Postprint: Leaf Morphological Characteristics and Leaf Area Estimation Models for Chinese Fir

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Abstract

Plant leaves are the most important sites for carbon and water exchange and energy balance processes, and serve as key reference parameters for model estimation in forestry and agricultural production management as well as for analyzing species structural variation-functional adaptation mechanisms. Using vernier calipers and a handheld leaf area meter, three directly measured indicators of single leaves of Chinese fir (Cunninghamia lanceolata) were measured: leaf length (LL), maximum leaf width (LWmax), and maximum leaf thickness (LTmax), along with five indirectly calculated indicators: leaf area (LA), average leaf width (LWmean), average leaf thickness (LTmean), leaf elongation rate (LE), and leaf perimeter (LP). The statistical distributions and correlations of the eight morphological indicators were analyzed, and multivariate linear regression models and nonlinear regression exponential models were used to fit seven morphological indicators against single leaf area of Chinese fir. The results showed that the majority of single leaf area values (95%CI) were distributed between 0.758-0.836 cm2, with leaf area showing the greatest degree of variation (CV=0.513). The correlations between leaf length, leaf width and leaf area reached extremely significant levels (r=0.896, 0.682). The multivariate linear model fitted for LA was: Y=-0.388+0.165X1-0.023X2+1.453X3 (R2=0.981, SE=0.053), where X1-X3 represent LP, LE, and LWmean, respectively. Considering simplicity, the univariate exponential model for LL is suitable for estimating LA: LA=0.1×(1+LL)1.398 (R2=0.77, 2=0.39). The research results provide a method for accurately estimating other leaf functional trait indicators and fundamental data for models estimating leaf area of Chinese fir.

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Preamble

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Leaf Morphological Characteristics and Leaf Area Estimation Models for Cunninghamia lanceolata

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Abstract

Plant leaves represent the most critical site for carbon-water exchange and energy balance processes. Leaf size directly affects light interception and carbon acquisition capacity. Leaf area (LA) and related traits such as specific leaf area (SLA), leaf area index (LAI), and normalized difference vegetation index (NDVI) serve as key indicators in crop breeding, agroforestry production and management, model estimation, and analysis of species structural variation and functional adaptation mechanisms. However, the uncertainty in needle leaf area measurements, due to measurement difficulties, hinders efficient production management, effective risk assessment, and the development of correlative research. Currently, instrument-based measurement methods are pervasive but lack calibration against manual measurements. Additionally, regression estimation models based on plant leaf area and morphometric characteristics have focused primarily on agronomic crops, fruits, and some broadleaf species, with limited research on needle leaf area estimation models.

This study used *Cunninghamia lanceolata*, a common pioneer tree species in southern China, to measure three direct leaf morphometric characteristics (leaf length, maximum leaf width, maximum leaf thickness) and indirectly calculate five indicators (mean leaf width, mean leaf thickness, leaf area, leaf elongation, leaf perimeter) using vernier calipers and a portable leaf area meter. We present the statistical distribution and correlation analysis of these eight morphological characteristics, fitting leaf area with the other seven indicators using multivariate linear regression models and nonlinear regression index models. Our findings demonstrate that: (1) through manual measurement, the credible single leaf area of Chinese fir ranges from 0.758–0.836 cm^2, with a maximum coefficient of variation (CV = 0.513); (2) leaf area shows extremely significant correlation with leaf length and width (r = 0.896, 0.682); (3) the most accurate multivariate linear regression model is LA = -0.388 + 0.165×LL - 0.023×LW + 1.453×LP

(R^2 = 0.981, RMSE = 0.053), where LL, LW, and LP represent leaf length, leaf width, and leaf perimeter, respectively. From the perspective of simplicity, a single-variable index model using leaf length is more suitable: LA = 0.1×(1 + 1.398^LL) (R^2 = 0.77, RMSE = 0.39). This study provides a method for instrument calibration and accurate estimation of other leaf functional traits for Chinese fir, offering foundational data for leaf area estimation models and improving their accuracy and stability.

Keywords: *Cunninghamia lanceolata*; morphological characteristics; leaf area; estimation model

1. Introduction

Plant leaves are considered the most important sites for carbon-water exchange and energy balance processes. Research on leaf structural and functional traits, including their response characteristics to external environments, coordination mechanisms, trade-off strategies, and structural variation, has attracted significant recent interest. Studies have expanded from individual plant leaf functional traits to community canopy, regional production management, and even global-scale biological functional geography, providing basis and validation for global productivity changes and metabolic theory. Leaf area (LA) refers to the single-sided projected area of individual or average leaves. Related indicators based on LA, including specific leaf area (SLA, leaf area per unit mass), leaf area index (LAI, leaf area per unit land area), and normalized difference vegetation index (NDVI), are key references for crop breeding, agroforestry management, model estimation, and functional adaptation mechanism analysis.

LA is closely related to plant photosynthesis, transpiration, and other physiological-ecological processes, and is commonly used for crop variety selection, yield estimation, and forest production assessment. LA and related indicators serve as important plant characteristic parameters in ecological models including canopy photosynthesis models, biomass models, global vegetation dynamics models (DGVM), and biogeochemical cycle process models. Additionally, researchers have reconstructed paleoclimate history and leaf evolution through morphological measurements of leaf fossils, and analyzed species structural variation and functional adaptation mechanisms by studying leaf morphological indicators individually or in combination.

However, accurate LA determination is fundamental to studying plant photosynthetic production and physiological-ecological processes. The uncertainty in Chinese fir LA values, reported between 0.6873–1.316 cm^2 through manual measurement, 2.242–4.364 cm^2 through instrumental methods, and 37–50 cm^2 through remote sensing models, hinders production efficiency and risk assessment effectiveness. The difficulty in measuring Chinese fir LA is one reason for this uncertainty. LA measurement methods include manual and instrumental approaches. Manual methods, while reliable and commonly used to calibrate indirect measurements, are labor-intensive and unsuitable for large-scale measurements. Instrumental methods are selective and affected by leaf flatness; significant sample damage can also produce large errors. Currently, most ground measurements use instrumental methods lacking manual calibration, with inconsistent comparisons between different methods.

LA can also be estimated through regression models based on simple measurements like leaf length and width, or composite indicators like length-width ratio and perimeter. While extensively validated as efficient and rapid, prediction models typically use only single-variable or multivariate models, with few comparative studies. Existing research focuses primarily on agricultural products, fruit trees, flowers, and broadleaf evergreen trees, where morphological indicator measurement is relatively simpler compared to coniferous species. Research on leaf area estimation models based on morphological indicators for coniferous species remains limited.

This study simultaneously measured Chinese fir single-leaf LA using both vernier calipers and a portable leaf area meter. We measured eight morphological indicators: leaf length (LL), maximum leaf width (LW_max), mean leaf width (LW_mean), maximum leaf thickness (LT_max), mean leaf thickness (LT_mean), leaf area (LA), leaf elongation (LE), and leaf perimeter (LP). Using both multivariate linear models and single-variable nonlinear models, we developed Chinese fir LA estimation models. This research provides practical significance for calibrating instrumental measurements, accurately estimating other leaf functional traits using Chinese fir LA, and promoting related continuous research, while filling data gaps and improving model accuracy and stability for Chinese fir plantation management.

2. Study Area

The study was conducted at the Huitong National Field Station for Scientific Observation and Research of Chinese Fir Plantation Ecosystem in Hunan Province (core production area) and the Nanwan Experimental Forest Farm in Xinyang, Henan Province (non-core area) (113°58 E, 31°53 N). Both locations have subtropical monsoon climates with mild temperatures. The altitude ranges are 270–400 m in Huitong and 300–1100 m in Xinyang, both characterized by low mountainous and hilly topography. Annual mean temperatures are 15.1–16.8°C, with annual precipitation of 1304.2 mm and 1106 mm, respectively. Annual sunshine hours exceed 1900 h, and relative humidity averages 80%. Both sites have mountainous yellow soil, providing suitable light and hydrothermal conditions for Chinese fir growth. Stand density is approximately 1900 trees/ha in Huitong and 1800 trees/ha in Xinyang.

3. Methods

During the peak growth period in July, we established 10 m × 10 m plots at both sites. Since LA is primarily influenced by light and water availability, we randomly selected healthy trees maintaining leaf age sequences without pest damage in each plot. Samples were collected from upper, middle, and lower canopy layers and immediately transported to the laboratory. As Chinese fir leaves are lanceolate rather than typical needles, the method of approximating needle bundles as cylinders for direct LA measurement is not applicable. We therefore measured individual leaves sequentially.

On each branch, three leaves were randomly selected, numbered, and measured using two methods:

(1) Vernier Caliper Method
Using vernier calipers (precision 0.002 cm), we measured leaf length (LL) from the petiole base to leaf tip, and leaf width (LW) and thickness (LT) at the 1/4, 1/2, and 3/4 positions along the leaf length. Three measurements were averaged for each position, and the mean of these three positions served as the leaf' s LW and LT values. This yielded three direct measurement indicators: LL, LW_max, and LT_max. Indirectly calculated indicators included LW_mean, LT_mean, LA (approximated as LL × LW_mean rectangle), LP (2×(LL + LW_mean)), and LE (LL/LW_mean).

(2) Portable Leaf Area Meter Method
Using a Yaxin-1242 leaf area meter (precision 0.001 cm^2), we directly obtained LL (0.01 cm precision), LW_max, and LA.

4. Model Selection and Fitting

To construct optimal estimation models between different morphological indicators and LA, we employed both multivariate linear regression and nonlinear exponential regression models. To explore the influence and contribution of different indicators to LA, we used stepwise variable selection for model optimization, choosing comprehensive multivariate linear models. For single-indicator LA estimation, we used univariate nonlinear exponential models. Data were preliminarily processed in Microsoft Excel 2010, with statistical analysis and model fitting performed using IBM SPSS Statistics 21.0. Model evaluation was based on adjusted R^2 and reduced chi-square statistics.

5. Results

5.1 Ecological Characteristics of Chinese Fir Leaf Morphological Indicators

Among the eight measured indicators, LA showed the highest variation (CV = 0.513), with values distributed as 0.797 ± 0.409 cm^2 (95% CI: 0.758-0.836 cm^2). The variation coefficients ranked as: LA > LE > LP > LL > LW_max > LW_mean > LT_max > LT_mean. LW_max and LW_mean showed the smallest variation (CV = 0.238, 0.224), with stable distributions: 0.292 ± 0.055 cm and 0.227 ± 0.043 cm, respectively. LT_max and LT_mean displayed leptokurtic distributions (kurtosis = 16.383, 13.851) with minimal deviation (MAD

= 0.011, 0.009 cm). LE showed the largest numerical range and greatest deviation (0.526–33.495, MAD = 4.628).

5.2 Correlation Among Morphological Indicators

Correlation analysis revealed that LA exhibited strong linear positive correlations with all indicators except LE and LP, which showed weaker linear relationships (r = 0.292, 0.244). LA was extremely significantly correlated with LL and LW (r = 0.896, 0.911; r = 0.682, 0.709). LL and LT showed extremely significant linear correlation (r = 0.999). All other indicator pairs showed varying degrees of significant correlation, except LW_mean with LP, which showed almost no correlation (r = 0.073), and the only negative correlation between LT_max and LP (r = -0.201).

shows the overall distribution characteristics of Chinese fir leaf morphometric values, while presents the Pearson correlation matrix among morphological indicators.

5.3 Multivariate Regression Models for Chinese Fir Leaf Area

Given the extremely strong correlation between LL and LT (r = 0.999) that violates variable independence, LL was excluded from multivariate linear regression to avoid multicollinearity. Using the complete substitution method, the initial model was:

LA = -0.397 + 0.164×LP - 0.022×LE + 1.253×LW_mean - 1.416×LT_max + 0.854×LT_mean (R^2 = 0.981, RMSE = 0.053)

Although well-fitted, the regression coefficients for LW_mean, LT_max, and LT_mean were not significant ($p > 0.01$). Stepwise optimization yielded the final model:

LA = -0.388 + 0.165×LL - 0.023×LW_mean + 1.453×LP (R^2 = 0.981, RMSE = 0.053)

This model achieves maximum goodness-of-fit with minimal variables, where all coefficients are significant. details the multivariate linear regression results.

5.4 Exponential Models for Chinese Fir Leaf Area

Following multivariate analysis, we developed single-variable nonlinear models. Based on scatterplot distributions, all seven indicators showed extremely significant relationships with LA ($p < 0.001$). The best-fitting models were:

- **Using LP**: LA = 0.1×(1 + 1.398^LP) (R^2 = 0.825, RMSE = 0.029)
- **Using LL**: LA = 0.1×(1 + 1.398^LL) (R^2 = 0.77, RMSE = 0.039)

Other models showed poorer fit: LA = 0.144×(1 + 7.973^LW_mean) (R^2 = 0.702, RMSE = 0.083) and LA = 0.046×(1 + 5.963^LT_max) (R^2 = 0.731, RMSE = 0.075). summarizes the exponential models, and [Figure 3: see original paper] illustrates the nonlinear fitting curves.

6. Model Validation

Validation of the optimal models—multivariate: LA = -0.388 + 0.165×LL - 0.023×LW_mean + 1.453×LP (R^2 = 0.981, RMSE = 0.053), and univariate: LA = 0.1×(1 + 1.398^LL) (R^2 = 0.77, RMSE = 0.039)—showed that predicted values closely matched measured values, with fitted lines approaching the Y = X line. The multivariate model showed high goodness-of-fit, with errors primarily occurring at extremely small leaves (<0.4 cm^2) where predictions underestimated actual values. The univariate model produced errors when LP and LL were large (>12 cm^2), with residuals distributed in the negative domain. Both models met estimation requirements, with significant errors only beyond the normal Chinese fir leaf area range.

[Figure 4: see original paper] shows the relationship between measured and estimated LA using the multivariate model, while [Figure 5: see original paper] displays residual plots for the nonlinear models based on leaf perimeter and leaf length.

7. Discussion

7.1 Characteristics of Chinese Fir Leaf Area

Chinese fir LA showed greater variation than other morphological indicators (CV = 0.513), consistent with findings for four southern broadleaf species. This may result from LA' s square-unit measurement, where methodological errors contribute more substantially than for other indicators. The lanceolate leaf shape results in greater LL variation than LW variation (CV = 0.411 vs. 0.238), providing more explanatory space for LA variation—contrasting with broadleaf studies where LW explains ~75% of LA variation. This indicates that LW' s influence on LA differs across leaf shapes.

Reported Chinese fir LA ranges vary widely (0.6873–1.316 cm^2 manual; 2.242–4.364 cm^2 instrumental; 37–50 cm^2 remote sensing). Our precise range of 0.758–0.836 cm^2 (SD = 0.409) shows larger standard deviation due to broader sampling across different stand ages, canopy layers, and leaf ages. The high variation in LT measurements reflects the precision required, though concentrated distributions indicate measurement reliability. LE' s large deviation stems from its derivation from LL and LW measurements, amplifying measurement errors.

7.2 Leaf Area Estimation Models for Chinese Fir

Multivariate regression revealed LP' s strongest direct influence on LA, though both LL and LW significantly affect LA. Since LP and LE are derived from LL and LW, knowing LL and LW allows LA estimation through these composite indicators. While multivariate models achieve high precision, their complexity can be cumbersome. For simplicity, the single-variable exponential model using LL is recommended: LA = 0.1×(1 + 1.398^LL) (R^2 = 0.77), consistent with mango and grape studies. The 23% unexplained variance likely reflects measurement error.

In broadleaf species, LW typically serves as the best estimator, but for Chinese fir' s narrow leaves, LL performs better due to its greater variation and measurement reliability. The weak correlation between LA and LT reflects indirect effects and measurement challenges at sub-millimeter scale. LE and LP, as calculated indicators, show strong linear correlation due to their shared base measurements.

8. Conclusion

This study analyzed relationships between LA and seven morphological indicators in Chinese fir. The credible leaf area range is (0.797 ± 0.409) cm^2, primarily distributed between 0.758–0.836 cm^2. Different indicators influence LA directly or indirectly, with LL and LW having greater direct impact. For simplicity, the single-variable exponential model using LL is suitable: LA = 0.1×(1 + 1.398^LL) (R^2 = 0.77, RMSE = 0.39). For precision, the multivariate linear model is superior: LA = -0.388 + 0.165×LL - 0.023×LW_mean + 1.453×LP (R^2 = 0.981, RMSE = 0.053). Both models meet estimation requirements, with significant errors only at extremely small or large leaf sizes beyond the normal range. These models enable non-destructive LA measurement, avoiding instrumental limitations while saving time and effort, providing practical value for Chinese fir plantation management and offering reference for other species.

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Note: Figure translations are in progress. See original paper for figures.