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Early Detection of Soybean Pest Infestation Using Hyperspectral Sensing and Machine Learning

Matheus Arroyo de Lima[a], Lúcio André de Castro Jorge[b], Ednaldo José Ferreira[b], Liang Zhao[a], Joaquim Cezar Felipe[a]

[a] Faculty of Philosophy, Sciences and Letters at Ribeirão Preto (FFCLRP), University of São Paulo, Ribeirão Preto, 14040-901, SP, Brazil.

[b] National Research Center for Development of Agricultural Instrumentation, Brazilian Agricultural Research Agency, São Carlos, 13561-206, SP, Brazil.

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Abstract.

The agricultural sector plays a central role in sustaining global food production, energy supply, and economic development. However, population growth, climate change, resource scarcity, and increasing sustainability demands have intensified production challenges. Pest and disease outbreaks are major contributors to crop losses worldwide, underscoring the urgent need for reliable methods capable of enabling early detection and timely intervention. In this context, leaf-level spectroradiometry has emerged as a promising approach, as it can capture subtle physiological and biochemical alterations that precede the onset of visible symptoms, thereby supporting proactive crop management strategies. Building upon this premise, this study investigates the application of supervised machine learning models in a controlled greenhouse experiment to diagnose stink bug infestations and caterpillar damage in soybean plants using spectroradiometric data. Plants were monitored over one week and grouped into stink bug infestation, caterpillar infestation, and non-infested control treatments. Three experimental scenarios were also defined: one multiclass classification including all groups and two binary classifications (control versus each pest). Performance was also evaluated daily to examine progression throughout the infestation period. Models were trained using the full spectrum and reduced subsets of the 20, 10, and 5 most informative wavelengths to evaluate dimensionality reduction. After removing noise-affected spectral bands, 1,594 wavelengths were retained for analysis. Statistical tests were applied to evaluate data distribution (normality) and class separability (ANalysis Of Variance), revealing significant differences mainly in the late ultraviolet (350–400 nm) and visible (400–700 nm) regions, indicating strong discriminatory potential. Feature selection and classification were conducted using K-Nearest Neighbors, Random Forest, XGBoost, Support Vector Machines, and Artificial Neural Networks. Feature importance analysis consistently identified the ultraviolet and visible regions as the most discriminative, with comparatively lower contribution from the near- and mid-infrared regions. Classification *performance was promising, achieving accuracies of 87% for stink bug detection, 78% for caterpillar detection, and 81% in the multiclass scenario. Reducing the feature space to the 20 most informative wavelengths resulted in an average accuracy decrease of only 3.5%, whereas reductions to 10 and 5 wavelengths led to decreases of 8.7% and 18.7%, respectively. Reducing dimensionality from 1,594 to 20 features maintained competitive performance, highlighting the feasibility of simplifying data acquisition systems. A progressive improvement in classification performance was observed over the course of each day of the week, suggesting increased spectral separability as infestation severity advanced, with the identification of the infestation occurring already in the early days. Overall, the findings demonstrate the potential of hyperspectral sensing combined with machine learning as an effective tool for early pest detection in soybean crops, supporting simplified sensing architectures and more precise, sustainable management within precision agriculture systems.*

Keywords.
Spectroradiometry;Soybean; Pest detection; Machine learning; Feature selection;Early pest detection;Precision agriculture.

Introduction

Soybean is one of the most important agricultural crops worldwide, standing out as a source of plant protein and oil for the global population (Iost Filho et al. 2022). This relevance is also significant in Brazil, which holds a prominent position in global soybean production and has soybean among its main agricultural commodities (Iost Filho et al. 2022; Oliveira et al. 2014). However, soybean yield stability is continuously threatened by biotic factors, including insect pests, which can reduce productivity, compromise production quality, and cause significant economic losses (Savary et al. 2019; Oliveira et al. 2014). At the global scale, pests and pathogens are associated with substantial losses in major agricultural crops, including soybean, while, in the Brazilian context, insect pests represent a significant source of productive and economic losses, reinforcing the need for efficient monitoring and management strategies (Savary et al. 2019; Oliveira et al. 2014).

Among the insect pests associated with soybean cultivation, defoliating caterpillars and stink bugs are among the groups of greatest economic importance, especially in the Neotropical region (Iost Filho et al. 2022). Caterpillars can cause damage by feeding on leaves, flowers, and pods, whereas stink bugs, due to their sucking feeding habit, are mainly associated with damage to pods and seeds (Iost Filho et al. 2022). In Brazil, species such as *Chrysodeixis includens* and *Spodoptera eridania* are cited among the caterpillars of importance for soybean, while *Euschistus heros* stands out among the most abundant and economically relevant stink bugs (Iost Filho et al. 2022; Hayashida et al. 2023). The management of these insects depends on adequate monitoring of field populations and decision-making based on control thresholds; however, traditional sampling methods can be time-consuming, labor-intensive, and difficult to apply over large areas, reinforcing the need for faster and more objective strategies to support pest detection and management (Iost Filho et al. 2022; Hayashida et al. 2023).

In this context, spectral sensing techniques have been investigated as promising tools for plant monitoring and for identifying biotic and abiotic stresses in agricultural systems (Galieni et al. 2021; Sarić et al. 2022; Terentev et al. 2022). The spectral reflectance recorded in plant tissues can vary according to the physiological status of the plant and is related to characteristics such as pigment concentration, cellular structure, water content, and leaf biochemical composition (Galieni et al. 2021; Ge et al. 2019; Sarić et al. 2022). For this reason, methods based on spectroscopy and hyperspectral imaging can provide non-destructive information on stress-related changes before symptoms become visually evident, favoring the development of approaches aimed at early detection and more timely management of agricultural diseases and pests (Galieni et al. 2021; Terentev et al. 2022).

Despite the potential of hyperspectral data, their use in agricultural classification problems presents important methodological challenges. These data generally include a large number of wavelengths, which increases the dimensionality of the dataset and may introduce redundancy among variables, noise, and information with limited relevance for classification (Hennessy et al. 2020; Yamada et al. 2024; Mensah et al. 2024). In this scenario, machine learning models have been employed to explore complex spectral patterns and handle high-dimensional data in agricultural applications, including models such as Support Vector Machine, Random Forest, XGBoost, k-Nearest Neighbors, and neural networks (Yamada et al. 2024; Huang et al. 2022; Mensah et al. 2024). In addition to classification, feature selection strategies are important for reducing dimensionality, removing redundant information, and identifying the wavelengths most relevant for class separation, potentially contributing both to improving model efficiency and to guiding the development of simpler sensors targeted at specific spectral ranges (Hennessy et al. 2020; Huang et al. 2022; Yamada et al. 2024).

Considering that previous studies have demonstrated the potential of hyperspectral data to characterize injuries caused by insects in soybean plants, and that the combination of spectral data and machine learning has shown promise for the early detection of biotic stresses in agricultural crops (Iost Filho et al. 2022; Yamada et al. 2024), this study evaluated the use of supervised machine learning models for the early detection of stink bug infestations and caterpillar damage in soybean plants, using leaf-level spectral reflectance data obtained from an experiment conducted in a greenhouse. Three classification scenarios were considered: a multiclass scenario involving control plants, plants infested with stink bugs, and plants subjected to caterpillar damage; and two binary scenarios comparing control plants with each type of infestation separately. In addition, model performance was evaluated daily throughout the experimental period, with the aim of investigating the temporal evolution of spectral separability and the possibility of early infestation identification.

In addition to evaluating classification performance, this study also investigated the impact of dimensionality reduction of the spectral data. This analysis is relevant because hyperspectral measurements generally contain a large number of wavelengths and may include redundant or weakly informative variables, which increases computational cost and hinders their application in simpler or real-time systems (Hennessy et al. 2020; Mensah et al. 2024; Ma et al. 2014). In this sense, wavelength selection makes it possible to reduce the number of variables used by the models, retaining only the spectral regions most relevant for class discrimination (Hennessy et al. 2020; Mensah et al. 2024). Previous studies have also indicated that the selection of appropriate spectral variables can improve model generalization, reduce redundant information, and support the construction of more efficient detection systems (Huang et al. 2022; Ma et al. 2014; Yamada et al. 2024). Based on this context, models trained with the full spectrum were compared with models trained using reduced subsets composed of the 20, 10, and 5 most informative wavelengths, with the objective of verifying whether a smaller number of bands would be sufficient to maintain performance close to that obtained with all available bands.

Materials and Methods

Greenhouse experiment and spectral dataset

The study was conducted based on a controlled greenhouse experiment using soybean plants subjected to different insect infestation conditions. The samples were organized into three experimental groups: non-infested plants, used as the control; plants subjected to stink bug infestation; and plants subjected to caterpillar damage. Monitoring was carried out over one week, allowing the evaluation not only of the spectral separation among treatments but also of the temporal evolution of plant responses during the infestation period. Measurements were obtained at the leaf level using reflectance spectroradiometry, with the objective of recording spectral changes associated with the evaluated conditions.

The spectroradiometric measurements were organized to represent the leaf reflectance response of soybean plants under each experimental condition. After the initial organization of the data, spectral regions affected by noise were removed, resulting in a final dataset composed of 1,594 wavelengths used in the analyses. This dataset was employed both for the evaluation of the full spectrum and for the subsequent comparison with reduced wavelength subsets, allowing the investigation of the effect of dimensionality reduction on the performance of the classification models.

Classification scenarios

Three classification scenarios were defined to evaluate the ability of the models to distinguish control soybean plants from plants subjected to different types of infestation. The first scenario corresponded to a multiclass classification, simultaneously considering the control, stink bug, and caterpillar classes. The other two scenarios were formulated as binary problems, comparing control plants with plants infested by stink bugs and control plants with plants subjected to caterpillar damage. This organization allowed the evaluation of both the overall separation among the three experimental groups and the ability of the models to individually identify each type of infestation in relation to non-infested plants. In addition, the scenarios were evaluated across the sampling days, allowing the investigation of the temporal evolution of model performance and their ability to identify infestations during the first days of the experiment.

Spectral preprocessing

Before applying the statistical tests and classification models, the spectral data were organized and preprocessed with the objective of removing regions affected by noise and retaining only wavelengths suitable for analysis. Noisy bands were excluded from the original dataset, resulting in 1,594 wavelengths retained for the experiments. This set was considered the full spectrum in the modeling stages. From this dataset, reduced feature subsets were also derived, composed of the 20, 10, and 5 most informative wavelengths, which were subsequently used to evaluate the impact of dimensionality reduction on model performance.

Statistical analysis of spectral bands

After preprocessing the spectral data, a statistical analysis was performed to evaluate the distribution of reflectance values and the separability among classes across the wavelengths. Initially, data normality was assessed to guide the interpretation of the statistical tests applied. Subsequently, analysis of variance (ANOVA) was used to identify wavelengths with significant differences among the experimental groups, considering the control, stink bug, and caterpillar classes. This approach is consistent with spectral studies that evaluate reflectance variation at each wavelength and use statistical tests to identify regions with greater discriminative potential among classes or experimental conditions (Hennessy et al. 2020; Li et al. 2023). The results were analyzed across the spectrum, with special attention to the near-ultraviolet region, between 350 and 400 nm, and the visible region, between 400 and 700 nm, since these ranges showed stronger evidence of separability among the treatments in the evaluated dataset.

Feature selection

Following the initial evaluation of the models using the full spectrum, a feature selection step was performed with the objective of identifying the most informative wavelengths for classifying the evaluated conditions. This step was necessary because hyperspectral data have high dimensionality and may contain redundant or weakly relevant wavelengths, which can increase model complexity and hinder their application in simpler detection systems (Hennessy et al. 2020; Mensah et al. 2024). Wavelength selection was conducted based on feature importance estimated by the XGBoost model, a strategy consistent with tree-based machine learning approaches, which are capable of ranking input variables according to their contribution to predictive modeling (Huang et al. 2022). Based on this ranking, three reduced subsets were defined, composed of the 20, 10, and 5 most informative wavelengths. These subsets were subsequently used as input for the classification models, allowing the comparison of performance obtained with the full spectrum and with more compact spectral sets.

Machine learning models

To evaluate the classification capacity of the spectral data, five supervised machine learning models were used: k-Nearest Neighbors (kNN), Random Forest, XGBoost, Support Vector Machine (SVM), and Artificial Neural Networks (ANN). These models were selected because they represent different classification strategies and are frequently employed in agricultural applications involving spectral and hyperspectral data (Mensah et al. 2024; Yamada et al. 2024). kNN was used as a classifier based on the proximity between samples in the feature space. Random Forest and XGBoost were employed as tree-based methods capable of handling nonlinear relationships, correlated variables, and high-dimensional data (Huang et al. 2022; Yamada et al. 2024). SVM was included due to its broad application in classification problems involving hyperspectral data and its ability to operate in high-dimensional feature spaces (Mensah et al. 2024; Yamada et al. 2024). Finally, artificial neural networks were evaluated for their ability to model complex and nonlinear relationships in the spectral data (Yamada et al. 2024). All models were trained under the three previously defined classification scenarios, using both the full spectrum and the reduced subsets composed of the 20, 10, and 5 most informative wavelengths.

Model evaluation

Model performance was evaluated using accuracy as the main metric, since this measure provides a general indication of the proportion of correctly classified samples in relation to the total number of evaluated samples (Dzurume et al. 2025). To avoid conducting the evaluation only on the data used to fit the models, the data were organized into training, validation, and test sets, a procedure commonly used to tune hyperparameters, reduce the risk of overfitting, and evaluate predictive capacity on samples not used during training (Mensah et al. 2024). The evaluation was conducted separately for the three defined classification scenarios, considering both the full spectrum and the reduced subsets composed of the 20, 10, and 5 most informative wavelengths. In addition, performance was analyzed daily throughout the experimental period, allowing the investigation of accuracy evolution during the infestation week and the assessment of the possibility of early identification of stress conditions.

Results and Discussion

Spectral separability among treatments

The statistical analysis of the spectral bands indicated that differences among the control, stink bug, and caterpillar classes did not occur uniformly across the entire spectrum. The regions with greater evidence of separability were mainly concentrated in the near-ultraviolet region, between 350 and 400 nm, and in the visible spectrum, between 400 and 700 nm, indicating that these ranges showed greater discriminative potential for distinguishing the evaluated conditions.

To provide an initial visual comparison among treatments, Figure 1 presents the mean leaf reflectance spectra of soybean plants under control, stink bug infestation, and caterpillar damage. The curves show differences in spectral response among treatments, especially in portions of the ultraviolet and visible regions, supporting the statistical evidence of spectral separability.

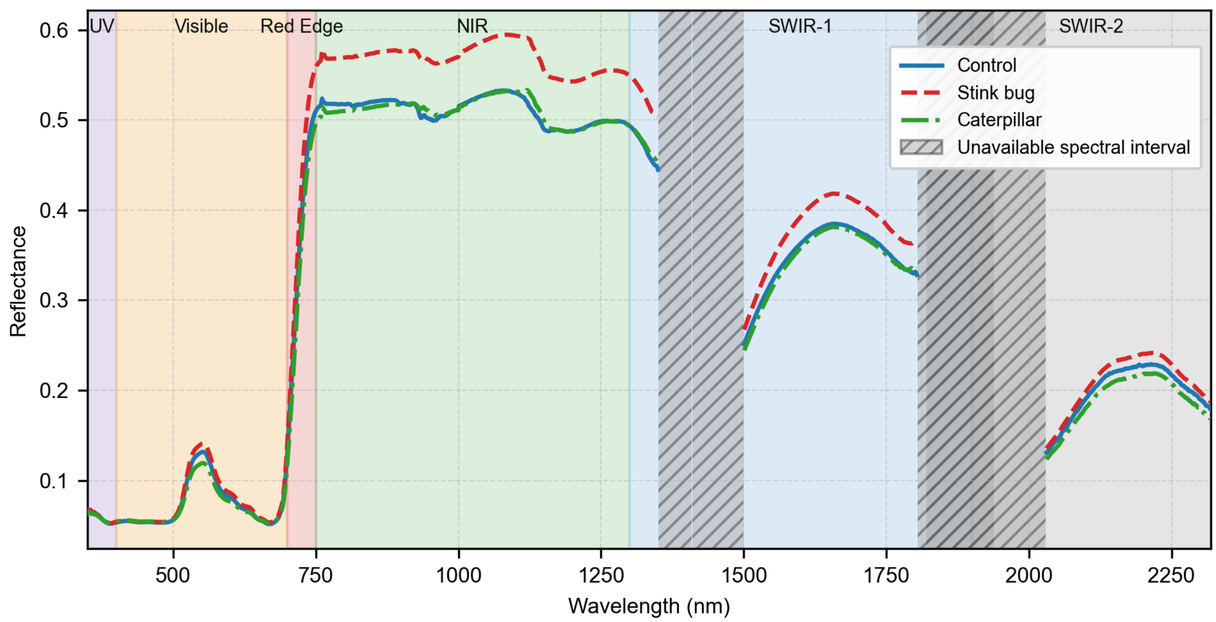

Figure 1 - Mean leaf reflectance spectra of soybean plants under control, stink bug infestation, and caterpillar damage.

This result is consistent with the sensitivity of these regions to changes in the optical properties of leaves, since the interaction of electromagnetic radiation with plant tissues depends on leaf structure and biochemical composition, including pigments, water, and dry matter compounds (Li et al. 2023). In particular, the visible region is strongly associated with absorption by photosynthetic pigments, such as chlorophylls and carotenoids, whereas stress-related changes can alter the relationship between the plant and electromagnetic radiation in specific spectral domains (Galieni et al. 2021; Ge et al. 2019). Thus, the greater separability observed in the near-ultraviolet and visible regions suggests that insect-induced damage may have caused detectable changes in leaf spectral response before or during the development of visual symptoms.

Feature importance and selected wavelengths

The feature importance analysis indicated that the wavelengths most relevant for classifying the evaluated conditions were mainly concentrated in the ultraviolet and visible regions, while the near-infrared and shortwave infrared regions showed a comparatively lower contribution. This pattern is consistent with the results of the statistical analysis, which also indicated greater separability in the 350–400 nm and 400–700 nm ranges.

The most informative wavelengths selected by feature importance analysis are shown in Fig. 2. The selected wavelengths were distributed across different spectral regions, but several of them were located in the late ultraviolet and visible portions of the spectrum, reinforcing the role of these regions in discriminating soybean plants under different pest-related conditions.

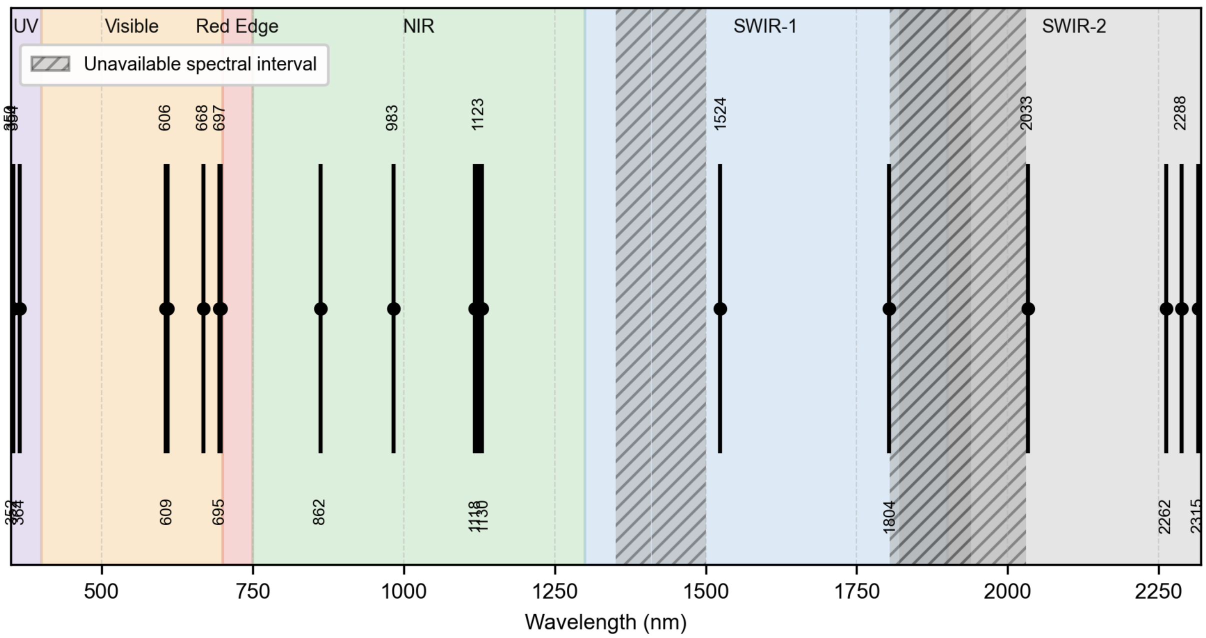

Figure 2 - Most informative wavelengths for soybean pest classification based on feature importance analysis.

The predominance of these regions suggests that changes associated with stink bug infestation and caterpillar damage may have affected optical properties related to pigments and other leaf biochemical components, since the visible region is strongly influenced by light absorption by photosynthetic pigments (Li et al. 2023; Galieni et al. 2021). In addition, the identification of a reduced set of relevant wavelengths reinforces the importance of feature selection in hyperspectral data, since this type of data generally has high dimensionality and may contain redundant or weakly informative variables (Hennessy et al. 2020; Mensah et al. 2024). Thus, the results obtained indicate that the discriminative information required for classification was not homogeneously distributed across the entire spectrum, but was more concentrated in specific ranges, especially in the near-ultraviolet and visible regions.

Classification performance using the full spectrum

The evaluation of the models using the full spectrum, composed of the 1,594 wavelengths retained after removing the bands affected by noise, indicated promising performance for classifying the evaluated conditions in soybean plants. In the binary scenario for stink bug detection, the models achieved an accuracy of 87%, while the detection of caterpillar damage reached an accuracy of 78%. In the multiclass scenario, simultaneously involving control plants, plants infested by stink bugs, and plants subjected to caterpillar damage, the accuracy was 81%. These results indicate that leaf reflectance patterns contain sufficient information to distinguish non-infested plants from plants affected by insects, although the separation among classes varies according to the type of infestation and the complexity of the classification scenario. This behavior is consistent with previous studies that demonstrated the potential of hyperspectral data and machine learning models to characterize injuries caused by soybean pests and to detect infestations early in agricultural crops (Iost Filho et al. 2022; Yamada et al. 2024). The difference among the scenarios also suggests that the spectral response associated with caterpillar damage and stink bug infestation may present distinct levels of separability, reinforcing the importance of evaluating both binary and multiclass classifications.

Early detection across infestation days

The daily evaluation of model performance indicated a progressive improvement in accuracy throughout the monitoring week, suggesting an increase in spectral separability between control plants and plants subjected to infestation as the exposure period to insects advanced.

This temporal behavior is presented in Figure 3, which shows the classification accuracy across infestation days using the full spectrum. Each panel corresponds to one classification scenario, allowing the performance of the models to be compared separately for stink bug detection, caterpillar damage detection, and the multiclass classification problem.

Figure 3 - Classification accuracy across infestation days using the full spectrum.

The identification of infestations during the first days indicates that leaf spectroradiometry, combined with machine learning models, can capture subtle changes before symptoms become fully evident. This result is consistent with the premise that hyperspectral sensors can support the early recognition of plant stresses through small variations in spectral reflectance (Terentev et al. 2022), as well as with studies that have demonstrated the usefulness of temporal assessment and machine learning models for detecting infestations in agricultural crops based on hyperspectral data (Yamada et al. 2024).

Effect of dimensionality reduction

The effect of dimensionality reduction on classification performance is shown in Figure. 4, which compares the accuracy obtained using the full spectrum and the reduced subsets composed of the 20, 10, and 5 most informative wavelengths. Each panel represents one classification scenario, while each line corresponds to a machine learning model.

Figure 4 - Classification accuracy using the full spectrum and reduced wavelength subsets.

Reducing the spectral input to the 20 most informative wavelengths resulted in an average accuracy decrease of only 3.5%, indicating that this subset preserved a substantial portion of the discriminative information contained in the full spectrum. In contrast, more aggressive reductions to 10 and 5 wavelengths led to average decreases of 8.7% and 18.7%, respectively, suggesting a progressive loss of relevant information for classification as fewer bands were retained.

These results are consistent with the literature on hyperspectral data, which highlights the importance of feature selection for reducing high dimensionality, redundancy among bands, and the computational cost of classification models (Hennessy et al. 2020; Mensah et al. 2024). Moreover, the maintenance of competitive performance using only 20 wavelengths reinforces the potential for simplifying spectral acquisition systems, since previous studies have also shown that band selection can reduce the number of required variables and support more efficient applications for detecting injuries or infestations in plants (Ma et al. 2014; Yamada et al. 2024). Therefore, the results suggest that approaches based on a reduced number of spectral bands may be promising for the development of simpler sensors targeted at specific wavelength ranges and potentially applicable to agricultural monitoring systems.

Conclusion

The results of this study demonstrated that leaf-level reflectance spectroradiometry, combined with supervised machine learning models, has potential for the early detection of stink bug infestations and caterpillar damage in soybean plants. The evaluated models were able to distinguish control plants from plants subjected to biotic stresses in both binary and multiclass scenarios, indicating that leaf spectral patterns contain relevant information for discriminating the evaluated conditions. The temporal analysis showed a progressive improvement in performance over the monitoring days, suggesting increased spectral separability as the exposure period to insects advanced, while also indicating that infestation identification was possible during the first days of the experiment. The statistical and feature importance analyses mainly highlighted the near-ultraviolet and visible regions as the most informative for classification. In addition, reducing the spectral set from 1,594 wavelengths to the 20 most relevant wavelengths maintained competitive performance, with only a small average reduction in accuracy. This result indicates the feasibility of more compact approaches, which may contribute to the future development of simpler, more targeted spectral acquisition systems applicable to pest monitoring in precision agriculture. Future studies should evaluate the generalization of this approach under field conditions, different cultivars, growing seasons, infestation levels, and sensor configurations with a smaller number of bands.

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