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A regional comprehensive soil quality evaluation method for orchard green agricultural development: Integrating soil fertility and environmental indicators in Hainan, China

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ABSTRACT

Effective soil quality evaluation can improve soil health and productivity as well as promote sustainable agricultural development. In this paper, a regional comprehensive soil quality evaluation method provides powerful tools for simultaneous assessment of the soil environment and soil fertility qualities based on an improved version of TOPSIS (Technique for Order Preference by Similarity to Ideal Solution, a mathematical calculation of multi-criteria decision analysis) combined with a fuzzy mathematical model. Eleven soil fertility and soil environment quality indices were selected to establish an index system for green agricultural development at the orchards in Hainan—a typical tropical fruit production area in southern China. Results showed that the soil fertility was primarily limited by three controlling factors: low total nitrogen (TN) content, low organic matter (OM) content, and acidic pH, indicating that these soils in the study area might experience poor nutrient and acidification problems. Besides, the soils were subject to minor pollution from heavy metals, with Chromium (Cr) and Lead (Pb) being the main contaminants affecting the soil environment quality. The soil quality index (SQI) exhibited a highly significant positive correlation with the soil fertility quality index (SFQI), suggesting that soil fertility is a crucial factor influencing soil quality. The average SQI value is 0.60 (ranging from 0.40 to 0.85), within the high grade, indicating an overall good soil quality in Hainan orchards. These findings provide a reference for classifying and defining soil quality, and understanding the current state of soil quality in Hainan orchards.

1. Introduction

Global food demand is projected to increase by 25–31 % by 2050 due to population growth (United Nations, 2019), presenting a critical challenge for agricultural systems. This surge threatens soil quality-a key determinant of ecosystem sustainability. According to Karlen et al. (1997), soil quality reflects a soil's ability to maintain biological productivity, regulate water and air quality, and promote environmental health within natural or managed ecosystems. Effective soil management hinges on identifying and monitoring the factors governing agricultural soil health (Herrick, 2000), as these directly influence long-term food security and ecological stability. As a critical natural resource, soils play a vital role in maintaining ecological equilibrium when utilized sustainably (Jha et al., 2010). However, improper land management may result in fertility degradation and environmental contamination (Tauqeer et al., 2022). Excessive agrochemical application not only disrupts soil nutrient balance, leading to acidification and salinization, but also introduces persistent pollutants like heavy metals. Thus, both soil fertility characteristics and heavy metal content serve as valuable indicators for evaluating soil quality. These dual pressures underscore the necessity for comprehensive soil quality evaluation systems that simultaneously assess fertility parameters and heavy metal

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contamination levels.

Soil quality is typically evaluated through an integrative analysis of multiple indicators, as it represents a complex property that cannot be fully captured by any single direct measurement (Karlen et al., 1997). Hence, effective soil quality evaluation is imperative for sustainable agricultural development, agricultural management, and governmental decision-making (Valani et al., 2020; Shao et al., 2021; Fan et al., 2021; Chen et al., 2022). Many soil quality evaluation methods exist; however, the majority of cases only consider the individual impacts of soil functions like fertility or pollution on soil quality, without considering their combined effects. In agricultural production systems, soil fertility represents the primary functional attribute in quality assessment. Therefore, various methodological approaches have been developed for soil fertility quality assessment, as detailed in Table S2. These include dynamic evaluation models to characterize temporal changes (Larson and Pierce, 1994), multiple variable indicator kriging approaches (MIK) for spatial pattern characterization (Diodato and Ceccarelli, 2004), fuzzy synthetic evaluation approaches to address parameter uncertainty (Yao et al., 2009), grey relational analysis (GRA) for multi-criteria optimization (Zhang et al., 2009), principal component analysis (PCA) for dimensionality reduction in multivariate datasets (Zhang et al., 2013), and integrated fertility indices (IFI) for comprehensive scoring (Wang et al., 2018). In industrial and mining regions where anthropogenic activities significantly impact soil systems, environmental quality assessment becomes paramount, with heavy metal contamination serving as a key quantitative indicator. Multiple established indices are available for evaluating metal pollution, including: the pollution index (PI) for single-element assessment (Zang et al., 2017); the Nemerow integrated pollution index (NIPI) for comprehensive multi-metal evaluation (Fei et al., 2019); the pollution load index (PLI) for overall contamination status determination (Maanan et al., 2015); the geo-accumulation index (I_{geo}) for anthropogenic contribution quantification (Muller, 1969); enrichment factors (EF) for source identification (Simonetti et al., 2003); and potential ecological risk index (ERI) for environmental hazard assessment (Hakanson, 1980). Detailed methodological specifications for these indices are provided in Table S2. While these assessment frameworks have proven effective within their respective domains, they typically operate as parallel but disconnected systems. Conventional assessments of soil environmental and fertility quality generally employ two distinct evaluation systems (see Table S2) (Fan. et al., 2021). The complex nonlinear interactions between heavy metals and nutrients pose significant challenges for the conventional methods outlined above to integrate both components in comprehensive soil quality evaluations. Traditional evaluation methods may struggle to balance these different factors while accounting for data uncertainty. Current practice under China's Environmental Quality Standards for Green Food Production Areas (MAPRC, 2021a,b) maintains a dichotomous evaluation framework, assessing soil heavy metal contamination and fertility parameters as independent components. However, integrated assessment of soil fertility and heavy metal contamination enables comprehensive evaluation of both nutrient supply capacity and pollution status, providing critical data for optimizing soil management strategies. This dual-parameter approach facilitates targeted remediation of contaminated areas while maintaining agricultural productivity within safe thresholds, thereby ensuring both crop safety and yield potential.

Since 2017, the Chinese government has raised the issues of food safety and agricultural green development to a highly significant national strategic level. For the purpose of agricultural green production, it is imperative to carry out comprehensive soil quality assessments, encompassing both soil environmental and fertility quality. Wang et al. (2018) and Fan. et al. (2021) adopted the modified Nemerow integrated pollution index (NIPI) method to comprehensively assess the soil quality of the wetland soil and plastic greenhouse production systems in China. Although the modified NIPI method (Wang et al., 2018; Fan et al., 2021) has demonstrated effectiveness in assessing integrated soil environment and fertility quality through its emphasis on limiting factors, this approach presents several limitations that require consideration. The method's exclusive focus on the poorest-performing indicator, (i) neglects the integrated contributions of all soil parameters, and (ii) may over-penalize systems with a single suboptimal indicator despite otherwise favourable conditions. Currently, integrated soil quality assessment frameworks incorporating both fertility and environmental parameters remain underdeveloped, with limited published case studies (Fan et al., 2021; Shao et al., 2021) and no nationally standardized protocols established in China. Thus, new assessment systems for soil quality that can evaluate soil environment and soil fertility indicators at a unified scale and integrate them are required for continuous sustainable agricultural development. This integration poses significant methodological challenges due to the fundamentally different nature of these indicator types and their complex interactions. Therefore, soil quality assessment requires a robust multi-criteria decision analysis (MCDA) approach capable of reconciling complex, often conflicting indicators (such as soil fertility and heavy metal contamination) which exhibit nonlinear interdependencies. The MCDA provides a systematic framework for synthesizing diverse information sources to support objective-oriented decision making. This approach facilitates comparative evaluation of alternatives through structured decision matrices, while ensuring transparent documentation of the analytical process (Jiang et al., 2015). Among various MCDA approaches, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) has emerged as a particularly effective methodology, demonstrating robust performance in multi-criteria evaluation scenarios (Simpson et al., 2011; Huang et al., 2011; Jiang et al., 2015; Yang et al., 2020; Zeng et al., 2021; Zhang et al., 2022; Zhu et al., 2023). The TOPSIS method evaluates alternatives through geometric distance measurements relative to both positive-ideal (optimal criteria values) and negative-ideal (worst criteria values) reference points, with superior alternatives demonstrating closer proximity to the ideal solution (Huang et al., 2011). This technique offers three distinct advantages in decision analysis: (1) comprehensive ordinal ranking capability, (2) compatibility with probabilistic assessments, (3) weight-dependent distance metric calculations, and (4) effective handling of nonlinear parameter relationships through computational algorithms (Simpson et al., 2011; Huang et al., 2011). However, a key limitation of conventional TOPSIS is its inability to process ambiguous or uncertain data, which is often inherent in environmental datasets (Gu and Song, 2009). To overcome this constraint, we incorporate fuzzy mathematical theory, which transforms qualitative and imprecise data into quantifiable membership functions, enabling standardized comparisons between disparate indicators (e.g., nutrient levels vs. pollutant concentrations). The hybrid fuzzy-TOPSIS model enhances assessment accuracy by normalizing heterogeneous soil parameters, and resolving trade-offs between fertility and contamination through a mathematically rigorous distance-based ranking system. This integrated approach is especially valuable in soil quality studies, where the interplay between beneficial and hazardous elements often follows non-uniform, threshold-dependent patterns. The fuzzy mathematical method can transform qualitative and imprecise data into quantifiable membership functions, enabling standardized comparisons between disparate indicators (Yao et al., 2009). Therefore, integrating TOPSIS with fuzzy mathematical theory presents an optimized approach for soil quality evaluation, particularly when addressing inherent data uncertainties and qualitative assessment parameters. To the best of our knowledge, an improved TOPSIS method with a fuzzy mathematical model has not been used for soil quality assessment studies.

To bridge this research gap, we selected orchard soils in Hainan Province as our study area. As the world's leading fruit producer, China accounts for 19.50 % of global orchard acreage and 32.35 % of total production (Ren et al., 2023). Hainan Island, often called China's "tropical fruit basket", maintains year-round fruit cultivation due to its unique greenhouse-like climate, making orchard farming a crucial economic sector. However, intensive farming practices have triggered soil degradation through erosion, acidification, and biodiversity loss (Sun et al., 2020; Li et al., 2022), compounded by emerging heavy metal contamination from both anthropogenic and geologic sources (Liang et al., 2019; Liu et al., 2017; Li et al., 2018; Yang et al., 2022). These dual pressures of ecological degradation and pollution accumulation create an urgent need for developing a comprehensive soil quality assessment method that can guide sustainable orchard management practices while ensuring environmental safety. The comprehensive soil quality evaluation method for green production in this study, combining an improved version of the TOPSIS method and a fuzzy mathematical model, was developed and applied to orchards in Hainan for the first time. First, we adopted standard scoring functions to standardise the data ranges of different indicators. Subsequently, a modified TOPSIS method was utilized to assess and integrate soil fertility and soil environment indicators, thereby deriving the soil quality index (SQI). The overall goals of this study were to (1) standardise the data ranges of the soil fertility and soil environment indicators using fuzzy membership functions, (2) evaluate the SQI using the modified TOPSIS method, integrating soil fertility and soil environment indicators, and (3) analyze the limiting factors of the SQI. The comprehensive soil quality evaluation methods in this study provide theoretical and practical support for sustainable agricultural production systems in Hainan orchards.

2. Materials and methods

2.1. Study area

This study conducts a comprehensive soil quality evaluation of the orchards in Hainan Province, southern China (18° 10´–20° 10´N, 108° 36´–111° 03´E) (Fig. 1).

2.2. Evaluation standards and evaluation items

A thorough soil assessment framework was devised in the study region, taking into account both heavy metal pollution and soil nutrients, to evaluate soil quality for green production in the study area. The

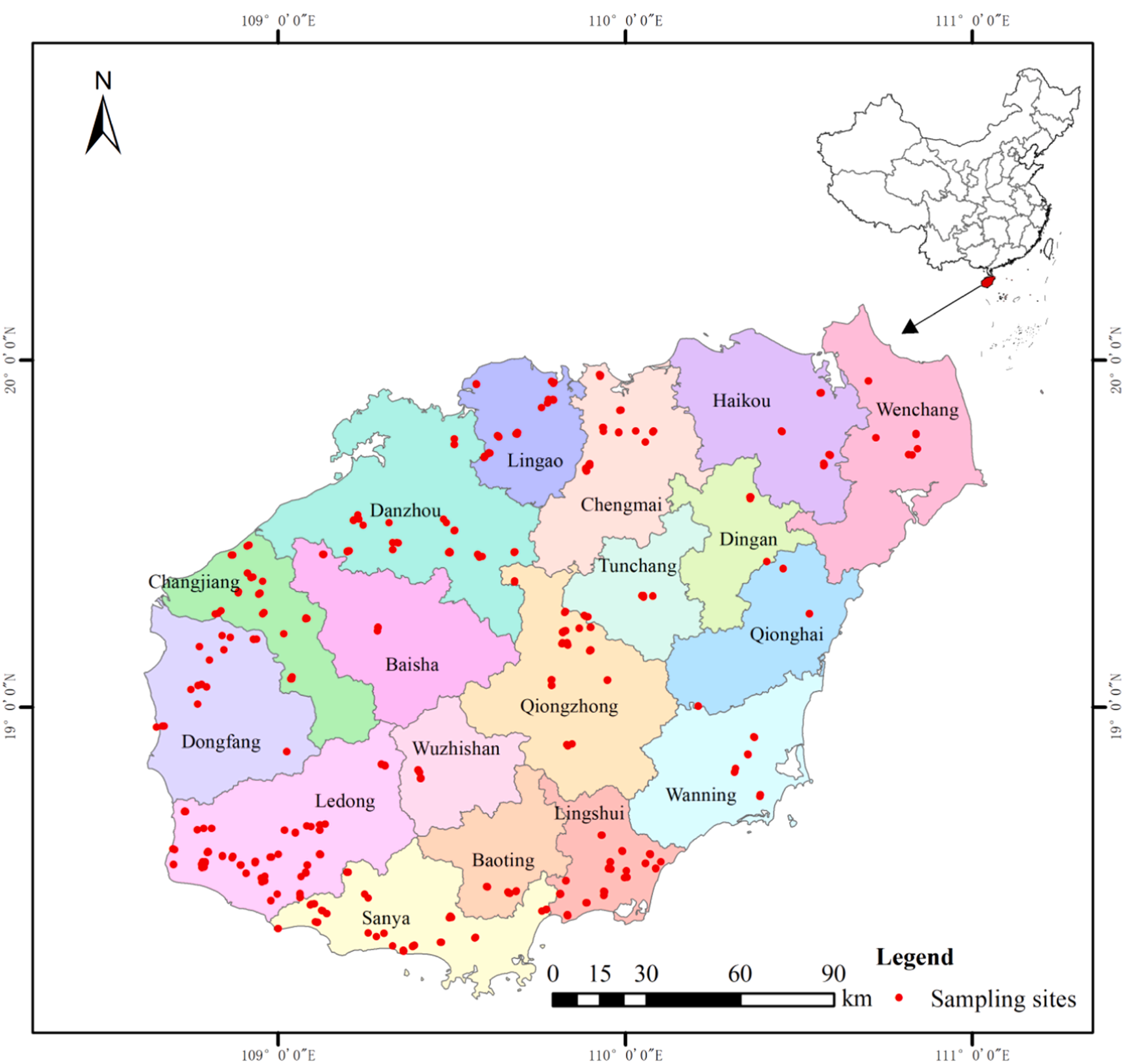


Fig. 1. The geographical location of the studied orchards.

comprehensive soil quality assessment was performed based on these processes (Fig. 2): (1) selection of proper indicators, (2) standardisation of the evaluating indicators using standard scoring functions, (3) evaluation of the soil fertility quality index (SFQI) using the fuzzy mathematical model, (4) assessment of the soil environment quality index (SEQI) using a modified NIPI method, (5) integration of soil fertility indicators with environmental indicators was performed using the modified TOPSIS method, leading to the computation of SQI, (6) analysis of the limiting factors of the SQI, and (7) method comparison between the previous minimum function method and the improved TOPSIS model introduced in present study. In this study, both SFQI and SEQI were calculated as intermediate outputs to serve two purposes. First, these indices enabled method comparison between the previous minimum function approach (where SQI=min(SFQI, SEQI)) and our proposed integrated evaluation framework combining fuzzy mathematics and the improved TOPSIS methods. Second, the derived SFQI and SEQI values allowed for correlation analysis with our final composite SQI, which helped elucidate the relative contributions of soil fertility quality versus environmental quality to the overall soil health assessment.

Based on “Environmental Quality Standards for Green Food Production Areas” (MAPRC, 2021a, NY/T 391–2021), the soil quality assessment framework incorporated six heavy metal indicators [total concentrations of lead (Pb), cadmium (Cd), mercury (Hg), chromium (Cr), copper (Cu), and arsenic (As)] and five fertility parameters [pH, total nitrogen (TN), available phosphorus (AP), organic matter (OM), and available potassium (AK)]. This dual-component evaluation system was established to provide a regional comprehensive assessment of orchard soils for green fruit farming in Hainan.

2.3. Soil sampling and laboratory analysis

A total of 450 orchard soil samples (~1 kg; 0–60 cm depth) were selected and collected from across the tropical fruit-growing area of Hainan. Three representative sampling points were selected for each orchard by means of purposive sampling. The sampling locations and corresponding geographical coordinates were recorded using a Global Positioning System (GPS) device. Each sample was mixed thoroughly and packed in a polyethylene bag. Laboratory procedures for soil samples included air drying, sieving using mesh widths of 0.149 mm, 0.250 mm, and 2.000 mm, and storing in bags until further analysis. The spatial distribution of sampling points is depicted in Fig. 1. The concentrations of Pb, Cd, Hg, Cr, Cu, and As, as well as pH, TN, AP, OM, and AK were determined for each sample according to the relevant national standards (see Table S3).

2.4. Standardisation of soil indicators using the fuzzy mathematical method

The fuzzy mathematical method employs a membership function to determine index membership (Zhao et al., 2021). As mentioned in Sections 2.2, 11 soil quality indicators were considered, namely OM, TN, AP, AK, pH, Pb, Cd, Hg, Cr, Cu, and As. Based on the fuzzy membership scoring function introduced by Karlen et al. (1997), the memberships of TN, AP, OM, and AK can be determined using the S-type membership function, as stated in Eq. (1) in Table 1. Moreover, pH conform with the parabolic or mid-poit type functions, as demonstrated by Eq. (2) in Table 1. The soil heavy metal pollution belongs to the inverted ‘S′ type function outlined in Table 1. In this study, we propose a transformation scoring function that considers both the soil background value and environmental quality evaluation standards as a result of transforming the PI into the same range (0.1–1.0) (Eqs. (3−4)). The fertility index (FI) represents the membership value of a fertility indicator (i.e. pH, OM, TN, AP, AK) using membership functions (Table 1) (range: 0.1–1.0). Similarly, the environmental index (EI) denotes the membership value of a single heavy metal pollution indicator (i.e. Cd, Pb, As, Cr, Hg, Cu) (Table 1), also normalized to the same range (0.1–1.0).

Fertility index (FI) and environmental index (EI) are derived through standardized membership function transformations to evaluate soil quality uniformly. All indicator thresholds and standardized membership functions were established based on local soil characteristics and management practices (Table1, Table S4-S5). According to the values of FI and EI, standardised scores of soil quality indicators were interpreted based on a three-component scale: worst (0.1), moderate (0.1–1.0), and best (1.0).

2.5. Assessment of the soil fertility quality

The fuzzy mathematical method was utilized for a comprehensive evaluation of the soil fertility quality index (SFQI). Five soil quality indicators (i.e. pH, OM, TN, AP, and AK) were normalised using membership function equation (1), as defined in Table 1. To calculate the soil fertility quality, each soil fertility indicator was weighted. The weights of the soil quality indicators were assigned using the correlation coefficient values obtained through the correlation coefficient method (Wang et al., 2020). The SFQI was calculated using the following equations:

$$\mathrm{SFQI} = \sum_{i=1}^{n} W_i \times \mathrm{FI}_i, \tag{5}$$

$$W_i = \frac{r_i}{\sum_{i=1}^{n} ri}, \tag{6}$$

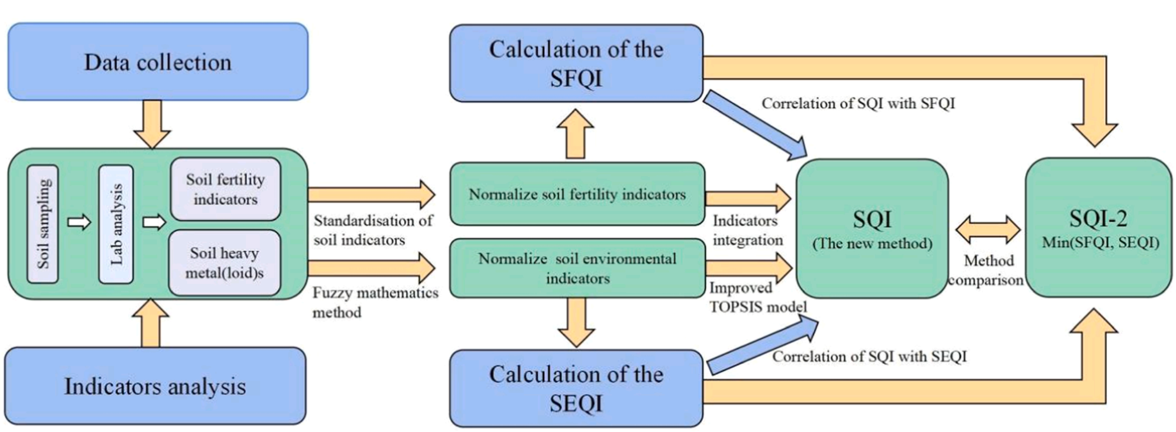
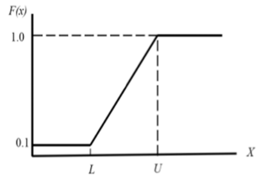
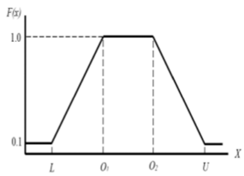
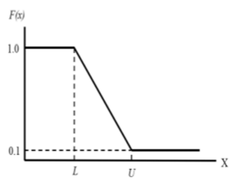


Fig. 2. Framework of this study.

Table 1
Standardisation of soil fertility and environmental indicators using membership functions.

Type	Broken line model	Standard score functions	Applicable indicators
"S" type		$F(\mathrm{x}) = \begin{cases} 0.1\ ,\ x \le L \\ 0.1 + \frac{0.9(x-L)}{(U-L)}, L < x < U \\ 1.0,\quad x \ge U \end{cases}$ (1)	Fertility index (FI) for OM, TN, AP, and AK
Parabolic or mid-poit type		$F(\mathrm{x}) = \begin{cases} 0.1 + \frac{0.9(x-L)}{(O_1-L)}, \mathrm{L} < x < O_1 \\ 1.0,\quad O_1 \le x \le O_2 \\ 1.0 - \frac{0.9(x-O_2)}{(U-O_2)},\quad O_2 < x < U \\ 0.1, x \ge U\ ,\ x \le L \end{cases}$ (2)	Fertility index (FI) for pH
Inverse "S" type		PI= x/x_{0i} (3) $F(\mathrm{x}) = \begin{cases} 1.0, \mathrm{PI} \le 1 \\ 1.0 - \frac{0.9(\mathrm{PI}-1)}{(\mathrm{PI}_{\max}-1)},\ 1 < \mathrm{PI} < \mathrm{PI}_{\max} \\ 0.1,\ \mathrm{PI} \ge \mathrm{PI}_{\max} \end{cases}$ (4)	Environmental index (EI) for soil pollutant content (Pb, Cd, Hg, Cr, Cu, and As)

Note: The standardized quality indicator score F(x) ranges from 0.1 to 1, with x representing the indicator value. Three types of relationships exist: "S" type, where a positive correlation between crop yield or growth and the indicator value within a specific range, unaffected by values outside that range; parabolic or mid-point type, where the indicator value is optimal within a certain range, increasing when below the lowest threshold and decreasing when above the highest; and inverse "S" type, which is similar to the "S" type but with a negative correlation. O_1 and O_2 represent the lower and higher thresholds in the standard score function, while L and U indicate the lowest and highest thresholds, respectively. x_{0i} refers to the background value of metal (i) in the research region (Table.S4). PI represents the pollution index of each heavy metals in the soil sample, and PI_{max} represents the value obtained by dividing the national limit value for each metal by the background value of metal (i) in the research region (Table.S4).

where the membership value of the fertility indicator is denoted as FI_i. The FI of OM, TN, AP, and AK were obtained using Eq. (1), and the FI of pH was obtained using Eq. (2). The weight of indicator i is denoted as W_i. The parameter r_i represents the average value of the correlation coefficients between the evaluation factors and the remaining factors, and "n" denotes the total number of indices involved. In short, SFQI value reflects soil fertility level. Higher SFQI indicates better fertility. Based on the SFQI values, five categories were established (Table S6).

2.6. Assessment of the soil environment quality

Following Wang et al. (2018) and Fan et al. (2021), the soil environmental quality index (SEQI), calculated using the modified NIPI following Eq. (7), reflects the combined pollution effects of all assessed heavy metals.

$$\mathrm{SEQI} = \sqrt{\left[(\mathrm{EI}_{\min})^2 + (\mathrm{EI}_{\mathrm{avg}})^2\right]/2} \tag{7}$$

The EI of Pb, Cd, Hg, Cr, Cu, and As were obtained using Eqs. (3−4) in Table 1. In the modified NIPI method, the minimum value of EI replaced the maximum PI value to reflect the worst environmental impact on the overall assessment. The average environmental index (EI_{ave}) and minimum environmental index (EI_{min}) represent the average and minimum values of various environmental indicators for a given soil sample. Eventually, SEQI was classified into five pollution levels (Table S6).

2.7. Comprehensive soil quality evaluation using the modified TOPSIS method

Based on the soil fertility and soil environment indicators, the modified TOPSIS method was used to comprehensively assess the soil quality of the orchard lands. The specific process for building a comprehensive assessment model for soil quality is as follows:

(1) Development of a standardised assessment matrix.

The original assessment indicator matrix for the soil quality in main orchard was set as follows:

$$\mathrm{X} = \mathrm{xij} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}, \tag{8}$$

where x_{ij} is the original assessment indicator matrix; i ranges from 1 to m; m represents the number of assessment samples; j ranges from 1 to n; and n denotes the quantity of assessment indicators.

To obtain the standardised assessment indicator matrix, we used a normalisation method to normalise the indicators. Based on the agronomic and environmental functions of the soil, each soil indicator was standardised and scored using one of the three membership function equations (i.e. Eqs. (1−4)) in Table 1 to avoid differences due to different indicator units. The standard scoring function converts the range of values of each indicator into dimensionless values ranging between 0.1 and 1.0. Therefore, the standardised matrix is obtained using Eqs. (9–10):

$$\mathrm{rij} = \mathrm{F}\left(\mathrm{x_{ij}}\right), \tag{9}$$

$$\mathrm{R} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}. \tag{10}$$

where r_{ij} represents the standardised value of the j assessment index for the i sample obtained by membership function equations (Table 1); R is the standardised evaluation index matrix.

(2) Determination of positive and negative ideal solutions.

The ideal solution and the negative ideal solution were obtained according to the standardised scores range of soil evaluating indicators (0.1–1.0). The positive ideal solution (PIS) is defined as $t_j^+ = 1.0$, while the negative ideal solution (NIS) is denoted as $t_j^- = 0.1$.

(3) Distance calculation.

Based on distance scales, Euclidean distance was used to calculate separation measures between index attributes and positive/negative ideal solutions (Eq. 11-12). Then, the distances from evaluation indicator to ideal solutions were determined.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(t_j^+ - t_{ij})^2} \tag{11}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(t_j^- - t_{ij})^2} \tag{12}$$

where t_{ij} is the normalised value in the i sample of index j, and t_j^+ and t_j^- represent the most favoured and least favoured values of the indexj, respectively.

(4) Calculation of the closeness between the evaluation indicator and the ideal solution.

The soil quality was expressed through the measurement of closeness degree, which allowed for the determination of the comprehensive soil quality based on the closeness degree in each soil sample according to Eq. (13).

$$C_i = \frac{D_i^-}{(D_i^+ + D_i^-)} \quad (\text{range}: \quad 0\text{–}1), \tag{13}$$

$$\text{SQI} = \quad C_i \tag{14}$$

where C_i ranges from 0 to 1. When the C_i attains a value of 1, then the object is far from the negative ideal solution, and the index is close to the positive ideal solution; thus, the index is optimal.

According to this study, a higher proximity coefficient indicates that the soil quality index is closer to the ideal point and has a higher SQI score. The soil quality was divided into five grades according to the SQI score (Table S6).

2.8. Data analysis

Descriptive statistics (minima, maxima, averages, etc.) were calculated using Microsoft Excel 2016. Spatial distribution maps were generated using ArcGIS 10.5 to analyze the spatial characteristics of SEQI, SFQI, and SQI in the study area. Pearson correlation analysis was performed using RStudio software. SPSS Statistics software (ver. 26.0, IBM, USA) was used to conduct PCA.

3. Results

3.1. Assessment of the soil fertility quality

3.1.1. Descriptive statistical analyses of soil fertility indicators

The descriptive statistics for OM, TN, AP, AK, pH, Pb, Cd, Hg, Cr, Cu, and As are summarised in Table 2. With the exception of pH, all other soil quality parameters exhibit moderate to significant variability, indicating that the soil quality parameters are highly variable. An average pH of 5.2 was found in the soil samples, and approximately 90.0 % of the soils had pH values below 7.0, indicating that most of the soils in the study area are acidic. Unlike pH, OM exhibited significant spatial variation across the study area. The OM values fluctuated between 0.522 g/kg and 64.2 g/kg, with a mean value of 13.0 g/kg, i.e. third-level OM standard (<15 g·kg^{-1}; MAPRC, 2021a). The TN content ranged from 0.0400 to 2.73 g/kg, with an average value of 0.682 g/kg, i.e. low-fertility level (<0.8 g/kg; MAPRC, 2021a). The available phosphorus (AP) and available potassium (AK) varied widely from 0.150 to 568.000 mg/kg and 1.00 to 1400.00 mg/kg, with mean values of 56.0 and 112.0 mg/kg, respectively. Overall, the study areas exhibited abundant levels of AP and AK.

3.1.2. Standardised scores of soil fertility indicators

The scoring functions for the soil fertility indicators are provided in Table 1. To provide a direct insight into the soil fertility level distribution, a split violin of the standardised scores of the soil fertility indicators was employed, as shown in Fig. 3. The standardised scores were interpreted using a three-component scale: worst (FI = 0.1), moderate (0.1 < FI < 1.0), and best (FI = 1.0). pH was scored based on “optimum” curves, which varied from 0.1 to 1.0, with a mean value of 0.37. Most fertility indicators, including OM, TN, AP, and AK, were evaluated using “more is better” curves, with higher values being correlated with higher indicator scores. Total nitrogen (TN) and organic matter (OM) had relatively lower FI values than those of other indicators; they varied between 0.1 and 1.0, with respective average values of 0.35 and 0.36, and only 36–38% of the orchard lands being rated as moderate and best with the remainder being rated as worse. The average FI values of AP and AK were 0.69 and 0.65, respectively, varying from 0.1 to 1.0. This suggests that P and K are prevalent in most soils across the study area.

3.1.3. Soil fertility quality index (SFQI)

To determine the SFQI while accounting for weights, we used Pearson correlation analysis to analyse the correlation coefficients of the

Table 2
Descriptive statistics of soil quality evaluation indexes in the study area.

Items	Range	Average	Standard Deviation (SD)	Coefficient of Variation (C.V)	Background Value[a]	NY/T 391-2021[b]			
						Standard values			Exceedance rates (%)
pH	3.7–8.6	5.2	0.96	0.18	-	< 6.5	6.5–7.5	> 7.5	-
Cd(mg/kg)	0.00450–0.420	0.0431	0.052	1.22	0.05	0.3	0.3	0.4	1.0
Hg(mg/kg)	0.00205–0.182	0.0351	0.025	0.70	0.03	0.25	0.3	0.35	0.0
As(mg/kg)	0.0319–74.4	3.91	7.42	1.90	1.14	25	20	20	3.0
Pb(mg/kg)	0.620–104	25.6	16.5	0.64	22.34	50	50	50	8.0
Cr(mg/kg)	0.320–752	55.0	104	1.90	15.24	120	120	120	10.0
Cu(mg/kg)	0.800–130	17.9	22.2	1.24	4.95	100	120	120	1.0
OM(g/kg)	0.522–64.2	13.0	7.90	0.61	-	-	-	-	-
TN(g/kg)	0.0400–2.73	0.682	0.42	0.62	-	-	-	-	-
AP(mg/kg)	0.150–568	56.0	83.7	1.50	-	-	-	-	-
AK(mg/kg)	1.00–1400	112	105	0.94	-	-	-	-	-

[a] Background values for soils in Hainan Province (CNEMC, 1990).
[b] Standard of green food-environment quality for production area (MAPRC, 2021a).

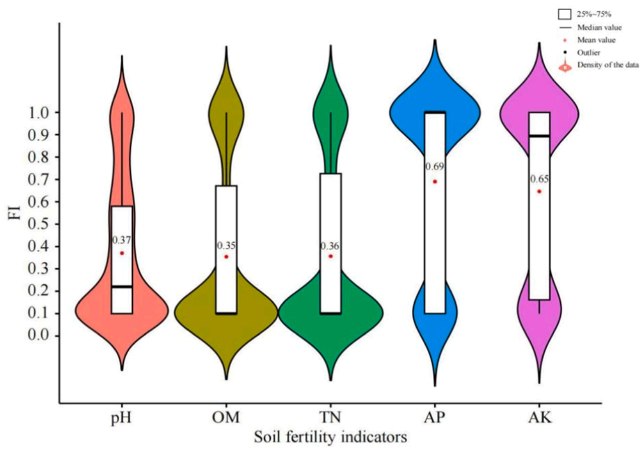


Fig. 3. Split violin of standardised scores of soil fertility indicators (n = 450).

five chosen soil fertility indicators in the study area (Fig. S1) and corresponding weights (Table S5). The SFQI of the soil ranged between 0.10 and 1.00, with a mean value of 0.46. To assess the soil fertility quality in conjunction with soil nutrients, the samples were further categorized into five distinct classes (I, II, III, IV, and V). Fig. 4 shows the spatial pattern of SFQI in the study area, revealing that most of the soil samples were categorized as III and IV—124 samples, accounting for 28.0%, and 95 samples, accounting for 22.0%, respectively. Conversely, 78 samples (accounting for 18.0%), 50 samples (accounting for 12.0%), and 103 samples (accounting for 23.0%) were classified as I, II, and V, respectively. These findings indicate that, overall, the soil in the study area was infertile. The dark red zone, where SFQI is less than 0.20, indicates unsatisfactory fruit growth in those areas.

3.2. Assessment of the soil environment quality

3.2.1. Descriptive statistical analyses of soil environment indicators

As showed in Table 2, the average concentrations of the heavy metals were 3.91 ± 7.4, 0.0351 ± 0.025, 55.0 ± 104, 0.0432 ± 0.052, 25.6

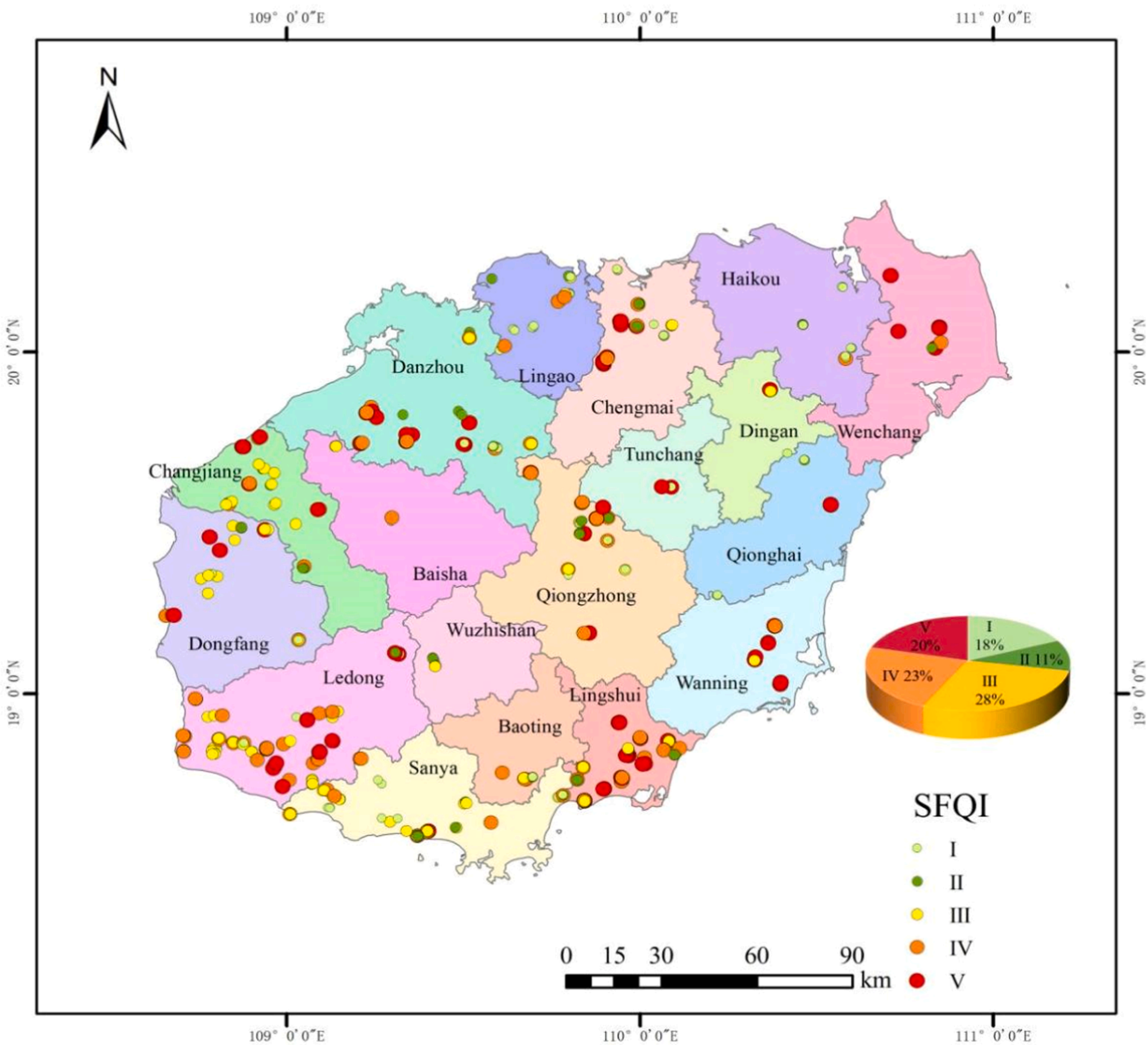


Fig. 4. Spatial pattern of SFQI in the study area.

± 16.4, and 17.9 ± 22.2 $mg \cdot kg^{-1}$ for As, Hg, Cr, Cd, Pb, and Cu, respectively. The coefficients of variation for soil heavy metals ranged from 1.90 to 0.64, following a decreasing order of As > Cr > Cu > Cd > Hg > Pb and implying a non-homogeneous spatial distribution of metals. With the exception of that of Cd, the mean values of the tested metals were lower than the background levels in the soil. Compared to the standard (MAPRC, 2021a), the percentages of Hg, Cd, Cu, As, Pb, and Cr exceeding the overall limits were 0.0%, 1.0%, 1.0%, 3.0%, 8.0%, and 10.0%, respectively. Usually, soil pollutant contents below reference limit values suggest minimal impact on the soil environment, while concentrations exceeding intervention values suggest significant pollution. Heavy metal(loid) pollution was generally safe in the study area, but locally, these metals were enriched to varying degrees. Upon examining the data, we can observed that there were varying degrees of local enrichment for these metals, despite the fact that heavy metal pollution in the area of study maintained a relatively safe threshold.

3.2.2. Standardised scores of soil environment indicators

To evaluate the overall pollution status of all tested heavy metals considering both soil background values and evaluation standards for green environmental quality (MAPRC, 2021a), the metals were scored based on "less is better" curves (Table 1), i.e. measured values are inversely proportional to assigned scores: lower measured values result in higher assigned scores. The scores of these soil environment indicators are shown in Fig. 5. All EI values were interpreted using a three-component scale: worst (EI = 0.1), moderate (0.1 < EI < 1.0), and best (EI = 1.0). The EI value of Cr was relatively lower in comparison to those of the other indicators. The average EI values for Cd, Hg, As, Pb, Cr, and Cu were 0.95, 0.95, 0.89, 0.75, 0.79, and 0.87, respectively, ranging from 0.1 to 1.0. Cr and Pb were the primary limiting constraints of the SEQI.

3.2.3. Soil environment quality index (SEQI)

The SEQI was determined using the modified NIPI (Eq. 7). Fig. 6 shows the SEQI levels at each sampling point. The SEQI values in research area varied from 0.28 to 1.00, with a mean value of 0.75. To comprehensively assess the soil environment quality with respect to all tested metals, the samples were further divided into six classes: I, II, III, IV, and V. According to the assessment of the soil environment quality, 200 samples (accounting for 45.0%), 128 samples (accounting for 28.4%), 116 samples (accounting for 26.0%), and six samples (accounting for 2.0%) were classified as I, II, III, and IV, respectively.

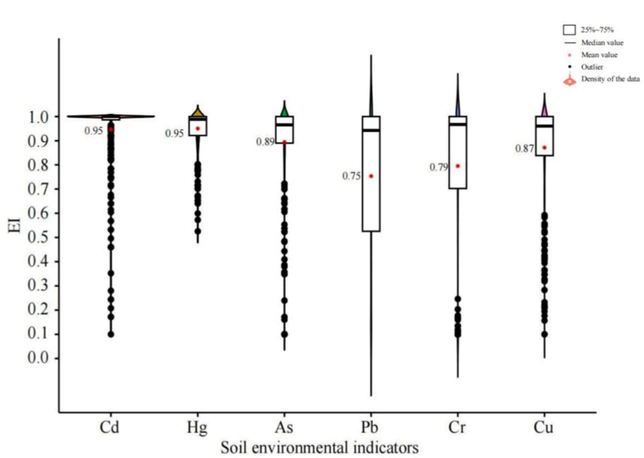


Fig. 5. Split violin of standardised scores of soil environmental indicators in soil samples (n = 450).

3.3. Assessment of the comprehensive soil quality evaluation

A modified TOPSIS method was applied to integrate the scores of 11 indicators (FI and EI) to compute the SQI for 450 orchard sites. Fig. 7 shows the SQI levels at each sampling point. The average SQI value was 0.60 (ranging from 0.40 to 0.85), within the high grade. The overall soil quality in the research area was satisfactory, with most samples having medium to very high soil quality levels. Of all soil samples, 56.0% exhibited Level III quality (i.e. intermediate soil quality), and the remaining 44% exhibited Level I and II qualities (i.e. excellent and good soil qualities, respectively).

4. Discussion

4.1. Correlations of SQI with SFQI and SEQI

A high SQI value in orchard land necessitates both fertile soil and excellent soil environmental qualities. A PCA was performed on the SQI, SFQI, and SEQI values to determine the main factors affecting soil quality (Fig. S2). The two main axes defined the spatial classifications of the SQI, SFQI, and SEQI. The first two PCs explained approximately 97.585% of the total variation, with PC1 explaining 56.097% and PC2 explaining 41.488%. PC1 had high loadings of SQI and SFQI. A strong positive correlation was observed between the SQI and SFQI, indicating that the low soil fertility levels primarily limited the SQI value in Hainan orchards. The average SEQI value in the Hainan orchards was 0.75, suggesting a minimal possibility of significant heavy metal contamination. Across all fruit-growing soils, the soil concentrations of SQI were significantly positively correlated with FI(pH), FI(OM), FI(TN), FI(AP), FI(AK), EI(As), EI(Pb), EI(Cu), and EI(Cr) (Fig. 8). Therefore, these indicators are more important than other indicators for soil quality evaluation. As a consequence, analysing the factors limiting the soil fertility and soil environment qualities to improve the SFQI and SEQI is crucial for improving the SQI in Hainan orchards.

4.2. Factors limiting the soil fertility quality

Nearly 85% of the fruit farming soils in the study area have become acidic (pH ≤ 6.5). A decline in soil pH can reduce nutrient availability, disrupt microbial communities, and increase toxic heavy metal availability, especially when the soil pH is lower than 4.5. The soil acidification in the study area probably results from the parent material, topography, soil texture, fruit harvest and pruning, and extensive fertilization, particularly excessive use of N and P fertilizers. The lateritic red soils developed from basaltic weathering products constitute the predominant soil type across the Hainan Island. Under tropical monsoon conditions characterized by high temperatures and abundant precipitation, these soils experience intensive mineral weathering and leaching processes. This leads to significant degradation of acid-buffering capacity, substantial losses of silica and base cations (Ca^{2+}, Mg^{2+}, K^{+}), and consequent enrichment of iron/aluminum oxides, ultimately forming highly weathered, acidic and infertile ferralsols with characteristically low pH (Pan et al., 2015). Moreover, reducing the inputs of fertilizers and using soil amendments appropriately can mitigate the soil acidification rate. Organic matter (OM) plays a significant role in determining the physical, chemical, and biological characteristics of soils. Nitrogen (N), phosphorus (P), and potassium (K) are nutrients essential for plant growth. The average concentrations (± standard deviation) of OM and TN were 13.2 ± 8.0 and 0.694 ± 0.423 $g \cdot kg^{-1}$, respectively, i.e. third-level standard of OM (<15 $g \cdot kg^{-1}$) and TN (<0.8 $g \cdot kg^{-1}$) in China (MAPRC, 2021a). Soils with deficient OM and TN contents should receive inputs of organic materials and N fertiliser in future production practices. The average concentrations (± standard deviation) of AP and AK were 59.5 ± 80.9 and 114 ± 104 $g \cdot kg^{-1}$, i.e. first-level standard of AP (>10 $mg \cdot kg^{-1}$) and AK (>100 $mg \cdot kg^{-1}$) in China (MAPRC, 2021a, NY/T 391–2021). Studies have shown that when the available P content

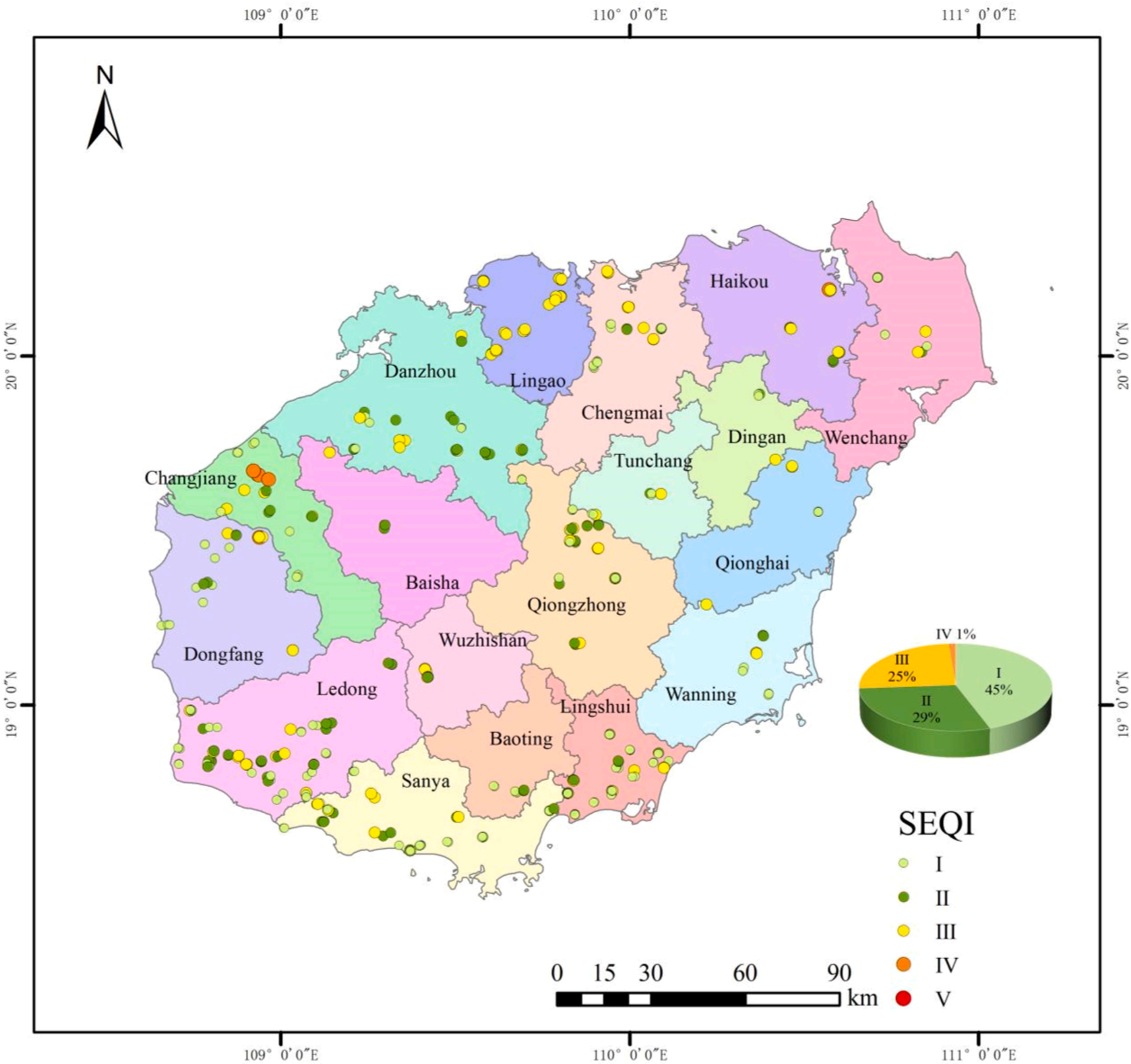


Fig. 6. Spatial pattern of SEQI in the study area.

is greater than 20 mg/kg, crops can obtain sufficient P from the soil (Zhang et al., 2006). In addition, from the perspective of environmental safety, the application of P fertilisers has resulted in wastage in many cases, increasing the environmental risks of phosphate fertiliser application. Therefore, orchards with high P contents should not receive P fertilisers, or the already applied P fertilisers should be reduced, to avoid physiological diseases.

The association between soil fertility factors and the SFQI was assessed using Pearson correlation coefficients (Fig. 8). Pearson analysis revealed that a strong positive correlation between the SFQI and FI (OM), FI(TN), and FI(AK), indicating that OM, TN, and AK are the main indices contributing to soil fertility. The correlations between FI(OM) and FI(AK) were similar to those between FI(TN) and FI(AK), i.e. relatively strong positive correlations. We found a strong association between FI(OM) and FI(TN), whereas the correlation between FI(pH) and FI(OM) was negative, indicating that an excessively high soil pH prevents organic matter decomposition.

Principal component analysis (PCA) was used to determine the factors contributing to soil fertility degradation. Table S7 denotes the relationships between the variables and components. Two main factors with eigenvalues > 1 were identified. Principal component (PC) 1 was mainly composed of SFQI, FI(OM), FI(TN), and FI(AK), whereas PC2 was mainly composed of FI(pH) and FI(AP). The total variance was primarily explained by PC1 and PC2, which contributed 48.838% and 20.028%, respectively. The results of Pearson correlation analysis and PCA indicated that the SFQI was highly affected by OM, TN, and AK in the study area.

4.3. *Factors limiting the soil environment quality*

To evaluate the factors limiting the soil environment quality, the Pearson correlation analysis results and PCA were applied to identify the sources of metal pollutants (Fig. 8 and Table S8). Positive correlation coefficients between two heavy metals indicated a similar

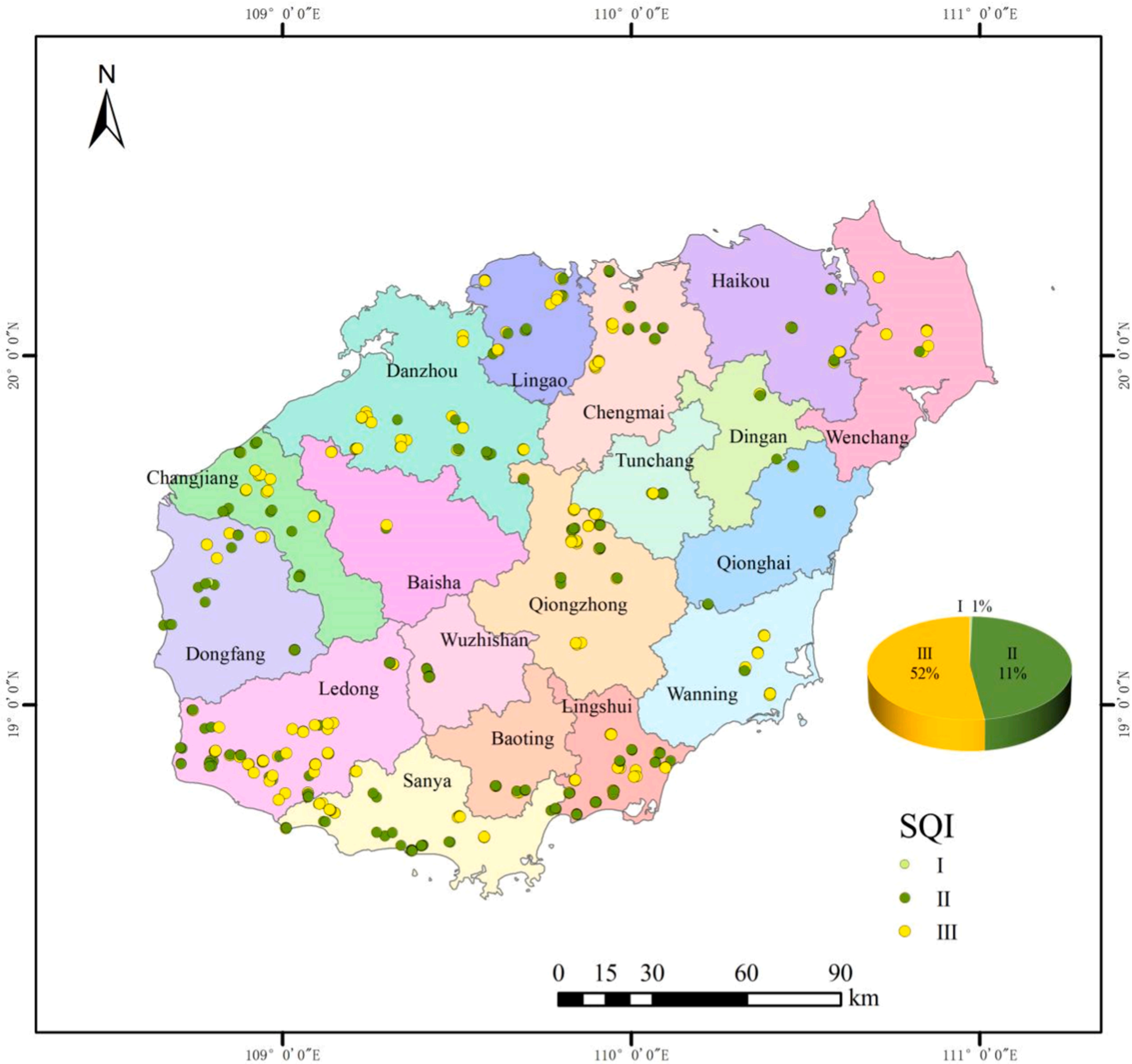


Fig. 7. Spatial pattern of SQI in the study area.

environmental origin. Furthermore, heavy metals exhibiting high loading values in the same group were likely to have a common source (Fan et al., 2021).

EI(Cr), EI(Cu), EI(Hg), and SEQI had high loadings in PC1 (> 0.5), indicating that three heavy metals mainly originated from the similar sources. This statement was supported by the significant positive correlation between EI(Cr) and EI(Cu) ($r = 0.77$), EI(Cr) and EI(Hg) ($r = 0.33$), and EI(Cu) and EI(Hg) (0.40). Similar results (Guo et al., 2015) indicated that parent material plays significant roles in determining the amounts and distributions of Cr and Cu. Thus, PC1 represents geological sources.

The PCA analysis demonstrated a clustering of SEQI, EI(Cd) and EI (Pb) in PC2, which accounts for 20.52% of the overall variance, indicating that Cd and Pb may share a similar source of origin. Previous studies have demonstrated that Cd can infiltrate soil via the application of pesticides, chemical fertilizers, and manure, thereby serving as a crucial marker of agricultural practices (Filzek et al., 2004; Shao et al., 2016; Mamut et al., 2018; Liang et al., 2019; Fei et al., 2019). The EI results for Cd indicated that anthropogenic activities served as the primary source of Cd. In general, crop production in Hainan often relies on the extensive use of pesticides and chemical fertilisers. Zhao et al. (2017) reported that commercial organic fertiliser in Hainan Province contained excessive levels of heavy metals, including Cd and Pb. Therefore, Cd and Pb likely originate from agricultural production activities. Thus, PC2 represents the influences of agricultural activities.

Principal component 3 (PC3), which has high loadings on As (0.741), accounted for 13.51% of the total variance in data. Mining and smelting activities have been reported as the primary sources of As in the environment. This conclusion is supported by the previous research findings of Zhong (2015), which indicated that the prevalent presence of arsenic (As) in the farmland of Hainan is attributed to local mining and exploration activities. Thus, PC3 represents the influences of mining activities. To summarize, the SEQI was highly affected by Cd, Pb, Hg, Cu, and Cr in the study area.

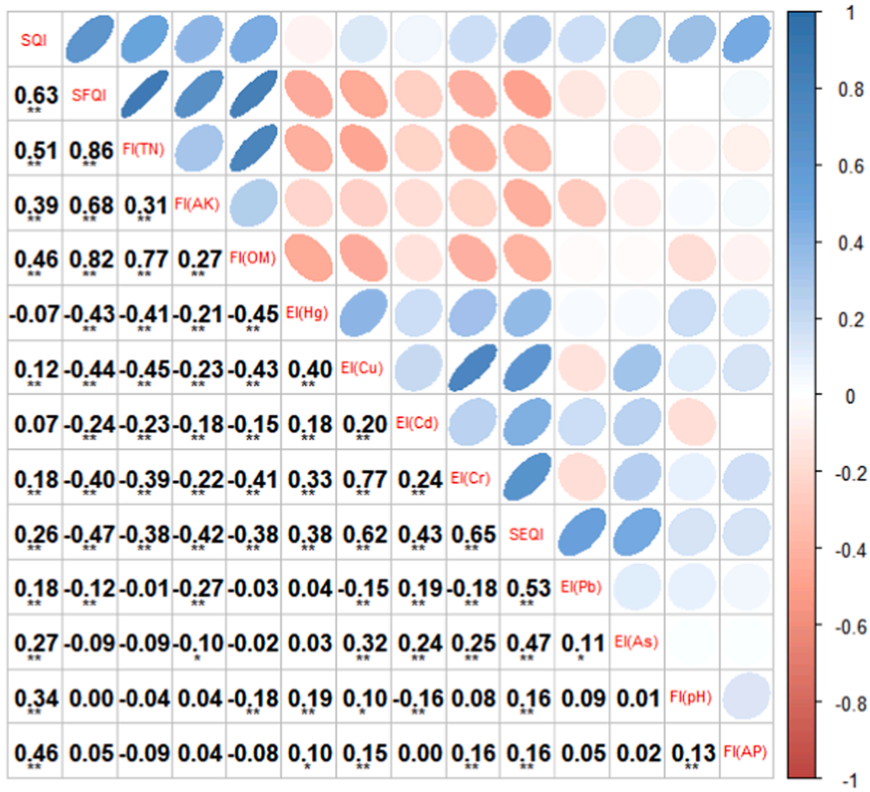


Fig. 8. Correlation matrixes of standardised scores of soil variables, SEQI, SEQI, and SQI. Note: "* *" denotes a extremely significant correlation at the 0.01 level; "* " represents a significant correlation at the 0.05 level.

4.4. Method comparison and limitations

The TOPSIS method has been extensively employed in factory locations, for comprehensive ecological risk assessments, land suitability, and for sediment quality evaluations (Mokhtarian and Hadi-Vencheh, 2012; Jiang et al., 2015; Ramya and Devadas, 2019; Ostovari et al., 2019; Yang et al., 2020). However, this method has not been used for comprehensive soil quality assessments. This study is the first to present a comprehensive soil quality evaluation of the orchard lands in Hainan, considering both the soil fertility and soil environment qualities and using the improved TOPSIS comprehensive evaluation method. Fig. 9 presents a comparison between the previous minimum function method reported by Fan et al. (2021) and Wang et al. (2018) and the improved TOPSIS model introduced in present study. Compared with the minimum function of the SQI reported by the previous studies, which focused on the adverse impact of the worst soil quality indicator on the SQI, the application of the TOPSIS method in this study has many advantages. Firstly, the TOPSIS method effectively utilizes the information of the soil quality assessment indices and offers strong operability and applicability. Secondly, its thorough and meticulous evaluation process ensures comprehensive results, accurately reflecting the differences among various assessment indices.

An important consideration in interpreting our soil quality assessment results is the inherent variability of soil properties across different geological contexts. While our evaluation framework focuses on functional soil parameters without distinguishing their origins, we recognize that certain observed characteristics - particularly acidic pH in basaltic weathering soils and elevated trace metal concentrations in ultramafic-derived soils - primarily reflect pedogenic processes rather than anthropogenic degradation. This is exemplified by our dataset, where 85% of samples classified as having acidic pH (<6.5) were partially derived from soil parent materials in Hainan (Table 2). Elevated concentrations of Cr and Cu in our dataset were predominantly observed in

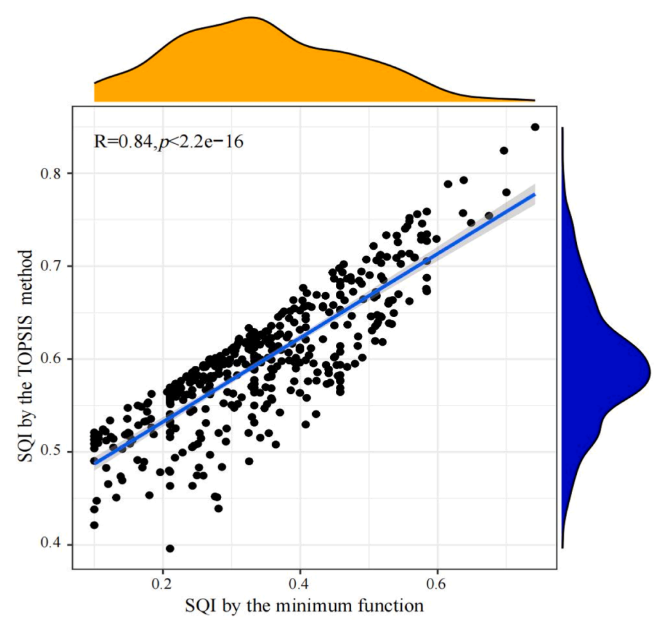


Fig. 9. Correlation between the SQI from the TOPSIS evaluation method and that from the minimum function method.

northern Hainan, consistent with previous findings of geogenic heavy metal enrichment in this region (Li et al., 2018; Gao et al., 2023; Yang et al., 2022). The spatial distribution patterns of these elements correlate strongly with the volcanic lithology characteristic of northern Hainan's pedological parent materials, as documented in prior geochemical investigations. Notably, the weathering of basaltic substrates in this area has been shown to naturally release these metallic elements into surface soils through pedogenetic processes. These observations underscore that while our standardized quality assessment provides consistent metrics for agricultural suitability comparisons, proper interpretation requires contextual understanding of local soil genesis. We therefore recommend that applications of this evaluation system in specific regions incorporate knowledge of dominant soil types and their characteristic property ranges to avoid misclassification of genetically determined features as quality limitations.

While the proposed soil quality evaluation framework provides a comprehensive assessment for tropical orchard systems in Hainan, several limitations regarding its broader applicability should be acknowledged. First, the indicator thresholds and scoring curves were specifically calibrated for local soil conditions, where excessive nitrogen accumulation is uncommon in orchard management practices. Consequently, the absence of an upper threshold for total nitrogen (TN) reflects this regional context but may not be appropriate for other agricultural systems where nitrogen oversupply could lead to environmental risks (e.g., leaching or eutrophication). Likewise, the approach to evaluating soil pH does not account for the natural variability in baseline pH across different soil types particularly those formed under distinct climatic or geochemical conditions. These context-dependent calibrations mean that direct application of our method to other regions or cropping systems would require validation and potential modification of scoring thresholds based on local edaphic and climatic conditions. However, the underlying framework—integrating both fertility and environmental indicators through standardized scoring approaches combined with an improved TOPSIS method—remains transferable as a methodological template. Future adaptations should consider region-specific factors such as dominant soil types, typical management practices, and environmental vulnerability priorities when establishing indicator thresholds and membership functions.

This study developed a comprehensive and accurate evaluation index system for soil quality in Hainan orchards; nevertheless, its performance is constrained by the current data acquisition limitations. Future studies should incorporate more physical and biological soil indicators in soil quality assessments. In this way, the evaluation index system will become even more comprehensive.

5. Conclusions

In this study, we assessed the soil quality for green production in Hainan orchards using a fuzzy mathematical method and an improved TOPSIS method to calculate the SQI. The assessment tool not only considers both the soil fertility and soil environment qualities but also sorts each site into different grades. Total nitrogen (TN) content, organic matter content, and acidic pH are the primary factors limiting the soil fertility quality in Hainan orchards, whereas Cr and Pb constitute the two key pollutants affecting the soil environment quality for the region. Overall, the primary limiter of soil quality is its fertility level. It is crucial to formulate scientific fertilisation and improvement strategies to improve the TN and OM levels and modify the soil acidification status in Hainan orchards. The current soil environment in Hainan orchards is not threatening. However, soil heavy metal accumulation poses a potential threat. This comprehensive assessment revealed the comprehensive soil quality and limiting factors in Hainan orchards, providing valuable insights for the sustainable development of a green production area. While developed for Hainan orchards, this method can be adapted to other regions through threshold calibration to accommodate local environmental conditions.

CRediT authorship contribution statement

Xiaofang Wu: Writing – original draft, Writing – review & editing, Supervision, Methodology. **Liqiang Zhang**: Writing – review & editing, Investigation. **Qiong Fan**: Resources, Methodology, Funding acquisition, Conceptualization. **Xiaogang Wang**: Resources, Investigation, Funding acquisition, Conceptualization. **Aini Deng**: Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Yi Xie**: Project administration, Methodology, Investigation, Funding acquisition. **Bingxia Su**: Software, Resources, Project administration, 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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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijagro.2025.100042.

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