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Research Article

Modelling of nitrogen content estimation in cotton based on UAV 'Spectrum-Image' data fusion

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Abstract

Nitrogen is crucial for crop growth, development, yield, and quality. Traditional nutrition monitoring relies on single data sources; however, spatial coverage and information limitations hamper the accuracy of such monitoring methods. The recently developed unmanned aerial vehicle (UAV) remote sensing technology has emerged as an efficient and convenient method of crop nutrition monitoring, which allows the integration of data from sources, such as hyperspectral and digital images, resulting in comprehensive and multi-angular insights. This study is aimed at enhancing crop monitoring accuracy by integrating multiple data types obtained at the UAV scale, using 'Xinluzao 53' cotton as an experimental subject. Nitrogen content was obtained via hyperspectral and digital imaging and the features of the two data sources analyzed by constructing four machine learning models: Ridge (RR), back-propagation neural network (BPNN), random forest (RF), and Bagging, which were integrated with the multilevel data fusion methods to obtain nutrition information. The results indicated optimal efficacy for RF together with the UAV 'spectrum-image' feature-level fusion framework, with a validation set R^2 of 0.915 and RMSE of 1.562, while the optimal decision-level fusion framework was found to be Bagging, with a validation set R^2 of 0.923 and RMSE of 1.488. UAV-based 'spectral-image' multilevel fusion frameworks were found to enhance the accuracy of monitoring, with the optimum decision-level fusion evaluation indices providing crucial theoretical support for precision agriculture in the future.

Keywords: cotton; data fusion; digital image; hyperspectral; nitrogen; UAV

Introduction

As an important economic crop, cotton holds a significant position in the national economies and social development of many countries. Nitrogen is a vital nutrient for crop growth and development, as it plays a key

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role in photosynthesis and physiological metabolism. However, an imbalance-whether deficiency or excess-can adversely affect cotton growth. Nitrogen deficiency restricts protein and chlorophyll synthesis, resulting in leaf yellowing and reduced photosynthetic activity. In contrast, excessive nitrogen stimulates excessive vegetative growth, delays crop maturity, and causes canopy overdevelopment with poor light penetration, which lowers photosynthetic efficiency and increases the likelihood of bud and boll shedding. These disruptions ultimately reduce yield and fiber quality (Qin *et al.*, 2025). Furthermore, excessive nitrogen fertilizer use can cause serious ecological and environmental issues (Anas *et al.*, 2020). Therefore, real-time, convenient, and accurate monitoring of the nitrogen content in cotton during growth is vital for determining the optimal nitrogen application, improving the quality and yield, and enhancing the nitrogen fertilizer utilization efficiency.

Traditional nitrogen monitoring methods, such as chemical titration and expert experience, have been gradually eliminated due to their time-consuming nature, laborious processes, and significant errors. Advances in science and technology have led to the introduction of spectral remote sensing technology, which provides new concepts and approaches to crop nutrient monitoring. The technology is highly sensitive, rapid, and non-destructive, rendering it a focal point for agricultural research. Spectral data analysis of specific nutrients in different wavelength bands can accurately reflect vegetation characteristics. For instance, Yao *et al.* (2024) and Sun *et al.* (2024b) used handheld spectral sensors to evaluate the potassium and nitrogen content in cotton and soybean, respectively. While digital cameras do not capture as wide a range of features as spectral sensors, their low cost and simple operation have garnered considerable interest, with scholars using image data from handheld digital cameras to assess the nitrogen levels in crops such as rice (Lee and Lee, 2013), cotton (Qin *et al.*, 2024), and maize (Zhang *et al.*, 2010; Sun *et al.*, 2024a).

Both spectra and images are thus crucial for monitoring crop nutrients, providing diverse data types. Hyperspectral data disperses the light that is reflected from crops into hundreds of consecutive bands, and the different reflectance for specific light wavelengths in association with varying nutrient levels allows the nutrient content of crops to be inferred. Conversely, digital images can be used to analyse the colour and morphology characteristics of crops, allowing indirect elucidation of the nutrient content. Hyperspectral data offer rich band information and cover the near-infrared band that is inaccessible via digital imaging, while digital images excel in terms of spatial resolution, accurately capturing colour and subtle morphological details that hyperspectral data cannot provide. These techniques thus complement each other, enhancing the comprehensive assessment of crop nutrient status.

Ground-based handheld devices, which are typically used to monitor crops on a local basis, are limited in their ability to cover expansive areas quickly and rely heavily on human input for data acquisition. Unmanned aerial vehicles (UAVs) offer a solution to these challenges (Cuaran and Leon, 2021), and can efficiently cover large areas of farmland in relatively short timeframes, enabling the acquisition of multi-source data via various sensors. This technological advancement provides effective support for crop nutrient management and decision-making (Zhu *et al.*, 2022). Blekanov *et al.* (2023) used UAV spectral data combined with machine-learning models to monitor the nitrogen status in food crops, with robust and reliable results, while Liu *et al.* (2023) used a UAV equipped with a digital camera to monitor the nitrogen content of cotton plants, and accurately mapped the nitrogen distribution across large areas using machine-learning models.

Traditional crop nutrition monitoring, which relies on single data sources such as ground-based hyperspectral or digital images, is limited in terms of spatial coverage and information. This study addresses these issues by using UAV with data fusion techniques, using cotton as the experimental subject. Two data sources, UAV hyperspectral and digital images, were thus employed to obtain spectral and image features, which were then integrated via a multilevel data fusion method, incorporating feature-level and decision-level fusion dimensions to predict cotton nitrogen content while improving the spatial coverage and enhancing the accuracy and stability of the model. The research findings obtained are expected to provide a scientific basis and theoretical framework for crop nutrient diagnosis and fertilizer application management.

Materials and Methods

Experimental environment

The experiment was conducted at the Shihezi Institute of Agricultural Science in the Xinjiang Uygur Autonomous Region in 2023. The soil texture of the experimental site is primarily loamy, with 50.90 mg kg^{-1} alkaline dissolved nitrogen, 19.20 mg kg^{-1} organic matter, 151 mg kg^{-1} effective potassium, and 18.52 mg kg^{-1} effective phosphorus. The study area was previously used to grow maize; however, the main local cotton cultivar 'Xinluzao 53' was investigated in this study. Five nitrogen application levels were included: N0 (0 kg hm^{-2}), N1 (120 kg hm^{-2}), N2 (240 kg hm^{-2}), N3 (360 kg hm^{-2}), and N4 (480 kg hm^{-2}), while phosphorus and potassium fertilizer were applied at a rate of 160 kg hm^{-2}. The fertilizers were applied via drip irrigation, which was performed eight times throughout the reproductive period. Planting was carried out following the pattern 'one film, three tubes, and six rows,' with plants spaced at 20 cm + 55 cm + 20 cm. Each nitrogen-treatment was replicated three times (Figure 1). All other field management practices were conducted according to local high-yield cultivation requirements.

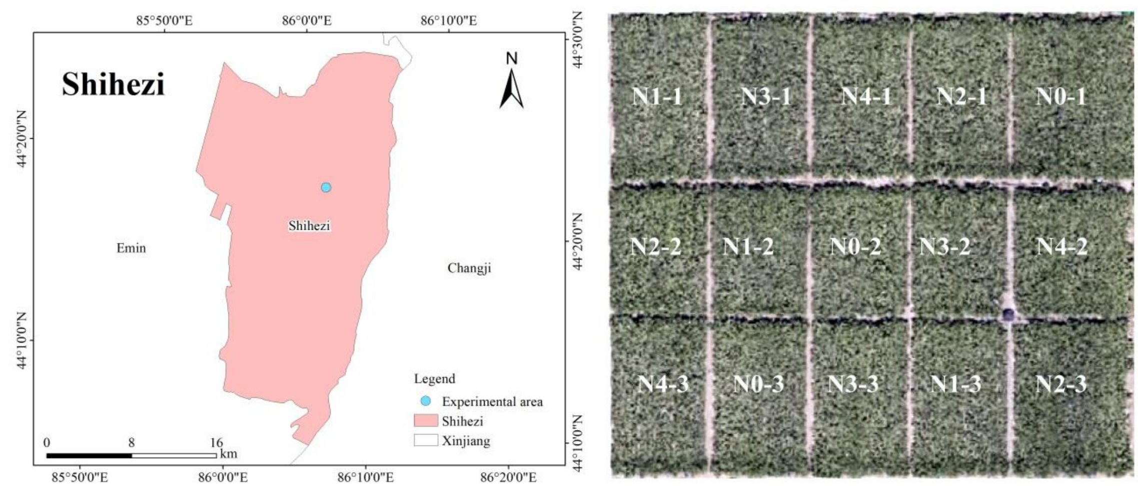


Figure 1. Location and overview of the experimental area (original images)

Data acquisition and processing

<u>UAV hyperspectral data acquisition and processing</u>

UAV data collection was conducted in six key cotton reproductive periods: budding, early flowering, full flowering, boll, full boll, and fluffing, with samples collected during the period 11:00-13:00 local time on sunny, cloudless days to minimize light and other environmental uncertainties. A DJI M600 UAV platform (DJ-Innovations, Shenzhen, CN) equipped with a Nano-Hyperspec hyperspectrometer (Headwall Photonics, Bolton, US) was utilized to acquire hyperspectral information concerning the cotton canopy in the 400-1000 nm wavelength range (Figure 2a), with a self-contained remote control with a screen utilized for path planning to avoid flight interference. The flight altitude was set to 20 m with the lens facing vertically downward, the heading and sidelobe overlap were set at 75%, and the collected data were spliced. Radiometric calibration was conducted using a calibration board, with digitally quantized values converted to surface reflectance and manual interpretation utilized to identify the cotton plots. The region of interest (ROI) was determined based on the ground sampling point locations, and the average spectral reflectance of the cotton canopy at the ROI was used as hyperspectral data.

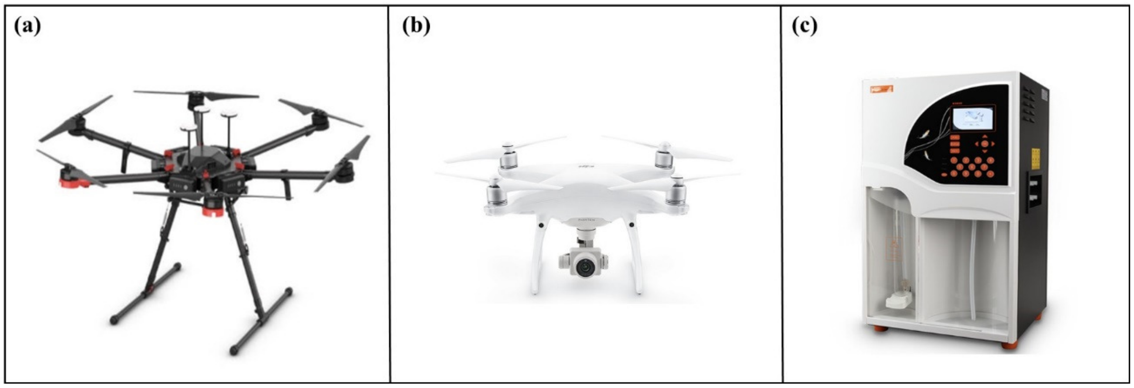


Figure 2. Data acquisition equipment (original images)
Note: (a) shows the UAV hyperspectral platform, (b) shows the UAV digital imagery platform, and (c) shows the Kjeldahl analyzer used for nitrogen determination

The UAV - acquired hyperspectral data were processed as follows. First, a Savitzky-Golay (SG) filter operation was used to reduce the noise and burrs in the raw spectra, with interpolation utilized to enhance the data for more accurate analysis and model establishment (Qiao *et al*., 2024). Second, first-order differentiation (D1) was performed to highlight the spectral features and structures, enhancing subtle changes while further reducing the noise influence (Shi *et al*., 2023). Pearson correlation analysis was then used to identify feature bands that were significantly correlated with the cotton nitrogen content at the 0.01 level, improving the performance and generalization ability of the inversion model. Finally, the Random Frog Leaping (RFL) algorithm, which simulates the process of a frog leaping in the search space, was employed to reduce the spectral feature dimensionality, reduce the feature covariance, and extract the spectrally sensitive band features.

UAV digital image acquisition and processing

UAV digital image acquisition was conducted under the same conditions as the UAV hyperspectral data, with the same height from the ground, sampling time, and frequency as described in Section 2.2.1. Cotton canopy digital images were captured using the DJI Phantom 4 Advanced UAV platform (DJ-Innovations, Shenzhen, CN) equipped with a 20-megapixel image sensor (Figure 2b). The on-board digital camera operated with a shutter speed of 1/240 s, and the lens was oriented vertically downward. JPG images were obtained at a resolution of 5472 × 3648 pixels to match the ROI locations of the hyperspectral data. Section 2.2.1 describes the hyperspectral data sources, covering the same ground area as digital image data sources; however, it exhibits significantly blurred or missing spatial resolutions.

The acquired UAV digital images were processed as follows: First, the RGB color space for the ROI was converted to the HSV color space, and statistical features, specifically the first-order moment (mean), were derived from the six component values obtained for both color spaces. The obtained features were then used to describe the color distribution and morphology in the UAV-captured cotton digital images (Anami *et al*., 2020). Textural analysis, including homogeneity, contrast, dissimilarity, entropy, and correlation, was performed for the R, G, and B components to explore features related to cotton quality. The gray-level co-occurrence matrix (GLCM) was computed with a step size of 1 in four directions (0°, 45°, 90°, and 135°), and the mean values of the texture features across these directions were used for analysis.

Cotton nitrogen content acquisition and processing

After acquiring UAV data, three cotton plants representing the overall growth level of the plot were destructively sampled. All plant parts were individually bagged and transported back to the laboratory in a small-insulated box equipped with an ice pack. Plants were defoliated at 105 °C for 30 min and then dried at a constant temperature of 85 °C until reaching constant weight. Cotton samples weighing 0.1000 g were then analyzed using a 1-in-10 000 balance. Nitrogen content was determined through digestion with H_2SO_4-H_2O_2 and measured using a Kjeldahl nitrogen tester (Figure 2c).

The total nitrogen content of the cotton was then summarized and processed, with null nitrogen data points that were assumed due to experimental error excluded as outliers.

Model construction and evaluation

Modelling approach

Ridge regression (RR) (Peng *et al.*, 2021b): A variant of the ordinary linear regression method that introduces an L2 regularization term in the loss function, also known as Tikhonov regularization. This regularization penalizes the regression coefficients, reducing their estimation bias and addressing the challenges of multicollinearity. Consequently, RR prevents the regression coefficients from becoming too large, mitigating the risk of overfitting. This method is particularly suitable for linear modelling in which several feature dimensions are present.

Backpropagation neural network (BPNN) (Ding *et al.*, 2022): A common artificial neural network that comprises input, hidden, and output layers. The BPNN training process consists of forward and backward propagation, with feature vectors entering from the input layer and passing through the hidden layer to reach the output layer. Input data are multiplied by a weight matrix, summed, and passed through a non-linear activation function (e.g. sigmoid or ReLU) in the hidden layers, producing the output for that layer. If the expected result (error between the output result and the actual label) is not obtained in the output layer, the errors are backpropagated. The neuron weight parameters in each hidden layer are updated iteratively to minimize the error.

Random Forest (RF) (Peng *et al.*, 2021a): A learner that uses multiple integrated decision trees to train and validate a dataset that is sampled from the training set through bootstrap and replacement, allowing multiple subsamples to be constructed. Decision trees are trained separately and combined for prediction. Instead of finding the maximum information gain of all features during feature splitting, a portion of the features is randomly selected and the optimal solution for splitting determined. RF typically exhibits good performance and is particularly effective for dealing with medium-sized datasets and complex non-linear relationships.

Bagging: This modelling approach is similar to RF in that it relies on integrated learning through bootstrap sampling and involves random sampling with replacement from the dataset. Each subsample is used to train a base learner, and the final prediction is the average of all results from the base learners. The method reduces model variance, improving its fit and generalization ability. In this study, RR served as the base learner for Bagging.

In this study, machine learning models were implemented using Python's scikit-learn library. The dataset was divided into training and validation sets. Except for the selection of base learners in the bagging models, all models were trained and evaluated using default hyperparameters to avoid potential optimistic bias caused by hyperparameter tuning. It should be noted that, owing to the limited number of agronomic samples and the fact that datasets are often collected under similar experimental conditions, previous studies commonly assumed that the distributions of the validation and test sets were highly similar. Accordingly, the dataset was typically divided into two parts (Song *et al.*, 2024; Wang *et al.*, 2025).

'Spectrum-image' data fusion modelling approach

Feature-level fusion involved extracting features from hyperspectral and digital images, combining the features and substituting into the machine learning regression algorithm to obtain the final inversion results (Figure 3a). The extracted hyperspectral sensitive bands, along with the color and texture features of digital images, were fused via cascading. RR, BPNN, RF, and Bagging were selected for model training and validation, and the optimal algorithm was used for the final feature-level fusion to estimate the nitrogen content of cotton.

Decision-level fusion involved constructing machine-learning models separately using the hyperspectral and digital image features of the cotton nitrogen content in two dimensions, with decisions based on the two nitrogen content prediction results (Figure 3b). Color and texture features of hyperspectral sensitive bands and digital images were substituted into RR, BPNN, RF, and Bagging for modelling, and the optimal cotton nitrogen content estimation values screened based on hyperspectral data and digital images. After cascading, the four machine-learning algorithms were re-nested and the prediction results of the optimal algorithm selected as the final decision-level fusion cotton nitrogen content estimation values.

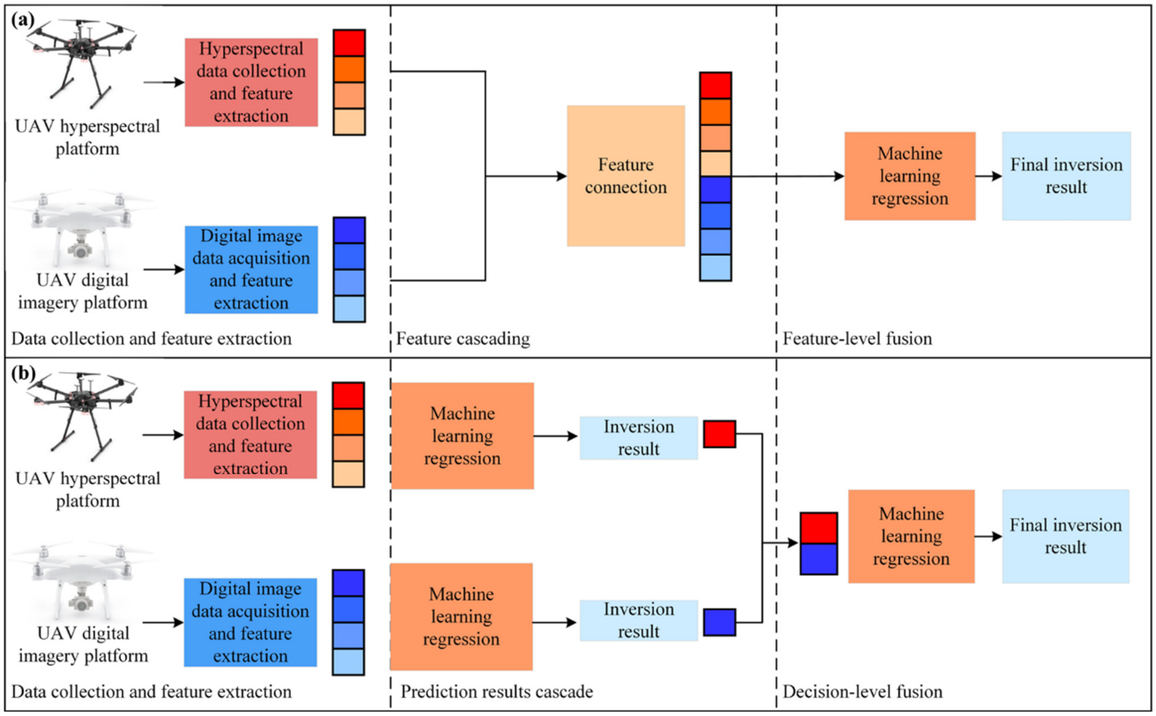


Figure 3. UAV spectral-image data fusion framework
Note: (a) shows the UAV hyperspectral platform, (b) shows the UAV digital imagery platform, and (c) shows the Kjeldahl analyzer used for nitrogen determination

Model evaluation indicators

Two evaluation indices, the coefficient of determination (R^2) and root mean square error (RMSE), were utilized to measure the fitting ability and prediction accuracy of each model. R^2 is used to quantify the extent to which a model explains the variance in the dataset, with values ranging from 0-1. A value of R^2 that is close to 1 indicates better model performance in explaining dataset variance, with superior fit. The RMSE indicates the average deviation between the predicted and actual values, with smaller RMSE values signifying higher prediction accuracy and reduced prediction error. The formulas used to obtain these indicators are:

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

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

where x_i is the predicted value, y_i is the actual value, $\overline{y_1}$ represents the average of the actual values, and n denotes the number of samples.

Results

UAV-based screening study of sensitive features for nitrogen content in cotton

UAV-based screening study of hyperspectral sensitive features for nitrogen content in cotton

The processing flow of UAV hyperspectral data is detailed in Section 2.2.1. Two hyperspectral-sensitive feature screening methods, SG-Pearson-RFL and SG-D1-Pearson-RFL, were investigated in this study. The screening results obtained using each method can be seen in Figure 4. SG-Pearson-RFL selected 30 feature bands, while SG-D1-Pearson-RFL selected 40 feature bands. While the bands screened by the two methods differed, they focused on a common band range, indicating high information content and explanatory power for the cotton nitrogen content. The sensitive feature locations were primarily concentrated at approximately 400 and 700 nm and in the near-infrared short-wavelength range. Previous researchers have frequently selected these bands for constructing spectral indices and nitrogen nutrition inversion models (Wang *et al*., 2011; Yin *et al*., 2022).

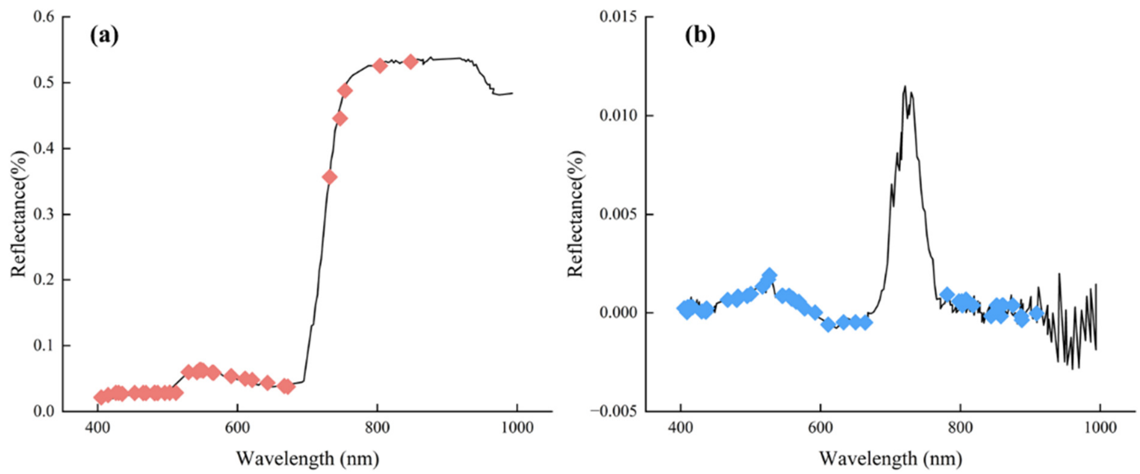


Figure 4 UAV hyperspectral sensitive feature screening results
Note: (a) shows sensitive features obtained from SG-Pearson-RFL, and (b) shows sensitive features obtained from SG-D1-Pearson-RFL

UAV-based screening study of digital image sensitive features for nitrogen content in cotton

The 6 color and 15 texture features extracted from the digital images described in section 2.2.2 were subjected to Pearson correlation analysis for cotton nitrogen content (Figure 5). The 21 image features show varying degrees of mutual predictability and correlation with each other, with the high correlation among some of the features leading to multicollinearity issues, causing the predictions of the model to become particularly sensitive to minor data changes, thus reducing the stability and interpretability. To address this challenge, principal component analysis (PCA) was used to map the high-dimensional feature space into a lower-dimensional space, effectively decreasing the feature correlation (Yang *et al*., 2016). The first 12 principal components were associated with a cumulative variance of 99.772 %, with the 13th component contributing only 0.067 % or < 0.1 %. Consequently, the first 12 principal components were selected as image-sensitive features for the subsequent modelling.

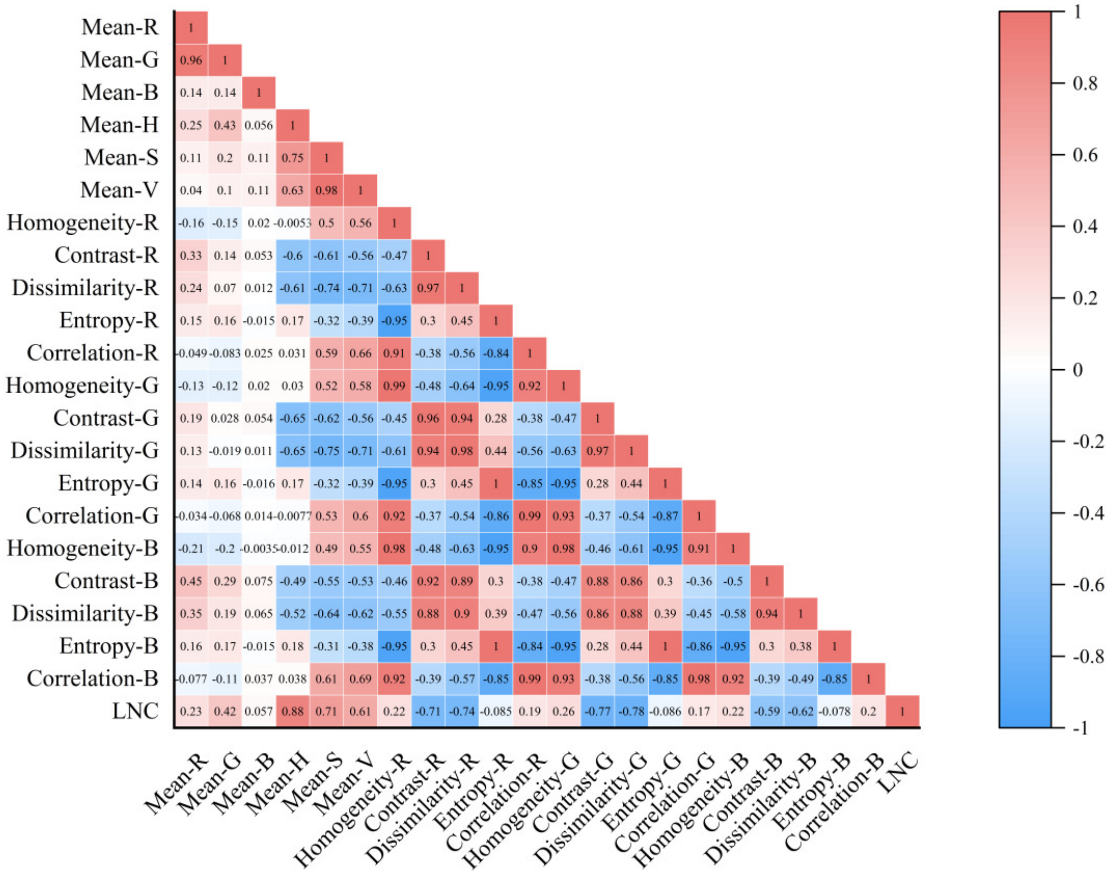


Figure 5. Heatmap showing correlation between features in the UAV digital images

Cotton nitrogen estimation model based on a single data source in fusion frameworks

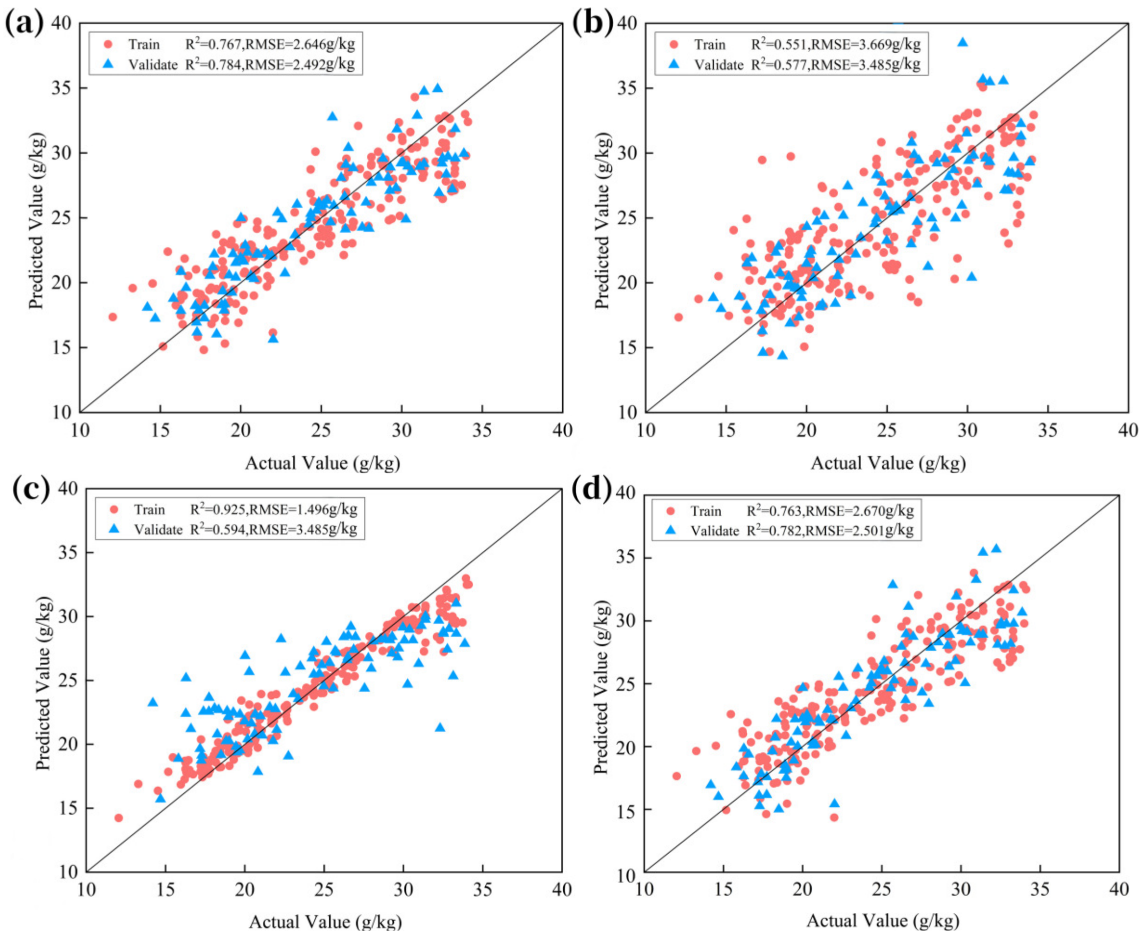
Cotton nitrogen content estimation model based on UAV hyperspectral data

A total of 312 cotton data samples were collected and divided into training and validation sets at a ratio of 7:3, resulting in 219 samples for training and 93 for validation. The spectral and image datasets were partitioned in a consistent manner to ensure identical sample division across both modalities, facilitating subsequent data fusion. Descriptive statistics of the nitrogen content dataset are presented in Table 1. The coefficients of variation (CVs) ranged between 20% and 30%, indicating a moderate level of variability in nitrogen content among samples. This degree of variation provides sufficient sample diversity for developing a robust nitrogen content monitoring model.

Table 1. Descriptive statistical analysis of nitrogen content in cotton leaves

Dataset	Sample No.	Max (g kg^{-1})	Min (g kg^{-1})	Mean (g kg^{-1})	CV (%)
Training	219	34.110	12.048	24.267	22.625
Validation	93	33.860	14.202	24.269	22.191
All	312	34.110	12.048	24.267	22.461

The hyperspectral-sensitive bands obtained using the SG-Pearson-RFL and SG-D1-Pearson-RFL methods mentioned in Section 3.1.1 were substituted into the RR, BPNN, RF, and Bagging models for analysis. Figure 6 shows the results of model fitting for the predicted-actual-values. The model constructed using features from the SG-D1-Pearson-RFL method exhibited higher overall accuracy and stability than that obtained using SG-Pearson-RFL. This improvement was attributed to the enhanced trend and variation of bands that was obtained through the first-order derivative process, which helped in capturing inter-sample differences, improving the signal-to-noise ratio and enhancing the model fitting and generalization ability. Substituting the SG-Pearson-RFL features into BPNN led to training and validation set R^2 values of only 0.551 and 0.577, respectively, indicating underfitting due to incomplete learning of the spectral-sensitive relationships involved in the cotton nitrogen content. However, substitution of the SG-D1-Pearson-RFL features into BPNN did not result in underfitting, reflecting the differing dataset feature distributions that led to the different modelling effects. Substituting SG-Pearson-RFL features into RF yielded a training set R^2 of 0.925 and validation set R^2 of 0.594. Similar to using the SG-D1-Pearson-RFL features as a substitute for BPNN, the model excelled in training; however, it faltered in validation, which was attributed to the screening of 50 sensitive bands with residual multicollinearity and noise. Fitting the RF training set exacerbated overfitting by capturing intricate noise and detail. Through comprehensive comparison, hyperspectral features from the SG-D1-Pearson-RFL method were substituted into the RR model to obtain the optimal evaluation indices, with the training set achieving an R^2 of 0.896 and an RMSE of 1.767 and the validation set achieving an R^2 of 0.862 and an RMSE of 1.988. RR effectively processes high-dimensional and collinear features by constraining the model parameters (Wu *et al*., 2024), and was therefore considered the optimal model for estimating the cotton nitrogen content from the hyperspectral data, forming the basis for the subsequent fusion frameworks.



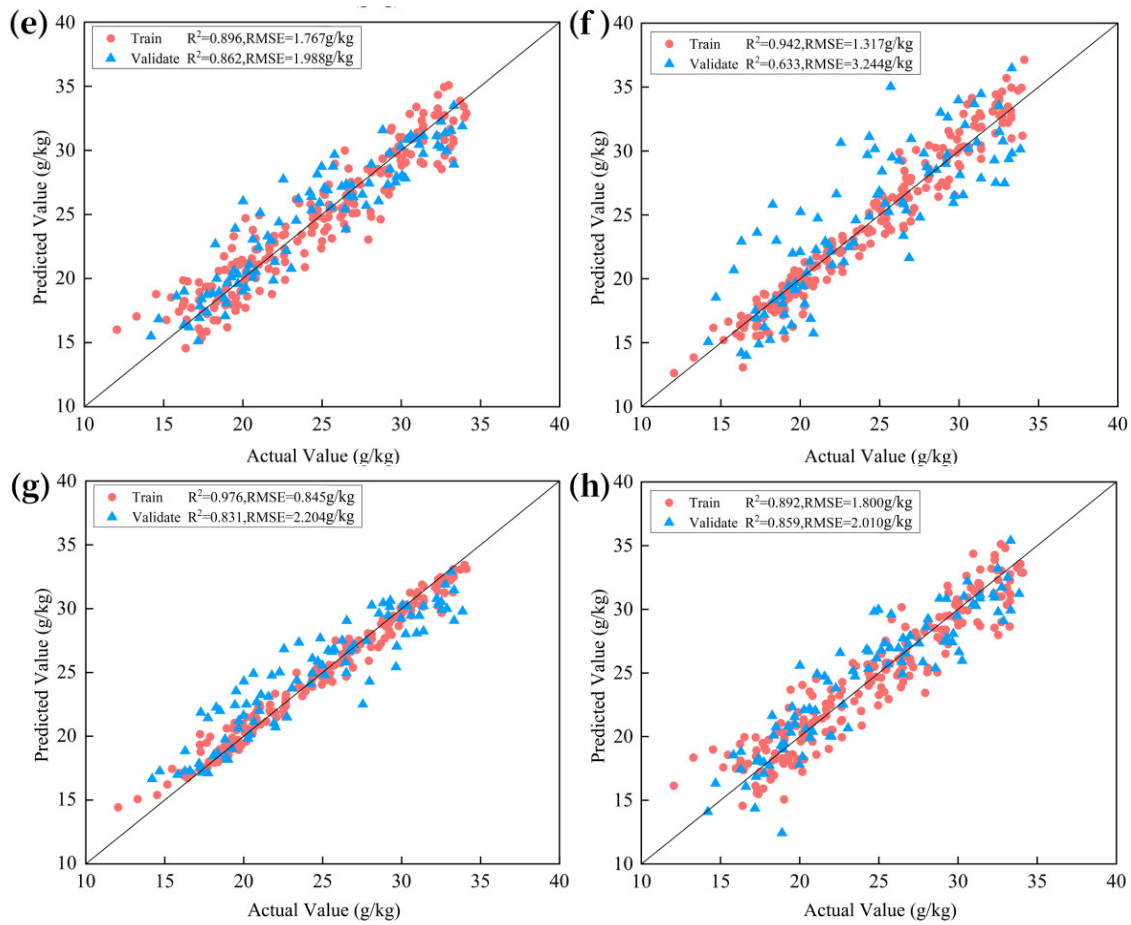


Figure 6. Predicted-actual-value fit of cotton nitrogen content based on UAV hyperspectral data
Note: (a)-(d) represent the RR, BPNN, RF, and Bagging models constructed using features obtained from the SG-Pearson-RFL method; (e)-(h) represent the RR, BPNN, RF, and Bagging models constructed using features obtained from the SG-D1-Pearson-RFL method

Cotton nitrogen content estimation model based on UAV digital images

The predicted-actual-value fitting results obtained using each model can be seen in Figure 7. Substitution of the 12 principal components of the digital images obtained in Section 3.1.2 into RR, BPNN, RF, and Bagging indicated good fitting and generalization effects for the four models., with the validation set R^2 exceeding 0.760 and the RMSE below 2.610. Compared to Section 3.2.1, the cotton nitrogen content estimation model based on digital images did not exhibit any noticeable overfitting or underfitting, which was attributed to the relatively small feature dimensions of the digital images. PCA dimensionality reduction retained important information that was related to the cotton nitrogen content while reducing the multicollinearity. Of the investigated models, Bagging achieved the best evaluation metrics, with a training set R^2 of 0.930 and RMSE of 1.449, and a validation set R^2 of 0.821 and RMSE of 2.265, showing a slight improvement compared to RR. As an ensemble learning algorithm, Bagging enhances model performance by combining multiple RR regression predictions; however, the improvement in accuracy was modest. This limited gain may be due to the high correlation between the base learners or the significant optimization potential in parameters like the number of base learners and sampling methods. Notably, since Bagging used RR as its base learner, the results were similar to those of RR. Future research should focus on optimizing the ensemble model's performance. Bagging was identified as the best model for estimating cotton nitrogen content based on digital images and was subsequently integrated into the fusion frameworks.

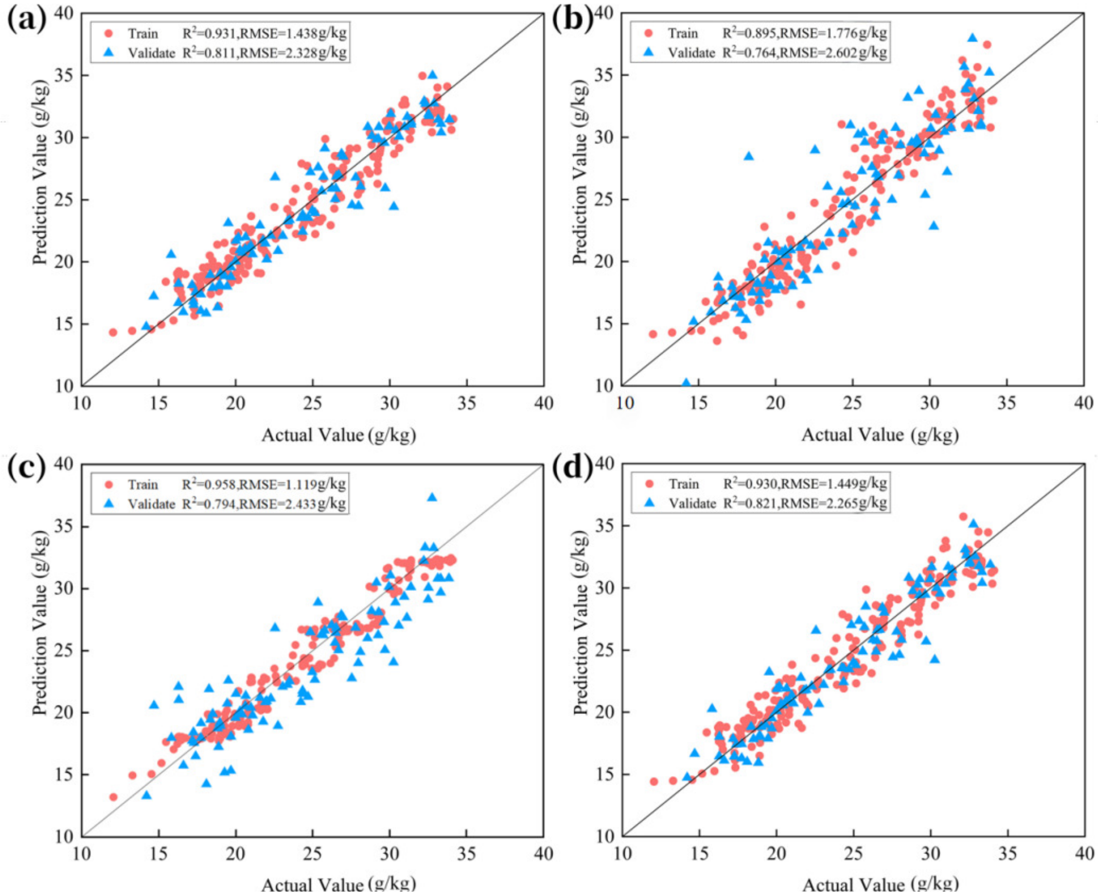


Figure 7. Predicted-actual-value fit of cotton nitrogen content based on UAV digital images
Note: (a)-(d) denote RR, BPNN, RF, and Bagging

Cotton nitrogen content estimation model based on UAV 'spectrum-image' data fusion

Cotton nitrogen content estimation model based on UAV 'spectrum-image' feature-level fusion

By cascading the hyperspectral and digital image features obtained in Section 3.1 into the RR, BPNN, RF, and Bagging models, as confirmed in Section 3.2.1, the model constructed by SG-D1-Pearson-RFL exhibited higher overall accuracy and stability than that of the SG-Pearson-RFL. The digital image feature principal components and sensitive SG-D1-Pearson-RFL bands were concatenated for feature-level fusion, with the resulting predicted and actual values for each model depicted in Figure 8. BPNN showed the weakest fitting and generalization performance, with a training set R^2 and RMSE of 0.892 and 1.799 and a validation set R^2 and RMSE of 0.614 and 3.328, respectively. This is because the performance of the model used for hyperspectral-based cotton nitrogen content estimation was suboptimal, with the feature-level fusion-added image features maintaining the inherent multicollinearity and noise and affecting the generalization ability of the BPNN. By comprehensive comparison, the feature-level fusion of 'spectrum-image' in RF had the best evaluation index value, with a training set R^2 of 0.986 and RMSE of 0.639, and a validation set R^2 of 0.915 and RMSE of 1.562. Compared to the optimal estimation model for a single data source, the validation set R^2 increased by 5.3-9.4 %, while the validation set RMSE decreased by 21.4-31.0 %.

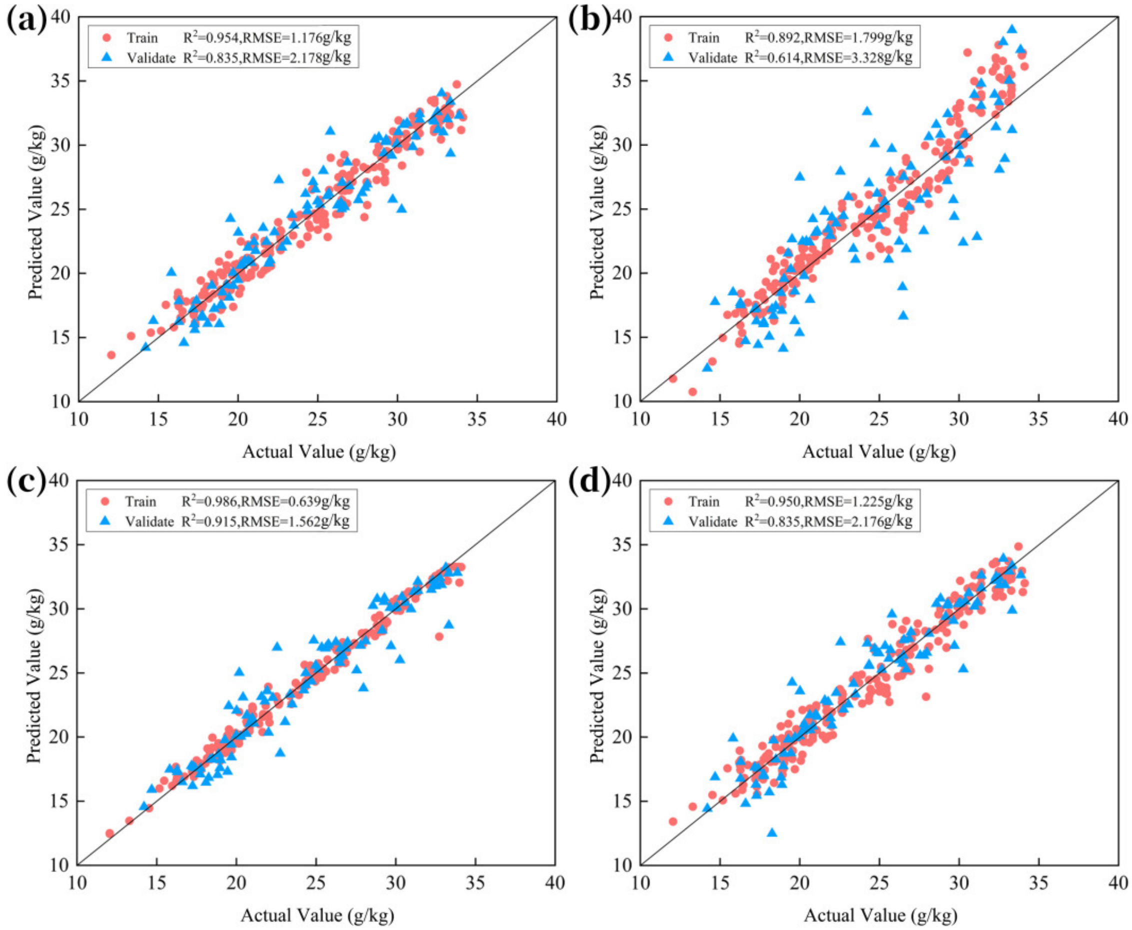


Figure 8. Predicted-actual-value fit of cotton nitrogen content based on UAV 'spectral-image' feature-level fusion

Note: (a)-(d) denote RR, BPNN, RF, and Bagging

Cotton nitrogen estimation model based on UAV 'spectral-image' decision-level fusion

The results of the optimal estimation model for cotton nitrogen content based on hyperspectral and digital images in sections 3.2.1 and 3.2.2 were combined for decision-level fusion involving RR, BPNN, RF, and Bagging. Figure 9 depicts the predicted-actual-value fitting of each model obtained from decision-level fusion. The validation set R^2 of > 0.910 for all four models indicates high effectiveness. This improvement was attributed to decision-level fusion, in which the decision results from two single data sources are re-evaluated. This approach, similar to that of a stacking ensemble-learning algorithm, combines the predictions of the base learners from individual data sources using meta-learner fusion and was found to improve the regression task prediction accuracy, enhance the robustness, and facilitate the matching of heterogeneous data. The feature input for the models consisted solely of two dimensions: the optimal predicted nitrogen content values from the hyperspectral and the digital images. This approach required fewer parameters for learning and reduced the risk of overfitting. Models in the low-dimensional feature space were also more stable and less affected by the complex relationships that are present in high-dimensional spaces. Additionally, because the low-dimensional feature space made it easier for the models to capture the main trends and relationships in the data during the fitting process, BPNN, RR, and Bagging produced similar prediction results. In a comprehensive comparison, the 'spectral-image' decision-level fusion in Bagging exhibited the best evaluation metric, with an R^2 of 0.987 and an RMSE of 0.632 for the training set, and an R^2 of 0.923 and RMSE of 1.488 for the validation set. The validation set R^2 improved by 6.1-10.2 % as compared to that of the optimal estimation models using a single data source, while the RMSE was reduced by 25.2-34.3 %.

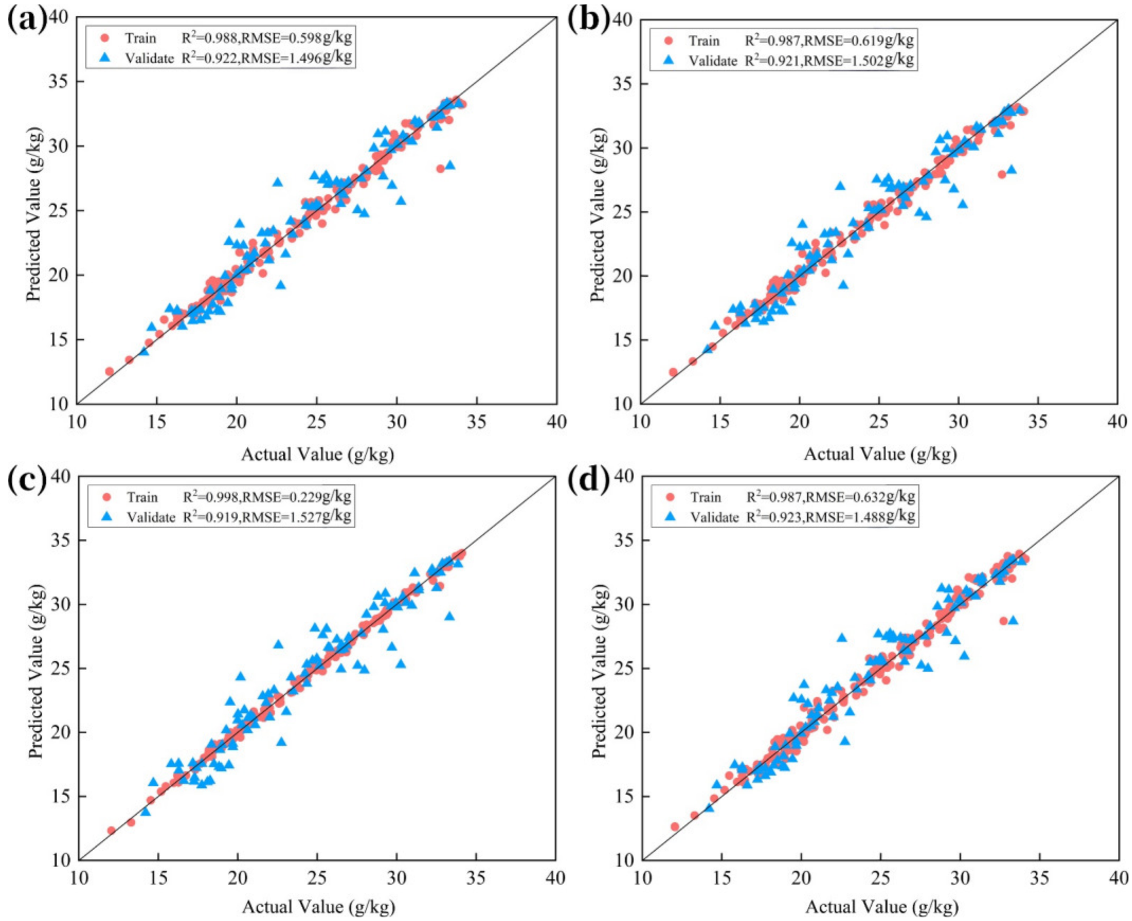


Figure 9. Predicted-actual-value fit of cotton nitrogen content based on UAV 'spectral-image' decision-level fusion

Note: (a)-(d) denote RR, BPNN, RF, and Bagging

Discussion

UAV hyperspectral remote sensing is a crucial tool for rapid and non-destructive crop nutrient monitoring. In this study, UAV hyperspectral monitoring was used the methods SG-Pearson-RFL and SG-D1-Pearson-RFL to screen spectral bands, a hyperspectral-based model for estimating cotton nitrogen content was constructed by substituting the selected bands into four machine learning types. Evaluation indices indicate that the D1 spectral processing method effectively eliminated the background influence, enhanced the spectrum resolution, clarified the distances between different features more clearly, and ultimately improved the model accuracy, which is consistent with the findings of Shi *et al*. (2023) and Cui *et al*. (2022). To address the poor fitting and generalization ability of the BPNN in the hyperspectral-based cotton nitrogen content estimation model, measures that can mitigate underfitting or overfitting should be employed in future studies: (1) penalizing the network weights to reduce model complexity; (2) combining outputs from multiple BPNNs to reduce model variance; (3) enriching training data to enhance model generalization ability; and (4) further decreasing the dimension of sensitive bands to simplify the model. Further research should focus on combining appropriate vegetation indices to construct a model for estimating cotton nitrogen nutrition and identifying the most intuitive, accurate, and user-friendly method for assessing nitrogen content in cotton as compared to the model constructed with sensitive bands.

Unlike the hyperspectral spectrum, digital images typically contain color channels in three bands (R, G, and B), with each pixel containing color and brightness information. In recent years, crop nutrient monitoring using digital imagery from drones has gained attention among researchers owing to its low cost and ease of application. In this study, models were constructed to estimate the nitrogen content of cotton by screening color and texture features in different spaces within the ROI. The features extracted from the digital images showed high correlation due to similar computational methods or feature descriptors, consistent with the findings of Li *et al*. (2022) and Zhang *et al*. (2022). PCA was used to reduce the feature dimensions while retaining important information related to the nitrogen content in the image features, thereby improving the stability and generalization ability of the model. Future research plans should include constructing a cotton nitrogen content estimation model that is based on convolutional neural networks (CNN) after expanding the image dataset. CNN can directly learn features from the original UAV image data and complete feature extraction and prediction tasks end-to-end, and has a strong non-linear fitting ability with more accurate elucidation of inverted cotton nitrogen content. However, CNN fitting requires a large dataset, and obtaining sufficient cotton nitrogen content data is challenging. Constructing a CNN to estimate the cotton nitrogen content using a small sample size remains a research challenge. Current solutions include transfer learning (Espejo-Garcia *et al*., 2022), original image enhancement, and simplified network structures (Hajabdollahi *et al*., 2019).

To address the limitations of using information from a single sensor, data fusion techniques were applied in this study for crop nutrient monitoring. This framework integrates data from multiple sources through specific methods and tools to generate higher-quality and more comprehensive information. At present, data fusion research is mainly conducted at three levels: data-level, feature-level, and decision-level fusion (Hall and Llinas, 1997). Data-level fusion operates directly on raw data, feature-level fusion combines feature vectors extracted from different data sources to generate new feature information or classification results (Gamba and Chanussot, 2008), and decision-level fusion further integrates the predicted outcomes from each data source (Zhou *et al*., 2023). In this study, UAV hyperspectral and digital image data were fused to extract multi-category phenotypic and nitrogen-related features, thereby improving the accuracy and precision of cotton nitrogen monitoring. Because data-level fusion requires that all data sources share consistent semantics and structure, it was not applied here. Instead, higher-level fusion at the feature and decision levels was implemented. The results demonstrate that these fusion strategies significantly enhance both the accuracy and stability of cotton nitrogen estimation, highlighting the superiority of UAV-based “spectrum-image” data fusion for crop nutrient monitoring. Overall, this work establishes a methodological framework that supports precise, efficient, and scalable monitoring of crop phenotypic parameters.

It should be noted that, due to sensor limitations, simultaneous multi-source data acquisition using a single UAV platform was not conducted in this study, although such integration could potentially improve spatial alignment and data acquisition efficiency. In addition to the data sources employed here, other sensing modalities may provide complementary nitrogen-related information from different perspectives. Furthermore, the iterative advancement of algorithms has also played a crucial role in promoting data fusion, making the fusion process more flexible and precise. Future research should further investigate the complementarity among diverse data sources, quantify its impact on model performance, and determine the optimal fusion strategy by balancing accuracy, computational efficiency, and cost.

Conclusion

In this study, multiple machine-learning models were constructed using UAV hyperspectral and digital images to estimate cotton nitrogen content. Feature- and decision-level fusion frameworks were utilized to enhance accuracy and stability in the inversion process. The following conclusions were drawn:

(1) UAV hyperspectral data processing with D1 highlights the rate of change and significantly enhances the accuracy of cotton nitrogen modelling. Optimal evaluation indexes were achieved when applying RR in the estimation of cotton nitrogen content under SG-D1-Pearson-RFL processing, with the training set showing an R^2 of 0.896 and RMSE of 1.767 and the validation set exhibiting an R^2 of 0.862 and RMSE of 1.988.

(2) Six color features and 15 texture features extracted from the UAV digital images exhibited multicollinearity. PCA was used for dimensionality reduction. The 12 principal components optimized the evaluation index of cotton nitrogen content using Bagging. In the training set, the R^2 was 0.930 with an RMSE of 1.449, while in the validation set, the R^2 was 0.821 with an RMSE of 2.265.

(3) Sensitive features and optimal models from the two data sources were embedded into a feature- and decision-level fusion framework. The 'spectrum-image' feature-level fusion enhanced the validation set R^2 by 5.3-9.4 % as compared to single data source models, reducing the RMSE by 21.4-31.0 %, while decision-level fusion increased the validation set R^2 by 6.1-10.2 % and decreased the RMSE by 25.2-34.3 % as compared to single data source models. These multilevel fusion frameworks are important for the precise monitoring of crop phenotype indicators.

Authors' Contributions

Conceptualization: SQ; Data curation: WB, YW, WW, ZW, and CZ; Formal analysis: SQ, MF; Funding acquisition: ZZ, QZ, and XL; Investigation: SQ,and MF; Methodology: SQ; Project administration: ZZ, LM, and QZ; Resources:SQ, YY, and HL; Software: SQ, MF; Supervision: ZZ, LM, and QZ; Validation: SQ; Visualization: SQ, MF; Roles/Writing - original draft: SQ, and MF; and Writing - review & editing:ZZ, LM, and QZ.

All authors read and approved the final manuscript.

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Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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