



Semi-supervised deep learning for multi-crop segmentation using Sentinel-1 and Sentinel-2 data in Haryana, India

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Received: 20 November 2025; Accepted: 08 June 2026

ABSTRACT

Accurate crop classification from satellite imagery is essential for agricultural monitoring; however, mapping the crop type in data-scarce regions remains challenging due to limited ground truth, spectral similarities between crops, and strong temporal variability. Supervised deep learning approaches are further constrained by their dependence on large annotated datasets. In this study, a semi-supervised framework based on R3Net a residual-recurrent refinement network, was developed to leverage both optical and SAR signals for pixel-level segmentation of winter (*rabi*) season crops [wheat (*Triticum aestivum* L.), mustard (*Brassica juncea* L.), and other classes] using multi-temporal satellite imagery. The architecture integrates parallel temporal encoders with recurrent units to capture spatial-spectral features and phenological dynamics across key growth stages. A confidence-aware pseudo-labeling strategy was introduced to effectively utilize large volumes of unlabeled data while suppressing uncertain predictions. The framework was evaluated against three baselines: fully supervised training, standard pseudo-labeling, and the mean teacher method. The supervised model achieved overall accuracy of 65.21% and a mean IoU of 48.55%, whereas the semi-supervised approaches significantly improved segmentation performance. Among all methods, the proposed confidence-aware R3Net achieved the best performance, with 76.05% overall accuracy and a mean IoU of 59.03%, including notable improvements in mustard segmentation. Testing on an independent geographic region (IARI 2022–23) further demonstrated robust generalisation capability, producing segmentation maps consistent with field boundaries and crop phenology.

Keywords: Crop segmentation, Mustard, Pseudo-labeling, Remote sensing, Wheat

Remote sensing plays an indispensable role in modern agricultural monitoring by enabling large-scale, timely and cost-effective access to multispectral, hyperspectral and radar observations. These satellite data support essential applications such as crop classification, yield forecasting, irrigation scheduling and food-security planning (Kussul *et al.* 2017, Jones *et al.* 2024). Wheat (*Triticum aestivum* L.) and mustard (*Brassica juncea* L.), which form the backbone of the rice (*Oryza sativa* L.)–wheat cropping system in northern India, are particularly important as they support household consumption and national food security (Kumar *et al.* 2018). Consequently, an accurate identification of such staple crops is therefore crucial for monitoring phenological stages, assessing seasonal production and informing agricultural policies (Cheng *et al.* 2016, Ramteke *et al.* 2023).

Deep learning architectures that combine convolutional neural networks (CNNs) with Long Short-Term Memory (LSTM) further improve segmentation by capturing temporal crop growth dynamics (Hochreiter and Schmidhuber 1997, Peña *et al.* 2014). Despite this progress, most research still relies on fully supervised settings, which restricts applicability in data-scarce agricultural regions (Chen *et al.* 2024a, Chen *et al.* 2024b). Acquiring such ground-truth labels across diverse and heterogeneous agricultural landscapes demands significant field labour and expert involvement, making fully supervised approaches expensive and difficult to scale (Kussul 2017, Song *et al.* 2025).

Semi-supervised learning (SSL) has emerged as a promising alternative by leveraging abundant unlabeled satellite imagery (Chen *et al.* 2022, Chen *et al.* 2023). Among SSL, pseudo-labeling techniques have shown strong potential by automatically generating labels for unlabeled pixels using high-confidence model predictions (Feng *et al.* 2025). These approaches have improved performance in land-cover mapping (Kwak and Kim 2023, Zhang *et al.* 2023), crop monitoring (Menezes *et al.* 2023) and urban feature extraction (Huang *et al.* 2024), and have proven

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useful for nitrogen estimation, weed detection, tree detection and crop classification (Menezes *et al.* 2023, Wang *et al.* 2023, Li *et al.* 2023, Luo *et al.* 2025).

To address this gap, we propose R3Net, a Residual-Recurrent Refinement Network explored confidence-aware pseudo-labeling (Menezes *et al.* 2023). R3Net fuses parallel residual encoders with LSTM-based temporal skip connections to capture multi-stage crop phenology. The model is evaluated against a supervised baseline, standard pseudo-labeling and mean teacher approaches, with identical data conditions. Furthermore, its testing on geographically distinct fields at ICAR-Indian Agricultural Research Institute, New Delhi to assess out-of-distribution generalisation.

MATERIALS AND METHODS

The study integrates multi-temporal optical and SAR satellite observations with a SSL framework for crop-type segmentation. The methodological workflow begins with satellite data acquisition and preprocessing, followed by ground truth annotation, temporal feature preparation, model development, SSL refinement, and evaluation.

Research terrain: The study was conducted in Haryana, India, an intensively cultivated state where wheat and mustard dominate the winter (*rabi*) season during 2023–24 (Bagaria and Surendra 2025). The region spans multiple agro-climatic zones and soil types (Ashish 2024), providing an ideal landscape to evaluate multi-temporal

crop segmentation approaches under varying biophysical conditions. Haryana experiences substantial climatic and agro-ecological variability, ranging from semi-arid regions in the south-west to relatively humid and intensively irrigated zones in the north-east, resulting in diverse cropping patterns and crop growth conditions.

Ground truth: During 2023–24, field-level ground truth (GT) data were collected from nine districts, viz. Hisar, Palwal and Jhajjar, Bhiwani, Mahendragarh and Rewari, Karnal, Kurukshetra and Panipat. These districts represent a mix of wheat-dominated, mustard-dominated and mixed cropping systems. The final dataset comprised 1,543 wheat fields, 774 mustard fields and 168 parcels representing other classes such as built-up areas, trees and mixed crops, forming a robust reference set for model development and validation. Fig. 1 presents the spatial distribution of labelled parcels across districts, the class-wise sample statistics, and a zoomed-in satellite view illustrating field-level annotation.

Satellite data acquisition and pre-processing: The dataset comprises temporal satellite images from Sentinel-1 (C-band SAR) and Sentinel-2 (Multispectral) sensors, captured across four key months of the crop growing season: November, December, February, and March, which represent key phenological stages of wheat and mustard. Each image includes seven bands: Blue (B2), Green (B3), Red (B4), NIR (B8), SWIR (B11), and radar bands VV and VH were clipped to the boundaries of the nine study districts separately, generating spatially uniform datasets

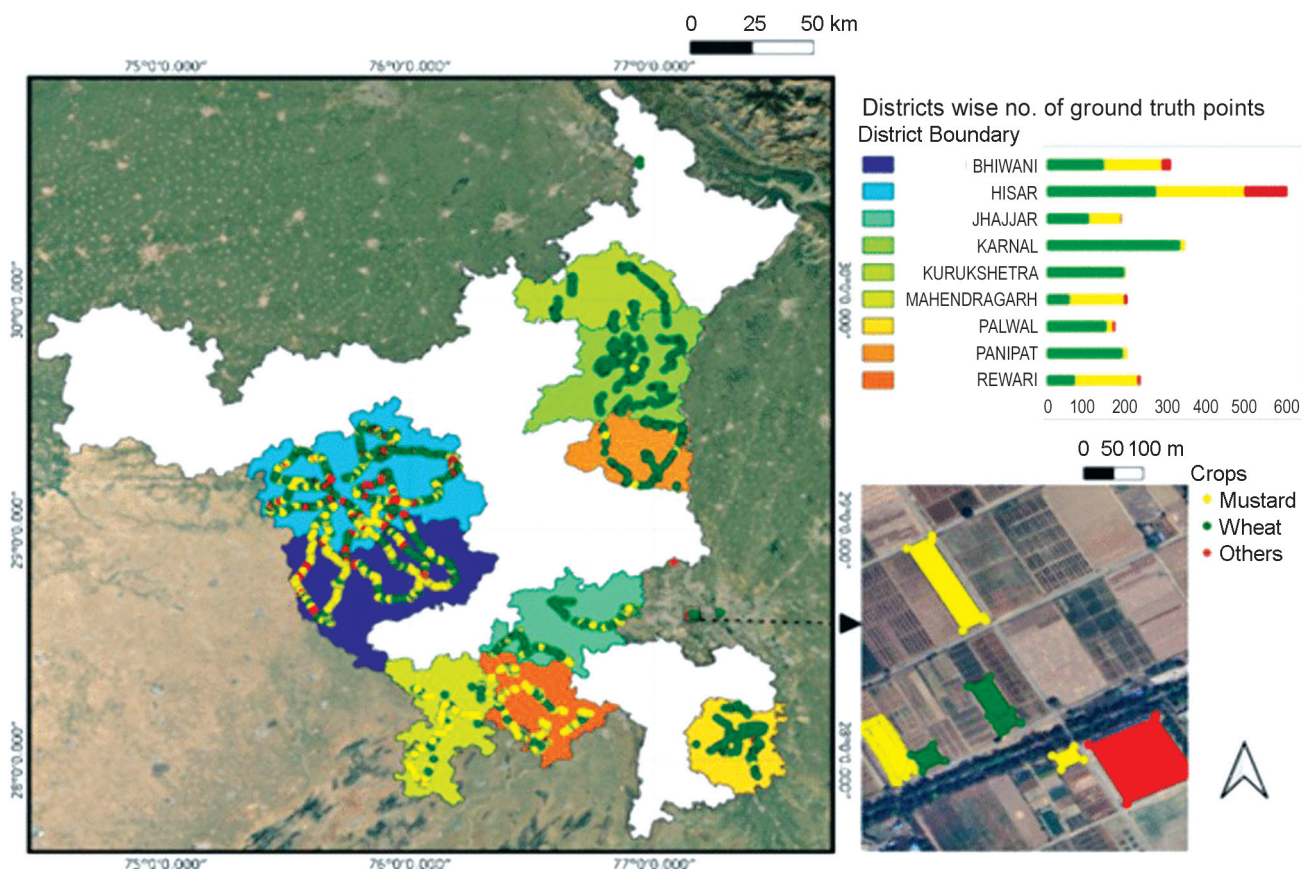


Fig. 1 Spatial distribution of ground-truth samples across nine districts of Haryana, including district-wise stacked-bar representation of parcel counts and detailed field-level annotations.

for subsequent processing. These bands were selected for their sensitivity to vegetation structure, chlorophyll concentration, canopy roughness and crop moisture levels. The spatial resolution of all bands was standardised to 10 m. The SWIR band B11, originally at 20 m, was resampled to 10 m using bilinear interpolation to maintain uniform spatial resolution across all features. Each pixel was represented by a 21-dimensional feature vector (7 bands $\times$ 3 months). Data were normalized using min-max scaling to ensure consistent input range for the model (Aksu *et al.* 2019).

Data preparation: The labeled dataset (L) comprised manually annotated patches, while a significantly larger unlabeled dataset (U) was sampled across the full study area using a sliding-window approach. These unlabeled patches contained the same multi-temporal satellite features but lacked segmentation masks. All satellite images were converted into 128×128 -pixel image patches. The dataset consists of 533 labelled image patches and 5019 unlabeled image patches, each having four temporal steps and seven spectral/radar bands. These two sets formed separate training pools for the supervised module and the SSL component, enabling effective utilisation of the extensive unlabeled satellite imagery.

Model architecture: R3Net is a deep learning architecture tailored for multi-class crop segmentation from temporal satellite imagery, particularly under SSL conditions shown in Fig. 2. The architecture extends the U-Net structure by incorporating residual units (Ronneberger *et al.* 2015), parallel temporal encoders and ConvLSTM-based fusion to capture spatio-temporal variations in wheat and mustard phenology.

Each temporal slice is processed through an independent encoder path composed of stacked residual encoder blocks. Each residual encoder block contains two convolutional layers followed by batch normalisation and ReLU activation. The block output is then passed through an additional pair of convolutional layers, after which a skip connection links the initial feature representation directly to the final output of the block. This residual linkage stabilises gradient flow and improves feature propagation. Four such blocks were arranged hierarchically, progressively downsampling the input and extracting multi-level spatial-spectral representations.

Temporal dependence between months is integrated through ConvLSTM units placed at corresponding encoder depths. Feature maps

from all temporal branches are concatenated and passed to ConvLSTM, enabling the network to learn growth-stage dynamics and temporal transitions. The decoder reconstructs dense crop maps using transposed convolutions and fuses skip connections from all ConvLSTM outputs. A channel-wise attention module at the bottleneck amplifies discriminative vegetation signals while suppressing background noise. The final segmentation is produced using a 1×1 convolution followed by softmax activation (Wang *et al.* 2018), generating per-pixel class probabilities for wheat, mustard and other land-cover categories.

SSL using confidence-aware pseudo labeling: To refine learning from limited L data, R3Net integrates an SSL refinement strategy based on modified pseudo-labeling algorithm. In this algorithm, confident predictions from U dataset are iteratively added as supervisory observations. The modified semi-supervised multi-class crop segmentation algorithm, referred as MOSS, is explained below:

Algorithm MOSS: MODified Semi-supervised multi-class crop Segmentation

Inputs:

Labeled dataset $L = \{(X_1, Y_1), (X_2, Y_2), \dots, (X_l, Y_l)\}$

Unlabeled dataset $U = \{X_{l+1}, X_{l+2}, \dots, X_{l+u}\}$

Deep model M (Our parallel encoder with LSTM Skip connection)

Confidence threshold $T=70$ to 90 for pseudo-labeling

Maximum training epochs $E=100$

Early stopping patience $P=10$

Initial supervised training epochs $E_0=30$

Pseudo-labeling update frequency $F=10$

Process Steps:

1. Initialize model M
2. Train model M on the labeled dataset L for E_0 epochs

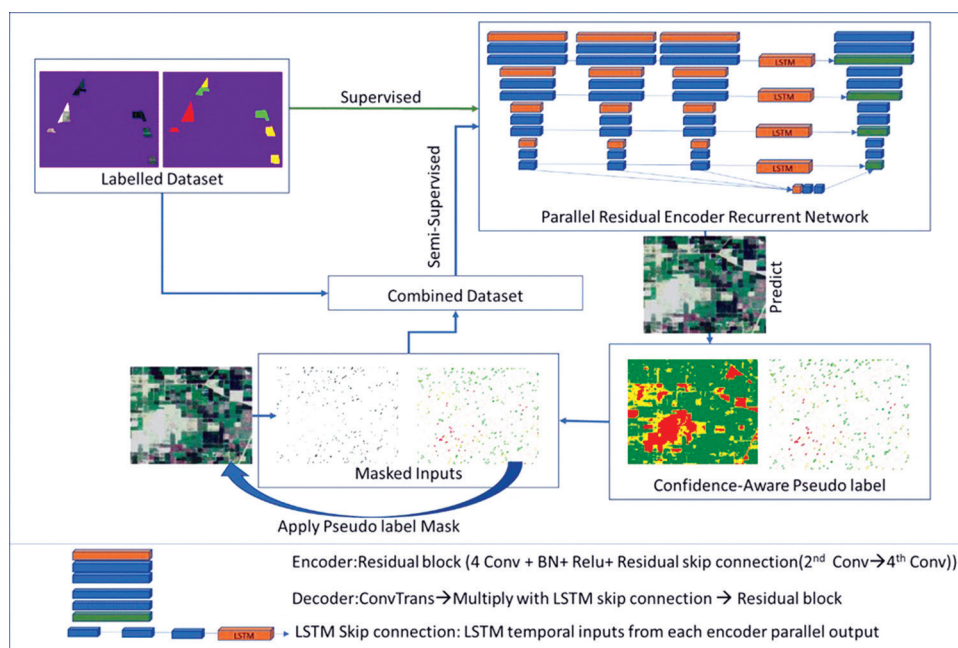


Fig. 2 Confidence-aware pseudo-labeling framework for semi-supervised classifier. Conv, Convolutional layer; BN, Batch normalisation; ConvTrans, Transposed convolutions.

3. Initialize best validation accuracy and early stopping counter $P=20$
4. For epoch $e = E_0 + 1$ to E :
 - a. If $(e - E_0) \bmod F = 0$:
 - i. Use current model M to predict labels for all $X_{i+1} \in U$
 - ii. For each $X_i \in U$
 - Compute predicted label: $\bar{y}_i = \arg \max_c \text{pred}(Y_i = c | X_i)$
 - Compute confidence: $\text{conf}_i = \max_c \text{pred}(Y_i = c | X_i)$
 - If $\text{conf}_i \geq T$, add $(X_i, \bar{y}_i)$ to pseudo-labeled set PL
 - If $PL < 25$ percent then $T = T - 2$
 - Else mask low-confidence prediction inputs as $(0,0)$ to pseudo-labeled set PL
 - iii. Update training set: $L' = L \cup PL$
 - b. Train model M for 10 epochs on L'
 - c. Validate model on a validation set:
 - If accuracy improves, update best accuracy and reset early stopping counter
 - Else, increment early stopping counter
 - d. If early stopping counter $\geq P = 10$, stop training

Output:

5. Save final validated model M .
Performance metrics accuracy, F1-score, and Intersection over Union (IoU).

To improve robustness, confidence filtering is applied at the pixel level by evaluating the softmax probability of each predicted class and only retaining predictions that exceed a predefined threshold. Smart input masking is then applied by zeroing out pixels in the input image where confidence is low, effectively preventing the model from reinforcing incorrect pseudo-labels during training. This prevents noise accumulation in the learning process. These U dataset pseudo-labels, combined with the L dataset, form an updated training set used for retraining the model periodically, enabling it to adapt to new patterns in the unlabeled data. This semi-iterative process is triggered at fixed intervals (F), with dynamic threshold adjustment to ensure sufficient high-confidence samples are included. The confidence threshold was dynamically reduced when the proportion of high-confidence pseudo-labels fell below 25%, ensuring sufficient reliable samples were retained for SSL training. This iterative refinement gradually increases the effective training set and improves generalisation across diverse agro-ecological zones without requiring additional field samples.

Experimental design and comparative methods: In this study, the proposed confidence-aware R3Net serves as the primary SSL segmentation framework and is evaluated against three comparative approaches a fully supervised baseline, standard pseudo-labeling, and the mean teacher model.

The supervised approach relies entirely on labeled data and serves as a reference point for measuring the improvements gained through SSL. Pseudo-labeling,

following Menezes *et al.* (2023), employs a self-training strategy in which the model generates high-confidence predictions that are then treated as pseudo-labels and incorporated into the training process alongside the labeled samples. The mean teacher model, as described in Tian *et al.* (2022), applies consistency regularisation through a teacher-student structure in which the teacher network is updated via an exponential moving average of the student's weight, ensuring that predictions remain stable under input perturbations. Building on these established SSL techniques, the confidence-aware R3Net selectively incorporates pseudo-labels based on softmax-derived confidence levels while suppressing inputs associated with low-confidence predictions, allowing the model to focus on reliable information during training.

Together, these methods represent the principal of supervised and SSL strategies used in satellite-based crop mapping, allowing a consistent and controlled comparison. The comparison focuses on quantifying how the proposed confidence-aware refinement in R3Net improves segmentation accuracy.

Training setup and hyper parameters: Training was performed using the Adam optimiser with categorical cross-entropy loss and accuracy as the primary evaluation metric. Early stopping monitored validation accuracy with patience of 15 epochs and restored the best-performing weights. Detailed training parameter and dataset distribution details shown in Table 1.

Evaluation metrics: The performance of the model is assessed using standard evaluation metrics commonly applied in segmentation research. Overall Accuracy (OA) measures the proportion of correct predictions out of all predictions made and is expressed as (Sokolova and Lapalme 2009):

$$\text{Overall accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP, True positive; TN, True negative; FP, False positive and FN, False negative.

To support the formulation of the F1 score, the definitions of the underlying classification components are provided. The F1 score provides a balanced measure of classification performance and is defined using precision and recall. Precision represents the proportion of correctly identified positive samples among all predicted positives, while recall measures the proportion of correctly identified positive samples among all actual positives and calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Using these, the F1 score is computed as:

$$\text{F1 score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 1 Training parameters and dataset distribution

Parameter	Value
Input patch size	128 × 128 × 7 (per time step)
Temporal depth	4 months (Nov, Dec, Feb, Mar)
Batch size	8
Optimiser	Adam
Learning rate	0.0001
Loss function	Categorical Cross-Entropy
Metrics	Accuracy
Epoch	100
Early stopping patience	15
GPU hardware	NVIDIA RTX A5000 (22 GB)
Total labeled samples	533
Total test samples	54
Total unlabeled samples	5019 patches
Training runtime	9–11 h (SSL full cycle)

Intersection over Union (IoU) quantifies the overlap between predicted and ground-truth regions and is formulated as (Everingham *et al.* 2010):

$$\text{IoU} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}}$$

To evaluate performance across all classes, the mean Intersection over Union (mIoU) is calculated as the average IoU across n classes:

$$\text{mIoU} = \frac{\sum_{i=1}^n \text{IoU}_i}{n}$$

These metrics collectively provide a comprehensive assessment of segmentation accuracy, class-wise performance, and overall model reliability.

RESULTS AND DISCUSSION

The quantitative comparison of the supervised and SSL approaches is presented in Table 2, which shows clear performance gains when unlabeled data are incorporated using pseudo-labeling, mean teacher, and the proposed confidence-aware strategy. The supervised baseline achieves an overall accuracy of 65.21% and a mean IoU of 48.55%, reflecting the limitations imposed by the scarcity of labeled field parcels. Misclassification is particularly noticeable in mustard, whose spectral signatures overlap substantially with wheat during early and mid-season growth stages.

Introducing standard pseudo-labeling leads to a substantial improvement, increasing accuracy to 71.97% and mean IoU to 54.52%. This confirms the advantage of utilising high-confidence predictions from the unlabeled dataset to reinforce crop-specific patterns, an effect also reported in earlier SSL remote sensing studies (Feng *et al.* 2020, Chen *et al.* 2022). The mean teacher approach further improves

performance to 74.95% accuracy and 57.10% mean IoU, owing to the teacher-student consistency mechanism that stabilises pseudo-label generation, consistent with findings by Chen *et al.* (2024a) and Li *et al.* (2024). Among all methods, the confidence-aware R3Net delivers the highest performance, achieving 76.05% accuracy and a mean IoU of 59.03%. The selective filtering of low-confidence pixels and masked-input strategy prevents error accumulation during pseudo-labeling and results in stable refinement of both field boundaries and class transitions. The observed improvements arise from two complementary components: ConvLSTM-based temporal modeling captures crop phenological dynamics across growth stages, while the SSL framework improves generalisation by incorporating reliable pseudo-labeled samples from unlabeled data.

These trends are further supported by the class-wise IoU comparison illustrated in Fig. 3. Wheat achieves the highest IoU across all models, increasing from 0.55 in the supervised baseline to 0.70 in the confidence-aware model. The largest relative improvement occurs in mustard, where IoU increases from 0.38–0.49. Mustard's phenological similarity to wheat has historically impaired segmentation performance in remote sensing applications, but the incorporation of temporal features and confidence-aware filtering in R3Net significantly reduces this confusion. The “Other” class also showed improvement from 0.54–0.58, with clearer delineation of trees, built-up areas, and mixed patches.

A qualitative comparison is shown in Fig. 4, presenting segmentation results on fields from the ICAR-Indian Agricultural Research Institute corresponding to the 2022–23 *rabi* season. This region is geographically distinct from the training area and belongs to a different year, making it an ideal benchmark for testing generalisation. Ground truth labels (Fig. 4a) use yellow to represent mustard and green for wheat, while the model predictions denote wheat in green, mustard in blue, and other classes in red (Fig. 4 b,c,e,f). The supervised model displays noticeable misclassification, between wheat and mustard areas (Fig. 4b).

Standard pseudo-labeling improves the structural consistency of predictions but introduces scattered errors across field interiors (Fig. 4c). Mean teacher produces smoother regions, yet some uncertainty persists along boundaries (Fig. 4e). In contrast, the confidence-aware

Table 2 Comparison across different SSL model vs supervised

Model	Accuracy	F1	F1	F1	Mean IoU
		Wheat	Mustard	Others	
Supervised	65.21	0.71	0.54	0.70	48.55
Pseudo Label	71.97	0.80	0.61	0.70	54.52
Mean Teacher	74.95	0.83	0.61	0.72	57.10
Confidence Aware	76.05	0.83	0.65	0.74	59.03

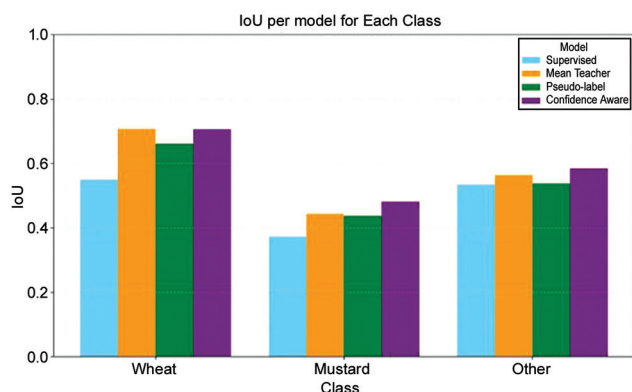


Fig. 3 Intersection-over-Union class wise comparison of supervised and SSL models.

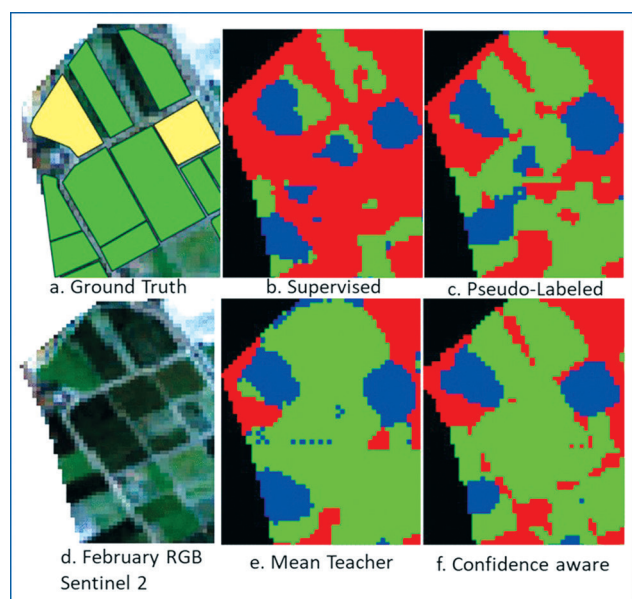


Fig. 4 Qualitative comparison of segmentation predictions on IARI fields corresponding to 2022–23 *rabi*, a geographically distinct region from the training data but sharing similar cropping patterns. (a) Ground truth annotations, (b) Supervised baseline, (c) Pseudo-labeled model, (d) Sentinel-2 RGB image (February), (e) Mean teacher, and (f) Confidence-aware model.

model closely resembles the ground truth (Fig. 4f). The February Sentinel-2 RGB patch in Fig. 4d demonstrates the underlying difficulty: wheat and mustard are visually similar at this phenological stage, showing why purely spectral segmentation fails without temporal modeling and confidence refinement.

These findings align with recent SSL segmentation literature, where pseudo-labeling, consistency regularisation, and contrastive feature stabilisation improve mapping accuracy in label-limited environments (Zhang *et al.* 2023, Wang *et al.* 2023, Liu *et al.* 2025). Most existing work has focused on urban and general land-cover mapping; however, the present study demonstrates that SSL approaches are equally beneficial in agriculture, where the temporal evolution of crop reflectance adds complexity.

Despite differences in soil background, field geometry, and seasonal progression between the training region in Haryana and the evaluation region at IARI, the confidence-aware R3Net maintains stable performance. This indicates strong transferability across geographic domains that share comparable crop calendars. The combined evidence from Table 2, Fig. 3, and Fig. 4 confirms that the proposed framework surpasses conventional supervised and existing SSL strategies in both accuracy and generalisation, offering a reliable and scalable solution for operational crop segmentation in diverse agricultural regions.

In conclusion, this work presented R3Net, a Residual-Recurrent Refinement Network, designed for SSL multi-class crop segmentation using multi-temporal satellite imagery. By integrating residual spatial encoding, LSTM-based temporal modeling, and a confidence-aware SSL refinement strategy, the framework effectively learns from limited labeled data and adapts to temporal crop phenology variations. The proposed approach demonstrated robust segmentation performances and also strong generalisation across unseen geographically distinct regions with similar cropping calendars, indicating its robustness. These characteristics highlight its potential for operational large-scale crop monitoring programmes, particularly in data-scarce agricultural regions where extensive field annotation is difficult and costly. Future work may explore integration with contrastive and cross-consistency strategies to further enhance generalisation across diverse geographies and growing seasons.

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