Research Article

Tree Species Classification by Employing Multiple Features Acquired from Integrated Sensors

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Abstract

Explicit information of tree species composition provides valuable materials for the management of forests and urban greenness. In recent years, scholars have employed multiple features in tree species classification, so as to identify them from different perspectives. Most studies use different features to classify the target tree species in a specific growth environment and evaluate the classification results. However, the data matching problems have not been discussed; besides, the contributions of different features and the performance of different classifiers have not been systematically compared. Remote sensing technology of the integrated sensors helps to realize the purpose with high time efficiency and low cost. Benefiting from an integrated system which simultaneously acquired the hyperspectral images, LiDAR waveform, and point clouds, this study made a systematic research on different features and classifiers in pixel-wised tree species classification. We extracted the crown height model (CHM) from the airborne LiDAR device and multiple features from the hyperspectral images, including Gabor textural features, gray-level co-occurrence matrix (GLCM) textural features, and vegetation indices. Different experimental schemes were tested at two study areas with different numbers and configurations of tree species. The experimental results demonstrated the effectiveness of Gabor textural features in specific tree species classification in both homogeneous and heterogeneous growing environments. The GLCM textural features did not improve the classification accuracy of tree species when being combined with spectral features. The CHM feature made more contributions to discriminating tree species than vegetation indices. Different classifiers exhibited similar performances, and support vector machine (SVM) produced the highest overall accuracy among all the classifiers.

1. Introduction

The spatial composition of tree species is essential for forest inventory and analysis, which benefits the conservation and exploitation policies of the forests. A great deal of forest management requires the information at tree species level [1–4]. Both governments and companies have spent a lot of money on forest surveys.

However, it is challenging to discriminate between tree species owing to the diversity of spatial distributions and the complexity of growing environments. In many cases, trees are close to each other, which cause mutual occlusion; besides, the lush weeds and stones bring much noise, which increases the difficulty in segmentation and classification [5]. The observation from a single perspective is unlikely to effectively distinguish fine tree species.

Remote sensing techniques have played an important role in tree species identification [6]. Various sensors have been utilized in tree species classification. Multispectral sensors like Landsat TM and ETM+ have helped to map forest cover and estimate vegetation parameters [7, 8]. Very high resolution (VHR) satellite sensors like Quickbird, Ikonos, and GeoEye have been known to be useful to discriminate tree species with high density of spatial distributions [9–10].
differs (PA) which is the dominating tree species covers about 50% of the whole region (mainly distributed around the roads or space areas). Other species are mainly distributed in the central area.

There are strong contrasts between the growing environments of the two study areas. Changshu area commonly has the same kinds of trees flocking together. However, Huanshi Park has more tree species and heterogeneous compositions. Most tree species in the study areas are representatives of the monsoon climate. In addition, the two study areas have different illumination conditions: Changshu area has a brighter illumination, while Huanshi Park has a darker illumination.

2.2. Data Collection

2.2.1. Airborne Image Data. The images have been acquired through LiCHy (LiDAR-CCD-Hyperspectral) airborne system from the Chinese Academy of Forestry (CAF), which is an integrated system comprising LMS-Q680i, DigiCAM-60, AisaEAGLE sensors, and a GPS/IMU in the same platform. LiCHy is a synthetic system that simultaneously acquires the hyperspectral images, LiDAR waveform and point clouds. It is capable of measuring the vegetation vertical structure, horizontal pattern, and foliar spectra at a very high spatial resolution. The flight altitude is about 1000 meters. Hyperspectral image data acquired by AisaEAGLE airborne hyperspectral sensor have 64 bands with spectral resolution of 9.2 nm and a spectral range from 400 nm to 970 nm. The spatial resolution of the hyperspectral image is 0.6 m for Changshu area and 0.5 m for Huanshi Park. The image size is 660 × 553 for Changshu area and 876 × 867 for Huanshi Park. The airborne LiDAR scan data have been collected by LMS-Q680i laser scanner at a wavelength of 1550 nm. The LiDAR and HSI data have been georeferenced using GPS and IMU data by the data provider.

The field data and the images for Huanshi Park were obtained on June 2013, while for Changshu study area, they were obtained on August 2013.

2.2.2. Field Data. To record the tree samples on the images and confirm that the samples were reliable, we acquired the ground reference data by field investigation, photo interpretation, and GPS devices. Based on the ground investigation, 761 pixels in the image were collected for Changshu study area and 1173 pixels were collected for the Huanshi Park scene. 10% randomly selected pixels of each class were employed as training samples. The accuracy will be calculated by 10 trails. Tables 1 and 2 list the information of the ground truth for both study areas.

3. Methods

3.1. Feature Extraction

3.1.1. Principal Component Analysis. Principal components analysis (PCA) [25] acquires the information from the original spectral vectors by multiplying a transformation matrix. PCA is exploited as a conventional linear dimensionality reduction (DR) algorithm without class label information and has a small calculated amount. In this study, we
extracted the first 10 principal components (PC) from the hyperspectral images. The feature numbers were previously determined. 10 features not only avoided large calculation amount but also contained the major spectral information.

3.1.2. Gabor Textural Features. 2D-Gabor textural features have performed very well in many applications of pattern recognition [26–28], but have not been widely used in tree species classification. We considered the calculation process in [26]: a Gabor function is defined as

$$\psi_{k,d}(x, y) = \psi_k(x) \cdot \exp \left( -\frac{\|k\|^2 \cdot \|\vec{r}\|^2}{2\delta^2} \right) \cdot \left[ \exp \left( i\vec{k} \cdot \vec{r} \right) - \exp \left( -\frac{\delta^2}{2} \right) \right],$$

where $\vec{r} = (x, y)$ is the image location in the spatial domain. The frequency vector $\vec{k}$ determines the scales and directions of Gabor functions. It is defined as

$$\vec{k} = \frac{\pi}{2f} \cdot \exp \left( i \cdot \left( \frac{\pi d}{8} \right) \right).$$

In our experiment, parameter $f$ was fixed to 2. Scale parameter $s$ ranged from 0 to 3 and direction parameter $d$
ranged from 0 to 7, which meant 4 scales and 8 directions. \( s \) and \( d \) were integers. Parameter \( \delta \) was fixed to \( 2\pi \) representing the number of oscillations under the Gaussian envelope. According to [28], the textural layers derived from the Gabor filters are the real part of convolving the image \( I(x, y) \) with different \( s \) and \( d \)

\[
F_{s,d}(x, y) = \psi_{s,d}(x, y) \ast I(x, y).
\]  

We extracted Gabor textural features from the first PC, for the first PC contained the most information.

3.1.3. Vegetation Indices. Based on hyperspectral bands, we extracted four common vegetation indices (VI), including the normalized difference vegetation index (NDVI), ratio vegetation index (RVI), green chlorophyll index (Cl\text{green}), and enhanced vegetation index (EVI). The computational formulas are shown as follows:

\[
\text{NDVI} = \frac{(\text{NIR} - R)}{(\text{NIR} + R)},
\]

\[
\text{RVI} = \frac{\text{NIR}}{R},
\]

\[
\text{Cl\text{green}} = \text{NIR} - \text{GREEN} - 1,
\]

\[
\text{EVI} = \frac{2.5(\text{NIR} - R)}{(\text{NIR} + 6R - 7.5B + 1)}.
\]

VI has been indicators of the vegetation [29–31]. The experiments would discuss whether they are contributive to the improvement of tree species classification. In the experiments, wavelengths of NIR, R, GREEN, and B were, respectively, 800 nm, 666 nm, 515 nm, and 407 nm.

3.1.4. Canopy Height Model. LiDAR point clouds were labeled by the TerraScan software. A digital surface model (DSM) was derived from LiDAR aboveground returns. A digital elevation model (DEM) was derived from ground surface points with the resolution coinciding with the hyperspectral images. As a result, we modeled the canopy height by subtracting DSM from DEM. In the study, CHM was directly acquired by data processing.

3.1.5. Gray-Level Co-Occurrence Matrix. Gray-level co-occurrence matrix (GLCM) is a common approach of textural presentation featuring by detecting the spatial correlation of the gray levels of the images. GLCM is obtained by calculating the gray-level conditions of two pixels keeping a certain distance in the image. The study extracted eight GLCM features from the first PC, namely mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation. The computational process was realized by ENVI software using the default parameters with a \( 7 \times 7 \) window size. The computational formulas can be found in [22].

3.2. Separability Analysis. Separability analysis is an important task of our work. Jeffreys-Matusita (J-M) distance [32] is used to analyze the separability of tree species. It provides the information about the separability between two classes. It also reflects the contributions of a certain group of features, e.g., vegetation indices and Gabor textural features. The J-M distance between the \( i \)th class \( w_i \) and the \( j \)th class \( w_j \) can be described as

\[
J_{ij} = \left( \int \left[ \sqrt{p(x/w_i)} - \sqrt{p(x/w_j)} \right]^2 dx \right)^{1/2},
\]  

where \( \sqrt{p(x/w_i)} \) and \( \sqrt{p(x/w_j)} \) means the likelihood probabilities of \( w_i \) and \( w_j \). It can be rewritten as

\[
J_{ij} = \sqrt{2[1 - \exp(-a)]},
\]

where \( a \) can be described as

\[
a = 1/8 \left( \mu_i - \mu_j \right)^T \left( \Sigma_i + \frac{\Sigma_j}{2} \right)^{-1} \left( \mu_i - \mu_j \right) + \frac{1}{2} \ln \left( \frac{1}{2} \left( \Sigma_i + \frac{\Sigma_j}{2} \right) \right),
\]

where \( \mu_i \) and \( \mu_j \) stand for the mean vectors of \( w_i \) and \( w_j \). \( \Sigma_i \) and \( \Sigma_j \) stand for the covariance matrices of \( w_i \) and \( w_j \).

J-M distance ranges from 0 to \( \sqrt{2} \). We used the squared J-M distance to describe the separability of two classes.

3.3. Classification Scheme

3.3.1. Classifiers. The study employed four classifiers to identify the tree species. \( K \)-nearest neighbor (KNN) [33] classifier is one of the simplest classifiers in machine learning. A sample to be predicted has \( K \) nearest samples (known samples) in the feature space. If the majority of the \( K \) samples belong to one class, the predicted sample belongs to the class.

Maximum-likelihood classifier (MLC) [34] assumes the distribution functions of all classes are subject to the normal distribution. The posterior probabilities of all predicted

| No. | Class (Latin name) | Training samples | Ground truth |
|-----|-------------------|------------------|--------------|
| 1   | Cedrus deceara (CD) | 16 | 161 |
| 2   | Sophora japonica (SJ) | 26 | 263 |
| 3   | Prunus cerasifera (PC) | 29 | 288 |
| 4   | Ginkgo biloba (GB) | 17 | 165 |
| 5   | Platanus acerifolia (PA) | 13 | 134 |
| 6   | Fraxinus chinesis (FC) | 6 | 62 |
| 7   | Albizia julibrissin (AJ) | 10 | 100 |
| Total | | 117 | 1173 |
samples are calculated based on Bayes discriminant criterion [35]. The class corresponding to the highest posterior probability is the predicted class.

Logistic regression (LR) [36, 37] is a kind of nonlinear regression based on sigmoid function. Logistic regression defines the odds of an event as the ratio of the probability of occurrence to that of nonoccurrence. Like MLC, the predicting process is featured by comparing between the probabilities.

Support vector machine (SVM) [38–40] has been widely used in classification problems for remote sensing images in recent years, especially for hyperspectral images [41, 42]. SVM is featured by mapping the initial feature space to a higher-dimensional space with the help of a kernel function, so as to “linearly” separate different classes.

3.3.2. Classification Schemes. In the data processing, we masked the tree cover by setting the threshold on CHM and NDVI. Specifically, the areas with CHM values higher than 2 and NDVI values higher than 0.15 were under consideration. Table 3 lists 6 designed schemes, which reflect different groups of features. By taking into account different schemes, we will detect the contributions of different features like PC, VI, CHM, GLCM, and Gabor by means of separability analysis and classification accuracy. In addition, the experiments were carried out, respectively, by 4 conventional classifiers under each scheme. The classifiers were kNN, MLC, LR, and SVM. Since the performance of kNN classifier is influenced by the k value [43, 44], we selected different k values in the experiments. The parameter k of the kNN classifier was, respectively, set to 3, 5, 7, and 10. The penalty factor and Gamma coefficient of SVM were determined by cross-validation. The experiments were based on 10 independent trials.

As discussed above, the overall work of the study can be illustrated by Figure 2.

4. Results

4.1. Separability by Different Features. Tables 4 and 5 list the computational results of J-M distances for both study areas. In general, Gabor textural features were the only group of features by which all the squared J-M distances reached 2 for both study areas, which means Gabor textural features gave the highest separability among all the feature groups. PC and GLCM features also led to high separability between all class pairs, but we discovered that the class pairs had similar separability by PC and GLCM. For example, tree species CC and PG had the lowest separability for Changshu dataset by PC, as well as GLCM; tree species FC had higher separability between all other tree species by PC for the dataset at Huanshui Park, while for GLCM the circumstance was nearly the same. In addition, even though PC and GLCM had

### Table 3: Details of the experimental schemes.

| No. | Designed schemes          |
|-----|---------------------------|
| 1   | PC                        |
| 2   | PC+VI                     |
| 3   | PC+CHM                    |
| 4   | PC+GLCM                   |
| 5   | PC+Gabor                  |
| 6   | PC+Gabor+VI+CHM           |
present very high J-M values (near to 2), the combination of them did not lead to an obvious increase. So PC and GLCM might have a strong correlation. VI yielded moderate J-M values. CHM was able to discriminate certain tree species, e.g., SB and PG had much higher J-M values by CHM. However, it did not work well with a larger number of tree species.

4.2. Classification Results. Tables 6 and 7 list the classification results of the tree species in both study areas, including the overall accuracy (OA) and kappa index.

It can be discovered from Tables 6 and 7 that we could hardly find good classification performance by only using PC features in specific tree species classification for both study areas, no matter which classifier was employed (scheme 1). Given the enough feature numbers and better properties, Gabor textural features improved the accuracy to the greatest extent (scheme 5) for both datasets. We further analyzed Gabor features with different scales and directions (Figure 3). The accuracy increased fast when the direction parameter was not greater than 4. When it was greater than 4, the accuracy maintained a high level and increased slowly. Though vegetation indices had indicative properties to tell the differences between vegetation and nonvegetation areas, they made less contribution to discriminating specific tree species (scheme 2). CHM

| Feature | Class | SJ | PC | GB | PA | FC | AJ |
|---------|-------|----|----|----|----|----|----|
| PC      | CD    | 1.973166193 | 1.970551732 | 1.995010947 | 1.999800792 | 2   | 1.999999479 |
| SJ      | 1.970387063 | 1.986013116 | 1.999536223 | 2   | 1.99999328 |
| PA      | 1.989495165 | 1.999469579 | 1.999193788 | 2   | 1.9999962 |
| GB      |       | 1.99999967 |
| VI      | CD    | 1.540788779 | 1.456786107 | 1.438512831 | 1.913655159 | 1.84290299 | 1.677184195 |
| SJ      | 1.535207649 | 1.497263425 | 1.976625988 | 1.885251944 | 1.539688642 |
| PA      | 1.383160174 | 1.944470948 | 1.819790614 | 1.594869491 |
| GB      |       | 1.941964809 |
| CHM     | CD    | 0.093841568 | 0.261134559 | 0.385106797 | 0.978713625 | 0.11112143 | 0.300475287 |
| SJ      | 0.374738187 | 0.25754443 | 0.626959646 | 0.08633305 | 0.064087957 |
| PA      | 0.258393392 |
| GB      | 0.345701487 |
| Gabor   | CD    | 0.193313281 | 1.999959401 | 1.982753874 | 1.995225152 | 1.999999999 | 1.974438056 |
| SJ      | 1.999799492 |
| PA      | 1.9998286 |
| GLCM    | CD    | 1.982753874 | 1.995225152 | 1.999999999 | 1.974438056 |
| SJ      | 1.974685138 |
| PA      | 1.999850495 |
| PC+GLCM | CD    | 1.999999748 | 1.99999998 |
| SJ      | 2   | 2   | 2   | 2   | 2   |
| PA      | 1.999999999 |
| FC      | 2   | 2   | 2   | 2   |
| GB      | 1.999999999 |
| PA      | 1.999999999 |
| PC      | 2   | 2   | 2   | 2   | 2   |
| GB      | 2   | 2   | 2   | 2   |
| PA      | 2   | 2   |
| FC      | 2   | 2   | 2   |

Table 6: Squared J-M distances for Huanshui Park dataset.
The classification results of the dataset for Changshu area.

| Classifiers | Items | Sc.1 | Sc.2 | Sc.3 | Sc.4 | Sc.5 | Sc.6 |
|-------------|-------|------|------|------|------|------|------|
| kNN (k = 3) | OA (%) | 83.56 | 85.37 | 86.54 | 79.41 | 97.62 | 96.52 |
|             | Kappa  | 0.780 | 0.804 | 0.820 | 0.725 | 0.968 | 0.953 |
| kNN (k = 5) | OA (%) | 82.43 | 85.06 | 86.12 | 79.43 | 94.23 | 94.02 |
|             | Kappa  | 0.765 | 0.800 | 0.815 | 0.725 | 0.923 | 0.920 |
| kNN (k = 7) | OA (%) | 82.27 | 85.05 | 86.82 | 79.40 | 92.76 | 92.77 |
|             | Kappa  | 0.763 | 0.800 | 0.824 | 0.724 | 0.903 | 0.903 |
| kNN (k = 10)| OA (%) | 83.38 | 85.12 | 87.40 | 79.66 | 88.84 | 90.32 |
|             | Kappa  | 0.777 | 0.801 | 0.831 | 0.727 | 0.851 | 0.871 |
| MLC         | OA (%) | 84.76 | 85.10 | 90.47 | 79.89 | 97.69 | 97.56 |
|             | Kappa  | 0.796 | 0.802 | 0.873 | 0.731 | 0.969 | 0.967 |
| Logistic    | OA (%) | 86.69 | 85.43 | 87.83 | 80.05 | 96.74 | 96.08 |
|             | Kappa  | 0.822 | 0.805 | 0.837 | 0.733 | 0.956 | 0.948 |
| SVM         | OA (%) | 89.72 | 89.99 | 91.79 | 88.17 | 99.54 | 99.66 |
|             | Kappa  | 0.863 | 0.866 | 0.890 | 0.842 | 0.994 | 0.995 |

Table 7: Classification results of the dataset for Huanshui Park.

| Classifiers | Items | Sc.1 | Sc.2 | Sc.3 | Sc.4 | Sc.5 | Sc.6 |
|-------------|-------|------|------|------|------|------|------|
| kNN (k = 3) | OA (%) | 47.90 | 48.91 | 51.67 | 46.60 | 63.96 | 64.83 |
|             | Kappa  | 0.367 | 0.381 | 0.412 | 0.351 | 0.565 | 0.574 |
| kNN (k = 5) | OA (%) | 48.99 | 49.09 | 51.30 | 45.99 | 59.30 | 60.50 |
|             | Kappa  | 0.377 | 0.377 | 0.405 | 0.340 | 0.505 | 0.521 |
| kNN (k = 7) | OA (%) | 48.51 | 49.68 | 49.51 | 44.26 | 55.26 | 55.67 |
|             | Kappa  | 0.368 | 0.384 | 0.380 | 0.317 | 0.457 | 0.458 |
| kNN (k = 10)| OA (%) | 46.83 | 48.24 | 50.20 | 43.66 | 52.71 | 52.93 |
|             | Kappa  | 0.346 | 0.363 | 0.387 | 0.304 | 0.420 | 0.420 |
| MLC         | OA (%) | 46.34 | 46.30 | 48.32 | 43.01 | 52.17 | 56.10 |
|             | Kappa  | 0.351 | 0.347 | 0.373 | 0.316 | 0.431 | 0.474 |
| Logistic    | OA (%) | 47.31 | 45.43 | 48.35 | 41.22 | 62.70 | 62.10 |
|             | Kappa  | 0.364 | 0.341 | 0.376 | 0.300 | 0.549 | 0.539 |
| SVM         | OA (%) | 50.49 | 50.26 | 52.46 | 50.01 | 65.09 | 67.38 |
|             | Kappa  | 0.393 | 0.389 | 0.416 | 0.389 | 0.577 | 0.605 |

features reflected the tree height information, but the feature did not improve the accuracy by a large margin with a higher number of tree species, for the height of several tree species may be close to each other (scheme 3). The classification results were in accordance with the statistical results of the separability analysis. The combination of GLCM did not give rise to the increase in the accuracy in the specific classification of tree species. The results might be caused by a strong correlation between spectral features and GLCM features. PC combined with Gabor textural features had already yielded fine results, while the accuracy had little improvement when VI and CHM were added. The classification results demonstrated the effectiveness of Gabor textural features in the identification of tree species with different numbers and configurations.

Different classifiers exhibited similar performances, and the accuracies had similar variation trends along with different input features. Particularly, knn classifier did not fit Gabor textural features well with a larger k. When more features were involved, the accuracy increased slowly with a larger k. While for a smaller k, the accuracy increased by a larger margin with more features. For example, for the dataset of Huanshui Park, the accuracy in scheme 1 was increased by 16.93% compared with scheme 6 when k = 3. However, only 11.51% for k = 5, 7.16% for k = 7, and 6.10% for k = 10. So a small k should be selected when more features were combined. Logistic regression exhibited similar performance with knn when k was 3. Compared with other classifiers, the results obtained by SVM showed a discernible increase for both study areas. Figure 4 shows the land cover maps of both study areas obtained by SVM for scheme 1 and scheme 6. The white region indicated the nonforest area.

The bar chart (Figure 5) showed that the accuracies increased obviously with the combination of Gabor textural features. However, neither VI nor CHM gave rise to remarkable improvements. Generally, the SVM classifier exhibited a discernible better performance and yielded the highest accuracy when more features were combined.

5. Discussion

5.1. Selection of Feature Groups. According to the experimental results of the two datasets, combined features performed better in both accuracy and visual perspective. The land cover maps (Figure 4) showed significant differences between scheme 1 (PC only) and scheme 6 (PC + Gabor + VI + CHM). Specially, Gabor textural features extracted from the hyperspectral images were strongly recommended in tree species classification. Both the separability analysis and the classification results demonstrated that Gabor textural features made more contributions to discriminating tree species in both heterogeneous and homogeneous distribution. Gabor textural features need little computation time and had enough feature numbers. In the experiments, we found that it was easy to select the...
parameters of Gabor textural features. When the direction parameter was greater than 4 and the scale parameter was greater than 2, the accuracy maintained a high level. In this study, we selected 4 scales and 8 directions, thus 32 Gabor features were yielded. The number of features was similar to the other applications of Gabor features [27, 28]. The reason for the effectiveness of Gabor textures in tree species classification may also lie in the fact that Gabor features are less sensitive to illumination variations [45]. Woods have complex illumination conditions because of complex spatial
distributions. This also explains why Gabor features performed well in the two study sites with different illumination conditions.

We believe the PC features were necessary because they contained the major information of hyperspectral images. VI did not make too much sense in discriminating specific tree species when being concatenated with other features according to the statistics of the accuracy (Tables 6 and 7). VI is effective in the identification between vegetation and nonvegetation, because the vegetation is always green. However, many tree species have a similar green degree, which makes it hard to identify tree species by VI. Nevertheless, we believe VI is necessary in the whole procedure, because it helped to extract the green cover in the first step. CHM always gave more improvement in accuracy than VI when being combined with spectral features. In addition, CHM made different contributions by different numbers and configurations of tree species when being concatenated with other features according to the statistics of the accuracy (Tables 6 and 7). VI is effective in the identification between vegetation and nonvegetation, because the vegetation is always green. However, many tree species have a similar green degree, which makes it hard to identify tree species by VI. Nevertheless, we believe VI is necessary in the whole procedure, because it helped to extract the green cover in the first step. CHM always gave more improvement in accuracy than VI when being combined with spectral features. In addition, CHM made different contributions by different numbers and configurations of tree species when being concatenated with other features according to the statistics of the accuracy (Tables 6 and 7).

6. Conclusions

In this study, multiple features of tree species were extracted from an airborne integrated system, including hyperspectral sensors and LiDAR devices with the same geographic reference. The experiments had been conducted in two study areas in China with different tree species configurations and growing environments. Then, a systematic research had been made to detect the contributions of different features and performances of different classifiers in a pixel-wised tree species classification.

The study highlighted the importance of employing multiple features to identify tree species. Through the experiments, we got which level of accuracy can be achieved by different features and classifiers in the pixel-wised tree species classification. The main conclusions of the study were as follows: (i) multiple features gave better identification results than the single group of features. (ii) Gabor textural features were effective in tree species classification in both heterogeneous and homogeneous growing environments. In contrast, the conventional GLCM textural features made less contribution in tree species classification. However, not all classifiers fit Gabor features well, like the \( k \text{NN} \) classifier with

![Figure 6: CHM ranges of both study areas.](image-url)
(iii) When the number of species was small, CHM made more contributions to identifying tree species, while for a bigger number of species and close tree height, CHM did not make much sense. iv) SVM always outperformed other classifiers under different circumstances in tree species classification, but it could not best identify all tree species. v) The integrated system with hyperspectral sensors and LiDAR device is necessary in the regional tree species identification.

This study will improve the detection of the individual trees [50–53] when layers of segmented tree objects are merged, thus providing more details for the applications of forests at tree level. As future work, more features should be exploited in tree species classification. Especially, classification maps of tree species from different scales should be integrated, which will be significant work for the tree species classification and the forest management. In addition, multiple features and different classifiers might be considered simultaneously by an approach featuring exploiting the best processing chain (a classifier combined with a group of features) for each specific tree class.

### Abbreviations

- **GLCM**: Gray-level co-occurrence matrix
- **CHM**: Crown height model
- **VHR**: Very high resolution
- **LiDAR**: Light detection and ranging
- **DR**: Dimensionality reduction
- **LiCHy**: LiDAR-CCD-hyperspectral
- **CAF**: Chinese Academy of Forestry
- **PCA**: Principal components analysis
- **PC**: Principal components
- **VI**: Vegetation indices
- **NDVI**: Normalized difference vegetation index
- **RVI**: Ratio vegetation index
- **CIgreen**: Green chlorophyll index
- **EVI**: Enhanced vegetation index
- **DSM**: Digital surface model
- **DEM**: Digital elevation model
- **J-M**: Jeffries-Matusita
- **kNN**: K-nearest neighbor
- **MLC**: Maximum-likelihood classifier
- **SVM**: Support vector machine

### Data Availability

Two kinds of data are involved in this study. One is the airborne image data, including hyperspectral image data with 64 bands and CHM products acquired from LiDAR sensors. All image data are available. The other is field data, including the locations, photos, tree names, and chlorophyll value of the leaf. The field data are available after we submit an application to the Chinese Academy of Forestry (CAF).

### Conflicts of Interest

The authors declare no conflict of interest.

### Authors’ Contributions

Guang Yang is the main author who proposed the basic idea and completed the experiments and the manuscript. Yaoalong Zhao provided the useful suggestions on designing the approaches involved in this study. Baoxin Li and Jiangbo Jing...
helped to modify the manuscript. Yuanyong Dian provided the data source along with the data processing.

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