Monitoring the Invasive Grass *Eragrostis Plana* with Artificial Intelligence: A Comparative Study of Hyperspectral Data and Drone-Based Object Detection

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Abstract.

The invasion of exotic plant species is recognized as one of the major threats to biodiversity and ecosystem stability worldwide. In the Brazilian Pampa biome, Eragrostis plana Nees (commonly known as Annoni grass) has become one of the most aggressive invasive species since its introduction in the 1950s. Currently occupying approximately 20% of the native grassland vegetation in the state of Rio Grande do Sul, this species exhibits high adaptive capacity, rapid propagation, and the absence of effective natural enemies, leading to significant ecological degradation and economic losses for livestock production systems. In this context, the development of efficient monitoring and detection strategies is essential to support early intervention and control efforts. This study consolidates two complementary approaches based on artificial intelligence for the identification and monitoring of E. plana in natural pastures of the Pampa biome: (i) spectral classification using machine learning algorithms and (ii) object detection in aerial imagery using RGB images and deep learning techniques. The first approach employed hyperspectral reflectance data collected with an ASD FieldSpec 4 spectroradiometer. After preprocessing, three datasets were generated: one containing 1,688 spectral bands, another with 30 bands selected through Random Forest importance analysis, and a third comprising 28 bands previously reported in the literature as relevant for vegetation discrimination. Four machine learning algorithms were evaluated (Random Forest, RPart, Support Vector Machines, and Artificial Neural Networks) using Leave-One-Out Cross

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Validation. To address class imbalance, the synthetic oversampling techniques ADASYN and Mixup were applied. The best performance was achieved by the RPart algorithm using the 30-band dataset combined with ADASYN, reaching a balanced accuracy of 0.727 and a sensitivity of 0.800. These results indicate that spectral signatures contain relevant information capable of differentiating Annoni grass from native vegetation, although the models still exhibit bias toward the majority class. The second approach explored automated detection of E. plana using aerial RGB imagery acquired by unmanned aerial systems. A dataset of 29 drone RGB images collected in native grasslands with high infestation levels in Pampa Biome was manually annotated using bounding boxes representing the "annoni" class. A pretrained YOLO architecture was fine-tuned for 100 training epochs, with model performance evaluated through 10-fold cross-validation. The results indicated limited detection performance, with a recall of 0.41 and a true positive rate of 0.39. The confusion matrix revealed a strong bias toward predicting the positive class, with a false positive rate of 1.00 and no correctly classified negative instances. These limitations are primarily attributed to the small dataset size and limited variability in the training samples. Overall, the findings demonstrate that artificial intelligence techniques (both spectral classification and deep learning-based image detection) show promising potential for supporting automated monitoring of E. plana. However, improvements in dataset size, class balance, and environmental variability are necessary to enhance model generalization and operational applicability. Future research should integrate larger multisource datasets and explore hybrid approaches combining spectral and spatial information to improve the detection and management of invasive species in natural grassland ecosystems.

Keywords.
Invasive species monitoring, Hyperspectral reflectance, Machine learning classification, Pampa biome

Introduction

The invasion of exotic plant species represents one of the most significant threats to biodiversity and ecosystem stability worldwide. In grassland ecosystems, invasive species alter ecological processes, reduce native biodiversity, and compromise ecosystem services (Polce et al., 2023). In the Brazilian Pampa biome, *Eragrostis plana Nees* (Annoni grass) has emerged as one of the most aggressive invasive species, occupying extensive areas of native grasslands and causing both ecological degradation and economic losses in livestock production systems (Ferreira and Filippi, 2010; Zabala-Pardo and Lamego,2024).

The success of *E. plana* is associated with its high reproductive capacity, long-term seed viability, adaptability to low-fertility soils, and absence of effective natural enemies (Lamego et al., 2023). These characteristics make its control particularly challenging once established, reinforcing the importance of early detection and continuous monitoring strategies (Zabala-Pardo and Lamego, 2024).

Traditional monitoring approaches, based on field surveys, are labor-intensive, time-consuming, and limited in spatial coverage (Rakgoale and Njoya, 2024; Zaka and Samat, 2024). In this context, remote sensing combined with artificial intelligence (AI) has emerged as a promising alternative for large-scale monitoring of invasive species (Rakgoale and Njoya, 2024; Zaka and Samat, 2024; Eskandari, 2026). Two main approaches have been explored: (i) spectral analysis, which captures physiological and biochemical differences between species (Khonina et al., 2024; Zaka and Samat, 2024), and (ii) image-based detection, which identifies spatial patterns and morphological features in aerial imagery (Teixeira et al., 2023; Rakgoale and Njoya, 2024).

Despite their potential, these approaches operate at different observational scales and present distinct methodological limitations. Spectral data provide high-dimensional information related to plant biochemical and physiological properties but often lack sufficient spatial context. Conversely, UAV-based RGB imagery offers detailed spatial information and morphological patterns, although species with similar canopy structures may remain difficult to discriminate. Consequently, recent studies have increasingly emphasized the integration of spectral and spatial information to improve vegetation classification performance (Li et al., 2024; Rakgoale & Njoya, 2024; Zhang et al., 2024).

Therefore, this study aims to integrate and comparatively analyze two complementary AI-based approaches for monitoring *E. plana* in the Pampa biome: hyperspectral classification using machine learning algorithms and object detection in drone-based RGB imagery using deep learning. The study seeks to evaluate their performance, identify limitations, and discuss their applicability within precision agriculture frameworks.

Material and Methods

2.1 Study Design

This study adopts a comparative experimental design integrating two independent datasets and analytical pipelines: (i) hyperspectral reflectance data analyzed through machine learning classifiers and (ii) aerial RGB imagery analyzed using deep learning-based object detection.

Both datasets were collected in native grasslands of the Pampa biome, Southern Brazil, under real field conditions and with support from Embrapa Pecuária Sul.

2.2 Hyperspectral Data Acquisition and Processing

Spectral data were collected using an ASD FieldSpec 4 spectroradiometer, covering wavelengths from 350 nm to 2500 nm. A total of 46 samples representing native vegetation and *E. plana* were obtained, including mixed-species samples.

Preprocessing involved noise removal in known unstable spectral regions (e.g., water absorption bands) and normalization. Three datasets were generated:

- Full dataset with 1,688 spectral bands
- Reduced dataset with 30 bands selected via Random Forest importance
- Literature-based dataset with 28 bands

Given the non-normal distribution of spectral data, non-parametric statistical tests (Kruskal–Wallis) were applied to assess separability among classes.

2.3 Spectral Classification Models

Four supervised machine learning algorithms were evaluated:

- Random Forest (RF)
- RPart (Decision Trees)
- Support Vector Machines (SVM)
- Artificial Neural Networks (ANN)

Due to class imbalance, oversampling techniques (ADASYN and Mixup) were applied. Model evaluation employed Leave-One-Out Cross Validation (LOOCV), ensuring robustness given the limited sample size (Silveira, 2025).

2.4 Drone-Based Image Acquisition and Annotation

RGB images were acquired using unmanned aerial vehicles at altitudes up to 80 meters in highly infested grasslands. A dataset of 29 images was manually annotated using bounding boxes representing the class “annoni”.

Annotation was performed using LabelImg, ensuring morphological consistency through expert agronomic validation. Only a single class was defined, focusing exclusively on the detection of *E. plana*.

2.5 Object Detection Model

A YOLOv5m architecture pretrained on the COCO dataset was fine-tuned using transfer learning. Training was conducted over 100 epochs, using 10-fold cross-validation (Lopes, 2026).

Performance evaluation included:

- Recall
- Precision
- F1-score
- Confusion matrix analysis

Threshold optimization was conducted based on confidence metrics.

Results and Discussion

3.1 Spectral Classification Performance

The spectral classification approach demonstrated moderate performance in distinguishing *E. plana* from native vegetation. The best results were obtained using the RPart algorithm with the 30-band dataset combined with ADASYN, achieving a balanced accuracy of 0.727 and sensitivity of 0.800.

These results indicate that spectral signatures contain discriminative information related to physiological and biochemical properties of the species, particularly in regions associated with chlorophyll absorption and water content.

However, model performance was affected by:

- Small sample size
- Class imbalance
- Mixed-species samples (spectral contamination)

These factors reduce class separability and introduce uncertainty in classification boundaries.

Fig 1. Spectral signatures of mixed and pure vegetation samples, showing high overlap between Eragrostis plana and native species across wavelengths, indicating challenges for spectral discrimination.

The spectral profiles presented in the Figure 1 reveal important insights into the potential and limitations of hyperspectral data for discriminating *Eragrostis plana* (Annoni grass) from native vegetation in the Pampa biome. The curves represent reflectance signatures across the visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) regions, capturing physiological, biochemical, and structural characteristics of different plant species and conditions.

A first relevant observation is the consistent spectral behavior across vegetation types in the visible region (400–700 nm), where reflectance is largely driven by pigment absorption, particularly chlorophyll and carotenoids. Most samples, including Annoni and native species, exhibit similar absorption features in the blue (~450 nm) and red (~670 nm) regions, along with a reflectance peak in the green (~550 nm). This spectral overlap indicates that VIS wavelengths alone provide limited discriminatory power, especially in heterogeneous grassland environments where multiple species share similar pigment compositions.

In contrast, greater separability emerges in the near-infrared region (700–1300 nm), which is strongly influenced by leaf internal structure and canopy architecture. Some Annoni samples (particularly nearly pure stands) exhibit higher reflectance values and more pronounced spectral plateaus in the NIR region compared to mixed or native vegetation. This suggests that differences in mesophyll structure, leaf density, and biomass may provide useful discriminatory signals. However, this distinction is not uniform across all samples, as mixed vegetation and varying infestation levels introduce substantial intra-class variability.

The shortwave infrared region (1300–2500 nm) further highlights variability associated with water content, cellulose, lignin, and other biochemical compounds. While some separation between classes can be observed, particularly in regions affected by water absorption bands (~1450 nm and ~1940 nm), the overall dispersion of curves indicates that SWIR-based discrimination is sensitive to environmental conditions, such as plant water status and stress levels. This reinforces the complexity of isolating species-specific signatures in field conditions.

A critical limitation evident in the analysis is the high degree of spectral overlap between Annoni and native species, especially in samples with mixed vegetation. In these cases, the recorded reflectance represents a composite signal from multiple species, which reduces class separability and introduces noise into the classification process. This effect is particularly problematic in natural grasslands, where spatial heterogeneity is intrinsic and difficult to control during data acquisition.

Additionally, the figure reveals significant intra-class variability within Annoni samples, influenced by factors such as phenological stage (e.g., flowering, senescence), moisture content, and grazing pressure. For instance, samples described as “seca,” “verde,” or “pisoteado” display noticeable differences in reflectance magnitude and curve shape. This variability challenges the assumption of a stable spectral signature for the species and complicates the learning process for classification algorithms.

Despite these challenges, the analysis supports the premise that specific spectral regions, particularly in the red-edge and NIR domains, contain relevant information for distinguishing *E. plana*. The recurrence of separability patterns in these regions aligns with known physiological differences related to chlorophyll concentration and canopy structure. This justifies the use of feature selection approaches (e.g., Random Forest importance) to identify the most informative wavelengths, as observed in the reduced 30-band dataset.

From a methodological perspective, the results highlight that the main limitation is not the absence of discriminatory information, but rather the complexity of isolating it under real-world conditions. Factors such as mixed samples, limited dataset size, and environmental variability reduce the signal-to-noise ratio and hinder model generalization.

In summary, the spectral analysis demonstrates that hyperspectral data hold significant potential for identifying *Eragrostis plana*, particularly when focusing on specific wavelength regions associated with plant physiology and structure. However, reliable classification requires careful handling of data heterogeneity, robust feature selection, and, ideally, integration with complementary spatial information. These findings reinforce the need for hybrid approaches that combine spectral and spatial data to improve the detection and monitoring of invasive species in complex grassland ecosystems.

3.2 Object Detection Performance

The YOLO-based approach showed limited performance, with recall of 0.41 and true positive rate of 0.39. The confusion matrix revealed a strong bias toward predicting the positive class, with no correctly classified negative samples.

This behavior indicates severe model overfitting and lack of generalization, primarily due to:

- Extremely small dataset (29 images)
- Absence of negative samples
- Low variability in environmental conditions

Additionally, the high visual similarity between *E. plana* and native grasses significantly challenges feature extraction in RGB imagery.

Fig 2. Example of the YOLO algorithm applied to a drone-captured image, highlighting the detected areas of Capim-Annoni with bounding boxes.

An example of the application of the YOLO algorithm to a real-environment photo is presented in Figure 2. The application of the YOLO object detection algorithm to the UAV-acquired image reveals both the potential and the limitations of deep learning approaches for detecting *Eragrostis plana* in natural grassland environments. The visual output indicates that the model successfully identifies a large number of candidate regions labeled as “annoni,” suggesting a high level of sensitivity to vegetation patterns that resemble the target species.

A notable characteristic of the result is the high density of predicted bounding boxes, many of which are associated with relatively low confidence scores (frequently around 0.10–0.30). This pattern indicates that the model is over-detecting, classifying a substantial portion of the scene as positive instances. While this behavior may increase recall, it strongly suggests a high false positive rate, consistent with the quantitative results reported in the model evaluation. In practical terms, this reduces the reliability of the model for operational monitoring, as large areas of native vegetation are likely being misclassified as *E. plana*.

From a structural perspective, the difficulty arises from the high visual similarity between *E. plana* and co-occurring native grasses. In RGB imagery, discriminative features are primarily limited to color, texture, and canopy structure. However, these features are often insufficient to distinguish species in heterogeneous grassland ecosystems, particularly under conditions of mixed vegetation and varying phenological stages. This limitation is clearly reflected in the spatial distribution of detections, which appear scattered across nearly the entire image rather than concentrated in biologically plausible infestation patches.

Another important observation is the lack of clear negative discrimination. The model appears unable to confidently identify background (non-annoni) regions, which results in a near absence of true negatives. This behavior is typically associated with dataset imbalance and insufficient representation of negative samples during training, a known limitation in small-scale ecological datasets. As a consequence, the model learns a biased decision boundary that favors the positive class.

Additionally, environmental factors such as illumination variability, shadowing, and differences in plant morphology due to grazing or growth stage further complicate the detection task. These factors introduce intra-class variability that is not adequately captured by the limited training dataset, thereby degrading model generalization.

Despite these limitations, the results demonstrate that YOLO is capable of learning spatial patterns associated with *E. plana*, particularly in cases where the plant forms visually distinguishable tufts. This suggests that, with improved training data, the approach could become a viable tool for large-scale monitoring. Specifically, performance improvements are expected through:

Expansion of the dataset with greater spatial and environmental variability:

- Inclusion of negative samples (non-infested areas)
- Use of higher-resolution imagery or multispectral data
- Adoption of hybrid models combining spectral and spatial features

In summary, while the YOLO-based detection approach shows promise for automated monitoring, its current performance is limited by dataset constraints and intrinsic challenges of RGB-based vegetation discrimination. These findings reinforce the need for multi-source data integration and more robust training strategies to achieve reliable detection of invasive species in complex grassland ecosystems.

3.3 Comparative Analysis: Spectral vs. Spatial Approaches

The comparison between the two approaches highlights a fundamental trade-off:

- Spectral approach → high feature richness, low spatial scalability
- Image-based approach → high spatial coverage, low discriminative power

Spectral data capture subtle physiological differences, enabling early detection, while drone imagery provides spatially explicit monitoring but struggles with species-level discrimination.

Both approaches suffer from similar structural limitations:

- Limited datasets
- Class imbalance
- Lack of variability

This convergence suggests that data-related constraints, rather than algorithmic limitations, are the primary bottleneck.

3.4 Implications for Precision Agriculture

From a precision agriculture perspective, the results indicate that neither approach alone is sufficient for robust operational monitoring. However, their combination presents a promising pathway.

A hybrid framework integrating spectral and spatial information could leverage:

- Spectral data for feature discrimination
- RGB imagery for spatial mapping

Such integration may improve both detection accuracy and scalability, aligning with the requirements of real-world monitoring systems.

Conclusion

This study demonstrates that artificial intelligence techniques offer promising tools for monitoring *Eragrostis plana* in natural grasslands. Both hyperspectral classification and drone-based object detection provide complementary insights, but their effectiveness is currently limited by data constraints.

The spectral approach achieved moderate classification performance, confirming the relevance of reflectance signatures for species discrimination. In contrast, the object detection approach showed limited performance due to insufficient and unbalanced training data.

The findings highlight that the main limitation is not the choice of algorithms but the quality and representativeness of the datasets. Improvements in data acquisition (particularly increasing sample size, class balance, and environmental variability) are essential to enhance model generalization.

Future research should focus on developing integrated multi-source frameworks combining spectral, spatial, and temporal data. Such approaches have the potential to significantly advance the monitoring and management of invasive species in precision agriculture systems.

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