

# A Remote Sensing–Based Methodology for Assessing Alternate Wetting and Drying Practices in Punjab

## Technical Note

This technical note presents a satellite-based methodology for monitoring the adoption of Alternate Wetting and Drying (AWD) in rice cultivation across Punjab. By combining L-band Synthetic Aperture Radar (SAR) data with machine learning and field validation, the study demonstrates a scalable approach to track irrigation practices, support water conservation efforts, and enable data-driven climate and agriculture interventions.

### Key Takeaways



Satellite monitoring can track irrigation practices at scale.



Satellite data should be combined with field validation.



Tree-based machine learning models perform well.



Higher observation frequency can improve accuracy.



Improved SAR data processing strengthens irrigation classification.



Digital monitoring of irrigation practices can support the implementation of incentive programs.

# 1. Introduction

Punjab, often referred to as the “land of five rivers,” is currently facing a serious groundwater crisis. Over the past several decades, agriculture in the state has been dominated by the paddy-wheat cropping cycle, which expanded rapidly after the Green Revolution in the 1960s. While this system significantly increased food production, it also led to a sharp rise in groundwater extraction, particularly for paddy cultivation, which requires large amounts of irrigation water.

**Today, the extensive use of continuous flood irrigation in rice fields is placing enormous pressure on Punjab’s groundwater resources.**

According to a study by the Central Ground Water Board, groundwater levels in the state could fall below 1,000 feet by 2039. At such depths, extracting water would become economically unviable for many farmers, posing a serious threat to the long-term sustainability of agriculture in the region.

In addition to groundwater depletion, rice cultivation, especially under continuously flooded irrigation also produces significant methane emissions, a potent greenhouse gas. Methane is released when flooded soils create anaerobic conditions, which promote the activity of methane-producing microorganisms.

To address these challenges, The Nature Conservancy is working with farmers through its program PRANA (Promoting Regenerative and No-burn Agriculture) to promote more sustainable farming



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practices. One such practice is Alternate Wetting and Drying (AWD), a groundwater conservation technique in which rice fields are allowed to dry periodically before being irrigated again. Research shows that, compared to continuous flooding, AWD can reduce irrigation water-use by 15-30% without yield loss, while also cutting methane emissions by 30-70%.<sup>1</sup>

Monitoring the adoption of Alternate Wetting and Drying (AWD) across large areas is challenging because it occurs at the level of individual fields and cannot easily be verified through field visits alone. Digital Monitoring, Reporting, and Verification (dMRV) systems offer a scalable solution by using satellite data and advanced analytics to observe agricultural practices remotely. In this study, The Nature Conservancy in India partnered with Mitti Labs to pilot the use of L-band radar satellite data combined with machine learning techniques. This approach helps detect changes in soil moisture and surface water over time, making it possible to identify irrigation patterns and assess AWD adoption across large rice-growing areas in Punjab.

<sup>1</sup>In: Water-wise rice production; IRRI, Plant Research International

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## From Water Crisis to Water Smart Farming



### Problem

- Groundwater depletion in Punjab
- High water demand from paddy-wheat cropping
- Declining water levels (projected below 1000 ft by 2039)
- Methane emissions from flooded fields

### Solution

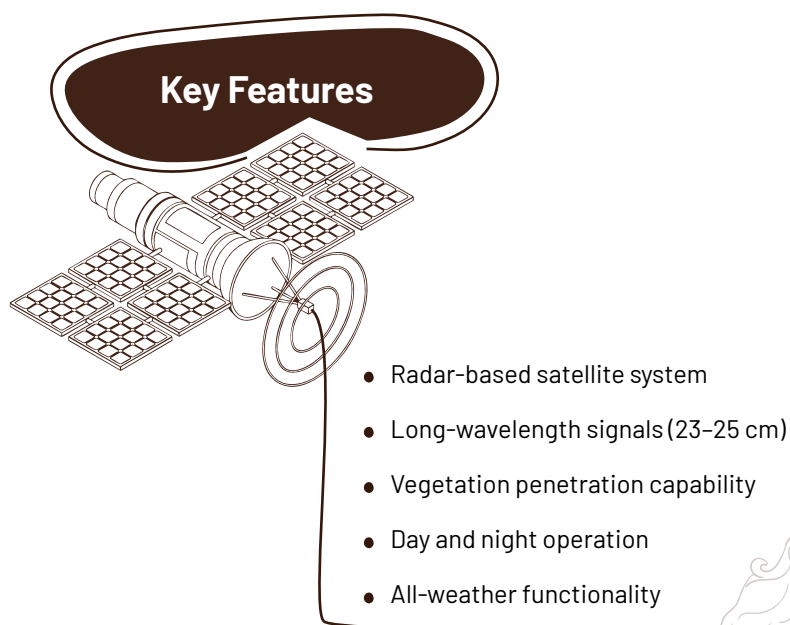
- Alternate Wetting and Drying (AWD) between irrigation cycles

### Impact

- Reduced water use (15-30%)
- Reduced methane emissions (30-70%)

## 2. What is an L-Band SAR Satellite System?

An L-band Synthetic Aperture Radar (SAR) satellite is a type of Earth observation satellite that uses radar signals to observe the Earth's surface. It uses an advanced satellite-based remote sensing system that operates at long wavelength microwave signals (approximately 23–25 cm) to capture detailed information about surface conditions. Its longer wavelength enables penetration through vegetation and interaction with underlying soil layers, while its ability to operate in all weather conditions - both day and night - makes it highly effective for monitoring soil moisture, crop status, and irrigation dynamics.<sup>2</sup>



<sup>2</sup>Spaceborne L-Band Synthetic Aperture Radar Data for Geoscientific Analyses in Coastal Land Applications: A Review | MDPI

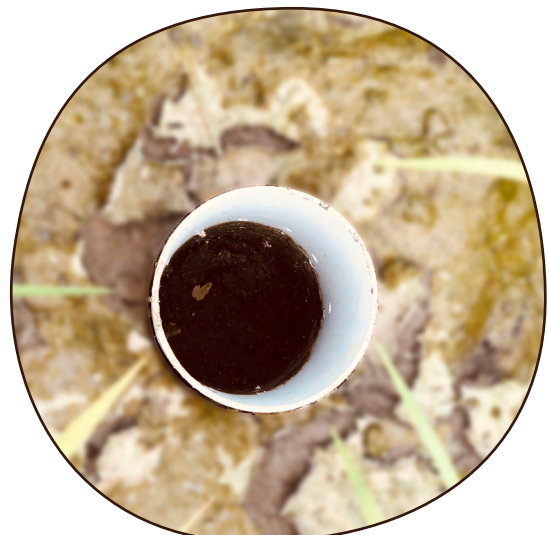
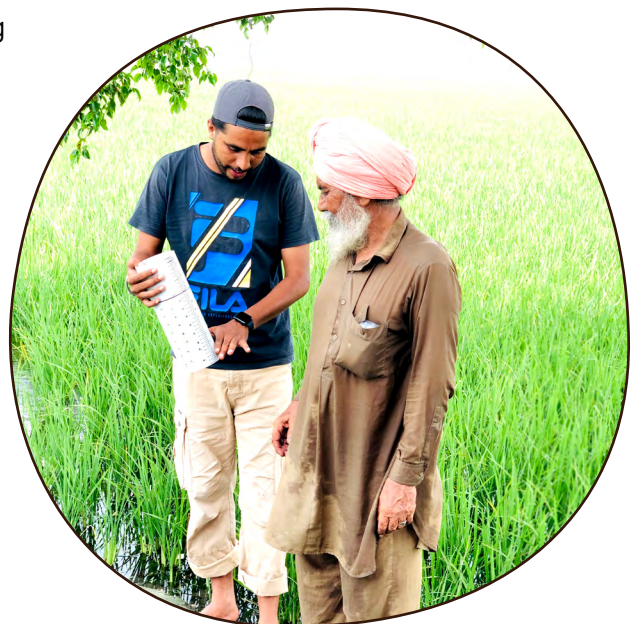
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### 3. Why was L-band SAR used to measure AWD adoption?

L-band SAR was selected due to its superior penetration capability compared to shorter wavelength systems like C-band and X-band. Its longer wavelength allows it to penetrate dense rice canopy and reliably sense variations in soil moisture and surface water conditions. In contrast, shorter-wavelength systems primarily interact with the upper portion of the crop canopy, making it more difficult to reliably observe conditions at the soil surface.

Under continuous flooding, fields remain full of water and the soil stays saturated. Under Alternate Wetting and Drying (AWD), farmers allow fields to dry periodically before irrigating again. These cycles create clear changes in soil moisture and surface water, which can be monitored. L-band radar's sensitivity to surface moisture allows researchers to distinguish between flooded and drying field conditions, making it particularly effective for large scale monitoring of AWD adoption.

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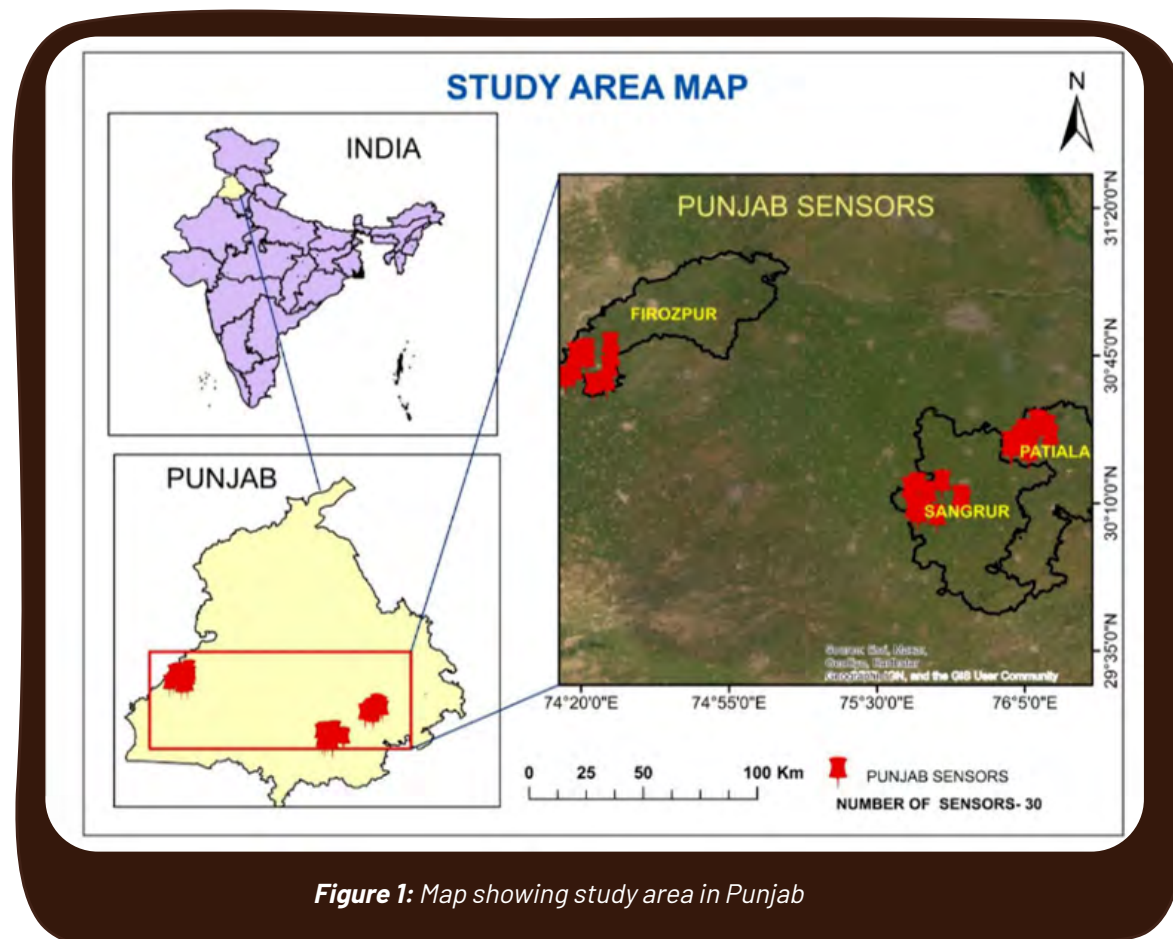
## 4. Approach and Data Collection Methodology

L-band SAR sensors were used to calculate the spatial extent and adoption rates of AWD practices in three districts of Punjab (Patiala, Firozpur, and Sangrur) (Figure 1) during the 2024 Kharif season (June to October).

**Satellite observations were used to track changes in soil moisture and surface water conditions across rice fields over time, while in-situ observations were used to validate digital results.**

Ground teams installed soil moisture sensors at 10 cm and 25–30 cm depths to measure changes in soil moisture and validate satellite data. Field campaigns were synchronized with satellite overpass schedules to ensure accuracy. In total, 4,352 field observations were recorded during the season.

During field visits, researchers classified fields into three categories based on visible surface conditions: “flooded” (standing water present), “wet” (saturated soil but no standing water), and “dry” (visible drying of the soil surface). These observations helped confirm whether satellite signals were correctly detecting field conditions.



*Figure 1: Map showing study area in Punjab*

## 5. Data Processing and Analysis

SAR data used in this study were obtained from the SAOCOM satellite constellation, an Argentine Earth-observation mission that operates using L-band Synthetic Aperture Radar.

**The satellite provides repeat observations over the study area approximately every 16 days, allowing researchers to track changes in field conditions throughout the rice growing season.**

Before analysis, the satellite data were processed to ensure that images captured on different dates could be reliably compared. This preprocessing stage included removing signal noise, correcting for terrain effects, and converting raw radar signals into standardized measurements representing surface conditions. From the processed satellite imagery, a set of 23 radar-based features was generated. In addition, seasonal statistical indicators such as minimum, maximum, range, and variance were calculated to capture changes in soil moisture and surface water conditions across the growing season.

Ground observations were then linked to the corresponding satellite pixels. To account for small inaccuracies in GPS locations, a 10-meter spatial buffer was applied when matching field observations to satellite data. Observation dates were also aligned within a  $\pm 2$ -day window to ensure that field measurements and satellite observations represented the same conditions.

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To prepare the dataset for model training, all features were standardized. Because some field conditions occurred more frequently than others, the dataset initially contained class imbalance. This was addressed using Synthetic Minority Over-sampling Technique (SMOTE), a method that generates additional synthetic samples for underrepresented classes while reducing samples from dominant classes. This process resulted in a balanced dataset of 1,400 samples per class.

Five machine learning models – Deep Neural Network (DNN), Wide & Deep Network, XGBoost, Random Forest, and LightGBM – were then trained to identify patterns in the satellite data corresponding to flooded, wet, and drying field conditions. Machine learning models are computer-based analytical tools that learn patterns from large datasets and apply those patterns to classify new observations. In this case, the models were trained using a combination of satellite and field observation data, enabling them to recognize the radar signatures associated with different soil moisture conditions and irrigation cycles.

The performance of the models was evaluated using commonly used statistical metrics such as accuracy (how often the model makes correct predictions), precision (how reliably it identifies a specific class), recall (how well it captures all relevant cases), and the F1-score, which balances precision and recall. Confusion matrices were also used to assess how frequently the model correctly or incorrectly classified flooded, wet, and dry field conditions.

All data preprocessing and analysis were conducted using the SNAP satellite processing toolbox (a widely used software platform for satellite data analysis) along with custom Python scripts developed to process and analyse the multi-date satellite dataset consistently.

## Model Performance Evaluation



### Accuracy

How often the model predicts correctly



### Precision

How reliably it identifies each class



### Recall

How well it captures all relevant cases



### F1-Score

The balance between Precision & Recall

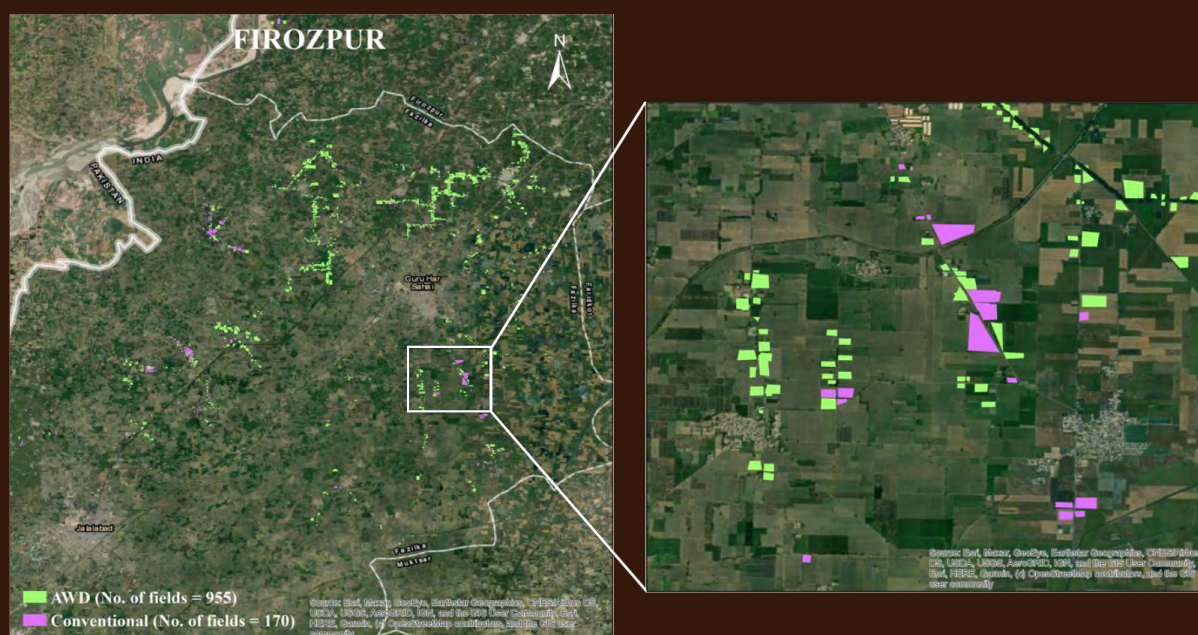


### Confusion Matrix

Tracks correct vs. incorrect classifications across flooded / wet / dry conditions

## 6. Model Training and Testing Results

A total of 4,352 field observations collected during the 2024 Kharif season were used to train and evaluate the five machine learning models. As previously explained, each observation recorded the field condition at the time of measurement and was classified as flooded, wet, or dry based on visible surface conditions and soil moisture readings.



**Figure 2:** Map of Firozpur region showing the spatial distribution of AWD and Conventional Flooding practices

To train the models, the dataset was divided into two parts. Seventy percent of the observations were used for training, allowing the models to learn patterns linking satellite signals to observed field conditions. The remaining 30% of the observations were used for testing, enabling researchers to evaluate how accurately the models could classify field conditions they had not previously encountered. The distribution of flooded, wet, and dry observations was kept consistent across both datasets.

Because flooded fields were more common than wet or dry fields, the dataset initially contained an imbalance between classes. To address this, the dataset was balanced by reducing excess flooded observations and increasing the number of wet and dry samples. A five-fold cross-validation approach was also applied, in which the training and testing process was repeated multiple times using different subsets of the data. This ensured that model performance results were reliable and not dependent on a single split of the dataset (Figure 2).

## 7. Model and Class-Specific Performance Results

Among the five models tested (Deep Neural Network (DNN), Wide & Deep Network, XGBoost, Random Forest, and LightGBM), the Random Forest model demonstrated the strongest overall performance. It achieved an overall accuracy of approximately 73%, outperforming the other models evaluated in the study.

The Random Forest model also showed strong performance across individual field condition categories. Flooded fields were identified with the highest accuracy (76.5%), followed by dry fields (72.1%) and wet fields (68.9%). The higher accuracy for flooded fields is expected, as standing water produces a clear and distinct radar signal.

Most classification errors occurred between wet and dry fields, where soil moisture conditions change gradually rather than abruptly. Despite these challenges, the model demonstrated a reliable ability to distinguish between different irrigation and moisture conditions across the study area.

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## 8. Conclusion

This study demonstrates the effectiveness of L-band SAR data for detecting and monitoring AWD implementation in rice cultivation. The developed Random Forest classification model achieved high accuracy (73%) in distinguishing between flooded, wet, and dry field conditions, enabling reliable identification of AWD practices across large agricultural landscapes.

This innovative digital methodology facilitates large scale monitoring of water saving agricultural practices, contributing to sustainable water management and climate smart agriculture initiatives. With further development, it could potentially support carbon credit programs by providing scalable evidence of AWD adoption. Overall, this approach represents a valuable tool for policymakers, extension services, and researchers working to reduce water use in rice growing regions.

Farmers following a meeting on agronomic practices © Manav Vikas Sansthan



## Key Takeaways



### **Satellite monitoring can track irrigation practices at scale.**

L-band SAR satellite technology makes it possible to monitor irrigation practices such as Alternate Wetting and Drying (AWD) across thousands of rice fields simultaneously, enabling large-scale tracking of AWD adoption at district or state level.



### **Satellite data should be combined with field validation.**

The accuracy of satellite-based monitoring improves when it is supported by ground observations such as soil moisture sensors and field surveys that confirm actual field conditions.



### **Tree-based machine learning models perform well.**

Among the models tested, tree-based models such as Random Forest showed the strongest performance, suggesting that relatively simple and robust models are well suited for classifying irrigation patterns from satellite data.



### **Higher observation frequency can improve accuracy.**

Increasing the frequency of satellite observations and expanding the use of automated soil moisture sensors can help detect irrigation cycles more precisely and reduce classification uncertainty.



### **Improved SAR data processing strengthens irrigation classification.**

Developing advanced SAR-derived features and improving data processing methods can significantly enhance the ability of machine learning models to accurately classify irrigation practices.



### **Digital monitoring of irrigation practices can support the implementation of incentive programs.**

Transparent satellite-based monitoring systems can help verify AWD adoption and support results-based incentive programs such as groundwater conservation schemes or carbon credit programs.

This study was carried out in association with Mitti Labs, under TNC's PRANA project. To know more about our work scan the QR code on the right.



## Together, we find a way.

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