

Article

Cunninghamia lanceolata Canopy Relative Chlorophyll Content Estimation Based on Unmanned Aerial Vehicle Multispectral Imagery and Terrain Suitability Analysis

Luyue Zhang ^{1,2}, Xiaoyu Su ^{1,2}, Huan Liu ^{1,2}, Yueqiao Zhao ^{1,2}, Wenjing Gao ^{1,2}, Nuo Cheng ^{1,2} and Riwen Lai ^{1,2,*} 

¹ College of Forestry, Fujian Agriculture and Forestry University, Fuzhou 350028, China; 1210430013@fafu.edu.cn (L.Z.)

² University Key Lab for Geomatics Technology and Optimized Resources Utilization in Fujian Province, Fuzhou 350002, China

* Correspondence: fjlrw@fafu.edu.cn

Abstract: This study aimed to streamline the determination of chlorophyll content in *Cunninghamia lanceolata* while achieving precise measurements of canopy chlorophyll content. Relative chlorophyll content (SPAD) in the *Cunninghamia lanceolata* canopy were assessed in the study area using the SPAD-502 portable chlorophyll meter, alongside spectral data collected via onboard multispectral imaging. And based on the unmanned aerial vehicle (UAV) multispectral collection of spectral values in the study area, 21 vegetation indices with significant correlation with *Cunninghamia lanceolata* canopy SPAD (CCS) were constructed as independent variables of the model's various regression techniques, including partial least squares regression (PLSR), random forests (RF), and backpropagation neural networks (BPNN), which were employed to develop a SPAD inversion model. The BPNN-based model emerged as the best choice, exhibiting test dataset coefficients of determination (R^2) at 0.812, root mean square error (RSME) at 2.607, and relative percent difference (RPD) at 1.942. While the model demonstrated consistent accuracy across different slope locations, generalization was lower for varying slope directions. By creating separate models for different slope directions, R^2 went up to about 0.8, showcasing favorable terrain applicability. Therefore, constructing inverse models with different slope directions samples separately can estimate CCS more accurately.

Keywords: multispectral remote sensing; SPAD; *Cunninghamia lanceolata*; vegetation indices



Citation: Zhang, L.; Su, X.; Liu, H.; Zhao, Y.; Gao, W.; Cheng, N.; Lai, R. *Cunninghamia lanceolata* Canopy Relative Chlorophyll Content Estimation Based on Unmanned Aerial Vehicle Multispectral Imagery and Terrain Suitability Analysis. *Forests* **2024**, *15*, 965. <https://doi.org/10.3390/f15060965>

Academic Editor: Eben N. Broadbent

Received: 14 April 2024

Revised: 27 May 2024

Accepted: 28 May 2024

Published: 31 May 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Chlorophyll serves as the primary pigment essential for photosynthesis within the forest canopy, enabling light absorption to fuel the Calvin cycle [1]. It stands as a key biochemical parameter within this ecosystem. The precise and prompt assessment of chlorophyll content not only aids in evaluating the photosynthetic capacity and physiological well-being of forest trees but also provides insights into their overall health status [2]. This information carries significant implications for estimating terrestrial carbon flux cycles and biomass levels.

Traditional methods for determining chlorophyll content in forest canopies, such as spectrophotometry and fluorescence analysis, are known for their superior accuracy [3,4]. However, these methods entail intricate and cumbersome operations, making sampling challenging and time-consuming while also consuming substantial energy. Moreover, the transportation of leaf blade chlorophyll samples can result in certain losses. In recent years, the handheld chlorophyll meter has gained popularity as a nondestructive and portable tool for assessing relative chlorophyll content (SPAD), which has been widely adopted in chlorophyll content analysis [5,6]. SPAD serves to quantify the greenness of plant leaves, with prior research demonstrating a significant positive correlation between SPAD and chlorophyll content, allowing for highly accurate conversions [1,7]. Despite

its advantages, the handheld chlorophyll meter is limited to contact measurements on individual samples, necessitating extensive sampling and limiting the scope of chlorophyll estimation. With ongoing advancements in remote sensing platforms, sensors, and data-processing methodologies, the field of remote sensing has alleviated the shortcomings of traditional survey methods, providing an effective alternative for rapidly and accurately collecting forest parameter data [8–11].

Among many remote sensing techniques, satellite remote sensing has been favored by many scholars in the estimation of chlorophyll content due to its ability to collect information over a wide range and multiple time phases [11–14]. However, as satellites fly along fixed orbits, their information collection for an area is cyclical, which makes it difficult for satellite remote sensing to meet the real-time probing of chlorophyll content of forest trees [15]. On the other hand, the lower spatial resolution makes it difficult for satellite remote sensing to focus on the monitoring of the canopy chlorophyll of a single tree, and makes it difficult for the spectral reflectance obtained from its collection to match with the canopy chlorophyll content obtained from ground surveys; thus, it also makes it difficult to match the spectral reflectance collected by satellite remote sensing with the canopy chlorophyll content obtained from ground surveys, thus reducing the accuracy of canopy chlorophyll content determination [16]. Compared with satellite remote sensing, unmanned aerial vehicle (UAV) remote sensing technology can not only meet the needs of large-scale chlorophyll content monitoring, but can also obtain higher-resolution remote sensing images according to the needs of users [17].

UAV remote sensing technology leverages hyperspectral or multispectral sensors to capture spectral images of the target area, enabling the estimation of chlorophyll content. Specifically, UAV hyperspectral technology has demonstrated exceptional accuracy in chlorophyll content estimation within plant canopies, owing to its broad response range and high resolution [18–21]. However, challenges such as high costs, data redundancy, processing complexity, and restrictive operational conditions have hindered its widespread adoption in practical forestry applications. In the past, multispectral cameras have been widely used for quantitative inversion of plant physiological parameters due to their low cost and practicality. Nevertheless, the spectral resolution of multispectral images is in the range of $\lambda/10$ order of magnitude, which is much higher than that of hyperspectral, in the range of $\lambda/100$ order of magnitude. As a result, it is more difficult for multispectral imagery to accurately capture changes in forest SPAD than hyperspectral imagery. Previous studies have attempted to enhance the prediction of plant canopy SPAD by modifying the features integrated into modeling [22–24] and by exploring and contrasting diverse model construction techniques [25–27]. However, factors like geographical region, lighting conditions, image capture elevation, and terrain can impact model construction and predictive performance [28,29]. Among them, terrain includes factors such as elevation, slope directions, and the slope of the forest planting site [30], and the influence of terrain on the construction of large-area models is difficult to control, and the poor applicability of the models to different topographies still exists in the field of remote sensing inversion of forest canopy SPAD, which is worth exploring further.

Cunninghamia lanceolata (Lamb.) Hook has a planted area of 9.90×10^6 hm² in China, with a volume of 7.55×10^8 m³, ranking first in the total area and volume of planted tree forests in the country [31], and the management of *Cunninghamia lanceolata* plantation forests is of great significance for timber production and maintenance of ecological functions [32]. The management and management of *Cunninghamia lanceolata* plantation forests are important in terms of timber production and maintenance of ecological functions. Among them, the judgment and monitoring of the health status of *Cunninghamia lanceolata* plantation forests is an important means to improve the quality and ecological benefits of *Cunninghamia lanceolata* plantation forests [33]. As one of the important indexes to measure the growth and health status of *Cunninghamia lanceolata*, the accuracy and timeliness of the observed values of the chlorophyll content are of great significance to the management

of *Cunninghamia lanceolata* and even to the country to guarantee the quality of timber and ecological safety.

In this study, the focus is on *Cunninghamia lanceolata* plantation forests, where a *Cunninghamia lanceolata* canopy SPAD (CCS) inversion model is established utilizing UAV multispectral imagery. The model aims to identify and select appropriate vegetation indices as independent variables, compare prediction performance across different modeling methods, and evaluate model applicability from a terrain perspective. The primary objective is to realize the accurate measurement of CCS in a wide range, and provide theoretical basis and technical support for the growth monitoring and health evaluation of *Cunninghamia lanceolata*.

2. Materials and Methods

2.1. Study Areas

The study area is situated within the state-owned forest region of Shunchang County, Nanping City, Fujian Province, China, and spanning longitudes 117°9′ to 118°4′ and latitudes 26°8′ to 27°21′. Encompassing a length of 74 km east to west and a width of 61 km north to south, the area experiences a humid monsoon climate characteristic of the central subtropical zone. Abundant rainfall and sunshine define the climatic conditions, with an average annual temperature of 19.2 °C and a frost-free period lasting 289 days. The average annual precipitation measures 2144 mm. The forested land boasts a deep and ample soil layer predominantly composed of red loam soil, with minimal barren soil patches. Forested areas dominate and exhibit high coverage rates, indicative of preferable forest quality. Spanning a total land area of 23,799.20 hm², the region features 161.95 m³/hm² of *Cunninghamia lanceolata* storage. Coniferous forests prevail as the predominant tree type, occupying 10,852.70 hectares with a storage capacity of 1,295,718 m³. These coniferous forests account for 46.39% of the total woodland area and 43.76% of the total forest area storage capacity in the region [34].

The study area is a *Cunninghamia lanceolata* plantation near-mature pure forest with a degree of depression of 0.7, a slope gradient of 30°, and slope lengths all greater than 60 m. The soil is a Class I fertile red loam, and the forest management type is general *Cunninghamia lanceolata* medium-diameter timber. In this study, based on the dichotomy of slope directions, the slope directions were divided into sunny and shady slope directions by using small-group contour maps combined with the use of a compass in the field [35] (Figure 1), and, at the same time, the slopes were equally divided into upper and lower parts. In addition, since most *Cunninghamia lanceolata* plantation forests in southern China are planted in hilly terrain, and elevation differences between hills are small, the elevation factor in terrain factors was not included in the discussion in this study.

2.2. Data Collection

2.2.1. Measurement of CCS

In March 2023, 270 *Cunninghamia lanceolata* samples were randomly selected from sample plots with different slope directions and slope locations in the *Cunninghamia lanceolata* plantation near-mature forest stand in Shunchang County, Nanping City, Fujian Province, China, and the distribution of the samples is shown in Figure 2. The sample canopy was divided into upper, middle, and lower layers, and within each layer, a number of unobstructed branches were cut from each layer using a tall branch shear with a pole length of 10 m. From the cut branches, 10–20 leaves were randomly selected, and the SPAD values of the selected leaves were measured immediately using a handheld chlorophyll meter (SPAD-502, Konica Minolta, Tokyo, Japan), and the average value of each leaf was calculated by taking 3 measurements at different parts of each leaf, and finally, 5 leaves were counted. The measured CCS for the upper location of sunny slope (USunny), the lower location of sunny slope (LSunny), the upper location of shady slope (UShady), and the lower location of shady slope (LShady) is shown in Figure 3.

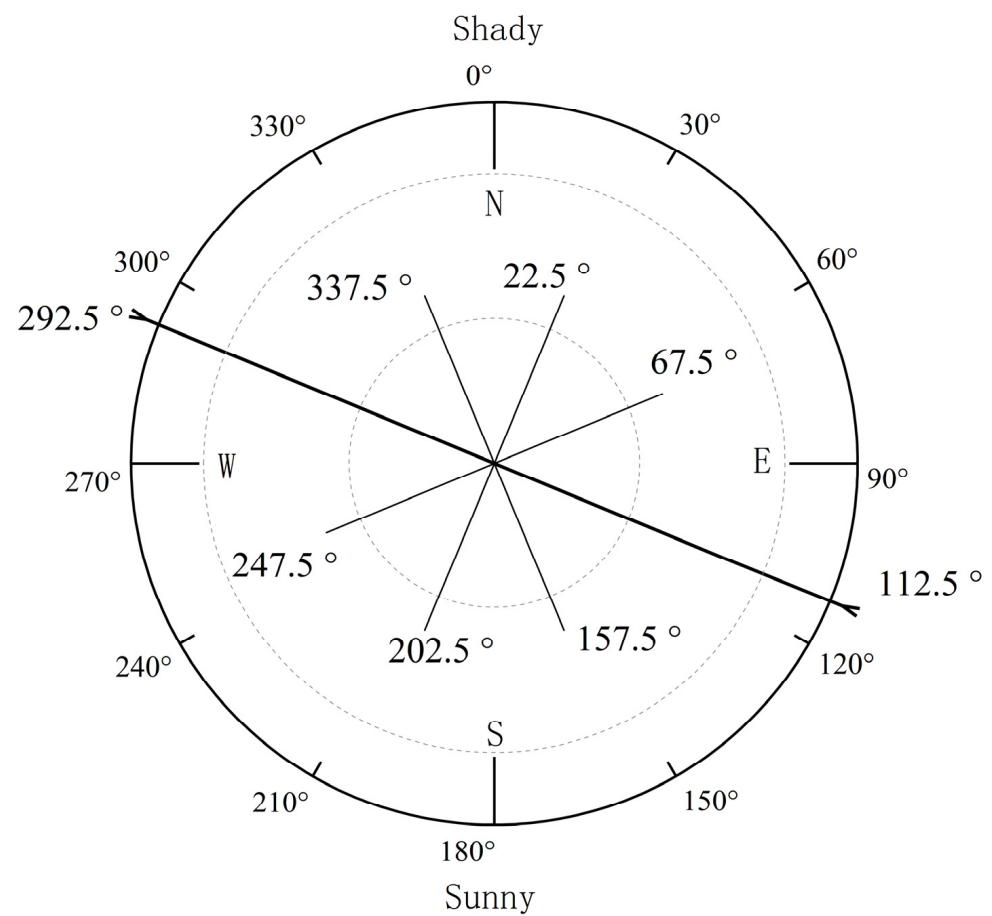


Figure 1. Dichotomous slope direction division.

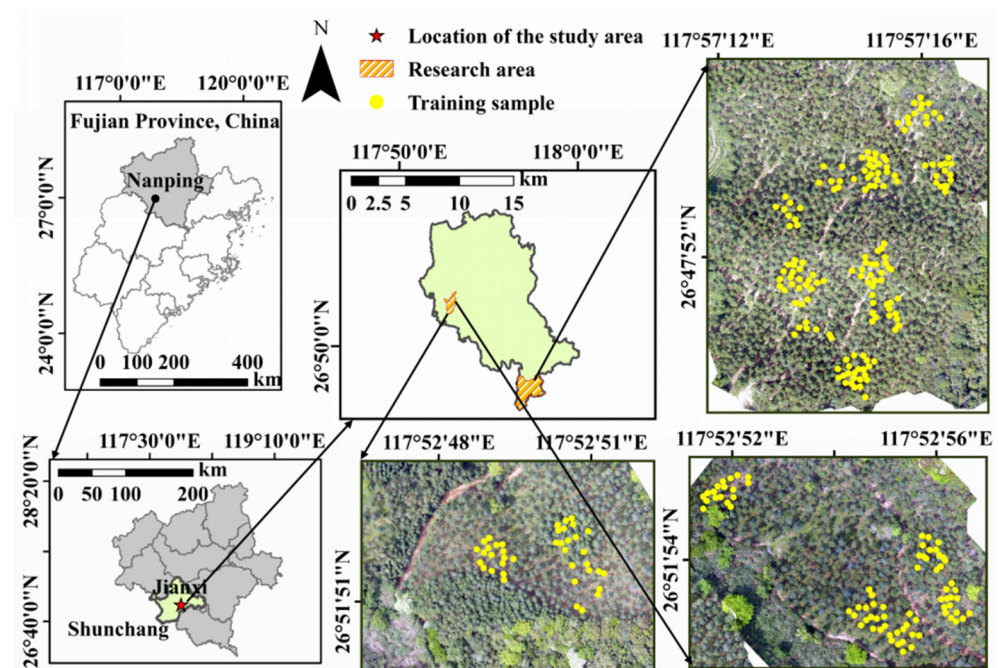


Figure 2. Study area and sample distribution.

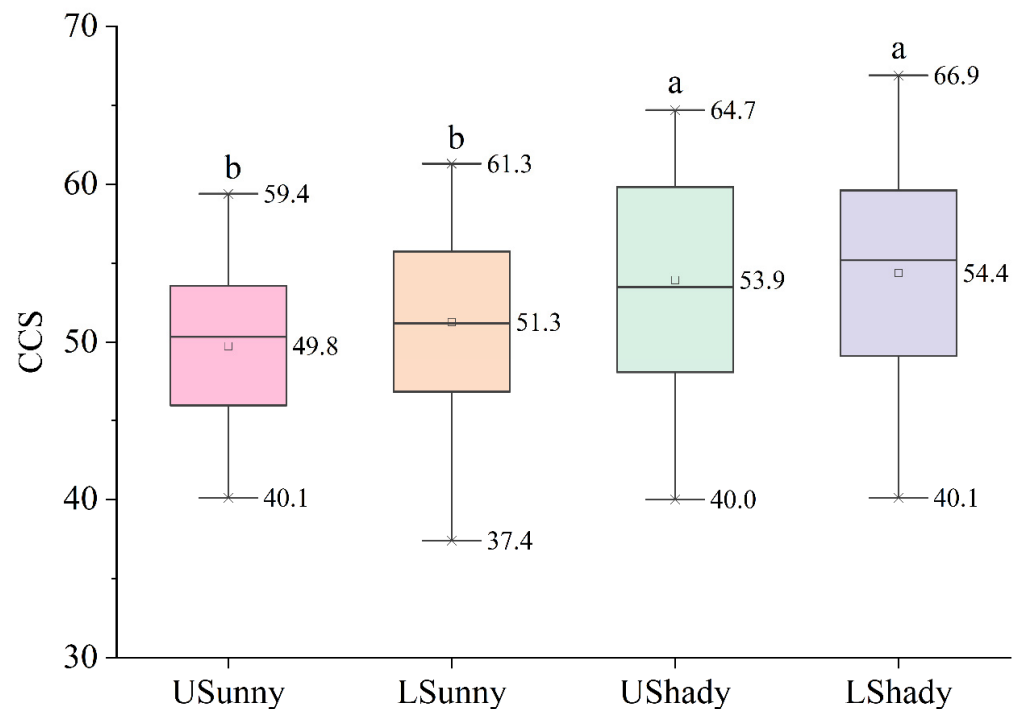


Figure 3. Measured CCS in different terrains. Values are maximum, mean, and minimum, respectively. According to one-way ANOVA, different letters above the box plots indicate significant differences in CCS among different terrains ($p < 0.05$).

2.2.2. Collection and Processing of UAV Imagery

A quadcopter mini UAV, DJI Phantom 4 equipped with a multispectral sensor, was used to collect remote sensing images of the *Cunninghamia lanceolata* artificial forest area. The camera can capture spectral images in five different spectral channels simultaneously. The five 2.08-megapixel monochrome sensors cover the following spectral bands: blue ($450 \text{ nm} \pm 16 \text{ nm}$), green ($560 \text{ nm} \pm 16 \text{ nm}$), red ($650 \text{ nm} \pm 16 \text{ nm}$), red-edge ($730 \text{ nm} \pm 16 \text{ nm}$), and near-infrared ($840 \text{ nm} \pm 26 \text{ nm}$).

In order to reduce the influence of shadows and solar light intensity on the inversion results, the cloudy and maximum solar altitude angle time period was selected for aerial photography operations. Based on previous studies combined with elevation and average stand height in the study area [29,36], the DJI Wizard P4 multispectral version was set to have a route altitude of 80 m, an overlap rate of 85% in the heading direction, an overlap rate of 80% in the side direction, and a gimbal pitch angle of 90° , and a route design of 90° was carried out based on the target area of the small-class. route design for semi-automatic aerial photography by UAV. After the remote sensing images were collected, DJI and ENVI 5.3 software were used to correct the radiation and remove the noise from the multispectral images.

2.3. Data Processing

2.3.1. Selection of Vegetation Indices

The spectral characteristics of green plant leaves and vegetation canopy, as well as their differences and changes, can reflect the vegetation information on remote sensing images. However, the spectral reflectance of forest vegetation is susceptible to the influence of various factors such as the ground, the atmosphere, the canopy structure, etc. [37,38], while the vegetation index can weaken the influence of external factors, enhance the sensitivity to changes in vegetation, and can quickly, simply, and efficiently measure the health of the vegetation growth and the coverage of the vegetation. Drawing on previous research and the spectral features of chlorophyll, this study employed ENVI 5.3 software to calculate 21 vegetation indices from the five monochrome spectral images collected by the UAV. The

formulas for these 21 vegetation indices are presented in Table 1. The relationship between each vegetation index and measured CCS was analyzed using SPSS 25, and the vegetation indices with significant correlations with CCS were screened as independent variables to participate in the CCS inversion modeling.

Table 1. Vegetation indices used in this study. B, G, R, RE, and NIR are the reflectance of the blue band, green band red band, red-edge band, and NIR band, respectively.

Vegetation Index	Acronym	Equation	References
Simple Ratio	SR	NIR/G	[38]
Green Chlorophyll Index	GCI	$NIR/G - 1$	[39]
Leaf Chlorophyll Index	LCI	$(RE - R)/(RE + G)$	[40]
Ratio Vegetation Index	RVI	NIR/G	[41]
Triangular Vegetation Index	TVI	$0.5[120(NIR - G) - 200(R - G)]$	[42]
Red Edge Chlorophyll Index	CI _{re}	$NIR/RE - 1$	[43]
Red-Edge Greenness Index	GIRE	G/RE	[44]
Infrared Percent Vegetation Index	IPVI	$NIR/(NIR + R)$	[45]
Normalized Difference Chlorophyll Index	NDCI	$(RE - R)/(RE + R)$	[46]
Red-Edge Normalized Difference Vegetation Index	NDRE	$(NIR - RE)/(NIR + RE)$	[47]
Normalized Difference Vegetation Index	NDVI	$(NIR - R)/(NIR + R)$	[48]
Renormalized Difference Vegetation Index	RDVI	$(NIR - R)/\sqrt{(NIR + R)}$	[48]
Red-Edge Difference Vegetation Index	DVIRE	$NIR - RE$	[49]
Green Normalized Difference Vegetation Index	GNDVI	$(NIR - G)/(NIR + G)$	[50]
Modified Chlorophyll Uptake Ratio Index	MCARI	$[RE - R - 0.2(RE - G)] \times RE/R$	[51]
Optimized Soil-Adjusted Vegetation Index	OSAVI	$1.16(NIR - R)/(NIR + R + 0.16)$	[37]
Red-Edge Ratio Vegetation Index	RVIRE	RE/NIR	[52]
Transformed Chlorophyll Absorption Reflectance Index	TCARI	$3[NIR - R - 0.2(NIR - G)(NIR/R)]$	[53]
Red-Edge Triangular Vegetation Index	TVIRE	$0.5[120(NIR - G) - 200(RE - G)]$	[44]
Red-Edge Infrared Percent Vegetation Index	IPVIRE	$NIR/(NIR + RE)$	[44]
Red-Edge Optimized Soil-Adjusted Vegetation Index	REOSAVI	$1.16(NIR - RE)/(NIR + RE + 0.16)$	[54]

In order to reduce the influence of background values on the vegetation index of the samples, this study constructed circular buffers with a radius of 0.5 m for each sample centered on the tree apex based on the canopy size measured in the field. The mean of the pixel values of each buffer was then extracted as the vegetation index value of each sample using ArcGIS 10.8.

2.3.2. Model Establishment

In this study, using the Python 3.7 software platform, three modeling methods were selected: partial least squares regression (PLSR), random forest regression (RF), and back-propagation neural networks (BPNN). Three vegetation indices with the highest correlation to the CCS were chosen as independent variables, while the measured SPAD served as the dependent variable for constructing the inversion model.

Previous studies have shown that the estimation models constructed by combinations of different vegetation indices have higher estimation accuracy and performance than single-band, single-variable estimation models [23]. However, the multicollinearity among the vegetation indices weakened their explanatory power for the estimation indexes. Therefore, in this study, PLSR was selected to build a linear estimation model of CCS, aiming at weakening the high correlation among the independent variables [55]. RF, on the other hand, as one of the most representative of the integration algorithms, is able to provide an assessment of the importance of each feature, which helps to understand which features contribute the most to the model. This ability of feature selection makes random forests more convenient in dealing with features of different scales, which demonstrates its powerful performance in a variety of realistic tasks [56,57]. BPNN, as one of the most widely used neural networks, has a powerful nonlinear mapping ability, which allows it to approximate any complex nonlinear function through a multilayer network structure. This makes BP neural networks have higher accuracy and stronger generalization ability when

dealing with data with complex nonlinear relationships [58]. However, in the construction of the BPNN model, too many input nodes not only increase the training time cost of the model, but also may cause the neural network to be too sensitive to the noise and redundant information in the input vectors, which reduces the generalization ability and prediction accuracy of the model. In order to avoid the above problems, principal component analysis (PCA) was used in this study for dimensionality reduction of the input data.

2.3.3. Accuracy Evaluation

After removing some outliers, the remaining 255 samples are divided into a training dataset with a sample size of 200 as well as a test dataset of 55 in the ratio of 8:2, while 25% of the samples from the training dataset are randomly selected for the test of model training performance. The performance and accuracy of the model were comprehensively compared using the model's coefficient of determination (R^2), root mean square error (RMSE), and relative percent difference (RPD). A higher R^2 closer to 1 during inversion modeling and test indicates higher estimation accuracy of the model. Similarly, a lower RMSE suggests better predictive performance, indicating smaller differences between predicted and observed values. For the evaluation criteria of RPD: when $RPD < 1.4$, the model is considered unable to predict the samples effectively; when $1.4 < RPD < 2$, the model demonstrates good predictive capability for the samples; and when $RPD > 2$, the model exhibits strong sample prediction ability. The formulas for evaluating model accuracy are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

$$SD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\hat{y}_i - \bar{y}_i)^2} \quad (3)$$

$$RPD = \frac{SD}{RMSE} \quad (4)$$

where the n is the number of samples, i is the sample ordinal number, y_i is the measured value of CCS, $\hat{y}_i$ is the predicted value of CCS, $\bar{y}_i$ is the mean of the measured value of CCS, and SD is the standard deviation of the model prediction.

3. Results

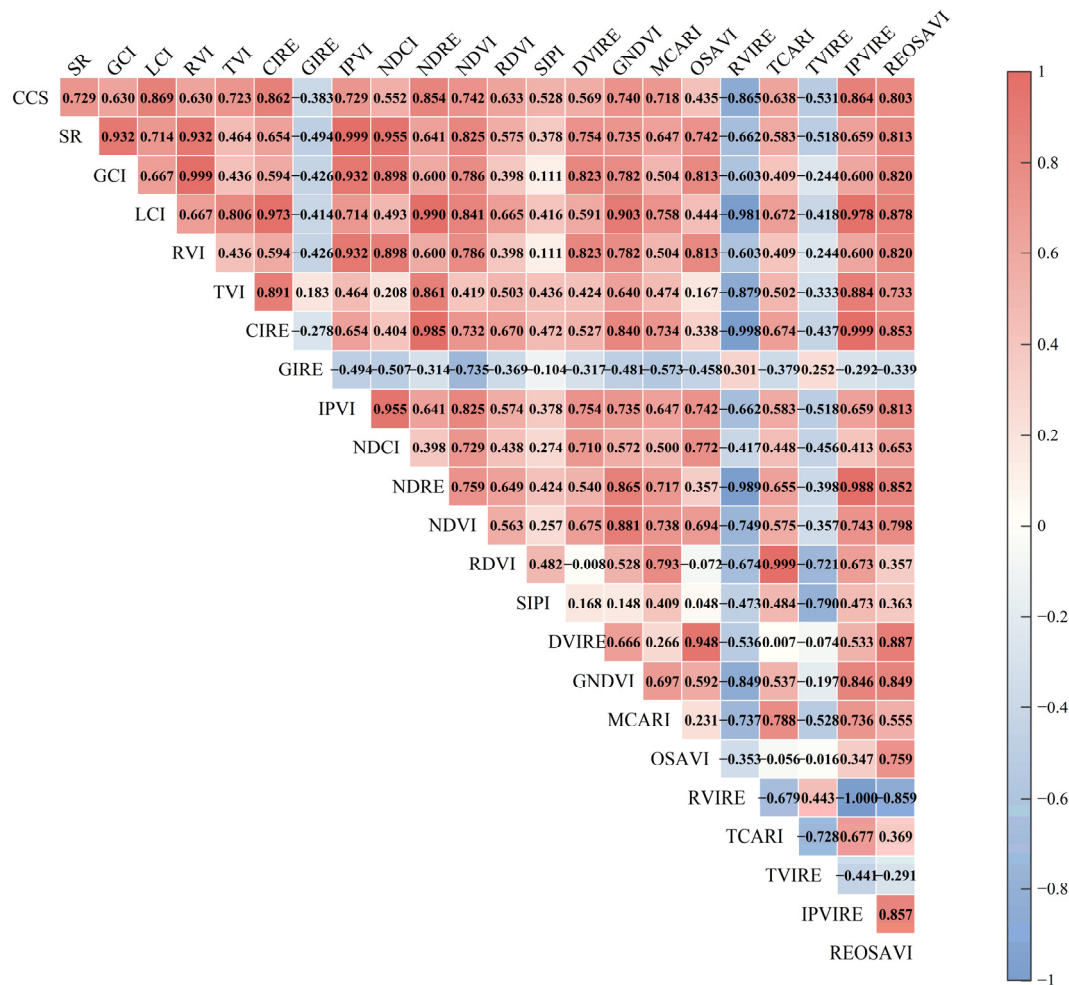
3.1. Correlation Analysis

The Pearson correlation analysis was conducted on the single-band spectral reflectance collected by the UAV and the CCS, with the results presented in Table 2. As shown in the table, except for the G band, all other single bands exhibit a significant correlation with the CCS ($p < 0.01$). Specifically, the R and B bands show a negative correlation with the CCS, while the NIR and RE bands display a positive correlation. Among these, the RE band demonstrates the highest correlation with the CCS, with a correlation coefficient of 0.682, followed by the NIR band with a correlation coefficient of 0.638. Within the visible light spectrum, the R band exhibits the highest correlation with the CCS, with a correlation coefficient of -0.446 .

A Pearson correlation analysis was performed on the selected 21 vegetation indices and the CCS (Figure 4). The results indicate that except for GIRE, RVIRE, and TVIRE, the remaining 19 vegetation indices are positively correlated with CCS, with significant correlations observed between CCS and the selected vegetation indices. Among them, LCI exhibits the highest correlation with CCS, with a correlation coefficient of 0.869, followed by RVIRE, IPVIRE, and Clre, with correlation coefficients of -0.865 , 0.864, and 0.862, respectively. In contrast, GIRE shows the lowest correlation with CCS, with a correlation coefficient of -0.383 .

Table 2. Correlation analysis between single-band spectral values and CCS. ** indicates that they are highly significantly correlated at the 0.01 level.

Band	SPAD
R	−0.446 **
G	−0.097
B	−0.216 **
NIR	0.638 **
RE	0.682 **

**Figure 4.** Correlation analysis between vegetation index and CCS.

3.2. Principal Component Analysis

From the correlation analysis between vegetation indices and CCS, it can be seen that there is a significant correlation between the vegetation indices constructed in this study and the measured CCS, and at the same time, there is a strong correlation between these vegetation indices; therefore, this study utilized the SPSS 25 software to carry out the principal component analysis on the 21 vegetation indices constructed, and to reduce the dimensionality of the data in order to eliminate the multicollinearity between the factors, while retaining the information of the original data. The principal components extracted after principal component analysis, and the scores of each factor are shown in Table 3.

The principal component analysis extracted four main components in each vegetation index, and the cumulative contribution rate of the four components reached 94%, which contained the vast majority of the information of the original parameters, and could replace the original parameters to build the prediction model.

Table 3. Classification of principal components of vegetation index and scores of each factor.

Vegetation Index	Principal Component			
	1	2	3	4
SR	0.244	0.141	−0.173	0.144
GCI	0.227	0.242	−0.043	0.038
LCI	0.252	−0.106	0.153	−0.114
RVI	0.227	0.242	−0.043	0.038
TVI	0.188	−0.204	0.366	0.211
CIRE	0.241	−0.166	0.205	−0.030
GIRE	−0.133	−0.111	0.339	0.469
IPVI	0.244	0.141	−0.173	0.144
NDCI	0.202	0.235	−0.292	0.172
NDRE	0.241	−0.148	0.214	−0.085
NDVI	0.242	0.090	−0.083	−0.250
RDVI	0.183	−0.305	−0.259	−0.100
SIPI	0.120	−0.247	−0.146	0.515
DVIRE	0.191	0.322	0.169	0.186
GNDVI	0.241	0.044	0.142	−0.265
MCARI	0.209	−0.166	−0.167	−0.255
OSAVI	0.166	0.405	0.027	0.085
RVIRE	−0.244	0.160	−0.195	0.039
TCARI	0.185	−0.299	−0.261	−0.098
TVIRE	−0.137	0.247	0.360	−0.376
IPVIRE	0.243	−0.163	0.198	−0.035
REOSAVI	0.246	0.106	0.206	0.108
Characteristic value	13.866	3.448	2.093	1.277
Accumulative contribution (%)	63.025	78.697	88.209	94.013

3.3. Modeling Results

In this paper, PLSR was selected to build a CCS inversion model with 21 vegetation indices as independent variables and measured CCS as dependent variable, and four principal components were selected based on the cumulative contribution of the independent variables, and the results showed (Figure 5a) that the RPDs of the model's training and test dataset were 2.306 and 2.185, respectively, which were greater than 2, and that the model possessed a better predictive ability of the samples; the RMSEs for both were 2.230 and 2.922, the R^2 s were 0.807 and 0.770, and the slopes of the fitted regression lines were 0.772 and 0.868, respectively. Compared with the training dataset, the slope of the regression line in the test dataset is closer to 1:1, but the overall prediction value of the test dataset is low and more discrete. Overall, the PLSR model has good predictive ability and can be used for CCS prediction.

In the inversion model built based on the RF algorithm, the parameters were selected using the grid search method, and the number of decision trees was finally selected to be 170, the maximum depth of the decision tree was 5, the minimum number of samples required to split the internal nodes was 5, the minimum number of samples required on the leaf nodes was 1, and the maximum number of features considered in the node splitting was 23. The training results show (Figure 5b) that the model's RPD for the training dataset and test dataset are 2.104 and 1.935, respectively, both higher than 1.4, and the model is able to predict the samples efficiently; the RMSEs for both are 2.471 and 2.937, respectively, and the R^2 s are 0.763 and 0.771, respectively, and the ratio of predicted and actual values of the model's test dataset is much closer to 1:1 in the interval of CCS < 50, and the ratio of predicted and actual values of the model's test dataset is much closer to 1:1 in the interval of SPAD > 50; the predicted CCS of the model is slightly lower than the measured CCS. Overall, the predictive ability of the CCS inversion model built based on the RF algorithm is good and can be used for CCS prediction.

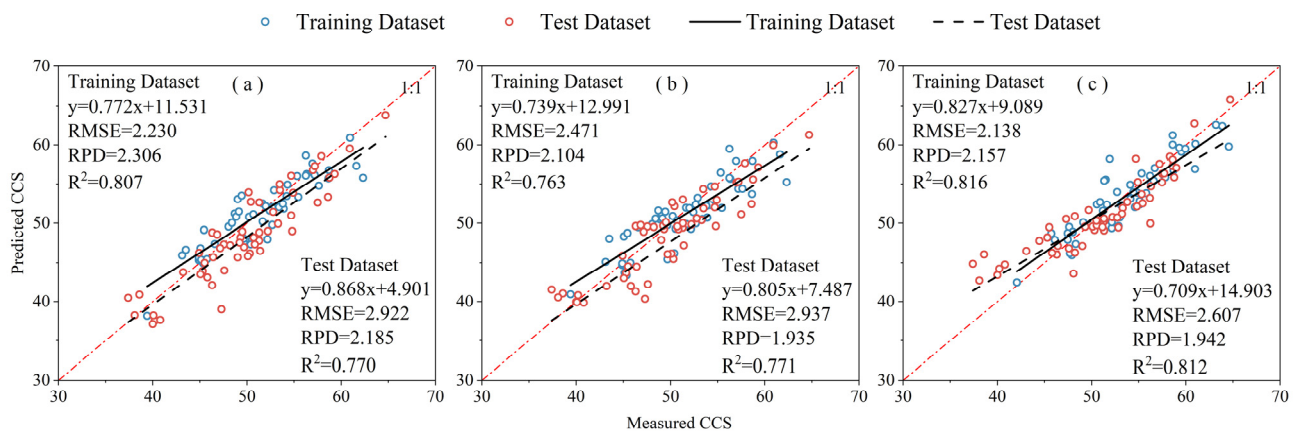


Figure 5. Prediction results of CCS models established using PLSR (a), RF (b) and BPNN (c) algorithms. In this figure, the blue open circles are the results of the testing of the model training capability during the model training process, and the red open circles are the results of the prediction of the test set using the trained model. The red line is the 1:1 regression line.

The BPNN model is mainly composed of input, hidden and output layers, and its hyperparameters mainly include the number of hidden layers and neurons, the learning rate, the number of training times, and the activation function. Among them, the number of layers of the neural network and the number of neurons in the hidden layer can affect the performance of the model to a large extent. Theoretically, the deeper the number of hidden layers, the stronger the model's ability to fit the function, but deeper layers may also bring problems such as overfitting; therefore, according to the trial-and-error method, this study chose to construct a neural network model containing four hidden layers.

When the number of nodes in the neural network is too large, not all neurons in the hidden layer can be adequately trained due to the limited amount of information in the training dataset, thus leading to overfitting. Even if the amount of information in the training data is sufficient, too many neurons in the hidden layer will increase the training time, thus making it difficult to achieve the expected results. Therefore, choosing the appropriate number of hidden layer neurons is equally important. The learning rate, as another important hyperparameter in the neural network model, controls how the gradient moves in each iteration to reach the optimal solution of the loss function, and its size determines the speed of the neural network's learning speed, and the appropriate learning rate can make the cost function converge to the minimum value at a suitable speed. The number of training times also has an important impact on the model performance, as too many training times will lead to overfitting of the model, while too few will easily lead to underfitting. Therefore, based on the previous research, this study adopts the "trial and error method", and finally sets the number of hidden layer neurons to 10, the learning rate to 0.001, and the number of training times to 200,000.

In addition, the activation function is the core parameter for neural networks to learn, understand and learn complex nonlinear functions; in this study, the construction of each hidden layer of the neural network used the hyperbolic tangent function (Tanh), which outputs between -1 and 1 , and it solves the problem that the Sigmoid function does not output centred on 0 .

In addition to this, regularization is used in this study to limit the range of values of the model parameters as a way to prevent overfitting of the BPNN model. The regularization method is divided into L1 regularization and L2 regularization, in which L1 regularization makes the model more inclined to select sparse features by adding a penalty term of L1 paradigm to the loss function of the model, which reduces unnecessary feature weights and improves the generalization ability, and L2 regularization quadratically constrains the parameters by summing up the squares of the individual elements in the weight vector and then solving for the square root to make the optimization solution stable fast, and makes

the weights smoother. Compared with L1 regularization, L2 regularization is more robust to outliers. In the construction of the BPNN-based chest diameter inversion model, L2 regularization is adopted for the constraints of the loss function, and its parameter is set to 0.0001.

Meanwhile, based on the results of principal component analysis of vegetation indices, this study constructed a CCS inversion model of the BPNN algorithm with the four component factors obtained from the weighted calculation of 21 vegetation indices as the independent variables, and the training results showed (Figure 5c) that the RPDs of the model's training and test dataset were 2.157 and 1.942, respectively, which were higher than 1.4, and that the model was able to predict the samples effectively; the two RMSEs are 2.138 and 2.607, and the R^2 s are 0.816 and 0.812, respectively, and the fitted regression lines of the training and test dataset are closer to the 1:1 regression line, with no systematic overestimation or underestimation, and in general, the prediction ability of the CCS inversion model based on the BPNN is better, and it is able to be used for the prediction of CCS.

In conclusion, the selected inversion algorithms in this study demonstrate good predictive abilities. However, based on a comprehensive assessment using R^2 and RMSE, the BPNN model had the best predictive performance, highest accuracy, and least dispersion on the test dataset, making it the best choice for CCS inversion.

3.4. Effects of Terrain on CCS Estimates

Based on the selected optimal CCS inversion model, the CCS of USunny, LSunny, UShady and LShady were inverted and the results are shown in Figure 6. It is obvious that the pre-predicted CCSs of UShady and LShady are close to the 1:1 regression line, with R^2 s of 0.791 and 0.803, respectively, and RPDs of 1.636 and 1.779, respectively, which are higher than 1.4, indicating that the models have good predictive ability for these sites. On the other hand, the predicted TCCs for USunny and LSunny were slightly lower than the actual TCCs, with R^2 s of 0.662 and 0.659 and RPDs of 1.638 and 1.076, respectively, where the RPD for LSunny was below 1.4, indicating the effective prediction ability of the model for these locations.

When comparing the predicted CCS results for the four different terrains, it is evident that the model's prediction accuracy is relatively similar for the upper and lower locations within the same slope location, with no significant differences in prediction capabilities. However, the selected best CCS model has significantly higher prediction accuracy and capability for samples on the shady slope compared to the sunny slope within the same slope direction. This indicates that slope direction can influence the accuracy of model predictions. Therefore, the best CCS model used in this study may not be applicable for predicting CCS of different slope directions.

Using the above conclusions, the training dataset was divided into two subsets: the sunny slope dataset and the shady slope dataset. The BPNN algorithm was then utilized to construct two separate CCS models: the sunny CCS model and the shady CCS model. Figure 7 illustrates the model prediction results and their performance on different slope locations. Both the sunny CCS model and shady CCS model achieved R^2 s of around 0.8, with RPDs of 2.381 and 2.015, respectively, both exceeding 2, indicating that both models have good sample predictive capabilities. The CCS of USunny and LSunny was predicted using the sunny CCS model, and the prediction results had an R^2 above 0.8 in both cases. Similarly, applying the shady CCS model to predict the CCS on the UShady and LShady resulted in an R^2 around 0.8 as well. This demonstrates that both models are highly adaptable to different slope direction and can be used to predict CCS in various terrains.

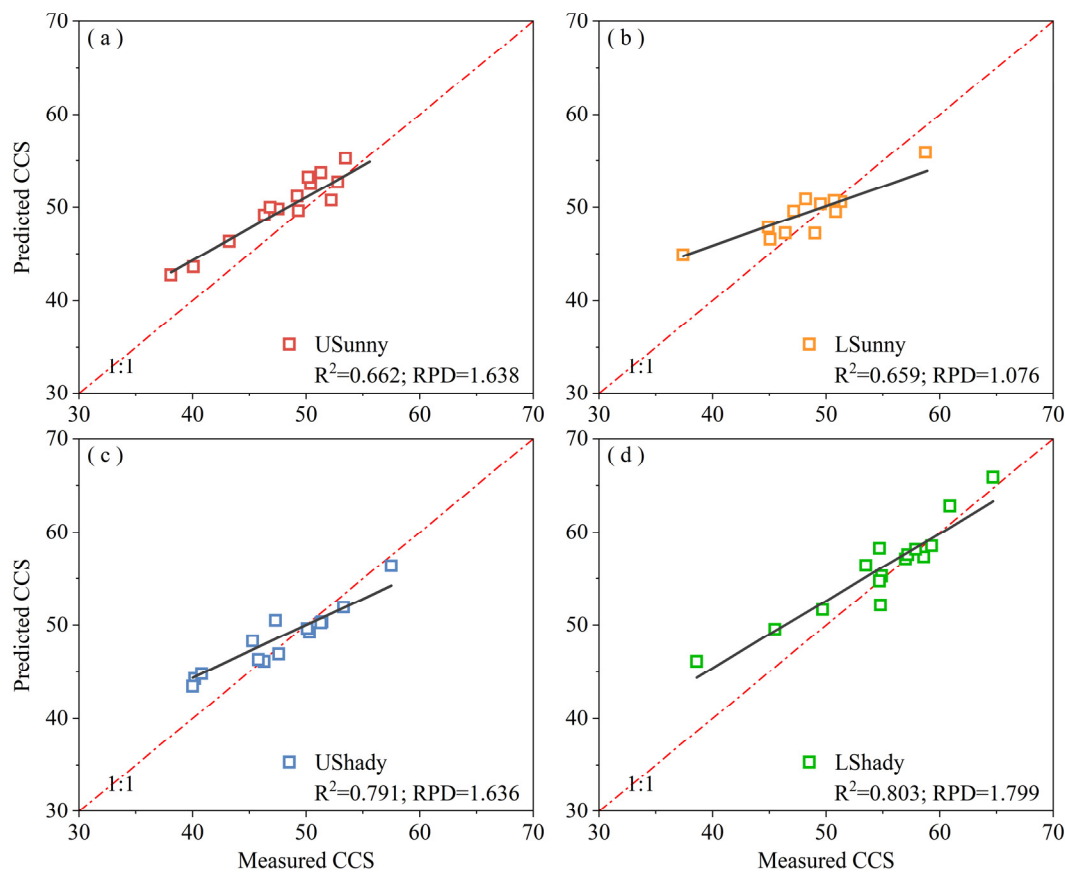


Figure 6. CCS predictions of the best CCS model for USunny (a), LSunny (b), UShady (c), and LShady (d). The red line is the 1:1 regression line.

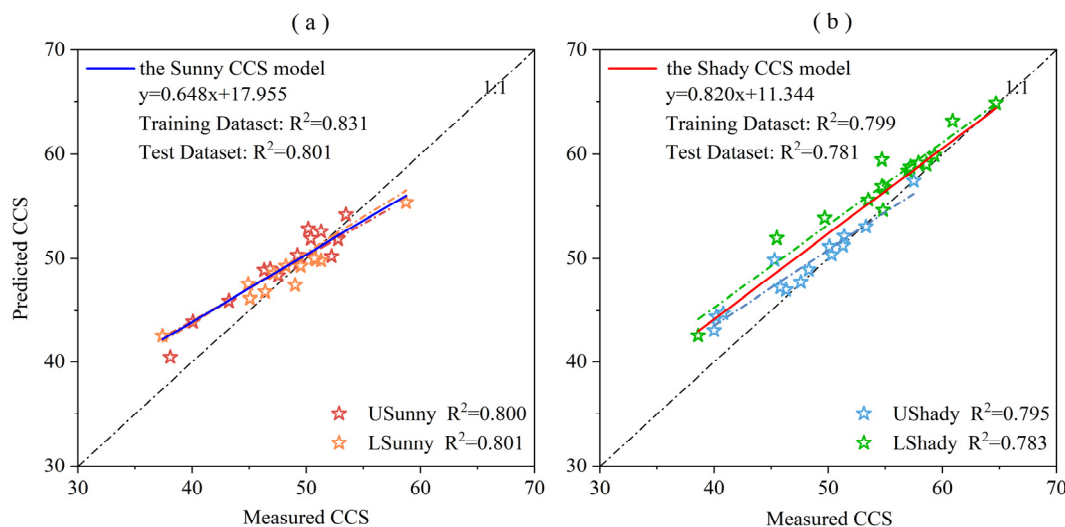


Figure 7. Predictive results and terrain applicability analysis of the Sunny CCS model (a) and the Shady CCS model (b). The black line is the 1:1 regression line.

The training dataset was divided into USunny dataset, LSunny dataset, UShady dataset, and LShady dataset. Based on the BPNN algorithm, separate models were built for USunny CCS model, LSunny CCS model, UShady CCS model, and LShady CCS model. Table 4 shows the accuracy assessment of modeling and testing for the four models. With the exception of USunny, all models achieved an accuracy of above 0.8, with RPD > 2, indicating that they all possess good predictive capabilities and accurate CCS forecasting.

Table 4. Construction results of CCS inversion models for four different terrains based on BPNN algorithm.

Model Type	Training Dataset			Test Dataset		
	RMSE	RPD	R ²	RMSE	RPD	R ²
USunny CCS model	1.904	2.250	0.845	2.047	2.059	0.793
LSunny CCS model	1.377	2.514	0.821	2.056	2.451	0.818
UShady CCS model	2.174	2.464	0.853	2.029	2.585	0.835
LShady CCS model	1.575	2.465	0.816	2.719	2.049	0.804

The study predicted the CCS in the study area using three categories of CCS inversion models, where the first category is the best CCS inversion model, while the second category includes the sunny CCS model and the shady CCS model. The third category comprises the USunny CCS model, LSunny CCS model, UShady CCS model, and LShady CCS model. Figure 8a shows the spatial distribution of predicted CCS for the three categories of CCS inversion models. The predictions of the first type of model differed significantly from the other two, with higher predictions in the sunny slope directions and lower predictions in the shady slope directions, whereas the second category model's CCS distribution is more similar to that of the third category model. Figure 8b illustrates the pixel distribution among CCS for the three categories of CCS inversion models. The proportion of pixels with CCS between 50–60 is the highest in all three predicted maps, whereas the proportion of pixels with CCS greater than 80 is the lowest. The predicted CCS for the shady slope is noticeably higher than that for the sunny slope across different terrains. However, there is no significant difference in the predicted CCS between the upper and lower slope locations. The distribution of CCS predictions in the 40–60 interval is similar between the first and third category models, but there is a notable overestimation in intervals higher than 60, indicating some error in CCS prediction by the first category model. However, the spatial distribution of CCS predicted by the third category and the second category models is similar, which confirms the applicability of the second category models across various terrains.

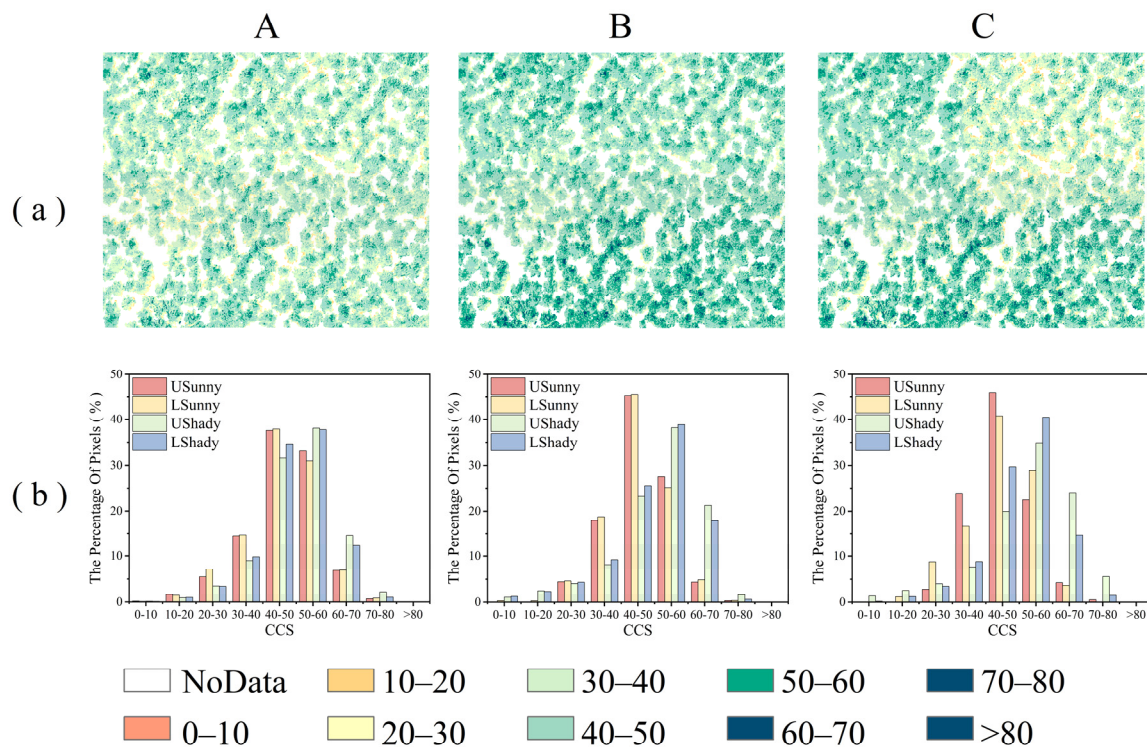


Figure 8. Distribution of CCS predictions for the first category model (A), the second category model (B), and the third category model (C) in the study area (a) and the percentage of pixels between each CCS tier (b).

4. Discussion

An analysis of the correlation between the selected 21 vegetation indices and CCS revealed that LCI, IPVIRE, and RVIRE displayed the highest correlation and explanatory power concerning CCS. This finding contrasts with the conclusion of Yuan et al. regarding the higher expressive capability of MCARI for predicting SPAD based on multispectral images of *Hopea hainanensis* [59]. It is known from previous studies on the correlation between SPAD and vegetation indices that the interpretation of SPAD varies among different plant species [60–63]. The spectral characteristics of plants are influenced by their unique structures, morphologies, and physiological features, and the biochemical composition and structure differ among different plant species, leading to varying absorption and reflection capacities of leaves in each spectral band. This divergence results in different plant populations' spectral characteristics having varying capabilities in interpreting SPAD.

Moreover, the involvement of the red-edge band in constructing these three vegetation indices demonstrates the red-edge band's heightened sensitivity to changes in SPAD. In this study's correlation analysis between the five spectral images collected by drones and CCS, a highly significant correlation at the 0.01 level was observed between the red-edge band and CCS. This conclusion, similar to the findings of Lu et al. in predicting SPAD of *Cinnamomum camphora* dwarf forest using drone multispectral images [64], further confirms the interpretive capability of the red-edge band for SPAD.

In addition to the choice of vegetation indices, the choice of modeling methods is another important factor affecting the estimation of CCS. Previous studies have shown that machine learning algorithms have stronger generalization capabilities and better predictive performance in constructing SPAD models compared to traditional linear models due to their robust noise resistance [65–67].

In this study, based on a comprehensive analysis of R^2 , RPD, and RMSE, the performance of a traditional linear model (PLSR) was compared with three machine learning models (SVR, RMSE, and BPNN). The results showed that the BPNN model, which uses backpropagation to iteratively adjust model weights, had the best predictive ability in CCS estimation. This conclusion is consistent with previous research indicating that the BPNN model performs better in constructing SPAD inversion models [60,68]. Compared with other machine learning algorithms, BPNN takes the backpropagation algorithm as the core, and adjusts the BPNN model weights and biases by continuously repeating the forward and backward propagation process of data and errors, so as to fit the complex mapping relationship between the input and output data from a large number of training data, and iteratively obtains higher network performance.

However, compared to the significant advantage of the BPNN model in SPAD inversion, PLSR is significantly better at predicting CCS than RF. This suggests that the linearity or nonlinearity of the model did not have a large impact on the construction of the CCS model, which is inconsistent with the conclusions reached in most studies, but is more similar to the findings of Jiang et al. in the estimation of chlorophyll in watersheds [69]. This may be due to the fact that the CCS measured in this study was centrally distributed around 50, making the RF overly concerned with data in that range, leading to a decrease in overall prediction accuracy. In addition, the strong correlation among the selected vegetation indices as shown in Figure 4 suggests potential multicollinearity among the features, and the PLSR model developed from principal component analysis effectively addresses issues of high intercorrelation among variables, resulting in comparable predictive accuracy among the three models. Therefore, future optimization efforts could focus on refining the choice of vegetation indices or considering multiple types of independent variables to reduce multicollinearity between variables.

Although the best CCS model established in this study has good prediction ability, the prediction accuracy of the model appears to be significantly different among different terrains, and unlike the model's stable prediction ability among different slope locations, its prediction generalization is lower among different slope directions. Compared with

slope location, slope directions have a greater impact on the prediction accuracy of the best CCS model, making the model not applicable to CCS prediction in different terrains.

The interpretation of multispectral imagery for CCS is mainly derived from the reflectance of the *Cunninghamia lanceolata* canopy to solar radiation, which is directly related to the radiation environment of the vegetation canopy. Variations in the radiation environment of the vegetation canopy are mainly defined by the quantity, quality, and directional distribution of incident radiation, and these factors are mainly defined by the dimension and terrain of the vegetation site.

The interpretation of CCS from multispectral imagery is mainly derived from the reflectance of the *Cunninghamia lanceolata* canopy to solar radiation, which is directly related to the radiation environment of the vegetation canopy. Variations in the radiation environment of the vegetation canopy are defined by the quantity, quality, and directional distribution of incident radiation, and these factors are mainly defined by the latitude and terrain of the vegetation site.

The different performance of the best CCS model in slope location and slope directions may be due to the fact that the study area is located in a hilly area, and there is not much difference in elevation between different slope locations, so there is no big difference in the quality and quantity of solar radiation received by the *Cunninghamia lanceolata* canopy between different slope locations, while the slope directions have a big influence on the incidence direction of solar radiation, and a change in the slope directions will lead to the difference in the incidence angle of radiation, which will directly affect the reflectance of *Cunninghamia lanceolata*. The effect of the change of slope directions will lead to the difference of radiation incidence angle, which will directly affect the reflectance of the fir canopy, and the result of this effect is that the more the slope directions are turned to the light-facing direction, the larger the spectral reflectance ratio is [70]. Additionally, as a heliophilous species, *Cunninghamia lanceolata* experiences different light and water distribution across various slope aspects, directly influencing its growth, yield, and function [71,72]. These internal variations cannot be perfectly interpreted by vegetation indices, thus limiting the model's adaptability. Based on the above factors, the following ways can be used in the future to reduce the influence of slope directions on the model prediction accuracy. First, the acquisition of multispectral images of the study area can be carried out at noon in cloudy weather as much as possible to reduce the influence of the directionality of solar radiation. Secondly, tilt photography can be used to obtain multi-angle multispectral information of the forest floor, and optimize the acquisition of spectral data of the forest floor from the perspective of forest canopy reflectance anisotropy [73], so as to reduce the influence of slope directions on spectral reflectance data. In addition, the feature parameters related to CCS can be further explored, and new vegetation indices or texture feature indices can be incorporated to achieve higher interpretation capability of CCS, so as to explore the CCS inversion model with better applicability.

However, as far as the above approaches are concerned, they do not completely eliminate the influence of terrain on the predictive ability of the model, so this study builds inverse models of CCS for different slope directions separately, aiming to seek for a better accuracy of CCS prediction. The model training results show that the sunny CCS model and the shady CCS model had higher predictive accuracy than the best CCS inversion model. Moreover, the predictive capabilities of the sunny CCS model and the shady CCS model did not vary significantly across different slope directions. Comparing the performance of the second category models and the third category models in predicting CCS across the study area, all six models exhibited strong predictive abilities with high similarity in the distribution patterns of CCS predictions. This confirms that the sunny CCS model and the shady CCS model have strong applicability across terrains. Therefore, in practical applications, separating inversion models for shady and sunny slopes can provide more accurate predictions of CCS. In addition, this study did not address the effect of elevation on model applicability.

In addition, there is still room for improvement in the following processes in this study: first, in the previous study, the SPAD can be calibrated to chlorophyll content with high accuracy, but there are still some errors in it [74,75], so this study can be followed up with a study on how to calibrate the CCS derived from the prediction to *Cunninghamia lanceolata* canopy chlorophyll content; second, this study has not elaborated on the effect of elevation on the applicability of the model, and so the model could not be applied in the prediction of CCS with large differences in stand elevation; third, this study used UAV remote sensing to estimate CCS with the aim of reducing the drawbacks of small range and long time in the investigation of chlorophyll process, but this study found that UAVs still have some limit in the investigation range in practical application due to signal reception and other problems, and currently, high-resolution satellites covering the whole world are constantly emerging, and scholars are also exploring the joint use of UAV and satellite data to carry out remote sensing investigations [76–78], so this study can be followed up with joint high-resolution satellite remote sensing to expand the application range of the CCS inversion model.

5. Conclusions

This study constructed a CCS inversion model based on multispectral images of near-mature *Cunninghamia lanceolata* forests acquired by drones and data from 200 collected SPAD samples. The research analyzed the terrain adaptability of the model, and the results showed the following:

Based on the correlation analysis between measured CCS and features extracted from multispectral drone images, a highly significant correlation at the 0.01 level was found between the red-edge band and CCS. The three vegetation indices with the highest correlation to CCS were LCI, RVIRE, and IPVIRE, all of which included the red-edge band in their construction, further confirming the close relationship between the red-edge band and CCS.

The principal component analysis of the vegetation indices constructed in this study shows that the correlation between the 21 vegetation indices is significant, and after dimensionality reduction of the vegetation index data, we can obtain four uncorrelated principal components, whose cumulative contribution rate is 94%, which contains most of the information of the original parameters, and can be used to establish prediction models instead of the original parameters.

Through a comprehensive analysis of R^2 , RPD, and RMSE, the BPNN model was identified as the best CCS model for predicting CCS. The model showed good performance with R^2 s of 0.816 and 0.812 for the training and test datasets, RMSEs of 2.138 and 2.607, and RPDs of 2.157 and 1.942, indicating high prediction accuracy and suitability for CCS prediction.

Using the established best CCS model, CCS was predicted for different terrains. The results showed similar prediction accuracy for CCS across different slope locations, but lower generalization across different slope directions. After separately modeling samples from different slope directions, both models showed R^2 above 0.8 and demonstrated strong applicability across terrains.

Author Contributions: Conceptualization, R.L.; Investigation, L.Z., Y.Z., W.G. and N.C.; Methodology, L.Z., X.S. and R.L.; Software, L.Z. and H.L.; Validation, X.S.; writing—original draft preparation, L.Z.; writing—review and editing, H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Forestry Peak Discipline Construction Project of Fujian Agriculture and Forestry University (72202200205).

Data Availability Statement: The data is available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhang, R.; Yang, P.; Liu, S.; Wang, C.; Liu, J. Evaluation of the Methods for Estimating Leaf Chlorophyll Content with SPAD Chlorophyll Meters. *Remote Sens.* **2022**, *14*, 5144. [\[CrossRef\]](#)
2. Li, J.; Lu, X.; Ju, W.; Li, J.; Zhu, S.; Zhou, Y. Seasonal changes of leaf chlorophyll content as a proxy of photosynthetic capacity in winter wheat and paddy rice. *Ecol. Indic.* **2022**, *140*, 109018. [\[CrossRef\]](#)
3. Phaenark, C.; Seechanhai, P.; Sawangproh, W. Metal toxicity in *Bryum coronatum* Schwaegrichen: Impact on chlorophyll content, lamina cell structure, and metal accumulation. *Int. J. Phytoremediation* **2024**, *26*, 1336–1347. [\[CrossRef\]](#)
4. Meng, F.; Chen, Z.; Wang, Y.; Multi-omics Analysis of Chlorophyll Metabolic Pathways in Tea Tree Varieties with Different Leaf Colors. *Molecular Plant Breeding*. 2024. Available online: <https://link.cnki.net/urlid/46.1068.S.20240305.1556.008.html> (accessed on 7 March 2024). (In Chinese).
5. Fu, X.Y.; Mo, W.P.; Zhang, J.Y.; Zhou, L.Y.; Wang, H.C.; Huang, X.M. Shoot growth pattern and quantifying flush maturity with SPAD value in litchi (*Litchi chinensis* Sonn.). *Sci. Hortic.* **2014**, *174*, 29–35. [\[CrossRef\]](#)
6. Rakib, M.; Borhan, A.; Jawahir, A. The relationship between SPAD chlorophyll and disease severity index in Ganoderma-infected oil palm seedlings. *J. Bangladesh Agric. Univ.* **2019**, *17*, 355–358. [\[CrossRef\]](#)
7. Celaledin, B.; Irem, T.; Hatice, T.; Mehmet, Y.; Mujde, K. Spad greenness to estimate genotypic variation in flag leaf chlorophyll in spring wheat under Mediterranean conditions. *Turk. J. Field Crops* **2015**, *20*, 1–8.
8. Saberioon, M.M.; Amin, M.S.M.; Anuar, A.R.; Gholizadeh, A.; Wayayok, A.; Khairunniza-Bejo, S. Assessment of rice leaf chlorophyll content using visible bands at different growth stages at both the leaf and canopy scale. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *32*, 35–45. [\[CrossRef\]](#)
9. Nguyen, H.T.; Lee, B.-W. Assessment of rice leaf growth and nitrogen status by hyperspectral canopy reflectance and partial least square regression. *Eur. J. Agron.* **2006**, *24*, 349–356. [\[CrossRef\]](#)
10. Zarco-Tejada, P.; Hornero, A.; Beck, P.; Kattenborn, T.; Kempeneers, P.; Hernández-Clemente, R. Chlorophyll content estimation in an open-canopy conifer forest with Sentinel-2A and hyperspectral imagery in the context of forest decline. *Remote. Sens. Environ.* **2019**, *223*, 320–335. [\[CrossRef\]](#)
11. Delloye, C.; Weiss, M.; Defourny, P. Retrieval of the canopy chlorophyll content from Sentinel-2 spectral bands to estimate nitrogen uptake in intensive winter wheat cropping systems. *Remote. Sens. Environ.* **2018**, *216*, 245–261. [\[CrossRef\]](#)
12. Wan, L.; Ryu, Y.; Dechant, B.; Lee, J.; Zhong, Z.; Feng, H. Improving retrieval of leaf chlorophyll content from Sentinel-2 and Landsat-7/8 imagery by correcting for canopy structural effects. *Remote Sens. Environ.* **2024**, *304*, 114048. [\[CrossRef\]](#)
13. Li, Y.; Ma, Q.; Chen, J.M.; Croft, H.; Luo, X.; Zheng, T.; Rogers, C.; Liu, J. Fine-scale leaf chlorophyll distribution across a deciduous forest through two-step model inversion from Sentinel-2 data. *Remote. Sens. Environ.* **2021**, *264*, 112618. [\[CrossRef\]](#)
14. Vincini, M.; Calegari, F.; Casa, R. Sensitivity of leaf chlorophyll empirical estimators obtained at Sentinel-2 spectral resolution for different canopy structures. *Precis. Agric.* **2016**, *17*, 313–331. [\[CrossRef\]](#)
15. Zhang, S.; Zhao, G.; Lang, K.; Su, B.; Chen, X.; Xi, X.; Zhang, H. Integrated Satellite, Unmanned Aerial Vehicle (UAV) and Ground Inversion of the SPAD of Winter Wheat in the Reviving Stage. *Sensors* **2019**, *19*, 1485. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Croft, H.; Chen, J.; Zhang, Y.; Simic, A. Modelling leaf chlorophyll content in broadleaf and needle leaf canopies from ground, CASI, Landsat TM 5 and MERIS reflectance data. *Remote. Sens. Environ.* **2013**, *133*, 128–140. [\[CrossRef\]](#)
17. Colomina, I.; Molina, P. Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS J. Photo-Grammetry Remote Sens.* **2014**, *92*, 79–97. [\[CrossRef\]](#)
18. Jihoon, S.; Gunhyeong, L.; TaeHo, K.; Hwa, C.K.; Min, H.S.; Hyuck, K.D.; JongCheol, P.; YoonKyung, C. Deep learning-based efficient drone-borne sensing of cyanobacterial blooms using a clique-based feature extraction approach. *Sci. Total Environ.* **2023**, *912*, 169540.
19. Zhang, A.; Yin, S.; Wang, J.; He, N.; Chai, S.; Pang, H. Grassland Chlorophyll Content Estimation from Drone Hyperspectral Images Combined with Fractional-Order Derivative. *Remote Sens.* **2023**, *15*, 5623. [\[CrossRef\]](#)
20. Sahoo, R.N.; Gakhar, S.; Rejith, R.G.; Verrelst, J.; Ranjan, R.; Kondraju, T.; Meena, M.C.; Mukherjee, J.; Daas, A.; Kumar, S.; et al. Optimizing the Retrieval of Wheat Crop Traits from UAV-Borne Hyperspectral Image with Radiative Transfer Modelling Using Gaussian Process Regression. *Remote Sens.* **2023**, *15*, 5496. [\[CrossRef\]](#)
21. Chuanmei, Z.; Jianli, D.; Zipeng, Z.; Jinjie, W.; Zheng, W.; Xiangyue, C.; Jingzhe, W. SPAD monitoring of saline vegetation based on Gaussian mixture model and UAV hyperspectral image feature classification. *Comput. Electron. Agric.* **2022**, *200*, 107236.
22. Lv, S.; Wang, J.; Wang, S.; Wang, Q.; Wang, Z.; Fang, Y.; Zhai, W.; Wang, F.; Qu, G.; Ma, W. Quantitative analysis of chlorophyll in *Catalpa bungei* leaves based on partial least squares regression and spectral reflectance index. *Sci. Hortic.* **2024**, *329*, 113019. [\[CrossRef\]](#)
23. Xiao, H.; Beibei, N.; Xinju, L.; Xiangyu, M. Unmanned aerial vehicle (UAV) remote sensing estimation of wheat chlorophyll in subsidence area of coal mine with high phreatic level. *Earth Sci. Inform.* **2021**, *14*, 2171–2181.
24. Naqvi, S.M.Z.A.; Awais, M.; Khan, F.S.; Afzal, U.; Naz, N.; Khan, M.I. Unmanned air vehicle based high resolution imagery for chlorophyll estimation using spectrally modified vegetation indices in vertical hierarchy of citrus grove. *Remote Sens. Appl. Soc. Environ.* **2021**, *23*, 100596.

25. Wang, Y.; Tan, S.; Jia, X.; Qi, L.; Liu, S.; Lu, H.; Wang, C.; Liu, W.; Zhao, X.; He, L.; et al. Estimating relative chlorophyll content in rice leaves using unmanned aerial vehicle multi-spectral images and spectral-textural analysis. *Agronomy* **2023**, *13*, 1541. [\[CrossRef\]](#)
26. Li, C.; Ma, C.; Chen, P.; Cui, Y.; Shi, J.; Wang, Y. Machine learning-based estimation of potato chlorophyll content at different growth stage using UAV hyperspectral data. *Zemdirb. Agric.* **2021**, *108*, 181–190. [\[CrossRef\]](#)
27. Qian, S.; Xiaohe, G.; Liping, C.; Xiaobin, X.; Zhonghui, W.; Yuchun, P.; Yunbing, G. Monitoring maize canopy chlorophyll density under lodging stress based on UAV hyperspectral imagery. *Comput. Electron. Agric.* **2022**, *193*, 106671.
28. Huaixing, X.; Juzhong, W.; Yiling, Q.; Lulu, H.; Yan, T.; Zhongsheng, Z.; Xiaojun, X.; Yufeng, Z. Estimating Leaf Chlorophyll Content of Moso Bamboo Based on Unmanned Aerial Vehicle Visible Images. *Remote Sens.* **2022**, *14*, 2864. [\[CrossRef\]](#)
29. Songtao, B.; Weizhen, L.; Minglu, T.; Qi, W.; Tao, Y.; Qingrui, C.; Linyi, L. Rice Leaf Chlorophyll Content Estimation Using UAV-Based Spectral Images in Different Regions. *Agronomy* **2022**, *12*, 2832. [\[CrossRef\]](#)
30. Wang, B.; Wang, Z.; Zhang, D.; Li, L.; Zhao, Y.; Luo, T.; Wang, X. Spatial and Temporal Variation in Primary Forest Growth in the Northern Daxing'an Mountains Based on Tree-Ring and NDVI Data. *Forests* **2024**, *15*, 317. [\[CrossRef\]](#)
31. State Forestry and Grassland Administration. *China Forest Resources Report (2014–2018)*; China Forestry Press: Beijing, China, 2019. (In Chinese)
32. Lu, L.-H.; Nong, Y.; Li, H.; Zeng, J.; Sun, D.-J.; Chen, L.; Ming, A.-G.; Yang, Y.-J. Effects of retention density on growth, biomass, and economic benefit of *Cunninghamia lanceolata* plantation. *Chin. J. Appl. Ecol.* **2020**, *31*, 717–724. (In Chinese)
33. Zhang, W.Q.; Fang, L.; Yang, J.; Zhang, W.D.; Yan, Y.; Yan, Q.L. Reconstruction of stand-replacement disturbance and stand age of Chinese fir plantation based on a Landsat time series in Huitong County, Hunan. *Chin. J. Ecol.* **2018**, *37*, 3467–3479. (In Chinese)
34. Zhou, X.; Hu, R.L. Analysis of the current situation of forest resources in state-owned forest farms in Shunchang County, Fujian Province. *Inn. Mong. For. Investig. Des.* **2021**, *44*, 13–19. (In Chinese)
35. Wen, M.L.; Chen, Y.; He, X.W.; Yang, L.; Zhou, Q. Distribution of collapsed gullies (Beng Gang) using GIS and verification of slope aspect selection. *Sci. Soil Water Conserv.* **2018**, *16*, 1–7. (In Chinese)
36. Luo, X.B.; Xie, T.S.; Dong, S.X. Estimation of Citrus Canopy Chlorophyll Based on UAV Multispectral Images. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 198–205. (In Chinese)
37. Zou, X.; Jin, J.; Möttus, M. Potential of Satellite Spectral Resolution Vegetation Indices for Estimation of Canopy Chlorophyll Content of Field Crops: Mitigating Effects of Leaf Angle Distribution. *Remote Sens.* **2023**, *15*, 1234. [\[CrossRef\]](#)
38. Verma, B.; Prasad, R.; Srivastava, P.K.; Yadav, S.A.; Singh, P.; Singh, R. Investigation of optimal vegetation indices for retrieval of leaf chlorophyll and leaf area index using enhanced learning algorithms. *Comput. Electron. Agric.* **2022**, *192*, 106581. [\[CrossRef\]](#)
39. Gitelson, A.A.; Gritz, Y.; Merzlyak, M.N. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. *J. Plant Physiol.* **2003**, *160*, 271–282. [\[CrossRef\]](#)
40. Datt, B. A New Reflectance Index for Remote Sensing of Chlorophyll Content in Higher Plants: Tests using Eucalyptus Leaves. *J. Plant Physiol.* **1999**, *154*, 30–36. [\[CrossRef\]](#)
41. Schuerger, A.C.; Capelle, G.A.; Di Benedetto, J.A.; Mao, C.; Thai, C.N.; Evans, M.D.; Richards, J.T.; Blank, T.A.; Stryjewski, E.C. Comparison of two hyperspectral imaging and two laser-induced fluorescence instruments for the detection of zinc stress and chlorophyll concentration in bahia grass (*Paspalum notatum* Flugge.). *Remote. Sens. Environ.* **2003**, *84*, 572–588. [\[CrossRef\]](#)
42. Chen, Z.; Jia, K.; Wei, X.; Liu, Y.; Zhan, Y.; Xia, M.; Yao, Y.; Zhang, X. Improving leaf area index estimation accuracy of wheat by involving leaf chlorophyll content information. *Comput. Electron. Agric.* **2022**, *196*, 106902. [\[CrossRef\]](#)
43. Gitelson, A.A.; Viña, A.; Arkebauer, T.J.; Rundquist, D.C.; Keydan, G.; Leavitt, B. Remote estimation of leaf area index and green leaf biomass in maize canopies. *Geophys. Res. Lett.* **2003**, *30*, 1248. [\[CrossRef\]](#)
44. Dube, T.; Mutanga, O.; Elhadi, A.; Ismail, R. Intra-and-Inter Species Biomass Prediction in a Plantation Forest: Testing the Utility of High Spatial Resolution Spaceborne Multispectral Rapid Eye Sensor and Advanced Machine Learning Algorithms. *Sensors* **2014**, *14*, 15348–15370. [\[CrossRef\]](#)
45. Gupta, S.K.; Pandey, A.C. PROSAIL and empirical model to evaluate spatio-temporal heterogeneity of canopy chlorophyll content in subtropical forest. *Model. Earth Syst. Environ.* **2021**, *8*, 2151–2165. [\[CrossRef\]](#)
46. Hong, S.; Minzan, L.; Yane, Z.; Yong, Z.; Haihua, W. Detection of Corn Chlorophyll Content Using Canopy Spectral Reflectance. *Sens. Lett.* **2010**, *8*, 134–139. [\[CrossRef\]](#)
47. Gu, C.; Li, J.; Liu, Q.; Zhang, H.; Liu, L.; Mumtaz, F.; Dong, Y.; Zhao, J.; Wang, X.; Liu, C. Retrieving decametric-resolution leaf chlorophyll content from GF-6 WFV by assessing the applicability of red-edge vegetation indices. *Comput. Electron. Agric.* **2023**, *215*, 108455. [\[CrossRef\]](#)
48. Hajek, P.; Mörsdorf, M.; Kovach, K.R.; Greinwald, K.; Rose, L.; Nock, C.A.; Scherer-Lorenzen, M. Quantifying the influence of tree species richness on community drought resistance using drone-derived NDVI and ground-based measures of Plant Area Index and leaf chlorophyll in a young tree diversity experiment. *Eur. J. For. Res.* **2024**, *143*, 141–155. [\[CrossRef\]](#)
49. Patrick, A.; Pelham, S.; Culbreath, A.; Holbrook, C.C.; De Godoy, I.J.; Li, C. High throughput phenotyping of tomato spot wilt disease in peanuts using unmanned aerial systems and multispectral imaging. *IEEE Instrum. Meas. Mag.* **2017**, *20*, 4–12. [\[CrossRef\]](#)
50. Qian, B.; Ye, H.; Huang, W.; Xie, Q.; Pan, Y.; Xing, N.; Ren, Y.; Guo, A.; Jiao, Q.; Lan, Y. A sentinel-2-based triangular vegetation index for chlorophyll content estimation. *Agric. For. Meteorol.* **2022**, *322*, 109000. [\[CrossRef\]](#)
51. Cao, Y.; Zhou, H.; Zheng, W. Study on Methods of Reducing Hyperspectral Data and Retrieving Chlorophyll Content from Rice Leaf. *J. Shenyang Agric. Univ.* **2019**, *50*, 101–107. (In Chinese)

52. De Sousa, C.; Souza, C.G.; Zanella, L.; De Carvalho, L. Analysis of Rapideye's Red edge band for image segmentation and classification. In Proceedings of the GEOBIA 2012: 4th International Conference on Geographic Object-Based Image Analysis, Rio de Janeiro, Brazil, 7–9 May 2012; Brazilian National Institute for Space Research: Paraíba Valley, Brazil, 2012; Volume 79, pp. 7–9.
53. Zhang, L.; Han, W.; Niu, Y.; Chávez, J.L.; Shao, G.; Zhang, H. Evaluating the sensitivity of water stressed maize chlorophyll and structure based on UAV derived vegetation indices. *Comput. Electron. Agric.* **2021**, *185*, 106174. [\[CrossRef\]](#)
54. Yang, G.; Niu, L. Retrieval of Chlorophyll Content in Ear Leaves of Summer Maize Based on UAV Multispectral Data. *Acta Agric. Jiangxi* **2022**, *34*, 8–12. (In Chinese)
55. Nakaji, T.; Oguma, H.; Nakamura, M.; Kachina, P.; Asanok, L.; Marod, D.; Aiba, M.; Kurokawa, H.; Kosugi, Y.; Kassim, A.R.; et al. Estimation of six leaf traits of East Asian forest tree species by leaf spectroscopy and partial least square regression. *Remote Sens. Environ.* **2019**, *233*, 111381. [\[CrossRef\]](#)
56. Yi, L.; Kangkang, W.; Ke, C.; Jianqiang, H.; Yong, Z.; Guang, Y.; Ning, Y.; Ben, N.; Bin, W.; Lei, W.; et al. Forecasting Monthly Water Deficit Based on Multi-Variable Linear Regression and Random Forest Models. *Water* **2023**, *15*, 1075. [\[CrossRef\]](#)
57. Amirruddin, A.D.; Muharam, F.M.; Ismail, M.H.; Ismail, M.F.; Tan, N.P.; Karam, D.S. Hyperspectral remote sensing for assessment of chlorophyll sufficiency levels in mature oil palm (*Elaeis guineensis*) based on frond numbers: Analysis of decision tree and random forest. *Comput. Electron. Agric.* **2020**, *169*, 105221. [\[CrossRef\]](#)
58. Dong, J.; Qin, W.; Mo, J. Low-Cost Multi-Objective Optimization of Multiparameter Antenna Structures Based on the 11 Optimization BPNN Surrogate Model. *Electronics* **2019**, *8*, 839. [\[CrossRef\]](#)
59. Yuan, Y.; Wang, X.; Shi, M. Prediction of relative chlorophyll content in *Hopea hainanensis* based on multispectral frequency domain features. *J. Beijing For. Univ.* **2023**, *45*, 42–52. (In Chinese)
60. Gao, C.; Li, H.; Wang, J.; Zhang, X.; Huang, K.; Song, X.; Yang, W.; Feng, M.; Xiao, L.; Zhao, Y.; et al. Combined use of spectral resampling and machine learning algorithms to estimate soybean leaf chlorophyll. *Comput. Electron. Agric.* **2024**, *218*, 108675. [\[CrossRef\]](#)
61. Qifu, L.; Cong, X.; Xueyu, T.; Lihua, C.; Jingmin, J.; Yanjie, L. Estimating canopy chlorophyll in slash pine using multitemporal vegetation indices from uncrewed aerial vehicles (UAVs). *Precis. Agric.* **2024**, *25*, 1086–1105.
62. Gao, G.; Zhang, L.; Wu, L.; Yuan, D. Estimation of Chlorophyll Content in Wheat Based on Optimal Spectral Index. *Appl. Sci.* **2024**, *14*, 703. [\[CrossRef\]](#)
63. Tripathi, R.; Mohanty, S.; Swain, C.K.; Das, S.; Nayak, P.; Moharana, K.C.; Mohapatra, S.D.; Goud, B.R.; Raghu, S.; Sahoo, R.N.; et al. Predicting chlorophyll and nitrogen content in rice using multiple regression models. *J. Plant Nutr.* **2024**, *47*, 881–904. [\[CrossRef\]](#)
64. Lu, X.; Wang, Q.; Zhang, H. Inversion of SPAD of *Cinnamomum camphora* Dwarf Forest Based on UAV Multispectral Remote Sensing. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 201–209. (In Chinese)
65. Harpinder, S.; Ajay, R.; Raj, S.; Brijendra, P. Estimation of chlorophyll, macronutrients and water content in maize from hyperspectral data using machine learning and explainable artificial intelligence techniques. *Remote Sens. Lett.* **2022**, *13*, 969–979.
66. Zhou, L.; Nie, C.; Su, T.; Xu, X.; Song, Y.; Yin, D.; Liu, S.; Liu, Y.; Bai, Y.; Jia, X.; et al. Evaluating the Canopy Chlorophyll Density of Maize at the Whole Growth Stage Based on Multi-Scale UAV Image Feature Fusion and Machine Learning Methods. *Agriculture* **2023**, *13*, 895. [\[CrossRef\]](#)
67. Feng, H.; Yang, Z.; Chen, H. Estimation of Summer Maize SPAD Based on UAV Multispectral Images. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 211–219. (In Chinese)
68. Zhang, X.; Yu, Z.; Li, H. Remote sensing estimation model of SPAD for rice leaves in Northeast China. *J. China Agric. Univ.* **2020**, *25*, 66–75. (In Chinese)
69. Bo, J.; Hailong, L.; Qianguo, X.; Jiannan, C.; Xiangyang, Z.; Lin, L.; Sisi, L.; Zhiming, Z.; Huiyan, X.; Ling, M. Evaluating Traditional Empirical Models and BPNN Models in Monitoring the Concentrations of Chlorophyll-A and Total Suspended Particulate of Eutrophic and Turbid Waters. *Water* **2021**, *13*, 650. [\[CrossRef\]](#)
70. Sun, W.-Q.; Zhao, Y.-S.; Tu, L.-L. Analysis of related factors of slope plant hyperspectral remote sensing. *Spectrosc. Spectr. Anal.* **2014**, *34*, 2495–2499. (In Chinese)
71. Dong, C.; Fang, L. Association Analysis between the Site Index Model and the Site Factors of *Cunninghamia lanceolata* Timber Forest in Western Zhejiang Province. *Nat. Environ. Pollution Technol.* **2019**, *18*, 359–368.
72. Wu, N.; Li, Z.; Liao, S. Spectral Characteristics and Influencing Factors of *Pinus kesiya* var. *langbianensis* Based on Airborne Hyperspectral Technique. *For. Res.* **2018**, *31*, 63–68. (In Chinese)
73. Deng, L.; Chen, Y.; Zhao, Y.; Zhu, L.; Gong, H.-L.; Guo, L.-J.; Zou, H.-Y. An approach for reflectance anisotropy retrieval from UAV-based oblique photogrammetry hyperspectral imagery. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102442. [\[CrossRef\]](#)
74. Coste, S.; Baraloto, C.; Leroy, C.; Marcon, É.; Renaud, A.; Richardson, A.D.; Roggy, J.-C.; Schimann, H.; Uddling, J.; Hérault, B. Assessing foliar chlorophyll contents with the SPAD-502 chlorophyll meter: A calibration test with thirteen tree species of tropical rainforest in French Guiana. *Ann. For. Sci.* **2010**, *67*, 607. [\[CrossRef\]](#)
75. Donnelly, A.; Yu, R.; Rehberg, C.; Meyer, G.; Young, E.B. Leaf chlorophyll estimates of temperate deciduous shrubs during autumn senescence using a SPAD-502 meter and calibration with extracted chlorophyll. *Ann. For. Sci.* **2020**, *77*, 30. [\[CrossRef\]](#)
76. Srivastava, P.K.; Rawat, R. Retrieval of leaf chlorophyll content using drone imagery and fusion with Sentinel-2 data. *Smart Agric. Technol.* **2023**, *6*, 100353. [\[CrossRef\]](#)

-
77. El-Alem, A.; Chokmani, K.; Venkatesan, A.; Rachid, L.; Agili, H.; Dedieu, J.P. How Accurate Is an Unmanned Aerial Vehicle Data-Based Model Applied on Satellite Imagery for Chlorophyll-a Estimation in Freshwater Bodies? *Remote Sens.* **2021**, *13*, 1134. [[CrossRef](#)]
 78. Zhen, J.; Jiang, X.; Xu, Y.; Miao, J.; Zhao, D.; Wang, J.; Wang, J.; Wu, G. Mapping leaf chlorophyll content of mangrove forests with Sentinel-2 images of four periods. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102387. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.