (SPSS) v.20.0 was used to carry out ANOVA followed by Duncan and Tukey tests, to determine both the difference between soil indicators means under different land uses, and the effect of land use types on SQI at 5 % and 1 % levels of significance ($p < 0.05$ and $p < 0.01$), respectively. SPSS was also used to establish association between indicators using Pearson correlation matrix., after which, PCA was performed to identify IKI set through Varimax with Kaiser Normalization [14,39,41].

Table 4
Relevant descriptive statistics of selected soil indicators.

Soil Indicators	Min	Max	Mean	SD	CV
Moisture (%)	7.10	31.69	13.49	5.34	39.60
BD (g/cm^3)	0.89	1.26	1.10	0.08	7.31
Ksat (cm/hr)	0.16	4.44	1.54	1.17	75.76
Sand (%)	38.00	52.00	45.42	3.93	8.66
Clay (%)	40.00	52.00	43.83	3.58	8.18
Silt (%)	4.00	16.00	10.75	3.17	29.45
BIR (cm/hr)	0.49	3.99	1.78	0.93	52.42
pH	6.77	8.27	7.44	0.36	4.78
EC (dS/cm)	0.08	0.32	0.17	0.06	37.37
N (%)	0.02	0.74	0.18	0.15	82.05
PO4–P (mg/kg)	1.10	262.99	37.61	56.47	150.13
Exch. K (meq/100g)	0.25	1.56	0.99	0.33	33.37
Exch. Na (meq/100g)	0.26	1.02	0.45	0.20	44.49
Na/K	0.21	2.35	0.56	0.47	83.34
Exch. Ca (meq/100g)	1.02	48.90	36.06	10.58	29.33
Exch. Mg (meq/100g)	0.37	6.37	3.85	1.15	29.99
Ca/Mg	2.76	15.37	9.44	2.81	29.81
CEC (meq/100g)	13.80	40.60	27.32	6.65	24.35
TOC (%)	0.17	7.35	1.83	1.50	82.05
OM (%)	0.29	12.67	3.16	2.59	82.05
MBN (ppm)	10.17	242.41	54.92	53.53	97.48
MBC (ppm)	12.18	438.31	139.14	109.65	78.81
PMN (ppm)	−2.27	13.14	4.39	3.71	84.60
SRM activity (mg/CO2/g)	1.30	9.70	6.40	2.03	31.75

Table 5
Mean values of the indicators with relevant descriptive statistics.

Soil Indicators		Means Values of Land Use Types			ANOVA Test		Duncan T-Test	Tukey HSD
		GL	CL	FL	F	Sig.		
Physical								
1	Moisture (%)	11.12	15.47	13.88	1.404	.268	.131	.245
2	BD (g/cm^3)	1.13	1.10	1.06	1.669	.212	.097	.174
3	Ksat (cm/hr)	1.14	1.63	1.84	.743	.488	.275	.471
4	Sand (%)	44.75	46.00	45.50	.190	.828	.570	.815
5	Clay (%)	43.25	43.50	44.75	.381	.688	.451	.698
6	Silt (%)	12.00	10.50	9.75	1.053	.367	.192	.347
8	BIR (cm/hr)	1.34	2.46	1.53	4.288	**.027**	.642	.083
Chemical								
9	pH	7.47	7.26	7.60	1.990	.162	.074	.143
10	Ec (dS/cm)	0.17	0.13	0.20	3.208	.061	.367	.052
11	N (%)	0.16	0.20	0.19	.176	.840	.594	.836
12	PO4–P (mg/kg)	63.24	22.57	27.03	1.278	.299	.182	.331
13	Exch. K (meq/100g)	1.02	0.90	1.05	.462	.636	.400	.639
14	Exch. Na (meq/100g)	0.44	0.51	0.40	.654	.530	.295	.503
15	Exch. Ca (meq/100g)	31.62	36.69	39.88	1.271	.301	.149	.276
16	Exch. Mg (meq/100g)	3.47	4.24	3.84	.894	.424	.220	.391
17	CEC (meq/100g)	26.68	26.83	28.45	2.203	.135	.633	.865
18	TOC (%)	1.57	2.02	1.90	.162	.851	.594	.836
19	OM (%)	2.72	3.49	3.27	.175	.840	.594	.836
Biological								
20	MBN (ppm)	21.57	58.98	84.20	3.334	.055	.313	.565
21	MBC (ppm)	122.15	143.07	152.19	.146	.865	.624	.859
22	PMN (ppm)	3.97	3.61	5.58	.619	.548	.335	.557
23	SRM activity (mg/CO2/g)	7.69	6.16	5.34	3.311	.056	.115	.249

3. Results and discussion

The coefficient of variation (CV) was used in the interpretation of soil indicators variability among land use types and within the entire watershed. Least variation (CV < 15 %) was observed through BD, Sand, Clay and pH; moderate variation (15 % < CV < 35 %) with Silt, K, Ca, Mg, Ca/Mg CEC and SRM activity. On the other hand, high variability (35 % < CV < 55 %) was observed through Moisture, BIR, EC and Na; and very high variability (CV > 55 %) through PO4–P, TOC, OM, MBN, Na/K, MBC and PMN (Table 4).

The high variation in most of the indicators can be explained by the combined effects of intrinsic processes such as climate/weathering, erosion, deposition, geology and regressive/progressive pedogenesis. These are further exacerbated by extrinsic processes due to anthropogenic activities such as poor land management strategies [22,51], poor solid waste management, soil erosion, lack of adequate sanitary facilities, extensive deforestation for the production of charcoal, wood, and firewood, poor physical urban planning, quarrying activities, and pollution from agrochemicals and alien and invasive species [6,22].

Table 5 shows the mean values of all selected physical, chemical and biological indicators. Except PO_4–P, OM and OC in GL, and Moisture content in both GL and FL, all the indicators mean values were within the good ranges in land use types as shown in Table 3, indicating soils with good health. Though the samples were taken far from each other to avoid similarities due to proximity (account for soil heterogeneity and spatial variability), when applying ANOVA F- test (Table 5), the level of significance p was found to be greater than 0.05 except for BIR ($p = 0.027$); and when applying Duncan and Tukey HSD tests (Table 5), all p values were higher than 0.05, indicating that there was no difference in the indicators mean values for the three types of land use. This confirms the homogeneity of soils within the catchment as reported by Ref. [8].

3.1. Soil physical indicators

Fig. 5a shows the physical indicators of the sampled soils within the study area. The soil moisture reached a maximum value under CL (15.47 %), followed by FL (13.88 %), which was significantly at par with GL (11.12 %). Moisture content was found to be within a good range only in CL, an indication of water stress to plants due to insufficient moisture (<15 %) in GL and FL [40]. The BD varied from 1.13 g/cm^3 to 1.06 g/cm^3. The higher BD was attained under GL (1.13 g/cm^3) followed by CL (1.10 g/cm^3), and the least under FL (1.06 g/cm^3). The observed higher BD in GL can be attributed to the low vegetation cover (grasses) leading to crusting of the soil surface, reduction of soil pores, and increase in soil compaction, because of the production of fine particles filling pores from the impact of raindrop, and the livestock hooves.

The lower BD in CL and FL can be explained, firstly by the considerable quantity of organic matter in FL due to decaying roots, branches and leaves (fallen litter) that covered the ground. Secondly, it can be explained by the applied land management practice (tillage) in the cultivated lands, which are regularly ploughed to depths of about 30 cm. This practice increases soil pores, and reduces compaction of the top soil, thus helping the crop roots to penetrate the soil and suck water easily [30,52]. Regarding the soil texture, 54 % of the 24 sites are categorized as sandy-clay, while 46 % as clay. Additionally, CL was characterized by 46 % sand, 43.5 % clay and 10.5 % silt, FL was made up of 45.5 % sand, 44.75 % clay and 9.75 % silt, while GL was composed of 44.75 % sand, 43.25 % clay

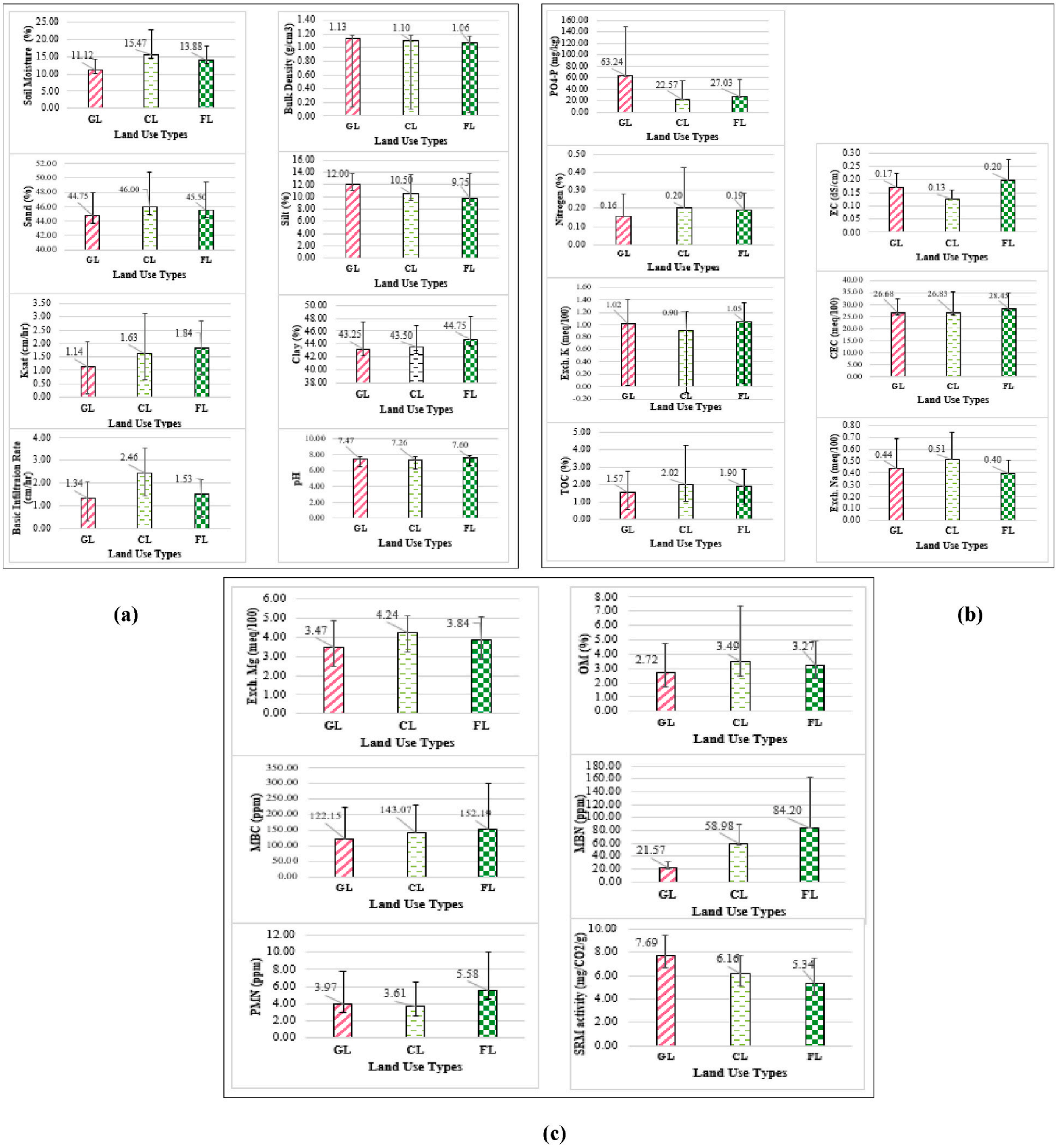

Fig. 5. Bar graphs showing the Soil Structure (a), Chemical (b) and Biological (c) Indicators according to Land Use Types.

and 10.5 % silt.

The high percentage of sandy-clay soils within the catchment can be attributed to washout erosion that carried fine clay/silt particles and left heavier aggregates of sand at the land surface during flooding. Ploughing increases soil surface pores leading to higher basic infiltration rate and soil moisture in CL than in FL at 2.46 cmh^{-1} and 15.47 %, respectively in CL, followed by FL (1.53 cmh^{-1} and 13.88 %), and lower in GL (1.34 cmh^{-1} and 11.12 %) due to compaction of the soil surface [4]. Hydraulic conductivity was found to be higher in FL (1.84 cmh^{-1}), followed by CL (1.63 cmh^{-1}), and lower in GL (1.14 cmh^{-1}). The higher Ksat in FL can be attributed to the presence of ground litter and macro-pores created by lateral tree roots. This means that water infiltrates more in FL followed by CL and least in GL. Ksat is a crucial structural indicator because it controls both the distribution of moisture content (based on soil depth), and water availability to plants. In soils with poor Ksat and poor hydraulic properties, water drainage and nutrient supply are altered, leading to poor crop productivity [8,53] as was observed in the GL.

Increased runoff and soil erosion are as a result of decreased soil infiltration capacity. The erosive strength and soil erosion increase in direct proportion to runoff [8]. conducted a study in the Kakia-Esamburmbur watershed and reported that the types of land use and land cover have a substantial impact on soil hydraulic characteristics, which in turn affects runoff generation and the manner in which runoff contributes to soil erosion in the catchment. Crop lands are the most sensitive to degradation, while forests act as the best soil conservation practice among the three land use types (GL, CL and FL).

3.2. Soil chemical indicators

The soil chemical indicators are represented using a bar graph as shown in Fig. 5b. The soil pH ranged from neutral (6.6–7.3) to highly alkaline (7.4–8.4). A pH range of 6.77–8 indicates the presence of $CaCO_3$ [22,47,54]. In terms of means, soil pH for the different land uses were: FL (7.60) > GL (7.47) > CL (7.26). Electrical Conductivity (EC) was highest in FL (0.20 $dScm^{-1}$), followed by GL (0.17 $dScm^{-1}$), and lowest in CL (0.13 $dScm^{-1}$). The lower EC values in CL and GL can be attributed to the exposure of these land uses to runoff and erosion, therefore the salt moved readily with water. Inversely, runoff and erosion are minimal in FL owing to the vegetation cover, thus retaining salt. However, these EC values were acceptable because they were all under and within the adequate range of 0.2–2 $dScm^{-1}$ [41].

The EC values are an indication of minimal soluble salts in the soil within the watershed, an indication of healthy soils (EC < 2 $dScm^{-1}$) [54]. Phosphorus (PO_4–P) values varied in the different land use types as follows: GL (63.24 $mgKg^{-1}$) > FL (27.03 $mgKg^{-1}$) > CL (22.57 $mgKg^{-1}$). The mean values under FL and CL have the same magnitude and were within the required range of 4.55–29.55 $mgKg^{-1}$ for plants growth, except under GL where it was above the optimum value (29.55–54.55 $mgKg^{-1}$). This is detrimental to the environment because it can cause eutrophication in aquatic systems by polluting surface water. The high concentration of PO_4–P can be attributed to livestock grazing, which sped up the system element cycle, impairing its absorption by plants, and increased animal waste in GL [55].

Exchangeable Potassium (K) values in the 24 sites were found to be under the acceptable thresholds of 0.2–2 $mgKg^{-1}$ both for plants growth and for animal health [38,47]. The mean values were similar in the three land use types with the highest value attained in FL (1.05 meq/100g), followed by GL (1.02 meq/100g), and the least in CL (0.9 meq/100g). Exchangeable Sodium had the same magnitude in the different types of land use and followed this trend: CL (0.51 meq/100g) > GL (0.44 meq/100g) > FL (0.40). Sodium is not required for plants growth; however, high amounts of salt are bad for soil permeability, structure, and plant growth. Fortunately, this is not a problem in the catchment because the mean values were within the recommended range of 0.3–0.7 meq/100g for plants growth [47]. Exchangeable Calcium mean values were as follows: FL (39.88 meq/100g) > CL (36.69 meq/100g) > GL (31.62 meq/100g). Exchangeable Magnesium content was moderate with mean values that have the same magnitude under all land use types, but following the following trend: CL (4.24 meq/100g) > FL (3.84 meq/100g) > GL (3.47 meq/100g). The CEC was high with respect to the acceptable range of 15–25 meq/100g under all the land use types. FL had the highest value of CEC at 28.45 meq/100g, followed by CL (26.83 meq/100g), then GL (26.68 meq/100g). The higher value of CEC in FL can be attributed to the combined effect of its higher clay value (44.75 %), and the significant amount of OM (3.27 %) allowing for the production of more basic cations (Na, K, Ca and Mg) compared to CL (43.50 % of clay and 3.49 % of OM) and GL (43.25 % of clay and 2.72 % of OM). The interpretations were made in conformity with [16,38,39,46,47].

Organic carbon, organic matter, and nitrogen were all higher in CL at 2.02 %, 3.49 % and 0.20 %, respectively. This was followed by FL at 1.90 %, 3.27 % and 0.16 %, then GL at 1.57 %, 2.72 % and 0.16 %. However, OC production (including OM) is impaired because the values were under or just close to the lower limit (2 %). The high values of organic carbon, organic matter and nitrogen in CL can be attributed to land management practices (crop residues, compost, and the use of artificial fertilizers (NPK)) applied by farmers. Moreover, the soil samples were collected just after harvesting, as such the farms were covered by very dense residues of maize and wheat (leaf litter and roots biomass). Consequently, the OM and related induced component quantities like OC and N were more in CL than in FL. However, in GL, the vegetation cover was not significant enough to induce production of biomass, hence, lower values of OM, OC and N due to minimal biomass decomposition [54].

3.3. Soil biological indicators

Fig. 5c displays the biological indicators of the sampled soils within the study area, represented using bar graphs. Microbial biomasses N (MBN) and C (MBC), and Potentially mineralizable N (PMN) were higher in FL (in terms of difference compared to CL and FL) at 84.20 ppm, 152.19 ppm and 5.58 ppm, respectively. For CL the values were 58.98 ppm, 143.07 ppm, 3.61 ppm, respectively, and 21.57 ppm, 122.15 ppm and 3.97 ppm, respectively in GL. The significant difference in the values can be explained by the long-term accumulation of SOC in surface layers of soils in FL, but not in the sub-layers [22,56]. Furthermore, the results revealed that microbial biomass rates are more sensitive to changes and management options than SOC, where insignificant differences were found. These are in line with a study conducted by Ref. [43], who suggested the use of the ratio MBC/SOC.

For soil respiration, referred to as Microbial activity (SRM activity), all sampled sites recorded values above the upper threshold (1.25 7.69 mg/CO2/g) in the following order: GL (7.69 mg/CO2/g) > CL (6.16 mg/CO2/g) > FL (5.34 mg/CO2/g). This implies that FL sequestered more carbon, followed by CL and a higher release of carbon in GL. Studies conducted by Refs. [48,57] show a favorable correlation between improvements in soil health and increase in soil respiration.

Table 6
Partial SQIs and relevant descriptive statistics according to Land Use Types.

Land Use	SPQI					SCQI					SBQI				
	Means	min	max	SD	CV	Mean	min	max	SD	CV	Mean	min	max	SD	CV
GL	0.01	0.01	0.02	0.00	6.02	0.52	0.43	0.61	0.06	10.73	0.58	0.43	0.74	0.12	21.10
CL	0.02	0.01	0.04	0.01	44.58	0.52	0.40	0.69	0.08	16.22	0.69	0.49	0.79	0.12	17.04
FL	0.02	0.01	0.02	0.00	13.07	0.55	0.45	0.95	0.17	30.26	0.70	0.53	0.79	0.10	14.65

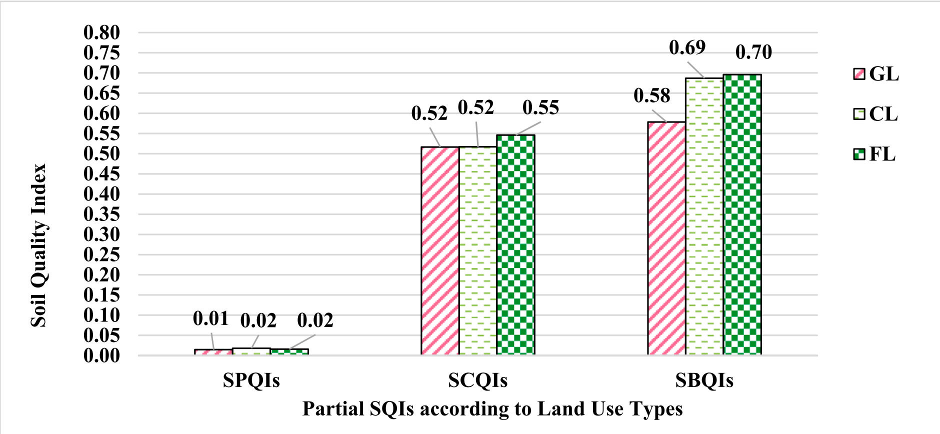

Fig. 6. Mean values of partial soil quality indexes according to land use types.

Table 7
A-SQI and relevant descriptive statistics according to land use types.

Land Use	A-SQI				
	Means	min	max	SD	CV
GL	0.58	0.55	0.63	0.03	5.02
CL	0.59	0.52	0.68	0.05	8.30
FL	0.61	0.57	0.77	0.07	10.73

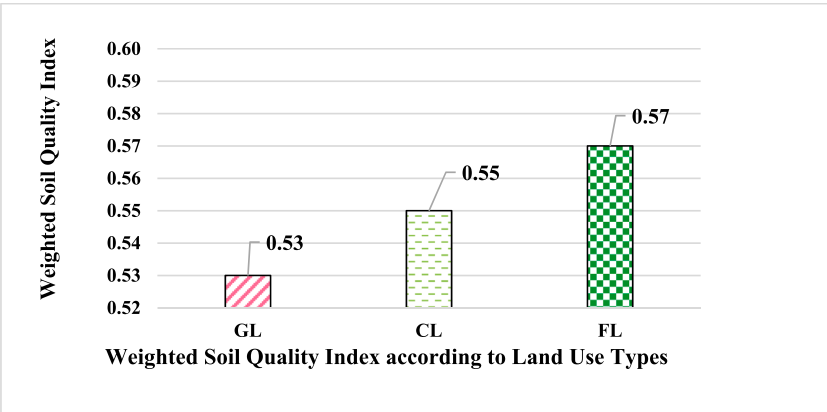

Fig. 7. Means values of A-SQI according to land use types.

3.4. Soil quality indices

3.4.1. Additive Soil Quality Index (A-SQI)

3.4.1.1. Partial indexes from Additive Soil Quality Index (A-SQI). The maximum SPQI value (0.04) was found in CL, and the average SPQI varied from 0.01 to 0.02. This is very weak, indicating that the soil structure in this catchment is very disturbed, signaling

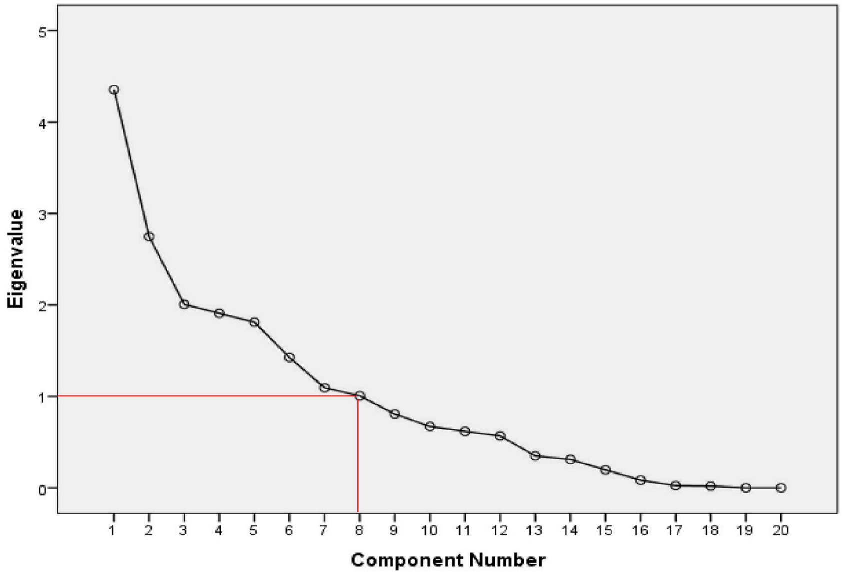

Fig. 8. Scree Plot Displaying PC_S and their Eigenvalues.

Table 8
PCs, communalities, eigen values, explained and cumulative variances, and calcultated weights.

Soil Indicators	Components								
	1	2	3	4	5	6	7	8	Communalities
Moisture	**.756**	−.296	.065	.098	−.132	.097	−.032	−.036	.702
BD	−.092	.038	.186	−.038	.315	**−.883**	.080	−.131	.948
Ksat	.299	.420	−.316	.060	.000	**.586**	.199	.147	.774
Sand	.243	.044	**.876**	.118	−.168	−.111	.266	.090	.962
Clay	.367	.158	**−.803**	.020	.088	.320	.086	−.212	.967
Silt	**−.717**	−.233	−.180	−.170	.109	−.224	**−.428**	.127	.891
BIR	.081	−.245	.024	.151	**−.729**	.097	.127	.310	.744
pH	.190	.156	.040	**.752**	.265	.298	.157	.111	.823
Ec	.112	.079	**.453**	.129	**.500**	**.569**	.146	−.117	.850
N	.032	**.964**	−.090	.010	−.017	.047	.075	.018	.948
PO4–P	−.265	−.396	−.099	**.535**	−.097	−.242	.352	−.036	.716
Exch. K	.482	.141	.013	**.524**	.050	.024	−.220	**−.543**	.873
Exch. Na	.096	−.328	**.608**	−.250	−.019	.110	−.246	−.094	.631
Exch.Ca	**.718**	.257	−.071	.197	−.081	.034	−.102	.340	.758
Exch. Mg	**.766**	.080	−.066	.037	.198	.040	.321	.052	.745
CEC	.207	−.048	−.040	**.853**	−.304	−.021	.141	.108	.899
TOC	.032	**.964**	−.090	.010	−.017	.047	.075	.018	.948
MBN	.109	.095	.126	.130	−.024	.133	−.107	**.847**	.801
MBC	.174	.137	.025	.208	−.007	.038	**.880**	−.054	.871
MN	.000	−.192	−.154	−.014	**.711**	−.076	.022	.124	.588
SRM	**−.477**	−.044	−.127	.081	**.433**	−.187	.101	.324	.591
Eigen values	4.757	2.898	2.006	1.937	1.820	1.481	1.112	1.018	
Variance Explained (%)	22.654	13.802	9.551	9.222	8.664	7.052	5.293	4.848	
Cumulative Variance (%)	22.654	36.456	46.007	55.229	63.893	70.945	76.239	**81.087**	
Calculated Weights	**0.279**	**0.170**	**0.118**	**0.114**	**0.107**	**0.087**	**0.065**	**0.060**	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

degradation. Regarding SCQI, the maximum values in sites and of averages were found in FL (0.95 and 0.55, respectively), followed by CL (0.69 and 0.52, respectively). Regarding SBQI, maximum values in sites and of averages were found in FL (0.79 and 0.70, respectively), followed by CL (0.79 and 0.49, respectively) as shown in Table 6 and Fig. 6. The SCQI and SBQI suggest that FL is the best land use type in terms of sustainability.

Moreover, the SPQI level of variation shows that minimal change has occurred in regards to the physical parameters, which are designated as inherent or non-dynamic. SCQI and SBQI are also called dynamic soil quality indexes because the changes are more pronounced due to hydro-climatic processes [22,33].

Table 9
Pearson correlation matrix for highly loaded factors from PC 1 to PC 6.

	Moisture	BD	Ksat	Sand	Clay	Silt	BIR	pH	EC	N	PO4–P	Exch. K	Exch. Na	Exch. Ca	Exch. Mg	CEC	TOC	PMN
Moisture	1																	
BD	−.122	1																
Ksat	.184	−.548**	1															
Sand	.226	.183	−.144	1														
Clay	.187	−.389	.616**	−.649[aa]	1													
Silt	−.492[a]	.213	−.518**	−.508[a]	−.326	1												
BIR	.302	−.364	.012	.235	−.152	−.120	1											
pH	.107	−.209	.283	.101	.180	−.329	−.026	1										
EC	.182	−.258	.183	.322	−.077	−.312	−.247	.421[a]	1									
N	−.206	−.042	.490[a]	−.009	.245	−.267	−.144	.154	.094	1								
PO4–P	−.078	.143	−.234	.041	−.132	.098	.164	.131	−.115	−.306	1							
Exch. K	.391	.017	.178	.084	.302	−.446[a]	−.095	.388	.193	.105	−.028	1						
Exch. Na	.109	−.016	−.157	.416[a]	−.432[a]	−.028	−.034	−.204	.068	−.369	−.152	−.025	1					
Exch. Ca	.300	−.274	.383	.175	.283	−.537**	.105	.347	.006	.245	−.117	.284	−.056	1				
Exch. Mg	.461[a]	−.104	.263	.144	.343	−.567**	.017	.402	.282	.147	−.097	.271	−.101	.610**	1			
CEC	.308	−.118	.197	.235	.104	−.410[a]	.411[a]	.586**	−.099	.008	.477[a]	.400	−.160	.297	.113	1		
TOC	−.206	−.042	.490[a]	−.009	.245	−.266	−.144	.154	.094	1.000**	−.306	.105	−.369	.244	.146	.008	1	
PMN	−.055	.241	−.012	−.178	.120	.085	−.298	.018	.189	−.099	.084	−.068	−.028	−.147	.005	−.107	−.099	1

[a] Correlation is significant at the 0.05 level. **. at the 0.01 level.

3.4.1.2. Results of Additive Soil Quality Index (A-SQI). The SQ class was determined using the classification table established by Refs. [38,52]. SQI values ranged from 0.55 to 0.63 for GL, 0.52, to 0.67 for CL and 0.57 to 0.77 for FL (Table 7, Fig. 7).

For GL, SQI values were all within the intermediate range (0.55 < SQI <0.70) [58]. For CL, two sites had their values below the intermediate range, considered as poor or low qualities (SQI <0.55), while the remaining six sites had intermediate qualities. For FL, SQI values in seven sites had their values within the intermediate quality range, except one site that was found to be of high soil quality (SQI >0.70). Additionally, 2 (8.33 %) of the studied lands had poor soil quality, 21 (87.5 %) sites had moderate or intermediate soil quality, and 1 (4.16 %) had very good or high soil quality. Regarding the average SQI scores, the three studied land use types had intermediate quality, but closer to the lower threshold (0.55) compared to the upper threshold (0.7). However, higher SQI average value (0.61) was found in FL, in comparison to CL (0.59) and GL (0.58). This means that a shift from FL to CL and GL causes land degradation, which leads to poor land quality [39]. The weakest soil structure of GL (SPQI of 0.01) explains its low ranking due to decreased stability and erosion resistance caused by grazing [55,59].

On the other hand, the average SQI scores showed little difference and change between land use types with respect to FL, CL and GL. This is because deforestation resulted in a secondary forest ecosystem in the watershed, leading to reduced vegetation system (fewer large trees compared to medium trees but more shrubs). The FL may even be referred to as "Shrub land (SL)" now, but still natural. This is attributed to the fact that FL have higher SCQI and SBQI, followed by CL and then GL. Therefore, it can be deduced that any land use change diminishing the natural ecosystem leads to loss of dynamic soil attributes [16,39].

It has been observed that the increase in plant biomass in Florida has led to a rise in SOC/TOM content, improved habitats for soil microorganisms, and enhanced stability of soil aggregates. On the other hand, the conversion of natural ecosystems to croplands and grasslands has reduced biomass, which in turn has affected soil nutrients [59,60]. This change is primarily caused by changes in the depth of the water table, which affects the balance between aerobic and anaerobic conditions. A decrease in water table depth leads to a shift from anaerobic to aerobic conditions in the soil, which accelerates the decomposition of organic input such as peat materials from vegetation on the ground, land burning, liming, fertilizing, and climate factors such as temperature and soil moisture [55].

3.4.2. Weighted Soil Quality Index (W-SQI)

3.4.2.1. Selection of identified key indicators (IKI) through Principal Component Analysis (PCA). Identified Key Indicators were performed using 24 soil physio-chemical and biological indicators through PCA, which grouped the variables into factors called Principal Components (PCs). To avoid redundancy, indicators derived from other parameters like OM, Na/K, Ca/Mg were removed from the total dataset before the PCA.

The scree plot (Fig. 8) shows a decreasing trend between the aforementioned factors and the eigenvalues as the number of components increases. A scree plot demonstrates the amount of variation that each PC extracts from the data. Eigenvalues, which essentially represent the degree of variation, are plotted on the y axis, while PCs number are plotted on the x axis. It is used to decide which key PCs to maintain. A perfect curve should be steep, bend at an "elbow" (here is where you cut off), then flatten out. In Fig. 8, from PC 8 onwards, an “elbow” was observed due to a sudden decline of the curve slope. It is noticeable that the first eight (08) PCs had eigenvalues >1 and accounted for 81.087 % of the data variability, therefore only the eight PCs were considered. Their eigenvalues ranged from 4.757 for PC 1 to 1.018 for PC 8 (Table 9).

Under PC 1, which explained 22.654 % of the variance, four (04) indicators with higher loading factors were considered, it included those with positive moderate loading factors Mg (0.766), Moisture (0.756) and Ca (0.718). Silt, which had a negative (−0.717) moderate loading factor was also selected. Among the highly loaded indicators, the correlation matrix (Table 9) showed that Mg and Moisture were weakly correlated (r < 0.5), while Mg, Ca and Silt were strongly correlated (r > 0.5), indicating that Mg is the most important factor. Therefore, only the two (Mg and Moisture) were retained as key indicators. Thus, PC 1 can be termed as the factor showing the interaction between basic cations, which are also soil macro-nutrients (i.e. Mg, Ca, K, CEC), moisture content and soil structure.

Under PC 2, which explained 13.802 % of the variance, two (02) indicators with similar very high positive loading factors were considered i.e. TOC (0.964) and N (0.964), since they had a very strong correlation (r = 1) between them (Table 9). Nonetheless, basing on literature review, only TOC was retained as a key indicator, thus, PC 2 may be termed as “total organic matter factor”.

Table 10
Pearson correlation matrix for Identified Key Indicators.

	Moisture	BD	Sand	BIR	Exch. Mg	CEC	TOC	MBN	MBC	MN
Moisture	1									
BD	−.122	1								
Sand	.226	.183	1							
BIR	.302	−.364	.235	1						
Exch. Mg	**.461***	−.104	.144	.017	1					
CEC	.308	−.118	.235	**.411***	.113	1				
TOC	−.206	−.042	−.009	−.144	.146	.008	1			
MBN	.102	−.179	.170	.189	−.002	.196+	.072	1		
MBC	.054	.074	.285	.056	.381	.310	.157	.025	1	
PMN	−.055	.241	−.178	−.298	.005	−.107	−.099	.029	−.084	1

[a]Correlation is significant at the 0.05 level. **. at the 0.01 level.

Table 11
W-SQI and relevant descriptive statistics according to land use types.

Land Use	W-SQI				
	Means	min	max	SD	CV
GL	0.53	0.32	0.64	0.10	18.02
CL	0.55	0.38	0.72	0.11	19.14
FL	0.57	0.48	0.70	0.07	12.57

Table 12
Criteria of classification for identified key indicators [39].

Index	W-SQI Grades				
	I	II	III	IV	V
W-SQI	Very Low 0–0.19	Low 0.20–0.39	Medium 0.40–0.59	Good 0.60–0.79	Very Good 0.80–0.99

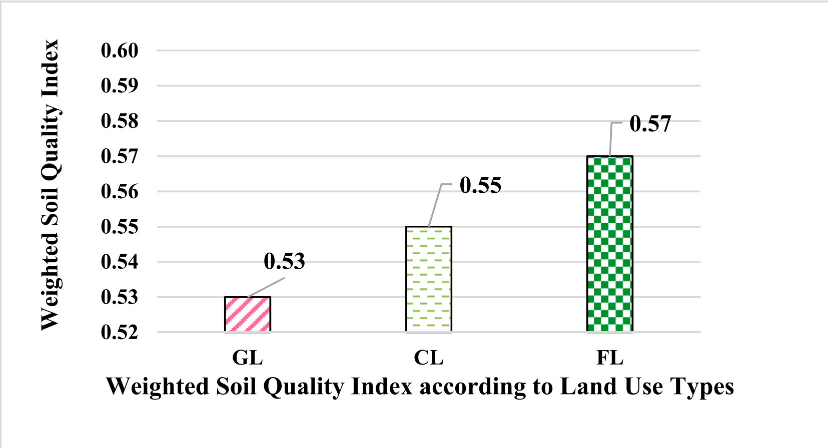

Fig. 9. Means values of W-SQI according to land use types.

Regarding PC 3, which explained 9.551 % of the variance, three (03) indicators were considered, i.e. Clay (−0.803) had a high negative loading factor, Sand (0.876) had a high positive loading factor, Na (0.608) and EC (0.453) had moderate positive loading factor. Sand was the highest weighted indicator having a high correlation with Clay (r = −0.649) (Table 9), hence only Sand was retained from PC3. Thus, PC 3 can be termed as the factor expressing the “effect of soil texture on soil salinity” because they were also significantly correlated.

Regarding PC 4, which explained 9.222 % of the variance, four (04) indicators were considered, i.e. P (0.535), K (0.524), pH (0.752) and CEC (0.853). The indicators had a moderate positive loading factors, with CEC having the highest value. Accordingly, only CEC which was the highest weighted indicator and also strongly correlated (Table 9) with the other weighted variables was retained from PC4. Thus, PC 4 can be termed as “soil macro-nutrients” group.

Concerning PC 5, which explained 8.664 % of the variance, three (03) indicators were considered, i.e. SRM (0.433), EC (0.500) and PMN (0.711) with moderate positive loading factors, and BIR (−0.729) with a moderate negative loading factor. BIR and PMN were the two (2) highly loaded variables and were weakly correlated (r = −0.298 < 0.5 in absolute value) (Table 9). BIR and PMN were retained as key indicators from PC 5. Thus, PC 5 may be termed as the factor expressing the “effect of BIR on nitrogen mineralization, soil salinity and respiration” because they were also significantly correlated.

Concerning PC 6, which explained 7.052 % of the variance, three (03) indicators were considered, i.e. EC (0.569) and Ksat (0.586) with moderate positive loading factors, and BD (−0.883) with a high negative loading factor. Thus, PC 6 expresses the “influence of BD on Ksat and EC”, it may be termed as “soil physical properties” (Table 9).

For PC 7, which explained 5.293 % of the variance, only MBC (0.880) has a higher loading factor. For PC 8, which explained 4.848 % of the variance, K (−0.543) with a moderate negative loading factor and only MBN (0.847) has a higher loading factor. Therefore, only BD, MBC and MBN were considered to be part of key indicators set in PCs 6, 7 and 8 because of their high loads. Moreover, PC 7 and PC 8 can be termed as “soil microbial biomass” factors, respectively “carbon” and “nitrogen”.

To conclude, the IKI is compound of a reduced set of ten (10) basic indicators: Mg, Moisture, TOC, Sand, CEC, BIR, PMN, BD, MBC and MBN. Among them, Mg and Moisture were strongly correlated, and CEC and BIR were also strongly correlated (Table 10).

Table 13
Partial SQI and relevant descriptive statistics according to land use types.

Land Use	SPQI					SCQI					SBQI				
	Means	min	max	SD	CV	Mean	min	max	SD	CV	Mean	min	max	SD	CV
GL	0.252	0.200	0.266	0.022	8.691	0.208	0.159	0.269	0.043	20.412	0.089	0.050	0.133	0.031	34.707
CL	0.219	0.172	0.255	0.035	16.133	0.218	0.056	0.352	0.091	41.545	0.115	0.065	0.144	0.030	25.775
FL	0.243	0.213	0.262	0.018	7.349	0.115	0.065	0.144	0.030	25.775	0.118	0.073	0.142	0.026	22.120

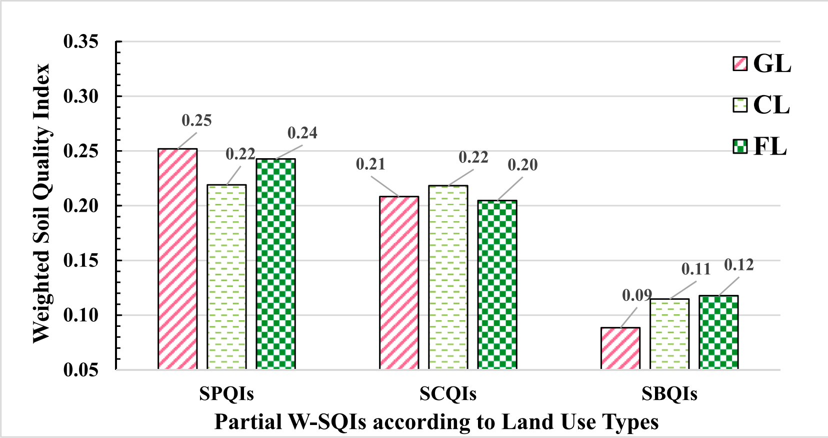

Fig. 10. Mean values of partial Soil Quality Indexes according to Land Use Types.

3.4.2.2. Results of Weighted Soil Quality Index (W-SQI). Applying PCs weights factors (Table 8) to IKI, the SQI developed through PCA resulted in Equation (8) and the results are as shown in Table 11:

$$W-SQI = \mathbf{0.279}S_{Mg} + \mathbf{0.279}S_{Moisture} + \mathbf{0.170}S_{TOC} + \mathbf{0.118}S_{Sand} + \mathbf{0.114}S_{CEC} + \mathbf{0.107}S_{BIR} + \mathbf{0.107}S_{PMN} + \mathbf{0.087}S_{BD} + \mathbf{0.065}S_{MBC} + \mathbf{0.060}S_{MBN} \tag{8}$$

The SQ class was established using the classification (Table 12) adopted from Ref. [39]. SQI values ranged from 0.32 to 0.64 for GL, 0.38 to 0.72 for CL and 0.48 to 0.70 for FL. For GL, one site was at "low" level ($0.20 < SQI < 0.39$), six at "medium" ($0.40 < SQI < 0.59$), and one at "good" ($0.60 < SQI < 0.79$). For CL, one site was at "low" level, five at "medium" and two at "good". For FL, two sites were at "good" level, then the remaining six were at a "medium" level. Overall, 2 (8.33 %) of the studied sites had "low" soil quality, 17 (70.83 %) had "medium" soil quality and 5 (20.83 %) had "good" soil quality.

Regarding the mean SQI scores (Table 11 and Fig. 9), the three studied land use types were all about intermediate or medium quality, but closer to the upper threshold (0.59). Higher SQI mean value (0.57) was again found in FL, in comparison to CL (0.55) and GL (0.53). This confirms the earlier deduction from the first indexing method that a shift from FL to CL/GL is a sign of land degradation, therefore resulting to negative impact on the quality of land.

3.4.2.3. Partial indexes from W-SQI. SQI was divided into components also called partial SQIs i.e. physical, chemical and biological for a better comprehension of the influence of each component on SQI and land degradation. However, some differences in regard to the components were noticed between the land use types (Table 13 and Fig. 10). FL has the second physical, chemical and first biological indices, followed by CL (third physical, second biological and first chemical indices) and GL. Higher contribution of biological and chemical indices to SQI explained the superiority of FL as reported by Ref. [17].

3.5. Evaluation and comparison of SQI computation methods

In terms of process, the A-SQI method does not require statistical pre-processing, unlike the W-SQI method, when selecting indicators.

In terms of results, the sensitivity follows an ascending trend with regard to magnitude: the higher the value, the greater the sensitivity. For A-SQI, the sensitivity value was 1.15 in GL, 1.30 in CL, 1.36 in FL, and 1.47 for the overall catchment, which was the highest value. From the results, 1.47 is the maximum SQI value (0.77) reported within the 24 sites in FL divided by the minimum SQI value (0.522) found in GL. This method using larger dataset (LDS) shows how the indexing method is more sensitive to changes in land uses and land management strategies.

For W-SQI, the sensitivity value was 2.0 in GL, 1.89 in CL, 1.46 in FL and 2.25 for the overall catchment, which is the highest value. As such, 2.25 was the maximum W-SQI value (0.72) reported within the 24 sites in CL divided by the minimum value (0.32) found in GL. However, this method of reducing data is more sensitive (2.25) compared to the first method which was less sensitive (1.47). It also demonstrated how SQI values are influenced by data selection, scoring and indexing approaches.

A-SQI mean values varied from 0.59 to 0.61, while W-SQI mean values varied from 0.53 to 0.57. In addition, when comparing the mean values of the two methods using ANOVA test, followed by Duncan and Tukey tests, they all resulted in no significant difference ($p \geq 0.341$) at 1 % and 5 % significance levels between and within land use means. Therefore, the two methods led to similar values but the variation is wider and well demonstrated with the weighting method because of its higher CV ranging from 12.57 to 19.14 % compared to A-SQI method where the CV ranged from 5.02 to 10.73 % [54]. It also highlights that selection of data using PCA is more sensitive, objective and helps to reduce biases of data selection from expert opinion and literature review, therefore superior. It also helps to save time and reduce cost of lab tests and intensive lab works when larger set of indicators, as confirmed by relevant authors

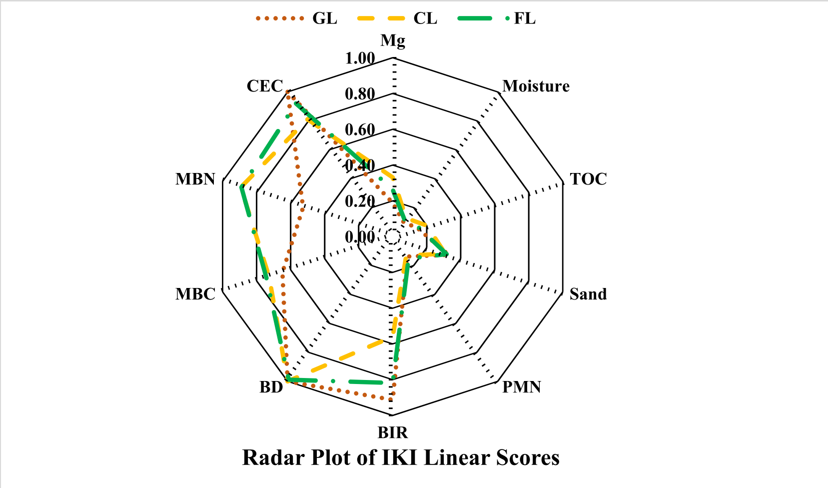

Fig. 11. Radar plot of IKI linear scores means.

such as Tesfahunegn (2014) [14] and Saleh et al. (2021) [41]. The two methods resulted to a same class of SQ "medium" for the different types of land use.

3.6. Limiting indicators among IKI

3.6.1. According to linear scores

The contribution of single indicators can only be made based on their linear scores. The radar plot (Fig. 11) shows the mean values of linear scores (Table 14) of the key indicators set (IKI). The three (03) lines crossing the ten (10) axes made by key indicators are land use types. The lines closed to the centroid or origin have lower linear scores, meaning low contribution, while lines towards the web periphery have lower linear scores, meaning higher contribution. PMN, TOC, Mg, Moisture and Sand appear to be more sensitive, therefore considered as limiting indicators, while BD, BIR, MBN, MBC and CEC are less sensitive.

3.6.2. According to linear scores and PCs weights

The contribution of the overall SQI (Table 15) is made by both linear scores (Si) of indicators and factors weights (Wi). The order of contribution was 18.68 % for CEC, 15.61 % for BD, 14.71 % for BIR, 14.26 % for Mg, 8.30 % for MBN, 8.26 % for MBC, 6.77 % for Sand, 5.75 % for Moisture, 5.16 % for TOC and 2.63 % for PMN as shown in Fig. 12. MBN, MBC, Sand, Moisture and TOC have contribution that was less than 10 %, and PMN less than 5 %. On the other hand, CEC, BD, BIR and Mg were found to be the major contributors (>10 %).

The contribution of Mg to SQI was highest under CL (17.61 %), followed by FL (12.84 %) and GL (12.35 %). For Moisture, it was highest under CL (6.46 %), followed by FL (5.60 %) and GL (5.19 %). TOC contributed maximum to SQI under CL (6.17 %), and minimum under GL (4.60 %). Sand contributed maximum to SQI under GL (7.07 %), and minimum under both FL and CL (6.63 %). PMN contributed maximum toward SQI under FL (2.92 %), and minimum under CL (2.40 %). For MBN, it was maximum under FL (9.44 %), and minimum under GL (5.76 %). For MBC, it was maximum under FL and CL (8.54 and 8.56 %, respectively), and minimum under GL (7.68 %). For BD, it was highest under GL (15.85 %), followed by CL (15.76 %) and FL (15.22 %). CEC contributed maximum

Table 14
Means values of IKI linear scores.

Land Use	Mg	Moisture	TOC	Sand	PMN	BIR	BD	MBC	MBN	CEC
GL	0.19	0.10	0.15	0.33	0.14	0.91	1.00	0.65	0.53	1.00
CL	0.33	0.13	0.20	0.31	0.13	0.56	1.00	0.73	0.89	0.81
FL	0.26	0.11	0.16	0.32	0.15	0.82	0.99	0.74	0.89	0.92

Table 15
Means values of IKI "Si * Wi".

Land use	Mg	Moisture	TOC	Sand	BIR	BD	MBC	MBN	PMN	CEC
GL	12.35	5.19	4.60	7.07	17.79	15.85	7.68	5.76	2.56	20.77
CL	17.61	6.46	6.17	6.63	10.84	15.76	8.56	9.71	2.40	16.79
FL	12.84	5.60	4.71	6.63	15.49	15.22	8.54	9.44	2.92	18.49
Mean	14.26	5.75	5.16	6.77	14.71	15.61	8.26	8.30	2.63	18.68

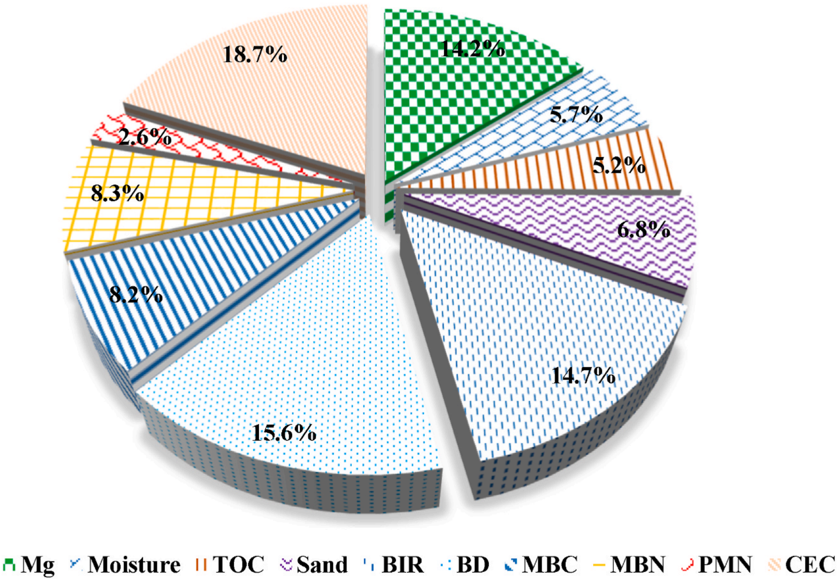

Fig. 12. Summary of IKI Contributions (%) to soil quality under land use types.

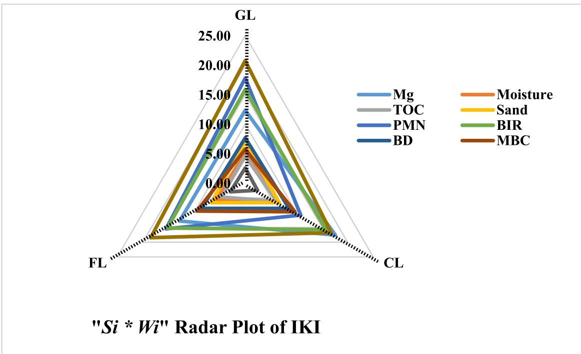

Fig. 13. Contribution (%) to W-SQI of the different IKI according to Land Use Type.

to SQI under GL (20.77 %), followed by FL (18.49 %) and the minimum was observed under CL (16.79 %).

Considering both linear scores and weights, Mg is not a limiting factor as indicated in the radar plot of linear scores. There is a change of limiting indicators sets from "PMN, TOC, Mg, Moisture and Sand" to "MBN, MBC, TOC, Sand, Moisture and PMN" using the product "Si * Wi" radar plot (Fig. 13). The lower contribution can be explained by indicators that do not fill both higher linear scores and higher PCs lower weights. Linear scores (0.1–1) accounted more than weights (0.06–0.279) because of their greater values.

The results show that these lands are impaired because of the low level of indicators identified as limiting, such as TOC that is considered by many authors as the best indicator. Moreover, TOC is very crucial for both nutrients cycle and for carbon sequestration [17,22,49].

3.7. Limitations and weaknesses of the models

Although many advantages were given by the methods used, many uncertainties and limitations may be noticed. The major ones are (i) the size of the original dataset may impact PCA when determining IKI set, meaning the PCA may not be efficient if the number of indicators is small. (ii) Indicators scores depend on threshold ranges, which were mainly determined based on literature review and on the author experience in order to properly match the biophysical and climatic conditions of the study area, thus it may have contained some errors. (iii) The SQI for all crops might be different from SQI for a specific crop and also depending on the managements practices used. (iv) The time, date and season of soil samples collection might have a significant impact on the indicators scores extent/magnitude, therefore it also has an impact on SQI values and the IKI set.

Indeed, each indicator amount, mainly intrinsic indicators varied based on the vegetation cover, which relied on the vegetation development stages (field preparation, seeding, growth, harvesting), and applied management practices. The indicators were also impacted by the climate and/or the season. These factors brought important changes on the set of limiting indicators. A study done by

Ref. [49] revealed that organic (composting) treatment gave higher SQI than other management practices. In our case, soil sampling was done during field preparation, where farmers used manure and compost, which may have led to higher OM/TOC, thus leading to a greater SQI than sampling done during postharvest period and dry season.

4. Conclusion

The objectives of this project were to evaluate the soil sustainability status of the catchment soils using (i) two types of indicators dataset (LDS and IKI), one linear scoring function (HLSF), two different SQ indexing methods (A-SQI and W-SQI) and (ii) discover both the most appropriate set of indicators and SQ indexing method through a comparison made possible by the sensitivity analysis and statistical studies. The investigation led to the following conclusions.

- The catchment soils physical, chemical and biological characteristics did not differ significantly from each other at a depth of 20 cm.
- The two SQ indexing methods both resulted in "medium" SQIs with FL having the highest SQI, followed by CL and GL.
- The A-SQI method provided an early warning regarding soil degradation severity since 95.84 % of soils were classified between poor and medium quality as detailed: 2 (8.33 %) of the studied lands had poor soil quality, 21 (87.5 %) had medium soil quality and only 1 (4.16 %) had very good or high soil quality, compared to W-SQI method, which led to 79.17 % of soils being classified between poor and medium quality.
- W-SQI method using PCA as data reduction tool was the most sensitive when evaluating SQI differences between land use types. Ten (10) basic indicators were included in the IKI dataset with at least one representing the three types of soil attributes: Mg, Moisture, TOC, Sand, CEC, BIR, PMN, BD, MBC and MBN.

Based on the results of the study, the researchers came to the conclusion that choosing a minimal dataset, such as the cost and time saving IKI set, is more advantageous for representing/predicting a sufficient SQI. Furthermore, the W-SQI method is more advantageous in Kenya as it is a developing country, where farmers do not have enough funds to assess a large set of indicators, therefore soil quality assessment requirements in policies need to be simple and affordable to be accepted. Following the national order to expand its agricultural land and meet the growing demand for food, the study county has been the main production area for livestock, maize and wheat. As long-term cultivation is maintained with poor sustainable land management (SLM) practices, land degradation processes will be exacerbated. Best SLM strategies, including soil water conservation practices should be identified, prioritized, implemented and monitored in order to prevent soil degradation and to maintain its sustainability and improve the quality of degraded soils, using SQI as a decision support tool. So much has been done to evaluate the soil quality, more needs to be done to come to definitive results in Kakia-Esamburmbur catchment by measuring soil quality periodically, and according to soil sub-layers and to existing land management strategies in CL. Indicators of pollution such as heavy metals should also be studied.

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Data availability statement

The supplementary data supporting the findings of this study are available online at https://data.mendeley.com/datasets/gcmtz82gnp/1.

Additional information

There is no extra information available for this paper.

CRediT authorship contribution statement

Wendyam Arsene Flavien Damiba: Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **John Mwangi Gathenya:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization. **James Messo Raude:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization. **Patrick Gathogo Home:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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