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Research Article

Keywords: Soil quality index, Tobacco-planting soils, Minimum data set, Network analysis, Driving mechanisms

Posted Date: May 19th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9536160/v1

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Additional Declarations: No competing interests reported.

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Abstract

Soil quality assessment systems are critical in guiding cultivation strategies. In this study, seven counties across five major cultivation zones of the 'Honghua Dajinyuan' flue-cured tobacco variety in Yunnan Province were selected as the research area.. The total dataset included seven chemical, six physical, and four biological indicators. To construct the minimum datasets (MDS), network analysis (NTA) and principal component analysis (PCA) were compared. Soil quality index (SQI) values were calculated by integrating the NTA- and PCA-derived weights using both linear and nonlinear (NL) scoring methods. NTA combined with NL scoring based on soil water content (SWC), mean weight diameter, and acid phosphatase activity (ACP) as the MDS indicators (SQI-NTA-MDS-NL) demonstrated the highest substitutability (linear regression = 0.54, correlation analysis = 0.74, $p < 0.001$). More than 70% of the sampling points exhibited moderate to low SQI values (0.32–0.55), with county rankings as follows: Mile > Eshan > Weishan > Huaning > Nanjian > Shilin. Structural equation modeling indicated that enzyme activity and soil physical properties exerted direct effects on SQI, whereas carbon and phosphorus limitations had indirect influences mediated by enzyme activity. SWC and ACP were dominant contributing factors. The key constraints to SQI improvement included inadequate soil moisture, low ACP activity, and elevated sand and silt contents. Adaptive microbial responses to drought and phosphorus limitation contribute positively to SQI enhancement.

Keywords: Soil quality index; Tobacco-planting soils; Minimum data set; Network analysis; Driving mechanisms

Introduction

Tobacco (*Nicotiana tabacum* L.) serves as one of the most economically significant crops worldwide and has its yield and quality closely linked to the sustainable development of the national tobacco industry. As the primary medium for tobacco cultivation, soil plays a critical role through its physical, chemical, and biological attributes, which collectively affect crop productivity and quality (Thomaz & Antoneli, 2022; Feng et al. 2023; Huan et al. 2024; Q. Xiao et al. 2024). The Soil Quality Index (SQI) offers an integrated evaluation of soil physical, chemical, and biological parameters, enabling a comprehensive assessment of soil fertility and production potential and thereby providing a scientific foundation for soil management decision-making (Bünemann et al. 2018). Consequently, the development of a robust soil quality assessment system for tobacco-planting soils is essential to support the selection of flue-cured tobacco cultivation areas, inform soil amelioration practices, and promote sustainable tobacco production (Supriyadi et al. 2014).

SQI calculation generally comprises three steps: indicator selection and weighting, indicator scoring, and integration of the weighted scores into a composite index (Andrews et al. 2002; Zhu et al. 2024). The selected indicators typically encompass conventional physical and chemical parameters along with increasingly emphasized biological indicators (Su et al. 2024; Vasu et al. 2024). Among biological indicators, soil extracellular enzyme activities originating from microbial metabolism, root exudation, and the decomposition of animal residues have been widely adopted because of their sensitivity and ecological relevance (Cao et al. 2023; P. Li et al. 2024; Teng et al. 2024). For instance, Cao et al. (2023) employed acid phosphatase (ACP), invertase, urease, and catalase activities to assess SQI in subtropical Chinese fir

71 plantations of varying ages. Li et al. (2024) utilized phenol oxidase and cellulase activities to
72 evaluate the long-term impacts of fertilization regimes on the SQI in single rice cropping
73 systems. In tobacco cultivation contexts, Teng et al. (2024) applied ACP and invertase for SQI
74 estimation in Guizhou Province. The stoichiometric characteristics of four extracellular
75 enzymes associated with carbon, nitrogen, and phosphorus cycling include ACP, β-glucosidase
76 (BG), leucine aminopeptidase (LAP), and N-acetyl-β-D-glucosaminidase (NAG). These have
77 been shown to effectively reflect microbial nutrient limitations, thereby informing precision
78 fertilization and sustainable tobacco production strategies (Jiang et al. 2022; C. Wang et al.
79 2022; Feng et al. 2023). Accordingly, ACP, LAP, BG, and NAG were selected as the
80 biological indicators for SQI computation in this study.
81 However, the inclusion of an excessive number of evaluation indicators not only increases
82 financial costs but also introduces the risk of multicollinearity (Bünemann et al. 2018). The
83 development of minimum datasets (MDS) enables the reduction of assessment costs while
84 maintaining evaluation accuracy and has been successfully implemented for soil quality
85 assessments across diverse regions, spatial scales, and agricultural management regimes
86 (Raiesi & Kabiri, 2016; Qian et al. 2023; Gan et al. 2024). As a conventional technique for
87 MDS construction, Principal component analysis (PCA) has been extensively adopted in
88 previous SQI studies (Andrews et al. 2002; Teng et al. 2024). In recent years, network analysis
89 (NTA) has emerged as an innovative approach to indicator screening in MDS construction
90 (Martín-Sanz et al. 2022; Raiesi & Beheshti, 2022; Zahedifar, 2023). A comparative study by
91 Martín-Sanz et al. (2022) revealed that the substitution efficiency of NTA-derived MDS for the
92 total dataset (TDS) (R^2 = 0.68) significantly outperformed that of PCA-based methods.
93 Similarly, Raiesi and Beheshti (2022) demonstrated that NTA could account for over 80% of
94 TDS variation with a limited set of indicators, substantially enhancing evaluation efficiency.
95 The high sensitivity of NTA-derived MDS was also confirmed by M. Gao et al. (2025).

Nevertheless, the application of NTA for indicator selection in tobacco-planting soil quality assessments has not yet been reported.

PCA and NTA not only facilitate indicator screening but also enable the calculation of indicator weights (Martín-Sanz et al. 2022; Raiesi & Beheshti, 2022; Lu et al. 2024; M. Gao et al. 2025). Alternative approaches, such as the entropy weight method (F. Guo et al. 2024), correlation coefficient method (Shantal et al. 2023), and comprehensive weighting strategy (Z. Chen & Shi, 2020), have also been employed for independent weight assignment. However, certain integrated methods that simultaneously perform indicator selection and weight determination may offer greater efficiency. Accordingly, this study adopted PCA and NTA for the direct computation of indicator weights.

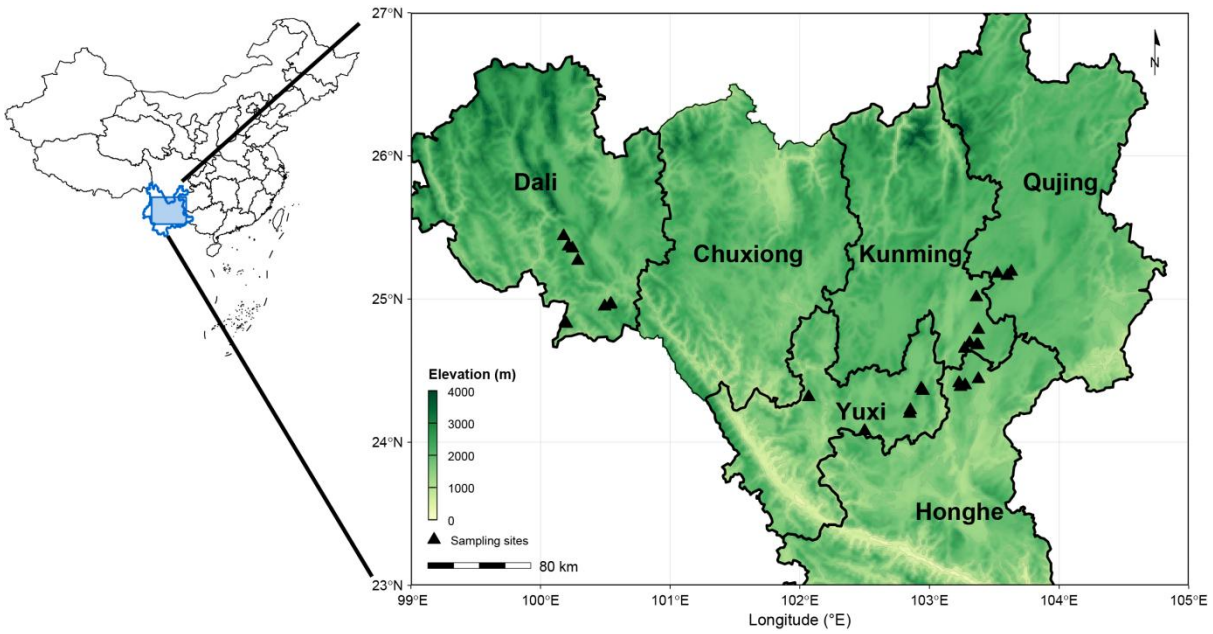
Prior to SQI computation, soil indicators with varying measurement units and numerical ranges should be transformed into standardized and comparable values (Andrews & Carroll, 2001). Common standardization methods include membership functions, as well as linear (L) and nonlinear (NL) scoring functions (Xu et al. 2021; F. Guo et al. 2024; C. Liu et al. 2025; L. Liu et al. 2025). Membership functions represent a conventional approach to indicator normalization (Wu et al. 2019; C. Liu et al. 2025). Linear scoring offers computational simplicity and reduced interpretative subjectivity, rendering it well suited for routine soil quality assessments (Vasu et al. 2024). In contrast, nonlinear scoring enables a more accurate representation of soil functional states and provides greater ecological relevance (Andrews et al. 2002). Numerous studies have examined the combined effects of linear and nonlinear scoring with MDS construction (Martín-Sanz et al. 2022; Raiesi & Beheshti, 2022; K. Li & Wang, 2023). Other studies have compared the outcomes of linear and nonlinear scoring integrated with various SQI calculation methods (Shi et al. 2019). In addition, some research has assessed evaluation effectiveness by combining scoring strategies with simple additive or weighted summation models under a unified SQI framework (M. Gao et al. 2025). Therefore,

121 the linear and nonlinear scoring functions can be integrated with indicator screening methods
122 and SQI calculation strategies to construct robust and context-specific soil quality assessment
123 systems and to evaluate their applicability and predictive performance across diverse soil
124 ecosystems (L. Guo et al. 2017; M. Gao et al. 2024; Lu et al. 2024).
125 Following soil quality assessment, the identification of influencing factors is essential to
126 inform soil quality improvement strategies. Previous studies have demonstrated that SQI can
127 be affected by soil physicochemical properties such as organic matter content, pH, and nutrient
128 availability (Chaudhry et al. 2024; Vasu et al. 2024), as well as by microbial activity (H. Liu et
129 al. 2022; Teng et al. 2024; Wan et al. 2024). Notably, soil limiting factors vary across
130 tobacco-planting regions (Y. Chen et al. 2023; Feng et al. 2023). As the largest flue-cured
131 tobacco-producing province in China, Yunnan plays a critical role as a raw material base for
132 major tobacco brands. Therefore, identification of key regulatory factors affecting
133 tobacco-planting soil quality holds considerable importance. Although obstacle degree models
134 have been applied to determine the limiting factors in SQI (L. Liu et al. 2025), the relationship
135 between SQI and these limiting factors remains insufficiently defined, thereby hindering the
136 advancement of targeted assessment and improvement efforts. This study focused on the
137 tobacco-planting soils from seven counties within the five major cultivation zones of the
138 'Honghua Dajinyuan' variety in Yunnan Province. This study aimed to: (1) construct an MDS
139 and determine indicator weights using PCA and NTA, combined with linear and nonlinear
140 scoring methods to calculate SQI, and identify the most suitable combination for soil quality
141 assessment in the study area; (2) evaluate the current status of tobacco-planting soil quality in
142 the region; and (3) identify the primary driving factors influencing SQI.

Methods

Study area

The study area comprises seven counties located within five primary tobacco-planting regions of the 'Honghua Dajinyuan (Hongda)' flue-cured tobacco variety in Yunnan Province (**Error! Unknown switch argument.**), including Shilin County (Kunming City), Weishan and Nanjian Counties (Dali Bai Autonomous Prefecture), Mile County (Honghe Hani and Yi Autonomous Prefecture), and Eshan and Huaning Counties (Yuxi City). The sampling sites are located between 100.2° and 103.6°E longitude and 24.1° and 25.4°N latitude, with elevations ranging from 1,600 to 2,300 m above sea level. The region is characterized by a northern subtropical humid climate, with average temperatures of 16.8 to 22.8°C during the growing season (April to September). Precipitation during this period ranges from 487.8 to 1,452.3 mm, with over 80% occurring in the rainy season (May to October), resulting in pronounced seasonal variation between dry and wet periods. The dominant soil types in the areas include Cambisols and Luvisols according to the WRB classification. The agricultural system primarily involves crop rotation, typically under a double-cropping regime, with two harvests per year. Common preceding crops in spring include wheat or rapeseed. Detailed information regarding the sampling sites is provided in Table S1.



160

161 **Fig. 1** Geographical location map of the study area.The elevation data were obtained from
162 'elevatr' package in R, the spatial projection coordinate system is WGS84, Map approval
163 number is GS (2025) No. 1508

164 Sample collection

165 Prior to tobacco transplanting in 2024, three adjacent field plots with uniform soil types,
166 identical preceding crops, and managed by the same farmer were selected at each sampling
167 site. Soil samples were collected from the 0–20 cm topsoil layer of each plot using a five-point
168 sampling method. After thorough homogenization, stones, crop residues, and other debris were
169 removed, and the soil was passed through a 2 mm sieve, sealed in bags, and transported to the
170 laboratory. A portion of the samples was air-dried at room temperature for the analysis of basic
171 physical and chemical properties, while the remaining portion was stored at -80°C for
172 subsequent determination of soil enzyme activities.
173 Soil water content (SWC) was determined by oven-drying at 105°C for 24 h. Bulk density
174 (BD) was measured using the cutting ring method. Mean weight diameter (MWD) was
175 determined by dry sieving, calculated according to L. Liu et al. (2024). Soil organic matter

(SOM) was quantified via potassium dichromate oxidation with external heating (NY/T 1121.6-2006). Soil pH was determined potentiometrically at a 2.5:1 water-to-soil ratio (NY/T 1377-2007). Available nitrogen (AN) was measured by alkaline hydrolysis-diffusion (LY/T 1228-2015). Available phosphorus (AP) was determined using ammonium fluoride-HCl extraction for acidic soils (pH < 6.5) or sodium bicarbonate extraction for neutral/calcareous soils (pH ≥ 6.5), both followed by molybdenum antimony colorimetry (NY/T 1121.7-2014). Available potassium (AK) was analyzed by ammonium acetate extraction and flame photometry (NY/T 889-2004). Total nitrogen (TN) was determined by the Kjeldahl method or elemental analyzer (LY/T 1228-2015). Total phosphorus (TP) and potassium (TK) were analyzed by alkaline fusion or acid digestion followed by colorimetry or ICP-OES analysis (LY/T 1232-2015; LY/T 1234-2015). ACP, BG, LAP, and NAG were measured using commercial assay kits (Suzhou Grace Biotechnology Co., Ltd.). Soil texture data (sand, silt, and clay fractions) were obtained from the 1:1,000,000 soil database of the Institute of Soil Science, Nanjing (Fischer et al. 2008). All measurements were conducted in triplicate, with blank controls and standard curve validations included to ensure analytical accuracy.

Soil quality assessment method

Significance testing ($p < 0.05$) was performed on 18 soil indicators, selecting 17 with significant regional differences for TDS. PCA and NTA were applied for MDS construction with calculated indicator weights. Linear and nonlinear scoring functions standardized the indicators. SQIs were then calculated by integrating the corresponding indicator weights and standardized scores. MDS substitutability for TDS was assessed via linear regression (R^2) and correlation analysis (r), with the highest correlation combination adopted as the final evaluation method. The specific procedures and analytical approaches are detailed below.

199 *Methods for MDS construction.* For the NTA method, the Spearman correlation coefficient
200 matrix among indicators was used as the adjacency matrix. The pairwise correlations between
201 soil variables were converted into a network consisting of multiple modules, where the nodes
202 represented the soil indicators, and the qualifying correlations were depicted as edges. The
203 node importance was quantified using eigenvector centrality. To ensure a robust modular
204 structure (modularity > 0.3) (Newman, 2004), the correlation thresholds were set at r > |0.43|
205 with $p < 0.05$, and correlations below this threshold were replaced with zero (Raiesi & Beheshti, 2022). The modules exhibiting non-zero eigenvector centrality values were retained,
207 and within each module, the indicator with the highest eigenvector centrality was selected to
208 construct NTA-MDS (Martín-Sanz et al. 2022). For the PCA method, the indicators with the
209 highest absolute loading values from principal components with eigenvalues greater than one
210 were selected to construct the PCA-MDS (Zahedifar, 2023).
211 *Weight determination method.* Following the approach proposed by Martín-Sanz et al. (2022),
212 the indicator weights were calculated using Eq.**Error! Unknown switch argument.** for the
213 PCA method and Eq.**Error! Unknown switch argument.** for the NTA method, respectively.

$$W_i = \%VarPC_i / \%VarTotal / \sum_{i=1}^{n} (\%VarPC_i / \%VarTotal) \quad \text{i}$$

$$W_i(NTA) = EC(M_i) / EC_{Total} / \sum_{i=1}^{n} (EC(M_i) / EC_{Total}) \quad \text{ii}$$

214 Where $\%VarPC_i$ is the percentage of variance explained by the principal component
215 containing indicator i; $\%VarTotal$ is the total percentage of variance explained by all selected
216 principal components; $EC(M_i)$ is the sum of eigenvector centrality of all variables in module M_i
217 where the indicator is located; EC_{Total} is the total eigenvector centrality of all variables in the
218 network; and n is the number of selected principal components or modules.
219 *Indicator scoring*. Linear and nonlinear scoring methods were employed to standardize all
220 indicators to a [0, 1] interval, accounting for three types of indicator characteristics: 'higher is
221 better', 'lower is better', and 'optimal range'. For the indicators with the 'optimal range' (e.g.,

the soil pH in this study), a piecewise function was applied whereby the values within the optimal range were assigned a standardized score of 1. For values outside this range, the score transformations corresponding to the 'higher is better' or 'lower is better' criteria were applied using Eqs.**Error! Unknown switch argument.**,**Error! Unknown switch argument.**,**Error! Unknown switch argument.** (Martín-Sanz et al. 2022). Specifically, for the 'higher is better' indicators such as BD, sand, and silt content, and for the "lower is better" indicators (all others), linear scoring was performed using Eqs.**Error! Unknown switch argument.** and **Error! Unknown switch argument.**, respectively (Xu et al. 2021). Nonlinear scoring was performed using Eq.**Error! Unknown switch argument.** (M. Gao et al. 2024).

$$S_L = \frac{x - x_{Min}}{x_{Max} - x_{Min}} \quad \text{iii}$$

$$S_L = 1 - \frac{x - x_{Min}}{x_{Max} - x_{Min}} \quad \text{iv}$$

Where x is the measured value of the indicator, x_{Max} is the maximum value of the indicator among all analyzed samples, and x_{Min} is the minimum value of the indicator among all analyzed samples.

$$S_{NL} = \frac{a}{1 + (\frac{x}{x_0})^b} \quad \text{v}$$

Where x is the measured value of the indicator; a is the maximum value obtained from the S-shaped curve (a = 1); x_0 is the mean value of the indicator among all analyzed samples; and b is the coefficient, which is -2.5 for the "higher is better" indicators and 2.5 for the "lower is better" indicators.

Soil quality index calculation. The soil quality index was calculated using Eq.**Error! Unknown switch argument.**:

$$SQI = \sum_{i=1}^{n} W_i S_i \quad \text{vi}$$

Where W_i is the indicator weight, and S_i is the indicator score (Raiesi, 2017).

Soil obstacle degree calculation. Upon the completion of the SQI calculation, the obstacle degree of each indicator was determined using Eq.**Error! Unknown switch argument.**. The obstacle severity was categorized into four levels based on the calculated values: no obstacle ($M_{ij} = 0$), mild obstacle ($0 < M_{ij} \leq 0.1$), moderate obstacle ($0.1 < M_{ij} \leq 0.2$), and severe obstacle ($M_{ij} > 0.2$) (L. Liu et al. 2025).

$$M_{ij} = \frac{W_i(1 - S_i)}{\sum_{i=1}^{n} W_i(1 - S_i)} \quad \text{vii}$$

Finally, microbial resource limitations were characterized based on soil enzyme activity, following the methodology previously established by Feng et al. (2023).

Statistical analysis

Shapiro-Wilk and Levene's tests assessed normality and variance homogeneity. ANOVA was applied for indicators meeting assumptions, while Kruskal-Wallis tests were used otherwise, followed by Dunn's test for pairwise differences ($p < 0.05$).

For MDS construction, NTA used the 'igraph' package and Gephi for visualization. The KMO (> 0.6) and the Bartlett's tests ($p < 0.05$) determined the suitability of PCA using 'FactoMineR' (Teng et al. 2024). Spearman's correlation and linear regression analyses were conducted to evaluate the validity of MDS as a substitute for TDS. Based on the equal interval classification principle, the full range of soil quality index values was evenly divided into five levels (Zárate-Salazar et al. 2024). Sample points from the highest and lowest quality levels were selected for two-tailed t-tests (Teng et al. 2024).

A structural equation model (SEM) was developed to examine the pathways through which soil physical properties, chemical properties, enzyme activity, microbial resource limitations, and obstacle degree (VIF < 10) influenced SQI. And piecewise least squares path analysis was conducted using the 'piecewiseSEM' package. The model fit was assessed using Fisher's C statistic ($p > 0.05$) and the coefficient of determination (R^2). Furthermore, a random forest algorithm was applied to evaluate the relative importance of each indicator in contributing to SQI, with permutation tests used to determine statistical significance. All analyses were performed in R Studio (version 4.1.2).

Results

Regional variations in soil properties

The soil organic matter content did not differ significantly among regions, ranging from 5.57 to 10.43 g/kg. The acidic conditions (pH 4.5–5.5) were observed in Huaning, Luliang, and Eshan; weakly acidic conditions (pH 5.5–6.5) in Nanjian, Shilin, and Mile; and neutral conditions (pH = 6.99) in Weishan. SWC was the highest in Mile. Weishan exhibited the highest values of TN, AP, MWD, ACP, BG, and LAP. It also had high silt content and low sand content.

The calculated enzyme stoichiometry revealed that most sampling points were distributed in the upper left quadrant, indicating a general prevalence of carbon and phosphorus (C&P) limitation across the study area. All vector angles exceeded 45°($p < 0.05$), suggesting consistent levels of phosphorus (P) limitation among regions. Luliang exhibited the shortest vector length, indicating the weakest carbon limitation, whereas Huaning reflected the most pronounced C limitation. The results of obstacle degree analysis identified SWC, soil texture components (Sand, Silt, and Clay), ACP, and NAG as the primary limiting factors across most regions.

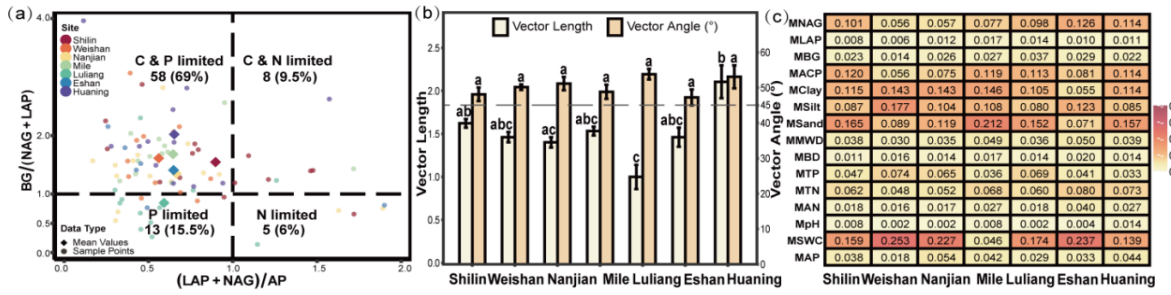


Fig. 2 Ecoenzymatic stoichiometry and obstacle degree analysis across different counties. This figure presents the ecoenzymatic stoichiometry scatter plot (a), vector length and vector angle analysis (b), and obstacle degree matrix (c) across different counties. Four sections in the plot depict carbon and phosphorus (C&P) limitation (upper left), carbon and nitrogen (C&N) limitation (upper right), phosphorus (P) limitation (lower left), and nitrogen (N) limitation (lower right). Bars represent mean ± standard error. Different letters indicate significant differences according to Dunn's multiple comparison test ($p < 0.05$). Vector length represents carbon limitation intensity; vector angle indicates N limitation (< 45°) or P limitation (> 45°). TK and AK indicators showed no obstacle ($M_{ij} = 0$) and are not plotted. (Abbreviations: AN, available nitrogen; AP, available phosphorus; AK, available potassium; TN, total nitrogen; TP, total phosphorus; TK, total potassium; SWC, soil water content; pH, soil pH; BD, bulk density; MWD, mean weight diameter; Sand, sand content; Silt, silt content; Clay, clay content; ACP, acid phosphatase; BG, β-glucosidase; LAP, leucine aminopeptidase; NAG, N-acetyl-β-glucosaminidase. Indicators prefixed with 'M' represent the obstacle degree of the corresponding parameter)

Table 1 Soil chemical, physical, and biochemical properties across seven counties in the study area

Category	Indicators		County						
			Shilin	Weishan	Nanjian	Mile	Luliang	Eshan	Huaning
Chemical Properties	SOM^{ns†}	(g/kg)	9.97 ± 1.08 a	9.9 ± 1.40 a	9.57 ± 2.03 a	10.11 ± 1.64 a	7.1 ± 0.79 a	10.43 ± 2.53 a	5.57 ± 0.99 a
	pH***		6.21 ± 0.28 a	6.99 ± 0.08 b	5.71 ± 0.20 ac	6.19 ± 0.31 a	5.26 ± 0.05 c	5.24 ± 0.11 c	4.75 ± 0.12 d
	AN***	(mg/kg)	148.16 ± 13.39 a	165.59 ± 8.08 a	167.32 ± 17.92 a	115.58 ± 19.39 abc	138.66 ± 17.86 ab	66.92 ± 21.93 c	90.99 ± 10.64 bc
	AP***	(mg/kg)	39.51 ± 6.51 ab	84.04 ± 10.84 c	24.13 ± 3.63 d	51.52 ± 14.39 ab	46.23 ± 6.13 ae	70.13 ± 15.32 ce	28.34 ± 6.12 bd

	AK**	(mg/kg)	359.00 ± 25.82 ab	325.25 ± 64.52 a	658.13 ± 81.88 c	418.00 ± 44.88 bd	402.08 ± 26.10 bd	651.00 ± 140.49 cd	531.83 ± 54.1 c
	TN**	(%)	0.12 ± 0.01 ab	0.18 ± 0.01 c	0.16 ± 0.01 cd	0.14 ± 0.01 ad	0.12 ± 0.01 be	0.13 ± 0.02 abd	0.10 ± 0.01 e
	TP***	(%)	0.07 ± 0.01 a	0.05 ± 0.01 bc	0.05 ± 0.01 b	0.10 ± 0.01 d	0.04 ± 0.01 c	0.09 ± 0.01 d	0.10 ± 0.01 ad
	TK***	(%)	0.25 ± 0.04 a	0.53 ± 0.07 b	0.84 ± 0.09 c	1.22 ± 0.18 c	0.44 ± 0.02 b	1.13 ± 0.27 c	0.85 ± 0.10 c
	SWC ***	(%)	2.07 ± 0.02 a	1.34 ± 0.03 b	1.52 ± 0.07 b	5.15 ± 0.33 c	1.72 ± 0.06 d	1.88 ± 0.21 ad	2.39 ± 0.26 a
	BD***	(g/cm^3)	0.98 ± 0.02 a	1.18 ± 0.02 bc	1.09 ± 0.05 d	1.12 ± 0.03 bd	1.20 ± 0.02 c	1.20 ± 0.05 bc	1.17 ± 0.03 bcd
Physical Properties	MWD **	(mm)	2.27 ± 0.13 b	3.02 ± 0.20 a	2.81 ± 0.21 ab	2.31 ± 0.21 b	2.21 ± 0.15 b	2.26 ± 0.30 b	2.17 ± 0.21 b
	Sand ***	(%)	49.00 ± 0.01 a	29.00 ± 0.01 b	36.40 ± 1.83 b	49.50 ± 0.15 c	49.00 ± 0.01 a	24.50 ± 3.5 b	47.83 ± 0.79 a
	Silt***	(%)	28.00 ± 0.01 a	50.00 ± 0.01 b	31.60 ± 2.09 a	27.50 ± 0.15 c	28.00 ± 0.01 a	28.83 ± 0.17 d	28.00 ± 0.01 a
	Clay ***	(%)	23.00 ± 0.01 a	21.00 ± 0.01 b	20.40 ± 0.13 b	23.00 ± 0.01 a	23.00 ± 0.01 a	45.00 ± 5.00 c	22.50 ± 0.34 a
	ACP ***	(μmol/d/g)	12.38 ± 1.17 a	27.07 ± 2.32 b	24.03 ± 3.51 c	16.19 ± 1.65 d	11.37 ± 1.51 a	23.31 ± 3.65 bc	12.67 ± 1.93 ad
Biochemical Properties	BG***	(μmol/d/g)	13.69 ± 0.88 a	22.25 ± 1.98 b	15.24 ± 2.14 a	14.86 ± 1.02 a	4.49 ± 0.75 c	14.43 ± 1.19 a	13.82 ± 0.88 a
	LAP ***	(μmol/d/g)	6.64 ± 0.76 a	8.54 ± 0.78 b	5.19 ± 0.69 ac	3.72 ± 0.48 de	2.60 ± 0.39 d	7.98 ± 1.89 ab	4.69 ± 0.66 ce
	NAG ***	(μmol/d/g)	3.24 ± 0.41 a	5.82 ± 0.29 b	5.94 ± 0.52 b	5.23 ± 0.52 b	2.98 ± 0.31 a	3.49 ± 0.46 a	2.58 ± 0.38 a

†: ns, $p > 0.05$, ** $p < 0.01$, *** $p < 0.001$. Values represent means ± standard error. Means followed by different lowercase letters are significantly different among counties (Duncan's multiple range test, $p < 0.05$)

Abbreviations: SOM, soil organic matter; pH, soil pH; AN, available nitrogen; AP, available phosphorus; AK, available potassium; TN, total nitrogen; TP, total phosphorus; TK, total potassium; SWC, soil water content; BD, bulk density; MWD, mean weight diameter; Sand, sand content; Silt, silt content; Clay, clay content; ACP, acid phosphatase; BG, β-glucosidase; LAP, leucine aminopeptidase; NAG, N-acetyl-β-glucosaminidase

MDS construction using NTA and PCA and selection of optimal evaluation approach

17 soil indicators exhibiting significant regional differences ($p < 0.05$) were included in TDS. Through NTA, three modules were identified from the correlation matrix network (Table S2) with a modularity value of 0.43.. The indicators with the highest eigenvector centrality were selected from each module to form NTA-MDS: SWC (1.00), ACP (0.60), and MWD (0.25).

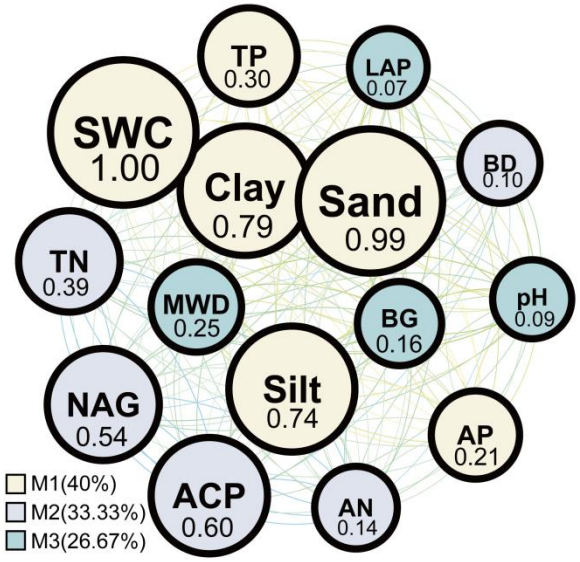


Fig. 3 Network analysis results. Correlation network using Fruchterman-Reingold layout showing three modules (M1-M3) with different colors. Modules with zero eigenvector centrality are excluded. Node size and numbers represent eigenvector centrality values. Edge colors represent module assignments. (Abbreviations: AN, available nitrogen; AP, available phosphorus; AK, available potassium; TN, total nitrogen; TP, total phosphorus; TK, total potassium; SWC, soil water content; pH, soil pH; BD, bulk density; MWD, mean weight diameter; Sand, sand content; Silt, silt content; Clay, clay content; ACP, acid phosphatase; BG, β-glucosidase; LAP, leucine aminopeptidase; NAG, N-acetyl-β-glucosaminidase)

Based on the PCA results presented in Table S3, the first five principal components with eigenvalues greater than 1 were extracted, cumulatively explaining 69.86% of the total variance. The indicators with the highest absolute loading values on each component were then selected to construct PCA-MDS: Silt, AK, Clay, SWC, and LAP.

Subsequently, SQIs were calculated by multiplying the standardized indicator scores with their corresponding weights (Table S4), resulting in four types of SQI based on the MDS (SQI-PCA-MDS-L, SQI-PCA-MDS-NL, SQI-NTA-MDS-L, SQI-NTA-MDS-NL) and four based on TDS (SQI-PCA-TDS-L, SQI-PCA-TDS-NL, SQI-NTA-TDS-L,

SQI-NTA-TDS-NL). Each MDS-derived result was compared with its corresponding TDS-derived counterpart. As illustrated in Fig. 4, the combination of nonlinear scoring with the NTA method (SQI-NTA-MDS-NL) demonstrated the highest correlation (r = 0.74) and coefficient of determination (R^2 = 0.54) and was thus identified as the optimal approach for SQI calculation in the study area.

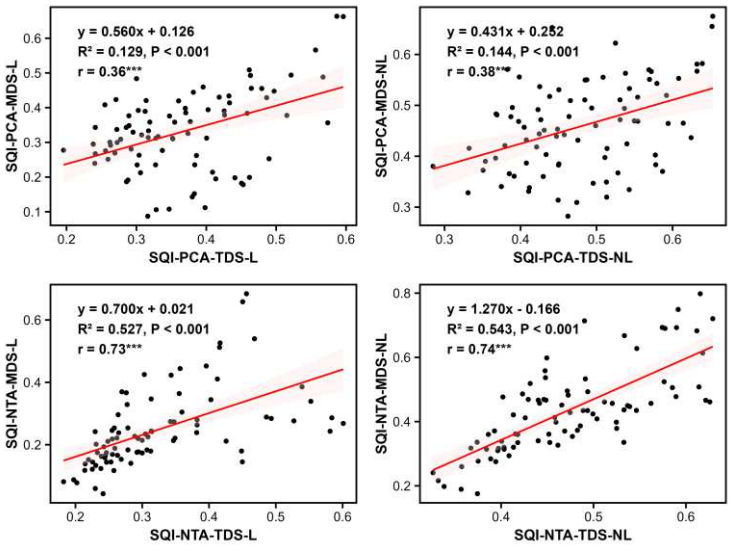


Fig. 4 Spearman correlation and linear regression analysis of MDS versus TDS. (Abbreviations: NTA, network analysis; PCA, principal component analysis; MDS, minimum dataset; TDS, total dataset; L, linear scoring method; NL, non-linear scoring method; r, Spearman correlation coefficient; R^2, coefficient of determination for linear regression; *** $p < 0.001$)

Regional soil quality assessment

Using SQI-NTA-MDS-NL to evaluate tobacco-planting SQI across seven counties, over 70% of the sampling points were classified as moderate to low in SQI. Mile exhibited the highest soil quality (SQI = 0.67 ± 0.02), while Luliang showed the lowest (SQI = 0.32 ± 0.02). The highest individual SQI value was recorded in Mile, whereas the lowest was observed in Eshan.

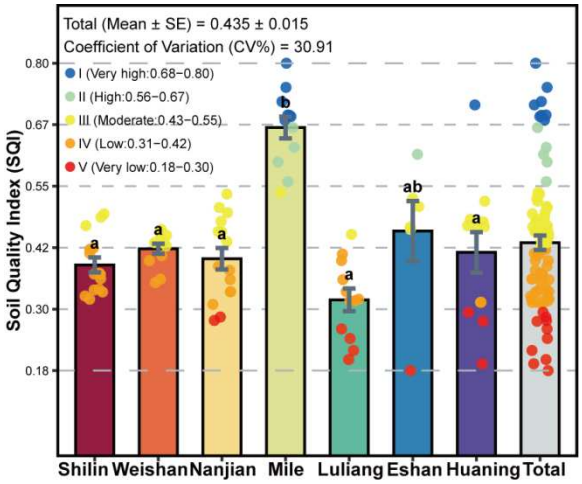
To compare the soil characteristics between the highest and lowest quality soils, eight sampling points from I and ten from V were selected. As presented in **Error! Unknown switch argument.**, the high-quality soil exhibited significantly higher values for SWC, ACP, TP, NAG, sand, TK, clay, AN, and BG and a significantly lower BD than the low-quality soil.

Table 2 Comparison of indicators between Group I (Very High SQI) and Group V (Very Low SQI)

Indicator	**SQI**	**SWC(%)**	**TN(%)**	**BD(g/cm^3)**	**ACP(μmol/d/g)**	**TP(%)**
GroupV	0.24	1.51	0.10	1.25	7.90	0.05
GroupI	0.72	5.56	0.16	1.08	20.47	0.10
Significance†	***	***	***	***	***	***
Indicator	**NAG(μmol/d/g)**	**Sand(%)**	**TK(%)**	**Clay(%)**	**AN(mg/kg)**	**BG(μmol/d/g)**
GroupV	3.19	45.50	0.60	21.50	88.04	9.31
GroupI	5.85	49.25	1.26	23.00	137.45	15.17
Significance	**	*	*	*	*	*
Indicator	**LAP(μmol/d/g)**	**Silt(%)**	**AP(mg/kg)**	**pH**	**MWD(mm)**	**AK(mg/kg)**
GroupV	4.79	30.00	41.48	5.25	2.27	401.90
GroupI	2.85	27.75	66.26	5.56	2.08	425.50
Significance	ns	ns	ns	ns	ns	ns

†: ns, $p > 0.05$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Abbreviations: SQI, soil quality index; AN, available nitrogen; AP, available phosphorus; AK, available potassium; TN, total nitrogen; TP, total phosphorus; TK, total potassium; SWC, soil water content; pH, soil pH; BD, bulk density; MWD, mean weight diameter; Sand, sand content; Silt, silt content; Clay, clay content; ACP, acid phosphatase; BG, β-glucosidase; LAP, leucine aminopeptidase; NAG, N-acetyl-β-glucosaminidase



358

359 **Fig. 5** Soil quality evaluation across seven counties based on SQI-NTA-MDS-NL. Bars
360 represent the mean ± standard error. Different letters indicate significant differences
361 according to Dunn's multiple comparison test ($p < 0.05$)

362 Drivers of soil quality index

363 The piecewise SEM model demonstrated an excellent fit (Fisher's C = 6.03, $p = 0.20$) and
364 explained 85% of the variance in the soil quality ($R^2 = 0.85$, Fig. 6). Significant direct effects
365 were observed for the soil physical properties ($\beta = 0.74$, $p < 0.001$) and soil enzyme activities
366 ($\beta = 0.31$, $p < 0.001$). Microbial resource limitation exerted a significant indirect effect on SQI
367 mediated by enzyme activity ($\beta = 0.42$, $p < 0.001$). Soil enzyme activities also had an indirect
368 negative effect on SQI through their influence on the obstacle degree ($\beta = -0.33$, $p < 0.001$).
369 The soil physical properties exhibited additional indirect effects on SQI via soil chemical
370 properties ($\beta = 0.64$, $p < 0.001$) and obstacle degree ($\beta = 0.55$, $p < 0.001$). Random forest
371 analysis accounted for 86.4% of the variance in SQI (**Error! Unknown switch argument.**b),
372 with the variable importance ranking identifying ACP (%IncMSE=17.51) and SWC
373 (%IncMSE=16.85) as the most influential predictors.

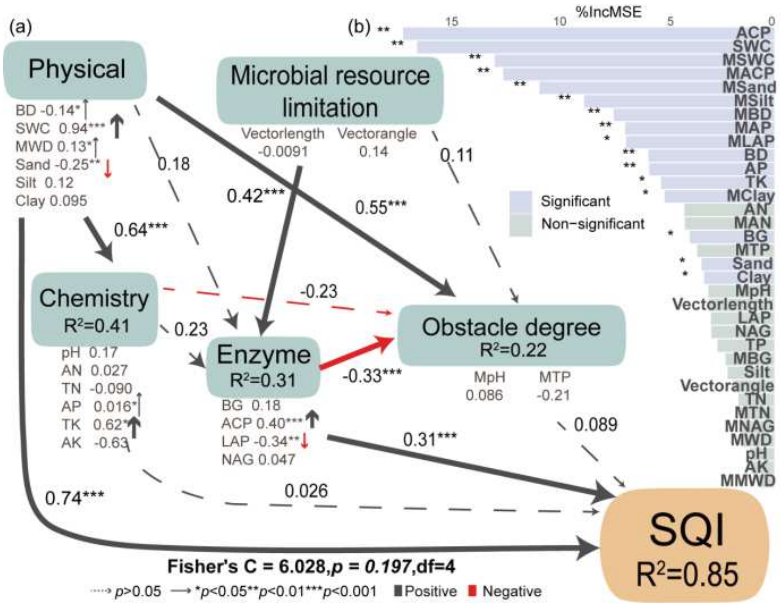


Fig. 6 Analysis of factors driving soil quality index.This figure presents the structural equation modeling (a) and random forest analysis (b). Numbers on the arrows represent standardized path coefficients. The R^2 represents the proportion of variance explained by predictors. Statistical significance is indicated at $p < 0.05$. (Abbreviations: AN, available nitrogen; AP, available phosphorus; AK, available potassium; TN, total nitrogen; TP, total phosphorus; TK, total potassium; SWC, soil water content; pH, soil pH; BD, bulk density; MWD, mean weight diameter; Sand, sand content; Silt, silt content; Clay, clay content; ACP, acid phosphatase; BG, β-glucosidase; LAP, leucine aminopeptidase; NAG, N-acetyl-β-glucosaminidase. Indicators prefixed with 'M' represent the obstacle degree of the corresponding parameter)

Discussion

Indicator selection for MDS using PCA and NTA

The construction of MDS for calculating SQI has been widely adopted as an effective strategy to reduce indicator redundancy and enhance evaluation efficiency (Vasu et al. 2016). In this

study, PCA and NTA were employed to construct MDS, contributing to the differences in indicator selection. PCA identified the indicators that contributed the most to the overall variance, including Silt, SWC, Clay, AK, and LAP (Table S3). NTA relied on inter-indicator correlations and functional connectivity, grouping indicators into modules and selecting representative indicators from each: SWC, ACP, and MWD (**Error! Unknown switch argument.**).

In this study, SWC was identified as a representative indicator using both PCA and NTA methods. This finding aligns with the results of L. Wang et al. (2025), who also identified SWC as a critical indicator in farmland soil assessments in black soil regions and reinforced its importance in SQI evaluation. Additionally, SWC was confirmed as a key determinant of SQI in the study area (**Error! Unknown switch argument.**). This finding was also supported by the substantial difference in SWC between the highest (5.56%) and lowest (1.61%) SQI grades (**Error! Unknown switch argument.**), which is consistent with previous research. L. Wang et al. (2025) demonstrated that soil moisture significantly affected soil aggregation and organic carbon distribution, making it a vital factor in soil quality regulation. In addition, Bünemann et al. (2018) emphasized the relevance of structural and textural indicators, such as Silt and Clay, in SQI frameworks, which can often serve as effective substitutes for full indicator sets. In this study, both Silt and Clay were selected through PCA, supporting the validity of indicator selection. The MWD indicator selected via NTA is known for its sensitivity to soil structure, biochemical characteristics, and management practices and contributes to various ecosystem services, including organic carbon sequestration, water infiltration, root growth, and microbial activity (Huang et al. 2025). Its utility has also been demonstrated by L. Liu et al. (2024), who used PCA to identify MWD as a key indicator due to its strong association with soil erosion resistance and structural recovery, further confirming its representativeness. Moreover, both PCA and NTA consistently included enzyme activity indicators in MDS. This is consistent

414 with the findings of L. Wang et al. (2023), who identified LAP and ACP via PCA as critical
415 indicators of soil biochemical activity and sensitive markers of soil health status. Teng et al.
416 (2024) performed PCA to select Silt, AK, and ACP for the SQI evaluation in Guizhou
417 tobacco-planting soils, showing the strong agreement with our selection. Collectively, these
418 findings confirmed that the indicators selected through PCA and NTA in this study were both
419 scientifically valid and practically reliable for soil quality assessment.
420 A comparison of the two MDS construction methods highlighted several advantages of the
421 NTA approach. First, NTA achieved higher efficiency by selecting only three indicators while
422 substantially increasing the weight assigned to SWC in the assessment (Table S4), thereby
423 enhancing its influence on the SQI calculation. Second, the selected ACP indicator was
424 validated using the random forest model as the most influential predictor of SQI. Third, the
425 selected MWD showed significant correlations with the Silt and Clay indicators identified by
426 PCA (Table S3), suggesting that MWD, as a structural indicator, can effectively substitute for
427 textural components in the PCA-based MDS. This finding is consistent with that of M. Gao et
428 al. (2024), who demonstrated that NTA outperformed PCA in terms of indicator screening
429 efficiency and accuracy. Therefore, NTA could offer a practical advantage by minimizing data
430 redundancy through the identification of functionally central indicators while preserving the
431 overall accuracy and representativeness of soil quality assessments.

432 Assessment and validation of SQI

433 In this study, the combination of NTA and nonlinear scoring exhibited the best performance,
434 demonstrating the highest substitutability of TDS. This is consistent with the findings of
435 previous studies (Martín-Sanz et al. 2022; Raiesi & Beheshti, 2022; M. Gao et al. 2024). The
436 superior performance of nonlinear over linear scoring when combined with NTA may be
437 attributed to its greater ability to capture the complex nonlinear relationships between soil

properties and functions, particularly in cases involving threshold effects (Andrews et al. 2002). Nonlinear scoring also exhibits a higher sensitivity to soil quality variation (Ellur et al. 2024), allowing for the detection of subtle but potentially meaningful fluctuations in soil function. This sensitivity is particularly advantageous in NTA frameworks, which typically select a limited number of key indicators. Under such conditions, the influence of each indicator is amplified, thereby increasing the importance of the scoring method applied. Conversely, most existing studies have only compared linear and nonlinear scoring in combination with NTA (Martín-Sanz et al. 2022; Raiesi & Beheshti, 2022; M. Gao et al. 2024). Future research should consider incorporating a broader range of scoring approaches, such as membership functions or Bayesian network-based scoring, to facilitate a more comprehensive evaluation of scoring method combinations within NTA-based soil quality assessment frameworks.

Mechanisms underlying SQI drivers and regional soil improvement strategies

The importance of soil physicochemical properties in tobacco planting soils has been extensively validated (Jiang et al. 2022; Zhai et al. 2022; Jiang et al. 2025). Consistent with our findings, a study by Thomaz and Antoneli (2022) in tobacco-planting regions of southern Brazil highlighted the significant contributions of soil aggregate stability and organic matter content to overall soil quality. Our results further demonstrated that soil chemical properties exerted a positive influence on soil quality when mediated by improvements in physical properties. Specifically, enhanced moisture availability and optimized soil texture facilitated the amelioration of regionally acidic pH and nutrient enrichment, thereby promoting regional improvements in SQI (**Error! Unknown switch argument.**a). Additionally, increased ACP activity was observed to directly contribute to SQI enhancement, consistent with the findings of Qu et al. (2025), who reported that P metabolism-related enzymes, including ACP,

462 significantly improved soil fertility in soybean systems. In this study, under P-limited
463 conditions, soil microorganisms responded adaptively by increasing ACP activity, which
464 exerted a positive effect on SQI. Under broader microbial resource limitations,
465 microorganisms tend to produce more extracellular enzymes associated with the acquisition of
466 limiting nutrients, thereby maximizing resource utilization efficiency (Sinsabaugh et al. 2009;
467 Cui et al. 2022; H. Zhang et al. 2024).
468 Microbial resource limitation was also found to exert an indirect influence on the soil obstacle
469 degree, thereby affecting overall soil quality. The obstacle degree model identifies the limiting
470 factors by integrating the indicator weights with the deviation between observed and optimal
471 values, enabling the determination of each factor's relative contribution to the soil quality
472 constraints (L. Liu et al. 2025). It was hypothesized that microbial enzymatic adaptation under
473 resource-limited conditions could alter the relative importance of obstacle degrees across
474 indicators, thus further influencing SQI (**Error! Unknown switch argument.**). Yang et al.
475 (2023) reported a positive correlation between SQI and vector angle in the northwestern
476 semi-arid region. Similarly, in this study, SEM (**Error! Unknown switch argument.**)
477 revealed that the vector angle representing P limitation and ACP was positively correlated with
478 SQI, whereas LAP associated with nitrogen metabolism exhibited a negative correlation.
479 These findings suggest that a shift from nitrogen to P limitation may be favorable for
480 enhancing soil quality. However, this study employed enzyme vector models to characterize
481 microbial nutrient limitations, which reflected only the potential enzyme activity. Therefore,
482 further validation through metagenomic sequencing is necessary to elucidate the mechanistic
483 links between nutrient limitations and soil quality.
484 According to the random forest analysis, the soil texture-related obstacles, MACP, and MSWC
485 were all significant factors affecting SQI. As a fundamental physical property, unbalanced soil
486 texture characterized by high Sand and Silt can substantially reduce soil fertility (Dexter,

2004). Regarding ACP activity, the results are consistent with those of Y. Chen et al. (2023) and Z. Wang et al. (2019), where the high obstacle degree associated with ACP activity (%IncMSE$_{MACP}$ = 12.79) suggested that limited enzyme activity constrained soil quality in Yunnan's tobacco-planting regions. This limitation might arise from the binding and stabilization of ACP in clay-rich soils (L. Liu et al. 2025). However, the predominance of Sand and Silt in the study area imposed unfavorable textural conditions, potentially inhibiting ACP activity and thereby amplifying the negative impact of texture on SQI. MSWC was also identified as a major constraint on SQI improvement, which was consistent with the findings of L. Liu et al. (2025), who reported moisture as a key limiting factor in Inner Mongolia based on obstacle degree modeling. W. Li et al. (2023) further demonstrated that under low soil moisture conditions (3%) compared to moderate levels (8%), there was an increase in the abundance of organic phosphorus mineralization genes but no significant change in phosphorus acquisition genes, resulting in inorganic phosphorus accumulation rather than recycling (Delgado-Baquerizo et al. 2013; Y. Gao et al. 2022). These trends aligned with our findings (**Error! Unknown switch argument.**), which indicated that low SWC stimulated ACP activity, leading to reduced TP and elevated AP. This suggested that microbial adaptation strategies, such as enhanced extracellular enzyme secretion and shifts in microbial community composition, could mitigate moisture limitations and improve SQI. However, the significantly negative correlation observed between SWC and C- and N-acquisition enzyme activities in this study contrasted with the results reported by Wen et al. (2025) in organic vegetable soils in Kunming, Yunnan, where elevated SWC enhanced the microbial production of C- and N-related enzymes and improved SQI. This discrepancy highlights the complexity and context-dependence of the interactions among moisture, enzyme activity, and soil quality, indicating the need for further research into their coupled mechanisms.

Therefore, soil quality management in the study area should prioritize moisture regulation and the enhancement of ACP activity, along with comprehensive improvement of soil physicochemical properties. With the exception of Mile, all six other counties experienced soil drought (**Error! Unknown switch argument.**). To address this, practices such as appropriately delayed planting (Alameda et al. 2012) or the application of soil warming and moisture conservation techniques, including conventional plastic film, biodegradable mulch, or cup covers, have been shown to effectively improve soil moisture conditions (Machanoff et al. 2022; Feng et al. 2023; Y. Wang et al. 2024). In addition to moisture management, the region exhibited broader soil quality challenges. These included low ACP activity in Shilin, Luliang, and Huaning, suboptimal SOM levels across all counties (below 15 g/kg, Y. Xiao et al. 2022), and acidic soils in Luliang, Huaning, and Eshan. To address these interconnected constraints, the application of biochar amendment is recommended as an integrated remediation strategy. Biochar has been demonstrated to enhance SOM content, promote ACP enzyme activity, and regulate soil pH (Ren et al. 2021; Feng et al. 2023). Additionally, its water retention capacity can be particularly beneficial for improving the moisture-holding properties of sandy soils (J. Zhang et al. 2021).

This study developed a soil quality index evaluation system suitable for tobacco-planting areas by integrating soil physical, chemical, and biological indicators to construct a minimum data set (MDS). Innovatively combining enzyme stoichiometry with the soil quality index, and employing structural equation modeling, obstacle degree diagnosis models, and random forest models, it revealed the driving mechanisms among soil physicochemical properties, enzyme activities, microbial resource limitations, and soil quality. The methodological framework can be directly applied for soil evaluation and obstacle diagnosis of different tobacco varieties and also serves as a reference for other agricultural ecosystems. This broad applicability stems from two aspects: firstly, the selected indicators are representative across different agricultural

systems and geographical regions; secondly, the advantage of indicator screening via network analysis is not confined to this specific area.

Limitations of the study

While the present study provided valuable insights into soil quality evaluation and limiting factor diagnosis in tobacco-planting areas, certain limitations remain. First, the research was conducted solely at a 20 cm soil depth. Increasing the number of sampling points and incorporating deeper soil profiles would enhance the precision and applicability of the results. Second, only enzyme activities were employed as biological indicators. Enzyme activity is a responsive indicator, capable of rapidly reflecting changes in the soil environment. Furthermore, it can be used to calculate microbial resource limitations, effectively supplementing the obstacle diagnosis model in identifying limiting factors. Nevertheless, it does not fully elucidate the mechanistic role of microorganisms in regulating soil quality. Future studies are recommended to incorporate techniques such as metagenomic sequencing to integrate soil microbial composition and diversity indicators into the soil quality calculation framework. Exploring the relative contributions of microbial adaptation strategies—such as element use efficiency, community composition succession, and functional changes—to soil quality would provide a more comprehensive basis for precise soil management in tobacco-planting areas.

Conclusions

This study validated the optimal soil quality assessment approach across seven counties in five major cultivation regions of the ‘Hongda’ tobacco variety and applied it to evaluate SQI and its driving factors in the study area. The network analysis combined with a nonlinear scoring method, using SWC, MWD, and ACP as the MDS indicators (SQI-NTA-MDS-NL),

559 demonstrated the highest substitutability for the total dataset and was thus established as the
560 optimal method. More than 70% of the sampling points exhibited moderate to low SQI values,
561 with Mile showing a higher SQI. Enzyme activity and soil physical properties exerted
562 significant direct and indirect influences on SQI, with SWC and ACP identified as the primary
563 determinants. C&P limitation had indirect effects on SQI, mediated by enzyme activity. The
564 major constraints on SQI were insufficient soil moisture, low ACP activity, and elevated Sand
565 and Silt. Microbial adaptation strategies to drought and phosphorus limitation contributed
566 positively to the maintenance and improvement of soil quality.

567 **Supplemental Material** Supplemental material includes detailed site characteristics across the
568 study region (Table S1), Spearman correlation matrices for soil quality indicators (Table S2),
569 complete principal component analysis results for both total and minimum data sets (Table S3),
570 and indicator weight distributions determined by PCA and NTA methods (Table S4).

571 **Acknowledgments** We are grateful to the Yunnan Malong Slope Farmland Soil Conservation
572 Science and Technology Backyard for their technical support.

573 **Author contributions** All authors contributed to the study conception and design.
574 Investigation was carried out by L.C., T.X., C.W., R.Z., J.Y., Y.Z., X.C., and J.W. Data
575 curation was performed by Y.Z., B.W., and Y.P. Formal analysis was conducted by R.Z. and
576 B.W. Resources were provided by L.C., Y.Q., C.W., J.Y., and X.C. Funding was acquired by
577 Z.J., S.Y., J.W., Z.T., Y.P., and T.X. The first draft of the manuscript was written by Z.J. and
578 S.Y. Manuscript review and editing were performed by Z.T. and Y.Q. All authors read and
579 approved the final manuscript.
580

Funding This study was financially supported by the Science and technology project of Yunnan China Tobacco Industry Co., Ltd (2024YL02), the Yunnan Provincial Reserve Talents for Young and Mid-dle-aged Academic and Technical Leaders (202405AC350040), the Special Basic Cooperative Research Programs of Yunnan Provincial Undergraduate Universities' Association (202401BA070001-106), the Scientific Research Foundation Project of the Yunnan Education Department (2025Y1088, 2026Y1128), the Science and Technology Plan General Project of Qujing Tobacco Company Xuanwei Branch (2024YNQJKJ05), the Yunnan Province College Students Innovation and Entrepreneurship Training Program (202411393011), and Yunnan Jude Tianheng Technology Co., Ltd (JD202509006-1).

Data availability Data will be made available on request.

Declarations

Conflict of interest The authors declare no competing interests.

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Financial interests The authors declare they have no financial interests

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