

Article

Combining UAV Remote Sensing with Ensemble Learning to Monitor Leaf Nitrogen Content in Custard Apple (*Annona squamosa* L.)

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Abstract: One of the most important nutrients needed for fruit tree growth is nitrogen. For orchards to get targeted, well-informed nitrogen fertilizer, accurate, large-scale, real-time monitoring, and assessment of nitrogen nutrition is essential. This study examines the Leaf Nitrogen Content (LNC) of the custard apple tree, a noteworthy fruit tree that is extensively grown in China's Yunnan Province. This study uses an ensemble learning technique based on multiple machine learning algorithms to effectively and precisely monitor the leaf nitrogen content in the tree canopy using multispectral canopy footage of custard apple trees taken via Unmanned Aerial Vehicle (UAV) across different growth phases. First, canopy shadows and background noise from the soil are removed from the UAV imagery by using spectral shadow indices across growth phases. The noise-filtered imagery is then used to extract a number of vegetation indices (VIs) and textural features (TFs). Correlation analysis is then used to determine which features are most pertinent for LNC estimation. A two-layer ensemble model is built to quantitatively estimate leaf nitrogen using the stacking ensemble learning (Stacking) principles. Random Forest (RF), Adaptive Boosting (ADA), Gradient Boosting Decision Trees (GBDT), Linear Regression (LR), and Extremely Randomized Trees (ERT) are among the basis estimators that are integrated in the first layer. By detecting and eliminating redundancy among base estimators, the Least Absolute Shrinkage and Selection Operator regression (Lasso) model used in the second layer improves nitrogen estimation. According to the analysis results, Lasso successfully finds redundant base estimators in the suggested ensemble learning approach, which yields the maximum estimation accuracy for the nitrogen content of custard apple trees' leaves. With a root mean square error (RMSE) of 0.059 and a mean absolute error (MAE) of 0.193, the coefficient of determination (R^2) came to 0.661. The significant potential of UAV-based ensemble learning techniques for tracking nitrogen nutrition in custard apple leaves is highlighted by this work. Additionally, the approaches investigated might offer insightful information and a point of reference for UAV remote sensing applications in nitrogen nutrition monitoring for other crops.

Keywords: canopy nitrogen content; UAV remote sensing; ensemble learning; Lasso model



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1. Introduction

Because of its unique flavor and great nutritional content, the custard apple tree is a popular fruit crop among customers [1]. The most crucial mineral nutrient component for fruit tree growth is nitrogen. Precision fertilization and management decision-making in orchards depend on quick, precise, dynamic, and extensive nitrogen monitoring and diagnosis [2]. As a reliable, effective, and broadly used detection method, remote sensing offers crucial information support for sustainable development and precise crop nutrient management [3]. In terms of managing orchards, including estimating leaf area [4], water content [5], and chlorophyll levels [6], it has had considerable success.

Satellite imagery [7], UAV remote sensing [8], and ground-based hyperspectral data [9] are all examples of remote sensing data. Hyperspectral data collection on the ground is labor-intensive, time-consuming, and prone to human error [10]. However, satellite remote sensing data has slow acquisition cycles, poor resolution, and is susceptible to cloud cover [11]. On the other hand, because of its versatility, quick and real-time data gathering capabilities, affordability, and superior image spatial resolution, Unmanned Aerial Vehicle (UAV) remote sensing technology has advanced quickly in crop nitrogen nutrition monitoring [12]. Based on this, UAV remote sensing technology demonstrates clearer advantages in tasks that require small-scale and high-frequency monitoring. However, elements like canopy shadows [13] and soil background [14,15] might degrade the quality of UAV photography by lowering the reflectance measured. To eliminate the impacts of soil background and canopy shadow, multispectral shadow indices [16] are therefore crucial.

Since drone technology has become so popular, numerous researchers have evaluated crop development and the general health trends of field crops using various spectral bands and vegetation indices obtained from UAVs. For instance, Lu et al. had encouraging findings when they combined UAV RGB photos with vegetation indices, plant height, and canopy coverage to quantify the nitrogen content of summer maize leaves [17]. Rich texture features found in high-resolution remote sensing photos are crucial for research since they are not affected by color or brightness [18]. In order to assess wheat nitrogen nutritional indices, Zhang et al. [19] combined spectral, thermal, and textural information with machine learning techniques. Additionally, Zhuang et al. [20] discovered that the best regression accuracy was obtained by using UAV-derived VIs and TFs as predictors for estimating tea plant LAI. This was more precise than using only VIs or multispectral bands. In a similar vein, Wang et al. [21] created a model that combined vegetation and texture indices and demonstrated great generalization ability while accurately assessing the nitrogen content of rice stems and leaves.

Based on spectral data, there are now four primary approaches for crop nitrogen status monitoring: physical models, parametric regression, linear non-parametric regression, and non-linear non-parametric regression (machine learning algorithms) [22]. As UAV technology advances, machine learning methods are being used more and more in UAV-based hyperspectral measurement research [23]. According to the literature, Liu et al. [24] developed a quantitative model using multiple linear regression (MLR) and backpropagation neural network (BPNN) algorithms to estimate the LNC of winter wheat at four growth stages. Jia et al. [25] used stepwise MLR and BPNN methods to predict the LNC of flue-cured tobacco leaves. After reducing dimensionality using the SPA, LASSO, and Elastic Net methods, Cao [26] constructed nine models to invert nitrogen content using multiple linear regression, stepwise regression, and partial least squares. A robust relationship between nitrogen content and spectral characteristics was established using inverse modeling techniques, providing a more complex and accurate estimation method. The performance of this method [27] was also demonstrated in the hyperspectral estimation of nitrogen content in tobacco leaves using UAVs. The development of UAV-based hyper-

spectral imaging technology provides a non-destructive and high-throughput approach for effectively monitoring the physiological and biochemical traits of crops [28]. Therefore, the use of UAV remote sensing to estimate LNC has become a key technical tool nowadays.

However, individual models frequently fall short of their full potential due to their limits in terms of complexity and data diversity [27,29]. Multiple separate machine learning models are combined in ensemble learning, which has benefits over single models, including increased generalization capabilities, decreased overfitting, and better prediction accuracy [30]. Ensemble learning predictive models include Bagging, Stacking, and Boosting. Stacking can give full play to the characteristics and advantages of the base model, and the choice of the base model is relatively flexible and can be adapted to different types of data and problems. An excessive number of base models increases the model complexity and computational cost, and previous studies usually chose linear models in the selection of meta-models [31]. This means that only the base model results are used as inputs to the meta-model, ignoring the performance of the base model. When the base model does not work well, simple stacking creates redundancy, and the meta-modeling results are compromised. Lasso regression [32] is added to the second layer of the model to apply weights to each base model, which aids in choosing the top-performing models because machine learning algorithms perform very differently.

The custard apple trees have high economic value, but their cultivation process lacks standardization and informatization. Therefore, the aim is to use remote sensing data to construct a crop nutrient monitoring model, targeting precise and real-time nitrogen content monitoring of the custard apple trees. In light of this, this study builds an ensemble model for nitrogen content estimate using a Stacking architecture that incorporates RF [33], GBDT [34], ADA [35], LR [36], and ERT [37] with UAV remote sensing data, spectral information, and texture characteristics. A well-balanced ensemble learning framework is created by applying Lasso regression to calculate the weights of the basic models. The effectiveness of the suggested ensemble learning approach for inverting the nitrogen content of custard apple plants is assessed, offering insightful information to direct agricultural production methods. The specific contributions of this study are as follows:

- (1) The NDCSI index was used to perform threshold-based removal of shadow noise and soil background in UAV imagery.
- (2) UAV remote sensing imagery data were collected, and LNC data were measured. Eleven typical VIs were constructed. The correlation coefficients between spectral features, texture features, and LNC were initially screened using Pearson correlation, and sensitive features were further selected through RF modeling.
- (3) To further improve the inversion quality of LNC, a Lasso-Stacking model with a feature selection function was constructed for nitrogen content monitoring in custard apple.

2. Materials and Methods

2.1. Study Area

The study region is situated at 101°47' E longitude and 25°20' N latitude in Yuanmou County, Kunming City, Yunnan Province. The topography of Yuanmou County is low in the center and high on the sides. It is situated in a low-elevation, low-latitude highland area. The subtropical monsoon climate of South Asia is what defines the warm climate. With an average yearly temperature of 21.9 °C, the region faces drought and little precipitation. It is a natural greenhouse because the temperature stays high all year round, and there is never any frost. Yuanmou is the perfect place to grow custard apples because of its special topographical circumstances. An overview of the study area is shown in Figure 1.

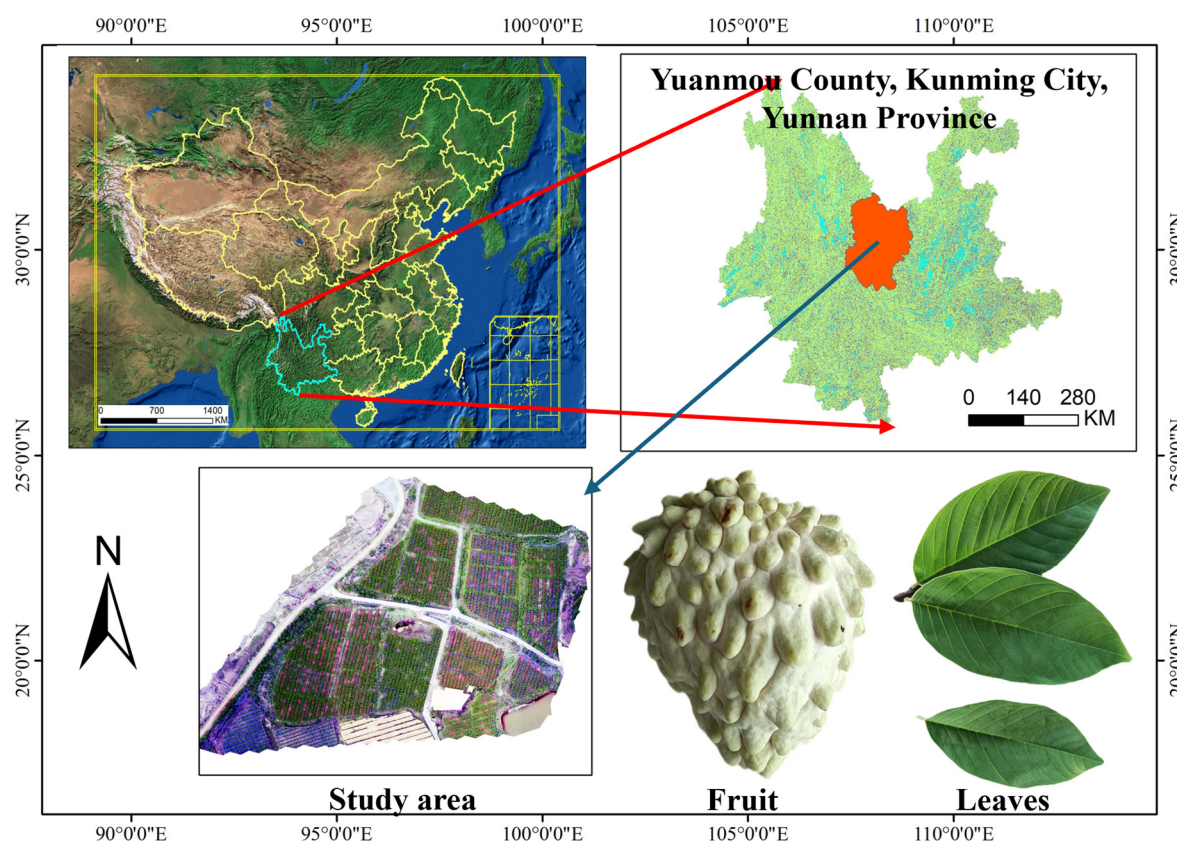


Figure 1. Geographical location of the study area.

2.2. UAV Imagery Acquisition and Preprocessing

With a maximum flight altitude of 6000 m, a maximum horizontal flight speed of 21 m per second, a maximum wind resistance speed of 12 m per second, a maximum tilt angle of 35 degrees, and a maximum flight duration of 46 min, the DJI Mavic 3M quadcopter (Shenzhen DJI Innovation Technology Co., Shenzhen, China) was the UAV utilized for this investigation. A 20-megapixel digital camera and four 5-megapixel multispectral cameras (for the green (G), red (R), red edge (RE), and near-infrared (NIR) bands) make up the image sensor system in use. The camera brand is DJI, and the model is the Mavic 3 Multispectral Camera. The visible light camera model is 4/3 CMOS, and the multispectral camera model is 1/2.8-inch CMOS. Table 1 provides a summary of the UAV camera parameters. Figure 2 shows a physical drawing of the drone. The drone was manufactured by China's Shenzhen DJI Innovation Technology Co., Shenzhen, China.

Table 1. Multispectral camera parameters for UAV.

Waveband Band	Central Wavelength (nm)	Spectral Bandwidth (nm)
G	560 nm + 16 nm	40 nm
R	650 nm + 16 nm	40 nm
RE	730 nm + 16 nm	20 nm
NIR	860 nm + 26 nm	30 nm



Figure 2. DJI Mavic 3M.

UAV imaging data collection was carried out in the custard apple orchard on 24 May 2023, 26 August 2023, and 1 November 2023. Imaging was done between 10:00 and 14:00 on clear, mostly cloudless weather days to guarantee data accuracy and dependability. The UAV flight area is within the range of latitude $25^{\circ}72'$ and longitude $101^{\circ}79'$. To get accurate reflectance data, a calibrated white reference panel was set up before every flight. The UAV's flight parameters were predetermined to be 6 m/s, 50 m height, 80% forward overlap, and 75% side overlap.

DJI Terra 3.1.0 and ENVI 5.6 software were used for image mosaicking and pre-processing following UAV image acquisition. Control points were used to apply geometric correction to the picture, and then a pseudo-invariant feature-based radiometric correction technique was used. This method used the reflectance data from the calibrated white reference panel to convert the multispectral images' digital number (DN) values to reflectance values. To enable later radiometric correction of the photos, the reflectance of the calibration panel was measured using an ASD spectrometer prior to each UAV flight. Following the calculation of the DN values for each spectral band in the multispectral images that corresponded to the target crop, the multispectral images were radiometrically corrected using the following formula [38]:

$$R_1 = \frac{D_{n1}}{D_{n2}} * R_2 \quad (1)$$

Theorem 1. *R₁ is the target point's reflectance, D_{n1} is the target point's average DN value, D_{n2} is the calibration panel's default DN value, and R₂ is the calibration panel's measured reflectance value (with values of 0.9459 for green, 0.9455 for red, 0.9487 for red edge, and 0.9395 for near-infrared).*

2.3. UAV Imagery Shadow Removal

The imagery is susceptible to influence from soil background and canopy shadows because of the substantial reflectance differences between soil and custard apple trees and the trees' intricate three-dimensional structure. The accuracy of inversion is impacted by this interference since it lowers the quality of the custard apple trees' reflectance data. These impacts can be successfully lessened by using a threshold segmentation technique. For efficient shadow removal, according to the experimental treatment of canopy shading by Luo, the Normalized Difference Canopy Shadow Index (NDCSI) [39] threshold of 0.3 [40] was obtained to have a better effect (Figure 3). The following is the NDCSI formula:

$$NDCSI = \frac{R_{NIR} - R_R}{R_{NIR} + R_R} \frac{R_{RE} - R_{REMIN}}{R_{REMAX} - R_{REMIN}} \quad (2)$$

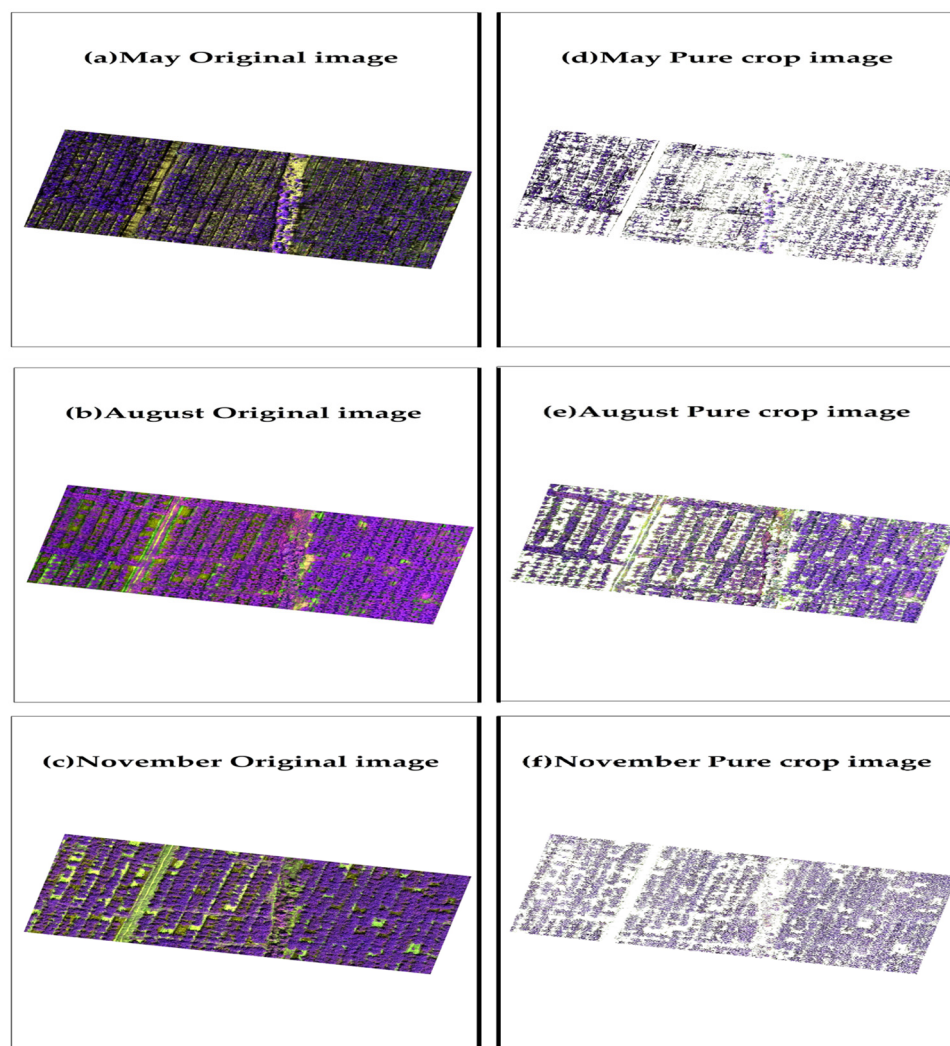


Figure 3. (a–f) show a comparison between the original images and the images with shadows and soil removed across three growth stages.

Theorem 2. R_{NIR} represents the reflectance in the near-infrared band, R_R represents the reflectance in the red band, R_{RE} represents the reflectance in the red-edge band, R_{REMIN} is the minimum value of the red-edge reflectance in the image, and R_{REMAX} is the maximum value of the red-edge reflectance in the image.

2.4. Information from the Ground Gathering and Measuring the Nitrogen Level in Custard Apple Leaves

Leaf samples from custard apple trees were gathered for this investigation in three crucial months: 24 May 2023, 26 August 2023, and 1 November 2023. In the 29 sampling areas distributed across six plots, three representative leaf samples from the custard apple trees were collected in each sampling area. The sampling points are shown in Table 2 below. Samples were first inactivated in the lab by heating them to 105 °C for 30 min, then drying them at 80 °C until their weight remained constant. An elemental analyzer was used to measure the amount of nitrogen. To quantify nitrogen, the samples were first burned at a high temperature, which allowed the nitrogen to react with the oxygen and create nitrogen oxides. These nitrogen oxides were then converted to nitrogen gas under the circumstances. Lastly, by measuring the amount of nitrogen gas generated, the analyzer determined the nitrogen content of the samples.

Table 2. Latitude and longitude of the leaf sampling points.

Sample	Latitude	Longitude
Sample 1	25.72087188	101.7975859
Sample 2	25.7208494	101.7974183
Sample 3	25.72138112	101.7974339
Sample 4	25.72137894	101.7977156
Sample 5	25.7212916	101.7974944
Sample 6	25.72169407	101.7970533
Sample 7	25.72078584	101.7969467
Sample 8	25.72124224	101.79706
Sample 9	25.72170824	101.7968015
Sample 10	25.72144288	101.7967326
Sample 11	25.72205578	101.7978633
Sample 12	25.72232165	101.7979453
Sample 13	25.7225071	101.7979962
Sample 14	25.722647	101.7978964
Sample 15	25.7223012	101.7978186
Sample 16	25.72183514	101.7986564
Sample 17	25.7219216	101.7983524
Sample 18	25.72219541	101.7983899
Sample 19	25.72257355	101.7984414
Sample 20	25.72248967	101.7986328
Sample 21	25.72218713	101.7985957
Sample 22	25.7215716	101.7990846
Sample 23	25.72172485	101.7989925
Sample 24	25.72230296	101.7989335
Sample 25	25.72242464	101.7991441
Sample 26	25.72145072	101.7982732
Sample 27	25.72123758	101.7981791
Sample 28	25.72109625	101.7980155
Sample 29	25.72087188	101.7975859

2.5. Extraction of Vegetation Indices from Multispectral Imagery

Compared to raw band reflectance, vegetation indices, which are derived from the reflectance values of multiple spectral bands, provide a more accurate assessment of vegetation health. These indices offer a rapid and efficient approach to evaluating plant status. Several vegetation indices, including the Modified Normalized Difference Red Edge (MNDRE), Normalized Red Index (NRI), Red Edge Simple Ratio (RESR), Transformed Normalized Difference Vegetation Index (TNDVI), Normalized Difference Vegetation Index (NDVI), Wide Dynamic Range Vegetation Index (WDRVI), Normalized Green Index (NGI), Modified Simple Ratio (MSR), Normalized Red Edge Index (NREI_R), Ratio Vegetation Index (RVI), and Normalized Red Edge Index (NREI), were calculated using the reflectance data from UAV imagery. Additionally, four spectral bands—green, red, red edge, and near-infrared—were included in the analysis alongside the original reflectance data. In each growth stage, among the 29 sampling areas, representative regions with uniform growth distribution were selected as data sources based on radiometrically corrected UAV remote sensing images combined with BeiDou Navigation Satellite System (BDS, Chance Location Network Ltd., Shanghai, China) coordinates of ground measurement points (as shown in Table 2). The area of each sampling region in the images was set to 20×20 pixels, totaling 400 pixels, which is considered to represent the leaf area of custard apple in UAV imagery. From these 400 pixels, the reflectance of G, R, RE, and NIR bands was extracted, and their average values were calculated to construct the spectral feature parameters. The

same method was applied to texture features. Table 3 presents the vegetation indices constructed using spectral bands from UAV imagery.

Table 3. Vegetation indices constructed using UAV spectral bands.

Vegetation Index (VI)	Formula	References
Modified Normalized Difference Red Edge (MNDRE)	$MNDRE = (NIR - RE + 2 \times R) / (NIR + RE - 2 \times R)$	[41]
Normalized Red Index (NRI)	$NRI = R / (NIR + R + RE)$	[41]
Red Edge Simple Ratio (RESR)	$RESR = RE / R$	[42]
Transformed Normalized Vegetation Index (TNDVI)	$TNDVI = \sqrt{(NIR - R) / (NIR + R) + 0.5}$	[43]
Normalized Difference Vegetation Index (NDVI)	$NDVI = (NIR - R) / (NIR + R)$	[44]
Wide Dynamic Range Vegetation Index (WDRVI)	$WDRVI = (0.12 \times NIR - R) / (0.12 \times NIR + R)$	[45]
Normalized Green Index (NGI)	$NGI = G / (NIR + G + RE)$	[46]
Modified Simple Ratio (MSR)	$MSR = (NIR / R - 1) / \sqrt{NIR / R + 1}$	[47]
Normalized Red Edge Index (NREI_R)	$NREI\_R = RE / (NIR + RE + R)$	[41]
Ratio Vegetation Index (RVI)	$RVI = NIR / R$	[48]
Normalized Red Edge Index (NREI)	$NREI = RE / (NIR + G + RE)$	[49]

2.6. Multispectral Image Texture Features

The Gray Level Co-occurrence Matrix (GLCM) is the most widely used technique for texture extraction in statistical methods, structured texture analysis, and spectral analysis. Eight GLCM-based texture features—Mean, Variance (Var), Homogeneity (Hom), Contrast (Con), Dissimilarity (Dis), Entropy (Ent), Second Moment (Sec), and Correlation (Cor)—were computed for every spectral band in this investigation. To increase the precision of estimating the nitrogen content of custard apple trees, these texture features offer important information on the structure and texture patterns of the canopy. The calculations [50] are as follows:

$$\text{Mean} = \sum_{i=0}^{G-1} i \cdot p(i) \quad (3)$$

$$\text{Variance} = \sum_{i=0}^{G-1} (i - \mu)^2 \cdot p(i) \quad (4)$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1 + (i - j)^2} \quad (5)$$

$$\text{Contrast} = \sum_{i,j} (i - j)^2 (i - j)^2 \quad (6)$$

$$\text{Dissimilarity} = \sum_{i=1}^G \sum_{j=1}^G p(i,j) \cdot |i - j| \quad (7)$$

$$\text{Entropy} = \sum_{i,j} p(i,j)^2 \quad (8)$$

$$\text{SecondMoment} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j) \cdot (i - \mu)(j - \mu) \quad (9)$$

$$\text{Correlation} = \frac{\sum_{i,j} (i - \mu)(j - \mu)p(i,j)}{\sigma_i \sigma_j} \quad (10)$$

Theorem 3. Where (i, j) represent the grayscale level indices, $p(i, j)$ is the joint probability of grayscale levels i and j in the GLCM (Gray Level Co-occurrence Matrix). μ is the mean grayscale value of the image, and σ is the standard deviation of the grayscale levels.

2.7. Development of the Stacking Ensemble Learning Method for Calculating LNC of Custard Apple Leaf

The LNC of custard apple trees is estimated in this study using a stacking ensemble learning framework. An ensemble learning technique called stacking improves overall predictive accuracy by combining the predictions of several base learners. Prediction accuracy is frequently greatly increased by stacking, which takes advantage of the advantages of various models. The base learners in this work were trained and estimated using 5-fold cross-validation. A meta-model for nitrogen content estimation was then trained using the estimation findings from these base learners. By removing estimation biases from the base learners, the meta-learner in the stacking model enhances the ensemble model's overall prediction accuracy and generalization capacity. RF, GBDT, ADA, LR, and ERT are among the base learners selected for this investigation. The ensemble model's meta-learner is chosen to be Lasso regression. Figure 4 illustrates the workflow design of the ensemble learning approach for estimating custard apple LNC.

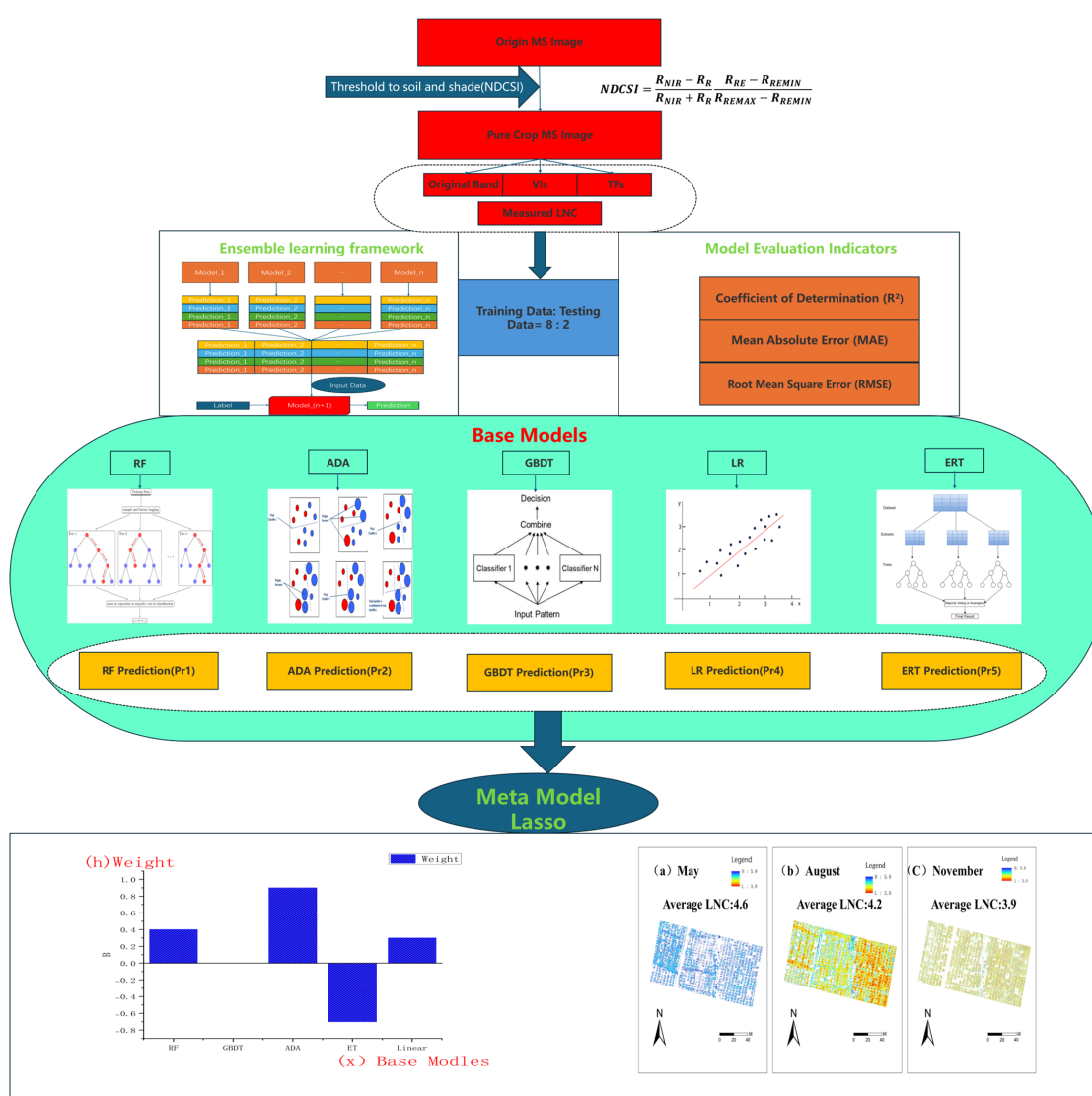


Figure 4. Design of an Ensemble Learning Workflow for Estimating LNC in Custard Apple.

2.8. Techniques for Ensemble Learning

The following models are selected as basis learners in the ensemble learning design: Lasso regression is employed as the meta-model, along with RF, GBDT, ADA, LR, and

ERT.RF is a decision tree-based ensemble learning technique. For classification or regression, it constructs several decision trees and aggregates their results. A random selection of features is used to determine the split at each node, and each tree is trained on a subset of the data. RF improves generalization skills and lessens model overfitting. Weighted voting is the foundation of the ensemble learning technique known as ADA.

To increase the predictive capacity of the model, it builds several weak classifiers, such as decision trees. Misclassified samples are given greater weights in each iteration, which forces later classifiers to concentrate more on these challenging cases. Assuming a linear relationship between the input and output variables, linear regression is one of the most basic regression models. LR and linear classifiers, such as logistic regression, are examples of common linear models. ERT is an RF variation. The main distinction is that the dividing method is more “extreme.” Instead of choosing the best split point, a random split point is selected for every feature in each tree. The model’s variety is increased by this method. A linear regression model called Lasso seeks to minimize both the L1 norm of the coefficients and the sum of squared residuals. A sparse model is produced via the L1 regularization term, which essentially performs variable selection by shrinking some coefficients to zero. By lessening susceptibility to noise in the training data, Lasso enhances the model’s capacity for generalization and helps avoid overfitting in high-dimensional data. It is rather easy to use and enables regularization settings to be changed to balance the model. The formula [51] is as follows:

$$asso = \min_{\beta} \left(\frac{1}{2n} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^p |\beta_j| \right) \quad (11)$$

Theorem 4. Represents the number of samples, p is the number of features, y_i is the true value of the i -th sample, x_{ij} is the value of the j -th feature for the i -th sample, β_0 is the intercept term, β_j is the regression coefficient for the j -th feature, and λ is the regularization parameter.

Lasso regression is employed as the meta-model to build the ensemble model, while RF, GBDT, ADA, LR, and ERT are chosen as foundation models. The performance of each base model in terms of its capacity to estimate the data is assessed using Lasso. To create 68 training samples and 18 validation samples, 86 chlorophyll content samples are randomly shuffled and divided into training and validation sets in an 80:20 ratio during the modeling phase. The estimation accuracy is assessed using the following metrics: RMSE, MAE, and R^2 . Among these, the estimation accuracy increases with R^2 being closer to 1 and MAE and RMSE values being smaller. The calculations [52,53] are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - x_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (12)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad (14)$$

Theorem 5. y_i represents the actual nitrogen content, x_i represents the predicted nitrogen content, $\bar{y}$ is the mean of the actual nitrogen values, and n is the number of samples.

Through the above data collection and feature extraction, this study prepares to compare five regression models and their ensemble effects. The next section will discuss in detail the construction and validation process of each model.

3. Results and Analysis

3.1. Correlation Analysis of Multispectral Spectral Features and Nitrogen Content

A correlation analysis was conducted between the spectral features and the obtained nitrogen content in the custard apple canopy. The results showed that the correlation coefficients between the four original bands (G, R, RE, NIR) and nitrogen content ranged from 0.027 to 0.554, with values of 0.554, 0.432, 0.027, and 0.136, respectively. According to Pearson correlation analysis, the G and R bands exhibited a moderate correlation with the nitrogen content in the custard apple canopy. The correlation coefficients between nitrogen content and the computed vegetation indices (MNDRE, NRI, RESR, TNDVI, NDVI, WDRVI, NGI, MSR, NREI_R, RVI, and NERI) ranged from 0.648 to 0.422. By integrating the correlations between the various spectral bands, a noticeable improvement was observed compared to the original bands, with a smaller variance. The correlation coefficients were as follows: 0.647, 0.509, 0.495, 0.477, 0.476, 0.469, 0.454, 0.453, 0.444, 0.433 and 0.422. According to Pearson correlation analysis, the vegetation indices all exhibited moderate to strong correlations with the canopy nitrogen content (LNC). Figure 5 presents the heatmap of spectral features with moderate or stronger correlations with LNC.

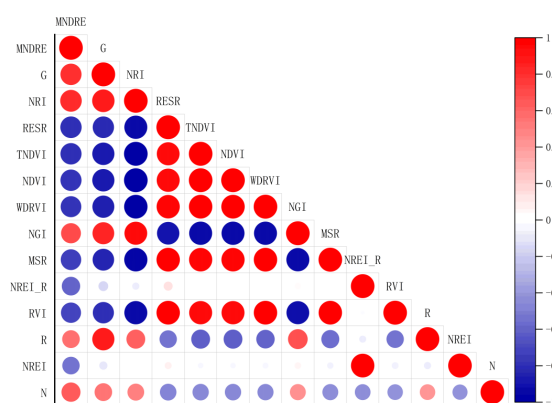


Figure 5. Presents the heatmap of spectral features with moderate or stronger correlations with the LNC of custard apple.

3.2. Nitrogen Content and Band Texture Features Correlation Analysis

The correlation analysis between all extracted multispectral texture features and the obtained LNC of custard apple is shown in Table 4. The results indicate that the texture indices of the red band exhibited a relatively strong correlation with the canopy nitrogen content, with correlation coefficients ranging from 0.348 to 0.548. In contrast, the texture indices of the red edge and near-infrared bands showed a weaker correlation, like the results observed for the red edge and near-infrared bands in the previous analysis. Table 4 presents the correlation values between the LNC of custard apple and UAV-derived spectral TFs.

Table 4. The correlation between the LNC of custard apple and the TFs of each spectral band.

TFs	Waveband			
	G	R	RE	NIR
Mean	0.064	0.503	0.205	0.249
Var	0.278	0.541	0.135	0.021
Hom	0.277	0.420	0.205	0.144
Con	0.278	0.506	0.151	0.018
Dis	0.163	0.548	0.007	0.147
Ent	0.094	0.517	0.276	0.298
Sec	0.214	0.459	0.180	0.123
Cor	0.116	0.348	0.182	0.183

3.3. Remote Sensing Modeling and Estimation of the Custard Apple Tree LNC

3.3.1. Selection of Input Feature Variables

To explore the optimal accuracy of three different input methods—spectral features, texture features, and the combination of spectral and texture features—random forest regression modeling was performed. The results are presented in Table 5. As shown in the table, the random forest model that combined both spectral and texture features as input achieved the highest accuracy. The modeling approach that incorporated texture features along with vegetation indices outperformed the modeling approach using single spectral features in estimating LNC. Specifically, the R^2 value increased by approximately 0.1 compared to using only spectral features, while both the MAE and RMSE decreased. Figure 6 presents the heatmap of the correlation between LNC and spectral as well as texture features. All features show a correlation with LNC greater than 0.4. Some spectral features have correlations with nitrogen content close to or exceeding 0.6, reflecting the direct influence of nitrogen content on vegetation reflectance. Although the correlation of texture features is slightly lower than that of some spectral features, they still exhibit significant correlations (all greater than 0.5). The correlation between spectral features and texture features is relatively low (represented by smaller dots in the heatmap), indicating that the two types of features are complementary in terms of information.

Table 5. Comparison of LNC Estimation Using Different Types of Feature Variables.

Input Variables	R^2	MAE	RMSE
VIs + R + G	0.539	0.229	0.081
TFs	0.614	0.215	0.067
VIs + TFs + R + G	0.621	0.216	0.066

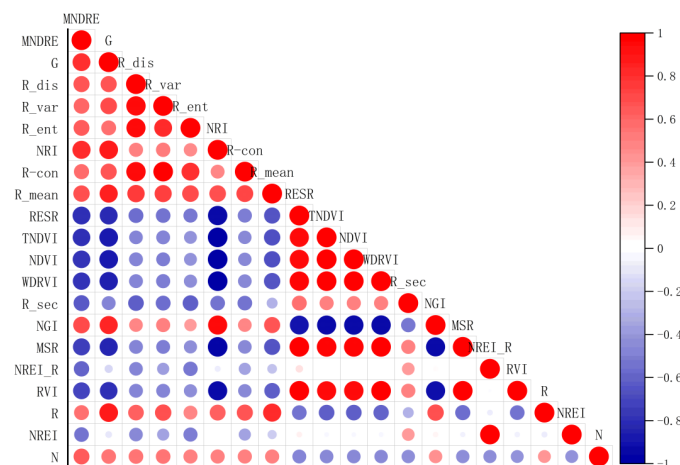


Figure 6. Heatmap of the correlation between custard apple LNC and the optimal input variables.

3.3.2. Inversion Modeling Using Ensemble Learning

The best input features were found and utilized in a stacking model to forecast the nitrogen content of the custard apple canopy following feature selection using Pearson correlation and variable selection using Random Forest. Data were standardized to minimize feature inconsistencies and improve model accuracy. Evaluation metrics for canopy nitrogen prediction using the Stacking-Lasso regression model and several base models are displayed in the following Table 5. While lower RMSE and MAE values suggest smaller disparities between anticipated and real values, showing stronger predictive potential for canopy nitrogen, higher values indicate better accuracy and regression performance. Every base model first made a primary regression prediction, and the second layer's Lasso used

the predictions as input. The final prediction was produced by Lasso by combining the outputs from the first-layer models. According to Table 5 and Figure 7, ERT and LR were comparatively weaker base models than ADA and RF. By analyzing the evaluation metrics in Table 5, it can be concluded that the performance of the ensemble learning model is superior to that of all the base models, although the improvement is relatively small. From the analysis of Figure 7, it is evident that the regression fit curve of the ensemble learning model is more concentrated around the trend line compared to the scatter points of the base models. This indicates that the stacking model is more accurate in capturing the main trend in the data. The stacking model demonstrates better performance in capturing the overall trend in the data, reducing overfitting, and improving prediction stability. Lasso functioned as the secondary learner in the ensemble framework of this study by automatically choosing and weighting the base models. By suppressing redundant or underperforming models, Lasso's regularization process successfully emphasized the models that made the biggest contribution to the total prediction. ADA and RF had strong positive weights, according to weight analysis, indicating that these models were able to collect crucial predictive data. In contrast, ERT had a negative weight, which Lasso used to challenge the idea that its predictions would contain some noise or inaccuracy. With a weight of zero, the GBDT model was eliminated without changing the results of the Stacking model, indicating that although its predictions overlapped with those of other models, they were less successful, which is why it was given zero weight. This weighting strategy successfully decreased duplication, increased prediction accuracy, and simplified the model. Table 6 presents the accuracy of the base models and the meta-model. To assess the significant differences in model performance, we conducted a paired t-test on MAE, RMSE, and R^2 values. The test results showed that the performance of the ensemble model (Stacking) significantly differed from all base models (RF, GBDT, ADA, ERT, and LR) in terms of MAE and RMSE ($p < 0.05$). For the R^2 metric, the difference between the Stacking model and RF and ADA models did not reach statistical significance, but the significance in MAE and RMSE still indicates superior overall performance. The ensemble model effectively reduced errors on the test set by combining the predictive capabilities of multiple base models. Figure 7 illustrates the fitting curve of the prediction model and the weights of the base models. From (a) RF, (b) GBRT, (c) ADA, (d) ERT, and (e) LR, it can be observed that the base models generally show good fitting ability in terms of overall trends but still exhibit some bias, with the data points in the high-value regions being more widely scattered. This suggests that single models may have limitations within certain specific ranges. In the (f) Stacking plot, it can be observed that the fitting curve of the ensemble model is more concentrated around the trend line, with data points being more tightly distributed compared to the base models. The Lasso meta-model effectively reduces model bias by integrating the outputs of the base models, enhancing the robustness of the predictions. The weight distribution in (g) shows that Lasso avoids the risk of overfitting a single model by assigning sparse weights to the base models in the ensemble.

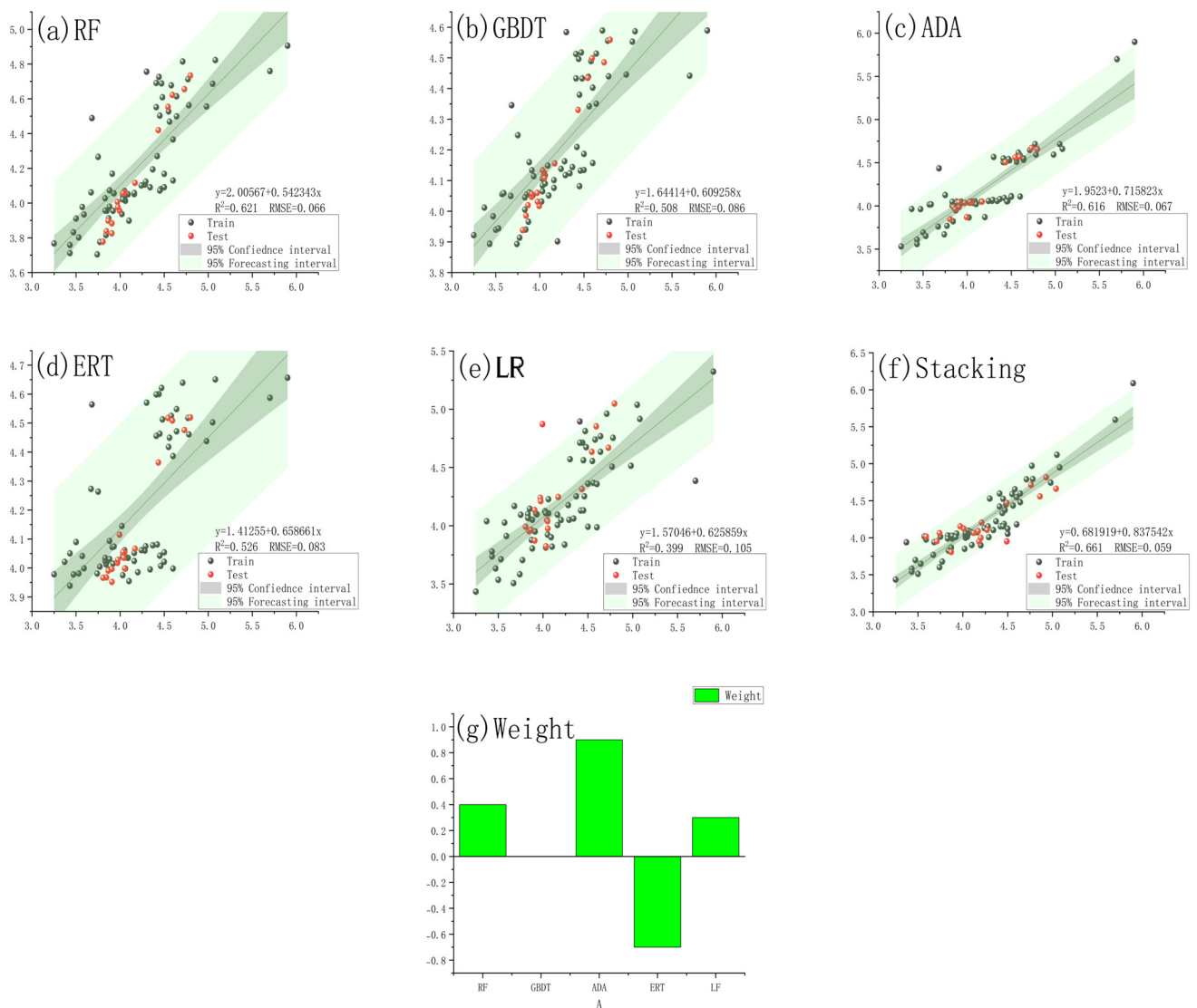


Figure 7. This illustrates the remote sensing estimation of custard apple leaf nitrogen content using different learning methods. (a–e) represent the fitting curves of the base models RF, GBDT, ADA, ERT, and LR, respectively. (f) shows the fitting curve of the meta-model, and (g) presents the Lasso weight graph.

Table 6. Evaluation metrics for base models and meta-models.

Model	R2	Train MAE	RMSE	R2	Test MAE	RMSE
RF	0.612	0.236	0.099	0.621	0.216	0.066
GBDT	0.477	0.270	0.135	0.508	0.237	0.086
ADA	0.763	0.184	0.061	0.616	0.215	0.067
ERT	0.410	0.296	0.152	0.526	0.247	0.083
LR	0.525	0.239	0.096	0.399	0.238	0.105
Stacking	0.851	0.153	0.038	0.661	0.193	0.059

3.3.3. Using Ensemble Learning for UAV-Based Nitrogen Content Estimation in Custard Apple Leaves

Spatial distribution maps of custard apple tree leaf nitrogen content during the three growth stages of May, August, and November were produced using the ensemble learning technique previously mentioned. Figure 8 shows clear trends in nitrogen content during various time periods. Concurrent fertilization techniques support the high nitrogen require-

ment in May when new leaves and shoots are growing vigorously. Usually, this leads to increased concentrations of nitrogen in the canopy. The trees still need nitrogen when they reach the fruit enlargement phase in August, but as the fruit develops, their need for other nutrients (like calcium and potassium) gradually rises, and their nitrogen concentration may stay mostly constant or even slightly decrease from earlier stages. Lower canopy nitrogen concentrations occur in November because of a decline in nitrogen demand when fruits mature. To prepare for growth the next year, trees may start storing nitrogen in their root systems during this time. All things considered, the average nitrogen content in May was 4.6, in August, it was 4.2, and in November, it was 3.9, the geographical distribution of nitrogen in the leaves seems to fit in nicely with the normal growth patterns of custard apple trees. Notably, certain regions show indications of nitrogen deficit in August, which is probably caused by fertilization techniques or environmental changes. This implies that during this crucial stage of growth, focused fertilization and water management, as well as prompt adaptation to shifting environmental conditions, may be advantageous. The LNC in May, August, and November gradually decreases, which generally follows the crop growth pattern. In August, there are a few locations where nitrogen content is missing, which highlights the significance of remote sensing. In future work, this can be used to timely supplement nitrogen fertilizer to ensure the yield and quality of the custard apple.

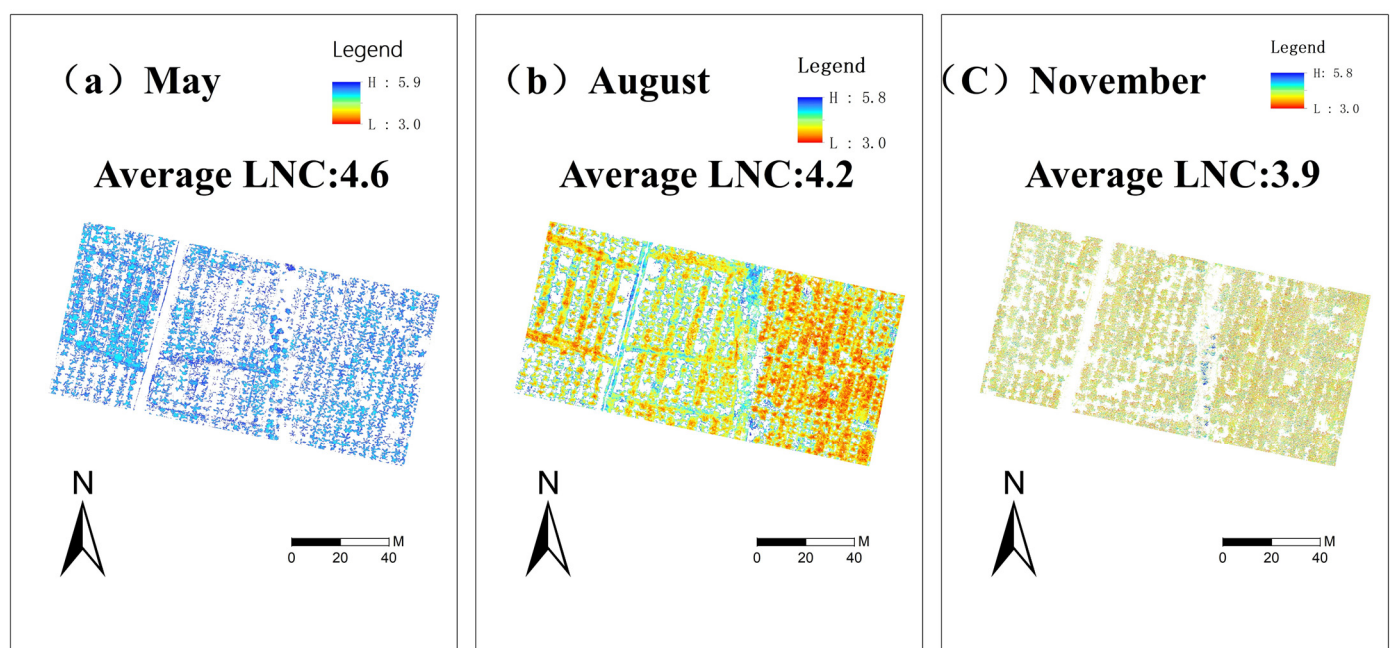


Figure 8. Remote Sensing Monitoring of Custard Apple Leaf Nitrogen Content Based on UAV Multispectral Imagery. (a–c) represent the remote sensing monitoring images of leaf nitrogen content in May, August, and November, respectively.

The above results show that the stacking model outperforms the base models in terms of overall performance and provides the LNC estimation maps. The next section will further explore the biological or physical reasons behind this performance improvement, as well as the issues related to model applicability.

4. Discussion

Numerous studies have investigated the estimation of canopy nitrogen content using remote sensing since it is a critical indicator of plant growth and development. It is useful to use UAVs to rapidly estimate the amount of nitrogen in custard apple canopies to improve yield and quality. However, there is frequently a lot of interference from shadow

and soil noise in UAV multispectral data. NDCSI can effectively eliminate interference caused by soil background and lighting variations. After preprocessing with NDCSI, the correlation of VIs significantly improves compared to the original imagery, with an increase of 0.2 or more in correlation strength. This improvement lays a solid foundation for more accurately reflecting crop nitrogen content. According to Xu et al. [54], nitrogen estimation can be improved by eliminating shadow and soil noise, which emphasizes the need for threshold-based preprocessing of multispectral shadow indices.

The relationship between crop physicochemical characteristics and spectral reflectance is successfully improved by this preprocessing step. Research on custard apple trees is still scarce despite the prevalence of studies on vegetative indices and textural characteristics in key staple crops. Our research shows that custard apple trees can benefit from the combination of vegetation indices and multispectral texture features for inversion modeling, which increases model accuracy. Through analysis, we found that spectral features can effectively reflect the growth, health status, and environmental conditions of plants, while texture features can reveal microscopic changes during the crop growth process. For instance, areas with higher nitrogen levels may exhibit more uniform textures, while low-nitrogen areas may show greater variation and irregularity. Spectral features primarily focus on the physiological state and growth condition of plants, whereas texture features emphasize spatial distribution and local variations. By combining both, the model can gain a more comprehensive understanding of the crop's nitrogen requirements and growth dynamics. Our findings are in line with those of Zhuang et al. [20], who discovered that adding texture features to inversion modeling in addition to vegetation indices produced models with higher accuracy than those that relied only on vegetation indices. For feature selection, this study used Random Forest and Pearson correlation, although these approaches were a little limited, especially for texture characteristics, where red band texture predominated because of its greater correlation. To improve the selection process, future research will examine a wider range of feature selection techniques. Furthermore, data richness and quality are crucial [55]; for more thorough data gathering, future research may incorporate hyperspectral and UAV digital imagery data. Ensemble learning [27,56] is a new machine learning method that combines several predictive models and capitalizes on their advantages to increase model robustness and accuracy. Consistent with earlier research [29,57], a Stacking-Lasso ensemble model that included RF, GBDT, ADA, LR, and ERT models produced better prediction results in this investigation. Even though ensemble learning increased accuracy for all base models, it only slightly outperformed the top-performing base model. Future studies will investigate various base models and alternative meta-model combinations. Due to its own intrinsic fitting capabilities, Lasso may run the danger of overfitting even if it can assist in feature selection and redundancy removal [58]. The overfitting issue can be effectively mitigated by adjusting the regularization parameters and using meta-modeling methods such as Ridge and Elastic Net. Adding a third model layer or looking for easier ways to determine weights could increase the accuracy and dependability of the model. The purpose of this study was to use UAV multispectral data to quickly and accurately predict canopy nitrogen for custard apple trees, which could help direct their growth. However, the study's application for widespread use was limited because it only covered one year. In the future, by acquiring data from more years and multiple locations, we will incorporate variables such as year and different geological characteristics into the model. This will help improve the model's ability to capture differences across years and locations, thereby enhancing its generalization ability and applicability. Future research will use multi-year experiments to collect additional data points and evaluate the findings [59], ultimately enhancing generalizability and usefulness in agricultural monitoring.

Although this study provides a UAV-based remote sensing method for nitrogen monitoring, several directions remain to be explored and optimized:

- **Integration of Multi-source Data:** We plan to integrate UAV remote sensing data with hyperspectral satellite data and ground sensor data to construct a more comprehensive multi-source data fusion framework. This will enhance the model's universality and its effectiveness in large-scale applications.
- **Expansion of Spatiotemporal Data:** The next step is to further integrate multi-year remote sensing data and multi-location monitoring data to address the challenges of nitrogen content monitoring under varying climatic conditions and crop cultivation patterns, thereby improving the model's generalization capability.
- **Model Optimization and Generalization:** We will explore more machine learning models (e.g., deep learning methods, ensemble learning) and investigate additional regularization techniques to tackle overfitting, aiming to further enhance the model's stability and prediction accuracy.

Through these efforts, we hope to extend this method to a wider range of agricultural monitoring applications.

5. Conclusions

When evaluating the nutritional growth state of fruit trees, nitrogen is an essential metric. In this study, multispectral canopy data collected by UAVs at various growth stages was used to quantify the nitrogen content of custard apple leaves. To track and evaluate the amount of nitrogen in the custard apple trees' canopy, a two-layer ensemble learning model was created. According to the investigation, the association between the acquired vegetation indices, textural features, and nitrogen content was much enhanced when canopy shadow and soil background noise were filtered using a spectral shadow index as opposed to raw data. The accuracy of nitrogen estimation was significantly higher in models that integrated textural data and vegetation indices than in models that only used vegetation indices. With R^2 values of 0.62 and 0.61, respectively, ADA and RF stood out among single machine-learning models for their strong stability and estimation accuracy. However, with an R^2 of 0.661, RMSE of 0.059, and MAE of 0.193, the Stacking ensemble model fared better than the individual models on average. As a filter to separate the performance of the underlying models, the second-layer Lasso model worked quite well. According to this study, monitoring nitrogen nutrition in custard apple leaves using UAV-based remote sensing and ensemble learning has a lot of potential. It may also be a useful guide for future studies on the management and development of custard apple trees.

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