WETLAND LOCALIZATION

Using Satellite Imagery and Deep Learning

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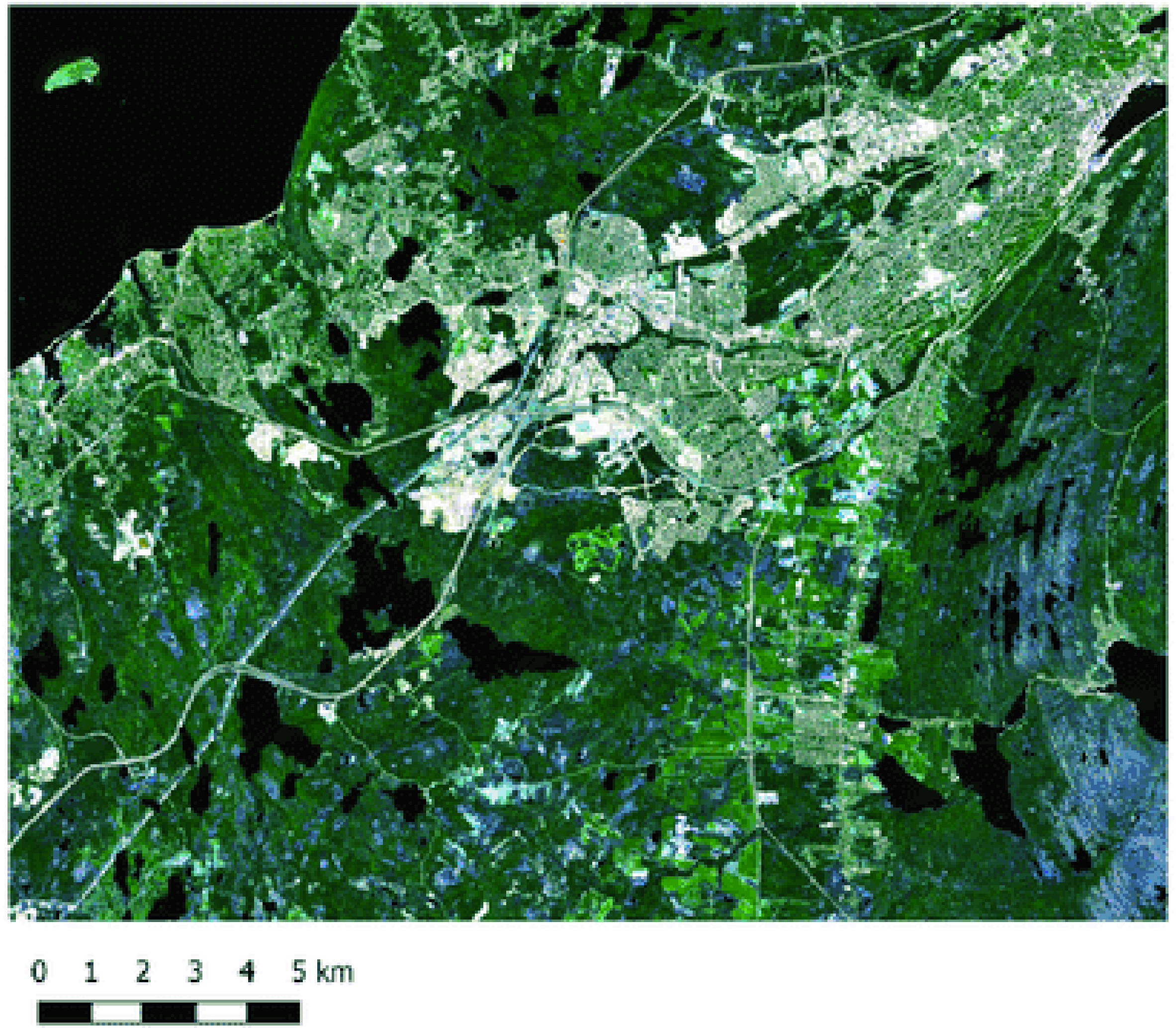


WHY WETLANDS MATTER?

Water Filtration

Recharge local groundwater and prevent downstream flooding. Trap nutrient and sediment pollution, sending cleaner water downstream.

Carbon storage

Wetlands only make up about 5–8% of the Earth's land, they hold between 20–30% of the planet's total soil carbon.

Biodiversity

Wetlands cover just 7 percent of the planet but are home to 40% of the world's biodiversity.

CHALLENGE & PROJECT OBJECTIVES

The main challenge is to accurately map wetlands despite the limitations of traditional fieldwork methods, which can be time-consuming and resource-intensive. This is crucial for monitoring and conservation, as knowing wetland locations helps optimize field expertise efforts and supports ecological studies.

Project Goal

Develop AI solution to predict wetland locations using satellite data, enhancing wetland detection capabilities.

Key Objectives

- Develop and enhance U-Net models for wetland segmentation.
- Explore pre-trained models from Hugging Face optimized for satellite imagery.
- Create effective data processing strategies to maximize limited dataset value.
- Develop methods for addressing cloud interference in satellite images.
- Demonstrate a working prototype for wetland detection.

Expected Impact

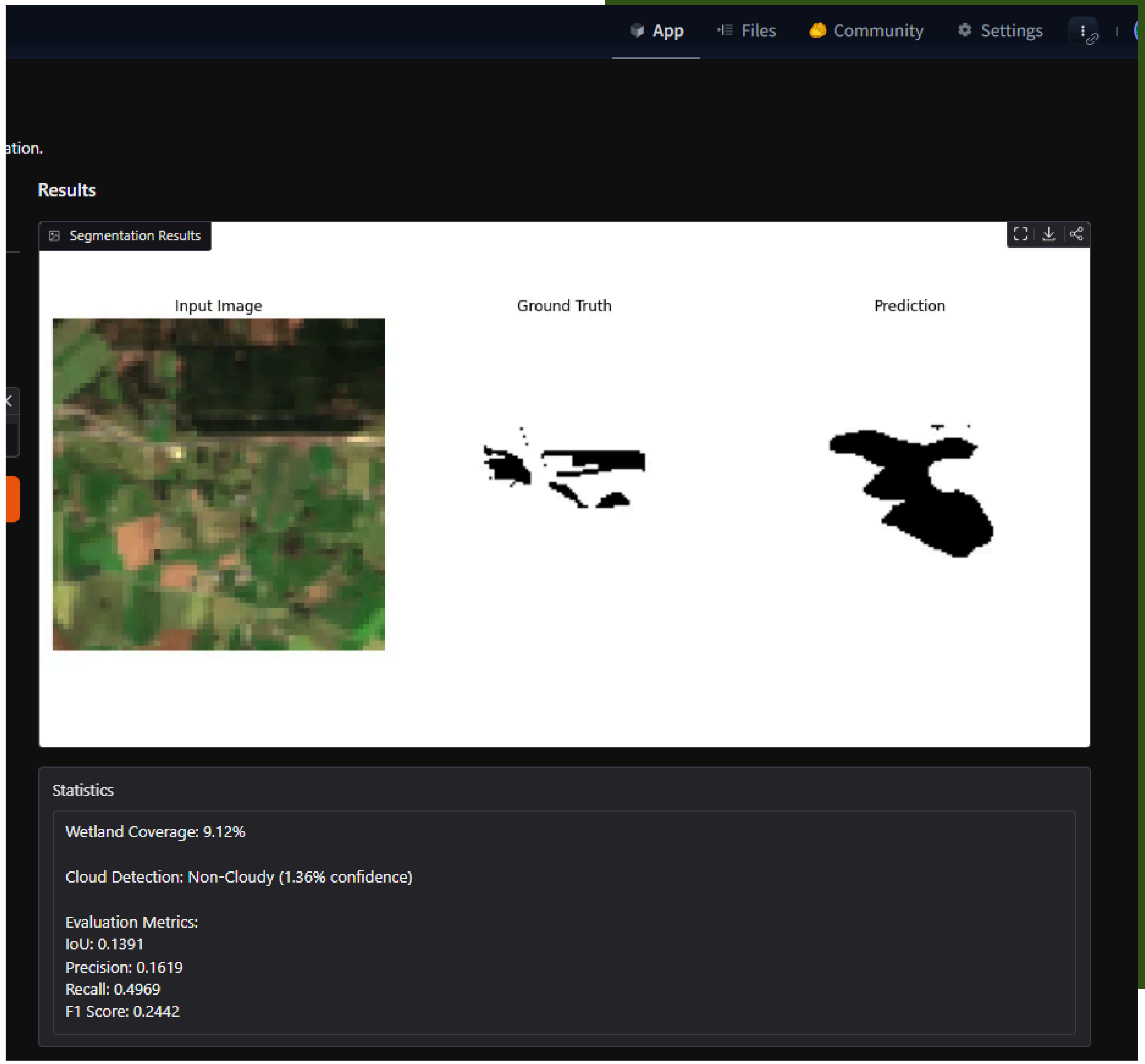
Create scalable, automated tools for environmental monitoring that reduce dependency on traditional field surveys and optimize conservation strategies.

WEB APP DEMO

- <u>This application</u> uses 2 models:

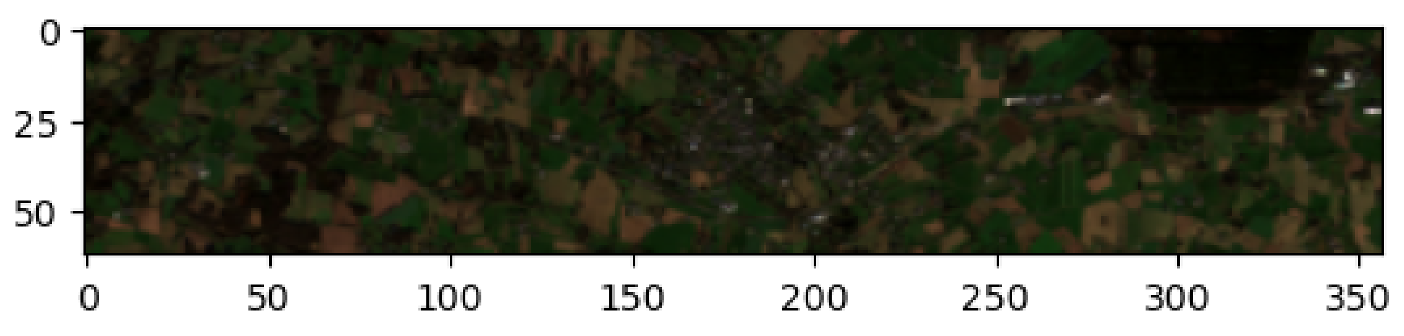
1. Wetland Segmentation Model:
   - Architecture: DeepLabv3+ with ResNet-34
   - Input: RGB satellite imagery
   - Output: Binary segmentation mask (Wetland vs Background)

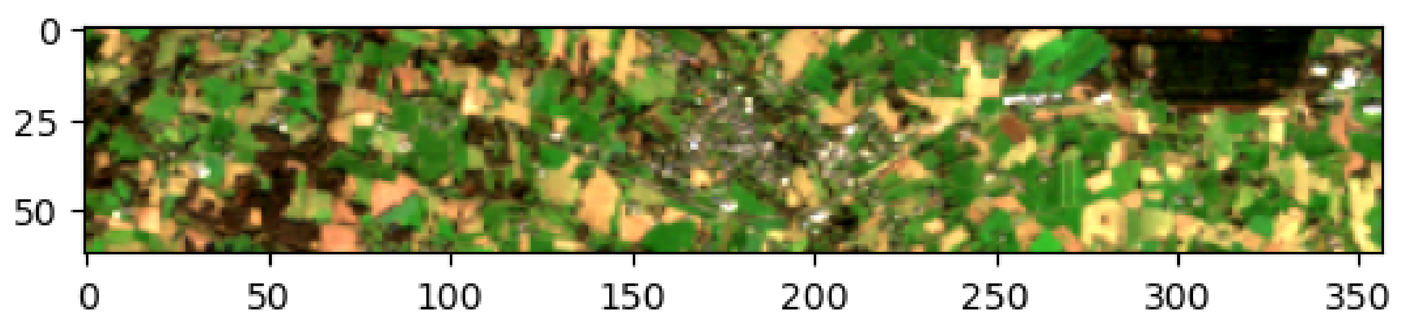
2. Cloud Detection Model:
   - Architecture: LightGBM Classifier
   - Input: CV features extracted from up to 10 image bands
   - Output: Binary classification (Cloudy vs Non-Cloudy) with probability

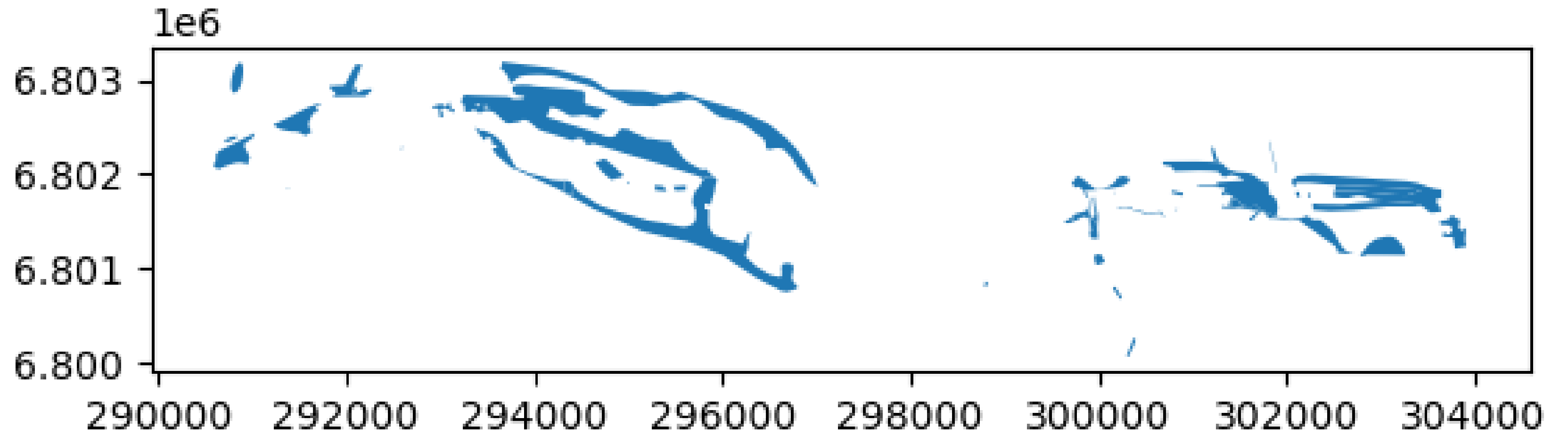


DATA OVERVIEW

- **Data Source**: 36 Sentinel-2 images (Jan 2021 - Dec 2023) of the same area in France
- **Image Properties**: 62×357 pixels, 54.85m resolution, GeoTIFF format with metadata
- **Bands**: 10 spectral bands available, with detailed metadata for RGB bands
- **Ground Truth**: Wetland shapefiles provided by client (Egis)
- **Class Imbalance**: Wetlands 8.93% (5.95M m^2) vs. Non-wetlands 91.07% (60.64M m^2)
- **Temporal Aspect**: Monthly images with minimal cloud coverage, chronologically ordered







DATA PROCESSING PIPELINE

Patching Strategy

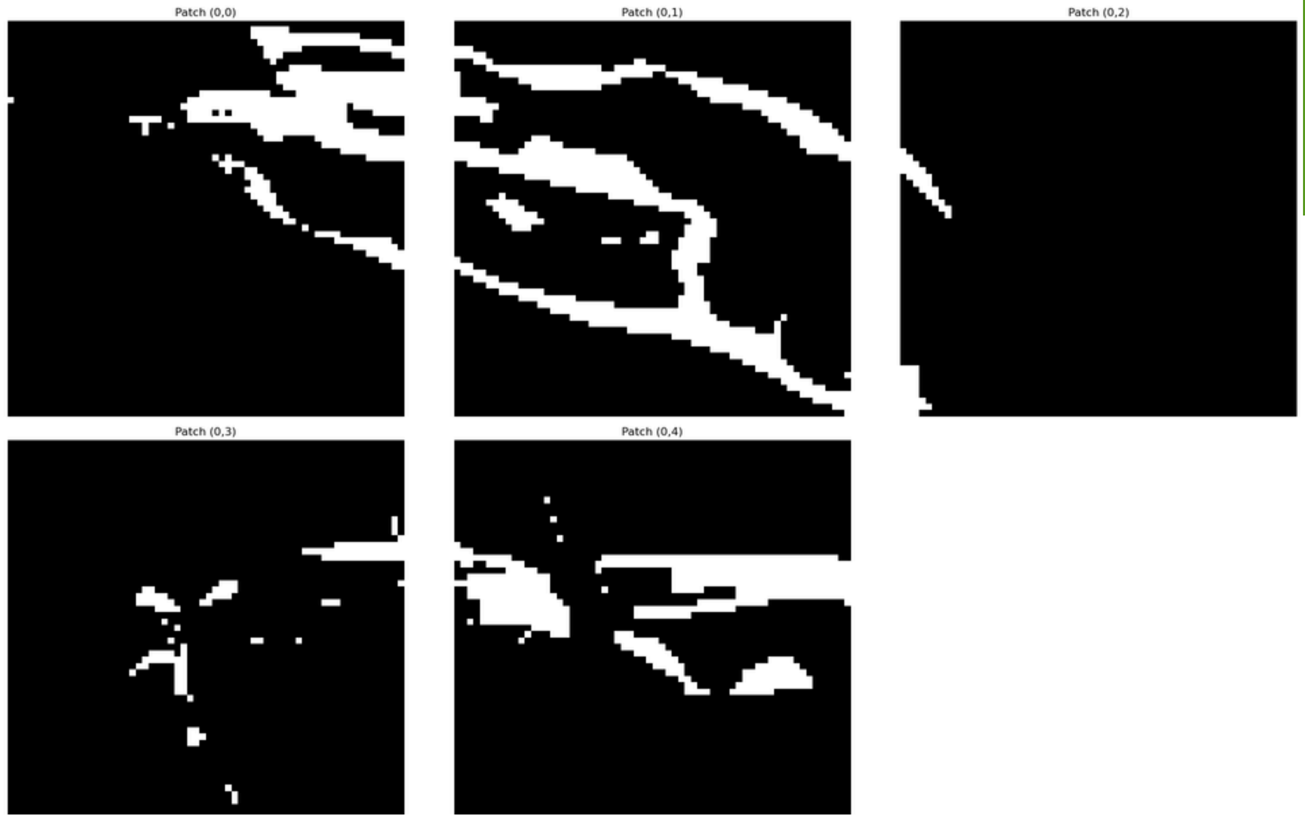
- Split each 62×357 pixel image into five 62×62 squares
- Cropped to 310 pixels width to enable even division
- Created 36×5=180 total image patches and corresponding mask patches

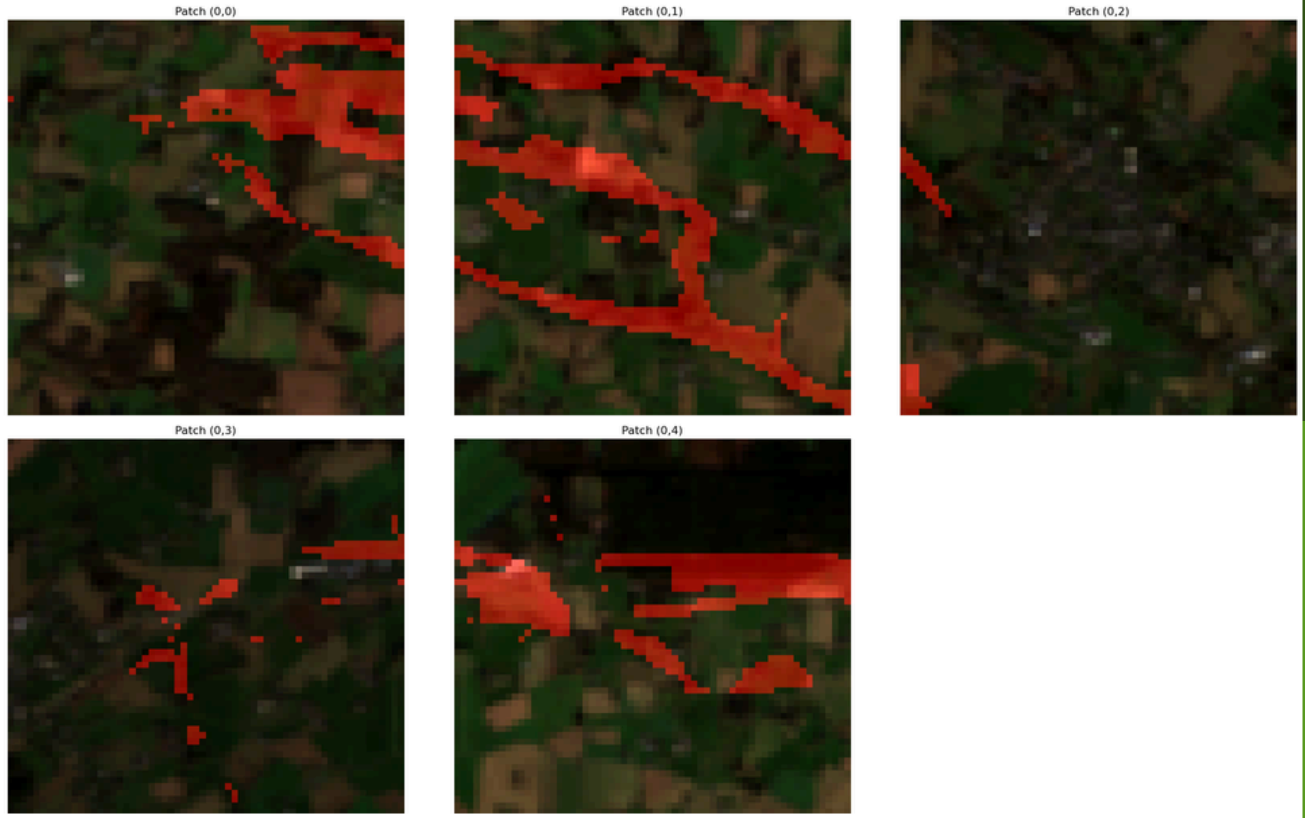
Cloud Detection

- Custom tool for initial manual classification (19.4% cloudy)
- Used band Coefficient of Variation as discriminative features
- Trained ML models for automated detection
- SHAP analysis for feature importance interpretation

Train/Validation/Test Split

- Structured split: 3 patches for training, 1 for validation, 1 for testing
- Consistent patch allocation across all 36 time periods
- Same regions in validation/test sets to prevent data leakage





FEATURE ENGINEERING

Band Selection

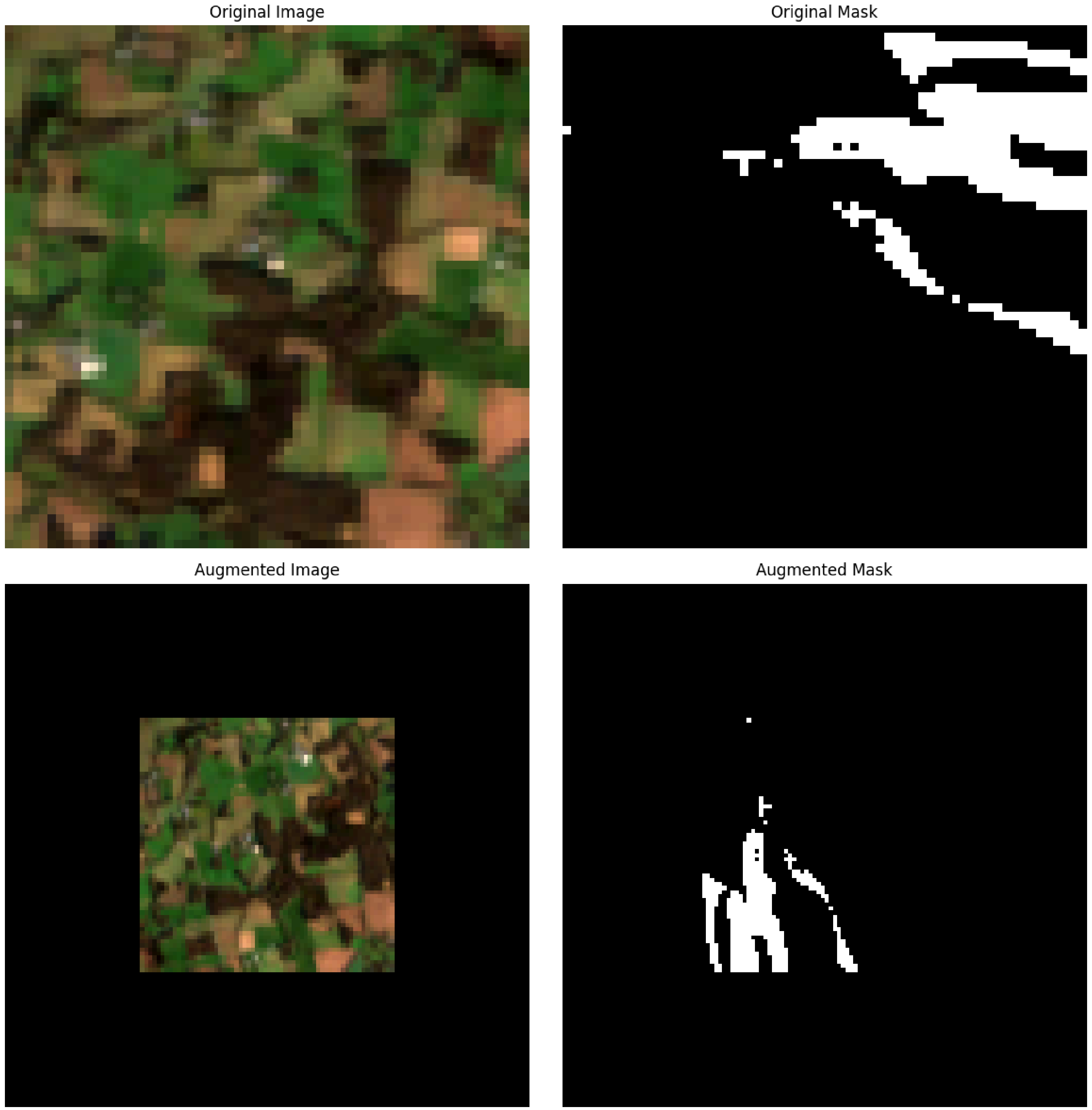
- RGB bands only for pre-trained models (U-Net, DeepLabV3+)
- Full 10 bands + calculated NDVI & NDWI for custom Small U-Net model
- Full 10 bands for cloud detection, calculated Coefficient of Variation (CV) for each tile and each band

Image Preparation

- Padding preferred over resizing to preserve mask quality
- Padding to 128×128 pixels for pre-trained model compatibility

Data Augmentation

- Horizontal flips, vertical flips, 90° rotations
- Random cropping to 128×128
- Consistent transformations for both images and masks via albumentations



MODEL ARCHITECTURE & EVALUATION

Small U-Net (from scratch)

- 12 input bands (10 original + NDVI & NDWI)
- Two consecutive 3×3 convolutional layers with Batch Normalization and ReLU
- Encoder-decoder structure with skip connections
- Binary segmentation output with sigmoid activation
- Trained with early stopping (patience=15, max epochs=100)

Pre-trained Models

- One fine-tuned model and one transfer-learning model each
- U-Net with ResNet34 encoder (ImageNet weights)
- DeepLabV3+ with ResNet34 encoder (ImageNet weights)
- 3 input channels (RGB), binary output

Cloud Detection Framework:

- **CV** calculated across all 10 bands as discriminative features
- **ML models comparison:** LightGBM, XGBoost & CatBoost, Random Forest

Loss Functions

- **DiceLoss** (all models) due to its effectiveness with imbalanced classes. Focuses on the overlap between predicted and ground truth segmentation

Key Metrics

- **Mean Intersection over Union (IoU)**: Background IoU, Wetland IoU, and IoU

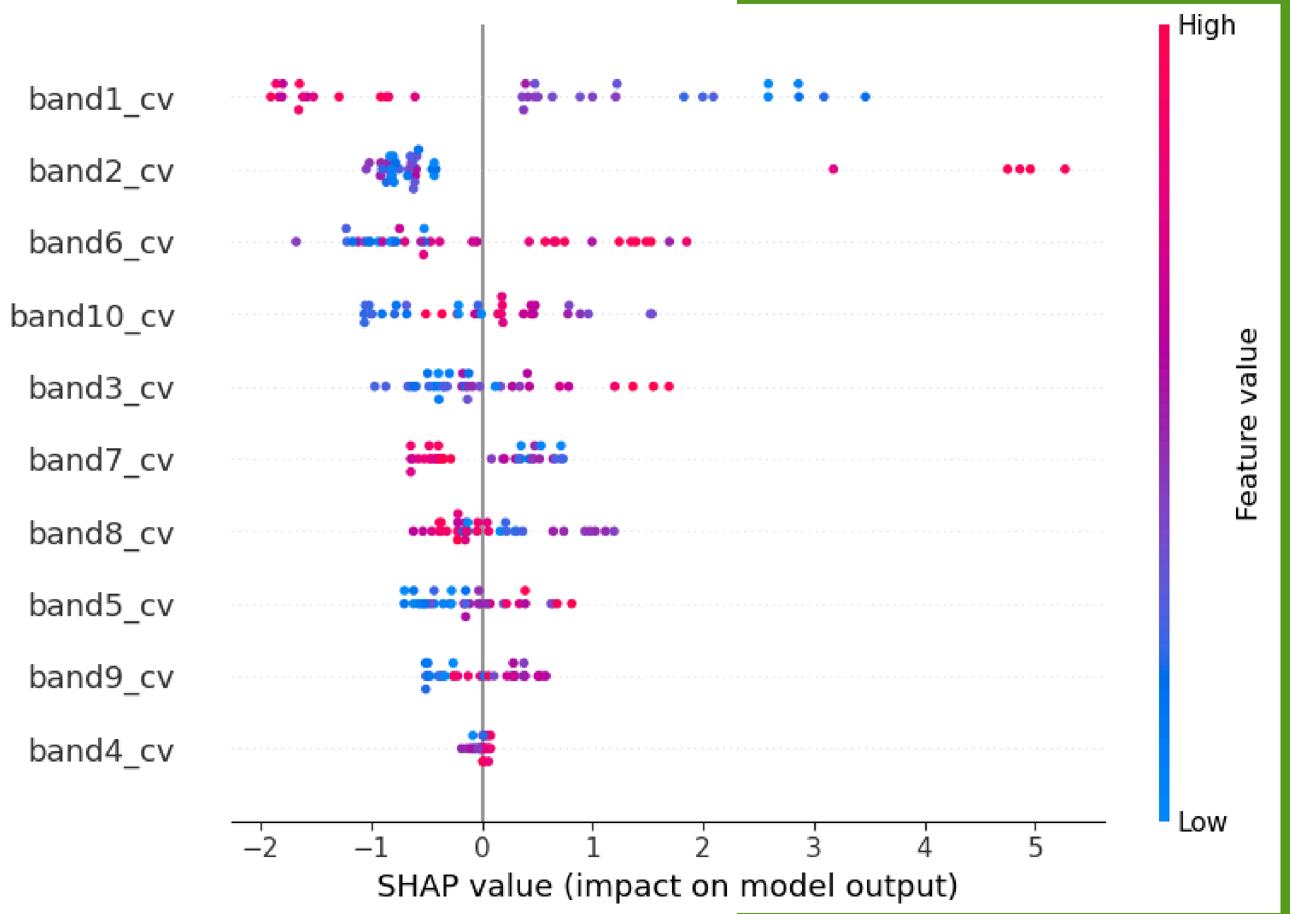
Analysis

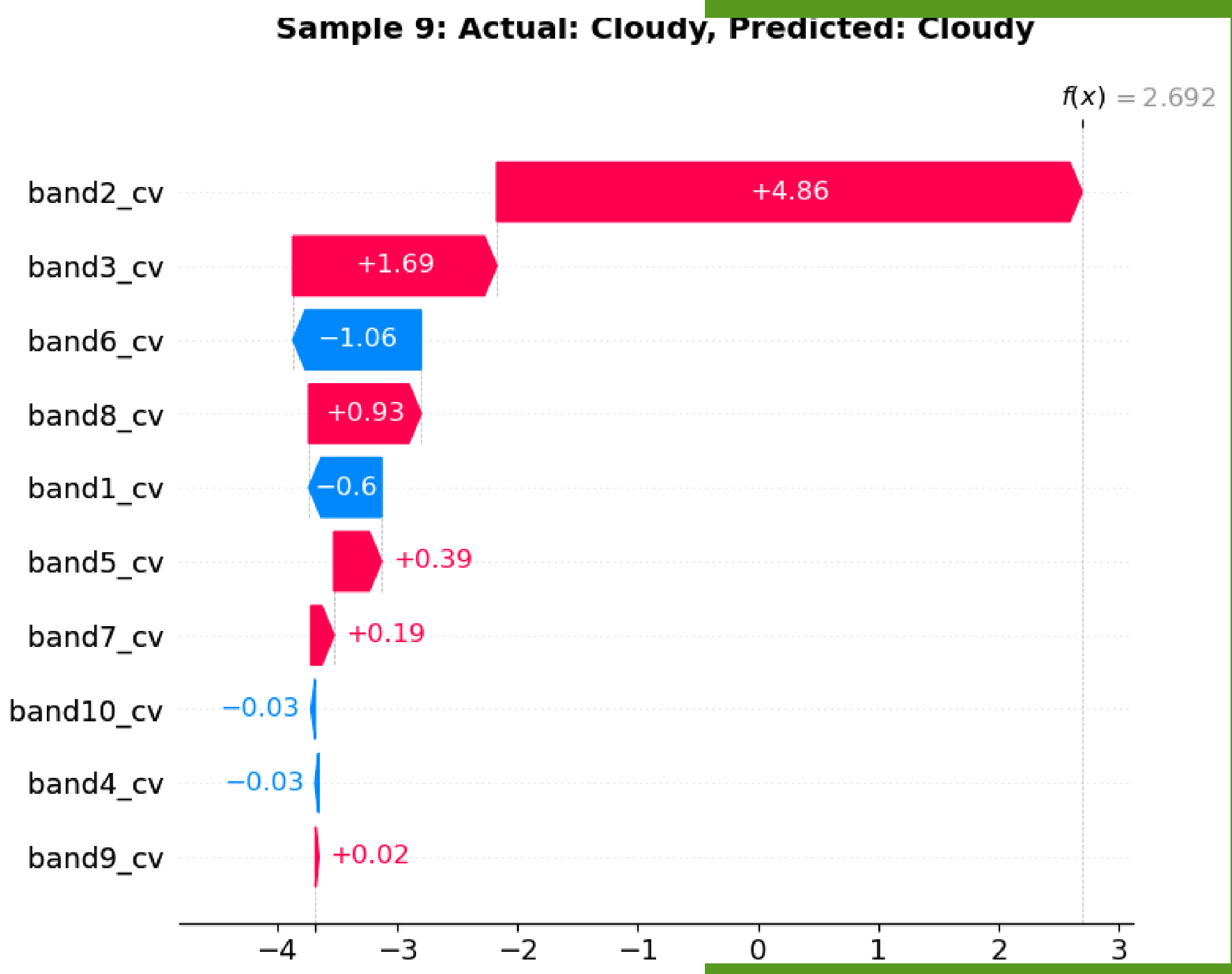
- Precision, Recall, F1 Score, Confusion matrix

RESULTS – CLOUDY IMAGE MODEL

Model	TP	TN	FP	FN	Precision	Recall	F1_Score
LightGBM	5	28	2	1	0.71	0.83	0.77
XGBoost	4	29	1	2	0.80	0.67	0.73
CatBoost	4	29	1	2	0.80	0.67	0.73
Random Forest	4	28	2	2	0.67	0.67	0.67

- **LightGBM** achieved the highest F1-score (0.77) for cloud detection.
- **Band 1** showed highest predictive importance in overall SHAP analysis.
- **Example patch analysis**: 96.15% confidence for cloud presence.





RESULTS – IMAGE SEGMENTATION

DeepLabV3+

- Best test performance with the Finetuned (FT).
- Better generalization to unseen data, despite its more modest training performance.

Unet

- Strongest training performance but signs of overfitting.
- Very low wetland IoU shows difficulty generalizing to unseen wetland patterns.

Small U-Net

- Limited learning capacity.
- Very poor wetland detection, limited capability for this task with available data volume.

Model	Epochs	Train_bg_iou	Train_wetland_iou	Train_mean_iou	Val_bg_iou	Val_wetland_iou	Val_mean_iou	Test_bg_iou	Test_wetland_iou	Test_mean_iou
DeepLabV3plus_FT	68	97.8	42.6	70.2	97.49	8.29	52.89	95.4	10.02	52.71
Unet_FT	88	99.31	76.4	87.85	97.9	6.71	52.31	96.25	5.34	50.8
DeepLabV3plus_TL	33	89.03	16.59	52.81	87.15	3.23	45.19	86.7	12.04	49.37
Unet_TL	28	87.79	16.3	52.05	85.13	3.03	44.08	84.73	11.53	48.13
SmallUNet	30	86.5	19.02	52.76	93.97	1.71	47.84	81.53	12.17	46.85

FT - Finetuned
TL- Transfer learning

KEY LIMITATIONS

01 Data Limitations

- Insufficient training samples for deep learning.
- Low resolution imagery (54.85m per pixel).
- Small patch sizes (62×62) incompatible with typical DL architectures.
- Need to remove cloudy patches from images, further reducing usable data.

02 Technical Constraints

- Pre-trained models restricted to RGB channels despite having 10 bands available.
- Cloud presence in nearly 20% of our dataset affecting feature extraction.
- Severe class imbalance making wetland detection particularly difficult.
- Absence of wetland-specific pre-trained models in the open source community.

FUTURE DIRECTIONS

Higher Quality Data Acquisition

- Collect 1000+ higher resolution Sentinel-2 patches with complete metadata
- Ensure image dimensions divisible by 8/32/64/128/256/512 for architecture compatibility
- Address class imbalance through targeted augmentation techniques

Advanced Technical Approaches

- Enhance cloud detection with improved deep learning methods
- Calculate additional spectral indices and band ratios for feature enrichment
- Explore traditional ML models (Random Forest, SVM) as comparative baselines

Multi-band Architecture Development

- Design architectures accepting all 12 bands (10 original + NDVI & NDWI)
- Implement true transfer learning with final layer fine-tuning
- Develop specialized wetland segmentation models for open source community

THANK YOU