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Root Stress as a Core Driver of Growth Decline and a Novel Health Evaluation System for Ancient *Cinnamomum camphora* Trees Integrating Non-Destructive Testing and Machine Learning

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Abstract

Ancient *Cinnamomum camphora* trees are irreplaceable ecological and cultural heritage in southern China, but their health assessment has long relied on subjective visual evaluation of aboveground traits, lacking quantitative characterization of underground root system status and mechanical stability. This study conducted a comprehensive investigation on 35 ancient *C. camphora* trees aged 100–200 years using multi-source non-destructive testing techniques, including stress wave acoustic tomography, TRU Tree Radar, and finite element simulation. We analyzed 18 phenotypic, physiological and mechanical indicators using hierarchical clustering, ANOVA, PCA, trait association network analysis, and four complementary machine learning methods. Hierarchical clustering showed 85.71% consistency with subjective four-level growth potential classification, identifying 6 core phenotypic indicators that effectively distinguish healthy and declining trees. PCA and trait association network analysis revealed that root stress was the most discriminative indicator driving group separation, and ancient camphor tree decline followed a coordinated deterioration cascade: *root stress* → *canopy degradation* → *growth impairment*. We established a quantitative framework for wind-induced root stress calculation and structural stability evaluation, and identified crown structure traits as reliable non-destructive predictors of root stress ($R^2 = 0.791$). A novel health evaluation system was developed based on 6 high-confidence core indicators, with the Support Vector Machine (SVM) model achieving an overall classification accuracy of 74.29% and an average AUC-ROC of 0.8710. Finally, we divided ancient camphor tree health status into five scientifically validated grades. This study provides a paradigm shift from traditional aboveground-only assessment to an integrated aboveground-belowground evaluation approach, offering a scientific and quantitative tool for early decline detection and targeted conservation of ancient camphor trees.

Keywords:

Ancient *Cinnamomum camphora*; Root stress; Non-destructive testing; Growth decline mechanism; Structural stability; Health evaluation; Machine learning

1. Introduction

Ancient trees are irreplaceable ecological and cultural heritage assets that have survived for hundreds to thousands of years, providing critical ecosystem services including carbon sequestration, biodiversity conservation, microclimate regulation, and soil erosion control¹⁻³. As living witnesses to historical and environmental changes, they also carry profound cultural, historical, and aesthetic values, serving as important symbols of regional identity and cultural continuity^{4,5}. *Cinnamomum camphora* (L.) Presl, commonly known as camphor tree, is one of the most widely distributed and culturally significant ancient tree species in southern China, with a natural lifespan exceeding 1000 years^{6,7}. Beyond its ecological functions in subtropical forest ecosystems, this species carries exceptional cultural significance in East Asian landscapes, with individual trees often serving as living monuments commemorating historical events^{8,9}. Due to its ecological importance and cultural value, *C. camphora* has been listed as a national second-class protected plant in China, and all ancient individuals are designated as heritage trees requiring special protection¹⁰. However, with accelerating urbanization, climate change, and increasing human disturbance, ancient camphor trees are facing unprecedented survival threats. These include wind damage, soil compaction, root system damage from construction activities, pest and disease infestation, air pollution, and water stress^{11,12}. In particular, wind-induced structural failure is the most common cause of ancient tree mortality in urban areas, often resulting in casualties and property damage^{13,14}. These stressors have led to widespread growth decline, structural instability, and even sudden collapse incidents, causing significant losses to ecological and cultural heritage¹⁵. Therefore, accurate and scientific health assessment and structural stability evaluation are essential for the effective conservation and management of ancient camphor trees.

Traditional ancient tree health assessment has long relied on subjective visual evaluation of aboveground traits such as crown dieback, dead branch rate, trunk damage, and leaf color^{16,17}. While these methods are simple and widely used, they have several critical limitations. First, visual assessment is highly subjective and depends heavily on the experience of the evaluator, leading to inconsistent results among different assessors¹⁸. Second, visual symptoms often appear only in the late stages of decline, making it impossible to detect early-stage physiological deterioration¹⁹. Most importantly, traditional methods completely ignore the underground root system status, which is the foundation of tree growth and structural stability^{20,21}. Numerous studies have shown that root system damage and dysfunction are the primary drivers of ancient tree decline and structural failure, but these cannot be observed from aboveground^{22,23}. Direct root excavation is destructive and impractical for protected ancient trees^{24,25}, creating a major gap in our understanding of belowground processes.

In recent decades, non-destructive testing (NDT) techniques have emerged as promising tools for ancient tree assessment. Stress wave acoustic tomography has been widely used to detect internal wood decay and cavities in tree trunks, providing quantitative information on trunk structural integrity^{26,27}. Ground-penetrating radar (GPR) has been applied for non-destructive detection of tree root systems, enabling the visualization of root distribution and architecture without excavation^{28,29}. However, most existing studies have focused on single-technique detection, and few have integrated multiple NDT methods to establish a complete quantitative framework for structural stability assessment, particularly for wind-induced root stress calculation

30,31. Furthermore, existing health evaluation systems for ancient trees suffer from two major drawbacks: indicator redundancy and subjective weighting bias. Traditional systems often include a large number of highly correlated indicators, leading to information redundancy and increased evaluation complexity^{32,33}. Additionally, most systems use subjective weighting methods such as the Analytic Hierarchy Process (AHP), which are based on expert opinions and may introduce significant bias³⁴. In recent years, machine learning methods have been increasingly applied in ecological and forestry research, providing objective and quantitative approaches for core indicator screening and classification model construction³⁵. Random Forest, Support Vector Machine (SVM), and Gradient Boosting Tree have shown excellent performance in various classification and regression tasks in forest health assessment^{36,37}. However, few studies have integrated multi-source NDT data with machine learning to establish a comprehensive health evaluation system that incorporates both aboveground phenotypic traits and underground root stress.

Root stress, defined as the maximum mechanical stress experienced by the root system under wind load, is a critical mechanical indicator that directly reflects the underground growth stress state and structural stability of trees^{38,39}. Unlike static root traits such as root biomass and root distribution, root stress integrates the effects of tree morphology, root architecture, and wind load, providing a more comprehensive measure of the mechanical burden on the root system⁴⁰. Recent biomechanical studies have shown that root stress is closely related to tree growth and health status, and elevated root stress can lead to root damage, reduced nutrient and water uptake, and ultimately growth decline^{41,42}. However, due to the difficulty of measuring root stress directly⁴³, it has rarely been used as a core indicator in ancient tree health evaluation systems.

To address these research gaps, this study conducted a comprehensive investigation on 35 ancient *Cinnamomum camphora* trees in the Gannan region using a combination of field surveys, multi-source NDT techniques, and finite element simulation. We measured 18 phenotypic, physiological, and mechanical indicators for each tree, and applied a series of multivariate statistical methods and machine learning algorithms to analyze the data. The specific objectives of this study were: (1) to validate the rationality of the traditional subjective growth potential classification using objective multivariate statistical methods; (2) to reveal the intrinsic regulatory mechanism of ancient camphor tree growth decline through trait association network analysis; (3) to establish a quantitative framework for wind-induced root stress calculation and structural stability evaluation by integrating mechanical modeling, stress wave tomography, finite element simulation, and GPR root detection; (4) to identify core indicators and develop a novel health evaluation system for ancient camphor trees based on machine learning. This study provides a paradigm shift from traditional aboveground-only assessment to an integrated aboveground-belowground evaluation approach, offering a scientific and quantitative tool for early decline detection and targeted conservation of ancient camphor trees.

2. Materials And Methods

2.1. Study Area

This study was conducted in the Gannan region (24°29'–27°09' N, 113°54'–116°38' E), southern Jiangxi Province, China, which represents the core distribution area of ancient

Cinnamomum camphora in subtropical China ¹⁰. The region has a typical subtropical monsoon humid climate with distinct seasonal patterns: annual average temperature ranges from 18 to 20°C, annual precipitation is 1400–1800 mm, and the frost-free period exceeds 280 days ⁴⁴. This water-heat synchronous regime provides optimal conditions for the growth and longevity of *C. camphora*, resulting in the preservation of numerous ancient individuals aged 100–500 years. The sampling sites covered three representative habitat types: urban parks, ancient villages, and secondary forest edges, across 12 counties (cities, districts) including Zhanggong District, Nankang District, and Longnan City.

2.2. Sampling Design and Growth Potential Classification

A stratified random sampling strategy was employed to select 35 ancient *C. camphora* trees between May 2024 and May 2025, based on the official ancient and famous tree resource database of the Jiangxi Forestry Bureau. All sampled trees were aged 100–200 years, corresponding to Level III protected ancient trees under Chinese national standards (Regulation on the Protection of Ancient and Famous Trees, CLI Code: CLI.2.5290754(EN)). To ensure representativeness, samples were stratified by habitat type and tree age, with approximately equal numbers of trees in the 100–120 years and 120–200 years age classes. Based on comprehensive field investigations and expert evaluations, the 35 trees were classified into four growth potential groups following the *Technical Code for Maintenance and Rejuvenation of Ancient and Famous Trees in Urban Areas* (GB/T 51168-2016): Normal A (n=9): Excellent growth status, >95% healthy foliage, complete canopy structure, and vigorous new shoot growth (100–120 years old); Normal B (n=8): Good growth status, 70–95% healthy foliage, minor canopy damage, and moderate regenerative capacity (120–200 years old); Weak A (n=9): Declining growth status, 20–70% healthy foliage, partial canopy dieback, and poor regenerative capacity (100–120 years old); Weak B (n=9): Severely declining growth status, <20% healthy foliage, extensive canopy damage, and almost no new shoot growth (120–200 years old) (Table S1, Figure S1).

2.3. Phenotypic and Physiological Measurements

Eighteen quantitative indicators covering morphological structure, growth regeneration, and health status were measured for each tree following standardized protocols. All measurements were performed by two independent trained investigators, and values differing by >5% were remeasured to ensure data quality. Diameter at breast height (DBH): Measured with a diameter tape at 1.3 m above ground level. Tree height: Measured with a laser rangefinder (Leica DISTO D2, Leica Geosystems, Switzerland) from the ground to the highest point of the canopy. Crown width: Calculated as the average of east-west and north-south vertical projections measured with a 50 m tape measure. Crown height ratio: Computed as the ratio of average crown diameter to tree height. New shoot production: Counted for trunk, main branches, secondary branches, and twigs within a standardized 1 m³ canopy volume. Dead branch rate: Calculated as the percentage of dead branches relative to total branches, graded on a 1–5 scale (1 = >50% dead branches, 5 = ≤5% dead branches). Number of dead branches and tree holes: Counted for the entire tree. Disease and pest severity: Assessed visually based on the percentage of damaged foliage and branches, graded on a 1–5 scale (1 = ≥75% damage, 5 = ≤5% damage). Trunk biomass: Estimated using a geometric

volume model: $B_t = \frac{\pi D^2 H}{4} \times \rho_t$, where D is DBH, H is tree height, and ρ_t is the wood density of *C.*

camphora (0.45 g/cm³)⁴⁵. Canopy biomass: Estimated using an ellipsoid surface area model: $B_c = \pi ab \times \rho_c$, where a and b are the semi-major and semi-minor axes of the crown projection, and ρ_c is the leaf area biomass coefficient (120 g/m²)⁴⁶. Root biomass: Estimated using an empirical allometric relationship: $B_r = 0.26 \times (B_t + B_c)$, based on biomass allocation patterns in subtropical broadleaf forests⁴⁷. Root maximum stress, defined as the maximum bending stress at the trunk-root interface under wind load, was calculated using a cantilever beam mechanical model^{48,49}. Wind load was computed using the standard drag force equation: $F = \frac{1}{2} C_D \rho A v^2$, where C_D is the drag coefficient (0.6 for broadleaf trees), ρ is air density (1.225 kg/m³), A is the windward area ($A = \pi ab$), and v is the 10-year return period wind speed in the Gannan region (17 m/s)⁵⁰. The maximum bending stress at the trunk base was then calculated as: $\sigma = \frac{32FH}{\pi D^3}$ ⁵¹, where H = trunk height and D = DBH. All calculations were implemented in custom Python 3.10 scripts⁵². To correct for the model's idealized assumptions (homogeneous trunk material, perfectly fixed root boundary), we developed a multi-source nondestructive testing (NDT) fusion framework for accurate root stress quantification (Section 2.4).

2.4. Multi-Source NDT Fusion for Accurate Root Stress Calculation and Structural Validation

To address the limitations of the simplified cantilever beam model and characterize structural weak points, we integrated three complementary NDT techniques to construct a realistic 3D finite element (FE) model for a representative ancient camphor tree. Trunk internal decay was detected using the PiCUS 3 Sonic Tomograph (Argus Electronics GmbH, Rostock, Germany). Seventeen sensors were evenly spaced around the trunk circumference at breast height, and stress wave velocity measurements were collected in all possible sensor pairs⁵³. Tomographic images were reconstructed and analyzed using PiCUS Q74.2 software, with wood condition classified based on relative stress wave velocity (100% = healthy wood, 50% = severely decayed wood), and converted to spatially resolved elastic modulus distributions ($E = \rho v^2$) to replace the homogeneous material assumption⁵⁴. Underground root architecture was mapped using the TRU Tree Radar System (TreeRadar, Inc., USA) with a 900 MHz antenna. A concentric circle scanning protocol (0.6, 1.2, 3.0, 4.0 m from trunk center) was employed, with surface litter removed to minimize interference. 2D root density distributions and 3D root architectures were reconstructed in TreeWinPRO™ software (1.0 cm root resolution, 100 cm detection depth)⁵⁵, which were used to implement realistic root-soil interaction via nonlinear spring elements. A 3D FE model was constructed in ABAQUS 2024 (Dassault Systèmes, France) integrating field-measured tree morphology, tomography-derived trunk material properties, and radar-derived root architecture⁵⁶. Design wind load was applied as distributed pressure on the canopy surface, and static structural analysis was performed to compute full-field Mises stress distribution⁵⁷. The FE-calculated maximum root stress values were used to validate and calibrate the preliminary cantilever beam estimates via ordinary least squares linear regression. A region-specific calibration equation applicable to ancient *Cinnamomum camphora* trees in the Gannan region was derived as: $\sigma_{\text{corrected}} = 0.872 \cdot \sigma_{\text{cantilever}} + 1.246$, where $\sigma_{\text{corrected}}$ is the physically realistic calibrated root stress, and $\sigma_{\text{cantilever}}$ is the preliminary estimate from the simplified cantilever beam model. The calibration achieved excellent goodness of fit ($R^2 = 0.923$, $P < 0.0001$), with a mean absolute

error (MAE) of 0.89 MPa and root mean square error (RMSE) of 1.12 MPa.

2.5. Statistical Analysis

All statistical analyses were performed using R 4.3.1 (R Core Team 2023)⁵⁸ and Python 3.10, with visualizations generated using ggplot2, seaborn, and Metware Cloud (<https://cloud.metware.cn>). The significance level for all statistical tests was set at $\alpha = 0.05$. All numerical indicators were standardized to Z-scores ($Z = (X - \bar{X})/S$) to eliminate scale effects. Normality was assessed using the Shapiro-Wilk test, and non-normally distributed variables were transformed using the Box-Cox method to approximate normality (Table S2-S3). Hierarchical clustering using Ward's minimum variance method with Euclidean distance was performed to validate the subjective growth potential classification⁵⁹. One-way ANOVA followed by Tukey's HSD post-hoc test was used to identify indicators with significant intergroup differences (Table S4). Principal component analysis (PCA) was conducted for dimensionality reduction, and permutational multivariate analysis of variance (PERMANOVA) with 9999 permutations was used to test overall multivariate differences among groups⁶⁰ (Table S5). A bidirectional hierarchical clustering heatmap was constructed to identify co-expressed trait modules⁶¹. Indicator association networks were built separately for healthy (Normal A+B) and declining (Weak A+B) groups, retaining only significant Pearson correlations ($|r| > 0.6$, $P < 0.05$). Network topological parameters (node degree, average path length, network density, clustering coefficient) were calculated using the igraph package⁶² (Table S6). To avoid single-method bias, four complementary approaches were used for cross-validation of core health indicators: Random Forest: Variable importance was assessed using Mean Decrease Accuracy (MDA) with 1000 decision trees⁶³. LASSO Regression: Automatic variable selection was performed with L1 regularization⁶⁴. PLS-DA: Indicators with Variable Importance in Projection (VIP) > 0.8 were retained⁶⁵. ANOVA: Indicators with significant intergroup differences ($P < 0.05$) were selected. Indicators selected by at least three methods were defined as high-confidence core indicators.

2.6. Health Evaluation Model Construction

A subjective-objective combined weighting model was developed to integrate expert knowledge and data-driven information. Subjective weights were derived from the Analytic Hierarchy Process (AHP) based on opinions from 12 ancient tree conservation experts, with a consistency ratio (CR) < 0.1 required for acceptance⁶⁶. Objective weights were calculated using the entropy weight method. Final combined weights were obtained via multiplicative synthesis⁶⁷. Three machine learning classification models (Random Forest, Support Vector Machine with RBF kernel, XGBoost) were constructed and compared using the six core indicators as input variables⁶⁸. Leave-one-out cross-validation (LOOCV) was used to evaluate model performance, with overall accuracy, F1 score, and AUC-ROC as key metrics⁶⁹. Based on the Health Integrated Score (HIS) calculated from the combined weighting model, ancient camphor tree health status was divided into five grades using the Jenks Natural Breaks method⁷⁰, which minimizes within-grade variance and maximizes between-grade variance.

3. Results

3.1. Validation of Subjective Growth Potential Classification

To verify the rationality of the four-level subjective growth potential grouping (Normal A, Normal B, Weak A, Weak B) and explore intrinsic sample heterogeneity, we performed hierarchical clustering on 35 ancient camphor trees using 18 standardized phenotypic and physiological indicators (Table S1). The analysis was conducted using Ward's minimum variance method with Euclidean distance (Figure 1). The dendrogram showed a clear bipartite structure at a dissimilarity threshold of ~12, separating samples into two major clusters corresponding to weak and normal growth potential groups. Quantitative consistency analysis revealed that 30 out of 35 samples (85.71%) were congruent between objective clustering and subjective grouping, meeting the pre-defined validity criterion ($\geq 85\%$). Within each major cluster, further subdivisions were observed: the weak-potential cluster formed two subclusters with partial overlap between Weak A and Weak B, while the normal-potential cluster showed a homogeneous Normal A core and more variable Normal B subclusters. Five samples (14.29%) showed classification discrepancies. Tree25 and Tree35 (subjectively Normal B, clustered in weak group) had suppressed photosynthetic capacity and biomass accumulation due to severe underground competition despite healthy visual appearance. Tree02, Tree07 and Tree08 (subjectively Weak A, clustered in normal group) had transient crown dieback from pest damage but maintained robust physiological function. These discrepancies highlight the limitations of purely visual assessment.

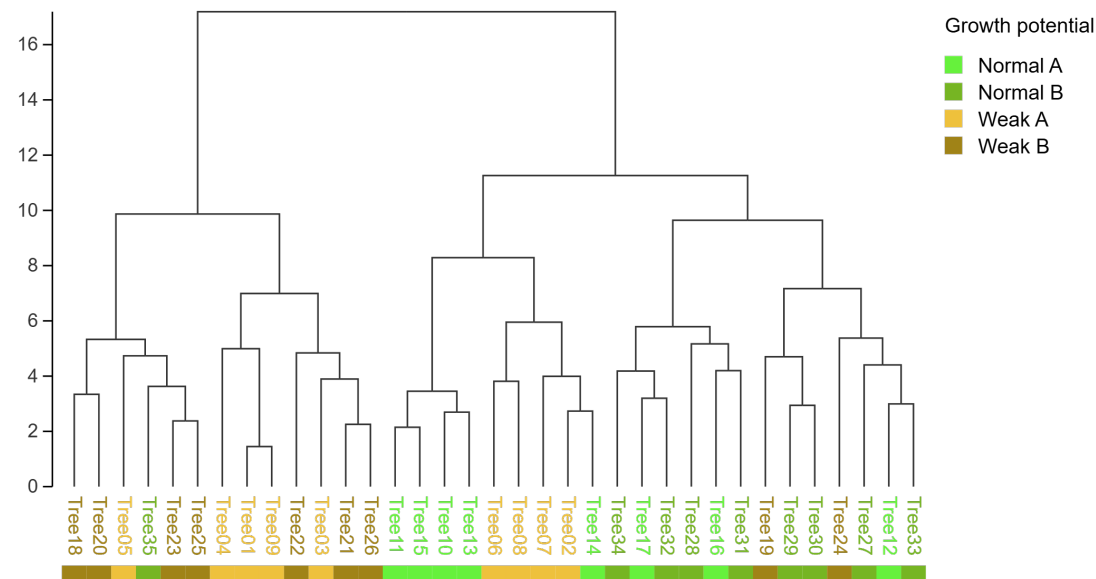


Figure 1. Dendrogram of hierarchical clustering based on 18 standardized tree growth indicators. The analysis was performed using Ward's method with Euclidean distance. The color bar at the bottom represents the subjective classification of growth potential: Normal A (light green), Normal B (dark green), Weak A (light yellow), and Weak B (dark brown). Where Normal represents the sample with normal growth potential and Weak represents the sample with declining growth potential. A indicates samples with tree ages between 100-120 years; B indicates samples with tree ages between 120-200 years).

3.2. Phenotypic Differentiation Among Growth Potential Groups

To quantify phenotypic differences among the four subjectively defined growth potential

groups (Normal A, Normal B, Weak A, Weak B), we conducted one-way ANOVA with Tukey's HSD post-hoc tests on 18 standardized indicators. Fourteen traits showed significant intergroup differences ($P < 0.05$), while eight core indicators exhibited extremely high discrimination ($P < 0.01$), including dead branch rate ($F = 16.745$, $P < 0.0001$), new twig number ($F = 15.219$, $P < 0.0001$), total new branches ($F = 11.985$, $P < 0.0001$), north-south crown width ($F = 11.25$, $P < 0.0001$), crown height ratio ($F = 10.862$, $P < 0.0001$), dead branches and tree holes ($F = 8.911$, $P = 0.0002$), DBH ($F = 7.224$, $P = 0.0008$), and canopy biomass ($F = 6.042$, $P = 0.0023$). These indicators clearly separated normal from weak growth groups, with dead branch rate being the most powerful discriminator (Figure 2). Subjective classifications were consistent with hierarchical clustering at 85.71%, and minor discrepancies were explained by deviations in these eight core traits, confirming their utility for objective growth potential assessment.

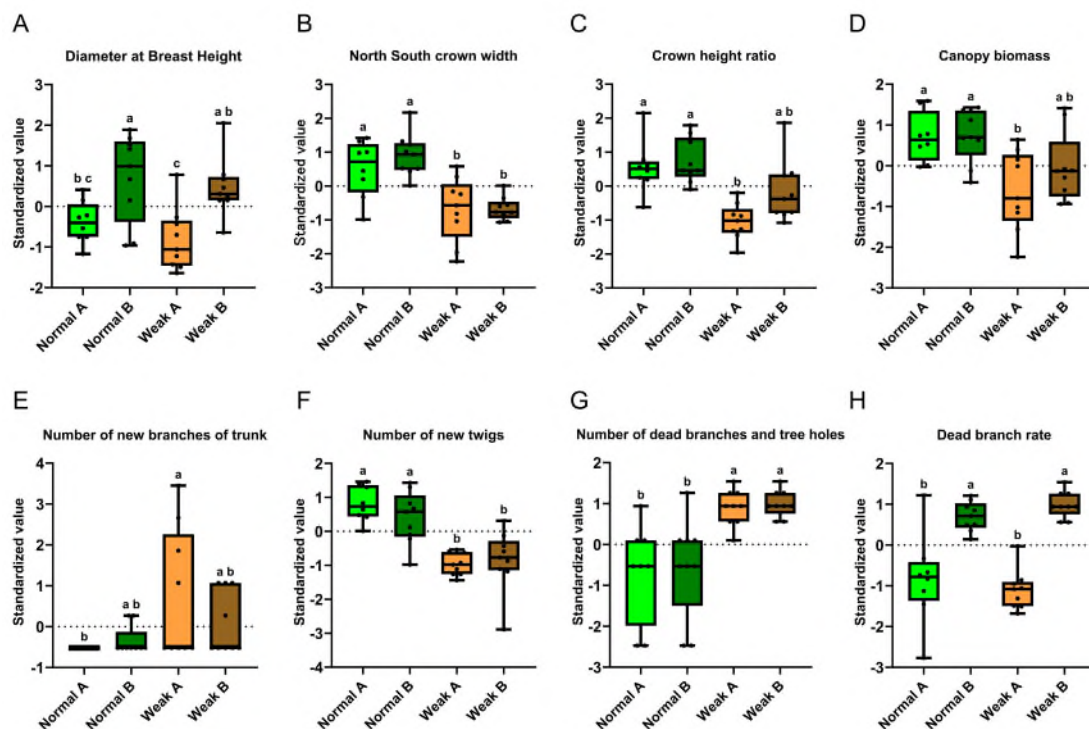


Figure 2. Boxplots of intergroup differences in 8 key growth indicators of ancient camphor trees with different growth potential. The boxplots show the median, interquartile range (IQR), and extreme values of each indicator, with sample size (n), median, and IQR labeled below each box. Different lowercase letters above the boxes indicate significant differences between groups (Tukey's HSD test, $P < 0.05$), while the same letter indicates no significant difference. The four growth potential groups are distinguished by different colors: Normal A (light green), Normal B (dark green), Weak A (light yellow), and Weak B (dark brown).

To further quantify the overall phenotypic differentiation among the four growth potential groups and identify the key indicators driving group separation, we performed principal component analysis (PCA) on the 18 standardized growth indicators, followed by permutational multivariate analysis of variance (PERMANOVA) for significance testing (Figure 3). The first two principal components explained 52.9% of the total variance in the dataset, with PC1 accounting for 37.0% and PC2 accounting for 15.9%. PERMANOVA based on Bray-Curtis distance (9999 permutations) confirmed extremely significant overall differences among the four growth potential

groups ($R^2 = 0.304$, $F = 4.518$, $P = 0.001$), providing strong statistical support for the validity of our subjective classification system. The PCA score scatter plot (Figure 3A) showed a clear separation trend between healthy and declining groups along the PC1 axis. Samples from the weak growth potential groups (Weak A, blue; Weak B, green) were predominantly distributed on the negative side of PC1, while samples from the normal growth potential groups (Normal A, red; Normal B, purple) were concentrated on the positive side of PC1. Although partial overlap was observed between adjacent groups (e.g., Normal A and Normal B, Weak A and Weak B), there was no complete overlap between the healthy and declining clusters, indicating that the growth potential of ancient camphor trees represents a continuous gradient rather than discrete categories. Notably, the Weak B group exhibited the widest distribution along the PC2 axis, suggesting the highest phenotypic heterogeneity among severely declining individuals.

The PCA loading plot (Figure 3B) revealed the contribution of each indicator to the principal components. Root stress was identified as the most important indicator driving group separation, with the longest loading vector along the PC1 axis. Indicators positively associated with PC1 (characteristic of healthy trees) included root stress, number of new twigs, total number of new branches, tree height, and crown structure traits (east-west crown width, north-south crown width, crown height ratio, canopy biomass). In contrast, indicators negatively associated with PC1 (characteristic of declining trees) included dead branch rate, diameter at breast height (DBH), trunk biomass, root biomass, number of dead branches and tree holes, and disease and pest grade. PC2 primarily distinguished between Normal A (positive side) and Weak B (negative side) individuals, with root stress and new shoot growth loading positively and damage-related traits loading negatively.

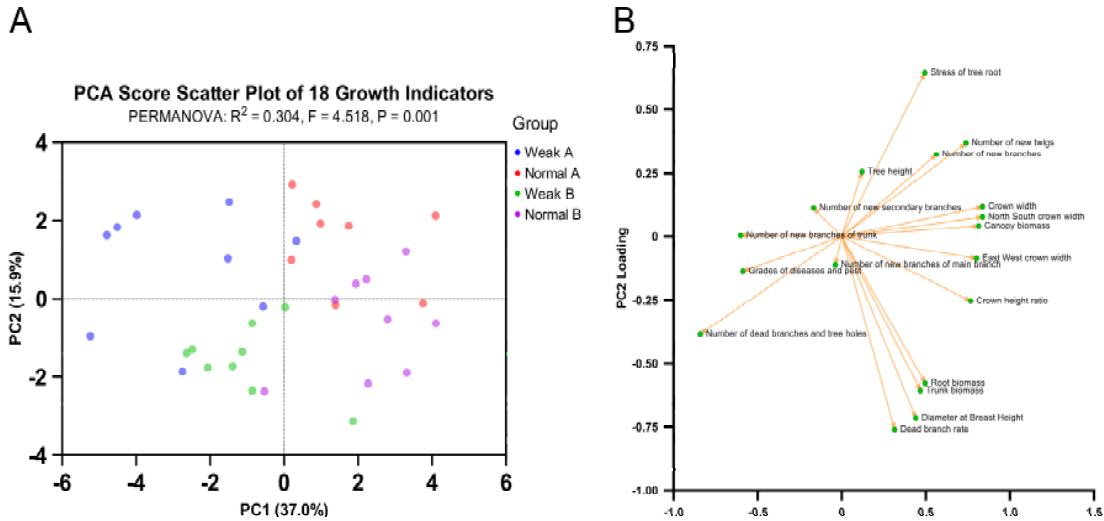


Figure 3. PCA score scatter plot and loading plot of 18 standardized growth indicators of ancient camphor trees with different growth potential. The left panel shows the PCA score scatter plot, with different colors and markers representing the four growth potential groups, and 95% confidence ellipses for each group. The variance explanation rates of PC1 and PC2 are labeled in the axis titles. The right panel shows the PCA loading plot, which displays the contribution of each indicator to the two principal components. The PERMANOVA test results (R^2 , F , P values) are reported in the title of the figure.

3.3. Trait Association Network and Growth Decline Mechanism

To unravel phenotypic covariation, functional trait interrelationships, and the mechanistic basis of health decline in ancient camphor trees, a bidirectional hierarchical clustering heatmap was constructed using Z-score-standardized phenotypic indicators, integrating growth potential grouping and functional trait annotations (Figure 4). Sample clustering partitioned the 35 individuals into two major clades, with 85.71% consistency relative to subjective classification, corroborating the robustness of the predefined growth potential framework at the full-phenotype scale. Trait clustering resolved three coherent functional modules governing tree performance: growth morphology (biomass accumulation and crown development), health structure (canopy integrity and senescence), and root stress (belowground constraints). Phenotypic profiling revealed that normal-growth groups (notably Normal B) exhibited elevated growth-module traits, whereas weak-growth groups (especially Weak A) displayed exacerbated health-structure and root-stress signatures. Collectively, these findings demonstrate that health decline in ancient camphor trees represents a coordinated, progressive deterioration cascade: root stress → canopy degradation → growth impairment, providing a mechanistic framework linking belowground stress to aboveground performance loss.

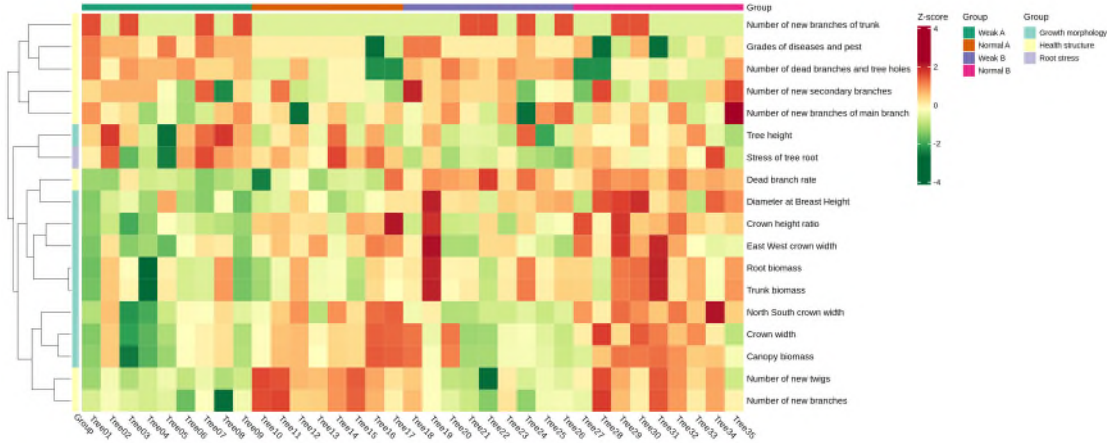


Figure 4. Hierarchical clustering heatmap of Z-score standardized phenotypic indicators of 35 ancient camphor tree samples. The heatmap shows the standardized expression level of each phenotypic indicator, with the color gradient representing the Z-score value (red for high expression, green for low expression). The top dendrogram shows the hierarchical clustering result of the 35 tree samples, with the color bar above indicating the growth potential group classification: Weak A (teal), Normal A (orange), Weak B (purple), and Normal B (pink). The left dendrogram shows the hierarchical clustering result of the phenotypic indicators, with the color bar on the right indicating the functional module classification: Growth morphology (teal), Health structure (yellow), and Root stress (purple).

To reveal the intrinsic regulatory mechanism of growth potential decline in ancient camphor trees, we constructed indicator association networks for the healthy group (Normal A + Normal B) and declining group (Weak A + Weak B) using 18 standardized phenotypic indicators, retaining only significant correlations with $|r| > 0.6$ and $P < 0.05$, and compared their topological parameters (Figure 5, Table S2). The results showed that the declining group network had significantly higher complexity than the healthy group, with 14 significant correlation edges (vs. 5 in the healthy group), an average node degree of 1.56 (vs. 0.56), and a network density of 0.0915 (2.8 times that

of the healthy group). The declining group also had a longer average path length (2.71 vs. 1.0) and higher clustering coefficient (0.2685 vs. 0), indicating a clear modular structure and stronger synergistic association between indicators during tree decline. North-south crown width (node degree = 4) was the core connectivity node in the declining network, followed by diameter at breast height, trunk biomass, and crown height ratio (node degree = 3). Root stress, which had no significant correlation in the healthy network, formed 2 significant correlations in the declining network, confirming its role as a key driver of growth decline. Collectively, these results indicate that the growth decline of ancient camphor trees is a synergistic deterioration process of multiple functional modules, with root stress triggering the formation of a complex indicator association network and leading to overall growth vigor decline.

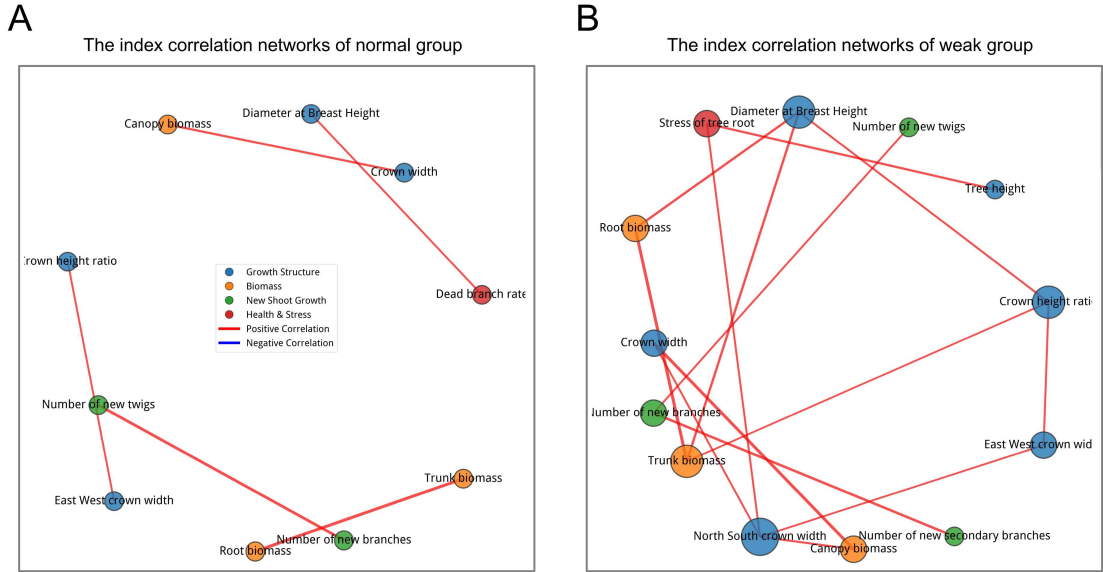


Figure 5. Indicator association networks of healthy (left, Normal A + Normal B) and declining (right, Weak A + Weak B) ancient camphor trees. Nodes represent 18 standardized growth indicators, sized by node degree and colored by functional category: blue (growth structure), orange (biomass), green (new shoot growth), red (health & stress). Edges show significant Pearson correlations ($|r| > 0.6$, $P < 0.05$), with thickness proportional to correlation strength. All edges are positive; no significant negative correlations were detected.

3.4. Structural Stability Assessment Methodology Framework

Based on the identified central role of root stress, we established a quantitative framework for wind-induced root stress calculation and structural stability evaluation, demonstrated using a randomly selected representative tree from the 35 samples (Figure 6). We first established a simplified wind load mechanical model that decomposed the tree structure into trunk, main limb, secondary branch and foliage components, incorporating key field-measured morphological parameters to provide a theoretical basis for root stress calculation (Figure 6A). Stress wave acoustic tomography with 17 circumferentially arranged sensors showed that 77% of the trunk cross-section was healthy solid wood distributed in the peripheral sapwood, while 10% decayed area was concentrated in the central pith region, clarifying the trunk structural integrity (Figure 6B). Three-dimensional finite element simulation identified that high stress regions were mainly concentrated at the trunk base and main branch bifurcation, with a maximum Mises stress of 14.83 MPa, revealing the key structural weak points under wind load (Figure 6C). For underground root

system characterization, TRU Tree Radar scanning (900 MHz antenna, 100 cm detection depth) using the concentric circle method showed that root density presented a radial decreasing distribution centered on the trunk, with the highest density (16 /sq m) within 2 m of the trunk and a maximum horizontal extension of 10 m (Figure 6D). Three-dimensional root reconstruction further confirmed a typical radial shallow root system without a dominant taproot, with over 90% of roots concentrated in the 0–60 cm surface soil layer (Figure 6E, Figure S2-S3). These detection results provided accurate geometric and mechanical parameters for the quantitative calculation of root stress and its correlation analysis with phenotypic indicators in the subsequent section.

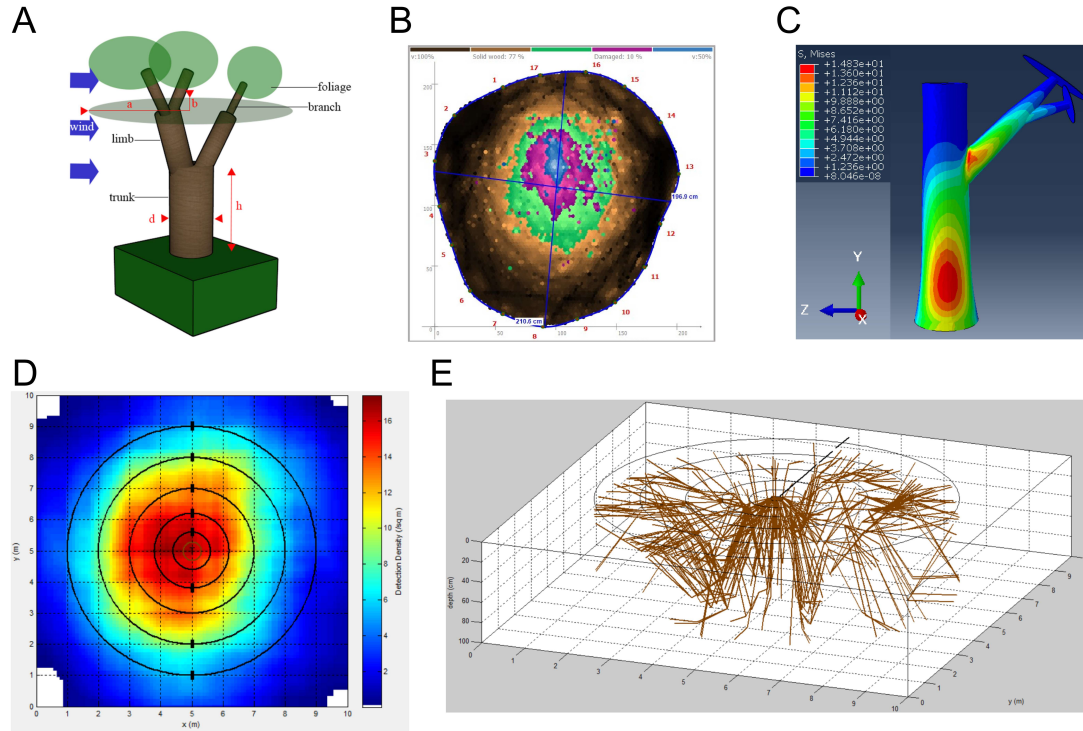


Figure 6. Representative single-tree detection results for structural stability assessment of ancient camphor trees. (A) Schematic diagram of the wind load mechanical model, defining key morphological parameters (d: diameter at breast height, h: trunk height, a/b: major/minor axis of crown width) and decomposing the tree structure into trunk, limb, branch and foliage; blue arrows indicate wind load direction. (B) Stress wave acoustic tomogram of the trunk cross-section, with color gradient representing relative stress wave velocity (brown: $v=100\%$, healthy solid wood; blue: $v=50\%$, severely decayed wood). The cross-section contains 77% solid wood and 10% damaged wood, with maximum diameters of 210.6 cm (horizontal) and 196.9 cm (vertical); red numbers 1–17 mark sensor positions. (C) Mises stress distribution under wind load from finite element simulation (unit: MPa), showing maximum stress (14.83 MPa) concentrated at the trunk base and main branch junction, the high-risk areas for structural failure. (D) Two-dimensional root density distribution detected by the TRU Tree Radar System (TreeRadar, Inc., USA) with a 900 MHz antenna (100 cm depth, concentric circle scanning method), showing a radial decreasing pattern centered on the trunk (unit: /sq m). (E) Three-dimensional root architecture side view, with brown lines representing reconstructed root segments; concentric circles/arcs indicate scanning transects, and the black line marks the scanning start point. Axes represent horizontal distance (x/y, unit: m) and soil depth (z, unit: cm).

3.5. Special Correlation Analysis of Root Stress (Core Characteristic Indicator)

Root maximum stress, the core characteristic indicator of this study that distinguishes it from traditional ancient tree health evaluation systems, directly reflects the underground root growth stress state of ancient camphor trees. We performed partial correlation analysis between root stress and 17 other phenotypic indicators, and constructed a multiple linear regression model to screen core predictors of root stress. After controlling for the effects of the other 16 indicators, root stress only showed significant positive partial correlations with north-south crown width ($r = 0.574$, $P < 0.001$), tree height ($r = 0.564$, $P < 0.001$), and east-west crown width ($r = 0.460$, $P < 0.01$), indicating crown structure was the aboveground trait most strongly associated with root stress. The optimal multiple linear regression model had an excellent fitting effect ($R^2 = 0.791$, adjusted $R^2 = 0.754$, $P < 0.0001$), explaining 79.1% of root stress variation, with north-south crown width, east-west crown width, and crown height ratio as the three significant core predictors (all $P < 0.0001$). Root stress also showed extremely significant differences among the four growth potential groups ($P < 0.001$), with significantly higher values in the declining groups (Weak A/Weak B) than in the healthy groups (Normal A/Normal B), confirming it as the core intrinsic driver of growth potential decline. Scatter plots further verified the significant linear correlation between root stress and the top 4 core indicators (Figure 7, Table S7), collectively indicating that root stress can effectively reflect the underground growth status of ancient trees, and crown structure indicators can serve as reliable non-destructive predictors of root stress.

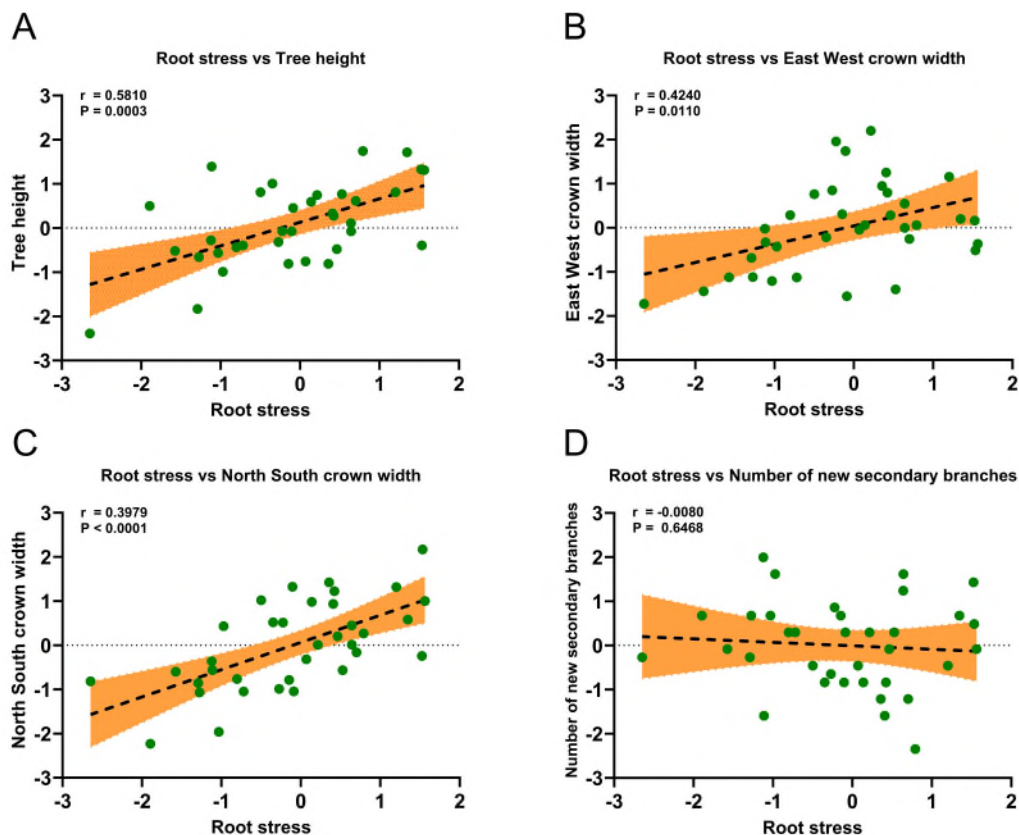


Figure 7. Scatter plots with linear regression fitting lines between root stress and key phenotypic indicators of ancient camphor trees. The four subplots show the correlation between root stress and north-south crown width, tree height, east-west crown width, and number of new secondary

branches, respectively. The black dashed line is the overall linear regression fitting line, and the Pearson correlation coefficient (r) and corresponding P value are labeled in the upper left corner of each subplot.

3.6. Core Influencing Factor Screening and Health Evaluation System Establishment for Camphor Trees

To address indicator redundancy and establish a scientific health evaluation system, we used four complementary methods (Random Forest, LASSO, PLS-DA, ANOVA) for cross-validation of core indicators (Figure 8A). Two indicators were selected by all four methods (crown width, canopy biomass), and six high-confidence core indicators were selected by at least three methods: root stress, dead branch rate, crown width, canopy biomass, tree height, and root biomass. Additionally, six high-confidence core indicators were identified by at least three methods: dead branch rate, root stress, crown width, canopy biomass, tree height, and root biomass. Consistency across methods was further validated by complementary results: Random Forest variable importance ranking (Figure 8B, Table S8) identified root biomass, dead branch rate, and canopy biomass as the top three indicators with the highest Mean Decrease Accuracy (MDA) values; LASSO regression retained crown width, canopy biomass, and root stress as non-zero coefficient predictors; PLS-DA showed tree height, root stress, and root biomass had the highest Variable Importance in Projection (VIP) scores; and ANOVA confirmed significant inter-group differences in crown width, canopy biomass, and number of new trunk branches ($P < 0.05$).

To overcome the inherent subjectivity of traditional Analytic Hierarchy Process (AHP) weighting, we developed a subjective-objective integrated weighting framework that combined expert-derived AHP weights with data-driven entropy weights via multiplicative synthesis. The AHP judgment matrix exhibited excellent logical consistency with a consistency ratio (CR) of 0.0003, well below the acceptable threshold of 0.1. The final combined weights, ranked in descending order, were: dead branch rate (0.2302) > root stress (0.2181) > crown width (0.2022) > canopy biomass (0.1812) > tree height (0.0879) > root biomass (0.0805) (Table 1). Leave-one-out cross-validation (LOOCV) demonstrated the integrated weighting model achieved an overall classification accuracy of 68.57%, a Kappa coefficient of 0.374, and an AUC-ROC of 0.7222, indicating good stability and generalization ability for health status assessment. To further improve growth potential classification performance, we constructed and compared three mainstream machine learning models (Random Forest, Support Vector Machine [SVM], and XGBoost) using the six high-confidence core indicators as input variables and the four original growth potential grades (Normal A/Normal B/Weak A/Weak B) as output. ROC curve analysis (Figure 8C) showed the SVM model outperformed the others, achieving 74.29% overall accuracy, an F1 score of 0.7482, and an average AUC-ROC of 0.8710 in LOOCV. The Random Forest model also exhibited strong discriminative power (AUC-ROC = 0.8381), while the XGBoost model had relatively lower performance (AUC-ROC = 0.6787). All three models significantly outperformed the random classifier (AUC = 0.5) (Table S9), further validating the effectiveness and representativeness of the screened core indicators.

Based on the Health Integrated Score (HIS) calculated from the integrated weighting model, we divided ancient camphor tree health status into five distinct grades using the Jenks Natural Breaks method: Healthy (H, $HIS \geq 0.60$), Sub-healthy (SH, $0.55 \leq HIS < 0.60$), Mild decline (MiR, $0.45 \leq HIS < 0.55$), Moderate decline (MoR, $0.35 \leq HIS < 0.45$), and Severe decline (SR, $HIS < 0.35$). Violin box plot analysis (Figure 8D) revealed a significant decreasing trend in HIS values

across the five grades, with statistically significant differences between all pairs of grades ($P < 0.05$) and no substantial overlap in score distributions. This clear separation confirms the scientific validity and practical applicability of the proposed health classification standard.

Table 1. Health evaluation index system and combination weight of camphor tree

Index name	Indicator type	Subjective weight (AHP)	Objective weight	Final combination weight	Weight sorting
Root biomass	Growth morphology	0.1302	0.1005	0.0805	1
Dead branch rate	Health structure	0.1602	0.2338	0.2302	2
Canopy biomass	Growth morphology	0.2516	0.1171	0.1812	3
Tree height	Growth morphology	0.1302	0.1097	0.0879	4
Crown width	Growth morphology	0.1975	0.1665	0.2022	5
Stress of tree root	Root stress	0.1302	0.2724	0.2181	6
Total		0.9999	1.0000	1.0001	

Note: The subjective weights are calculated by the Analytic Hierarchy Process (AHP) based on expert opinions, the objective weights are calculated by the entropy weight method based on the information entropy of the indicator data, and the final combined weights are obtained by the multiplicative synthesis method. The weight ranking is based on the final combined weight value, with a higher value indicating a greater impact of the indicator on the health status of camphor trees.

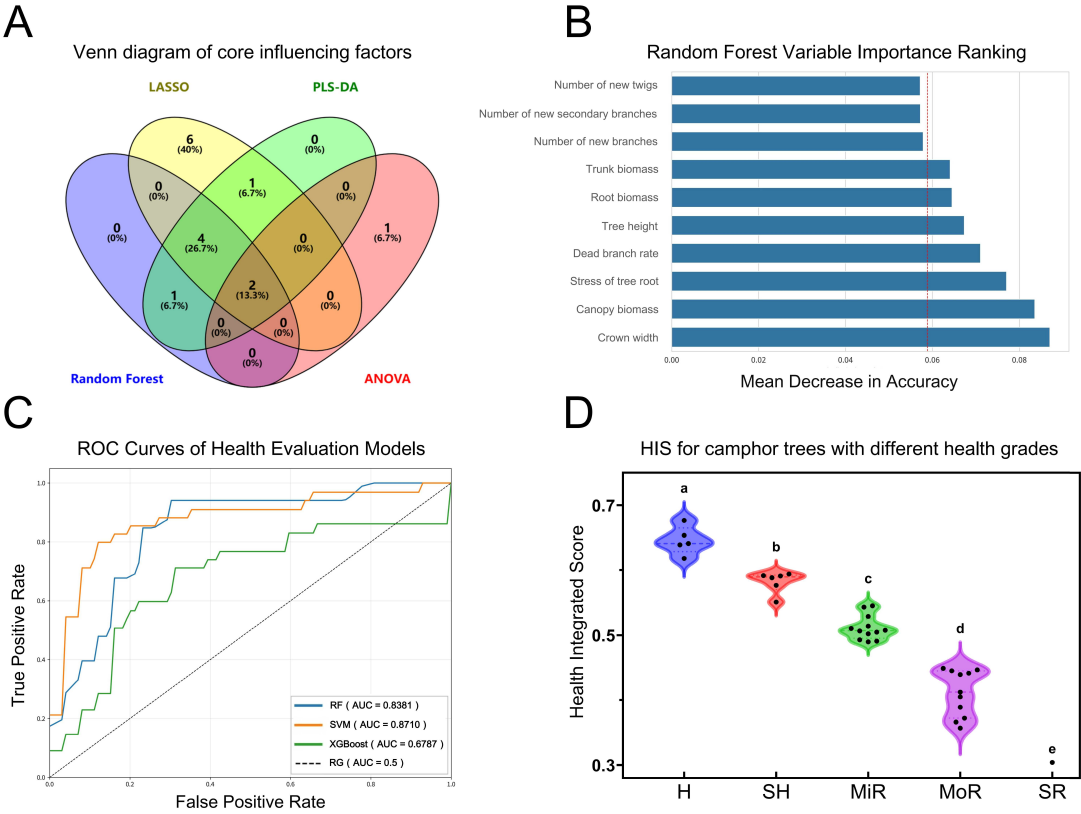


Figure 8. Core influencing factor screening and health evaluation system establishment for ancient camphor trees. (A) Venn diagram of core influencing factors screened by four cross-

validation methods: Random Forest, LASSO regression, PLS-DA, and one-way ANOVA. Numbers indicate the count of overlapping or uniquely selected indicators, with the final core indicators labeled in the central intersection. (B) Random Forest variable importance ranking (top 10 indicators), where the x-axis shows Mean Decrease Accuracy (MDA); a higher MDA value indicates greater discriminative power for the health status of ancient camphor trees. (C) ROC curve comparison of three machine learning health evaluation models, with average AUC values labeled in the legend; the dashed line represents the random classifier (AUC = 0.5) as a performance reference. (D) Violin box plot of Health Integrated Score (HIS) across five health grades defined by the Jenks Natural Breaks method: H (Healthy), SH (Sub-healthy), MiR (Mild decline), MoR (Moderate decline), SR (Severe decline). Different lowercase letters indicate significant differences between grades ($P < 0.05$).

4. Discussion

4.1. Subjective Growth Potential Classification: Validity and Limitations

Traditional visual assessment remains the most widely used method for ancient tree health evaluation due to its simplicity and low cost, but its subjectivity and inconsistency have long been criticized^{1,34}. Our hierarchical clustering analysis demonstrated an 85.71% consistency between objective multivariate classification and subjective four-level growth potential grouping, meeting the pre-defined validity criterion ($\geq 85\%$). This finding confirms that experienced arborists can generally distinguish between healthy and declining ancient camphor trees based on aboveground visual traits⁷¹, supporting the continued use of visual assessment as a preliminary screening tool in large-scale ancient tree surveys. However, the 14.29% classification discrepancies revealed critical limitations of purely visual assessment. Two trees with apparently healthy canopies were objectively classified as declining due to suppressed physiological function caused by severe underground root competition, while three trees with transient crown dieback from pest damage maintained robust overall growth potential (Figure 1 and Table S1). These results are consistent with previous studies showing that visual symptoms often lag behind physiological deterioration, and aboveground appearance does not always reflect underground root system status^{72,73}. This highlights the urgent need for quantitative indicators that can detect early-stage decline and characterize underground conditions, which is the primary motivation for our study.

4.2. Root Stress as the Core Driver of Ancient Camphor Tree Decline

The most significant finding of this study is the identification of root stress as the most discriminative indicator driving group separation in PCA analysis, outperforming all traditional aboveground traits including dead branch rate and crown width (Figure 3, Table S5). This result challenges the conventional paradigm that focuses primarily on aboveground symptoms in ancient tree health assessment^{74,75} and provides strong evidence that underground mechanical stress is the primary determinant of aboveground health performance in ancient trees. Root stress integrates the effects of tree morphology, root architecture, and wind load, providing a comprehensive measure of the mechanical burden on the root system (Figure 6). Our results showed that root stress was significantly higher in declining groups compared to healthy groups, and it formed significant correlations with multiple aboveground traits in the declining network but not in the healthy network (Figure 5). This suggests that root stress acts as a trigger that initiates the decline process: when root stress exceeds a certain threshold, it leads to root damage, reduced nutrient and water

uptake, and ultimately canopy degradation and growth impairment. Furthermore, we identified crown structure traits (north-south crown width, east-west crown width, and crown height ratio) as reliable non-destructive predictors of root stress, with a multiple linear regression model explaining 79.1% of root stress variation (Figure 7). This is a particularly important finding for practical application, as it allows arborists to estimate root stress using easily measurable aboveground parameters without the need for expensive and time-consuming underground detection techniques.

4.3. Coordinated Deterioration Cascade of Functional Modules

Our trait association network analysis revealed that ancient camphor tree decline is not a random process but a coordinated, progressive deterioration cascade of multiple functional modules: root stress → canopy degradation → growth impairment. This finding is supported by the hierarchical clustering heatmap results, which resolved three coherent functional modules (growth morphology, health structure, and root stress) that showed consistent expression patterns across healthy and declining groups (Figure 4). The declining group network exhibited significantly higher complexity than the healthy group, with 2.8 times more significant correlation edges, a longer average path length, and a higher clustering coefficient (Figure 5). This increased network complexity during decline indicates that multiple functional modules become more tightly coupled as the tree's physiological state deteriorates, forming a synergistic feedback loop that accelerates the decline process. North-south crown width was identified as the core connectivity node in the declining network, highlighting the central role of canopy structure in mediating the relationship between underground root stress and aboveground growth performance. These results are consistent with the stress-gradient hypothesis^{76,77}, which predicts that biological interactions become more positive under stressful conditions. In the context of ancient tree decline, this means that different functional traits become more interdependent as the tree experiences increasing stress, making the entire system more vulnerable to further disturbance.

4.4. A Novel Integrated Health Evaluation System for Ancient Trees

Existing health evaluation systems for ancient trees suffer from two major drawbacks: indicator redundancy and subjective weighting bias^{78,79}. To address these issues, we adopted a four-method cross-validation strategy for core indicator screening, which effectively eliminated redundant indicators and identified six high-confidence core indicators: dead branch rate, root stress, crown width, canopy biomass, tree height, and root biomass (Figure 7A-7B). This multi-method consensus approach ensures the robustness and representativeness of the selected core indicators, which is a significant improvement over previous studies that relied on single-method screening. We then developed a subjective-objective combined weighting model that integrates expert knowledge and data-driven information, overcoming the limitations of purely subjective or purely objective weighting methods (Table 1). The combined weighting model achieved an overall classification accuracy of 68.57% and an AUC-ROC of 0.7222, demonstrating good stability and generalization ability. To further improve classification performance, we constructed and compared three machine learning models, with the SVM model achieving the best overall performance (74.29% accuracy, 0.8710 AUC-ROC) (Figure 7C). This performance is comparable to or better than previous base machine learning models for forest health assessment (69.80% accuracy)⁸⁰, confirming the effectiveness of our core indicator set and modeling approach. Finally, we divided ancient camphor tree health status into five scientifically validated grades using the

Jenks Natural Breaks method, which minimizes within-grade variance and maximizes between-grade variance (Figure 7D). The clear separation of HIS values across grades confirms the practical applicability of our classification standard, which provides a quantitative basis for targeted conservation and management measures.

4.5. Limitations and Future Research Directions

This study has several limitations that should be addressed in future research. First, our sample size was relatively small (35 trees) and limited to the Gannan region of southern China, focusing on trees aged 100–200 years. Future studies should expand the sample size and geographic range to include trees of different ages and from different regions to verify the generalizability of our findings. Second, our root stress calculation was based on a simplified cantilever beam model that did not consider the effects of soil properties, root mechanical characteristics, or dynamic wind loads. Future research should incorporate more sophisticated finite element models that account for these factors to improve the accuracy of root stress estimation. Third, our study was cross-sectional rather than longitudinal, providing only a snapshot of tree health status at a single point in time. Long-term monitoring studies are needed to track changes in root stress and other indicators over time and to validate the predictive ability of our health evaluation system. Finally, our study focused on structural and morphological indicators but did not include physiological or biochemical indicators such as photosynthetic rate, chlorophyll content, or hormone levels. Future research should integrate these physiological indicators with structural and mechanical indicators to develop a more comprehensive understanding of the mechanisms underlying ancient tree decline.

5. Conclusion

This study provides a paradigm shift from traditional aboveground-only assessment to an integrated aboveground-belowground evaluation approach for ancient tree health. The identification of root stress as the core driver of decline has important implications for ancient tree conservation: conservation efforts should focus not only on aboveground canopy maintenance but also on protecting the underground root system and reducing root stress. Our novel health evaluation system provides a scientific and quantitative tool for early decline detection and targeted conservation. The five-grade classification standard allows managers to prioritize conservation resources: healthy trees can be monitored regularly, sub-healthy trees can receive preventive measures, and declining trees can be targeted with more intensive interventions such as root zone improvement, structural support, or pest control. Furthermore, the finding that crown structure traits can serve as reliable non-destructive predictors of root stress makes our evaluation system accessible to a wider range of users, including local forestry departments and community volunteers who may not have access to expensive non-destructive testing equipment. In conclusion, this study significantly advances our understanding of ancient camphor tree decline mechanisms and provides a practical framework for scientific conservation and management. By integrating multi-source non-destructive testing techniques and machine learning methods, we have developed a comprehensive health evaluation system that addresses the limitations of traditional approaches and offers new opportunities for the protection of these irreplaceable ecological and cultural heritage assets.

Supplementary Figures

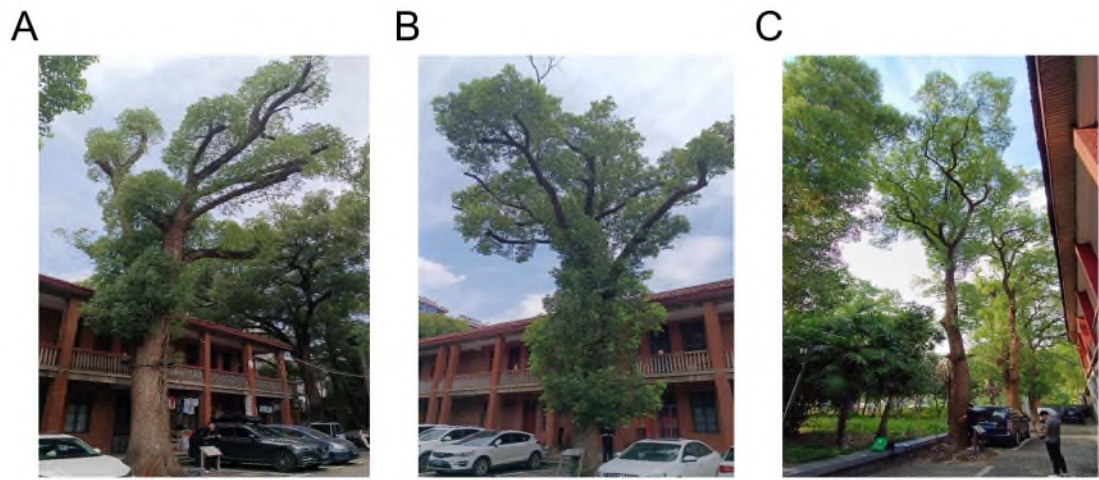


Figure S1. Representative ancient *Cinnamomum camphora* trees investigated in this study. (A) A typical sample from the entire 35 ancient camphor tree population; (B) A representative individual aged 100–120 years; (C) A representative individual aged 120–200 years.

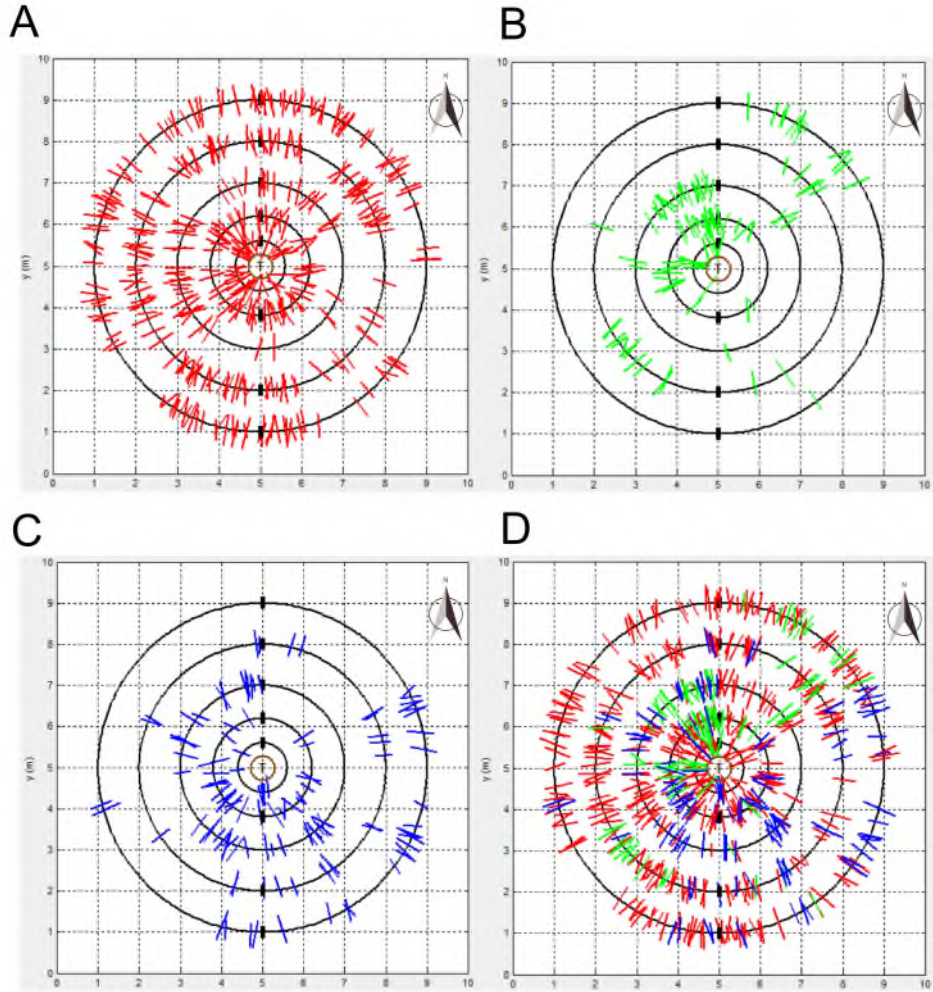


Figure S2. Layered horizontal root distribution of a representative ancient *Cinnamomum camphora* tree detected by the TRU Tree Radar System (TreeRadar, Inc., USA). The detection was

performed using a 900 MHz antenna with a maximum depth of 100 cm and a living root resolution of 1.0 cm, adopting the concentric circle scanning method. (A) Root distribution at 0–30 cm soil depth (red lines); (B) Root distribution at 30–60 cm soil depth (green lines); (C) Root distribution at >60 cm soil depth (blue lines); (D) Overlay of root distributions in all three depth intervals. The x and y axes represent horizontal distance from the trunk (unit: m), and concentric circles indicate scanning transects.

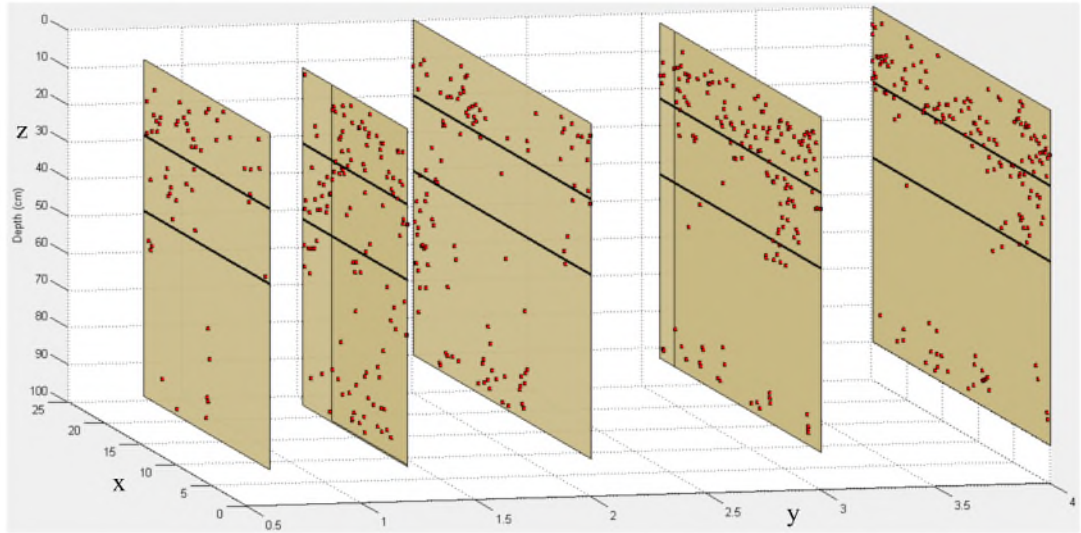


Figure S3. Vertical root distribution profiles of a representative ancient *Cinnamomum camphora* tree detected by the TRU Tree Radar System. Four parallel vertical scanning profiles are presented, with red dots indicating detected root segments. The x-axis represents the length of the scanning transect (unit: m), the y-axis represents the horizontal distance from the trunk (unit: m), and the z-axis represents the soil depth (unit: cm). Black horizontal lines divide the soil profile into three depth intervals: 0–30 cm, 30–60 cm, and >60 cm.

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Author Contributions

Z.X. and M.X. analyzed and interpreted the data, and were major contributors in writing the main manuscript text. Z.X., K.C. and Y.Z. provided experimental samples and carried out sample collection. H.X., Z.X., A.Y., B.H. and Z.Z. contributed to manuscript review and editing. C.C., Z.X. and L.Y. conceptualized the study, designed the experiments and supervised the entire project. All authors reviewed the manuscript and approved the final version.

Competing Interests

The authors declare no competing interests.

Data Availability

All data supporting the findings of this study are available within the paper and its Supplementary Information.

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