How Effective Are Foundation Models for Crop Type Mapping Using Hyperspectral Imaging? A Comparative Study of Machine Learning, Deep Learning, and Geospatial Foundation Models

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Abstract

Accurate and precise information on cultivated crop types is essential for studies related to food security, crop yield prediction, and yield gap analysis. Crop type mapping using remote sensing plays a crucial role in these applications, with multi-spectral imagery (MSI) widely employed alongside machine learning (ML) and deep learning (DL) methods. However, multi-spectral sensors often fail to differentiate crops with similar spectral signatures, whereas hyperspectral imaging (HSI) enables more precise discrimination with its high spectral resolution. Additionally, ML and DL algorithms often struggle to generalize well in data-scarce scenarios due to their reliance on extensive labeled ground truth data. Addressing these challenges, geo-spatial foundation models (GFMs) (i.e., very large deep learning models) trained on large-scale datasets have emerged as a promising alternative, using self-supervised learning (SSL) to improve classification in low-label environments. This study evaluates the performance of traditional machine learning algorithms, including Support Vector Machines (SVM) and Random Forests (RF), deep learning models such as Convolutional Neural Networks (CNN) and HybridSN, and GFMs, specifically HyperSIGMA and Prithvi-EO-1.0, using the Indian Pines benchmark dataset, a widely used hyperspectral dataset for agricultural land cover classification. The key novelty of this work is the adaptation of Prithvi-EO-1.0, a multi-spectral foundation model to HSI. The models were tested across four different scenarios with a reduction in training data, and their performance was evaluated using Overall Accuracy (OA), and Kappa (K) coefficient to analyze their generalization capabilities. The results indicate that HybridSN achieved the highest accuracy in most scenarios, with OA reaching up to 99.8%, demonstrating its ability to capture spatial-spectral relationships. HyperSIGMA, a vision transformer-based foundation model for HSI analysis outperformed all models when trained on only 1% of the labeled data, highlighting the advantage of self-supervised learning in low-label scenarios. Furthermore, the adaptation of Prithvi-EO-1.0 to hyperspectral data achieved an OA up to 97%, demonstrating that multi-spectral foundation models can be successfully adopted for hyperspectral data with appropriate fine-tuning and optimization techniques. These findings offer key insights into the conditions where GFMs outperform traditional ML and DL approaches, particularly in overcoming data limitations for agricultural applications. This research paves the way for advancing large-scale crop-type mapping using HSI through the application of GFMs.

Keywords: Hyperspectral Imaging, Crop-Type Mapping, Machine Learning, Deep Learning, Geospatial Foundation Models

1. INTRODUCTION

Food security is a major concern today, and many scientific efforts are focused on producing accurate information about the geographical distribution of crops (Meng et al., 2021) . This information is essential for public and private stakeholders to support effective land use management (McCormick et al., 2025), crop area monitoring (Ouzemou et al., 2018), yield estimation (Yang et al., 2019), and soil conservation (Elbouanani et al., 2025). In this context, remote sensing has become an indispensable technique for large-scale agricultural mapping, offering a cost-effective means to classify crop types over large-scale landscapes (Kamenova et al., 2024).

In previous studies (Alami Machichi et al., 2022, Moumni and Lahrouni, 2021), multi-spectral imagery (MSI), such as that provided by Sentinel-2 or Landsat missions, has been widely used in combination with machine learning (ML) and deep learning (DL) techniques to produce crop maps. However, the limited number of spectral bands in MSI often fails to distinguish between crop types with similar spectral signatures, particularly during early growth stages or in mixed cropping systems (Bostan et al., 2016).

On the other hand, hyperspectral imaging (HSI), with its high spectral resolution across hundreds of narrow bands ranging from 400 nm to 2500 nm, provides more detailed spectral information, making it better suited for crop discrimination (Aneece et al., 2022). This rich spectral detail enables the identification of fine differences in crop biophysical and biochemical characteristics (Thenkabail et al., 2000). However, exploiting this potential relies heavily on effective classification algorithms that can assign each pixel to a specific crop type based on spectral-spatial features (Guerri et al., 2024).
To address this, various supervised classification models have been applied to HSI data. Traditional ML algorithms, such as Support Vector Machines (SVMs) and Random Forests (RFs), have been widely used due to their robustness, simplicity, and interpretability (Alami Machichi et al., 2023). These models primarily rely on spectral information and manual feature engineering, treating each pixel as an independent observation. However, this pixel-wise approach overlooks the spatial context within the imagery, which is often crucial for distinguishing between crop types that exhibit similar spectral responses but differ in spatial structure. As a result, their ability to capture complex spatial–spectral relationships is limited, reducing their effectiveness, particularly in heterogeneous agricultural landscapes.
To overcome these limitations, DL approaches have emerged as a powerful alternative for hyperspectral image classification. Unlike traditional ML methods, DL techniques can automat-

ically learn complex and hierarchical features from raw data, reducing the need for manual feature design (Ang and Seng, 2021). In particular, Convolutional Neural Networks (CNNs) have shown great promise in modeling both spectral and spatial dimensions of HSI. By applying convolutional filters across the spatial domain, CNNs can capture local textures while simultaneously extracting relevant spectral patterns.

More advanced hybrid architectures, such as the Hybrid Spectral–Spatial Network (HybridSN) (Roy et al., 2020) and CVTNet (Marjani et al., 2024) models that fuse CNNs with Vision Transformers, extend this capability by combining 3D and 2D convolutions, and in some cases, attention-based mechanisms, to jointly process spatial and spectral information. This fusion enables the models to capture both localized features and broader contextual relationships, allowing for more accurate classification of crops with fine differences. These models have achieved strong results on several benchmark datasets (e.g., Indiana Pines, Salinas) highlighting their potential for advancing large-scale crop mapping using hyperspectral imaging. For instance, CVTNet achieved an overall accuracy (OA) of 0.92, significantly surpassing traditional methods such as Random Forest (RF), which reached an OA of 0.81. This notable improvement (approximately 11%) demonstrates that incorporating Transformer architectures with CNNs allows for richer spectral–spatial feature extraction compared to conventional pixel-based approaches. However, their effectiveness comes at a cost. They typically require large volumes of labeled data to train effectively, which is often unavailable in many agricultural regions. In addition, their deep and complex architectures demand substantial computational resources, including access to high-performance computing (HPC) infrastructure, which can be a limiting factor for researchers or institutions with limited computing capacity.

Recent developments in artificial intelligence (AI), particularly in self-supervised learning (SSL) and transformer-based architectures, have led to the emergence of geospatial foundation models (GFMs) (Lu et al., 2025). GFMs are large-scale DL architectures trained on extensive unlabeled geospatial datasets through SSL. The primary idea behind GFMs is to first learn generalized, transferable representations from large amounts of unlabeled data, then fine-tune the learned knowledge for specific tasks using much smaller labeled datasets (Xie et al., 2024). This process significantly reduces the need for extensive labeled training data, addressing one of the major challenges in remote sensing and hyperspectral analysis. GFMs typically employ Transformer-based architectures due to their powerful self-attention mechanisms, which excel at capturing long-range dependencies and complex spatial–spectral relationships within hyperspectral data. Recent examples include HyperSIGMA (Wang et al., 2024), specifically designed for hyperspectral data, and Prithvi-EO 1.0 (Jakubik et al., 2023), pretrained on NASA's multispectral Harmonized Landsat Sentinel-2 (HLS) dataset covering the contiguous United States.

In this study, we evaluated the performance of classical ML algorithms (SVM and RF), deep learning models (CNN and HybridSN), and GFMs (HyperSIGMA and Prithvi-EO 1.0) for crop type classification using the Indian Pines benchmark dataset. Specifically, the key novelty of this work lies in the adaptation of Prithvi-EO 1.0, a GFM pretrained exclusively on multispectral imagery, to the hyperspectral domain. This adaptation is expected to leverage pretrained knowledge from large-scale multispectral data and provide valuable representations for hyperspectral crop classification. Thus, the objectives of this study were to: (1) investigate the effectiveness and feasibility of adapting a multispectral pretrained foundation model to hyperspectral data, compared to traditional ML, DL, and hyperspectral-specific foundation model, and (2) evaluate the robustness and generalization capability of these models under varying levels of labeled data availability. This approach aims to provide novel insights into the potential of multispectral-to-hyperspectral transfer learning, particularly in scenarios where labeled hyperspectral data is scarce or costly to obtain.

2. MATERIALS AND METHODS

2.1 Dataset

This study employs the well-known Indian Pines dataset (Figure 1), a widely used benchmark in the hyperspectral image classification community (Marion F. Baumgardner et al., 2015). The dataset was acquired in June 1992 by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor over agricultural fields in northwestern Indiana, USA. It contains diverse crop types and land cover categories, making it suitable for testing and comparing traditional machine learning, deep learning, and foundation model-based classification methods.

The hyperspectral image comprises 220 spectral bands covering the visible to shortwave infrared (400–2500 nm) range. Following standard preprocessing, 200 bands are retained after removing those severely affected by atmospheric water absorption. The image has a spatial resolution of approximately 20 meters per pixel and dimensions of 145×145 pixels, resulting in a total of 21,025 pixels, of which 10,249 are labeled.

The dataset represents a mixture of row crops such as corn, soybeans, and wheat, along with other vegetation types and man-made surfaces. Its complexity arises from the presence of multiple crop management practices (e.g., no-till, min-till), small and irregular field shapes, and mixed land use, making it a suitable for evaluating spatial–spectral classification approaches. Table 1 presents the list of land cover and crop classes included in the dataset.

Table 1. Class labels in the Indian Pines dataset.

Class ID	Class Name
0	Background
1	Alfalfa
2	Corn-notill
3	Corn-mintill
4	Corn
5	Grass-pasture
6	Grass-trees
7	Grass-pasture-mowed
8	Hay-windrowed
9	Oats
10	Soybean-notill
11	Soybean-mintill
12	Soybean-clean
13	Wheat
14	Woods
15	Buildings-Grass-Trees-Drives
16	Stone-Steel-Towers

2.2 Methodology

The overall workflow of this study is illustrated in Figure 2. The approach consists of three main stages: data preparation, model evaluation, and performance analysis. The Indian Pines hyperspectral dataset was used as the primary input, including a

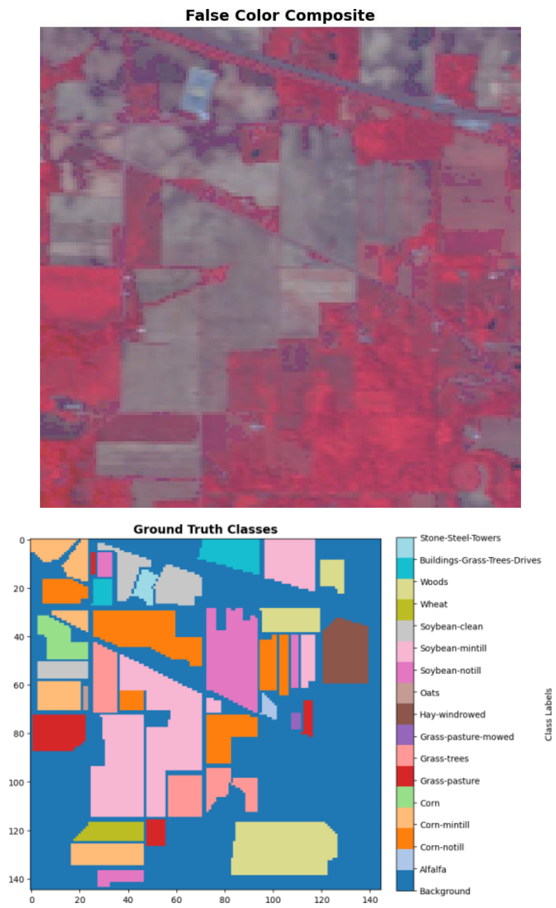

Figure 1. Top: false-color composite of the Indian Pines dataset. Bottom: Ground truth map showing crop and land cover classes.

hyperspectral cube captured by the AVIRIS sensor and a corresponding land cover ground truth map with 16 annotated classes.

Five classification models were evaluated, grouped into three methodological approaches: traditional ML (SVM and RF), deep learning (1D-CNN and HybridSN), and GFMs (HyperSIGMA and Prithvi-EO 1.0). Each model was independently trained and evaluated under multiple experiments to assess their performance.

Four experimental scenarios were explored to simulate varying levels of training data availability as shown in Table 2:

Scenario	Train (%)	Valid. (%)	Test (%)
S1	70	15	15
S2	50	25	25
S3	15	15	70
S4	1	0	99

Table 2. Data split for each experimental scenario.

Each model was tuned using a test subset to optimize hyperparameters. For each scenario, performance was assessed using standard metrics, including OA, and the Kappa coefficient. The best-performing models across S1–S3 were selected and further evaluated under extreme low-label conditions in S4 to assess their potential in data-scarce environments.

2.3 Classification Methods

To explore the effectiveness of different approaches for hyperspectral crop classification, three groups of models were selected: traditional ML algorithms, DL models, and GFMs. This section provides a brief description of each method evaluated in this study.

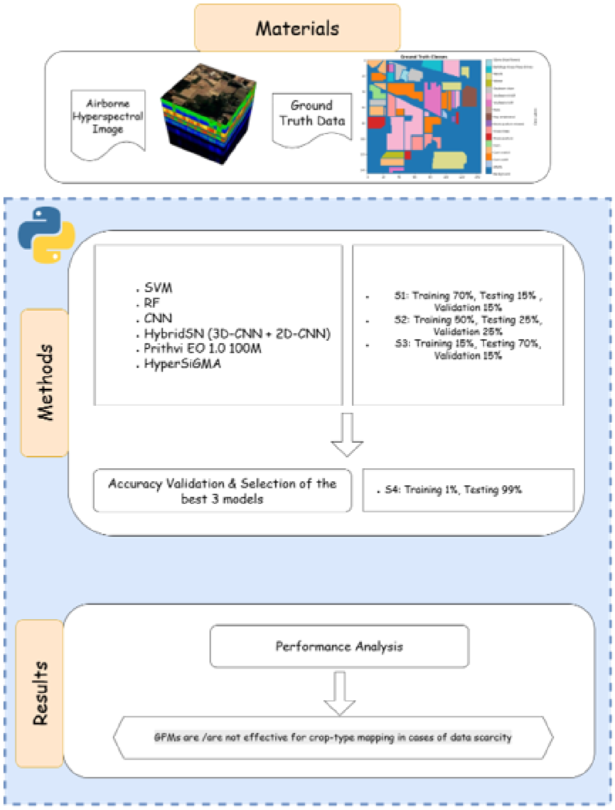

Figure 2. The study's methodology

2.3.1 Traditional Machine Learning Models: The first group includes two widely used traditional classifiers: SVM and RF. These models were applied to per-pixel spectral vectors without incorporating spatial information. The SVM model utilized a radial basis function (RBF) kernel due to its effectiveness in high-dimensional spaces and its ability to perform well with limited training samples. The RF model, an ensemble-based approach, was selected for its robustness to overfitting, capacity to handle noisy data, and interpretability through feature importance scores. Both model's hyperparameters, including the number of trees for RF and the regularization parameter C for SVM, were optimized using the validation data.

2.3.2 Deep Learning Models: Two DL architectures were implemented to benefit from the rich spectral and spatial information of HSI. The first is a one-dimensional convolutional neural network (1D-CNN), which applies convolutions along the spectral axis of each pixel vector. This model captures local spectral features efficiently and serves as a lightweight baseline, although it does not incorporate spatial context. The second model is the Hybrid Spectral–Spatial Network (HybridSN). This architecture combines three-dimensional (3D) and two-dimensional (2D) convolutional layers to jointly capture spectral–spatial dependencies. The 3D convolutions first extract features across spectral and spatial dimensions simultaneously from local image patches. These are followed by 2D convolutions that refine spatial feature hierarchies. This hybrid design offers a balance between modeling complexity and classification accuracy, and has shown superior performance on benchmark HSI datasets. All deep learning models were trained using the categorical cross-entropy loss function and optimized using the Adam optimizer. Input patches were normalized and extracted using a fixed spatial window size of 25×25 pixels, centered on each labeled sample. Each model was trained for 100 epochs. Hyperparameters, including learning rate, number of filters, and convolution kernel sizes, were optimized to achieve optimal performance under each experimental scenario.

2.3.3 Geospatial Foundation Models: The third group comprises (GFMs), which are pretrained using SSL on large-scale remote sensing datasets. These models are designed to generalize across tasks and input domains, reducing the need for large labeled datasets. Two transformer-based GFMs were evaluated in this study: HyperSIGMA and an adapted version of Prithvi-EO 1.0. HyperSIGMA is a vision transformer-based model specifically designed for hyperspectral image interpretation. It was pretrained on a large-scale hyperspectral dataset, HyperGlobal-450K, using masked autoencoding. The model includes a Sparse Sampling Attention (SSA) mechanism to handle spectral–spatial redundancy and a Spectral Enhancement Module (SEM) to fuse spatial and spectral tokens effectively. In this study, the HyperSIGMA backbone was kept frozen, and only the classification head was fine-tuned using labeled samples from the Indian Pines dataset. Prithvi-EO 1.0 is a foundation model originally pretrained on multispectral imagery from NASA's Harmonized Landsat Sentinel-2 (HLS V2 L30) product. To adapt it to hyperspectral data, a spectral simulation step was introduced. Specifically, each Sentinel-2 band was approximated by aggregating hyperspectral bands within a ±50 nm window around the band's center wavelength λ_c, using a Gaussian weighting average. The weights were computed as:

$$w(\lambda) = \exp\left(-\frac{(\lambda-\lambda_c)^2}{2\sigma^2}\right) \tag{1}$$

where λ = hyperspectral band wavelength
λ_c = hyperspectral band's center wavelength
σ = spread of the Gaussian kernel

This spectral projection reduced the hyperspectral image cube to six bands, aligning with the input format expected by the Prithvi-EO 1.0 model. The resulting inputs were then processed through the frozen encoder of Prithvi-EO 1.0, while a lightweight multi-layer perceptron (MLP) classifier was trained on the extracted embeddings. The complete adaptation pipeline is illustrated in Figure 3.

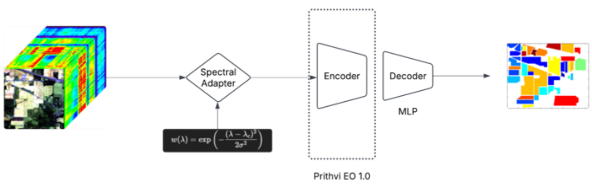

Figure 3. Proposed Approach

The classification models were implemented using a combination of established ML and DL libraries. Traditional ML algorithms were developed using the scikit-learn library, while the DL models were implemented in TensorFlow. GFMs were developed using PyTorch. All experiments were conducted using Python 3.12.3 on the Toubkal Supercomputer with 244 TB of RAM, and more than 8 PB of storage capacity. This infrastructure enabled efficient training and inference, particularly for DL and foundation model experiments requiring substantial computational resources.

3. RESULTS AND DISCUSSION

The performance of the evaluated models was assessed using OA and Kappa coefficient under four experimental scenarios (S1–S4), simulating different levels of labeled data availability. Figure 4 presents the OA and Kappa values for each model across these scenarios.

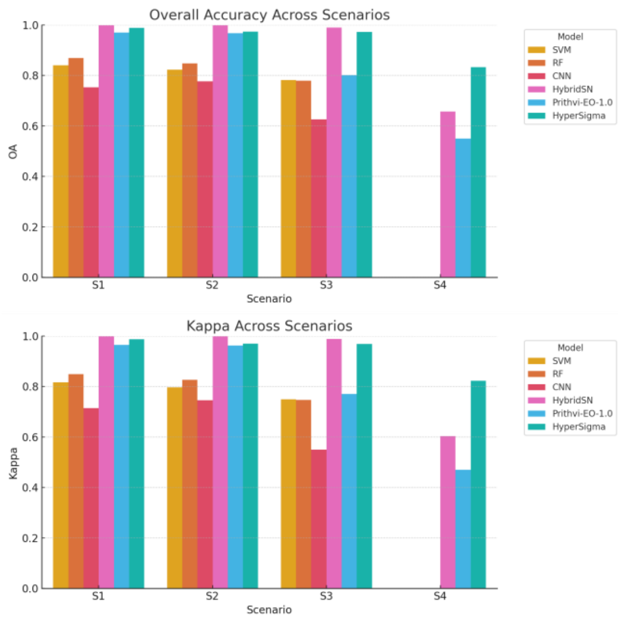

Figure 4. Top: false-color composite of the Indian Pines dataset. Bottom: Ground truth map showing crop and land cover classes.

HybridSN consistently achieved the highest classification accuracy in scenarios S1 to S3, with OA values exceeding 98.9 % and Kappa values above 0.98. This superior performance is attributed to its hybrid architecture that effectively captures spectral–spatial features through a combination of 3D and 2D convolutions. The application of PCA to reduce the hyperspectral data to 16 components contributed to computational efficiency without significant loss of discriminative information. However, under the extremely low-label S4 scenario, HybridSN's performance declined (OA = 65.75%), indicating its reliance on sufficient labeled data for optimal performance. Additionally, HyperSIGMA demonstrated robust performance across all scenarios. Its architecture, combining a transformer backbone with self-attention mechanisms, enables modeling of long-range spectral–spatial dependencies. The self-supervised pretraining allows the model to learn rich and reusable representations without relying on labels. Notably, HyperSIGMA maintained strong generalization under the extremely low-label S4 scenario, highlighting its potential in label-scarce environments. In the other hand, Prithvi-EO 1.0, adapted via spectral downsampling to match its multispectral pre-training, performed well in scenarios S1 and S2. However, its performance declined in S3 and S4, likely due to the limited spectral richness (only six synthetic bands) and the absence of fine-tuning of the encoder, which may have restricted domain adaptation to the hyperspectral characteristics of the Indian Pines dataset.

Traditional machine learning models showed moderate performance under higher-label conditions (S1–S2), with RF outperforming SVM. However, both methods experienced performance degradation in S3, indicating their limited generalization capacity in data-scarce scenarios.

Additionally, The CNN baseline showed lower accuracy across all scenarios, particularly in S3 (OA = 62.58%), reflecting its limited ability to model spatial context in hyperspectral data when trained solely on 1D spectral information.

All in all, the results reveal distinct performance influenced by model architecture, supervision level, and input representation. For instance, HybridSN demonstrated strong performance under high-label conditions. However, its decline in S4. One potential enhancement is the integration of attention modules such as channel or spatial attention to enable the model to dynamically focus on informative regions and mitigate the over-reliance on abundant supervision. For GFMs like HyperSIGMA and the adapted Prithvi-EO 1.0, performance under low-label regimes could be further improved through efficient fine-tuning techniques such as Low-Rank Adaptation (LoRA) (Ulku et al., 2024). LoRA introduces trainable, low-rank parameter matrices into frozen transformer layers, allowing models to adapt to new tasks with minimal computational overhead and without altering the original pretrained weights. This is particularly advantageous in hyperspectral contexts, where training data is scarce and full fine-tuning of large models is often impractical. In the case of classical ML models, such as SVM and RF, their current pixel-based approach overlooks spatial dependencies that are crucial for resolving ambiguities between spectrally similar classes. Future work should consider incorporating spatial features explicitly (Brenning, 2023), for example through Spatial RF (Georganos et al., 2021) or Spatial XGBoost (Grekousis, 2025), which integrate neighborhood context into tree-based decision processes. Such adaptations could significantly improve the robustness and accuracy of these models, especially in large agricultural landscapes where spatial coherence provides vital discriminative features.

The current evaluation, conducted on the Indian Pines benchmark dataset, was intended as an exploration of the proposed methodology and its component models. Although this dataset remains a valuable reference in hyperspectral image classification, its limited spatial extent and class variability restrict its representativeness of large-scale agricultural land.

To assess the scalability and practical relevance of the proposed approach, future research should focus on large-scale implementations using space-borne hyperspectral platforms such as EnMAP, PRISMA, or DESIS. These missions provide continuous narrow-band spectral coverage at broader spatial scales, making them well suited for regional to national crop type mapping (Bourriz et al., 2025). Applying foundation models in these contexts, particularly when combined with auxiliary data such as phenology, weather, and topography could enhance both the accuracy and the interpretability of crop classification outputs. Such advancements are essential for translating methodological improvements into actionable insights for agricultural policy, sustainability, and food security.

4. CONCLUSION

This study presented a comparative evaluation of traditional machine learning (ML) algorithms, deep learning (DL) models, and geospatial foundation models (GFMs) for hyperspectral crop type classification. Using the Indian Pines benchmark dataset, the objective was to assess how well these models perform under varying levels of label availability, with a focus on identifying robust solutions for data-scarce scenarios, a common limitation in operational agricultural monitoring.

The results demonstrated that models capable of jointly learning spatial and spectral features, particularly HybridSN and HyperSIGMA, significantly outperformed classical approaches. HybridSN achieved near-perfect accuracy in high-label settings due to its hierarchical spectral–spatial feature extraction, while HyperSIGMA exhibited the strongest performance in low-label settings (S4), underscoring the value of large-scale self-supervised pretraining. The adaptation of Prithvi-EO 1.0, a multispectral foundation model, to the hyperspectral domain using a Gaussian-weighted spectral projection proved promising, achieving high accuracy in moderately supervised scenarios. However, its performance degraded under low-label conditions, pointing to the need for further domain adaptation techniques such as Low-Rank Adaptation (LoRA) to improve cross-modal transferability without retraining large models from scratch.

In addition, the study highlighted the limitations of classical ML models (SVM, RF), which, while interpretable and lightweight, lacked the capacity to capture complex spectral–spatial interactions and generalize well in label-constrained environments. Future adaptations, such as Spatial RF or Spatial XGBoost, may help integrate local context and enhance their utility in operational scenarios.

While the proposed workflow was validated using a benchmark dataset, its real potential lies in large-scale agricultural mapping. Future work should apply these models to spaceborne hyperspectral imagery (e.g., EnMAP, PRISMA, DESIS, PACE), especially in light of the growing democratization of high-resolution imaging spectroscopy. These missions are increasingly making detailed spectral information accessible across broad spatial and temporal extents, supporting the transition from research-oriented analysis to operational crop mapping to support food security and sustainable land management.

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