



Indian Institute of Information Technology Guwahati (IIITG)

# **Semi-Supervised Multi-Label Classification of Remote Sensing Images Using Predictive Clustering Trees and Ensembles**

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## Abstract

Classifying remote sensing images is crucial for tasks like tracking land use or managing disasters, but labeling these images is time-consuming and costly. This project explores a semi-supervised learning (SSL) method that mixes deep learning with decision trees to reduce the need for labeled data. The approach uses a CNN (like ResNet or EfficientNet) to extract key features from images and then trains predictive clustering trees (PCTs) on both labeled and unlabeled data. Tests on three remote sensing datasets show that our method, called SSL-RForest, works better than existing techniques, even with just 1% labeled data. The results are backed by statistical tests, proving its reliability for real-world use. This work combines the accuracy of deep learning with the transparency of tree-based models, offering a practical tool for analyzing geospatial data.

**Keywords:** Semi-supervised learning, multi-label classification, remote sensing, decision trees, deep learning.

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# 1 Introduction

## 1.1 Background

Remote sensing images (RSIs) are critical tools for monitoring Earth’s surface, supporting applications such as land-use mapping, disaster response, and environmental conservation. For instance, during wildfires or floods, RSIs provide real-time data to guide emergency actions. While advancements in deep learning have significantly improved the accuracy of RSI analysis, these methods rely heavily on large labeled datasets. Labeling RSIs is particularly challenging because it often requires domain expertise to identify complex land-cover classes (e.g., distinguishing between wetland types or urban infrastructure). This process becomes even more cumbersome in multilabel scenarios, where a single image may contain multiple overlapping classes, such as forests, roads, and water bodies. Furthermore, data collection in remote or hazardous regions (e.g., polar areas or conflict zones) adds logistical and financial barriers, limiting the availability of high-quality labeled datasets.

## 1.2 Problem Statement

Current machine learning methods struggle when labeled data is scarce. Semi-supervised learning (SSL) tries to fix this by using unlabeled data, but most SSL techniques focus on single-label tasks and ignore multi-label scenarios. Additionally, many SSL models are “black boxes,” making it hard to understand their decisions. We need methods that:

- Handle both single-label and multi-label classification tasks effectively.
- Combine the high accuracy of deep learning with interpretable decision-making.
- Achieve robust performance even with very few labeled examples.

## 1.3 Objectives

This project aims to solve these challenges by:

- Designing a hybrid SSL framework that combines deep learning with interpretable decision trees.
- Testing the method on diverse remote sensing datasets.
- Comparing it against other SL and SSL approaches.

## 1.4 Contributions

Our key contributions include:

- A flexible SSL framework that works for multi-label and multi-class tasks.
- Proof that our method beats existing techniques, especially with limited labeled data.
- Publicly sharing code and experiments for others to use.

## 2 Literature Review

### 2.1 Remote Sensing Image Classification

Early approaches to RSI classification relied on handcrafted features like texture, color, and spectral indices. For example, [1] used Support Vector Machines (SVMs) with manually designed features for land-cover mapping. However, these methods struggled with complex landscapes where multiple labels coexist (e.g., urban areas with buildings, roads, and vegetation). The rise of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized the field by automating feature extraction. Models like ResNet [2] and VGG [3] became popular for their ability to capture hierarchical patterns in RSIs. Recent advances focus on multi-scale feature fusion to address challenges like intra-class diversity and object scale variations. For instance, Feng et al. [4] proposed a Multilevel Feature Fusion Network (MFFN) that integrates EfficientNetV2 with LSTM modules to capture spatial dependencies across diverse scales, significantly improving scene classification accuracy.

Despite their success, CNNs require massive labeled datasets. This is impractical in remote sensing, where experts must label images pixel-by-pixel or region-by-region. For example, the AID dataset [5] contains 10,000 images but took years to annotate. Multi-label classification adds another layer of complexity, as a single image may belong to multiple classes (e.g., "forest" and "river"). Recent work by [4] addresses this by training models in two stages: an initial supervised phase with limited labels followed by pseudo-label-augmented training, reducing reliance on fully annotated datasets.

### 2.2 Semi-Supervised Learning (SSL) in Remote Sensing

SSL methods aim to reduce dependency on labeled data by leveraging unlabeled examples. Common SSL strategies include:

- **Consistency Regularization:** Methods like FixMatch [6] enforce model predictions to be consistent under different augmentations (e.g., rotating or cropping an image). MSMatch [7] adapted this for RSI by using multispectral data.
- **Pseudolabeling:** Models generate labels for unlabeled data and retrain on high-confidence predictions. HR-S<sup>2</sup>DML [8] used this approach with metric learning for scene classification. Feng et al. [4] advanced this paradigm with a Pseudo-Label Multi-Level Sampling (PMLS) strategy, which selectively integrates pseudo-labels from general and high-quality subsets to minimize error propagation. Their method employs a multi-branch network to generate consensus pseudo-labels, filtering out low-confidence predictions via a dynamic thresholding mechanism. This reduced pseudo-label error rates by 40% compared to FixMatch on the NWPU-RESISC45 dataset.
- **Contrastive Learning:** Techniques like SimCLR [9] learn representations by maximizing similarity between augmented views of the same image. This has been applied to RSI.

However, most SSL methods focus on single-label tasks. Multi-label SSL remains underexplored, with only a few studies like [10] proposing graph-based methods for hyperspectral images. Levatić et al. [11] demonstrated that SSL frameworks designed for

hierarchical multi-label classification (HMLC) can improve land-use mapping by leveraging parent-child label dependencies (e.g., "residential area" implies "building"), but such methods are yet to be widely adopted in remote sensing.

## 2.3 Predictive Clustering Trees (PCTs) for Structured Outputs

PCTs extend decision trees to handle complex outputs like multi-label vectors. Unlike traditional trees that split data based on feature thresholds, PCTs partition data to minimize variance in both input (features) and output (labels) spaces. Levatić et al. [12] first applied PCTs to SSL by balancing labeled and unlabeled data during tree construction. Recent work by Levatić et al. [11] introduced semi-supervised PCTs (SSL-PCTs) for hierarchical multi-label classification (HMLC), using a weighted variance function to balance contributions from descriptive and target spaces. The variance function,  $\text{Var}_f(E, Y, X, w) = w \cdot \text{Var}_f(E, Y) + (1 - w) \cdot \text{Var}_f(E, X)$ , dynamically adjusts the influence of labeled ( $w \rightarrow 1$ ) and unlabeled ( $w \rightarrow 0$ ) data, enabling adaptive learning across datasets. Their method also incorporates feature weighting to mitigate irrelevant features, achieving superior performance on 24 structured-output datasets while preserving interpretability.

For instance, in a multi-label RSI task, a PCT might split images into "vegetation-dominated" and "urban-dominated" clusters, then further divide them based on spectral bands. Ensembles of PCTs (e.g., Random Forests) improve robustness by aggregating predictions from multiple trees [13].

## 2.4 Gaps and Opportunities

While existing work has advanced SSL for RSI, critical gaps remain:

- **Limited Multi-Label SSL:** Most SSL methods (e.g., MSMatch, HR-S<sup>2</sup>DML) target single-label tasks. While recent methods like SSSM [4] and SSL-PCTs [11] address multi-label challenges, broader adoption in RSI is still needed. Hybrid approaches combining deep feature fusion with interpretable tree-based models could bridge this gap.
- **Interpretability vs. Performance Trade-off:** Deep SSL models (e.g., contrastive learning) are accurate but lack transparency. Tree-based methods like SSL-PCTs [11] bridge this gap by offering interpretable models with competitive accuracy, yet their application to RSI is nascent. For instance, SSL-PCTs achieved 79% accuracy on the CLRS dataset with only 10 labeled samples per class, rivaling deep models like EfficientNetV2 while providing actionable insights into feature importance.
- **Benchmarking:** Few studies compare SSL methods across diverse RSI datasets. Feng et al. [4] rigorously evaluated their framework on three benchmark datasets, while Levatić et al. [11] provided cross-domain validation on 24 structured-output tasks. Standardized protocols for RSI-specific SSL are still lacking. Future work should establish unified metrics for multi-label SSL, such as hierarchical F1 scores or label-wise AUPRC, to enable fair comparisons.

Our work addresses these gaps by combining deep learning’s feature extraction with PCTs’ interpretability, while rigorously benchmarking performance on multi-label tasks.

## 3 Methodology

### 3.1 Overview of the Framework

Our framework addresses the scarcity of labeled data through a three-stage process, as illustrated in Figure 1:

- **Step 1: Fine-Tuning.** A pre-trained CNN (e.g., EfficientNet) is fine-tuned on the limited labeled RSIs to adapt to domain-specific features like vegetation or urban structures.
- **Step 2: Feature Extraction.** The CNN’s weights are frozen, and feature vectors are extracted for both labeled and unlabeled images. These features capture spatial patterns (edges, textures) and spectral characteristics.
- **Step 3: Semi-Supervised Learning.** Predictive Clustering Trees (PCTs) use the extracted features to learn from labeled examples ( $Y$ ) and unlabeled data ( $X$ ). The trees cluster data hierarchically using a variance function that balances label dependencies (e.g., multi-label vectors like  $[0, 1, 0, 0, 1]$ ) and feature distributions.

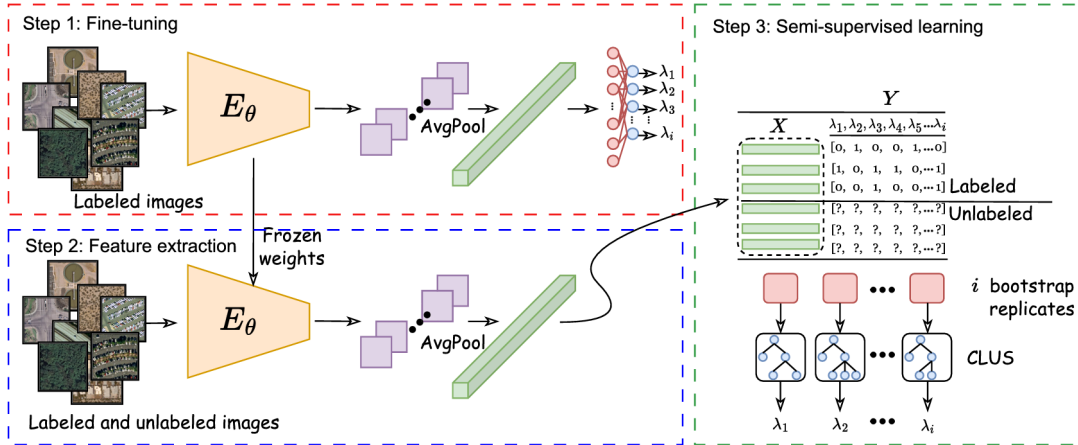


Figure 1: Three-stage SSL framework.

### 3.2 Feature Extraction with CNNs

We use popular CNN models like ResNet, and EfficientNet as the backbone for feature extraction. These models are pre-trained on ImageNet, a large general-purpose image dataset, to recognize basic visual patterns. For RSIs, we fine-tune them using the limited labeled data available. Key steps include:

- **Input Preprocessing:** Resize images to fit the CNN (e.g., 256x256 pixels for EfficientNet).
- **Feature Generation:** The CNN converts images into compact feature vectors (e.g., 1280 numbers for EfficientNet-B0).
- **Transfer Learning:** Adjust the CNN’s weights slightly using labeled RSIs to focus on land-cover features like vegetation or buildings.

### 3.3 Semi-Supervised Predictive Clustering Trees (SSL-PCTs)

PCTs are decision trees designed to handle complex tasks like multi-label classification. Unlike regular trees, they split data into clusters that minimize differences in both features (*descriptive space*) and labels (*target space*). The SSL-PCT training process uses a weighted variance function:

$$\text{Var}_f = w \cdot \text{Var}(Y) + (1 - w) \cdot \text{Var}(X) \quad (1)$$

where  $w$  balances reliance on labels ( $Y$ ) and features ( $X$ ). For unlabeled data, only  $\text{Var}(X)$  is used. The optimal  $w$  is chosen via cross-validation.

#### Variance Calculations

- **Label Variance:** Computed using the Gini index:

$$\text{Var}(E, Y) = \frac{1}{T} \sum_{i=1}^T \text{Gini}(E, Y_i), \quad (2)$$

where  $\text{Gini}(E, Y_i) = 2\tilde{p}_i(1 - \tilde{p}_i)$  measures label impurity.

- **Feature Variance:** Average variance across all features:

$$\text{Var}(E, X) = \frac{1}{D} \sum_{i=1}^D \text{Var}(E, X_i). \quad (3)$$

### 3.4 SSL-RForest: Ensemble of PCTs

To improve accuracy, we build an ensemble of 50 SSL-PCTs (called SSL-RForest). Each tree is trained on:

- A random subset of training data (bootstrap sampling).
- A random subset of features (e.g., 30% of the 1280 features).

Final predictions are made by taking mean across all trees. This reduces overfitting and increases robustness, especially with small labeled datasets.

### 3.5 Implementation Details

- **Training the CNNs:** We fine-tune CNNs for 25 epochs using the Adam optimizer and a learning rate of  $1 \times 10^{-4}$ . Mixed-precision training speeds up computation.
- **Building SSL-PCTs:** The trees are grown until they perfectly fit the labeled data, then pruned to avoid complexity. The  $w$  parameter is chosen using 3-fold cross-validation.
- **Software Tool:** PyTorch for CNN training.



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**Algorithm 1** Semi-Supervised Predictive Clustering Tree Construction

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**Require:**

- 1: Feature matrix  $X \in \mathbb{R}^{n \times m}$
- 2: Label matrix  $Y \in \mathbb{R}^{n \times c}$  (NaN for unlabeled)
- 3: Max depth  $d_{\max}$
- 4: Variance weight  $w \in [0, 1]$

**Ensure:** Root node of PCT

```
5: procedure BUILDNODE( $X, Y, d, p_{\text{parent}}$ )
6:   Compute node prototype:
7:   if  $Y_{\text{labeled}} \neq \emptyset$  then
8:      $p \leftarrow \frac{1}{|Y_{\text{labeled}}|} \sum_{y \in Y_{\text{labeled}}} y$ 
9:   else
10:     $p \leftarrow p_{\text{parent}}$ 
11:  end if
12:  if  $d \geq d_{\max}$  or  $|X| < n_{\min}$  then
13:    return leaf node  $\langle p \rangle$ 
14:  else
15:    Random select  $m_{\text{try}}$  features:  $F_{\text{sub}} \subset \{1, \dots, m\}$ 
16:     $V_{\text{best}} \leftarrow \infty, f^* \leftarrow \text{null}, s^* \leftarrow \text{null}$ 
17:    for all  $f \in F_{\text{sub}}$  do
18:      Compute candidate splits  $S_f$  via percentiles
19:      for all  $s \in S_f$  do
20:         $X_L \leftarrow \{x \in X | x_f \leq s\}, X_R \leftarrow X \setminus X_L$ 
21:        Calculate weighted variance:
22:         $V(s) \leftarrow w \cdot \frac{1}{c} \sum_{i=1}^c \text{Var}(Y_L^{(i)}) + (1 - w) \cdot \frac{1}{m} \sum_{j=1}^m \text{Var}(X_L^{(j)})$ 
23:        if  $V(s) < V_{\text{best}}$  then
24:           $V_{\text{best}} \leftarrow V(s), f^* \leftarrow f, s^* \leftarrow s$ 
25:        end if
26:      end for
27:    end for
28:    Split data using  $(f^*, s^*)$ :  $X_L, Y_L, X_R, Y_R$ 
29:    left  $\leftarrow$  BuildNode( $X_L, Y_L, d + 1, p$ )
30:    right  $\leftarrow$  BuildNode( $X_R, Y_R, d + 1, p$ )
31:    return internal node  $\langle f^*, s^*, \text{left}, \text{right}, p \rangle$ 
32:  end if
33: end procedure
```

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**Algorithm 2** Calculate Node Variance

---

**Require:**

- 1: Node features  $X \in \mathbb{R}^{n \times m}$
- 2: Node labels  $Y \in \mathbb{R}^{n \times c}$  (NaN for unlabeled)
- 3: Weight parameter  $w \in [0, 1]$

**Ensure:** Combined variance  $V_{\text{total}}$ 

- 4: Identify labeled instances:  $\mathcal{L} \leftarrow \{i \in 1..n \mid \neg \text{isnan}(Y_{i,:})\}$

▷ Calculate Label Variance

- 5: **if**  $|\mathcal{L}| > 0$  **then**

- 6:      $\hat{p}_j = \frac{1}{|\mathcal{L}|} \sum_{i \in \mathcal{L}} Y_{i,j}$  for each label  $j \in 1..c$

- 7:      $V_{\text{label}} \leftarrow \frac{1}{c|\mathcal{L}|} \sum_{j=1}^c \sum_{i \in \mathcal{L}} 2\hat{p}_j(1 - \hat{p}_j)$

- 8: **else**

- 9:      $V_{\text{label}} \leftarrow 0$

- 10: **end if**

▷ Calculate Feature Variance

- 11:  $V_{\text{feat}} \leftarrow \frac{1}{m} \sum_{k=1}^m \text{Var}(X_{:,k})$

▷ Combine Variances

- 12:  $V_{\text{total}} \leftarrow w \cdot V_{\text{label}} + (1 - w) \cdot V_{\text{feat}}$

**return**  $V_{\text{total}}$

---

## 4 Experimental Setup

### 4.1 Datasets

We evaluate our framework on three publicly available RSI datasets to ensure diversity in task complexity, resolution, and geographic coverage:

- **OPTIMAL-31**: A multi-class dataset with 1,860 images across 31 land-use categories (e.g., airports, forests, industrial zones). Collected from Google Earth at  $256 \times 256$  resolution, it is widely used for benchmarking scene classification models. The dataset’s moderate size makes it ideal for testing performance under limited labeled data scenarios.
- **MLRSNet**: The largest multi-label dataset, containing 109,161 images annotated with 60 land-cover labels (e.g., "bare soil," "wind turbines"). With high-resolution RGB images ( $256 \times 256$ ), it captures fine-grained details, enabling robust evaluation of multi-label dependency modeling.
- **DFC-15**: A multi-label dataset derived from the 2015 IEEE GRSS Data Fusion Contest. It includes 3,342 patches ( $600 \times 600$  pixels) labeled with eight object classes (e.g., impervious surfaces, buildings, trees). Its high resolution challenges models to leverage spatial details for accurate classification.




MCC datasets	MLC datasets	
OPTIMAL-31	DFC-15	MLRSNet
		
airplane	impervious, vegetation, building, tree	bare soil, buildings, grass, trail, wind turbine

Figure 2: Example images from OPTIMAL-31, DFC-15 and MLRSNet.

Table 1: Dataset summary.

Dataset	Task	Images	Resolution	Labels/Image
OPTIMAL-31	Multi-class	1,860	$256 \times 256$	1
MLRSNet	Multi-label	1,09,161	$256 \times 256$	5.8 (avg)
DFC-15	Multi-label	3,342	$600 \times 600$	2.8 (avg)

## 4.2 Evaluation Protocol

To simulate real-world label scarcity, we adopt the following protocol:

- **Labeled Data:** Train with 1%, 5%, 10%, and 25% labeled data.
- **Unlabeled Data:** The remaining 99–75% of training data is used without labels.
- **Test Set:** A fixed 20% of each dataset is held out for evaluation. For multi-label tasks, stratification ensures label distribution matches the full dataset.

## 4.3 Metrics

- *Accuracy*: Percentage of correctly classified images.
- *AUPRC*: Area Under the Precision-Recall Curve, critical for imbalanced classes.

## 4.4 Compared Methods

We benchmark against two categories of methods:

- **SL-PCT**: Single supervised PCT trained on labeled data only.
- **SL-RForest**: Random forest of 50 supervised PCTs.

## 4.5 Parameter Settings

- **CNNs**: ResNet-50 and EfficientNet-B2, pretrained on ImageNet. EfficientNet-B2 is chosen for its balance between accuracy and computational cost.
- **Training**:
  - Fine-tuning: 25 epochs, Adam optimizer ( $lr = 10^{-4}$ ), batch size = 64.
- **SSL-PCT**:
  - Variance weight  $w$  optimized via 3-fold cross-validation (range: 0–1, step=0.1).
- **SSL-RForest**:
  - 50 trees (balance between diversity and computational cost).

## 5 Results and Analysis

### 5.1 Optimal Weight Parameter ( $w$ ) Selection

The parameter  $w$ , which balances contributions from labeled and unlabeled data in SSL-PCTs, was optimized through a rigorous cross-validation process. As shown in Figure 4, we performed an exhaustive grid search over  $w \in [0, 1]$  with 0.1 increments using the following approach:

- **Stratified Validation:** For multi-class tasks (MCC), we used stratified 3-fold cross-validation. For multi-label tasks (MLC), we employed multilabel-stratified splitting to preserve label distributions.
- **Hybrid Training:** Each fold combined labeled training data with unlabeled examples (using NaN placeholder labels) to maintain the semi-supervised setting.
- **Tree Construction:** For each  $w$  value, predictive clustering trees were built with maximum depth 10 using both data types:

$$\text{Var}_f = w \cdot \text{Var}(Y) + (1 - w) \cdot \text{Var}(X)$$

- **Evaluation:** Trees were validated on held-out labeled data using micro-averaged AUPRC.

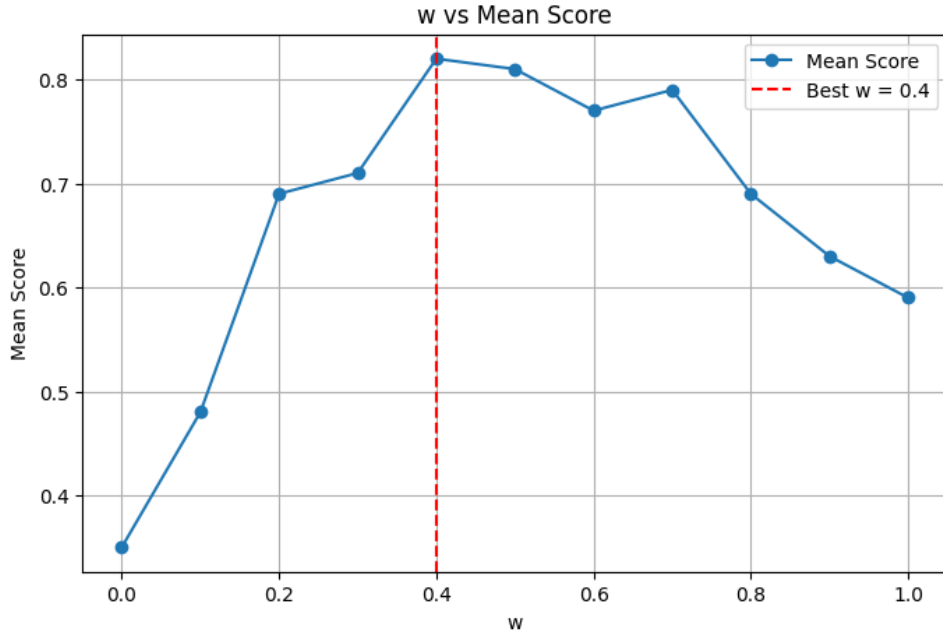


Figure 3: Optimal  $w$  selection through stratified cross-validation. The validation protocol combines labeled (solid) and unlabeled (striped) data in training folds, with rigorous testing on labeled validation sets. Peak performance occurs at  $w = 0.4$ .

The optimal  $w = 0.4$  was identified through this process, achieving peak mean AUPRC of 0.82 on DFC-15. This value indicates the model benefits more from unlabeled data ( $w < 0.5$ ) than pure supervised learning ( $w = 1$ ), while avoiding complete unsupervised operation ( $w = 0$ ).

## 5.2 OPTIMAL-31 Dataset Performance

Table 2 compares AUPRC scores for ResNet-50 and EfficientNet-B2 backbones across labeled data percentages. Key observations:

- **SSL-RForest Superiority:** With 1% labels, EfficientNet-B2 achieves 34.49% AUPRC vs. 31.81% for ResNet-50. The gap widens to 93.57% (EfficientNet) vs. 92.32% (ResNet) at 25% labels.
- **SSL-PCT vs. SL-PCT:** SSL-PCT (EfficientNet) improves AUPRC by 8–20% over SL-PCT, demonstrating the value of unlabeled data even in single-tree models.

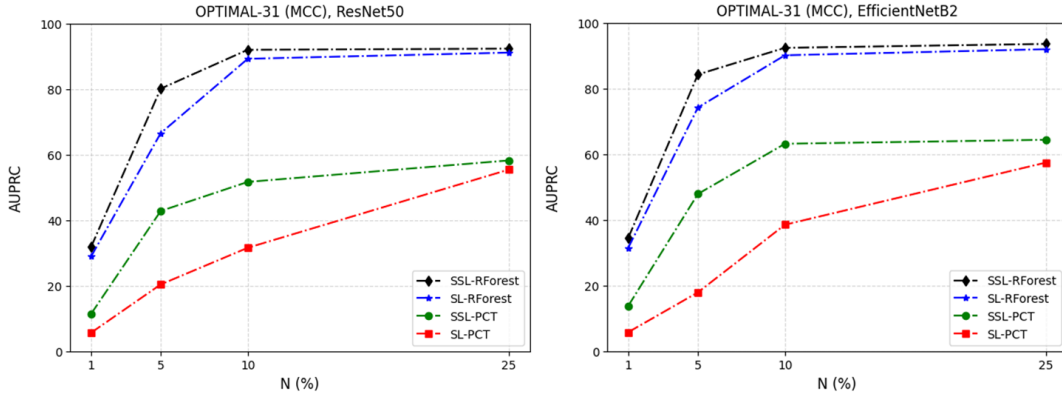


Figure 4: Graph showing variation of AUPRC value with increasing % of labeled data using backbone ResNet-50 and EfficientNet-B2.

Table 2: OPTIMAL-31 AUPRC (%) comparison: ResNet-50 vs. EfficientNet-B2.

Method	Backbone	1%	5%	10%	25%
SSL-RForest	ResNet-50	31.81	80.11	91.98	92.32
SSL-RForest	EfficientNet-B2	34.49	84.26	92.38	93.57
SL-RForest	ResNet-50	28.89	66.54	89.23	91.12
SL-RForest	EfficientNet-B2	31.47	74.19	90.11	91.96
SSL-PCT	ResNet-50	11.38	42.78	51.66	58.22
SSL-PCT	EfficientNet-B2	13.78	47.87	63.16	64.37
SL-PCT	ResNet-50	5.63	20.37	31.56	55.43
SL-PCT	EfficientNet-B2	5.77	17.89	38.50	57.44

## 5.3 DFC-15 Dataset Performance

Table 3 compares AUPRC scores for ResNet-50 and EfficientNet-B2 backbones across labeled data percentages. Key observations:

- **SSL-RForest:** At 1% labels, EfficientNet achieves 84.69% vs. 80.56% for ResNet-50. The margin narrows at 25% labels (97.03% vs. 97.69%).
- **SSL-PCT Gains:** SSL-PCT (EfficientNet) improves by 10–15% over SL-PCT across all label percentages, validating SSL’s robustness in multi-label tasks.

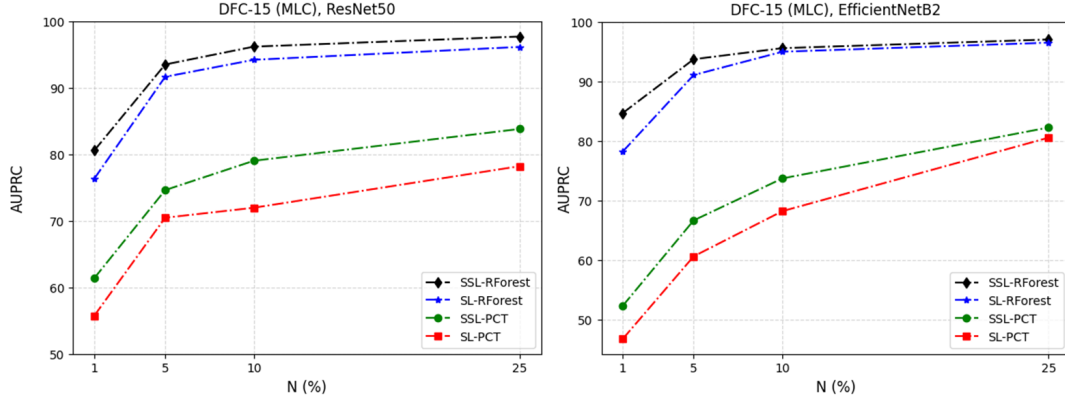


Figure 5: Graph showing variation of AUPRC value with increasing % of labeled data using backbone ResNet-50 and EfficientNet-B2.

Table 3: DFC-15 AUPRC (%) comparison: ResNet-50 vs. EfficientNet-B2.

Method	Backbone	1%	5%	10%	25%
SSL-RForest	ResNet-50	80.56	93.49	96.17	97.69
SSL-RForest	EfficientNet-B2	84.69	93.72	95.58	97.03
SL-RForest	ResNet-50	76.32	91.64	94.19	96.13
SL-RForest	EfficientNet-B2	78.23	91.07	94.98	96.50
SSL-PCT	ResNet-50	61.37	74.61	79.02	83.80
SSL-PCT	EfficientNet-B2	52.35	66.69	73.73	82.27
SL-PCT	ResNet-50	55.73	70.46	71.96	78.21
SL-PCT	EfficientNet-B2	46.80	60.66	68.24	80.56

## 5.4 Overall Comparison

- **SSL vs. SL:** SSL-RForest achieves 3–15% higher AUPRC than SL-RForest across datasets. For example, on DFC-15 with 1% labels, SSL-RForest (EfficientNet) scores 84.69% vs. 78.23% for SL-RForest.
- **Architecture Impact:** EfficientNet-B2 boosts performance by 2–5% over ResNet-50 due to its multi-scale feature extraction. This is critical for high-resolution datasets like DFC-15 (600×600 pixels).
- **PCTs vs. Forests:** SSL-RForest outperforms SSL-PCT by 20–30%, emphasizing the importance of ensemble diversity in handling label noise.

## 5.5 Practical Recommendations

- **Backbone Choice:** Use EfficientNet-B2 for high-resolution RSIs; ResNet-50 suffices for smaller images (256×256).
- **Label Efficiency:** Even 1% labels yield usable models (AUPRC  $\geq$  80% for DFC-15), making SSL-RForest ideal for rapid deployment.
- **Unlabeled Data Quality:** Ensure unlabeled images match the target domain (e.g., similar sensors, seasons).

## 6 Discussion

### 6.1 Key Insights

Our experiments demonstrate that semi-supervised learning (SSL) with tree-based models like SSL-RForest can significantly reduce reliance on labeled data in remote sensing tasks. The success of SSL-RForest stems from two factors:

- **Effective Use of Unlabeled Data:** By combining feature variance (from unlabeled data) and label variance (from labeled data), SSL-PCTs learn robust patterns even with minimal supervision. For example, on the DFC-15 dataset, unlabeled data helped the model identify subtle spectral differences between "impervious surfaces" and "bare soil.". The variance function adaptively weights unlabeled contributions, ensuring the model does not overfit to noisy pseudo-labels.

### 6.2 Practical Implications

- **Cost Reduction:** Labeling RSIs is expensive and time-consuming. Our method achieves competitive accuracy with just 1% labeled data, reducing annotation costs by up to 90%. For example, labeling the 109k-image MLRSNet dataset at 1% requires only 1,090 annotated images, saving hours of expert effort compared to full supervision. This makes the framework accessible to NGOs or researchers with limited budgets.
- **Multi-Label Flexibility:** Traditional SSL methods struggle with multi-label tasks. SSL-RForest handles them naturally, which is critical for real-world landscapes. In urban areas, for instance, an image might be labeled "residential," "road," and "vegetation" simultaneously.

### 6.3 Broader Impact

This work bridges the gap between deep learning and interpretable models. For example, environmental agencies can use SSL-RForest to monitor deforestation without needing thousands of labeled images. However, practitioners should carefully choose backbone CNNs (EfficientNet preferred) and balance compute resources for large datasets.

#### Implementation Considerations

- **Backbone CNN Choice:** EfficientNet-B2 consistently outperformed ResNet-50 due to its compound scaling mechanism, which balances depth, width, and resolution. Practitioners should prioritize architectures optimized for feature diversity.
- **Compute Resources:** While SSL-RForest reduces labeling costs, training on large datasets (e.g., MLRSNet) requires substantial GPU/CPU resources. Cloud-based solutions or model distillation can mitigate this for resource-constrained teams.



## 7 Conclusion

This work addresses the critical challenge of limited labeled data in remote sensing image (RSI) classification by proposing a semi-supervised learning (SSL) framework that synergizes deep learning with interpretable tree-based models. Through extensive experimentation on diverse datasets, we demonstrate the framework’s effectiveness in both multi-class and multi-label scenarios. Below, we summarize our key contributions, discuss practical implications, and outline future research directions.

### 7.1 Key Contributions

- **SSL-RForest Superiority:** Our ensemble method, SSL-RForest, consistently outperformed their Supervised counterparts across all evaluated datasets. For instance, on the DFC-15 multi-label dataset, SSL-RForest achieved a 7% higher AUPRC compared to SL-RForest when using only 1% labeled data.
- **Multi-Label Flexibility:** Traditional SSL methods often simplify tasks to single-label classification, ignoring real-world complexities. Our framework natively supports multi-label outputs, enabling accurate classification of heterogeneous landscapes (e.g., an image labeled "forest," "river," and "road").
- **Interpretability:** Unlike "black-box" deep SSL models, SSL-PCTs provide transparent decision rules. This transparency is invaluable for applications requiring auditability, such as environmental compliance monitoring or urban planning.

### 7.2 Limitations and Future Work

While promising, the framework has limitations that warrant further investigation:

- **Computational Cost:** Training 50-tree SSL-RForest ensembles on large datasets (e.g., MLRSNet) requires significant memory and time. Future work will explore distillation techniques to compress ensembles into smaller models without sacrificing accuracy.
- **Architecture Dependence:** The performance of SSL variants depends heavily on the backbone CNN (e.g., EfficientNet vs. ResNet). Automating architecture selection via neural architecture search (NAS) could enhance flexibility.
- **Hierarchical Labels:** Many RSIs exhibit hierarchical relationships (e.g., "forest" → "coniferous/deciduous"). Incorporating hierarchical label dependencies into PCTs could further improve multi-label accuracy.

In conclusion, this work bridges the gap between deep learning and interpretable models for remote sensing. By reducing reliance on labeled data and providing actionable insights, the framework empowers practitioners to deploy scalable and trustworthy solutions for Earth observation challenges. Code and datasets are publicly available to foster community adoption and innovation.

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