Postprint: Wheat Lodging Area Identification Using UAV Multispectral Remote Sensing Images at Different Spatial Resolutions

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Abstract

[Objective/Significance] Rapid and accurate assessment of crop lodging disaster conditions requires timely acquisition of information such as lodging location and area. Currently, UAV remote sensing-based identification of crop lodging lacks corresponding technical standards, which is not conducive to standardizing UAV data acquisition procedures and proposing problem solutions. This study aims to investigate the influence of different spatial resolution UAV remote sensing imagery and feature optimization methods on the identification accuracy of wheat lodging areas. [Methods] Following wheat lodging, three flight altitudes (30, 60, and 90 m) were established to obtain Digital Orthophoto Maps (DOM) and Digital Surface Models (DSM) at different spatial resolutions (1.05, 2.09, and 3.26 cm). Five spectral features, two height features, five vegetation indices, and forty texture features were extracted from the different spatial resolution images to construct a full feature set. Three feature selection methods (ReliefF algorithm, RFRFE algorithm, and Boruta-Shap algorithm) were employed to screen and construct feature subsets. Subsequently, three object-oriented supervised classification methods—Support Vector Machine (SVM), Random Forest (RF), and K Nearest Neighbor (KNN)—were utilized to construct wheat lodging classification models, clarify appropriate classification strategies, and establish a lodging classification technical pathway. [Results and Discussion] The results indicate that SVM classification performance was overall superior to RF and KNN. When image spatial resolution varied within the 1.05–3.26 cm range, both the full feature set and the three optimized feature subsets achieved highest classification accuracy at 1.05 cm resolution, outperforming 2.09 and 3.26 cm. Comparative analysis revealed that the Boruta-Shap feature optimization method could simultaneously achieve dimensionality reduction and classification accuracy improvement while adapting to spatial resolution variations. At 3.26 cm image resolution, overall classification accuracy decreased by 1.81%

and 0.75% compared to 1.05 cm and 2.09 cm, respectively. At 2.09 cm image resolution, overall classification accuracy decreased by 1.06% compared to 1.05 cm, demonstrating relatively small classification accuracy differences across flight altitudes. At 90 m altitude, overall classification accuracy reached 95.6% with a Kappa coefficient of 0.914, meeting classification accuracy requirements. [Conclusion] By selecting appropriate feature selection methods, classification accuracy can be maintained while effectively reducing lodging classification differences caused by spatial resolution variations. This facilitates increasing flight altitude, expanding wheat lodging monitoring area, and reducing operational costs, providing references and support for establishing crop lodging information acquisition strategies and wheat disaster assessment.

Full Text

Wheat Lodging Area Recognition Method Based on Different Spatial Resolution UAV Multispectral Remote Sensing Images

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Abstract

[**Objective**] Rapid and accurate assessment of crop lodging disasters requires timely acquisition of information such as the location and extent of lodging. Currently, there are no technical standards for crop lodging identification based on UAV remote sensing, which hinders the standardization of data acquisition workflows and problem-solving approaches. This study aims to investigate the effects of different spatial resolution UAV remote sensing images and feature optimization methods on the accuracy of wheat lodging area identification.

[**Methods**] After wheat lodging occurred, three flight altitudes were established to obtain digital orthophoto maps (DOM) at different spatial resolutions (1.05 cm, 2.09 cm, and 3.26 cm). A full feature set was constructed by extracting 5 spectral features, 2 height features, 5 vegetation indices, and 40 texture features from these multi-resolution images. Three feature selection methods—ReliefF algorithm, RF-RFE algorithm, and Boruta-Shap algorithm—were employed to screen and construct optimized feature subsets. Subsequently, three object-oriented supervised classification methods—Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN)—were used to build classification models for wheat lodging. The optimal classification strategy was identified and a technical pathway for lodging classification was established.

[**Results and Discussion**] The results demonstrated that the SVM classifier consistently outperformed RF and KNN across all scenarios. The highest classification accuracy was achieved at the 1.05 cm spatial resolution, surpassing the performance at 2.09 cm and 3.26 cm resolutions. Comparative analysis revealed that the Boruta-Shap feature optimization method could both reduce dimensionality and improve classification accuracy while adapting to spatial resolution variations. At 3.26 cm resolution, the overall classification accuracy reached 95.6% with a Kappa coefficient of 0.914, meeting the requirements for classification precision. The relative differences in classification accuracy between different flight heights were minimal: compared to 1.05 cm resolution, the overall accuracy decreased by only 1.06% at 2.09 cm and 1.81% at 3.26 cm.

[**Conclusions**] By selecting appropriate feature selection methods, classification accuracy can be maintained while effectively reducing lodging classification differences caused by spatial resolution variations. This approach facilitates increased flight altitude, expanded monitoring area, reduced operational costs, and provides reference and support for establishing crop lodging information acquisition strategies and wheat disaster assessment protocols.

Keywords: wheat lodging; UAV; flight altitude; feature selection; classification model; SVM; RF; KNN

1. Introduction

Wheat is one of China's major food crops, accounting for approximately 20.1% of total grain production in 2021 and serving as a critical cornerstone for national food security [1]. With global climate change, extreme weather events occur frequently, exposing crops to lodging threats during growth. When wheat lodging occurs, nutrient and water transport in plants is obstructed, severely affecting grain filling and causing yield and quality losses, while also hindering mechanized harvesting and increasing production costs [2,3]. Rapid acquisition of crop lodging area provides technical support for disaster assessment, post-disaster remediation, and agricultural insurance claims [4].

Traditional crop lodging surveys rely primarily on manual field measurements using Global Positioning System (GPS) devices and tape measures, which is labor-intensive, time-consuming, and inefficient [5]. The rapid development of remote sensing technology offers possibilities for large-scale, rapid monitoring of crop lodging. Compared with satellite and ground-based remote sensing, UAV remote sensing offers advantages of high precision, low cost, strong operability, and high spatiotemporal resolution, providing rapid support for disaster emergency response [6]. Tian et al. [7] extracted spectral reflectance, vegetation indices, texture features, and color features from UAV remote sensing images to optimize classification image features and construct a high-accuracy rice lodging monitoring model. Zhao et al. [8] used visible-light images and Digital Surface Models (DSM) obtained at 30 m flight altitude for wheat lodging classification research, achieving precise identification of lodging areas. Sun et al. [9] utilized feature transformation preprocessing of UAV multispectral images at 60 m flight altitude to achieve high-precision monitoring of maize lodging areas based on extracted features.

However, research based on single flight altitude has significant limitations, as different flight scenarios result in different remote sensing image resolutions, affecting the stability of UAV image feature data and reducing monitoring accuracy and efficiency. Additionally, remote sensing spatial theory development considers the relationship between scale and the inherent spatial attributes of geographic entities, making it more meaningful to select appropriate spatial resolutions for research. Flores and Zhang [10] used machine learning and deep learning algorithms to analyze UAV data from three flight altitudes (15, 46, and 91 m), finding that flight altitude significantly affected classification accuracy, with ResNet101 achieving similar classification performance on data collected at 91 m as at 15 m, thereby improving data acquisition and processing efficiency. Huang et al. [11] compared different supervised classification methods for extracting wheat lodging area from UAV multispectral images at different resolutions, establishing a suitable spatial resolution range. Yu et al. [12] evaluated wheat lodging segmentation accuracy using UAV remote sensing images at 20, 40, 80, and 120 m flight altitudes, finding that classification accuracy decreased with increasing flight altitude. These studies demonstrate that UAV-based crop monitoring research has primarily focused on optimal spatial resolution scenarios, while neglecting model differences, applicability, and flight efficiency across various flight scenarios.

Given that appropriate feature optimization methods can not only reduce data dimensionality and improve model accuracy but also ensure feature selection stability, robustness, and high generalization capability without being significantly affected by data fluctuations [13], this study investigates different feature selection methods combined with classifiers to analyze differences among various image spatial resolutions. We explore model adaptability and robustness across different spatial resolution images, optimize flight strategies through appropriate classification approaches, improve UAV flight efficiency, reduce crop monitoring costs, and achieve efficient monitoring of crop lodging areas.

2. Materials and Methods

2.1 Study Area Overview

The study area is located in the Henan Agricultural University Science and Education Park in Yuanyang County, Xinxiang City, Henan Province. The terrain is flat, situated in the central North China Plain, with a temperate continental climate. The average annual temperature is approximately 14.5°C, average annual precipitation is about 550.4 mm, and annual sunshine duration is approximately 2407 hours. The cropping system is primarily winter wheat-summer maize double cropping. During the 2021 wheat grain-filling stage, heavy rainfall and strong winds occurred in central and northern Henan, causing partial lodging in the wheat planting area of the Yuanyang Science and Education Park. The geographic location, plot distribution, and lodging conditions of the experimental area are shown in [Figure 1: see original paper].

2.2 Data Acquisition and Processing

A DJI M600 six-rotor UAV equipped with a K6 multispectral imager was used to acquire multispectral images of the actual wheat lodging area. The sensor has five multispectral channels: blue band (450$\pm 10 nm), greenband(550\pm 10 nm), redband(685\pm 10 nm), red-edgeband(725\pm 10 nm), andnear-infraredband(780\pm$10 nm). On the third day (May 5, 2021) and twelfth day (May 17, 2021) after lodging occurred, under clear, windless, and cloudless weather conditions, three UAV flight altitudes were set: 30, 60, and 90 m, corresponding to spatial resolutions of 1.05, 2.09, and 3.26 cm, respectively. Specific parameters are listed in .

The camera shooting mode used equal interval photography with 75% forward overlap and 70% side overlap. The gimbal pitch angle was set to 90°, while a handheld Real-Time Kinematic (RTK) receiver measured precise geographic coordinates of Ground Control Points (GCPs). Pix4Dmapper software was used to stitch the acquired UAV multispectral images and generate DSM and Digital Orthophoto Maps (DOM). ENVI5.3 software was then applied for geometric and radiometric correction of the generated images to obtain surface reflectance information and elevation data for the study area. Based on visual interpretation and the characteristics of the remote sensing images, classification rules were established after image segmentation. eCognition9.0 software randomly selected 196 Regions of Interest (ROI) to define training samples and 137 ROI to define validation samples for regional classification research. The specific technical route is shown in [Figure 2: see original paper].

2.3 Research Methods

This study aims to investigate the effects of different UAV flight altitudes, classification methods, and feature selection methods on wheat lodging classification and identification. First, UAV multispectral remote sensing images from different flight altitudes collected three days after lodging were preprocessed. Three types of features were selected to construct the feature set: spectral features (band reflectance and vegetation indices), texture features extracted from spectral bands, and DSM generated from UAV 3D point clouds to represent elevation information. Object-oriented classification methods including Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) were employed to train classification models using both full feature sets and feature subsets (ReliefF, RF-RFE, and Boruta-Shap) at different spatial resolutions.

The optimal classification strategy was identified by comparing classification accuracy, robustness, and overall efficiency.

2.4 Image Feature Extraction

Vegetation indices highlight specific characteristics or details of vegetation in images through combined operations of reflectance at two or more wavelength ranges. Based on previous research findings, this study selected common vegetation indices as listed in .

Texture features characterize large numbers of similar and regular or irregular elements and graphic structures in UAV images, describing the spatial variability of spectral bands. Since texture filtering of each spectral band reflects different feature information, this study used Gray Level Co-occurrence Matrix (GLCM) to extract texture features from five multispectral bands, obtaining 40 feature images. Specific texture feature parameter calculation formulas can be found in reference [18].

DSM represents a ground elevation model that includes surface features such as trees, buildings, and crops, encompassing elevation information for surface objects beyond the bare ground. The experimental area has flat terrain, so using DSM alone could reflect height characteristic changes of lodged wheat. Therefore, the mean height (Hmean) and standard deviation (Hsd) extracted from DSM were used for wheat lodging classification.

2.5 Feature Selection Methods

Feature selection quality significantly affects classifier performance. High data dimensionality can cause the "curse of dimensionality," making it necessary to eliminate features with low correlation or irrelevance to improve modeling efficiency while ensuring classification accuracy.

(1) ReliefF Feature Selection. This algorithm randomly selects a sample R from the training set, finds k nearest neighbors from the same class (Near Hit) and k nearest neighbors from each different class (Near Miss), then updates the weight of each feature based on distances between R and its Near Hits and Near Misses. After repeating this process m times, the average weight of each feature is obtained. Features with weights above a threshold are retained, or only the top n features with the highest weights are kept.

(2) RF-RFE Feature Selection. Using RF as the base classifier, this method quantitatively evaluates the importance of each feature and introduces variables in descending order of importance to determine classification accuracy. The process involves training a model with all features, calculating and ranking feature importance, removing the least important feature, retraining the model with the new dataset, and repeating until no variables remain. The optimal feature subset is selected by comparing classification performance at each iteration.

(3) Boruta-Shap Feature Selection. Boruta-Shap is a wrapper feature selection method that combines the Boruta algorithm with Shapley values. This combination outperforms the original permutation importance method in both speed and feature subset quality. It helps mitigate the impact of selecting high-frequency or high-cardinality variables while providing a better feature subset and more accurate global feature ranking for model interpretation, reducing data overfitting. Currently, this algorithm is widely applied across different fields, demonstrating excellent performance in feature set optimization and model accuracy improvement [21,22].

2.6 Classification Methods

eCognition9.0 software was used for object-oriented classification of remote sensing images. Multi-scale segmentation is the most critical step in object-oriented classification research. Through repeated experimental verification, appropriate segmentation parameters were determined to achieve optimal results: a segmentation scale of 1, shape factor of 0.1, and compactness of 0.5. Since the study area adopted a small-plot planting pattern, these parameters were finalized after multiple trials. Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN) classifiers were selected as crop lodging classification methods.

2.7 Accuracy Evaluation

The confusion matrix is calculated by comparing the location and classification of each measured pixel with the corresponding location in the classification image, serving as an indicator for evaluating model results. Overall Accuracy (OA) represents the ratio of correctly classified pixels to total pixels, while the Kappa coefficient measures classification accuracy. These two common metrics were selected to evaluate the correctness of wheat lodging identification, as shown in equations (6) and (7) [19]:

$$OA = \frac{\sum_{i=1}^{n} x_{ii}}{N} \times 100\%$$

$$Kappa = \frac{N\sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{n}(x_{i+} \times x_{+i})}$$

where N represents the total number of validation samples, n represents the total number of columns in the confusion matrix, x_{ii} represents the pixel count at row i and column i of the confusion matrix, and x_{i+} and x_{+i} represent the sums of rows and columns in the confusion matrix, respectively.

3. Results

3.1 Lodging Classification Based on Full Feature Set

To compare the effects of multi-feature information on crop lodging classification under different flight altitudes, SVM, RF, and KNN classifiers were used to model the full feature set. OA and Kappa coefficients were used to evaluate classification model accuracy, with results shown in . Within the resolution range of 1.05–3.26 cm, image variations had the same impact on the three different classifiers, with 1.05 cm identified as the optimal resolution and classification accuracy decreasing as resolution decreased. Specifically, when resolution decreased from 1.05 to 3.26 cm, the overall classification accuracy ranges for SVM, RF, and KNN were 90.4%–93.7%, 85.7%–89.7%, and 79.8%–85.1%, respectively, with SVM significantly outperforming RF and KNN.

Further examination of relative differences in overall classification accuracy between spatial resolutions showed that for SVM, accuracy decreased by 1.19%, 3.65%, and 2.43% when comparing 1.05 vs. 2.09 cm, 1.05 vs. 3.26 cm, and 2.09 vs. 3.26 cm, respectively. Corresponding decreases for RF were 2.51%, 4.67%, and 2.10%, while KNN showed decreases of 3.40%, 6.64%, and 3.13%. Thus, based on the full feature set combination from remote sensing images, the SVM model achieved optimal classification performance at 1.05 cm spatial resolution. Classification results are shown in [Figure 3: see original paper]. As resolution decreased, misclassification and omission errors increased, with more homogeneous ground objects being classified into different categories, leading to the "salt-and-pepper effect."

3.2 Lodging Classification Based on ReliefF Algorithm

The ReliefF feature selection algorithm was applied to screen 52 feature variables from the full feature set under three different flight scenarios. With a threshold of 0.02, features with weights greater than 0.02 were selected for the ReliefF feature subset ([Figure 4: see original paper]). At resolutions of 1.05, 2.09, and 3.26 cm, the numbers of selected variables were 12, 8, and 6, respectively. As shown in , within the resolution range of 1.05–3.26 cm, the overall classification accuracy ranges for SVM, RF, and KNN were 89.8%–91.6%, 83.5%–85.2%, and 78.2%–83.4%, respectively. The classification performance of SVM and RF decreased with increasing flight altitude.

Relative differences in overall classification accuracy between spatial resolutions showed that for SVM, accuracy decreased by 1.21%, 2.00%, and 0.78% when comparing 1.05 vs. 2.09 cm, 1.05 vs. 3.26 cm, and 2.09 vs. 3.26 cm, respectively. Corresponding decreases for RF were 0%, 2.04%, and 2.04%, while KNN showed decreases of 2.33%, 6.65%, and 4.22%. These results demonstrate that across the three different flight scenarios, the SVM classifier achieved significantly higher classification accuracy than RF and KNN with strong generalization capability. Using the ReliefF algorithm to screen feature sets at different spatial resolutions reduced the number of features while maintaining optimal classification performance for the SVM model at 1.05 cm resolution, achieving an OA of 91.6% and Kappa coefficient of 0.867.

3.3 Lodging Classification Based on RF-RFE Algorithm

At the three flight altitudes, the RF-RFE algorithm quantitatively evaluated the importance of each feature and introduced variables in descending order of importance to determine classification accuracy. The numbers of selected variables were 11, 6, and 6 at spatial resolutions of 1.05, 2.09, and 3.26 cm, respectively, with feature selection results shown in [Figure 5: see original paper]. Within the resolution range of 1.05–3.26 cm, the overall classification accuracy ranges for SVM, RF, and KNN were 90.3%–92.0%, 84.3%–86.0%, and 78.9%–82.8%, respectively ().

Relative differences in overall classification accuracy between spatial resolutions showed that for SVM, accuracy decreased by 0.767%, 1.88%, and 1.11% when comparing 1.05 vs. 2.09 cm, 1.05 vs. 3.26 cm, and 2.09 vs. 3.26 cm, respectively. Corresponding decreases for RF were 0.116%, 1.90%, and 2.02%, while KNN showed decreases of 2.86%, 4.94%, and 2.03%. These results indicate that across the three different flight scenarios, the SVM classifier achieved higher classification accuracy than RF and KNN with relatively stable performance. The SVM model demonstrated optimal classification performance at 1.05 cm spatial resolution, achieving an OA of 92.0% and Kappa coefficient of 0.854.

3.4 Lodging Classification Based on Boruta-Shap Algorithm

The Boruta-Shap algorithm was used to screen feature subsets from the full feature set. Features with importance scores higher than shadow features were labeled green and defined as important variables for model construction. The numbers of selected variables were 39, 43, and 35 at spatial resolutions of 1.05, 2.09, and 3.26 cm, respectively, with feature selection results shown in [Figure 6: see original paper]. Within the resolution range of 1.05–3.26 cm, the overall classification accuracy ranges for SVM, RF, and KNN were 93.9%–95.6%, 85.8%–90.7%, and 81.3%–84.7%, respectively, with overall classification performance decreasing as flight altitude increased ().

Relative differences in overall classification accuracy between spatial resolutions showed that for SVM, accuracy decreased by 1.06%, 1.81%, and 0.75% when comparing 1.05 vs. 2.09 cm, 1.05 vs. 3.26 cm, and 2.09 vs. 3.26 cm, respectively. Corresponding decreases for RF were 3.66%, 5.71%, and 1.98%, while KNN showed decreases of 1.68%, 4.18%, and 2.46%. These results demonstrate that across the three different flight scenarios, SVM and RF showed relatively small differences between altitudes with stable performance. The SVM model achieved optimal classification performance at 1.05 cm spatial resolution, with an OA of 95.6% and Kappa coefficient of 0.914.

3.5 Adaptability Analysis of Lodging Classification Models

Considering the growth recovery effect after lodging, UAV multispectral images from 12 days after lodging were processed using the same methodology for comparative validation, with results shown in . Within the resolution range of 1.05-3.26 cm, the overall classification accuracy ranges for SVM, RF, and KNN were 81.9%-87.5%, 74.4%-79.9%, and 86.2%-90.4%, respectively. The SVM classifier generally outperformed RF and KNN. While the full feature set achieved the highest classification accuracy, it was more sensitive to height features with greater variation range. In contrast, the Boruta-Shap feature subset was less sensitive to height features, demonstrating greater robustness while maintaining high classification accuracy.

For different resolution remote sensing images, the optimal spatial resolution was 1.05 cm, with classification accuracy decreasing overall as spatial resolution decreased. As shown in [Figure 7: see original paper], UAV multispectral images collected shortly after lodging (May 5) produced higher classification accuracy compared to images collected after a period of time (May 17), regardless of the feature set used. This indicates that the early lodging stage provides better color contrast, while stems partially recover upright growth over time, leading to natural color loss and similar texture structures that reduce classification accuracy.

4. Discussion and Conclusion

4.1 Discussion

UAV image spatial resolution, determined by flight altitude, directly affects monitoring efficiency and precision. Therefore, the impact of remote sensing image resolution on model stability must be considered when establishing crop lodging area classification models. The results show that increasing UAV altitude to 90 m significantly improves flight efficiency for wheat lodging area monitoring. For the same monitoring range, data acquisition time is reduced to approximately 1/6th of that at 30 m, and the number of images decreases from 62 to 6, demonstrating that increased altitude substantially enhances monitoring efficiency.

This study investigated the effects of different spatial resolution remote sensing images on wheat lodging area classification results using multiple classification features. By establishing three different flight scenarios (spatial resolutions of 1.05, 2.09, and 3.26 cm), the results indicate that 1.05 cm spatial resolution is optimal for wheat lodging area identification. As image spatial resolution decreases, overall classification performance gradually deteriorates, positioning accuracy declines, and spatial consistency of classification results worsens. However, obtaining high spatial resolution requires low flight altitude, which reduces monitoring efficiency. Therefore, UAV remote sensing monitoring of wheat lodging should not solely pursue high spatial resolution but must comprehensively consider flight costs, image acquisition and processing efficiency, and classification accuracy to find an appropriate balance based on specific requirements.

Feature selection is a crucial data preprocessing technique that can significantly improve machine learning algorithm performance and enhance model stability and applicability [20]. Compared with other feature optimization methods, the Boruta-Shap algorithm reduces the number of features by including only relevant features without affecting model performance. Adding Shapley values to the Boruta algorithm enhances important features, providing a better feature subset and more accurate global feature ranking for model interpretation and reducing data overfitting. This algorithm is currently widely applied across different fields, demonstrating excellent performance in feature set optimization and model accuracy improvement [21,22].

Different feature selection methods employ different criteria for screening parameter variables, resulting in substantial differences for different target attributes. Even under the same dataset conditions, different feature selection methods yield varying performance improvements for models [23,24]. This study compared classification accuracy using the full feature set, ReliefF feature subset, RF-RFE feature subset, and Boruta-Shap feature subset. The Boruta-Shap feature selection method achieved the best performance, reducing data dimensionality and improving computational speed while maintaining high classification accuracy. Under the three spatial resolution conditions (1.05, 2.09, and 3.26 cm), the overall classification accuracies were 95.6%, 94.6%, and 93.9%, respectively.

Feature selection stability is also an important consideration, as high stability facilitates the screening of relevant variables, improves feature credibility, model robustness, and performance, and enhances model interpretability [25,26]. Comparing different feature sets, the object-oriented SVM classifier combined with the Boruta-Shap feature optimization algorithm demonstrated strong application and promotion advantages for lodging area identification in multi-altitude remote sensing images. The relative differences in overall classification accuracy between spatial resolutions of 1.05 vs. 2.09 cm, 1.05 vs. 3.26 cm, and 2.09 vs. 3.26 cm were only 1.06%, 1.81%, and 0.75%, respectively, indicating small differences in accuracy metrics and strong model adaptability across different flight altitudes. Therefore, selecting appropriate feature selection methods can achieve high-precision crop lodging area identification while reducing the influence of image spatial resolution on model stability, thereby helping to increase flight altitude, expand monitoring range, improve UAV operation efficiency, and reduce flight costs.

This experiment utilized low-altitude UAVs equipped with multispectral sensors, establishing three flight altitudes (30, 60, and 90 m) and using three object-oriented classification methods (SVM, RF, and KNN) to train models on full feature sets and feature subsets (ReliefF, RF-RFE, and Boruta-Shap). When lodging occurs during the early grain-filling stage, lodged wheat can partially recover upright growth over time, causing canopy structure changes that result in different texture features obtained from UAV images at different times. The spectral changes in the early lodging stage depend primarily on stem and leaf conditions, while over time, the spectral characteristics of lodging are gradually determined by the ear, leading to differences in remote sensing monitoring analysis methods and lodging accuracy at different time periods [27,28]. The lodging monitoring strategy and method established in this study utilized images from three days after lodging. To verify the stability and applicability of the lodging classification model, UAV image data from 12 days after lodging were used for validation. The results showed that although lodging classification accuracy decreased somewhat, the lodging area could still be well identified, providing technical reference and timing selection guidance for accurate lodging area monitoring. In practice, lodging monitoring should be conducted as early as possible to ensure more precise monitoring of areas and extents, facilitate timely post-disaster remediation measures, accelerate plant recovery growth, and minimize the adverse effects of lodging.

4.2 Conclusion

This study comprehensively considered the effects of UAV flight altitude, feature selection, classifier methods, and flight date on wheat lodging classification accuracy. It compared the impacts of different resolution remote sensing images on classifiers and feature selection methods, and systematically examined UAV monitoring results for wheat lodging from the perspectives of classification accuracy, robustness, and overall efficiency. The SVM classifier demonstrated higher classification accuracy and better generalization than RF and KNN. The Boruta-Shap optimized feature set performed best, reducing data dimensionality while maintaining high accuracy and improving data processing efficiency. The combination of Boruta-Shap and SVM significantly improved classification accuracy, enhanced data stability, reduced classification accuracy differences between different flight altitudes, and expanded the selection range of UAV flight altitudes and monitoring periods. Based on specific requirements and actual conditions, a balance between classification accuracy and efficiency can be sought, providing information reference for selecting appropriate flight altitudes and corresponding image resolutions in practical production applications.

This experiment focused only on lodging classification in small-scale variety planting areas. Future research should collect larger lodging areas for further validation, conduct feasibility analysis on the transferability of lodging models across different periods and regions, and further refine wheat lodging grade classification to comprehensively evaluate the impact of lodging stress on wheat growth and yield. This will provide multiple feasible solutions and technical support for disaster assessment and remediation measure formulation.

Conflict of Interest Statement: The authors declare that they have no conflicts of interest regarding the publication of this research.

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Note: Figure translations are in progress. See original paper for figures.