

Research Article

Assessment of soil health of different perennial tree species in orchard of coarse loamy Typic Haplustepts soil of Punjab

Nongmaithem Shitaljit Singh

Department of Soil Science and Agricultural Chemistry, School of Agriculture, Lovely Professional University, Phagwara-144411 (Punjab), India

Thounaojam Thomas Meetei* 

Department of Soil Science, College of Agriculture, Rani Lakshmi Bai Central Agricultural University, Jhansi-284003 (Uttar Pradesh), India

Department of Soil Science and Agricultural Chemistry, School of Agriculture, Lovely Professional University, Phagwara-144411 (Punjab), India

Yumnam Bijilaxmi Devi

Natural Resource Management, College of Horticulture and Forestry, Rani Lakshmi Bai Central Agricultural University, Jhansi, Uttar Pradesh 284003, India

*Corresponding author: E-mail: thounaojamtmeetei@gmail.com

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How to CiteSingh, N. S. *et al.* (2025). Assessment of soil health of different perennial tree species in orchard of coarse loamy Typic Haplustepts soil of Punjab. *Journal of Applied and Natural Science*, 17(2), 845 - 859. <https://doi.org/10.31018/jans.v17i2.6246>**Abstract**

Assessment and quantification of soil health through the Soil Quality Index (SQI) is an important tool for the comparative evaluation of different land use systems. The present study aimed to evaluate the long-term effects of four different perennial orchards (>8 years)- kinnow (*Citrus nobilis* x *Citrus deliciosa* L.), guava (*Psidium guajava* L.), mango (*Mangifera indica* L.), and ber (*Ziziphus mauritiana*) on soil health attributes concerning different soil functions in surface (0–20 cm) and sub-surface (20–40 cm) soil layers. The effectiveness of these orchards in improving soil health was compared with that of a natural forest and cultivated agriculture (maize; *Zea mays* L.). Different perennial orchard plantations exhibited varying values for soil health attributes. Principal component analysis (PCA) identified soil texture as the primary factor influencing soil function in the selected orchards due to monsoonal flooding and erosion. The SQI values revealed that in surface soil (0-20 cm), kinnow (0.836) and guava (0.848) orchards had values comparable to the natural forest (0.857), whereas mango (0.727) and ber (0.708) orchards had even lower values than the cultivated agriculture (0.817). In the sub-surface soil (20-40 cm), cultivated agriculture (0.653) revealed the lowest SQI values, highlighting the importance of perennial tree species in improving sub-surface soil health through the high return of root biomass. The study concluded that kinnow and guava orchards improved soil health by preventing land degradation, whereas mango and ber orchards had a lower potential for this purpose. Proper management practices can help sustain soil health and prevent degradation.

Keywords: Perennial tree species, Orchard, Soil health, Soil quality index (SQI)**INTRODUCTION**

Soil is a vital natural asset that is pivotal in sustaining life on Earth. It comprises a diverse mixture of minerals, water, air, organic materials, and living organisms, forming the basis for the growth and progress of plants. The concept of soil health encompasses the capacity of soil to perform essential functions sustainably, including the recycling of nutrients, retention and absorption of water, and promoting biodiversity (Tahat *et al.*, 2020). Preserving soil health is of utmost importance in agri-

culture, forestry, horticulture, and natural resource management, as it contributes to ensuring food security, environmental sustainability, and resilience to climate change. Unfortunately, human actions pose significant risks to soil health, resulting in the degradation and deterioration of soil quality (Mandal *et al.*, 2020). The increasing population has led to the extension of farming practices that aggravate the soil health deterioration processes (Hossain *et al.*, 2020). This deterioration has far-reaching consequences for human well-being and the functioning of ecosystems. Since soil is a

non-renewable resource, once degraded, it cannot be reclaimed within a short period of time (Clunes *et al.*, 2022). It is imperative to protect and enhance soil health by adopting sustainable land management practices that promote soil productivity, biodiversity, and resilience. However, for any management practices to be effective, it is of utmost importance to assess the soil health. This assessment helps to determine the type of problem associated with the soil, thereby identifying management practices that could be implemented to improve production (Eze *et al.*, 2022).

Fruit tree cropping systems are an age-old practice that has been in use since time immemorial (Saroj and Krishna, 2023). They play a major role in shaping a country's economy and nutritional advantage, as fruits are an excellent source of vitamins, minerals, and fiber. Agriculture alone cannot support the growing population's economy and the nutrition required, which is expected to peak at 11.2 billion in 2100 (O'Sullivan 2023). To contribute to the worldwide food crisis and nutrition, fruit farming is gaining popularity in the current era. However, the progressive decrease in yield and quality is a global problem due to the intensive fruit tree cropping system. Different technologies have been implemented to cope with the low production and nutrition of fruit farming. However, the major factor affecting production and nutrition is the deterioration of soil health (Tahat *et al.*, 2020).

Soil health encompasses the physical, chemical and biological properties of soil. It reflects both the quality and quantity of fruit produced. The increasing population is the major factor that leads to soil health deterioration. Various problems emerge in the soil due to specific human activities, rendering the soil unsuitable for fruit tree cultivation. The intensive practices of fruit tree cropping and excessive application of agrochemicals exacerbate the situation, leading to further negative consequences (Lykogianni *et al.*, 2021). Therefore, identifying the problems associated with soil health is crucial for implementing management practices that sustain soil for improved production. Since soil health is a combination of soil's physical, chemical, and biological properties, all three components are interrelated; each supports the others and vice versa. In current farming practices, there is a predominant focus on soil fertility, with the belief that it is the sole factor in improving soil health (Sofa *et al.*, 2022). However, soil fertility will only improve once the physical and biological properties of the soil are enhanced. Therefore, it is crucial to address all aspects of soil health to identify the problem, ensuring that the soil effectively nourishes fruit trees in a highly productive manner.

Assessment of soil health and predicting the problem associated with better management practices have been a considerable discussion in agriculture. However, in orchards where different fruit tree farming takes

place, soil health assessment is neglected due to the effort required to create an agreement on a common set of rules for evaluation. Soil that is seen as good in one type of farming might not be seen the same way in another type of farming. This makes it challenging to figure out if the soil is in good health or not. Since time immemorial, farmers have judged soil health using descriptive or qualitative terms for sustainable crop production (Crookston *et al.*, 2022). They believe that soil containing higher clay per cent, dark color soil and few other qualitative indicators are more productive. Since soil health is also a qualitative term, soil health by itself is not enough to determine problems linked to a specific fruit tree system solely based on a limited study of soil parameters. Over the years, a progressive shift has shifted from soil qualitative to quantitative assessment. Therefore, to assess the overall soil health response to different land use systems or any cropping patterns, a soil quality index (SQI) is commonly used.

The Soil Quality Index (SQI) serves as a quantitative indicator for assessing the soil's capacity to perform various functions (Karlen *et al.*, 2003). Andrews *et al.* (2002) came up with a popular way to measure SQI, and since then, many scientists have used this method in different areas and for different farming purposes. However, limited information is available regarding how different tree species in perennial orchard of coarse loamy typic haplustepts soil of Punjab, India, respond to soil health and quality parameters. Therefore, the present study examined the impacts of 10-year-old perennial orchard farming utilizing four perennial fruit tree species on soil quality attributes (physical, chemical, and biological) in the experimental orchard of coarse loamy Typic Haplustepts soil of Punjab. For a comparative study with the perennial orchard, one natural forest and agricultural (maize) land use system were included. Different perennial fruit tree species have varying abilities to either improve or degrade soil health, which can be assessed by comparing them with natural forests and cultivated agricultural land using estimates from the Soil Quality Index (SQI) at two depths.

MATERIALS AND METHODS

Study description

The study was carried out at the orchard farm of Lovely Professional University, Punjab, India, located in Phagwara, Kapurthala district, lies between 31°14'24.22"N latitude and 75°41'54.89"E longitude, situated at an elevation of 254 meters above sea level. Phagwara lies within Punjab's central plain area, one of the six agroclimatic zones in the state (Fig. 1). The primary soil type prevalent in the area is tropical arid brown soil. This type of soil is often deficient in nitrogen, potassium, and phosphorus. The region mainly encompasses the river tract situated between the Beas and Black

Bein, referred to as 'BET'. South of the Black Bein is an area known as 'Dona', indicating that the soil comprises two main components, with sand being predominant over clay (Central Ground Water Board). The soil color of the study area is grey to greyish brown, a function of pH, redox reaction and organic matter. The texture varies from sandy loam or sand (typic haplustepts) on the surface and sub-surface. The structure of most of the soil, both on the surface and sub-surface in the area, is sub-angular blocky (Rafie and Kumar, 2021).

The climate of the study area is classified as humid subtropical and semi-arid, characterized by extreme temperatures in both summer and winter seasons with a mean annual air temperature of 27.85°C and annual rainfall typically varies between 500-750 mm, with a significant portion occurring during the South-West monsoon between July and September. The summer months, spanning from April to June, are hot and dry, while July to September brings hot and humid weather. Cold winters prevail from November to January, followed by a mild climate in February and March. Summer temperatures can reach highs of 48°C and lows of 25°C, whereas winter temperatures range from 19°C to -1°C.

Soil sample collection and analysis

Soil samples were collected from the surface (0-20 cm) and sub-surface (20-40 cm) layers of kinnow (*Citrus*

nobilis x *Citrus deliciosa* L.), guava (*Psidium guajava* L.), mango (*Mangifera indica* L.), and ber (*Ziziphus mauritiana*) grown in the experimental orchard of Lovely Professional University before the onset of the monsoon in March 2022. Representative composite soil samples were collected from each block. These composites were prepared by mixing soils collected from beneath the canopy of the fruit trees and between the tree species. From each block in the orchard, which comprised kinnow, ber, mango, and guava, 3 composite soils were collected from two different depths, totalling 28 samples. Following the same method of soil collection from the surface and sub-surface, 12 composite samples were also collected from both the natural forest and cultivated maize field using a zig-zag sampling method using a screw augur. The collected composite soil samples were air-dried at room temperature, crushed, and finely ground to pass through a 2 mm sieve for subsequent examination. They were then kept dry to assess their physical and chemical soil properties. Air-dried samples sieved through the 2 mm sieve were used for soil textural analysis using a Bouyoucos hydrometer method (Bouyoucos, 1951), soil bulk density (BD) by core method using cores of 6.0 cm in height and 6.0 cm in diameter (Blake and Hartge, 1986). The in-situ infiltration rate (IR) was assessed using a double -ring infiltrometer at 3 randomly selected sites within each of the 6 land use categories in the surface soil

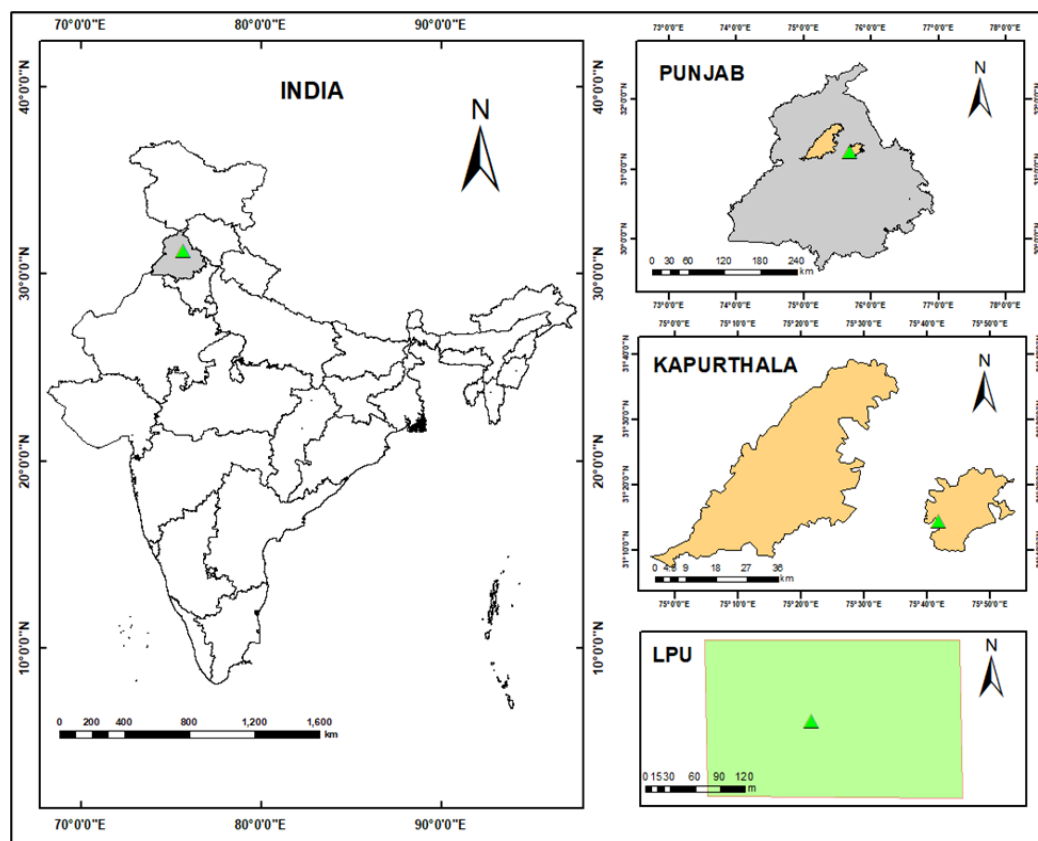


Fig. 1. Map showing the study area of the LPU Orchard Farm

(Middleton, 1930). The pH and EC of the soil suspension, i.e., 1:2 (soil: water), were measured by a pH meter and a conductivity meter, respectively (Jackson, 1973). Soil available nitrogen (N) was determined by the alkaline potassium permanganate method (Subbiah and Asija, 1956), available phosphorus (P) by Olsen extraction method (Olsen, 1954), available potassium (K) by 1 M NH_4OAC and measured by a Flame photometer (Hanway and Heidel 1952), same extractant were used to determine the sodium (Na) content in soil. Available sulfur (S) was determined by the turbidimetric procedure (Chesnin and Yien, 1950), exchangeable Ca+Mg were by complex titration method (Barrows and Simpson, 1962) and cation exchange capacity (CEC) by indirect measurement of Na using flame photometer (Bower *et al.*, 1952). Meanwhile, 0.5mm sieved samples were used to analyse dichromate oxidizable SOC using a rapid titration method using a diphenylamine indicator (Walkley and Black, 1934). For biological property analysis, fresh undisturbed soil samples were collected and immediately sealed in plastic bags, then kept in the refrigerator at 2°C. From these sub-samples, dehydrogenase enzyme activity (DHA) were determined by triphenylformazan (TPF) reduction method (Casida, 1977), basal respiration (BR) by alkali trap method (Mac Fayden 1970) and soil microbial biomass carbon (SMBC) by chloroform fumigation extraction method (Vance *et al.*, 1987).

Development of soil quality index (SQI)

First, based on the three primary functions of the soil viz filtering and buffering (environmental goal), nutrient cycling (productivity and environment goal), soil biological properties and soil health indicators were selected for indexing overall properties of the soils of selected different land uses. Since all the selected indicators do not represent the properties of the study location, selected minimum data sets (MDS) were generated using principal component analyses (PCA), which represent the potential soil quality indicators that define the properties of the selected land uses (Andrews *et al.*, 2002). The MDS generated was again converted into a unit less score of 0 to 1 scale through simple scoring methods using three types of regular scoring functions viz. (i) More is better, (ii) Less is better, (iii) and Optimum is better (Amorim *et al.*, 2020). This step scales and normalizes physical, chemical and biological indicators to be combined into composite indices (Mao *et al.*, 2019). The notion that “less is better” was used for the bulk density and Na content, as the low values of these factors indicate better aeration and less soil dispersion, respectively. On the other hand, the infiltration rate (IR), all the essential nutrients (Av. N, P, K, S, Ca and Mg), CEC, also the biological properties, SMBC, BR and DHA were grouped under “more is better”, as more the entry of water, more the essential nutrients and CEC

more is the soil function. The soil health attributes pH, EC, sand%, silt%, and clay% were categorized as optimum and better. For these indicators, threshold values were decided and both scoring functions were used. If the value obtained from the analysis is less than the threshold value then the “more is better” function was considered, after which the “lower is better” function was used as described above (Sharma *et al.*, 2005; Zeraatpisheh *et al.*, 2020). Weights were assigned to the potential soil quality indicators based on their significance. The weight for each variable in the MDS was determined by dividing the indicator communality value by the total communality of the chosen components. After this, the individual scores (V_i) and assigned weights (W_i) were multiplied to obtain the weighted scores (0 to 1 scale), which were then summed up to get the soil quality index (SQI) representing the soil's state or condition of each land uses in the study (Equation) (Andrews *et al.*, 2002). In this case, a higher index score is assumed to indicate better soil quality or better soil function performance.

$$\text{Soil Quality Index (SQI)} = \sum_{i=1}^n W_i V_i$$

Where W_i = Weight of variables and V_i = Score of variables

Data analysis

For the data digitization after analysis, Microsoft excel, 2010 was used. After digitization, principal component analysis (PCA) was employed to remove redundant variables from the experiments and generate the MDS that define the most potential soil health indicators. For employing PCA, IBM SPSS statistics version 26 and R programming were used. For the surface soil only five (5) PCs were selected based upon the eigen value greater than 1 (one) that contributes 88.03% of the total variance. Similarly, for the sub-surface soil, PCs with eigenvalues greater than 1 were retained, only four (4) PCs were obtained, contributing to 79.28% cumulative variance. It was expected that the variables with high factor loading and principal components with high eigenvalues would be the variables that best represent system properties. Under each PCs selected based on the eigenvalue each variable was assigned a weight or factor loading and kept for further analysis. Absolute values within 0.70 (70%) of the chosen PC were considered highly weighted factor loading. The variable with the largest factor loading (absolute value) among well-correlated variables was selected for the MDS and was retained, while the rest were excluded from further analysis and discarded. For the mean data comparison, Duncan's Multiple Range Test (DMRT) was employed using SPSS. PCA correlation circle and contribution bar were generated using R program software.

RESULTS AND DISCUSSION

Characteristics of the soils

Soil physical properties under different land uses (Table 1) revealed that the bulk density of both the surface (0-20 cm) and sub-surface (20-40 cm) soil varied between 1.45 to 1.59 Mg m⁻³ and 1.53 to 1.77 Mg m⁻³, respectively. However, these values were statistically at par with each other. Overall, the values indicated a relatively high bulk density, with no notable variations observed among the land use systems for either depth. The high bulk density may be attributed to repeated tillage operations (Orzech *et al.*, 2021) and heavy traffic on the field, leading to increased soil compaction (Pulido-Moncada *et al.*, 2019). The lack of variation in bulk density among the land use systems within the small-acre LPU field suggests that the size of the field may have contributed to this uniformity. Furthermore, the textural classes of the studied land use systems fall under the coarse fraction (sandy loam to sand), with sand percentages ranging from 74.60% to 88.60% and 72.93% to 86.60% for the surface and sub-surface soil, respectively, with low silt and clay fractions. This disparity can be attributed to mismanagement practices such as intensive cultural practices, conventional tillage methods commonly employed, coupled with rainfall (flood during monsoon season) and excessive irrigation, which led to erosion and the removal of clay and silt particles. Such practices often lead to reduced cohesion among soil particles and the erosion of finer particles from the topsoil (Tarolli and Straffellini, 2020). Furthermore, it is important to note that elevated sand content in soils is often associated with intensified fertilizer and irrigation practices in agriculture (Huang and Hartemink, 2020) and is commonly observed in salt-

affected soils found in arid and semi-arid regions (Hengl *et al.*, 2017). This high sand % in soil resulted in a higher value of IR, with ber recorded highest value, followed by mango and is statistically at par with each other. Regarding clay content, the cultivated agriculture exhibited significantly higher values than the other land use systems, followed by guava and natural forest. This may be attributed to the construction of agricultural field bunds, which prevent the loss of finer soil particles compared to other land use systems in open fields (Wolka *et al.*, 2021). Overall, there was an increase in clay content across all the land use systems from the surface to the sub-surface, which is supported by several authors (Naylor *et al.*, 2022; Laskar *et al.*, 2021; Piotrowska-Długosz *et al.*, 2022). In the present study, this increase is due to the eluviation of finer particles to deeper depths along with rain and irrigation water (Sauzet *et al.*, 2023); a significant increase was recorded under guava and ber. The orchard under ber, mango, and kinnow showed progressively lower clay content. Due to the distribution of soil primary particles, the textural classes of the different land use systems vary depending on the amount of finer particles retained. The textural class of four land use systems was classified as loamy sand (kinnow, guava, mango, forest), one as sandy loam (agriculture), and one as sandy (ber) in the surface soil. In the case of guava and ber, the textural classes changed from surface to sub-surface due to significant changes in clay content from surface to sub-surface soil.

Significant differences existed in the values of various chemical indicators (Table 2). Soil pH of the studied land use systems varied from 6.75 to 8.13 and 6.60 to 7.79 in surface and sub-surface soils, respectively. There were significant changes in soil pH from surface

Table 1. Interaction effects of different land-use systems on soil physical properties of coarse loamy Typic Haplustepts soil of Punjab at two depths

Landuse type	Depth (cm)	BD (mg/m ³)	Sand (%)	Silt (%)	Clay (%)	Textural class	Infiltration (mm/hr)
Kinnow	0-20	1.52 ^{ns} (±0.10)	81.60 ^c (±0.30)	12.33 ^b (±3.21)	6.07 ^c (±0.03)	LS	17.02 ^d (±0.33)
	20-40	1.59 ^{ns} (±0.10)	80.27 ^b (±2.0)	13.33 ^a (±3.21)	6.40 ^c (±0.50)	LS	-
Guava	0-20	1.45 ^{ns} (±0.20)	80.60 ^d (±4.0)	10.33 ^c (±1.00)	9.07 ^b (±2.52)	LS	16.52 ^e (±0.36)
	20-40	1.53 ^{ns} (±0.10)	76.60 ^c (±3.61)	11.33 ^{ab} (±2.89)	12.07 ^a (±0.50)	SL	-
Mango	0-20	1.59 ^{ns} (±0.20)	87.26 ^a (±3.00)	6.67 ^e (±2.08)	6.07 ^c (±0.58)	LS	22.31 ^b (±0.98)
	20-40	1.63 ^{ns} (±0.10)	86.60 ^a (±0.50)	6.67 ^c (±0.58)	6.70 ^c (±0.30)	LS	-
Ber	0-20	1.52 ^{ns} (±0.10)	88.60 ^a (±2.00)	6.33 ^d (±0.58)	5.07 ^c (±0.58)	S	26.52 ^a (±0.58)
	20-40	1.55 ^{ns} (±0.20)	86.06 ^a (±1.73)	7.67 ^{bc} (±0.58)	6.30 ^c (±0.50)	LS	-
Forest	0-20	1.50 ^{ns} (±0.30)	85.27 ^b (±2.00)	6.33 ^d (±3.21)	8.40 ^b (±3.00)	LS	20.44 ^c (±0.34)
	20-40	1.73 ^{ns} (±0.20)	81.60 ^{ab} (±2.00)	8.00 ^{bc} (±2.08)	10.40 ^b (±0.50)	LS	-
Agriculture	0-20	1.54 ^{ns} (±0.20)	74.60 ^e (±3.00)	14.00 ^a (±1.73)	11.40 ^a (±1.15)	SL	15.26 ^e (±0.55)
	20-40	1.77 ^{ns} (±0.20)	72.93 ^c (±0.38)	14.67 ^a (±0.31)	12.40 ^a (±0.30)	SL	-

Different small letters between columns and * between the two depths indicate significant differences; (P<0.05) according to DMRT for separation of means; Values in parenthesis indicate standard error of mean (n=18); ns= Not significant; LS=Loamy sand; SL=Sandy Loam; S= Sandy

Table 2. Interaction effects of different land use systems on soil chemical properties of coarse loamy Typic Haplustepts soil of Punjab at two depths

Land use type	Depth (cm)	pH	SOC (%)	Av.N (kg/ha)	Av.P (kg/ha)	Av.K (kg/ha)	Av.S (kg/ha)	Ca+Mg (meq/100gsoil)	SAR (%)	EC (dS/m)	CEC (Cmol ⁺ /kg)
Kinnow	0-20	8.13 ^{a*} (±0.12)	0.39 ^b (±0.20)	221.61 ^{a*} (±19.16)	19.82 ^{bc} (±0.06)	98.93 ^{b*} (±8.48)	12.66 ^a (±4.12)	12.23 ^b (±0.06)	5.87 ^{ab} (±0.15)	0.77 ^{a*} (±0.02)	12.23 ^{b*} (±0.10)
	20-40	7.37 ^{ab} (±0.33)	0.17 ^{ab} (±0.09)	121.26 ^{ns} (±26.11)	22.04 ^b (±2.64)	85.87 ^{bc} (±2.82)	12.76 ^a (±5.99)	1.85 ^b (±0.17)	5.14 ^b (±0.32)	0.731 ^{abc} (±0.01)	10.87 ^b (±0.10)
Guava	0-20	7.34 ^{c*} (±0.04)	0.38 ^{b*} (±0.03)	196.52 ^{ab} (±31.57)	25.71 ^b (±7.26)	92.59 ^{bc*} (±1.71)	12.69 ^a (±48.33)	9.26 ^a (±0.24)	4.69 ^c (±1.02)	0.75 ^{bc*} (±0.01)	9.26 ^{e*} (±0.10)
	20-40	7.43 ^{ab} (±0.04)	0.23 ^{ab} (±0.06)	100.35 ^{ns} (±69.84)	28.63 ^b (±9.58)	87.36 ^{bc} (±1.12)	12.79 ^a (±59.78)	3.72 ^a (±0.40)	4.81 ^c (±1.89)	0.739 ^{ab} (±0.02)	8.76 ^e (±0.10)
Mango	0-20	7.75 ^{b*} (±0.04)	0.48 ^b (±0.08)	146.35 ^{abc} (±38.32)	25.04 ^b (±6.63)	84.37 ^c (±1.71)	11.98 ^b (±8.01)	10.45 ^b (±0.29)	6.66 ^a (±0.21)	0.74 ^c (±0.01)	10.45 ^{d*} (±0.20)
	20-40	7.26 ^b (±0.16)	0.33 ^a (±0.15)	87.81 ^{ns} (±54.68)	40.52 ^b (±31.97)	76.91 ^c (±5.52)	11.98 ^b (±1.88)	1.48 ^b (±0.24)	6.60 ^a (±0.10)	0.745 ^a (±0.03)	9.23 ^d (±0.10)
Ber	0-20	7.36 ^{ab*} (±0.02)	0.17 ^b (±0.12)	150.53 ^c (±43.45)	16.40 ^{bc} (±6.65)	98.93 ^b (±4.66)	12.59 ^a (±3.49)	11.31 ^b (±0.43)	4.63 ^b (±0.90)	0.73 ^c (±0.01)	11.31 ^{c*} (±0.30)
	20-40	7.46 ^{ab} (±0.04)	0.14 ^b (±0.10)	73.56 ^{ns} (±62.72)	18.13 ^b (±6.55)	95.20 ^{bc} (±4.88)	12.35 ^{ab} (±43.36)	1.77 ^b (±0.38)	4.62 ^b (±0.86)	0.719 ^c (±0.01)	9.76 ^c (±0.20)
Forest	0-20	6.66 ^d (±0.03)	0.93 ^{a*} (±0.35)	129.62 ^{bc} (±44.05)	14.07 ^c (±1.48)	106.03 ^b (±3.60)	11.89 ^b (±26.72)	14.33 ^b (±0.18)	5.23 ^b (±0.80)	0.73 ^c (±0.01)	14.33 ^{a*} (±0.20)
	20-40	6.60 ^c (±0.26)	0.20 ^b (±0.09)	175.62 ^{ns} (±12.54)	14.63 ^b (±1.52)	102.29 ^b (±3.42)	11.98 ^b (±16.41)	1.71 ^b (±0.17)	5.23 ^b (±0.61)	0.724 ^{bc} (±0.02)	12.23 ^a (±0.10)
Agriculture	0-20	7.55 ^b (±0.02)	0.33 ^{b*} (±0.12)	146.35 ^{abc} (±69.09)	80.93 ^a (±6.5)	148.59 ^a (±15.21)	12.61 ^{a*} (±1.66)	8.38 ^a (±0.35)	2.48 ^c (±0.21)	0.76 ^{ab*} (±0.01)	8.38 ^{f*} (±0.20)
	20-40	7.79 ^a (±0.36)	0.15 ^{ab} (±0.02)	83.63 ^{ns} (±44.05)	81.49 ^a (±6.67)	142.24 ^a (±24.26)	12.66 ^a (±1.26)	3.55 ^a (±0.68)	2.25 ^c (±0.10)	0.750 ^a (±0.02)	7.56 ^f (±0.20)

Different small letters between columns and * between the two depths indicate significant differences (P<0.05) according to DMRT for separation of means; Values in parenthesis indicate standard error of mean (n=18)

to sub-surface in the kinnow, guava, mango, and ber orchards. However, there were no significant differences between forest and cultivated agriculture. As a result of the higher pH values observed in these land use systems, the calcium (Ca) and magnesium (Mg) content were also relatively elevated. The agricultural land use system exhibited the lowest Ca+Mg content. Previous studies have reported a positive correlation between pH and Ca+Mg content (Moradi *et al.*, 2019; Luo *et al.*, 2020; Farhangi-Abriz and Ghassemi-Golezani, 2021), which is also reflected in the present study. The kinnow, mango, ber orchards, and the natural forest demonstrated comparable Ca+Mg content, with slightly higher values observed in the forest land use system compared to the kinnow orchards. However, due to their sandy soil texture, Guava orchards had slightly lower cation exchange capacity (CEC) than the other orchards. Sandy soils generally have lower CEC, base saturation, and fertility.

The natural forest in the present study showed a notable increase in soil organic carbon (SOC) content, which was significantly higher compared to other land use systems. This disparity can be attributed to the accumulation of canopy debris, resulting in a higher biomass litter layer (Zhang *et al.*, 2020). Conversely, the Ber orchards exhibited lower SOC content due to the removal of canopy litter after harvest. It is widely recognized that sandy soils tend to have lower SOC contents compared to other soil types (Pärmpuu *et al.*, 2022). Regarding available nitrogen (Av N) content, both the kinnow and guava orchards demonstrated significantly higher levels than other land use systems, and they were statistically similar. With soil depth, a significant decrease in Av N was recorded in kinnow, whereas no significant differences were observed for the other land use systems. There were no statistical differences among all land use systems for the sub-surface soil. The elevated nitrogen content in the kinnow and guava orchards can be attributed to fertilizer application or a rich biomass litter layer (Marañón-Jiménez *et al.*, 2022). In the cultivated agriculture land use system, phosphorus content was significantly higher than other land use systems, suggesting a higher input of chemical fertilizers and its residual effect (Iqbal *et al.*, 2021).

Potassium content varied from medium to low across different land use systems, with significantly higher levels observed in the agriculture land use system. The kinnow, guava, and ber orchards showed statistically comparable potassium contents, while the cultivated land use system exhibited higher levels, potentially due to crop residue burning or increased fertilizer application, such as muriate of potash (MOP). Sulfur content was statistically comparable among the kinnow, guava, ber, and agriculture land use systems, with relatively

higher levels observed. This may be attributed to the application of single super phosphate (SSP) and nutrient sulphur are contributed from it. In contrast, the mango orchard and natural forest, with low available phosphorus (Av P) content, had lower sulfur levels than other land use systems. The sodium adsorption ratio (SAR) of the mango orchard was statistically the highest among all but was on par with kinnow, which can be attributed to its positive correlation with the soil pH of these systems (Ghazali *et al.*, 2020). The lowest SAR value was recorded under cultivated agriculture, comparable among the kinnow, guava, and mango orchards, while the natural forest showed slightly higher sodium levels, next to the mango and kinnow orchards. The SAR value for all land use systems was statistically similar at both the depths. The cultivated agriculture land use system recorded the lowest SAR, which may be attributed to the use of different forms of fertilizers and irrigation that reduce the Na content in the soil (Dincă *et al.*, 2022). The kinnow orchards, because of its highest exchangeable Ca+Mg and soluble salts, recorded significantly higher electrical conductivity (EC) compared to the other land use systems, followed by agriculture, guava, and the remaining land use systems (mango, ber, and forest), which had statistically comparable EC values. The forest land use system exhibited significantly higher cation exchange capacity (CEC) than other land use systems, indicating a greater capacity for nutrient retention. On the other hand, the agriculture land use system had the lowest CEC values. In the present study, there was a significant decrease in CEC values across all land use systems.

The surface soil (0-20 cm) exhibited Soil Microbial Biomass Carbon (SMBC) ranging from 164.46 $\mu\text{g g}^{-1}$ to 303.93 $\mu\text{g g}^{-1}$ (Table 3). In the sub-surface soil layer (20-40 cm), the SMBC varied from 97.09 $\mu\text{g g}^{-1}$ to 263.43 $\mu\text{g g}^{-1}$. The natural forest exhibited significantly higher SMBC in both depths than other land use systems, whereas cultivated agriculture had the lowest SMBC content. The increased SMBC in the forest soil can be attributed to the greater accumulation of canopy litter, which enhances soil organic carbon levels and subsequently promotes the growth of microbial populations on the soil surface (Wu *et al.*, 2019; Tiwari *et al.*, 2019). The lowest in the cultivated land could be attributed to soil tillage practices and the absence of fallen litter canopies, leading to reduced microbial populations and soil surface exposure after tillage (Gruba and Mulder, 2015). The reduced microbial population in the agriculture field can be attributed to factors such as the application of chemical fertilizers, removal and burning of crop residues, and intensive tillage practices, all of which have negative effects on soil microorganisms (Sarkar *et al.*, 2020; Fu *et al.*, 2021; Shen *et al.*, 2019). Basal respiration (BR) both in the surface and sub-

surface soil was significantly higher in the forest soil compared to other land use systems, representing the activity of the soil organisms. This can be attributed to the higher value of SOC and SMBC in the forest soil as well as higher temperatures prevailing in the forest environment, which lead to an increased release of CO₂ (Massaccesi *et al.*, 2020). The forest was followed by kinnow, Guva and Ber. Similarly, in the sub-surface soil layer (20-40 cm), the natural forest still displayed the highest BR values, followed by the guava orchard and agriculture field. The BR of the kinnow orchard and cultivated land were statistically comparable, while mango orchards exhibited the lowest BR among the different land use systems. The forest land use system consistently demonstrated the highest BR values, indicating enhanced microbial activity and CO₂ release. Dehydrogenase activity in soil is positively correlated with the microbial population. The natural forest displayed the highest dehydrogenase activity, 0.291; however, it was at par with mango, kinnow, and guava (Table 3). The ber orchard showed an average dehydrogenase activity, whereas the cultivated agriculture had the lowest dehydrogenase activity. The low dehydrogenase activity observed in agriculture can be attributed to their low microbial populations and the residual effects of chemical fertilizers (Luo *et al.*, 2015), which can suppress soil microbial communities. Conversely, the agriculture field exhibited low dehydrogenase activity, suggesting a lower presence of living organisms in this land use system, possibly due to extensive tillage practices or the persistence of applied chemical fertilizers (Szostek *et al.*, 2022).

Principal Component Analysis

A significant correlation (Fig. 2 and Fig. 3) in both surface and sub-surface soil among all the variables indicated that different orchard perennial trees, forests, and cultivated agriculture significantly influenced specific soil health indicators. All soil health indicators do not need to influence soil quality equally. Through PCA, the most influential or representative soil health indicators for the surface (0-20 cm) soil were identified (Table 4). Using PCA, 5 principal components (PCs) were retained by selecting only eigenvalues greater than 1, contributing to a cumulative variance of 88.03%. PC1 explained 43.25% of the variance with an eigenvalue of 7.78 and was closely related to the filtering and buffering function. From PC1, sand % was retained, having the highest positive factor loading of 0.943. Similarly, from PC2, SMBC was retained, explaining 17.35% of the variance with an eigenvalue of 3.12, and was closely related to the soil biological function of soil. The percent variance of PC3, PC4, and PC5 was 12.72%, 8.15%, and 6.57%, respectively. The highest factor loadings of 0.775, 0.662, and 0.639 for pH, Av N, and BD were retained for developing the soil quality index. PC3 and PC5 of the PCA were closely related to the filtering and buffering function, while PC4 was related to the nutrient cycling functions of soil. For sub-surface soil, only four (4) principal components (PCs) explaining a cumulative variance of 79.28% were retained under similar conditions, with eigenvalues greater than 1. Depending on the factor loading of each PC, sensitive indicators were selected to represent the most dominant and reliable soil health indicators of the sub-

Table 3. Interaction effects of different land use systems on soil biological properties of coarse loamy Typic Haplustepts soil of Punjab at two depths

Land use type	SMBC (µg/g)	SMBC (µg/g)	BR (µg Co ₂ /g/DW/hr)	BR (µg Co ₂ /g/DW/hr)	DHA (µg/g/hr)	DHA (µg/g/hr)
	0-20	20-40	0-20	20-40	0-20	20-40
Kinnow	291.11 ^{b*} (±5.31)	227.23 ^b (±0.60)	4.51 ^{b*} (±0.19)	2.50 ^b (±0.30)	0.243 ^{ab*} (±0.01)	0.211 ^{ab} (±0.02)
Guava	204.37 ^{d*} (±0.59)	176.83 ^d (±1.70)	3.92 ^{c*} (±0.17)	2.78 ^{ab} (±0.20)	0.265 ^{ab} (±0.01)	0.224 ^{ab} (±0.05)
Mango	190.10 ^{e*} (±9.37)	165.67 ^e (±3.11)	2.42 ^{d*} (±0.22)	1.67 ^c (±0.40)	0.233 ^{ab} (±0.03)	0.237 ^a (±0.05)
Ber	229.03 ^{c*} (±5.35)	197.27 ^c (±3.07)	3.89 ^{c*} (±0.28)	2.43 ^b (±0.20)	0.222 ^b (±0.01)	0.191 ^{ab} (±0.05)
Forest	303.93 ^{a*} (±3.45)	263.43 ^a (±5.73)	5.17 ^{a*} (±0.33)	3.23 ^a (±0.20)	0.291 ^a (±0.05)	0.246 ^a (±0.06)
Agriculture	164.77 ^{f*} (±4.74)	97.09 ^f (±2.65)	4.22 ^{bc*} (±0.23)	2.76 ^{ab} (±0.20)	0.202 ^b (±0.06)	0.142 ^b (±0.05)

Different small letters between columns and * between the two depths indicate significant differences (P<0.05) according to DMRT for separation of means; Values in parenthesis indicate standard error of mean (n=18)

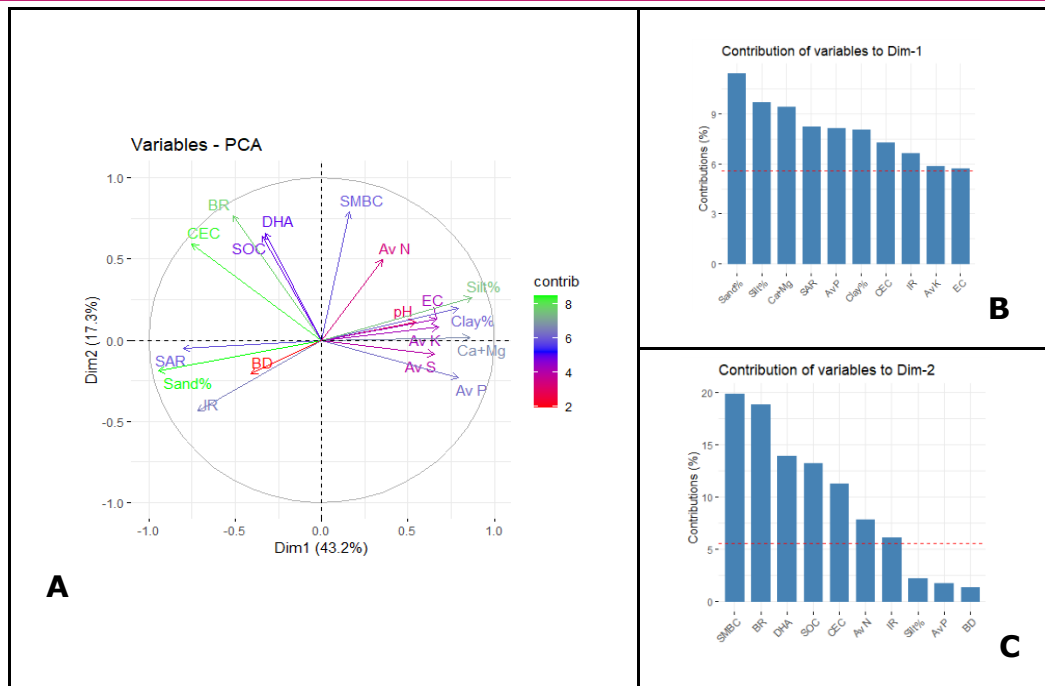


Fig. 2. For surface soil (0-20 cm) A. A correlation circle representing the original variables as vectors in a two-dimensional space formed by the two principal components (PCs). B. Contributions of variables to PC 1. C. Contributions of variables to PC 2

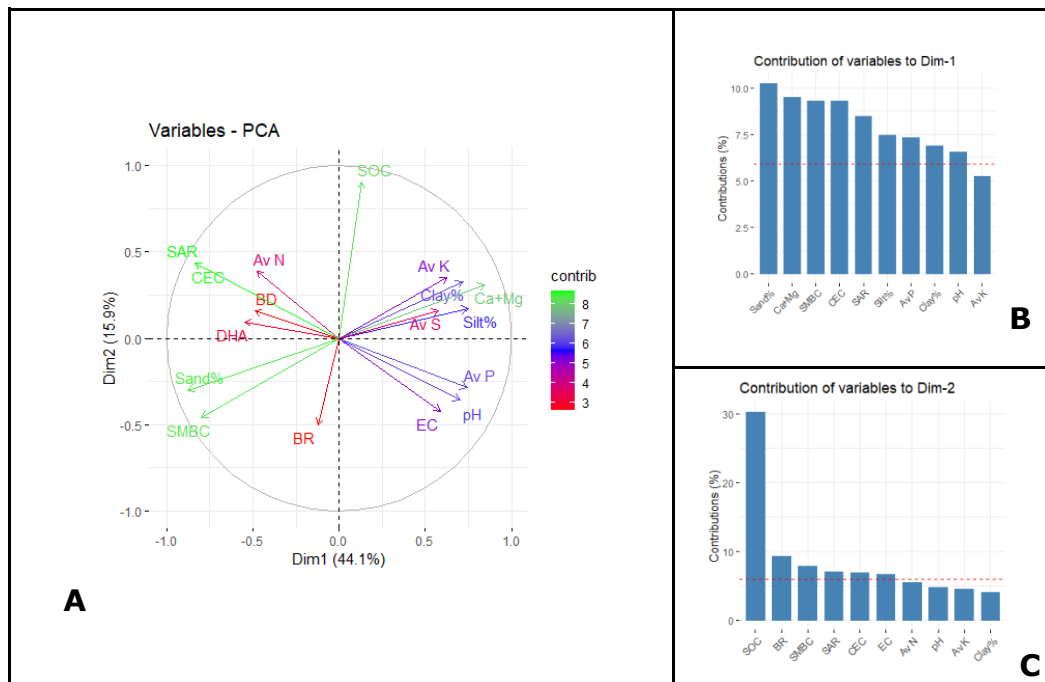


Fig. 3. For sub-surface soil (20-40 cm) A. A correlation circle representing the original variables as vectors in a two-dimensional space formed by the two principal components (PCs). B. Contributions of variables to PC 1. C. Contributions of variables to PC 2

surface soil (20-40 cm) (Table 5). From PC1, which accounted for 44.12% of the variance, sand with the highest factor loading of 0.877 was retained. Similarly, from PC2, PC3, and PC4, with respective variances of 15.90%, 11.30%, and 7.96%, the soil health indicators with the highest factor loading SOC (0.905), BR (0.701), and BD (0.608) were retained.

Based on the commonalities value, the assigned weight

of the selected sensitive indicators using PCA follows the decreasing order of sand% > Av N > SMBC > pH > BD for surface soil, whereas for sub-surface soil, it follows the decreasing order of SOC > Sand% > BR > BD. The soil quality index value varied among different land use systems, with varying combinations of tree species, in the research conducted. Through the implementation of principal component analysis, it became

apparent that only five variables (referred to as indicators) for surface soil and four variables for sub-surface soil were capable of explaining the variation in soil function across the different land uses. By considering the diverse soil properties identified through the PCA analysis, the soil quality index for each land use was determined, allowing for comparative studies to be conducted. Analysis of variance of the SQI for the surface soil of the studied perennial tree orchard plantation, in comparison with the natural forest and cultivated agriculture, revealed that the natural forest (0.857) recorded a significantly higher SQI value than the other orchard systems and cultivated land use system. Following the natural forest, the perennial orchard of guava recorded a significantly higher SQI value followed by kinnow, cultivated agriculture, ber and mango. When compared with cultivated agriculture, there was an improvement of around 3.65% and 2.27% in the SQI value for guava and kinnow, respectively. However, for the remaining orchard tree plantations, i.e. mango and ber, the SQI value decreased by 11.02% and 13.34%, respectively, compared to the cultivated agriculture. Similarly in the sub-surface soil the natural forest recorded a significantly higher SQI value (0.788) than the other land use systems, suggesting the most prominent land use system to improve or sustain the soil health. In

subsurface soil, the cultivated agriculture shows the lowest value; however, it is statistically at par with the other orchard soil. In the sub-surface soil, when compared to the cultivated agriculture, the SQI value of guava increased by 14.30% and 8.29% for the kinnow. Even the mango and guava soil can see some improvement in the subsurface soil when compared to the cultivated agriculture. It can also be seen from Table 6 that there was no significant change in SQI value from the surface to the sub-surface for the perennial orchards of guava, mango, and ber. However, for the other land uses in the present investigation, namely, kinnow, natural forest, and cultivated maize, a significant decrease in the SQI value was observed. In cultivated maize. There was approximately a 20.07% reduction in SQI; in the natural forest and kinnow plantations, the reductions were 8.05% and 14.83%, respectively. These smaller changes in SQI value from surface to sub-surface in the different tree plantations (both natural forest and perennial orchards) suggested that root biomass returns to the soil, resulting in higher SQI values than cultivated maize.

From the SQI value (Table 6), it can be inferred that soil health deterioration among all the land use systems occurred in order of natural forest<orchards<cultivated agriculture. The natural forest's soil binding capacity,

Table 4. Identification of most sensitive soil health attributes of surface soil (0-20cm) of coarse loamy Typic Haplustepts soil of Punjab through PCA analysis

Principal components	PC1	PC2	PC3	PC4	PC5	Communalities
Eigen value ^a	7.784	3.122	2.29	1.466	1.182	
Percent	43.246	17.345	12.723	8.145	6.568	
Cumulative percent	43.246	60.592	73.315	81.46	88.028	
Eigen vectors						
pH	.547	.112	.775	.050	-.089	.923
EC	.668	.129	.561	-.011	.263	.847
Av N	.351	.494	.260	-.662	.265	.943
Av P	.794	-.231	-.185	.256	.370	.921
Av K	.675	.078	-.156	.568	.250	.872
BR	.160	.766	.032	.519	-.149	.937
SMBC	-.514	.787	.294	.171	-.155	.991
SOC	-.343	.642	-.481	-.014	.203	.802
SAR	-.800	-.052	.390	-.080	.286	.884
Ca+Mg	.856	.015	-.353	-.172	-.152	.911
Clay%	.792	.195	-.470	-.067	-.015	.891
Sand%	-.943	-.190	.120	-.042	-.117	.955
Silt%	.868	.261	.309	.109	.167	.957
BD	-.408	-.207	.197	.083	.639	.663
Av S	.652	-.087	.453	-.078	-.411	.813
CEC	-.751	.592	.112	.253	-.045	.993
IR	-.718	-.437	.052	.292	.012	.795
DHA	-.324	.659	-.250	-.350	.149	.746

Bold factor loadings correspond to the indicators included in the MDS

Table 5. Identification of most sensitive soil health attributes of sub-surface soil (20-40cm) of coarse loamy Typic Haplustepts soil of Punjab through PCA analysis

Principal components	PC1	PC2	PC3	PC4	Communalities
Eigen value	7.501	2.703	1.921	1.352	
Percent	44.123	15.9	11.298	7.955	
Cumulative percent	44.123	60.023	71.322	79.276	
Eigen vectors					
pH	.701	-.359	-.411	.077	.794
EC	.589	-.422	.456	-.027	.734
Av N	-.478	.386	-.389	.088	.537
Av P	.741	-.287	-.033	-.332	.744
Av K	.626	.351	-.163	-.512	.804
BR	.133	-.501	.701	-.101	.900
SMBC	-.834	-.458	.012	.264	.956
SOC	-.123	.905	.501	.227	.810
SAR	-.798	.435	-.106	.100	.868
Ca+Mg	.844	.311	.281	.014	.888
Clay%	.718	.329	.439	.213	.861
Sand%	-.877	-.301	-.091	-.176	.898
Silt%	.748	.174	-.054	.139	.612
BD	-.490	.158	.293	-.608	.721
Av S	.577	.159	-.243	.581	.754
CEC	-.834	.433	.035	.103	.895
DHA	-.548	.095	.617	.105	.701

Bold factor loadings correspond to the indicators included in the MDS

facilitated by tree species and the substantial biomass return to the soil, contributes to a higher tolerance limit for erosion (Mosier *et al.*, 2021). This enhanced erosion tolerance could explain the higher clay percentage observed in these systems, resulting in good soil physical properties. Nevertheless, the availability and retention of soil nutrients are influenced by the soil organic carbon (SOC) content. Natural forests exhibited higher SOC values compared to other land use systems. This can be attributed to regular leaf litter accumulation, the absence of physical disturbances like tillage or crop cultivation for extended periods, and slower organic

matter decomposition (Prescott and Vesterdal, 2021). As a result of the increased biomass return and higher SOC values, nutrient availability, including nitrogen (Av. N), phosphorus (P), and potassium (K), is also enhanced in these systems.

On the other hand, orchard and agriculture land use systems recorded low nutrient availability. The higher soil quality index (SQI) observed in the surface soil of agriculture land use systems compared to some of the orchard plantations (Mango and ber) may be attributed to crop rotation practices. In agriculture, the rotation of crops contributes to improved soil health. Conversely,

Table 6. Quantification of landuse effects on soil health attributes

SI No.	Landuse types	SQI	
		0-20	20-40
1	Kinnow	0.836c	0.712ab*
2	Guava	0.848b	0.762ab
3	Mango	0.727e	0.709ab
4	Ber	0.708f	0.658b
5	Forest	0.857a	0.788a*
6	Agriculture	0.817d	0.653b*

in orchards, the repeated removal of biomass for aesthetic purposes and the excessive exposure of the surface soil may result in lower soil health, thus leading to a lower SQI value. However, in kinnow and guava, the SQI value was higher than that of the cultivated agricultural system.

PCA is a data reduction method that simplifies the complexity of variables and observations. The correlation circle of the first two principal components (PC1 and PC2), which account for the maximum variance, illustrates the relationships between the original variables by creating new dimensions (PCs). The angles between the vectors, or between the vectors and the principal component axes, provide valuable insights. Suppose the angle between the vectors is close to 0° or 180°. In that case, the variables were strongly positively or negatively related, respectively, while vectors at 90° indicate that the variables were mostly independent. When the vectors are perpendicular (90°) to the PCs, the contribution of that vector among the variables is at its maximum. A correlation circle, displaying the original variables as vectors in a 2-dimensional space created by the first two principal components (PCs), PC1 and PC2, represented a total variance of 60.5% with eigenvalues of 7.78 and 3.12, respectively, in the surface soil. The contributions were based on the cosine squared. The maximum contribution of the variables in the figure was indicated by color and the angle of the variables relative to the PC axes. Green indicates a higher contribution, while red indicates a lower contribution. Additionally, the line length associated with the variables indicated their contribution, with longer lines suggesting a greater contribution and vice versa. From Fig. 1 and Fig. 2, it is evident that the percentage of sand is represented by its absolute value, and its position relative to the PC1 axis indicates a strong negative correlation with PC1, followed by silt percentage. Conversely, in PC2, SMBC was highly correlated with PC2, showing a high factor loading, followed by BR, due to its perpendicular orientation to the PC2 axis. In the subsurface soil (Fig. 2), sand still showed the highest factor loading, lying perpendicular to PC1, indicating the maximum contribution, followed by Ca+Mg. In PC2, SOC showed the maximum contribution and had a positive relationship with all the nutrients present in the soil, followed by BR. These results indicate that the study area has experienced significant soil erosion, leading to an increase in sand percentage and a decrease in clay percentage. The findings also suggest that poor management of the perennial orchard tree plantation contributes to soil degradation and declining soil health. However, the high factor loading and strong correlation of SMBC, SOC, and BR with other variables highlight the vital role of microorganisms in maintaining soil health.

Conclusion

In the present study, the soil quality of different perennial orchards was compared to that of natural forest and cultivated agriculture using the Soil Quality Index (SQI). The findings revealed that soil texture, particularly the sand content, was the most important factor contributing to soil health in the study area. Furthermore, the SQI values indicated that the kinnow (*C. nobilis* x *C. deliciosa* L.) and guava (*P. guajava* L.) orchards had comparable values to the natural forest, whereas the mango (*M. indica* L.) and ber (*Z. mauritiana*) orchards recorded even lower values than the cultivated agricultural land (Maize; *Z. mays* L.). The subsurface soil followed the same trend; however, the SQI values of all the orchard trees were statistically similar, with cultivated agriculture showing the lowest values. This highlights the role of perennial trees in maintaining soil health in the subsurface layers due to their high root biomass. The principal component analysis (PCA) revealed that the perennial orchards on coarse loamy Typic Haplustepts soils in Punjab were susceptible to erosion. Therefore, it is essential to implement proper conservation practices for soil preservation, nutrient cycling, maintaining organic matter, and managing fertilizers, especially for the mango and ber orchards, to ensure sustainable soil health.

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Conflict of interest

The authors declare that they have no conflict of interest.

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