DESIGN PROJECT - SIE 2024

NOVEL REMOTE SENSING METHODOLOGY TO DETECT IRRIGATED CROPS FROM SATELLITE IMAGERY

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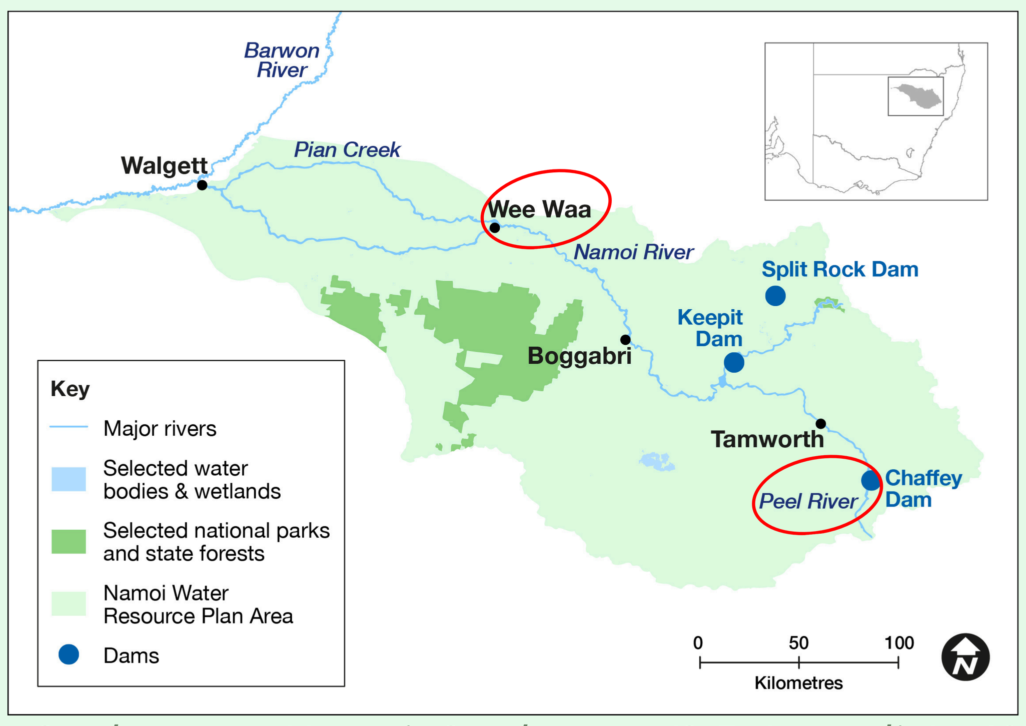
CONTEXT

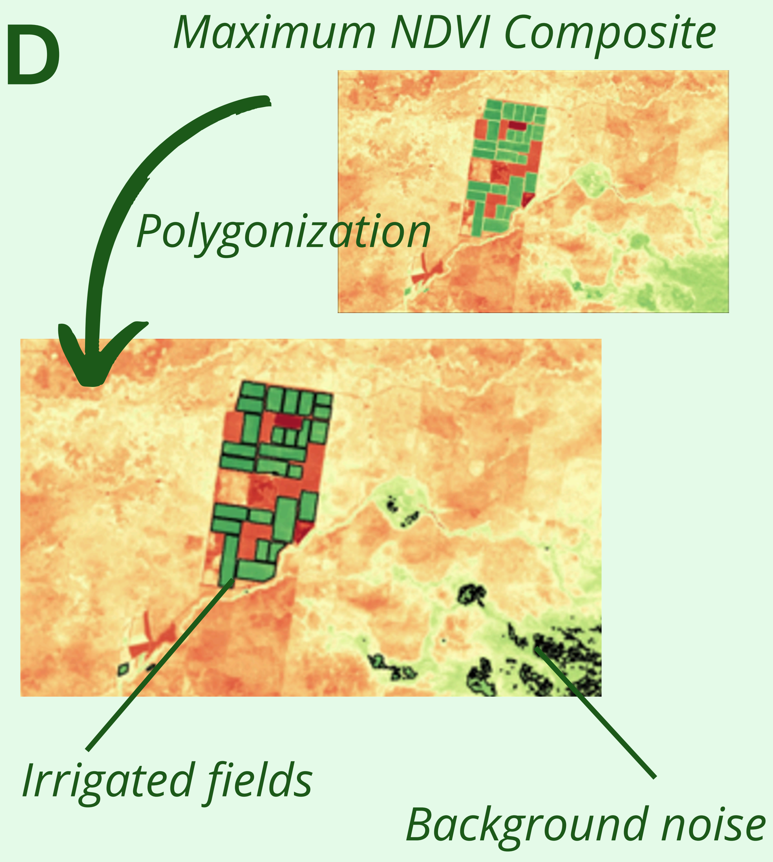
Australia, with its vast territory, experiences diverse climate zones ranging from tropical to arid regions. This variability, compounded by climate change, poses challenges for water management, particularly in agriculture, where water is a vital resource. The projects aims to refine the **detection of irrigated crops** in NSW by leveraging **satellite imagery** and advanced technologies in order to help the NSW Governement to optimize water allocation.



<u>Study area:</u> Namoi Catchment (S-E Australia), 42 000km², irrigated area represents 3% of the zone. Data used is from WeeWaa and PeelRiver Regions

CURRENT METHOD

The NSW Government has developped a method to detect irrigated crops. They currently use the **maximum NDVI** over the season (December-April) and perform a **manual validation** on each polygon. This time-consuming method is effective but offers scope for improving precision.



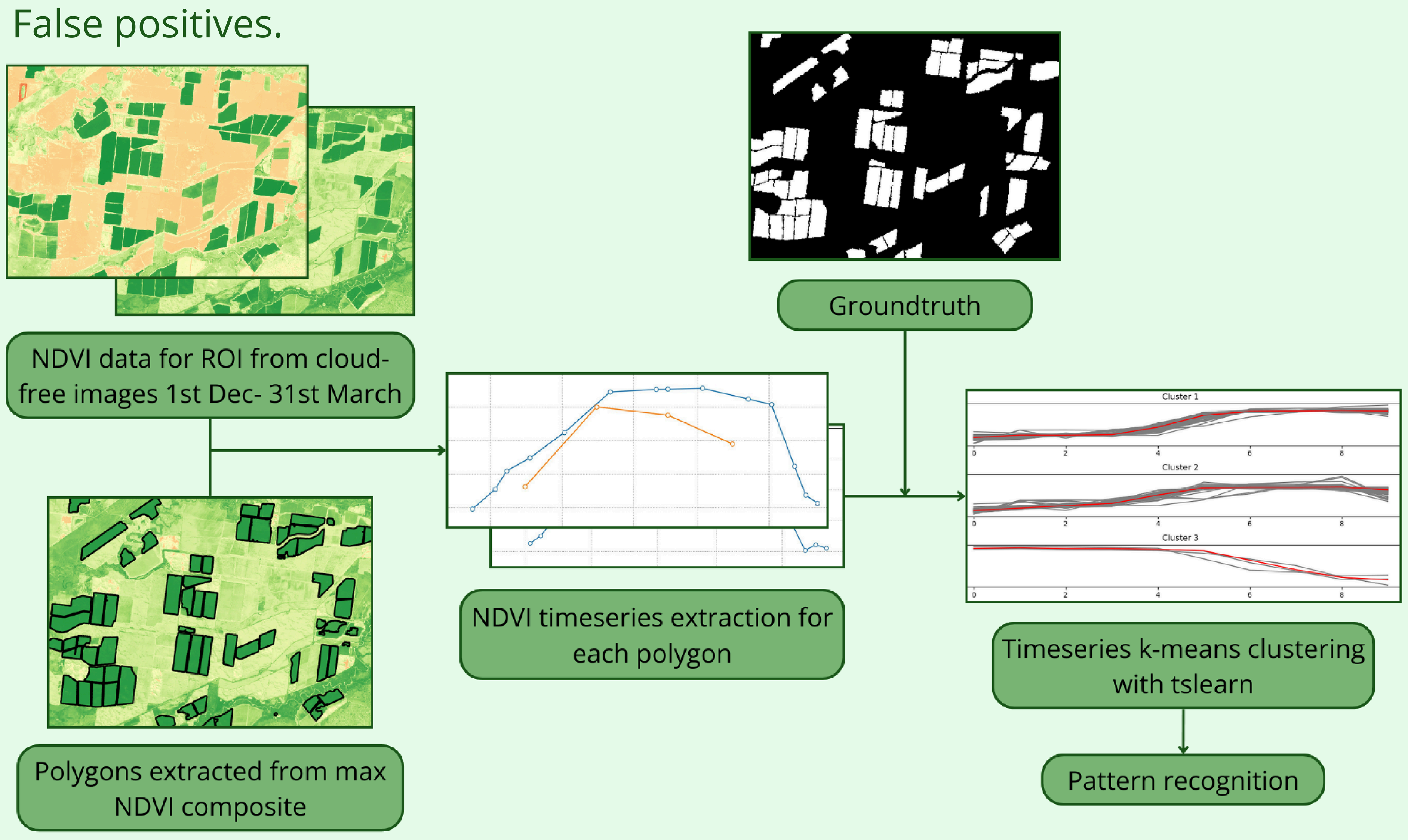
OBJECTIVES

Reduce the false positive (parcels incorrectly indicated as crops). Two methods are proposed in order to:

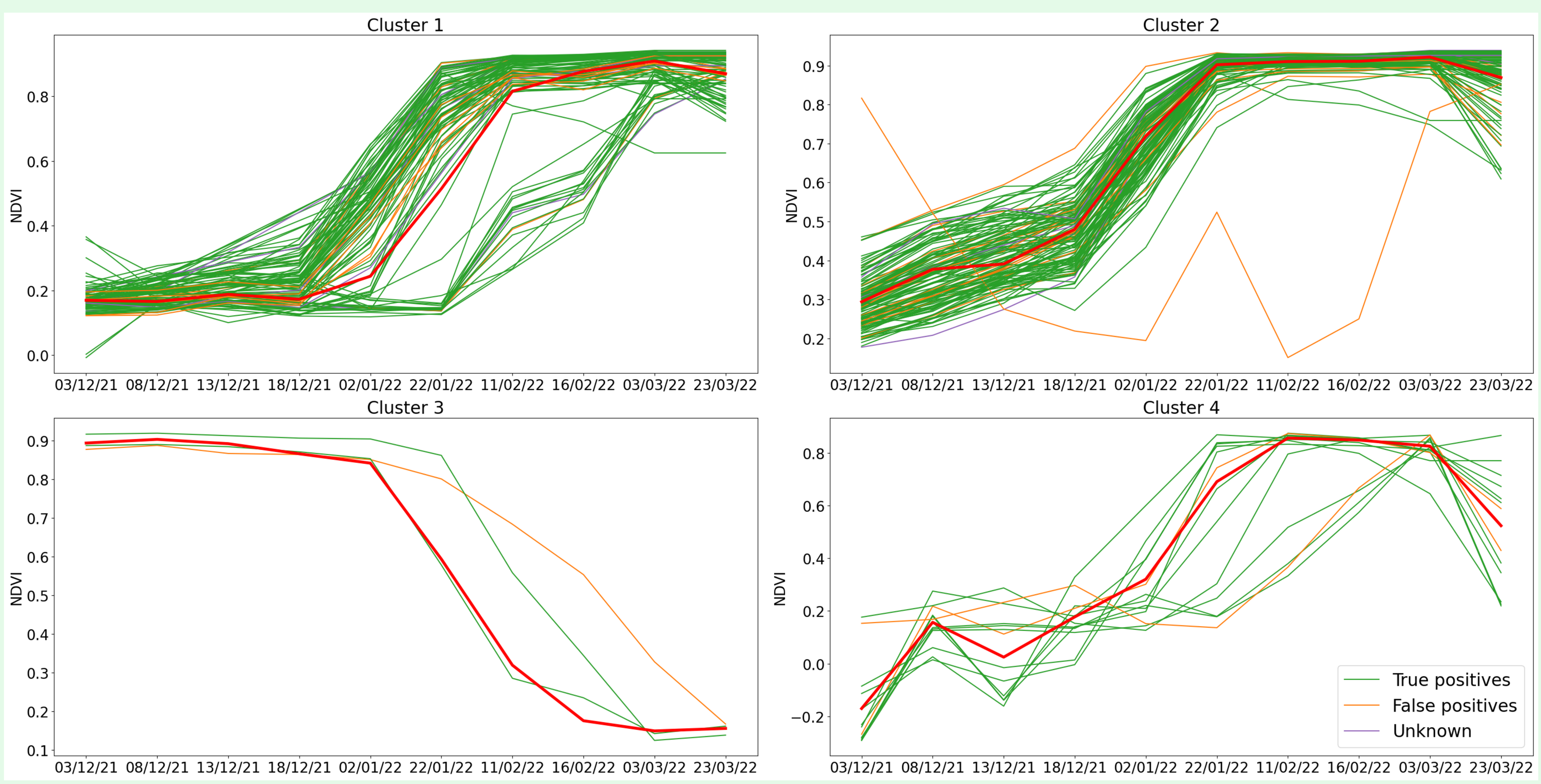
A. Improve the current method (NDVI Curve Fitting)
B. Propose an alternative method (Deep Learning model)

A. NDVI CURVE FITTING

Method that allows to group detected polygons according to the shape of their NDVI curve. Groundtruth is used to distinguish True positives from False positives.



RESULTS A



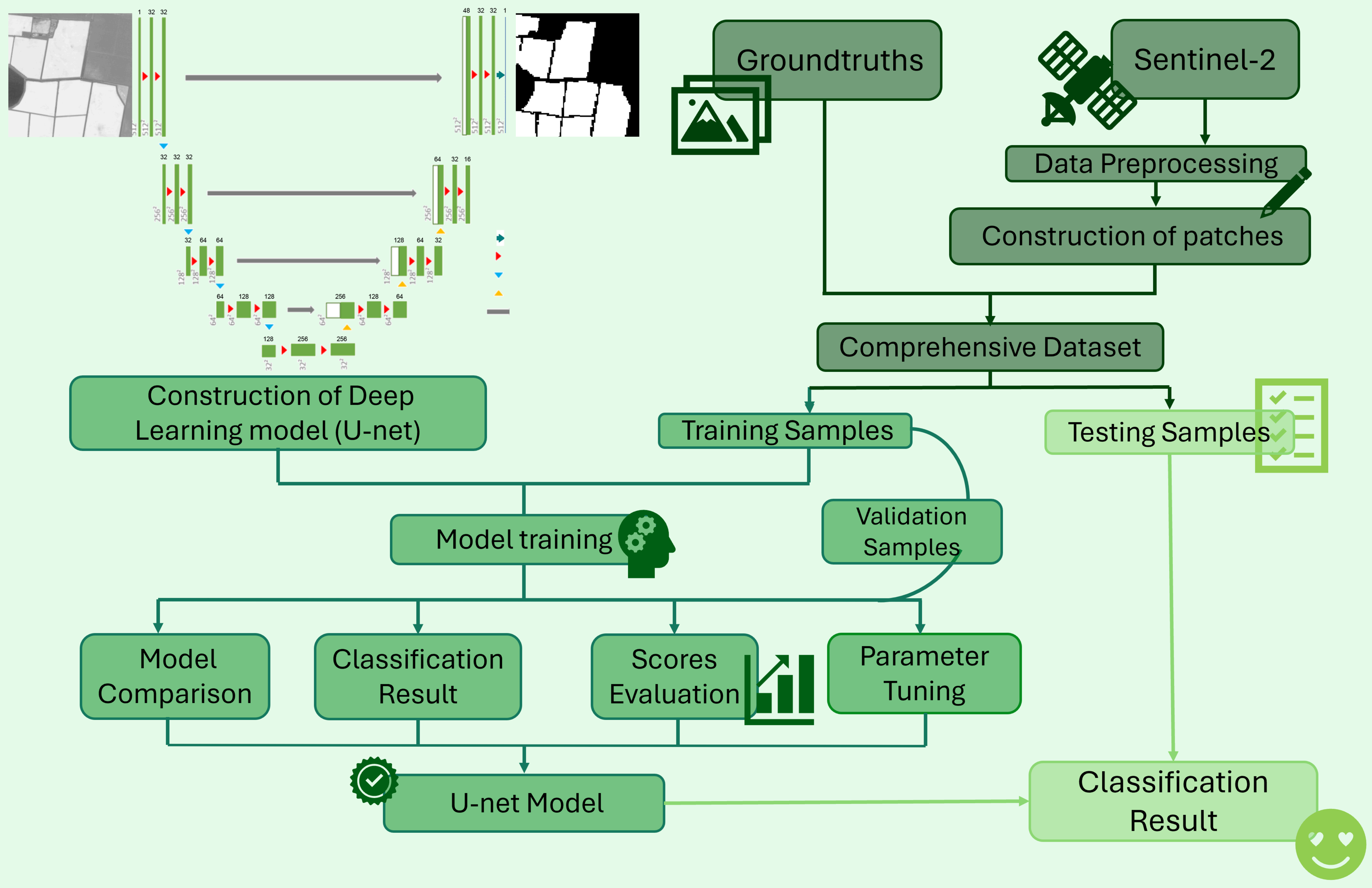
Clusters for the WeeWaa region, the red curves represent the four main NDVI patterns.

In **Clusters 1 and 2** we can observe a typical NDVI curve that represents the growth and maturity of healthy crops → irrigated. **Clusters 3 and 4** could correspond to non-irrigated crops.

B. DEEP LEARNING

The process can de decomposed in three main steps :

1. Creation of a comprehensive dataset
2. Model Training
3. Model Testing and Prediction



RESULTS B

Creation of the patches 256x256 pixels

Image from Sentinel 2 (WeeWaa) and its associated Groundtruths

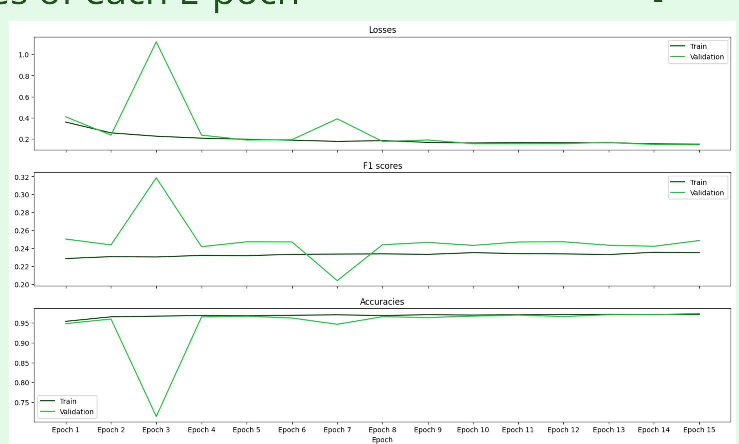
Input of the U-net : batches (size = 32 patches)
Iteration : 15 epochs

Keep best E-poch to test the model on another dataset (PeelRiver)

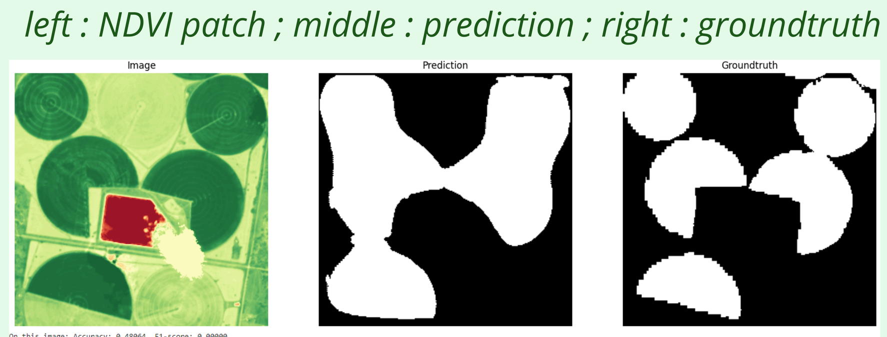
best E-poch =3

	Accuracy	*F1-Score*
Train on WeeWaa	0.715	0.319
Test on PeelRiver	0.719	0.306

Result : Scores of each E-poch
- Losses
- F1-score
- Accuracy



Prediction a patch from PeelRiver
left : NDVI patch ; middle : prediction ; right : groundtruth



<u>Accuracy vs. F1 Score:</u> The high accuracy juxtaposed with the low F1 score suggests **overfitting** to the majority class (class 0 = not a crop) due to significant **class imbalance**, not fully addressed by the weighted loss function.

<u>Possible Improvements:</u> Improve minority class representation, adjust hyperparameter, explore others architectures, train on more data.

CONCLUSION

Improving the current method for detecting irrigated crops has been challenging due to the diversity of data. While the clustering method is not determinative, it allows to reduce false positives, facilitating manual verification. The deep learning model shows promise, but addressing class imbalance is essential to improve overall model performance. The obtained outcomes encourage further optimization of these methodologies.