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The Classification of Log Decay Classes and an Analysis of Their Physical and Chemical Characteristics Based on Artificial Neural Networks and K-Means Clustering

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Abstract: Most existing methods for determining log decay levels normally use variations in log surface characteristics, and the results are subject to human subjectivity, which is uncertain and inaccurate. In order to investigate a novel method for the quantitative determination of log decay levels, we randomly selected log samples from four species (*Pinus tabulaeformis*, *Larix principis-ruprechtii*, *Betula albosinensis* and *Quercus aliena* var. *acuteserrata*) with different levels of decay and determined their basic physicochemical characteristics in the laboratory. An artificial neural network (ANN) model was used to predict the hardness values of the log samples with different levels of decay at different moisture contents. The hardness was then used as a clustering factor to quantify the decay levels of the log via K-means clustering analysis. The variations in and correlations between the basic physicochemical factors of the log specimens were investigated between the different decay classes and between the different tree species, and then ANOVA and correlation analysis were used to verify the reliability of the clustering results. The results showed that the prediction of the hardness of the decayed log by the ANN was very effective and that the highly significant variability in the dry matter content, basic density and some basic chemical element contents between the log samples that were classified into different decay grades confirmed the reliability of the clustering results. This study explores an innovative method for the quantitative determination of log decay classes.

Keywords: log; hardness; artificial neural network (ANN); K-means clustering; physicochemical characteristics

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1. Introduction

Logs are important components of forest ecosystems and have received increasing amounts of attention because of their importance in ground maintenance, biodiversity conservation and carbon and nutrient cycling [1,2]. A log is defined as a log fragment with a diameter of 10 cm or more at the thickest end, a length of more than 1 m, and an inclination of 45° or more from the vertical [3]. Logs are coarse woody residue, as are standing dead trees, root stumps and dead branches. These forms of woody residue can be created by competitive exclusion during tree growth, the natural mortality of old trees, other natural factors (such as rain, snow and fire) and human disturbance (such as logging) [1]. Typically, the decomposition of a downed log occurs through a combination of respiration, leaching and natural shattering, which is a very complex process that does not always occur continuously [1,4,5]. The decay level of the log is generally classified from I to V. At different decay levels, the physicochemical properties of the log (i.e., density, hardness, moisture content, cellulose content, nitrogen (N) and phosphorus (P) content, etc.) change accordingly.

Log decay includes the process of carbon that is fixed in the log and released into nature [6], which is an important link within the material cycle of forest ecosystems that can maintain the stability and biodiversity of forest ecosystems, provide necessary living environments, and nutrients for decomposers (such as insects and invertebrates) and promote the rapid renewal of forests [7]. At the same time, different kinds of logs have different decay dynamics. There are many factors that affect the decomposition of logs, and the interactions between them are complex. Additionally, because log decomposition takes a long time (i.e., decades or even centuries), the factors of log decomposition have not been studied enough and need to be further explored in depth [8]. The density of the log is the main physical indicator of the log decay process; meanwhile, the hardness of the log is another indicator that is used to evaluate decay. The determination and analysis of the density and hardness of logs with different decay processes can help judge the decay class of logs more accurately.

Commonly used log decay class systems mainly rely on morphological characteristics that can be easily observed and recognized in the field [9], such as the presence of bark and branches, log form and color, the shape and integrity of the main trunk, etc. These characteristics have been used as a basis for constructing grading index systems, and other characteristics of the log have been combined to create the final systems. The earliest decay class system was the five-level classification system proposed by Logel in 1972. Then, thanks to continuous improvement from many other scholars, the decay class system for logs that is currently in use was formed [10–12]. This classification system is the most widely used and is the preferred system for many scholars for the classification of log decay classes.

This traditional grading system can quickly and roughly determine the decay class of a log, but it also has certain limitations. In general, the determination of the decay class of a log is usually based on the human judgment of experienced workers, meaning some other subjective factors can be introduced that may affect the results of the rest of the experiments based on the determined decay class [13]. In addition, there is a lack of parameterized indicators to describe the decomposition dynamics of the log [14].

The relative density of the log is species-specific and is one of the most important indicators for judging the level of decay [15,16]. The density of the log can very closely be related to species, the growing environment, microbial colonization, and the time of death of the log, with a less dense log being more susceptible to decomposition and exhibiting a higher respiration rate [17]. There is a strong relationship between log density and decay class [18], with log density appearing the greatest at the time of death and decreasing throughout the respiration [1,19], leaching and natural comminution process until all nutrients have entered the soil [20].

As the decay process proceeds, the hardness of the log changes, and in the early stages of decay, this hardness may even decrease faster than the density [14]. Additionally, some logs may become hard and non-decayable on their surface due to environmental factors [1], thus affecting the determination of the decay class. In addition, the hardness of the log gradually decreases with the loss of mass during decay, and the rate of decline is related to the species [21], meaning that the change in hardness is not uniform and the decaying log tends to show local variations in hardness under the action of decomposers [22].

Logs are mainly composed of lignin, cellulose and hemicellulose [23], the content of which also affects the decay process of the log to some extent [24,25]. All three have differences in degradability and structure: cellulose and hemicellulose are single chains of glucose molecules that have simple structures [26], and so can be more easily degraded by various organisms in the early and middle stages of decomposition and are usually considered as the main sources of C in forests [27]; lignin is an aromatic compound with a more complex structure that can only be degraded by specific soil microorganisms and is more resistant to decay than cellulose and hemicellulose [14,28–31]. Lignin is commonly found in higher plants, and studies have shown that lignin content has a greater effect on the decomposition of logs than other chemical contents [32], meaning that lignin may decompose the fastest during early log decomposition [33]. Cellulose and hemicellulose are the main components of plant cell walls and are important energy sources for microorganisms that are involved in the decomposition of logs [34], so the degree of decomposition for cellulose and hemicellulose can be correlated with the decay of the log and there is a relationship between the decay grade of the log and cellulose and hemicellulose contents.

There is no systematic and quantitative method to determine the decay class of logs, so the judgment of log decay classes in the field mainly relies on some visible characteristics (i.e., the structural integrity of leaves, the decay of heartwood and sapwood, the decay of the crown and branches, etc.) and human qualitative judgment, which can be influenced by human subjective factors and the environment. Hardness is the easiest physical factor to measure, and it can quantitatively reflect changes in log decay in the field, but there is no standard for determining the decay class according to the hardness value. Therefore, it is important to develop a set of simple, efficient, scientifically sound and applicable criteria for determining log decay classes in the field.

In this study, log samples from four typical tree species in the Huoditang forest area of the Qinling Mountains were used as research objects for the following objectives: (1) to determine the hardness, density, elemental contents and environmental factors of decayed log and systematically analyze the relationships between each index; (2) to conduct quantitative grading based on the results of cluster analysis and construct an artificial neural network model to determine the decay class of the log from the measured hardness values. In this study, we innovatively propose a quantitative determination method for the decay grade of logs, which could provide a scientific basis for the determination of the decay class of logs.

2. Materials and Methods

2.1. Site

The present study was carried out in the 33°25′–33°29′ N and 108°25′–108°30′ E area of the southern slope of the middle part of the Qinling Mountains. The altitude of the study area was 800–2500 m above sea level, with a mean annual precipitation of 900–1200 mm and evaporation of 800–950 mm. The average annual temperature was 8–10 °C, with 1100–1300 h of sunshine. The growing season last for 6 months. The terrain in the area is diverse, with broken slopes and steep mountains. The vegetation in the study area was rich and diverse. The main tree species were *P. tabulaeformis*, *B. albosinensis*, and *Pinus. armandii* and *Q. aliena* var. *acuteserrata*.

2.2. Materials

In this study, 46 log samples from four major forest trees (*P. tabulaeformis*, *L. principis rupprechtii*, *B. albosinensis*, and *Q. aliena* var. *acuteserrata*) with different levels of decay from the Huoditang area of the Qinling Mountains were collected using the quadrat method.

2.3. Experimental Procedures

2.3.1. Determination of Basic Factors

The samples were collected from the field, and for larger, mildly decayed logs, we utilized a hacksaw to cut 5 cm thick discs. For heavily decayed logs, we extracted partial samples using a knife and packed them into an aluminum box of known volume. Then, these were placed in an oven at 75–85 °C and dried to a constant weight. The dry weight m_1 of each sample was recorded. The dried samples were sprayed with water for 2 h, 4 h, 6 h, 8 h and 10 h. The wet weights m_2 of each sample was then also measured. Following treatment, spraying was continued until the specimens reached water saturation, at which point the water saturation weight m_3 of each specimen was recorded. The volume V_0 of each specimen under water saturation was determined using the drainage method, and the basic density and dry matter content (DMC) of each specimen were also calculated. The National Renewable Energy Laboratory (NREL) method [35] was used to determine the acid-soluble lignin, acid-insoluble lignin, cellulose, hemicellulose, glucose and xylose contents of the samples.

$$Basic\ density = \frac{m_1}{V_0} \tag{1}$$

$$Dry\ matter\ content \quad DMC = \frac{m_1}{m_3} \tag{2}$$

$$moisture\ content = \frac{m_2 - m_1}{m_2} \times 100\% \tag{3}$$

where m_1 is the dry weight of a specimen, m_2 is the wet weight of a specimen, V_0 is the wet volume of the sample under saturated water absorption, and m_3 is the weight of the specimen under saturated water absorption.

2.3.2. Determination of Hardness

To determine the hardness of the specimens, their moisture contents were calculated, and the hardness of the cross-sections was determined in accordance with the established method (i.e., the "Method for Determination of Hardness of Log") using a Universal Mechanical Experiment Instruments.

2.3.3. Data Analysis

- Artificial Neural Network

Since each indicator had different dimensions and dimensional units, this situation affected the results of data analysis, and in order to eliminate the dimensional impact between indicators, data normalization was required to solve the comparability between data indicators. At the same time, in order to speed up the convergence of the model, we chose to normalize the data first [36]. The normalization of the indicator data could be expressed as follows:

$$Ti = \sum\nolimits_{i=1}^{N} i \tag{4}$$

$$\hat{i} = \frac{i}{Ti} \tag{5}$$

where i represents the measured value of the experimental sample for each indicator, Ti represents the measured total value of all experimental samples for each indicator, and $\hat{i}$ is the normalized data for each experimental sample measurement for each indicator.

We developed a three-hidden layer artificial neural network using a Python open-source library (PyTorch), in which the first and second layers used a rule as the activation function and the third layer used sigmoid as the activation function (Figure 1). Considering that tree species are categorical variables and cannot directly participate in ANN calculations, they need to be encoded. We used One-hot Encoding to convert all the categories of each multiple-category feature, which had m categories, into m binary features. To be specific, we encoded *P. tabulaeformis*, *L. principis rupprechtii*, *B. albosinensis* and *Q. aliena* var. *acuteserrata* as 1000, 0100, 0010, and 0001, respectively. This approach ensured that each feature corresponded to a specific category and effectively captured their characteristics. Our neural network structure consisted of one input layer, three hidden layers, and one output layer. The input layer comprised 13 neurons corresponding to 13 feature inputs, including varieties of trees 1, varieties of trees 2, varieties of trees 3, varieties of trees 4, moisture content, DMC, basic density, acid-insoluble lignin content, acid-soluble lignin content, cellulose content, hemicellulose content, glucose content, and xylose content, with 184 sets of data (175 sets as training data (95%) and 9 sets as the test data (5%)). We set the learning rate to 0.0001, the number of epochs to 1000, and the loss function to MSE loss.

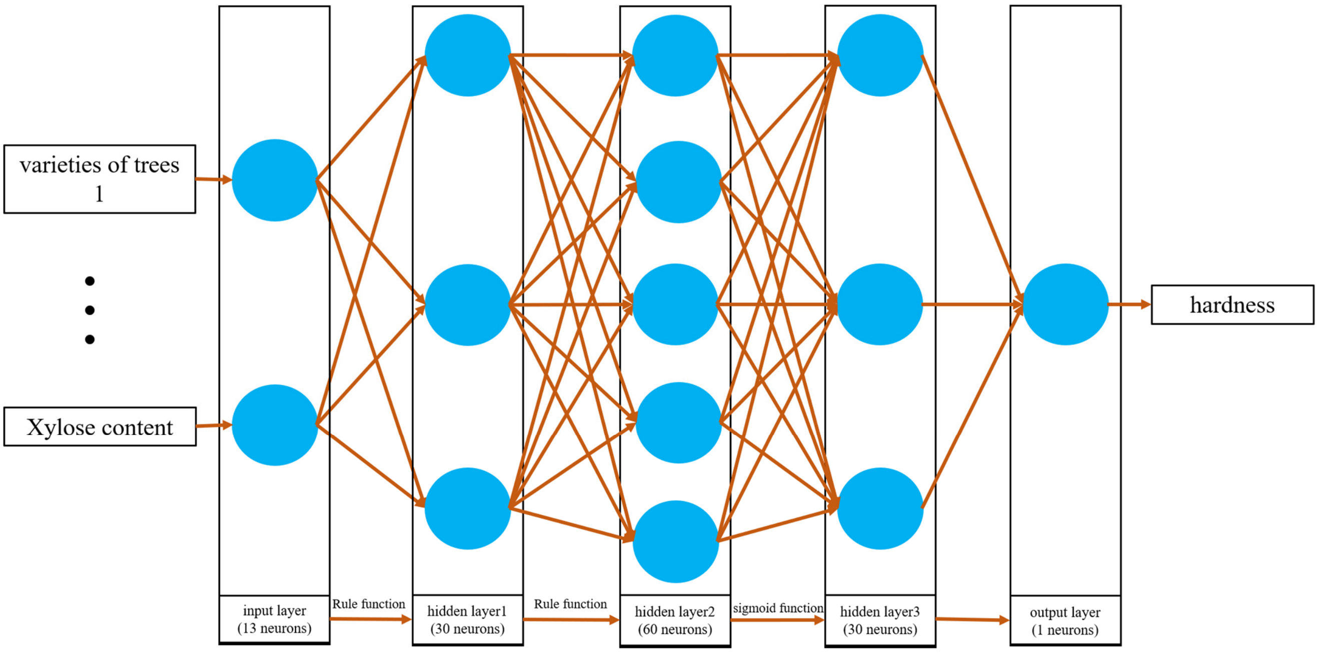

Figure 1. The artificial neural network structure.

The mean absolute percentage error (MAPE), root mean square error (RMSE), and determination coefficient (R^2) was utilized to evaluate the performance of the ANN. The MAPE and RMSE values were considered the most important performance criteria, while R^2 was used to measure how much of the original data could be explained by the established model. When the RMSE and MAPE values approached 0 and R^2 approached 1, ANN predictions were optimum [37].

$$MAPE = \frac{1}{N}\left\{\sum_{i=1}^{N}\left[\left|\frac{x_i - y}{x_i}\right|\right]\right\} \times 100 \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{7}$$

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - y)^2}{\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{9}$$

where y_i represents the experimental output, x_i represents the predicted output, N represents the total number of samples and $\overline{x}$ represents the mean of the predicted outputs.

- Hardness clustering

In this study, the K-means clustering method was used to cluster the hardness values for different moisture contents. Due to the limited indicators considered in the clustering process, we did not take the dimensional effect on experimental results into account and used raw data to visually present the clustering results. We also analyzed the differences in the hardness values among different tree species and found no significant variations among the selected tree species. Thus, the tree species factor was not considered in this study.

- Normal distribution test and ANOVA

In different clustering results, there were significant differences in the number of different tree species among different decay classes. To ensure consistency in the number of samples in each set of experiments, we randomly selected 60 sets of data for normal analysis testing and ANOVA. The analysis of variance (ANOVA) was performed by classifying the differences between the categories into random differences, between-category differences and between-case differences. Only between-class differences and between-case differences needed to be considered and the homogeneity of variance ensured that the between-case differences between the categories were consistent. Additionally, between-category differences were expressed as the mean of each category. Firstly, a normal distribution test was performed on the other determination factors based on the results of the cluster analysis. A kurtosis absolute value of less than 10 and a skewness absolute value of less than 3 were accepted as the normal distribution. ANOVA was performed on the other factors based on the clustering results, and the results of the normal distribution test. A homogeneity of the variance test was performed using Levene's test, and a significance level of greater than 0.05 was considered to meet the condition of the homogeneity of variance. ANOVA and Pearson correlation analysis was used to compare the differences between the tree species, decay classes, and the content of each physicochemical characteristic to test whether the differences were significant and whether there were correlations between the factors. The graphics were drawn using Origin 2022 drawing software.

Based on the clustering results, we attempted to judge the decay classes of the decayed log samples by calculating the Euclidean metric of the hardness of the decayed logs from the center of each cluster.

We calculated the Euclidean metric from the row data to the cluster centers as follows:

$$Euclidean\ metric = \sqrt{\left(\hat{h} - \widetilde{h_i}\right)^2} \tag{10}$$

where $\hat{h}$ is the hardness data and $\widetilde{h_i}$ is the hardness data of the clustering centers, respectively.

This specific method is shown in the following flowchart(Figure 2):

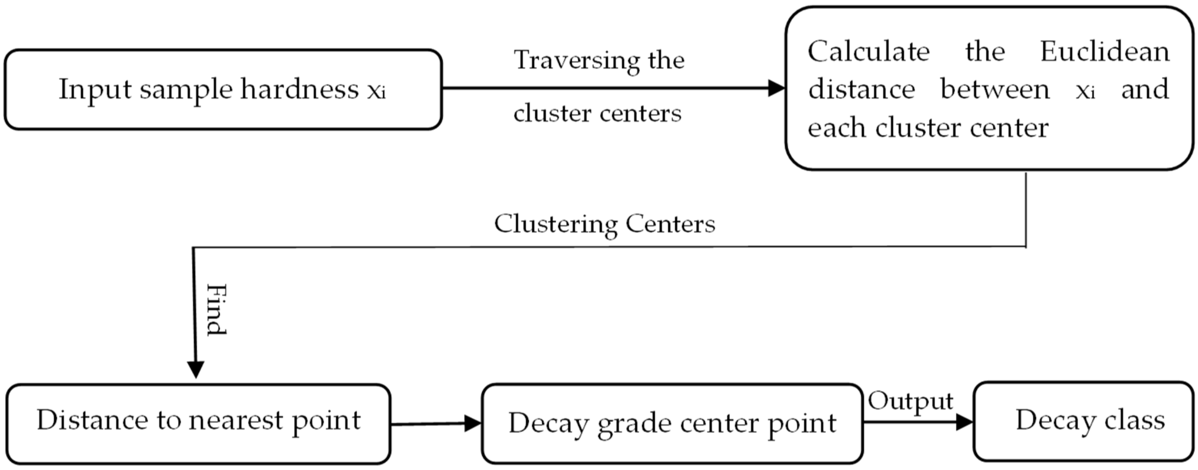

Figure 2. A method of quantitatively dividing the level of log decay by hardness value.

3. Results

3.1. Prediction of the Hardness Value of Log under Different Levels of Decay and Different Moisture Content Conditions Using an ANN

The MAPE was determined to be 0.02069, 0.02134 and 0.01716 for the prediction of the hardness values for the training, test and overall datasets (Table 1). The training set RMSE was 1.0264, the test set RMSE was 0.6187, and the overall dataset RMSE was 0.9756, indicating that the ANN could predict changes in the hardness of the log under different levels of decay and moisture content conditions using the MAPE and RMSE criteria.

Table 1. The evaluation results for the predicted changes in the hardness of logs under different levels of decay and different moisture content conditions.

Performance Criteria	Data Sets		
	Training Data	**Testing Data**	**All**
MAPE	0.02069	0.02134	0.01716
RMSE	1.0264	0.6187	0.9576
R^2	0.9925	0.9964	0.9931

The R^2 values for the training, test and overall datasets were 0.9925, 0.9964 and 0.9931, respectively. They were all above 0.99, indicating that the model fitted the regression well. The testing set R^2 values was higher than the training set R^2 values, indicating that the model was not overfitted. In both the training and test sets (Figure 3), the predicted hardness values converged into a straight line, indicating that they were close to the actual distribution of the hardness values and that the artificial neural network model was very accurate in predicting the hardness values of the logs under different levels of decay and different moisture content conditions.

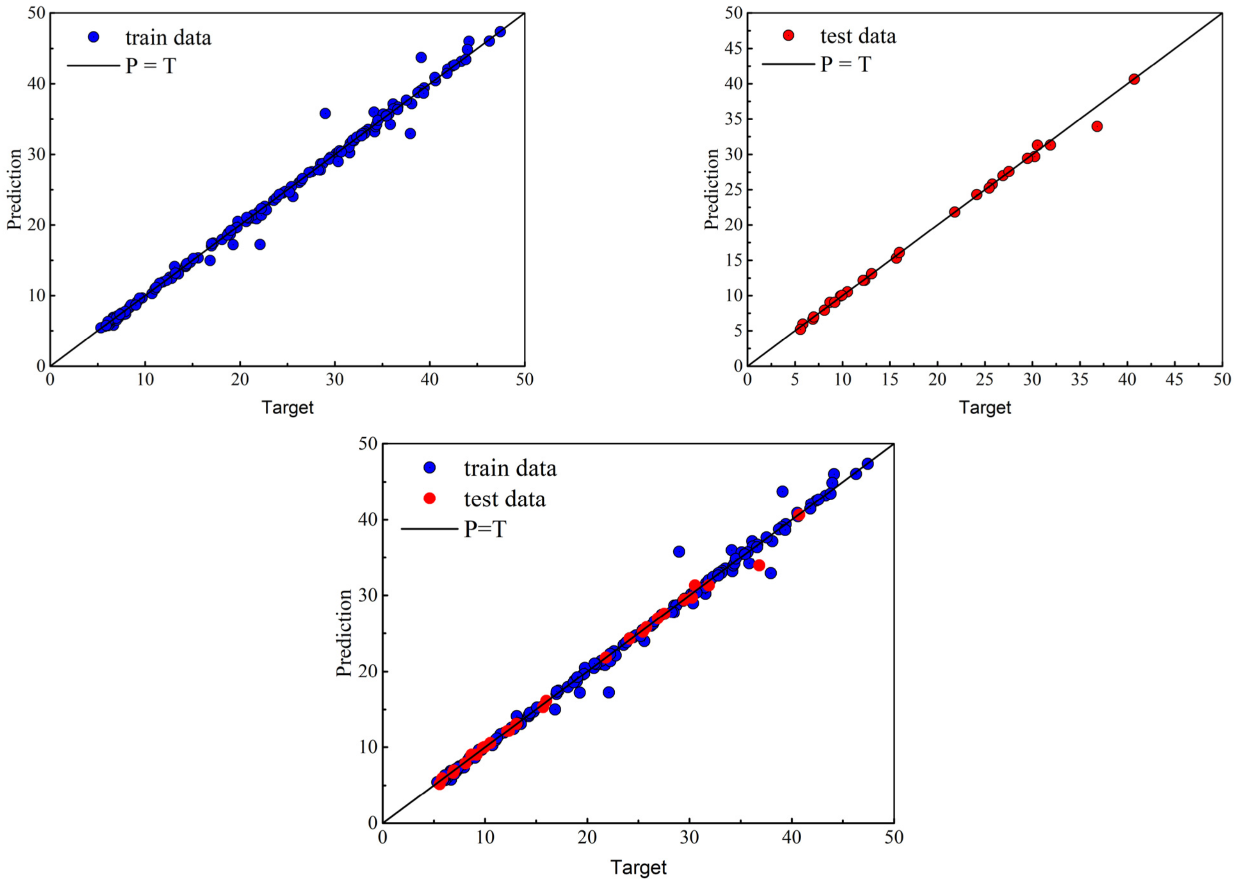

Figure 3. The Q–Q plots of the relationships between the actual and predicted hardness values of the log samples.

3.2. K-Means Clustering Analysis and the Classification of Log Decay Classes Based on the Hardness of Log

With reference to the hardness values under different moisture content conditions, a total of five clustering centers were classified (Figure 4). The hardness value of the level 1 cluster center was 41.57 N/mm^2, the hardness value of the level 2 cluster center was 32.17 N/mm^2, the hardness value of the level 3 cluster center was 22.50 N/mm^2, the hardness value of the level 4 cluster center was 14.36 N/mm^2, and the hardness value of the level 5 cluster center was 7.64 N/mm^2. Most specimens had hardness values concentrated in the level 2 cluster (54 samples), while the smallest number of specimens was concentrated in the level 1 cluster (21 samples).

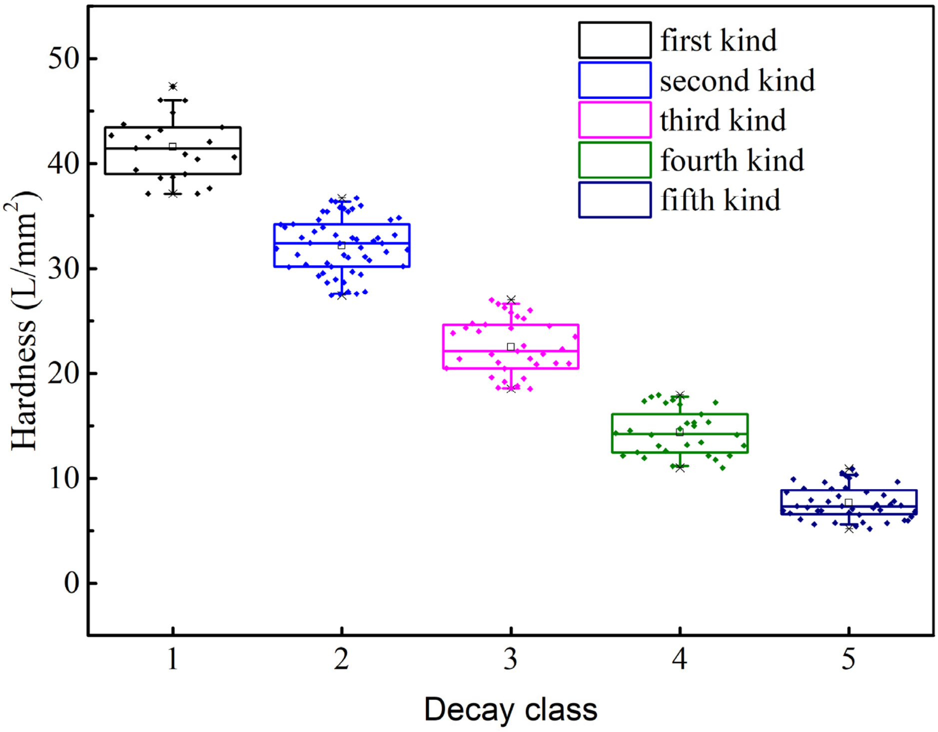

Figure 4. The projections of the different ranges of hardness values among the different decay classes. The total number of samples involved in clustering was 184.

The hardness values of the wood gradually decreased from level 1 to level 5 cluster centers. The range of variation in the hardness values was insignificant between the level 1 and level 3 clusters, all of which were above 31 N/mm^2. From the level 3 to level 4 clusters, a significant change in hardness was observed, but between the level 4 and level 5 cluster centers, the change in hardness was insignificant. The results of the ANOVA analysis show that there were extremely significant differences in DMC, BD, Ce, Glu, and H among different decay classes, which proved the robustness of the clustering results (Table 2).

Table 2. ANOVA test for the differences in physicochemical properties among different tree species and decay classes (hardness clustering results). (*p*-value) TS, tree species; DC, decay class; BD, basic density; ASL, acid-soluble lignin; AIL, acid-insoluble lignin; Ce, cellulose; He, hemicellulose; Glu, glucose; Xyl, xylose; H, hardness.

Indictors / *p*-Value	DMC	BD	ASL	AIL	Ce	He	Glu	Xyl	H
TS	0.496	0.496	0.041	0.000	0.000	0.000	0.000	0.000	0.971
DC	0.000	0.000	0.668	0.789	0.000	0.295	0.000	0.032	0.000

Therefore, we hypothesized that the basic physicochemical characteristics of wood could be used as inputs to predict the hardness values of logs using our ANN. We input the predicted hardness values and calculated the Euclidean distance between the hardness values and each hardness cluster center. Then, the cluster center corresponding to the minimum value of the distance was found to be the decay grade of the wood.

3.3. Physicochemical Characteristics of Logs with Different Decay Grades

DMC, basic density and hardness showed a highly significant ($p < 0.01$) negative correlation among the different decay classes of the same species, i.e., the DMC, basic density and hardness values of each species decreased as the decay level increased (Figure 5). The cellulose content of *P. tabulaeformis*, *L. principis rupprechtii* and *B. albosinensis* all showed a highly significant ($p < 0.01$) negative correlation with the decay classes of the log. *L. principis rupprechtii* showed a significantly ($p < 0.05$) negative correlation with the acid-insoluble lignin content and highly significant ($p < 0.01$) positive and negative correlations with acid-soluble lignin and cellulose contents, respectively, between the different levels of decay. *B. albosinensis* showed a highly significant ($p < 0.01$) positive correlation with acid-insoluble lignin content and highly significant ($p < 0.01$) negative correlations with acid-soluble lignin and hemicellulose content. *Q. aliena* var. *acuteserrata* showed a significant ($p < 0.05$) positive correlation with the acid-insoluble lignin and acid-soluble lignin contents and a significant ($p < 0.05$) negative correlation with the hemicellulose content. The rest of the factors were not significantly correlated. The variations in glucose and xylose contents among the different decay classes of the same tree species were consistent with the variations in the cellulose and hemicellulose contents, respectively.

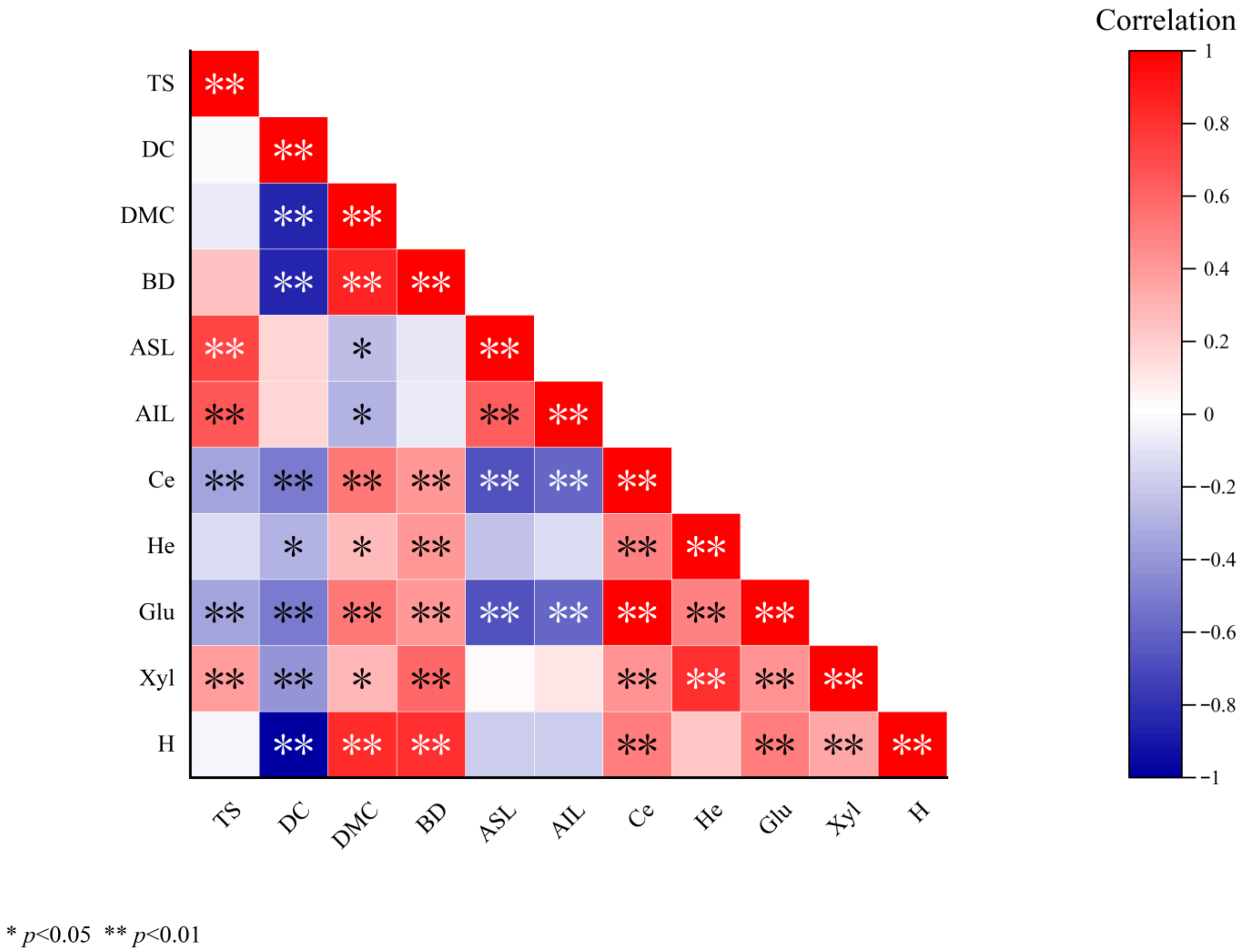

Figure 5. The correlation analysis between the various indicators between the decay classes and tree species. * $p < 0.05$; ** $p < 0.01$; TS, tree species; DC, decay class; BD, basic density; ASL, acid-soluble lignin; AIL, acid-insoluble lignin; Ce, cellulose; He, hemicellulose; Glu, glucose; Xyl, xylose; H, hardness. Red labels indicate positive correlations and blue labels indicate negative correlations.

There were highly significant ($p < 0.01$) differences in DMC, basic density, acid-insoluble lignin content and hardness among the decay classes of the same tree species (Figure 6). The acid-insoluble lignin contents of *B. albosinensis* and *Q. aliena* var. *acuteserrata*, the cellulose contents of *B. albosinensis*, *L. principis rupprechtii* and *Q. aliena* var. *acuteserrata*, and the hemicellulose contents of *L. principis rupprechtii* and *Q. aliena* var. *acuteserrata* all showed highly significant ($p < 0.01$) differences between the decay classes. All the factors for all the species showed decreasing trends with increasing decay levels, except for acid-soluble lignin and acid-insoluble lignin contents, which showed increasing trends.

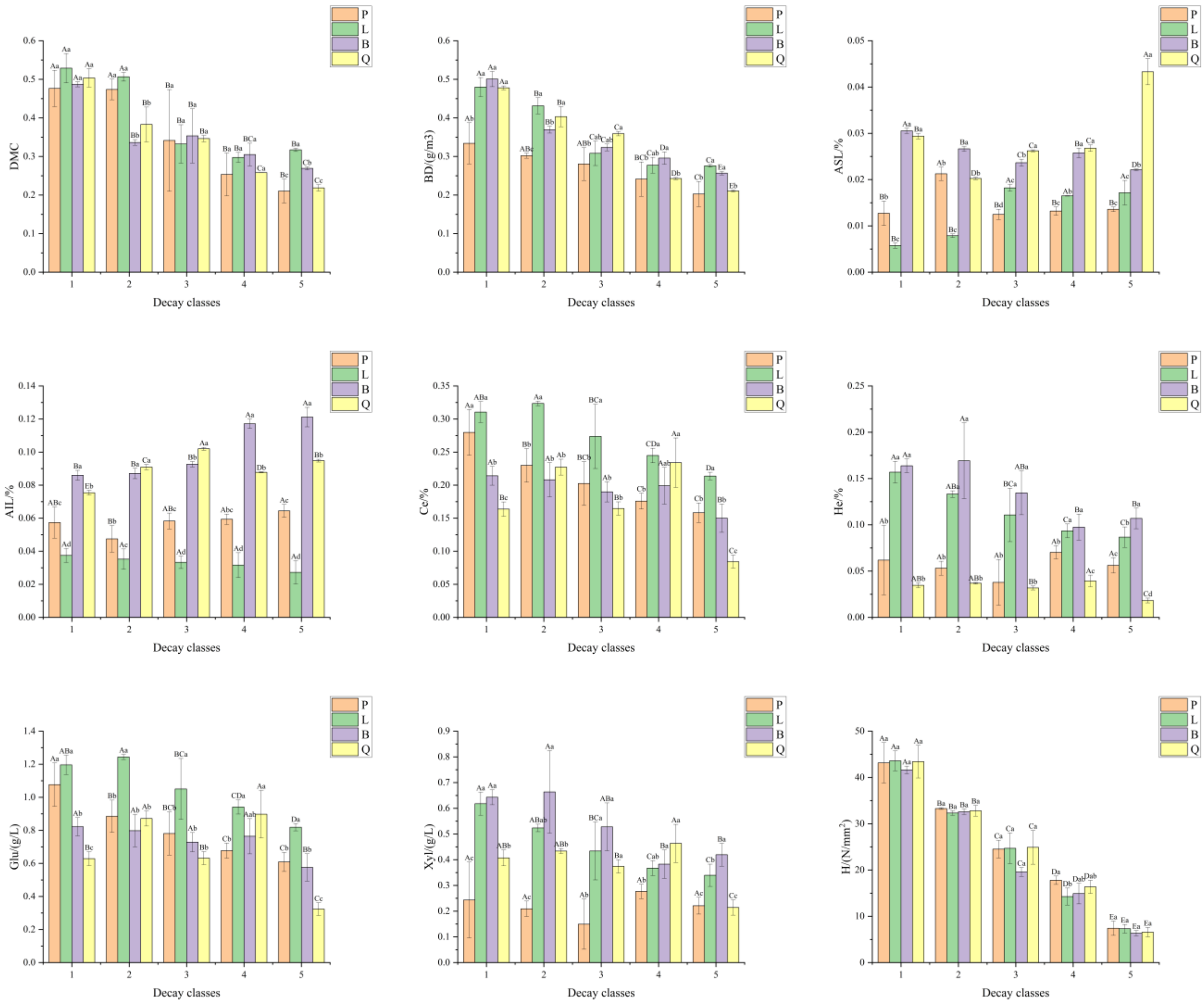

Figure 6. Variations in the physicochemical factors of different tree species and different decay classes. BD, basic density; ASL, acid-soluble lignin; AIL, acid-insoluble lignin; Ce, cellulose; He, hemicellulose; Glu, glucose; Xyl, xylose; H, hardness. P, *P. tabulaeformis*; L, *L. principis rupprechtii*; B, *B. albosinensis*; Q, *Q. aliena* var. *acuteserrata*. Different small letters within the same decay class or capital letters within the same tree species are significantly different ($p < 0.05$).

There were highly significant ($p < 0.01$) differences in acid-insoluble lignin, acid-soluble lignin and hemicellulose contents between different species with the same decay class and highly significant ($p < 0.01$) differences in the basic density and cellulose content between species with a decaying class of 1, 2 or 5. However, there were no significant differences in the hardness values between the species with each decay class ($p > 0.05$).

4. Discussion

In this paper, we present a novel method to quantitively determine log decay grades according to changes in log hardness. In the process of collecting the samples, we judged and recorded the qualitative decay classes of the collected samples with reference to the qualitative classification method proposed by Yan et al. [9]. The existing qualitative decay classification methods are susceptible to human subjectivity, and the results can be inaccurate [13]. At the same time, the number of indicators used in existing qualitative decay classification methods is large; the processes are complex, the types of species investigated, and the criteria used can vary, thereby preventing comparisons. By contrast, quantitative judgments can determine log decay grades more easily, more accurately, and faster, especially in the field.

The physicochemical factors of log decay that were used in this study were found to be closely related to other factors of the log, such as density, moisture content, cellulose content and lignin content, in many existing studies [38,39]. Wang et al. employed the lignin and cellulose content as indicators to assess the decay level of *Pinus. koraiensis* and *Juglans mandshurica* Maxim., and elucidated the mechanisms underlying the changes in lignin, cellulose, and hemicellulose content during log decomposition [40]. Oberle et al. used an osmometer to measure the mechanical parameters related to the hardness of the decaying log and found that the relationship between log density and hardness varied with the coarse woody debris (CWD) values of three key factors: moisture content, species and the degree of decay [14]. This confirmed the usefulness of estimating the density of decaying logs using hardness values. However, they only observed samples from 1–3-year-old logs, which is not representative of the complete log decay process. Due to the long-term nature of the log decay process, only randomly selected log specimens with different levels of decay from the understory were used for our experimental research analysis in this study.

Existing studies have shown that logs have a good ratio of mechanical strength to density [41]. The present study innovatively introduced hardness as a physical characteristic for the classification of log decay classes and demonstrated the reliability of the clustering results through differential variations in representative physicochemical characteristics during the decay process. However, due to the long-term nature of the understory decay process and the random nature of the sampling process, the effects of the causes of decay, the diameter of the decayed log, heartwood and sapwood, the elemental contents and the environment were not taken into account in this study. Therefore, more factors should be considered and investigated in future studies to determine the effects of changes in hardness during the log decay process. Additionally, due to environmental factors during the decay process and human factors during sample collection, the effects of bark, sapwood and core wood on the lignin, cellulose and hemicellulose contents were also not considered in this study.

A complete set of hardness measurements for decaying logs has not yet emerged. Compared to standing timber, the hardness of fallen timber tends to decrease as the decay grade increases and the porosity within the fallen timber increases. At a certain moisture content, the decaying log has a softer texture. Some existing log hardness values have traditionally been known as Janka and Brinell hardness, but they are only suitable for laboratory conditions or for the determination of standing logs [42]. Oberle et al. measured the hardness of decaying logs using a similar instrument to the penetrometer and examined the mechanical properties of logs to illustrate how their mechanical properties change over time as the log decays [14]. It has also been shown that as dead logs are exposed to sunlight and extreme temperatures for long periods of time, they gradually develop a hard decay-resistant crust. To address this particular situation and the problem that hardness cannot be measured in the late stages of decay when specimens have been dissected, we developed an artificial neural network to predict the changes in the hardness of logs during the decay process using some basic physicochemical characteristics. Van Nguyen et al. proposed a novel experimental approach for the prediction of changes in the hardness of the log using artificial neural networks [43]. In comparison, training and validation data values were similar when the artificial neural network was used to predict the missing hardness values in this study, subjectively indicating that the predictions were reliable.

As the level of decay increased, the dry matter content, basic density, cellulose content, hemicellulose content and hardness of the log samples from the four species all showed downward trends, which was in agreement with the results of other studies [44–47]. The main reason for this was that, with the passage of time, the degree of decay increased, and the log was subjected to leaching, external forces and microbial decomposition, resulting in a gradual decrease in the material content of the log [20]. The acid-soluble and acid-insoluble lignin contents both increased with the increase in decay grade. This was possible because lignin degradation was slower due to the preferential degradation of cellulose by fungi; thus, the lignin contents increased in the decaying log [48–50].

It is well known that the hardness of the log depends on other characteristics of log chemistry and anatomy in addition to some basic physical characteristics, including the spatial distribution of internal cellulose micro-angles and voids, which vary considerably between species [51]. However, in this study, we did not consider the internal material pore structure of the decaying log from each species, which included both broadleaf and coniferous species from different elevations in the Qinling Mountains, although there were significant differences in the material contents between species. In the future, a more suitable method to determine the hardness of the decaying log should be developed to take into account the differences between tree species in different climatic zones in order to improve existing quantitative hardness classification systems.

5. Conclusions

The main objective of this study was to develop a classification system that was suitable for the quantitative classification of the decay grade of logs. The three basic indices of MAPE, RMSE and R^2 were used to verify the prediction accuracy of log hardness values under different decay degrees and moisture contents using an artificial neural network model. By analyzing the correlations between and variations in the basic physicochemical characteristics of log samples with different decay grades, the feasibility of quantitatively judging the log decay grade using the log hardness value as the main clustering factor was supported. With the increase in the decay grade of the log, the basic density, dry matter content, cellulose content, hemicellulose content and hardness value of the log showed downward trends, while the acid-soluble and acid-insoluble lignin contents showed upward trends. The quantitative log decay grade classification system proposed in this study was more reliable than the current subjective classification system. In the future, more decaying samples from different tree species should be collected and examined to identify more factors that could be used to explore changes in the internal pore structure of logs with different degrees of decay so as to improve the applicability and reliability of this proposed system.

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