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ARTICLE

Classification of Principal Wood Species in China Based on the Physiomechanical Properties

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ABSTRACT

Many tree species are planted in China with variable properties and usage. Toward exploring the structure-properties relationships of wood and classifying the species more reasonably, the physiomechanical properties of the domestic wood species in China were analyzed statistically. According to the correlation analysis, the mechanical properties were closely related to the wood density. Except impact toughness and cleavage strength, the correlation coefficients between mechanical properties and densities were more than 0.8. However, shrinkage properties showed fewer correlations with densities, and the coefficient was no more than 0.7. Primary component analysis was proved to be feasible to explore the information of the physiomechanical properties. Two principal components (PC1 and PC2) could account for most of the information. PC1 and PC2 were designated as density-dominated and shrinkage-associated factors, respectively. The domestic wood species in China could be classified into 4 clusters based on their physiomechanical properties. According to the cluster results, reasonable grading was proposed for air-dried density, volume shrinkage, modulus of rupture, compression strength parallel to grain and hardness in cross section. The statistical results brought insights into analyzing the physiomechanical properties of domestic Chinese wood species, which was helpful for developing strategies of tree breeding and technologies of wood processing.

KEYWORDS

Chinese wood species; physiomechanical properties; primary component analysis; cluster analysis; grading

1 Introduction

Wood is a biologically renewable resource in the process of human life and production. There are more than 60,000 tree species recorded worldwide, and more than 4,000 species are found in China [1]. The application range of wood is quite wide. Some wood species are suitable for building and construction. Some are commonly used for manufacturing furniture and floor, and some are particularly suitable for papermaking [2,3]. The different applications are attributed to the variability and heterogeneity of the structural constituents of wood. To better understand the "structure-properties-applications" relationships of wood and more efficiently use of wood, reasonable classification of wood species is very important.

It is widely recognized that wood can be classified based on its structural features, including the anatomical characteristics [4], surface color [5–7] and texture characteristics [8–10]. Chao et al. [8] classified wood species based on the surface texture. By using algorithm logic, the recognition rate was as high as 98%. Bardarov et al. [4] proposed a computer vision method to characterize the location, arrangement and morphology of vessel pores. By using these characteristics of vessel pores, an algorithm of classification was developed. Yang et al. [7] compared the variation in color features, and achieved a better classification of common tree species from the northeastern area of China.

Wood is composed of a certain proportion of cellulose, hemicellulose and lignin. The chemical composition of wood varies at different levels (species, cell and cell wall). The chemical spectroscopy is capable of extracting and analyzing the difference of chemical components, and wood species can be classified consequently [11–13]. Lavine et al. [12] extracted the Raman spectrum characteristics from several wood species, and classified the tropical and temperate woods. Yang et al. [14] investigated the classification of softwood and hardwood by using near infrared spectroscopy (NIR). Carballo-Meilan et al. [13] investigated the chemical differences of cellulose, hemicellulose, and lignin in wood and used Fourier infrared spectroscopy and multivariate analysis to classify wood samples.

The variations of structure and chemical characteristics behave as different physiomechanical properties of wood. Among the numerous properties, density determines the physiomechanical properties of wood to a large extent, which is reflected in the availability of a wide range of wood materials properties [15–18]. It is reasonable to classify wood species based on density and a series of physiomechanical properties. In the past, people mainly relied on experiences to classify wood species, and the results were often subjective and arbitrary. In modern research works, statistical analysis is powerful for processing complex data and analyzing the inter-relations [19]. Statistical methods, including correlation analysis, principal component analysis (PCA) and cluster analysis, are frequently used in wood science [20–23]. Caixeta et al. [24] used cluster analysis to classify eucalyptus of different genotypes according to their physical, mechanical and chemical properties. Zhao [25] established a database for Shanxi commercial timber by an expert system, and a classification of 60 wood species was obtained according to the suggestions from the expert system. Guo et al. [26] evaluated the effect of heat treatment on the properties of wood, and performed a cluster analysis on the measured properties. Hannrup et al. [27] studied the genetic relationship between families by analyzing the correlation between density and tracheid size of early- and latewood. Booi et al. [28] dissected a large number of fossil woods of Araceae and 6 modern species, and distinguished the fossil and modern woods by multivariable PCA. Vieira et al. [29] analyzed the acquired near-infrared spectra of three sections of wood by PCA, and distinguished the wood and charcoal of 4 tree species in the Myrtaceae family. These results prove that the statistical methods are applicable to the analysis of physiomechanical properties of wood.

Although statistical analysis has been used for processing complex data in wood science, the classification of wood species with respect to their physiomechanical properties is rare. The reason is twofold: 1) There are many physiomechanical properties, and these properties have certain variations among and within wood species [30]; 2) The recognition accuracy is low when extracting information from the properties [31]. Rational classification based on the physiomechanical properties is helpful for exploring the "properties-applications" relationships of wood and its rational utilizations. Hence, in this study, we attempted to classify the domestic wood species in China based on their physiomechanical properties. The numerous properties were dimensional reduced by the statistical analysis methods, including correlation analysis, PCA and cluster analysis. Based on the statistical analysis, the rational classification of domestic wood species in China was proposed, as well as the grading of the properties was designated.

2 Materials and Methods

2.1 Original Data

Original data of the physiomechanical properties were adopted from the book "Wood Physical and Mechanical Properties of Main Tree Species in China" [32]. A total of 283 wood species were collected by several universities and institutes of China. 21 physical and mechanical properties were tested, including basic density (BD_{en}), air-dried density (AD_{en}), radial shrinkage coefficient (Sh_R), tangential shrinkage coefficient (Sh_T), volume shrinkage coefficient (Sh_V), modulus of elasticity (MOE), modulus of rupture (MOR), shear strength in radial section (SS_R), shear strength in tangential section (SS_T), compression strength in longitudinal (CS_L), radial (CS_R) and tangential direction (CS_T), local compression strength in radial (LCS_R) and tangential direction (LCS_T), tension strength in longitudinal direction (TS_L), impact toughness (IT), hardness in cross (H_C), radial (H_R) and tangential section (H_T), cleavage strength in radial (ClS_R) and tangential section (ClS_T). The above-mentioned properties of all the wood species are compiled in Supplementary Material **S1**. Concerning the forest management, which may influence the wood quality [33], the specific factors such as soil quality, fertilizer categories, sunlight, and precipitation caused the property differences between and within wood species. In this article, at least 5 samples were taken from the same tree species, and the property data were used for analyzing the structure-property relationships. Environmental factors were neglected.

2.2 Methods

For ease of the description for the statistical analysis, in this study, the wood species were taken as samples, and the properties were taken as variables.

2.2.1 Correlation Analysis

Correlation analysis refers to the analysis of two or more correlated variables factors, so as to measure the closeness of the two variables [34]. The correlation coefficient r_{XY} was calculated as:

$$r_{XY} = \frac{Cov_{XY}}{\sqrt{Var_X Var_Y}} \tag{1}$$

where X and Y are any two variables among the 21 collected ones; Cov_{XY} is the covariance of X and Y. Var_X and Var_Y are the variances of X and Y, respectively. r_{XY} ranges between –1 and 1. When the value was higher than 0, there was a positive correlation between X and Y, and vice versa.

2.2.2 Principal Component Analysis (PCA)

PCA refers to replacing the original variables with fewer new variables, and making these fewer variables retain as much of the information reflected by the original variables as possible [35] .

PCA was carried out by the statistical software, SPSS version 17.0 (SPSS Inc., Chicago, IL, USA). Firstly, the average value ($\bar{x}_k$) and standard deviation (S_k) of each variable X were calculated. Secondly, all the variables were standardized (x'_{ik} or x'_{jk}) to make sure the value of the variance of each variable was 1. Then, the correlated matrix R of the variable and the standardized correlation coefficient r_{ij} were calculated

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1p} \\ \vdots & \ddots & \vdots \\ r_{p1} & \cdots & r_{pp} \end{pmatrix} \tag{2a}$$

$$r_{ij} = \left(\sum_{k=1}^{n} x'_{\mathrm{ik}} \cdot x'_{\mathrm{jk}}\right)/(n-1)\ (\mathrm{i,j} = 1, 2\ldots, \mathrm{p}) \tag{2b}$$

$$x'_{\mathrm{ik}} = \frac{X_{ik} - \overline{x}_{\mathrm{k}}}{S_{\mathrm{k}}} \; (\mathrm{i} = 1, 2 \ldots, \mathrm{n}; \mathrm{k} = 1, 2 \ldots, \mathrm{p}) \tag{2c}$$

where x is each property, p is the quantity of variables (21), n is the total number of the samples (222). According to the matrix R, non-negative eigenvalues (λ_p) and eigenvectors were calculated with a total number of p ($\lambda_1 > \lambda_2 > \ldots > \lambda_p \geq 0$) [36]. Based on the eigenvectors and the standardized properties (x_s), new variables (Z_1, Z_2, ..., Z_p) were created to present all the physiomechanical properties.

Dimensionality reduction was carried out by calculating the ratio of variances (a):

$$a = \left(\sum_{i=1}^{m} S_{ik}\right) / \left(\sum_{j=1}^{p} S_{jk}\right) \tag{3}$$

where m is the number of principal components, S_{ik} and S_{jk} are the variances. Once the value of a was higher than 0.85, the information of the original variables (x_1, x_2, ..., x_p) was basically remained.

2.2.3 Cluster Analysis

Cluster analysis is a method for merging data structures into categories when there is no prior classification. When using the cluster analysis, the tree species were classified based on their physical and mechanical properties [37]. The main processes of the cluster analysis are depicted as follows:

(1) A standardized transformation was performed by the Eq. (2c).

(2) The Euclidean distance (D_{ij}) between any two samples was calculated as:

$$D_{\mathrm{ij}=} \left[\sum_{k=1}^{i} (x'_{ik} - x'_{jk})^2 \right]^{\frac{1}{2}} (\mathrm{i}, \mathrm{j} = 1, 2, \ldots, \mathrm{n}; \mathrm{k} = 1, 2, \ldots, \mathrm{p}) \tag{4}$$

(3) The distance between category and category was calculated. n samples were divided into M categories. The sum of squared deviations $\left(S_i^{(M)}\right)$ of class I was calculated as:

$$S_i^{(M)} = \sum_{i=1}^{ni} (X_{ij} - \overline{x}j)^{\mathrm{T}} (X_{ij} - \overline{x}j) \tag{5}$$

where n_i is the number of samples of category I. Two categories (Gp, Gq) in the samples were assumed. If Gp and Gq were combined into G_k , the sum of the squares of the deviations increased after the combination $\left(D_{pq}^2\right)$ was calculated as:

$$D_{pq}^2 = s_{\mathrm{k}} - s_{\mathrm{p}} - s_{\mathrm{q}} \tag{6}$$

where S_k, S_p, S_q are the sum of squares of deviations of classes G_k, G_p, G_q, respectively. The two categories with the smallest increase in the sum of squared deviations were selected and merged into a new category. Step 3 was repeated until all samples were combined into one category.

(4) A clustering pedigree diagram was drawn.

(5) The optimal number of categories was determined according to the aggregation coefficient.

3 Results and Discussion

3.1 Correlation Analysis

The correlation coefficient of any two properties among the 21 ones is shown in Fig. 1. All the coefficients were higher than 0, indicating the positive correlations among the physical and mechanical properties of wood. All the mechanical properties were positively correlated with the density (BD_{en} or AD_{en}). The wood density represented the amount of polymeric substances in the wood cell wall per unit volume. Wood with higher density could bear greater forces, behaving as stronger mechanical capacity [38]. Therefore, densification treatment was an effective way to improve the mechanical properties of low-density wood products [39]. However, some other factors also influenced the mechanical properties, such as the micro-structure and chemical components [40,41]. For instance, the intercellular force between cells relied on the concentration of lignin. The atypical lignin distribution in the compound middle lamellae of eastern leatherwood endowed the flexibility while the strong lignification in vessels endowed the rigidity [42].

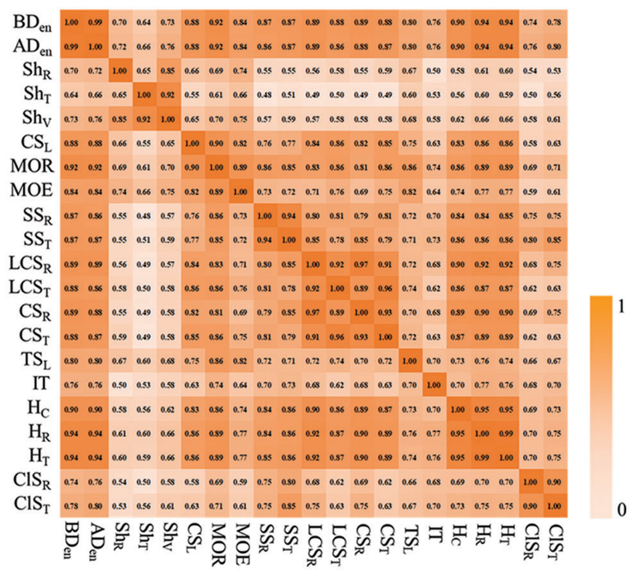

Figure 1: Correlation coefficient matrix among 21 properties. Scale ranged from 0–1

However, the correlation coefficient between TS_L and BD_{en} (or AD_{en}) was only around 0.8, which was obviously lower than that between CS_L and density (>0.87). When subjected to longitudinal tension, the mechanical capacity was mainly dependent on the covalent bond of the molecular chain in cellulose, and the microfibril angle had a significant influence on the value of TS_L [43,44]. In addition, density was indeed the main factor affecting wood physiomechanical properties, but some of the internal factors of the wood had an insignificant impact.

The correlation coefficient between shrinkage and density was less than 0.7, because shrinkage was largely dependent on micro-structure of wood, such as the microfibril angle, the arrangement of fiber and ray cells, the ratio of early- and latewood, and the radial position of wood [45–49]. According to Zhang et al. [50], AD_{en} and Sh_T were the key characteristics for domestic gymnosperms species in China, while AD_{en} and Sh_R were the key characters of angiosperms. Such a variation was attributed to different forms of wood rays.

3.2 Principal Component Analysis

Based on the results shown in Fig. 1, there were some correlations among the 21 properties. Hence, it was reasonable to process the data of the properties by dimensionality reduction. The cumulative contribution rate of the first two principal components (PC1 and PC2) was around 85% (Fig. 2), i.e., most of the information about the 21 properties could be dimensionally reduced by PC1 and PC2. Consequently, the PCA analysis was minimized to PC1 and PC2 for grouping the properties.

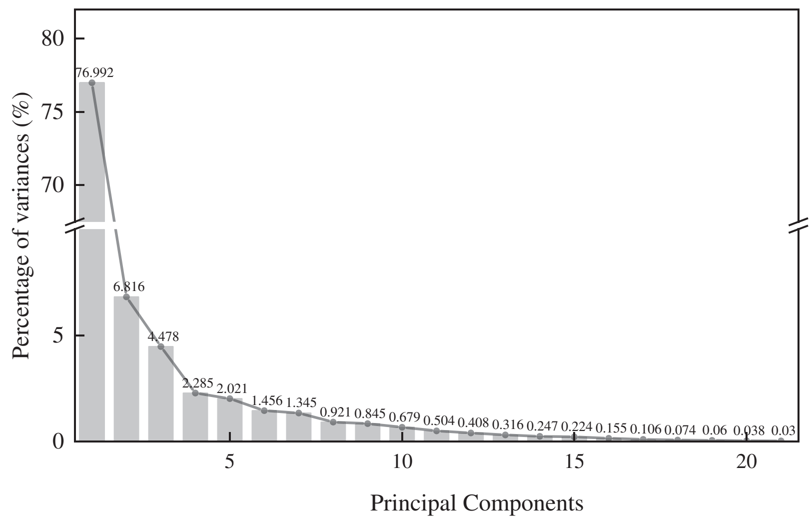

Figure 2: Percentage of variances as a function of principal components

The plotted scores of PC1 *vs*. PC2 are displayed in Fig. 3. The plots of density and mechanical properties concentrated together and showed strong positive loadings with PC1 (scores ≥ 0.8). The plots of the remaining properties-Sh_T, Sh_R and Sh_V concentrated together as another group. The scatter between the two groups confirmed the lower correlations between shrinkage and other properties. Based on the results shown in Fig. 3, PC1 and PC2 were explained as density-dominated and shrinkage-associated factors respectively. In such a case, the data from PC1 and PC2 were reasonable for presenting most of the information for the physiomechanical properties of wood.

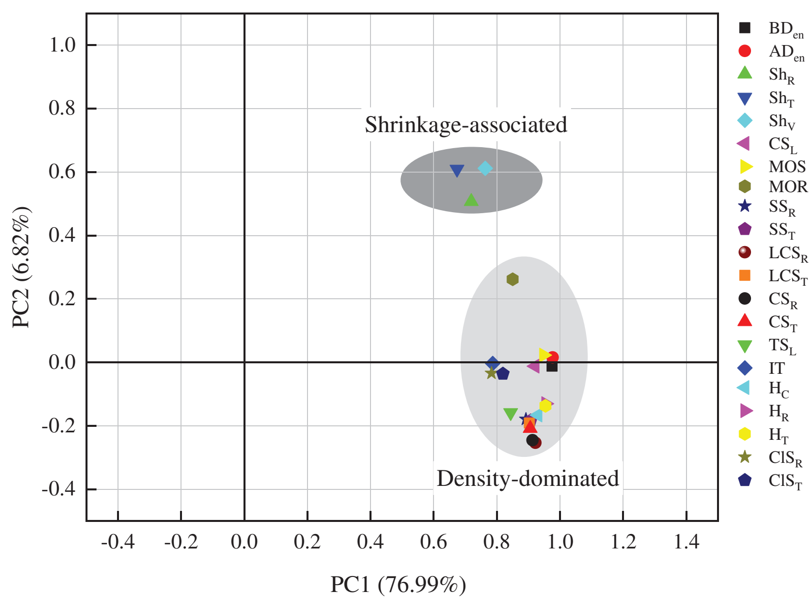

Figure 3: Plotted scores of PC1 *vs*. PC2 for all the properties

The PC1 and PC2 scores of all the wood species were calculated and are displayed in Fig. 4. To determine the distribution pattern of the PC1 *vs*. PC2 plots, all the species were classified based on the levels of AD_{en} (Fig. 4a), Sh_v (Fig. 4b), CS_L (Fig. 4c) and MOR (Fig. 4d). There was a clear boundary among the adjacent levels in Figs. 4a and 4b, indicating that the classification result based on PCA was basically consistent with that from the values of AD_{en} or Sh_v. However, the boundary in Figs. 4c or 4d was not as clear as that in Figs. 4a or 4b. When PCA was carried out, some of the mechanical property information was lost through the dimensionality reduction. The boundary variation manifested that PC1 and PC2 successfully represented the information of AD_{en} and Sh_v, and PCA results were effective when classifying wood species.

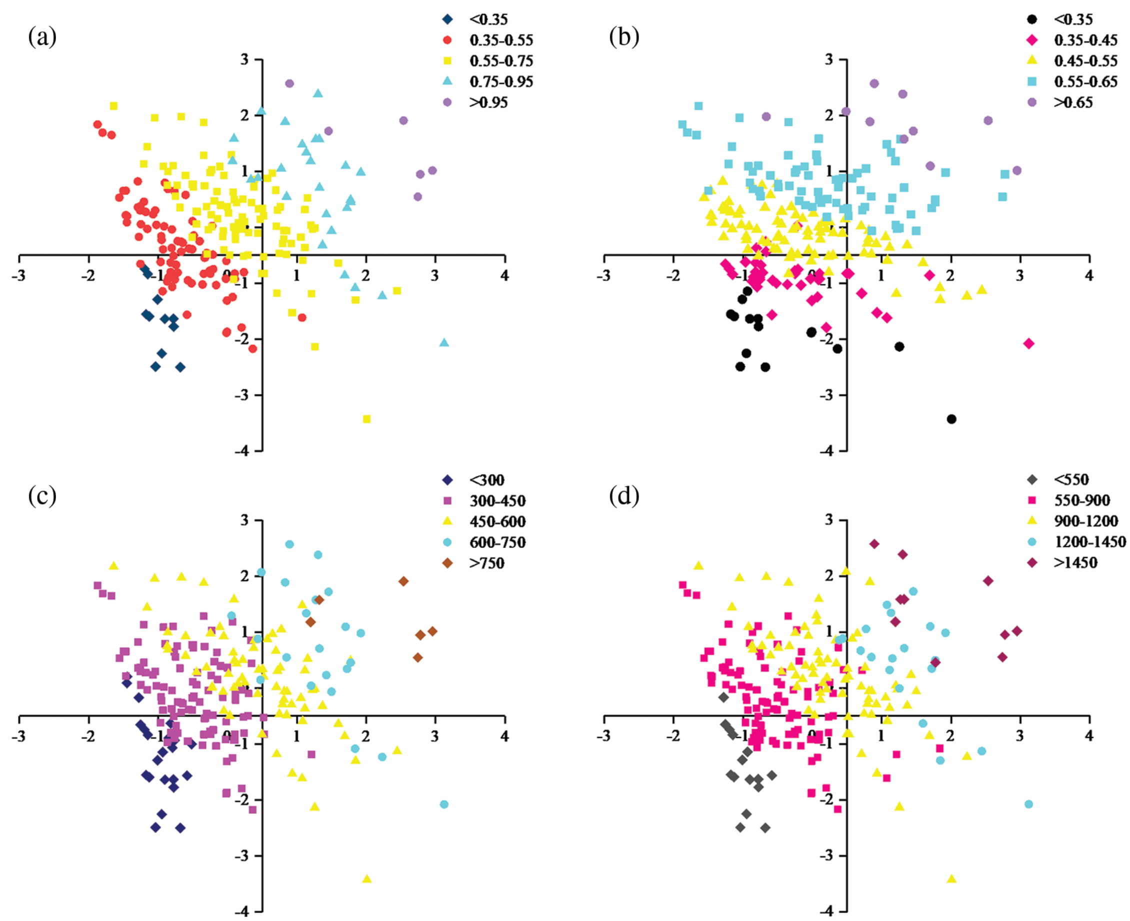

Figure 4: Sample ranking chart divided by (a) Air-dried density, (b) Volume shrinkage, (c) Compression strength parallel to grain, and (d) Modulus of rupture

3.3 Cluster Analysis

The optimal number of clusters was determined by the elbow method when evaluating the aggregation coefficient [51]. According to Fig. 5, the turn point of the aggregation coefficient ranged between 4 and 5. Firstly, the species were classified into 4 clusters. Clusters # 1, # 2, # 3 and # 4 contained wood species counts of 69, 72, 55 and 26, respectively. The species counts when classifying in 5 clusters were 69, 28, 44, 55 and 26, for Clusters # 1*, # 2*, # 3*, # 4* and # 5*, respectively. When comparing the wood species in the clusters, the sum of the counts in Clusters # 2* and # 3* was equal to that in Cluster # 2.

To evaluate the performances of the cluster analysis, the average values of the properties in each cluster were calculated, and those of the selected properties are displayed in Fig. 6. When classifying in 4 clusters, all the average values of the properties were in the following order: Cluster # 1 < Cluster # 2 < Cluster # 3 < Cluster # 4, and there were significant variations of the properties ($p < 0.05$). However, no significant variation of the properties was found when classifying in 5 clusters, especially among Clusters # 2*, # 3* and # 4*, indicating there were indistinct boundaries among the 5 clusters.

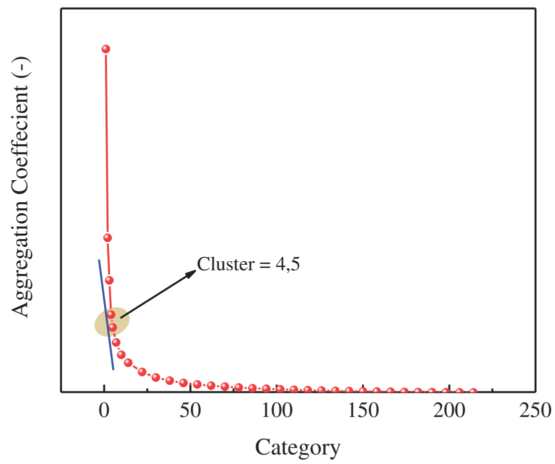

Figure 5: Aggregation coefficient as a function of cluster number. Significant decrease at the position of elbow (*blue tangent*)

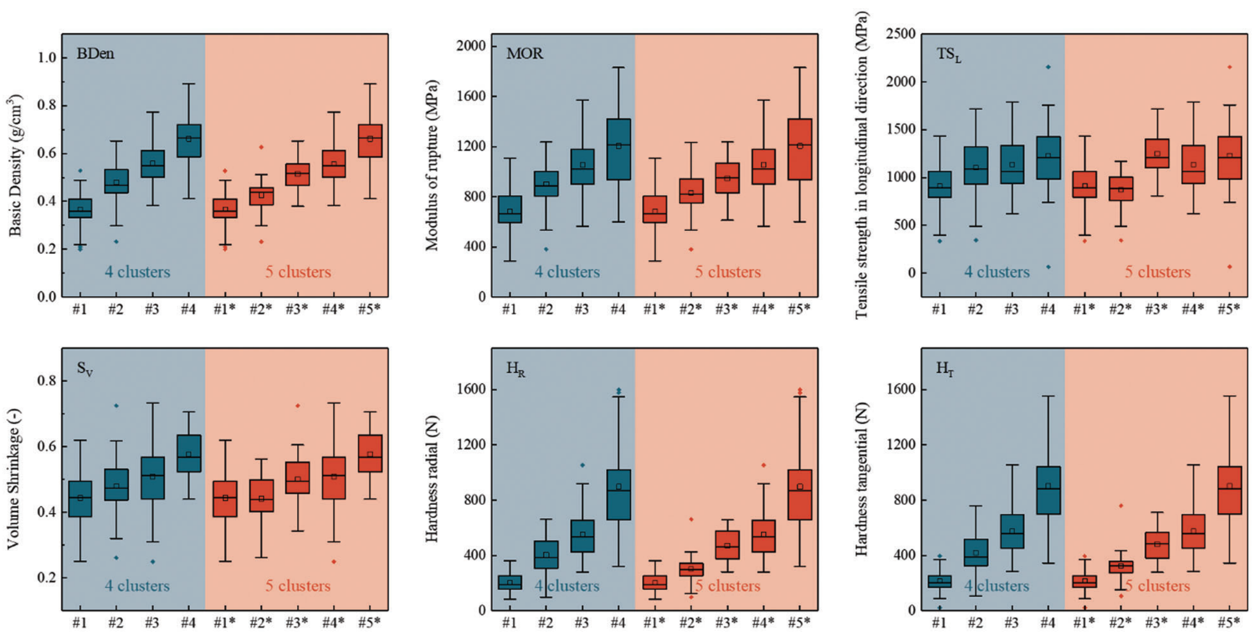

Figure 6: The average value of the selected properties of when classifying in 4 or 5 clusters

Based on the results in the 4 clusters, the grading levels for the properties were calculated. In Fig. 7, the grading levels for the selected properties are shown (lower panels in blue), together with the grading results reported by the book "Wood Physical and Mechanical Properties of Main Tree Species in China" (upper panels in red). There were discrepancies for the grading between these two series of results. The grading results reported by the book had similar spans in the adjacent levels. Taking Ad_{en} as an example (Fig. 7a), the spans of the levels–lower, low, medium, high were 0.35, 0.2, 0.2 and 0.2 g/cm^3, respectively. However, the spans were 0.5, 0.13 and 0.1 g/cm^3, for the grading levels # 1, # 2 and # 3, respectively. The compact spans for # 2 and # 3 were also found for the properties of S_v (Fig. 7b), CS_L (Fig. 7d) and MOR (Fig. 7e). The proportions of the species number were much more uniform when dividing into 4 clusters, indicating these representative clusters could explain most of the information of the properties.

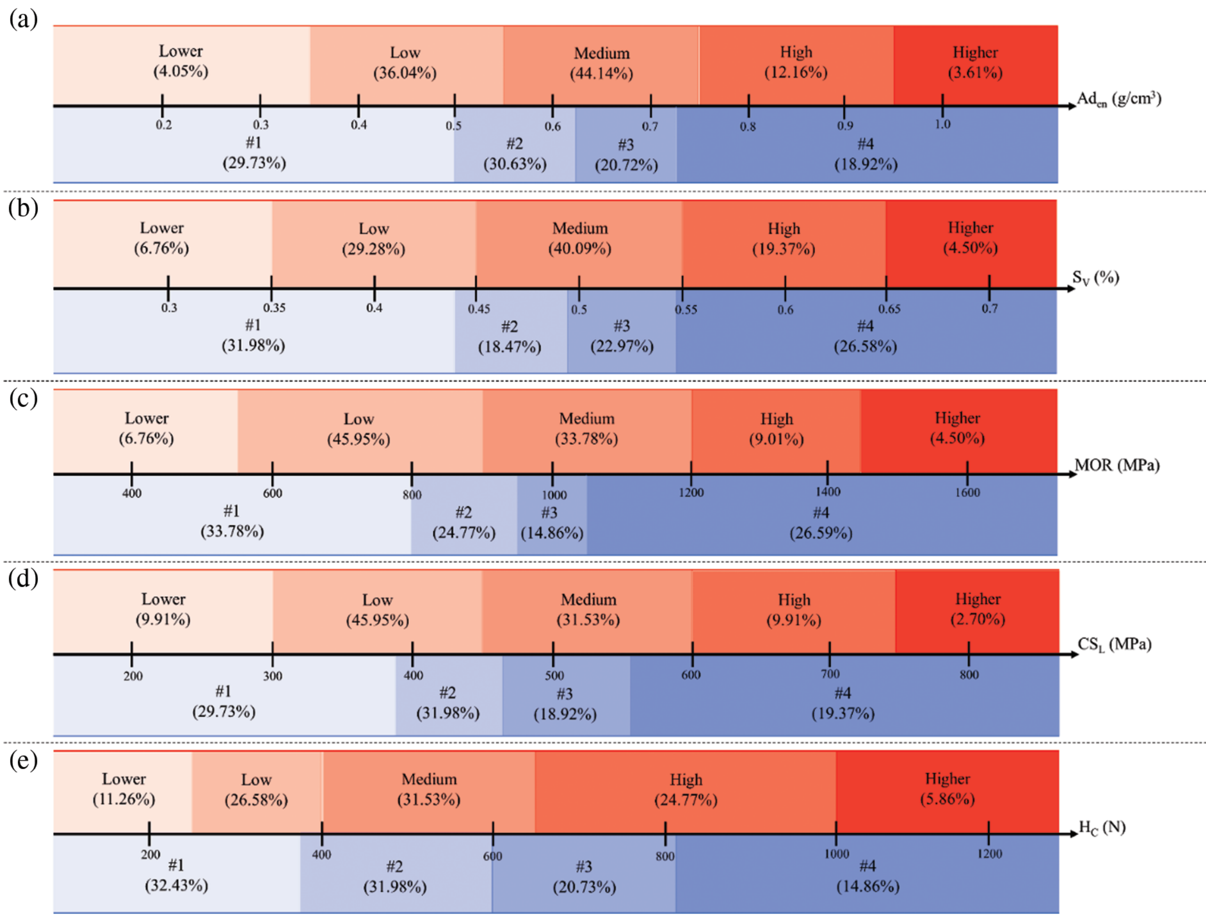

Figure 7: Grading results for (a) Air-dried density. (b) Volume shrinkage. (c) Modulus of rupture. (d) Compression strength parallel to grain, and (e) Hardness in cross section based on cluster analysis (*lower panels in blue*) and results from "Wood Physical and Mechanical Properties of Main Tree Species in China" (*upper panels in red*)

Previous studies showed that the classification and identification of certain wood species, and the classification was merely used to analyze the physiomechanical properties of wood. Reasonable classification was the inevitable development approach and effective way to improve the technology for wood utilization. In this study, the grading results brought insights into analyzing the properties of domestic Chinese wood species, especially for the plantation species, and the findings extended the understanding of the "structure-properties-applications" relationships.

4 Conclusion

The physiomechanical properties of the domestic wood species in China were statistically analyzed for classification of these species. Based on the correlation analysis, PCA and cluster analysis, the conclusions were as follows:

1) The mechanical properties were closely related to the air-dried (or basic) density. Except impact toughness and cleavage strength, the correlation coefficients between mechanical properties and densities were higher than 0.8. Shrinkage properties showed less correlations with densities, and the coefficients was around and even lower than 0.7.

2) PCA was feasible to explore the information of the physiomechanical properties of wood. Two principal components (PC1 and PC2) could account for most of the information. The densities and mechanical properties had larger loading with PC1, and shrinkages were much associated with PC2. Hence, PC1 and PC2 were designated as density-dominated and shrinkage-associated factors, respectively.

3) The domestic species in China could be classified into 4 clusters based on their physiomechanical properties. According to the cluster results, reasonable gradings for the air-dried density, volume shrinkage, modulus of rupture, compression strength parallel to grain and hardness in cross section were proposed.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

1. Beech, E., Rivers, M., Oldfield, S., Smith, P. P. (2017). GlobalTreeSearch: The first complete global database of tree species and country distributions. *Journal of Sustainable Forestry, 36(5),* 454–489. DOI 10.1080/10549811.2017.1310049.
2. Chen, B. W., Zhai, S. C., Kan, Y. N., Fan, X. D., Wang, X. Z. et al. (2021). New insights into Chinese traditional handmade paper: Influence of growth age on morphology and cellulose structure of phloem fibers from *Pteroceltis tatarinowii*. *Cellulose, 28(15),* 9943–9957. DOI 10.1007/s10570-021-04150-9.
3. Chen, X. J., Sun, C., Wang, Q., Tan, H. Y., Zhang, Y. H. (2022). Preparation of glycidyl methacrylate grafted starch adhesive to apply in high-performance and environment-friendly plywood. *International Journal of Biological Macromolecules, 194,* 954–961. DOI 10.1016/j.ijbiomac.2021.11.152.
4. Bardarov, N., Todorov, V., Christoff, N. (2021). Geometric and topological bases of a new classification of wood vascular tissues part 1: Shape and arrangement classifications of vessels. *Sustainability, 13(14),* 7545. DOI 10.3390/su13147545.
5. Zhuang, Z. L., Liu, Y., Ding, F. L., Wang, Z. G. (2021). Online color classification system of solid wood flooring based on characteristic features. *Sensors, 21(2),* 336. DOI 10.3390/s21020336.
6. Butler, D. A., Brunner, C. C., Funck, J. W. (2002). Wood-surface feature classification via extended-color imagery. *Forest Products Journal, 52(6),* 80–84. DOI 10.1121/1.427195.
7. Yang, S. C., Wang, K. Q., Dai, T. H., Bai, X. B. (2007). Analysis of wood classification using L~*a~*b~* color space. *Forestry Machinery & Woodworking Equipment, 35(10),* 28–30.
8. Chao, X. F., Fan, L. H., Cai, C., He, D. J. (2018). Wood texture classification and identification based on multi-feature extraction and selection. *Modern Agricultural Science and Technology, 18,* 118–120.
9. Ibrahim, I., Khairuddin, A. S. M., Arof, H., Yusof, R., Hanafi, E. (2018). Statistical feature extraction method for wood species recognition system. *European Journal of Wood and Wood Products, 76(1),* 345–356. DOI 10.1007/s00107-017-1163-1.
10. He, T., Liu, S. J., Lu, Y., Jiao, L. C., Yin, Y. F. (2021). Advances and prospects of wood identification technology coupled with computer vision. *Journal of Forestry Engineering, 6(3),* 18–27. DOI 10.13360/j.issn.2096-1359.202007014.

11. Tsuchikawa, S. (2007). A review of recent near infrared research for wood and paper. *Applied Spectroscopy Reviews, 42(1),* 43–71. DOI 10.1080/05704920601036707.
12. Lavine, B. K., Davidson, C. E., Moores, A. J., Griffiths, P. R. (2001). Raman spectroscopy and genetic algorithms for the classification of wood types. *Applied Spectroscopy, 55(8),* 960–966. DOI 10.1366/0003702011953108.
13. Carballo-Meilan, A., Goodman, A. M., Baron, M. G., Gonzalez-Rodriguez, J. (2014). A specific case in the classification of woods by FTIR and chemometric: Discrimination of Fagales from Malpighiales. *Cellulose, 21(1)*, 261–273. DOI 10.1007/s10570-013-0093-2.
14. Yang, Z., Liu, Y. N., Lv, B., Xie, X. Q. (2011). Rapid classification of softwood and hardwood by near infrared spectroscopy of wood tangential section. *International Conference on Mechatronics and Applied Mechanics (ICMAM 2011)*, pp. 1624–1627. Hong Kong, China.
15. Eder, M., Schaffner, W., Burgert, I., Fratzl, P. (2021). Wood and the activity of dead tissue. *Advanced Materials, 33(28),* 202001412. DOI 10.1002/adma.202001412.
16. Billard, A., Bauer, R., Mothe, F., Colin, F., Christine, D. et al. (2021). Vertical variations in wood basic density for two softwood species. *European Journal of Forest Research, 140(6),* 1401–1416. DOI 10.1007/s10342-021-01402-y.
17. Wang, X. Z., Huang, Y. Q., Lv, C. L., Wang, J. F., Wang, S. Q. et al. (2022). Multi-scale investigation of the mechanical properties of Loblolly pine wood at elevated temperature. *Wood Material Science & Engineering, 1–8(3),* 1–8. DOI 10.1080/17480272.2022.2053203.
18. Wang, X. Z., Chen, X. Z., Xie, X. Q., Wu, Y., Zhao, L. G. et al. (2018). Effects of thermal modification on the physical, chemical and micromechanical properties of Masson pine wood (*Pinus massoniana* Lamb.). *Holzforschung, 72(12),* 1063–1070. DOI 10.1515/hf-2017-0205.
19. Chia, K. S. (1999). Multivariate statistical analysis: A brief introduction. *Annals of the Academy of Medicine, 28(6),* 879–880.
20. Ma, T., Inagaki, T., Tsuchikawa, S. (2020). Rapidly visualizing the dynamic state of free, weakly, and strongly hydrogen-bonded water with lignocellulosic material during drying by near-infrared hyperspectral imaging. *Cellulose, 27(9),* 4857–4869. DOI 10.1007/s10570-020-03117-6.
21. Awais, M., Altgen, M., Mkel, M., Altgen, D., Rautkari, L. (2020). Hyperspectral near infrared image assessment of surface acetylated solid wood. *ACS Applied Bio Materials, 3(8),* 5223–5232. DOI 10.1021/acsabm.0c00626.
22. Zhang, X., Ji, Z., Zhou, X., Ma, J. F., Hu, Y. H. et al. (2015). Method for automatically identifying spectra of different wood cell wall layers in raman imaging data set. *Analytical Chemistry, 87(2),* 1344–1350. DOI 10.1021/ac504144s.
23. Runoz, G., Encinas, J. I., de Paula, J. E. (2019). Wood density as an auxiliary classification criterion for botanical identification of 241 tree species in the order Sapindales. *European Journal of Forest Research, 138(4),* 583–594. DOI 10.1007/s10342-019-01190-6.
24. Caixeta, R. P., Trugilho, P. F., da Silva Rosado, S. C., Lima, J. T. (2003). Properties and classification of wood for selecting Eucalyptus genotypes. *Revista Árvore, 27(1),* 43–51. DOI 10.1590/s0100-67622003000100006.
25. Zhao, Y. K. (1998). An expert system for wood classification and grading. *Scientia Silvae Sinicae, 34(1),* 81–89.
26. Guo, F., Huang, R. F., Lu, J. X., Chen, Z. J., Cao, Y. J. (2014). Evaluating the effect of heat treating temperature and duration on selected wood properties using comprehensive cluster analysis. *Journal of Wood Science, 60(4),* 255–262. DOI 10.1007/s10086-014-1403-5.
27. Hannrup, B., Danell, O., Ekberg, I., Moell, M. (2001). Relationships between wood density and tracheid dimensions in *Pinus sylvestris* L. *Wood and Fiber Science, 33(2),* 173–181.
28. Booi, M., van Waveren, I. M., van Konijinen-van Citter, J. H. A. (2014). Wood anatomical variability in early Permian 'Araucarioids'. *IAWA Journal, 35(3),* 307–331. DOI 10.1163/22941932-00000068.
29. Vieira, H. C., dos Santos, J. X., da Silva, E. L., Rios, P. D., de Muniz, G. I. B. et al. (2021). Potential of the near-infrared spectroscopy for the discrimination of wood and charcoal of four native Myrtaceae species in Southern Brazil. *Wood Material Science & Engineering, 16(3),* 188–195. DOI 10.1080/17480272.2019.1689296.
30. Tumenjargal, B., Ishiguri, F., Aiso, H., Takahashi, Y., Nezu, I. et al. (2020). Physical and mechanical properties of wood and their geographic variations in *Larix sibirica* trees naturally grown in Mongolia. *Scientific Reports, 10(1),* 12936. DOI 10.1038/s41598-020-69781-7.

31. Rajagopal, H., Khairuddin, A., Mokhtar, N., Ahmad, A., Yusof, R. (2019). Application of image quality assessment module to motion-blurred wood images for wood species identification system. *Wood Science and Technology, 53(4),* 967–981. DOI 10.1007/s00226-019-01110-2.
32. Research Institute of Wood, Industry Chinese Academy of Forestry (1982). *Wood physical and mechanical properties of main tree species in China*. China: Forestry Publishing House.
33. Grigoreva, O., Runova, E., Alyabyev, A., Hertz, E., Voronova, A. et al. (2021). Influence of different forest management techniques on the quality of wood. *Journal of Renewable Materials, 9(12),* 2175–2188. DOI 10.32604/jrm.2021.016387.
34. Zhou, Y., Zhang, Q., Singh, V. P., Xiao, M. Z. (2015). General correlation analysis: A new algorithm and application. *Stochastic Environmental Research and Risk Assessment, 29(3),* 665–677. DOI 10.1007/s00477-014-0970-8.
35. Krzanowski, W. J. (1992). A user's guide to principal components. *Journal of the Royal Statistical Society Series A, 155(1),* 173–174. DOI 10.2307/2982678.
36. Hansen, E. R. (1963). On cyclic Jacobi methods. *Journal of the Society for Industrial & Applied Mathematics, 11(2),* 448–459. DOI 10.1137/0111032.
37. Frades, I., Matthiesen, R. (2010). Overview on techniques in cluster analysis. *Methods in Molecular Biology, 593,* 81–107. DOI 10.1007/978-1-60327-194-3.
38. Missanjo, E., Matsumura, J. (2016). Wood density and mechanical properties of *Pinus kesiya* Royle ex Gordon in Malawi. *Forests, 7(7),* 135. DOI 10.3390/f7070135.
39. Hajihassani, R., Ghahri, S., Zamani, S. M., Nourbakhsh, A. (2022). Performance of densified wood glulam as building bio-material. *Journal of Renewable Materials, 10(2),* 511–526. DOI 10.32604/jrm.2022.017781.
40. Wang, X. Q., Keplinger, T., Gierlinger, N., Burgert, I. (2014). Plant material features responsible for bamboo's excellent mechanical performance: A comparison of tensile properties of bamboo and spruce at the tissue, fibre and cell wall levels. *Annals of Botany, 114(8),* 1627–1635. DOI 10.1093/aob/mcu180.
41. Kovryga, A., Stapel, P., van de Kuilen, J. W. G. (2020). Mechanical properties and their interrelationships for medium-density European hardwoods, focusing on ash and beech. *Wood Material Science & Engineering, 15(5),* 289–302. DOI 10.1080/17480272.2019.1596158.
42. Mottiar, Y., Gierlinger, N., Jeremic, D., Master, E. R., Mansfield, S. D. (2020). Atypical lignification in eastern leatherwood (*Dirca palustris*). *New Phytologist, 226(3),* 704–713. DOI 10.1111/nph.16394.
43. Barnett, J. R., Bonham, V. A. (2004). Cellulose microfibril angle in the cell wall of wood fibres. *Biological Reviews, 79(2),* 461–472. DOI 10.1017/S1464793103006377.
44. Ocloo, J. K., Laing, E. (2003). Correlation of relative density and strength properties with anatomical properties of the wood of Ghanaian *Celtis* species. *Discovery and Innovation, 15(3–4),* 186–196.
45. Hai, P. H., Jansson, G., Hannrup, B., Harwood, C., Thinh, H. H. (2009). Use of wood shrinkage characteristics in breeding of fast-grown *Acacia auriculiformis* A. Cunn. ex Benth in Vietnam. *Annals of Forest Science, 66(6)*, 611. DOI 10.1051/forest/2009048.
46. Leonardon, M., Altaner, C. M., Vihermaa, L., Jarvis, M. C. (2010). Wood shrinkage: Influence of anatomy, cell wall architecture, chemical composition and cambial age. *European Journal of Wood and Wood Products, 68(1),* 87–94. DOI 10.1007/s00107-009-0355-8.
47. Patera, A., van den Bulcke, J., Boone, M. N., Derome, D., Carmeliet, J. (2018). Swelling interactions of earlywood and latewood across a growth ring: Global and local deformations. *Wood Science and Technology, 52(1),* 91–114. DOI 10.1007/s00226-017-0960-3.
48. Xue, Q. W., Sun, W. S., Fagerstedt, K., Guo, X., Dong, M. R. et al. (2018). Effects of wood rays on the shrinkage of wood during the drying process. *BioResources, 13(3),* 7086–7095.
49. Xing, X. Y., Wang, B. B., Guan, Y., Zhou, L., Liu, Y. M. et al. (2022). Study on the radial variation in sectional wood properties from different Catalpa bungei clones. *Journal of Forestry Engineering, 7(2),* 72–77. DOI 10.13360/j.issn.2096-1359.202105033.

50. Zhang, M. X., Ji, C. J., Zhu, J. L., Wang, X. P., Wang, D. H. et al. (2017). Comparison of wood physical and mechanical traits between major gymnosperm and angiosperm tree species in China. *Wood Science and Technology, 51(6),* 1405–1419. DOI 10.1007/s00226-017-0954-1.
51. Thorndike, R. (1953). Who belongs in the family? *Psychometrika, 18(4),* 267–276. DOI 10.1007/BF02289263.