

# Cloud Segmentation for Satellite Imagery

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Computer Vision

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3 - CHALLENGES

4 - METHODOLOGY

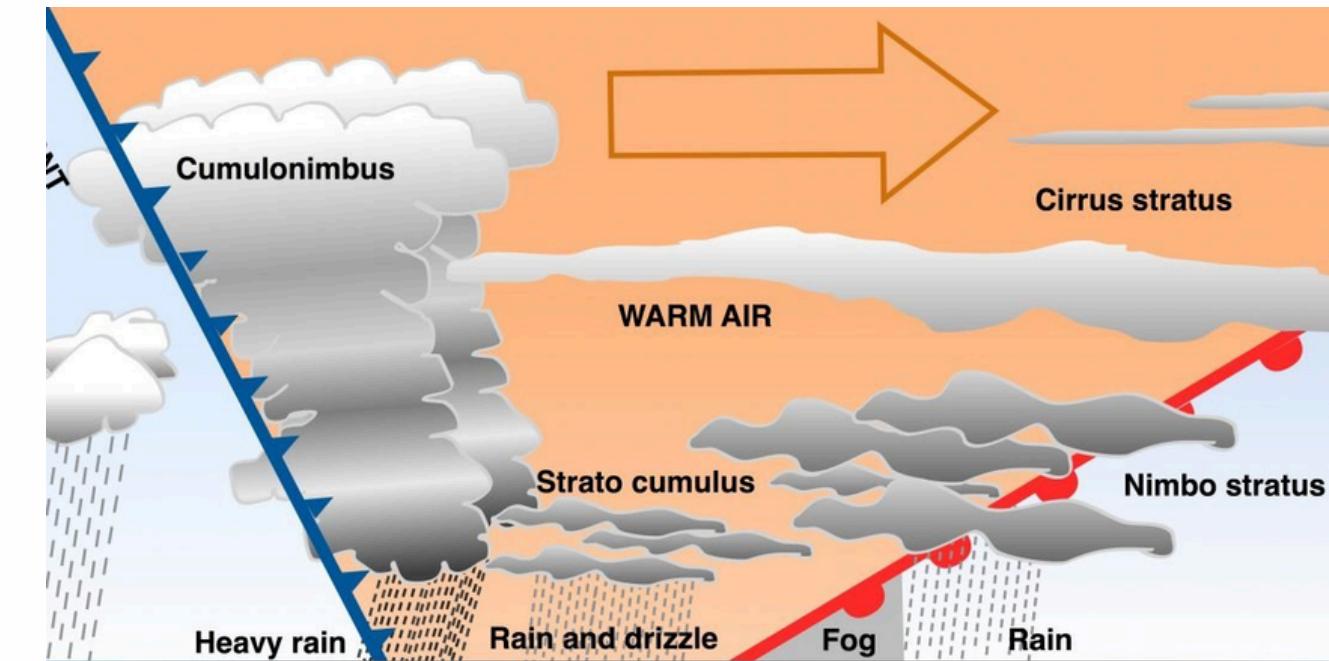
5 - RESULTS

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# INTRODUCTION

Clouds play a crucial role :

- producing precipitation
- regulating Earth's temperature by reflecting solar radiation and trapping heat.



# PROBLEM DEFINITION

$I$  : multi-spectral satellite image, where  $I(x, y, b)$  represents the intensity of the pixel at position  $(x, y)$  in spectral band  $b$ .

$M$  : binary mask

$$M(x, y) = \begin{cases} 1 & \text{if } I(x, y) \geq \tau \\ 0 & \text{otherwise} \end{cases}$$

where  $\tau$  is a threshold chosen to determine whether a pixel is classified as a cloud or not.

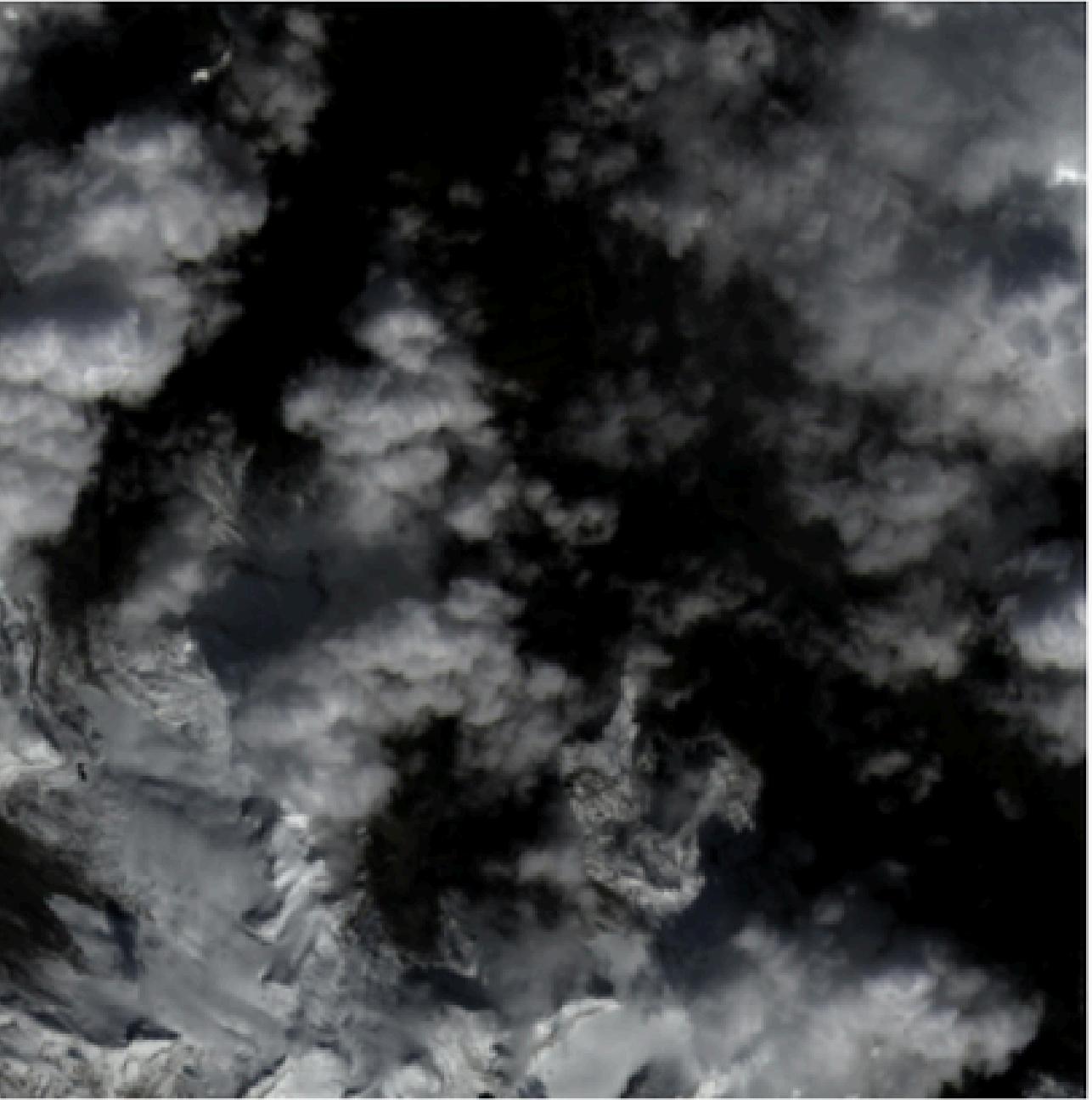
# CHALLENGES

Several challenges :

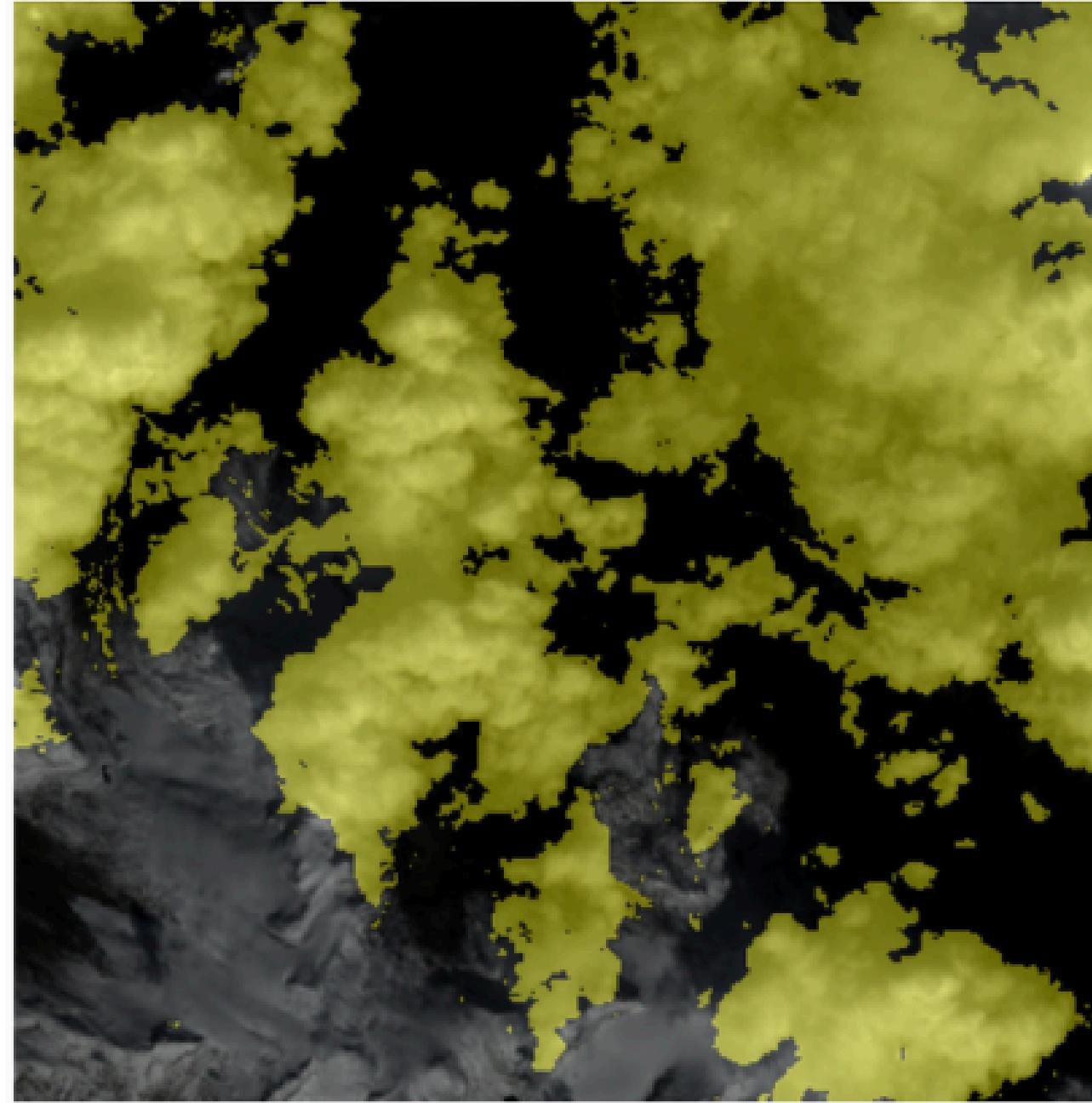
- High variability in clouds appearances
- Surface features (e.g., snow, ice) can exhibit reflectance properties
- Lighting conditions and atmospheric effects

# CHALLENGES

Original RGB

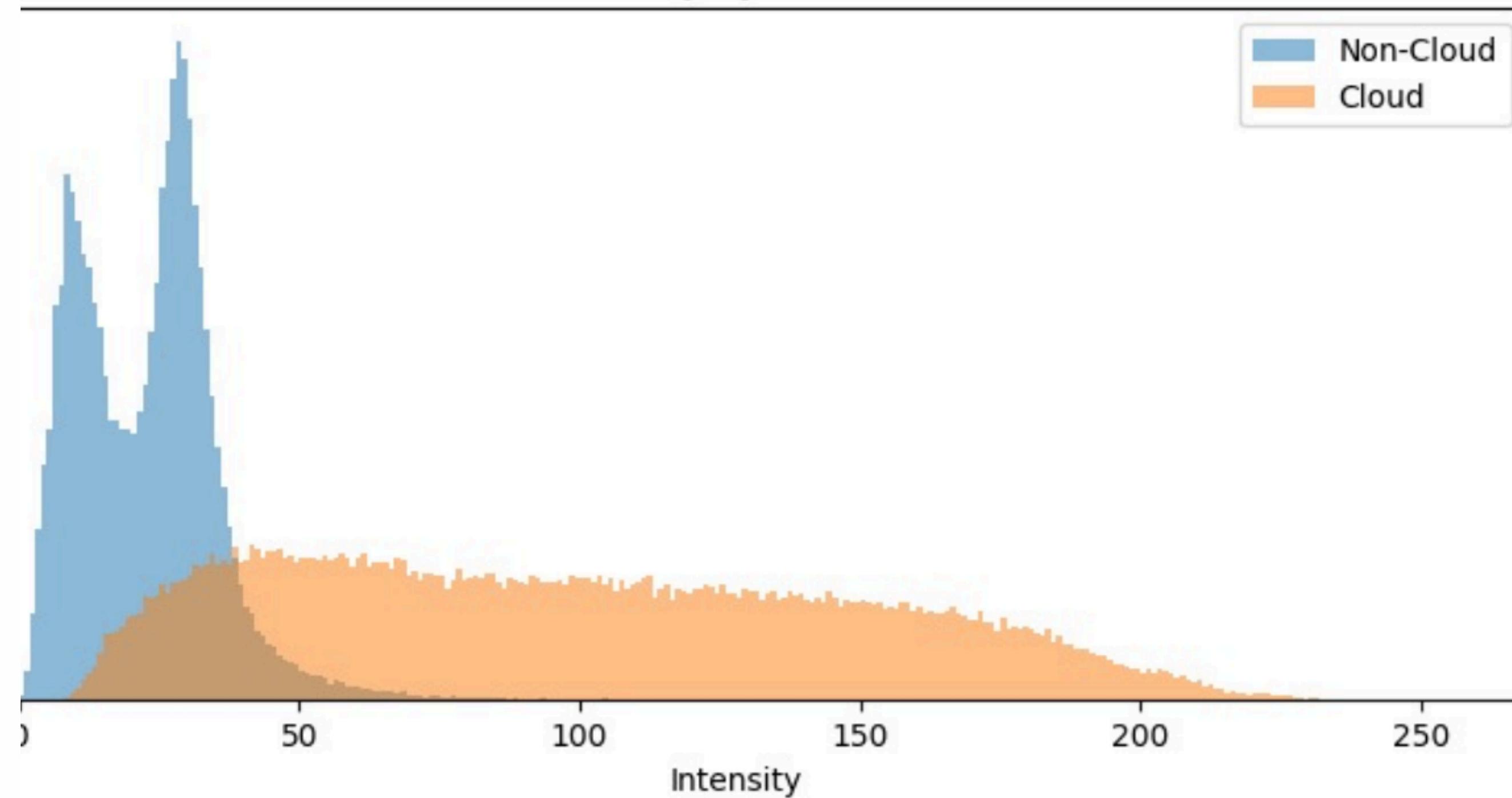


Ground Truth



# CHALLENGES

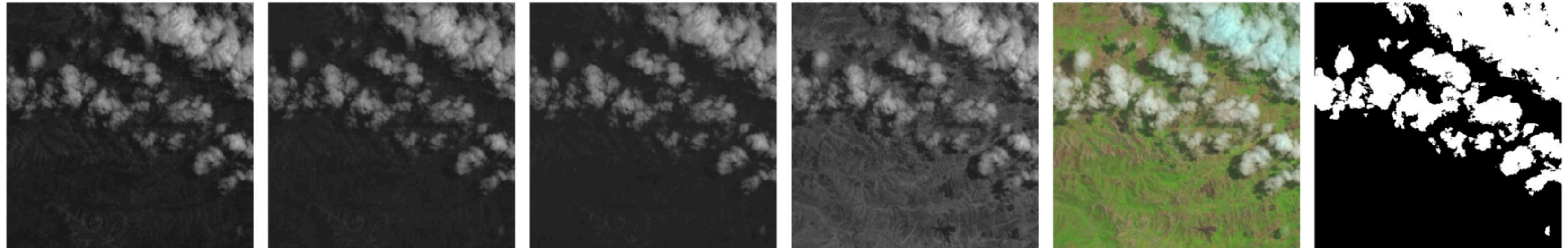
Red Band Intensity by Ground Truth Mask



# METHODOLOGY

## Data Preprocessing : 38-Cloud” dataset, S. Mohajerani and al.

- 38 Landsat 8 scenes
- Each image contains four spectral bands: red, green, blue, and near-infrared (NIR),
- Ground truth masks



# METHODOLOGY

## Computer Vision Methods Selection : Otsu

Find the optimal threshold that maximizes the inter-class variance between the background and foreground pixels.

### Inter-Class Variance:

$$\sigma_b^2(t) = \omega_0(t)\omega_1(t) [\mu_0(t) - \mu_1(t)]^2$$

### Optimal Threshold:

$$t^* = \arg \max_t \sigma_b^2(t)$$

# METHODOLOGY

## **Computer Vision Methods Selection : Watershed**

Morphological technique that treats images as topographic surfaces to delineate regions based on gradient magnitudes.

**Distance Transform** : Create a "height map," where each pixel's value represents its distance to the nearest background pixel.

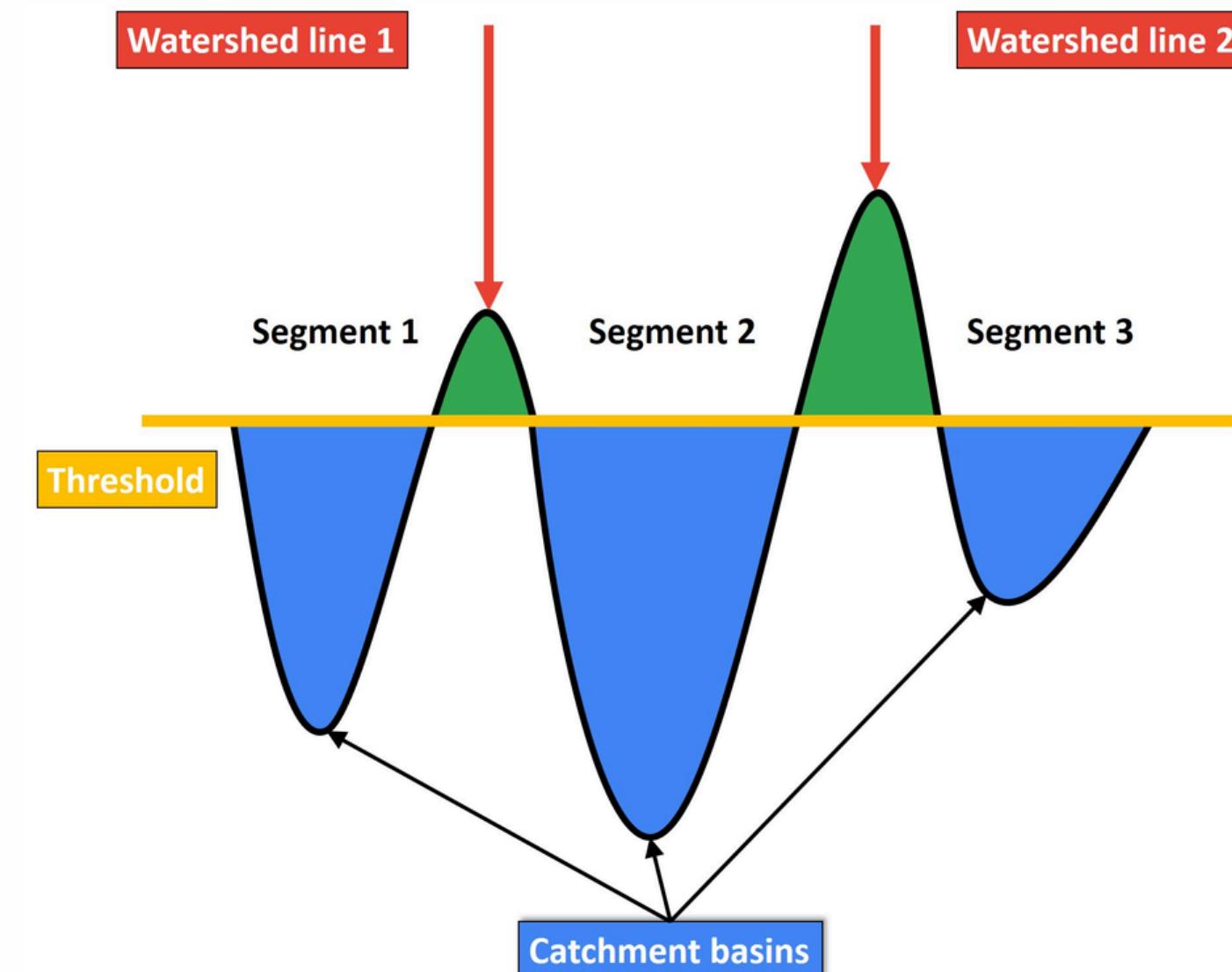
$$D(x, y) = \min \sqrt{(x - x')^2 + (y - y')^2}$$

# METHODOLOGY

## Computer Vision Methods Selection : Watershed

**Watershed Transform** : Assigns each pixel to a catchment basin based on the gradient flow

$$W(x, y) = \arg \min_{m \in M} \text{dist}(P, m)$$



# METHODOLOGY

## **Supervised Methods Selection : Gaussian Naives Bayes (GNB)**

Probabilistic classifier that applies Bayes' theorem, enabling effective classification of cloud and non-cloud pixels based on spectral features.

**Bayes' Theorem for Classification:** The posterior probability of class k given a feature vector x is:

$$P(k|x) = \frac{P(x|k) \cdot P(k)}{P(x)}$$

# METHODOLOGY

## **Supervised Methods Selection : Histogram-based**

Uses the distribution of pixel intensities across spectral bands to distinguish between cloud and non-cloud pixels.

**Histogram Computation and Probability Conversion:** computes histograms for each class and converts them into probabilities using Laplace smoothing

$$P(x|k) = \frac{\text{counts}_k(x) + 1}{\sum(\text{counts}_k + 1)}$$

## **Log-Likelihood Calculation for Classification :**

$$\log P(k|x) = \sum_{i=1}^n \log P(x_i|k) + \log P(k)$$

# METHODOLOGY

## **Supervised Methods Selection : Decision Tree**

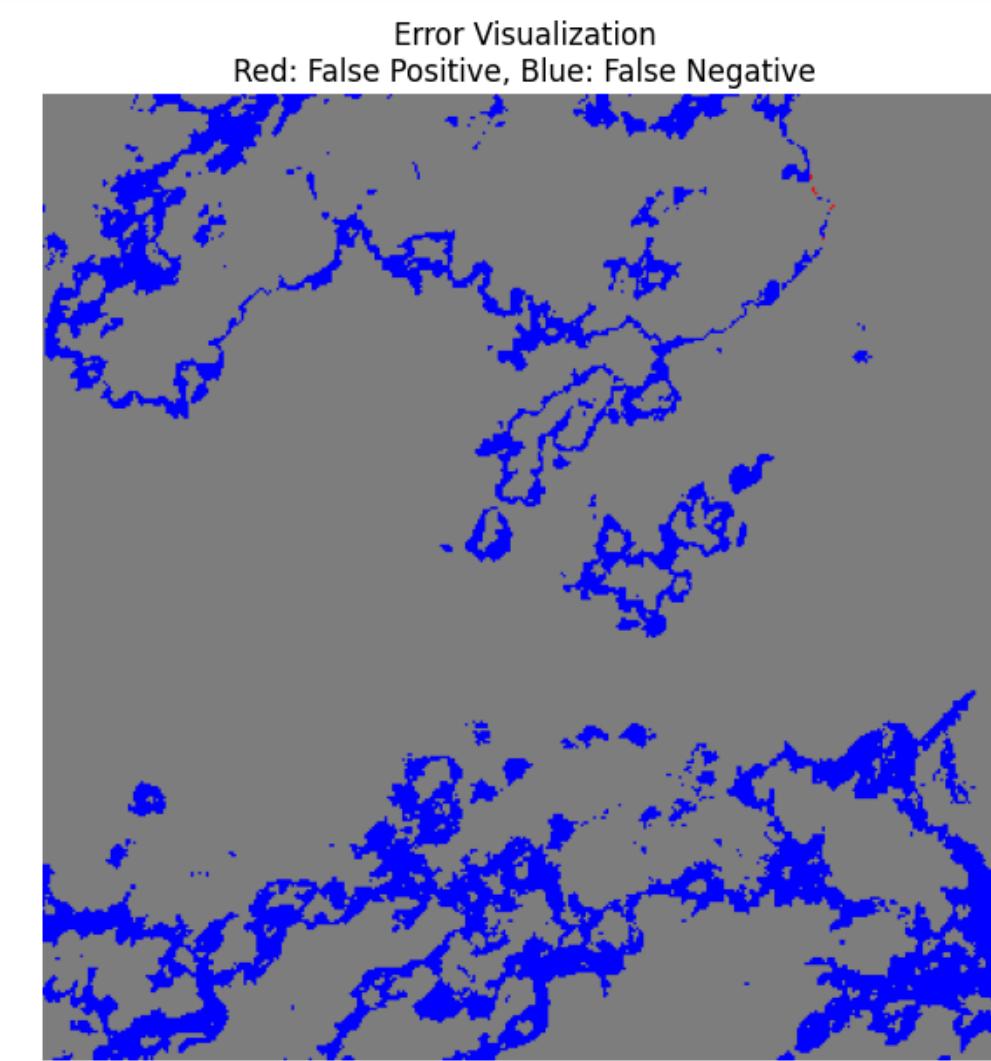
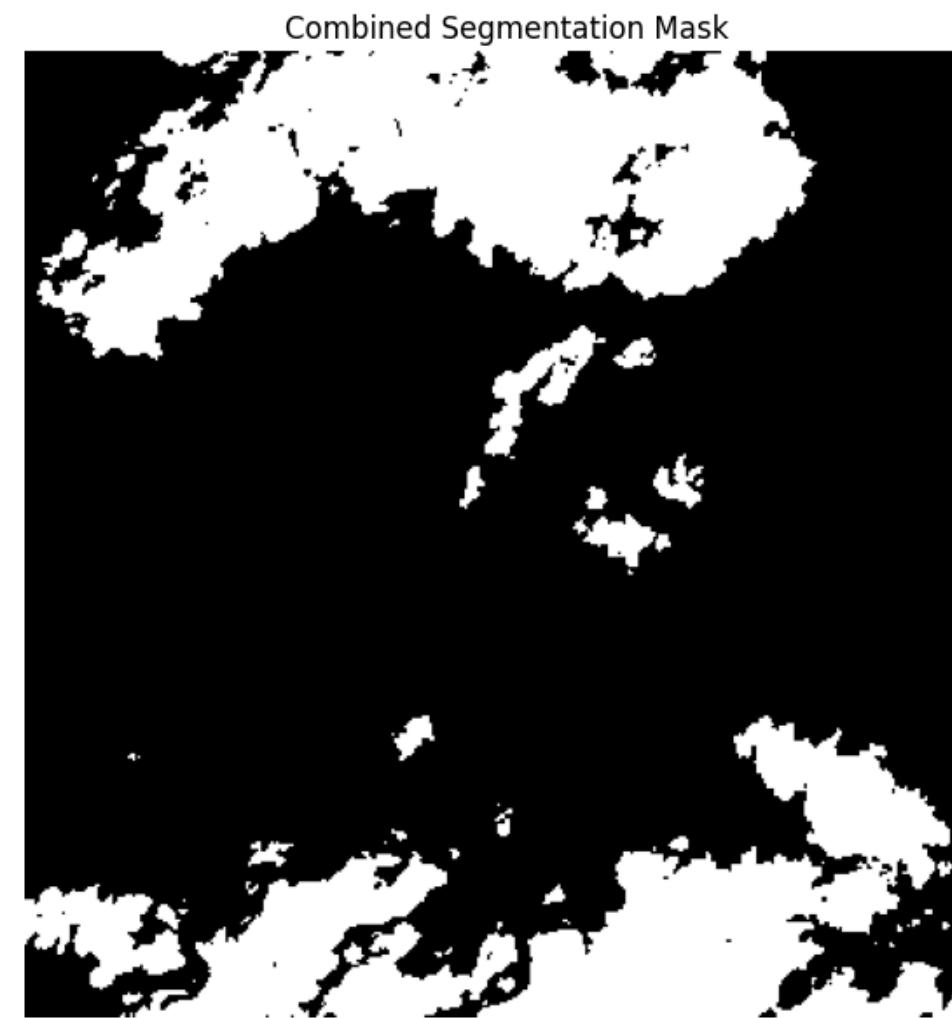
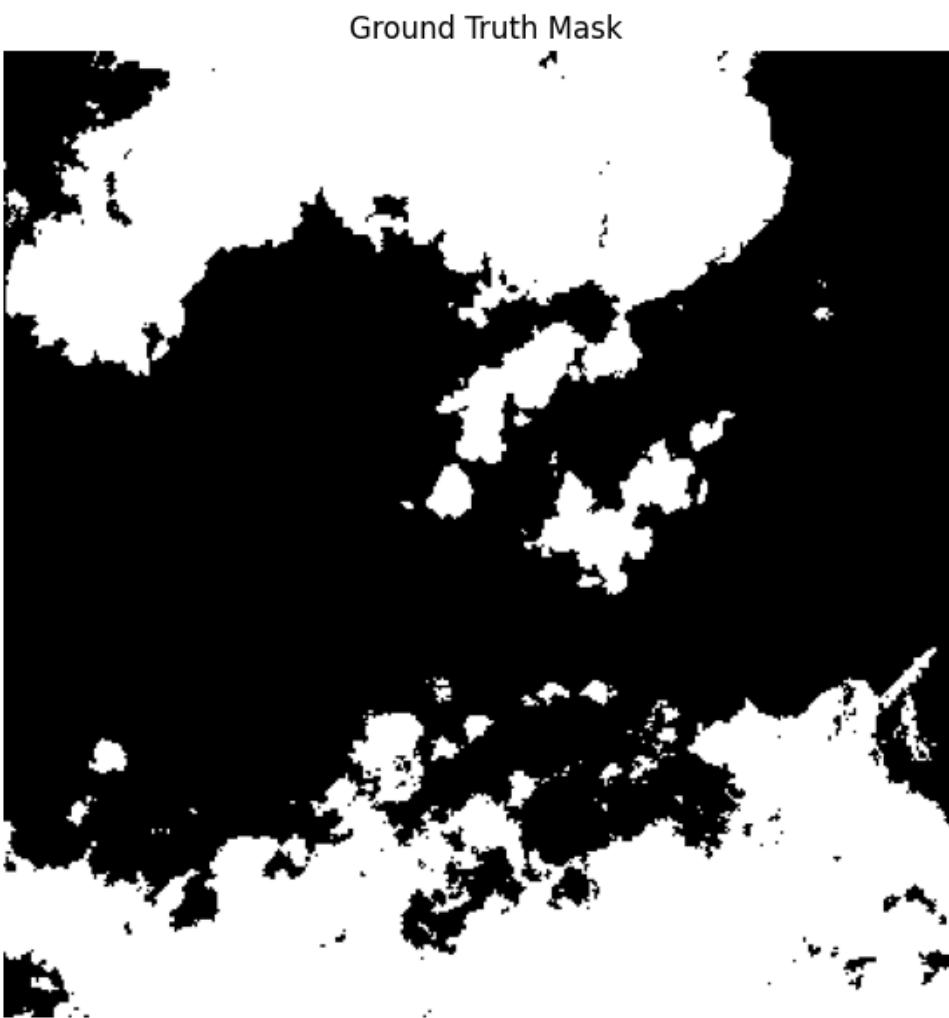
Trained per pixel to learn the most efficient decision boundaries between cloud and non-cloud pixels.

**Gini Impurity Minimization:** Every new split aims to minimize the impurity of the two leaves it generates.

$$G = 1 - \sum_{i=1}^K p_i^2$$

# RESULTS

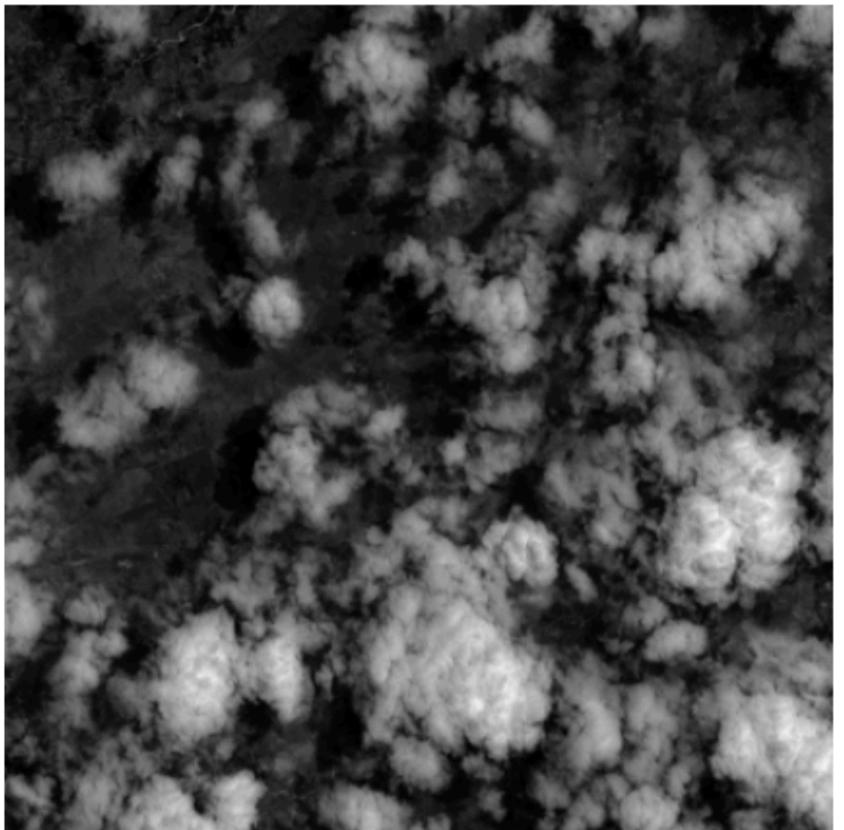
## Otsu



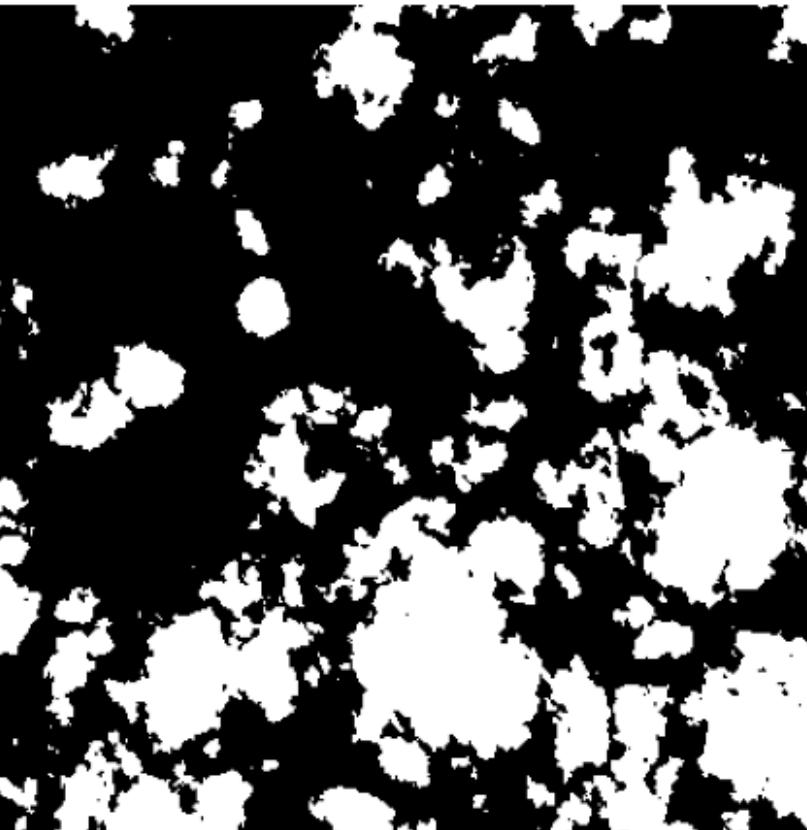
# RESULTS

## Otsu VS Watershed

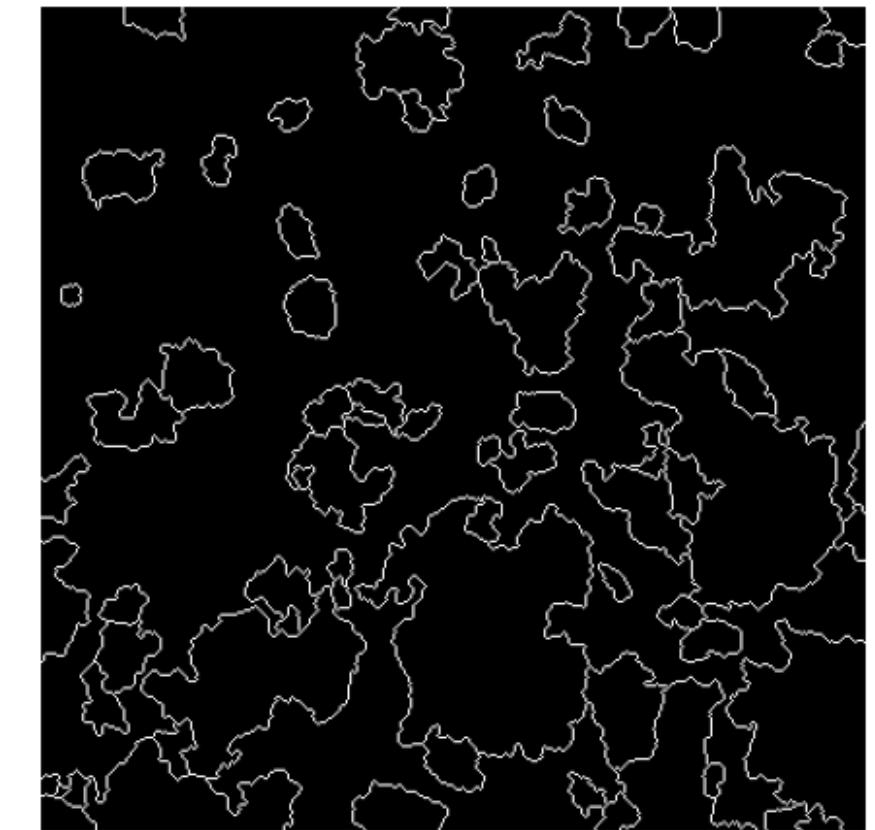
Original Image (Red Band)



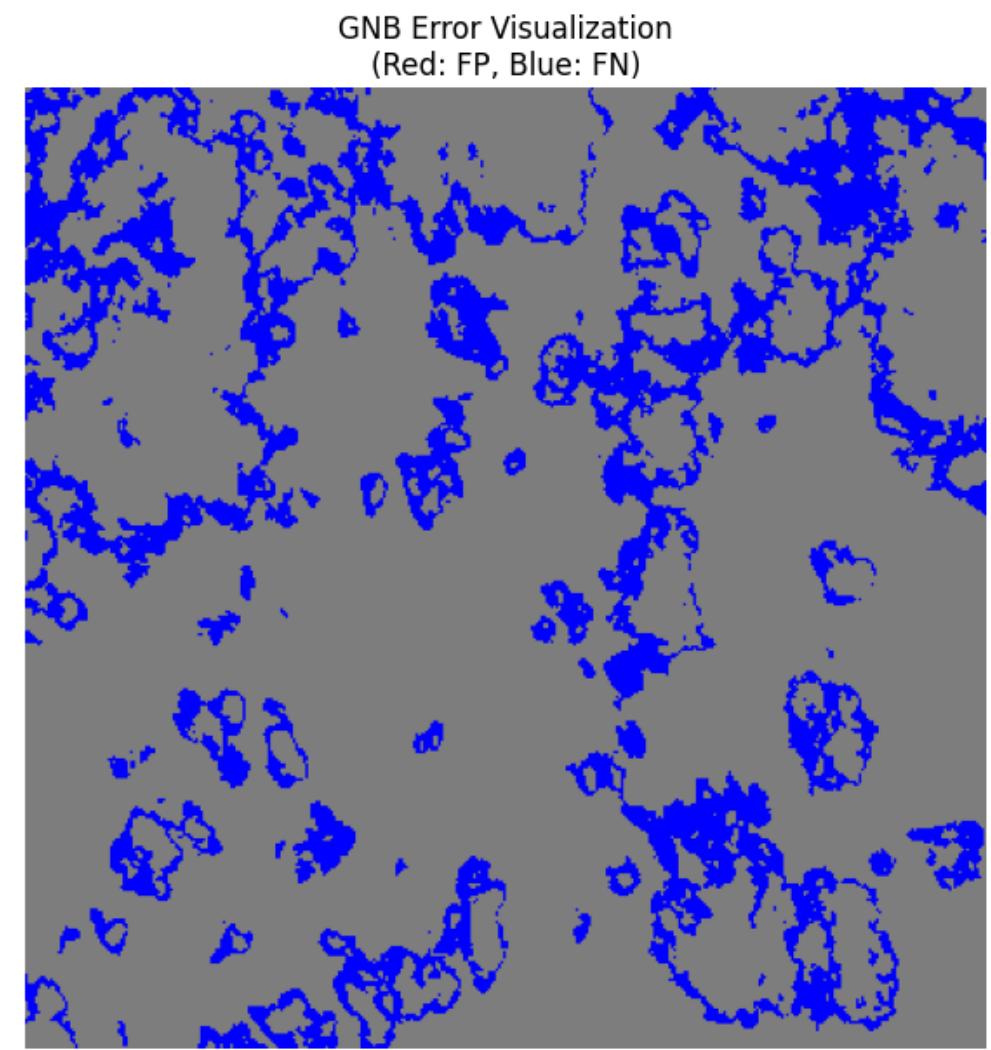
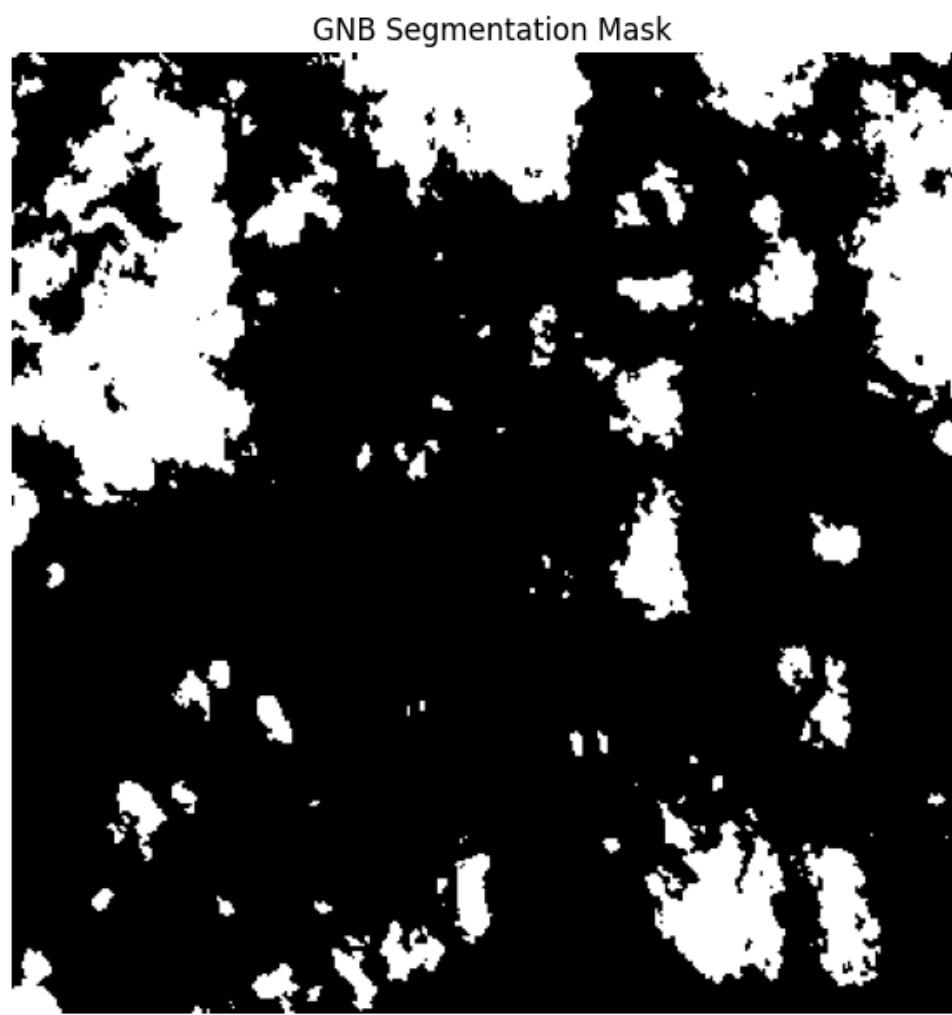
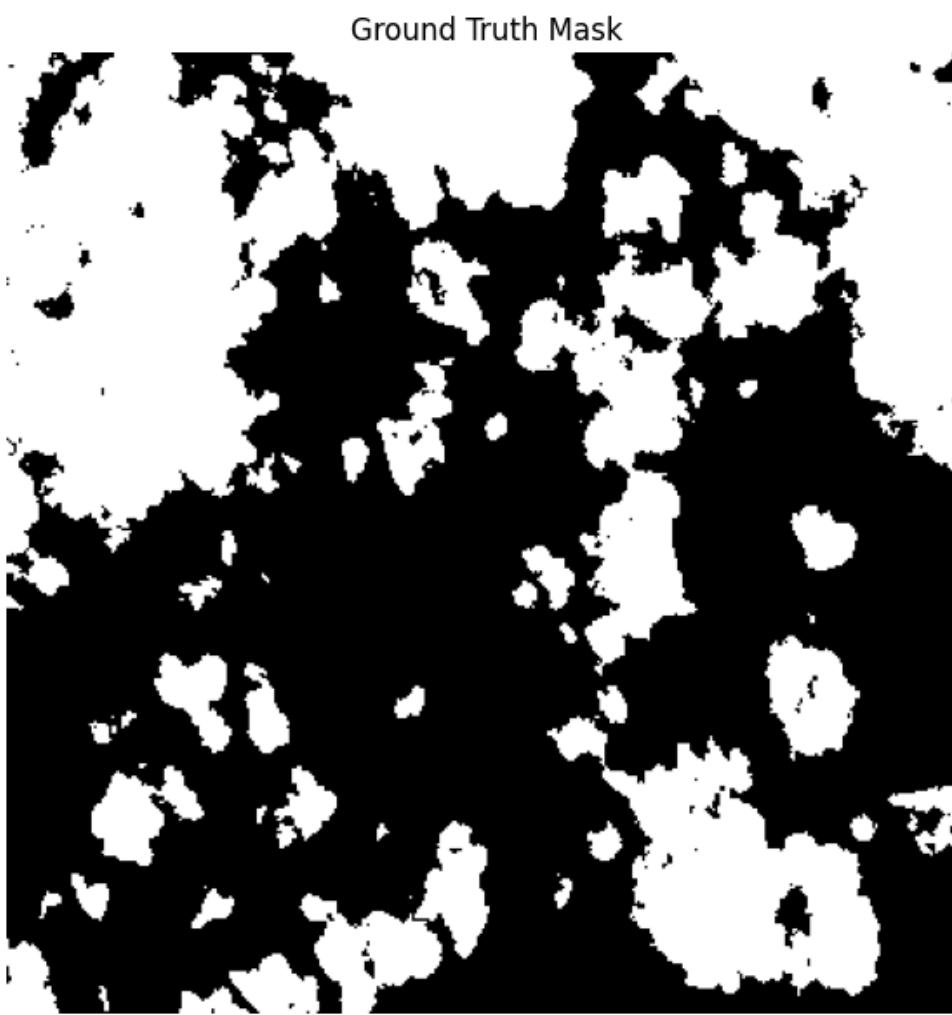
Otsu's Thresholding



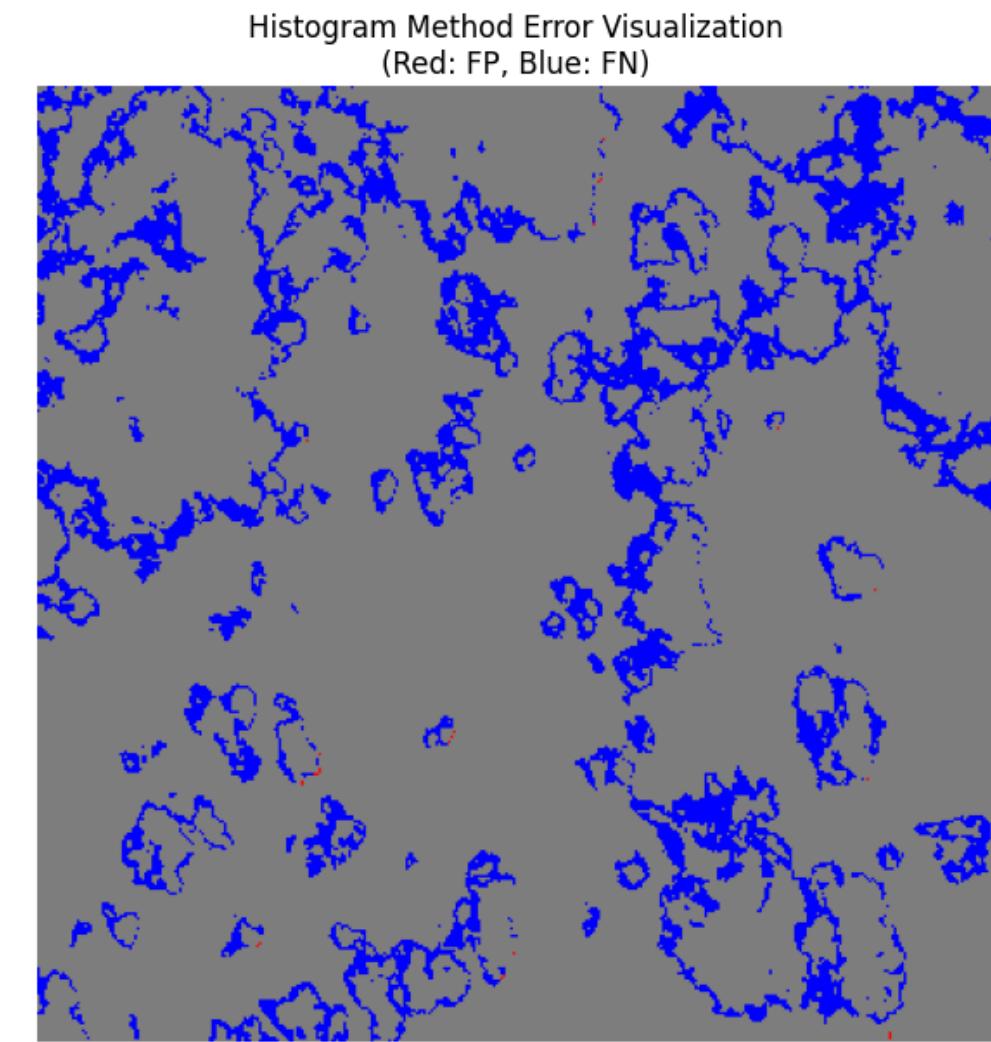
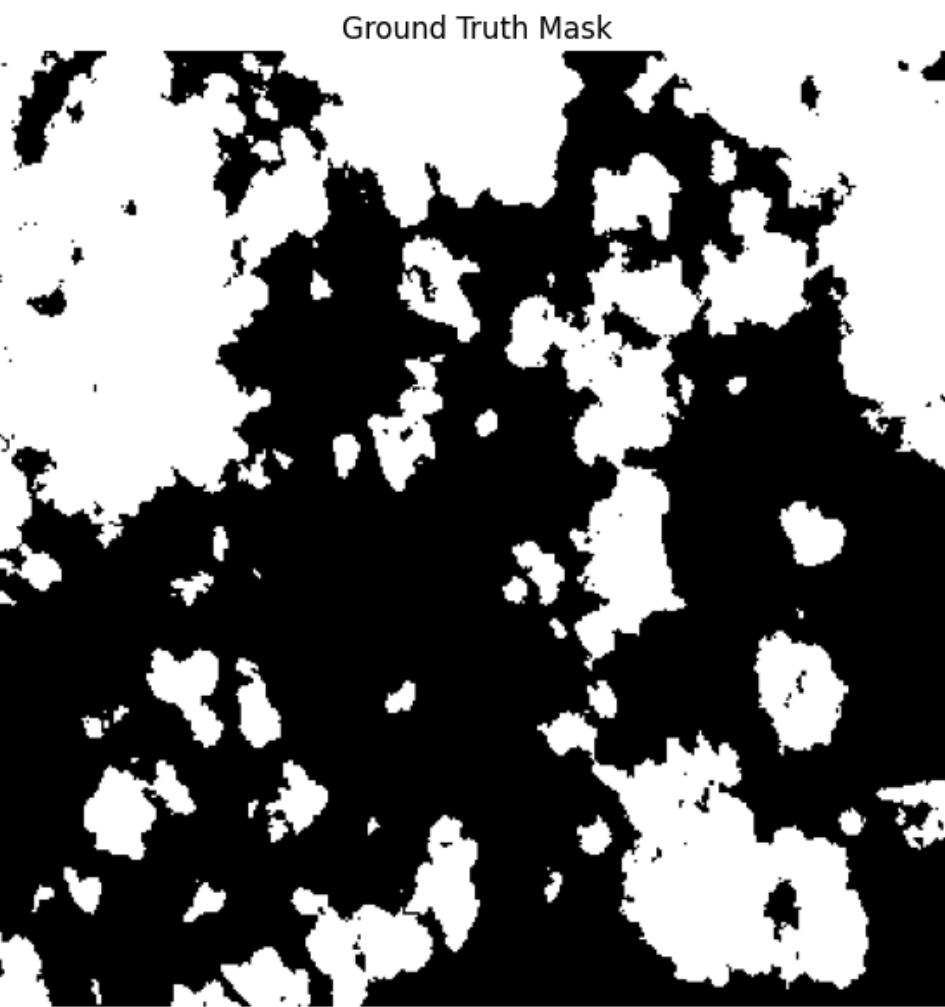
Optimized Watershed



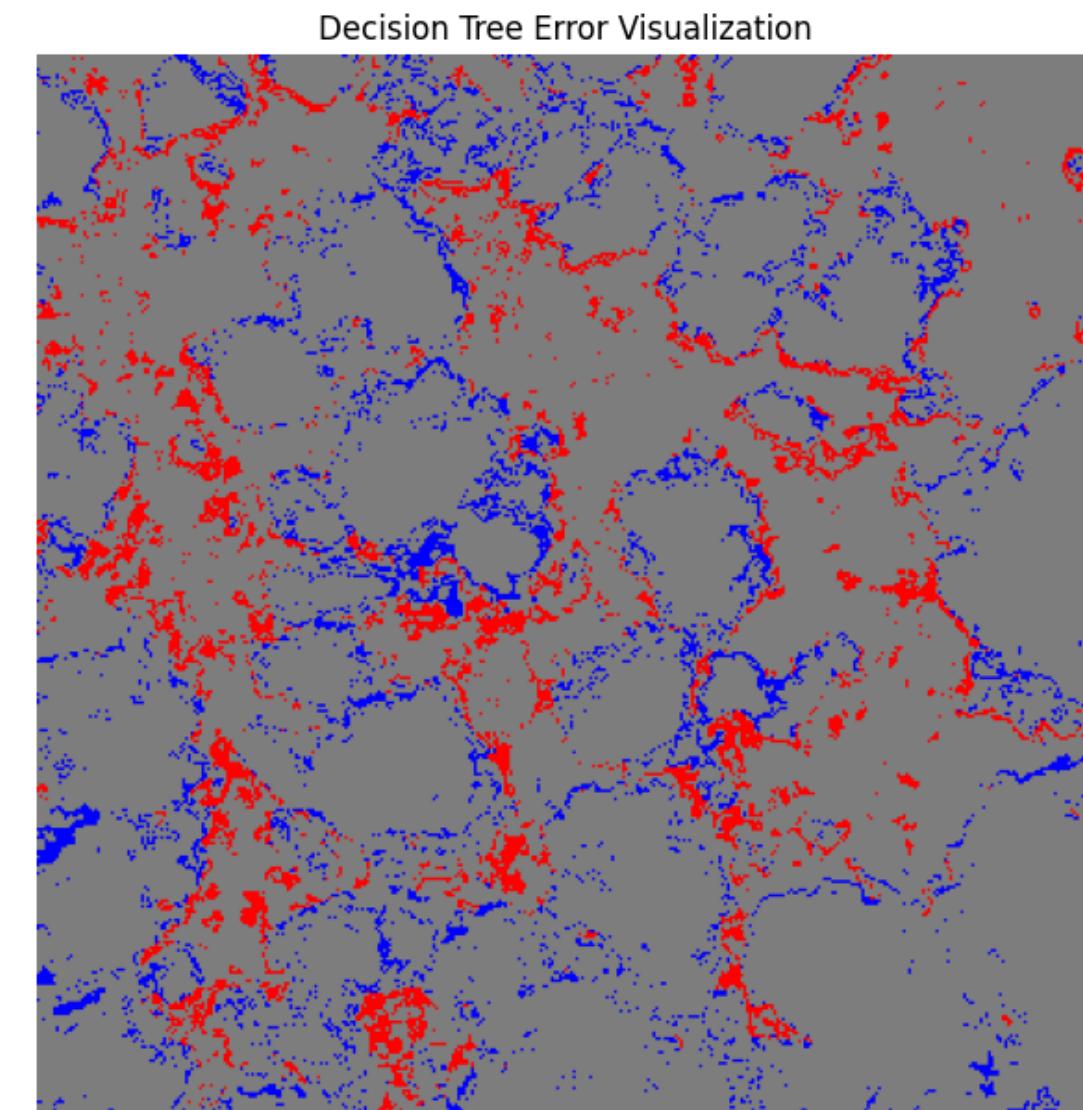
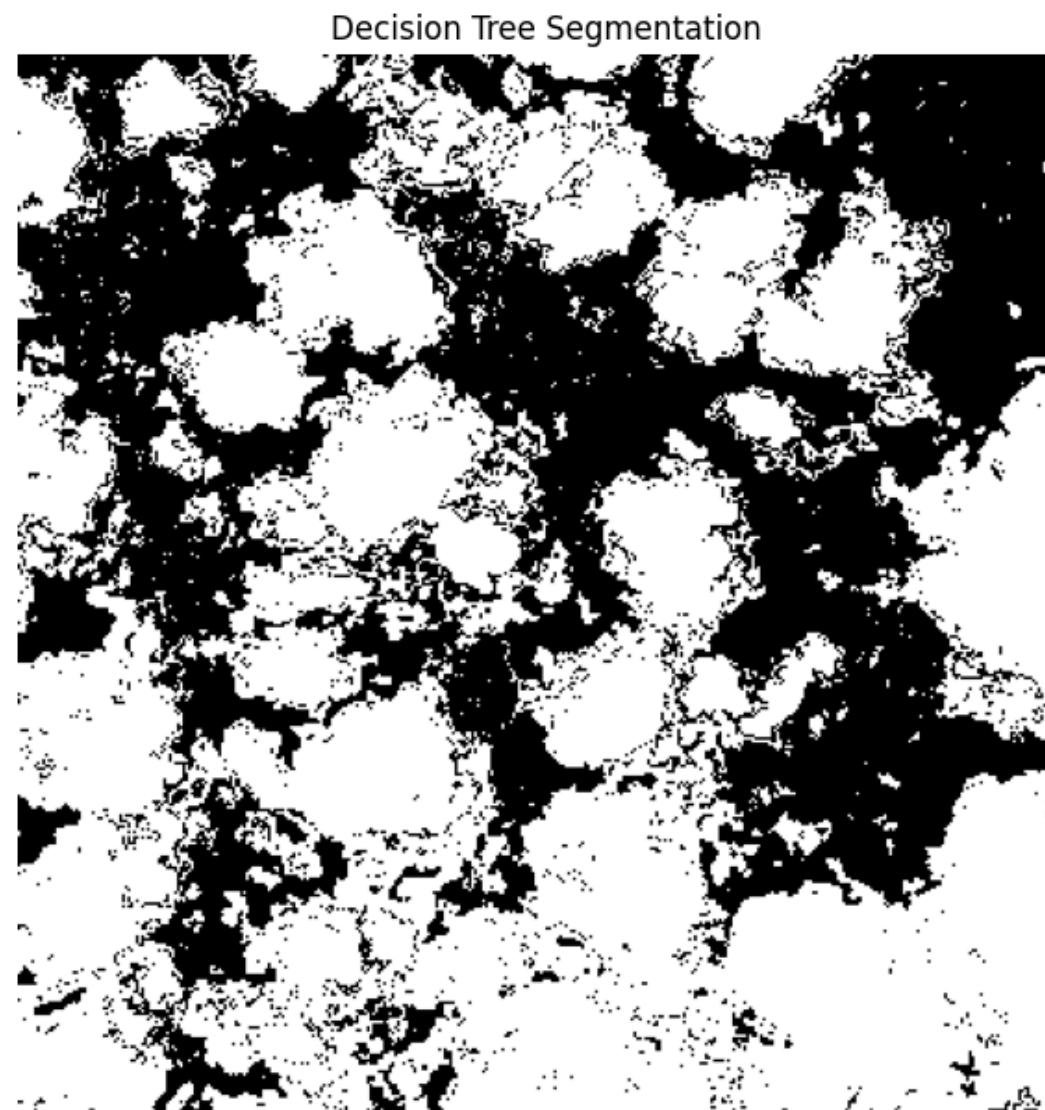
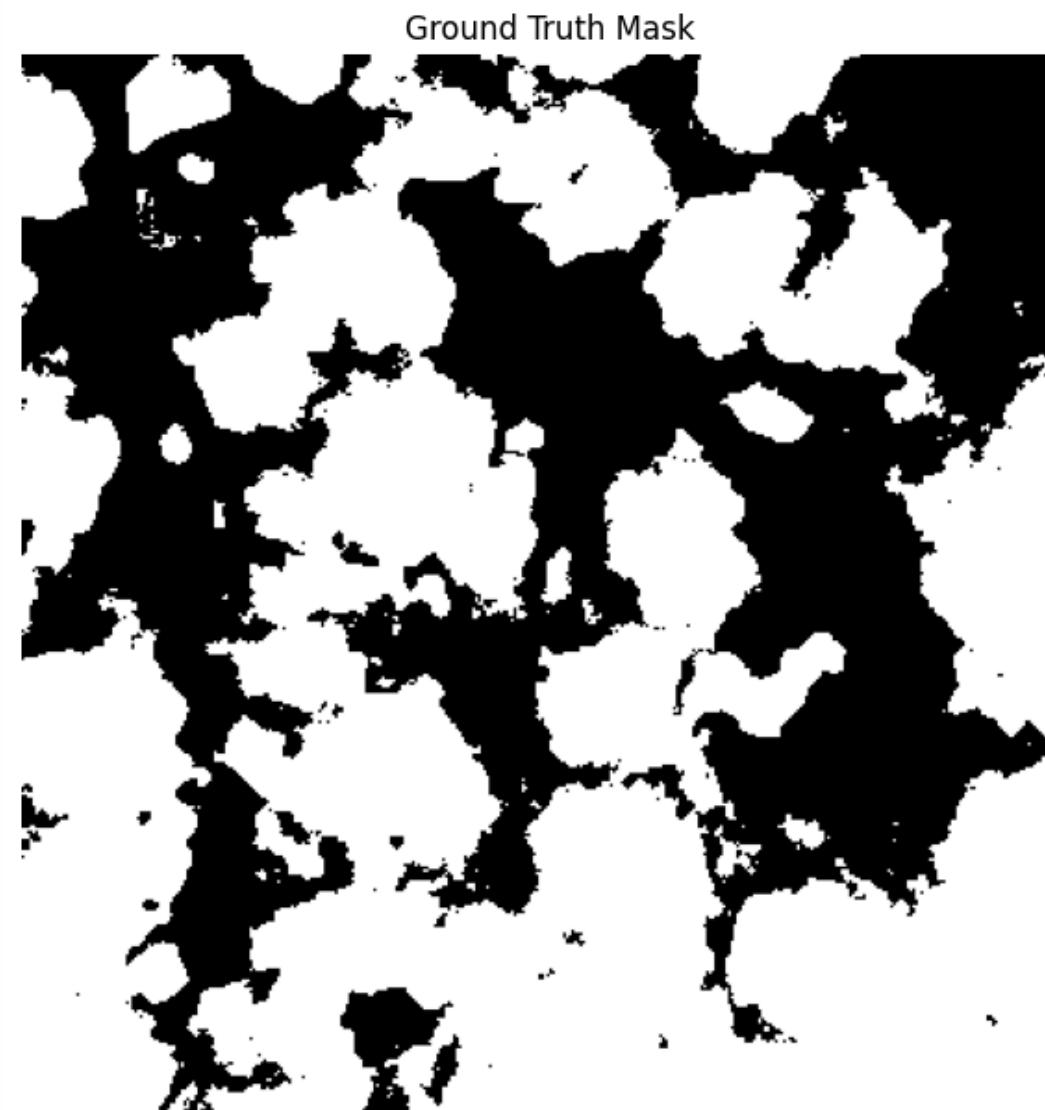
# RESULTS



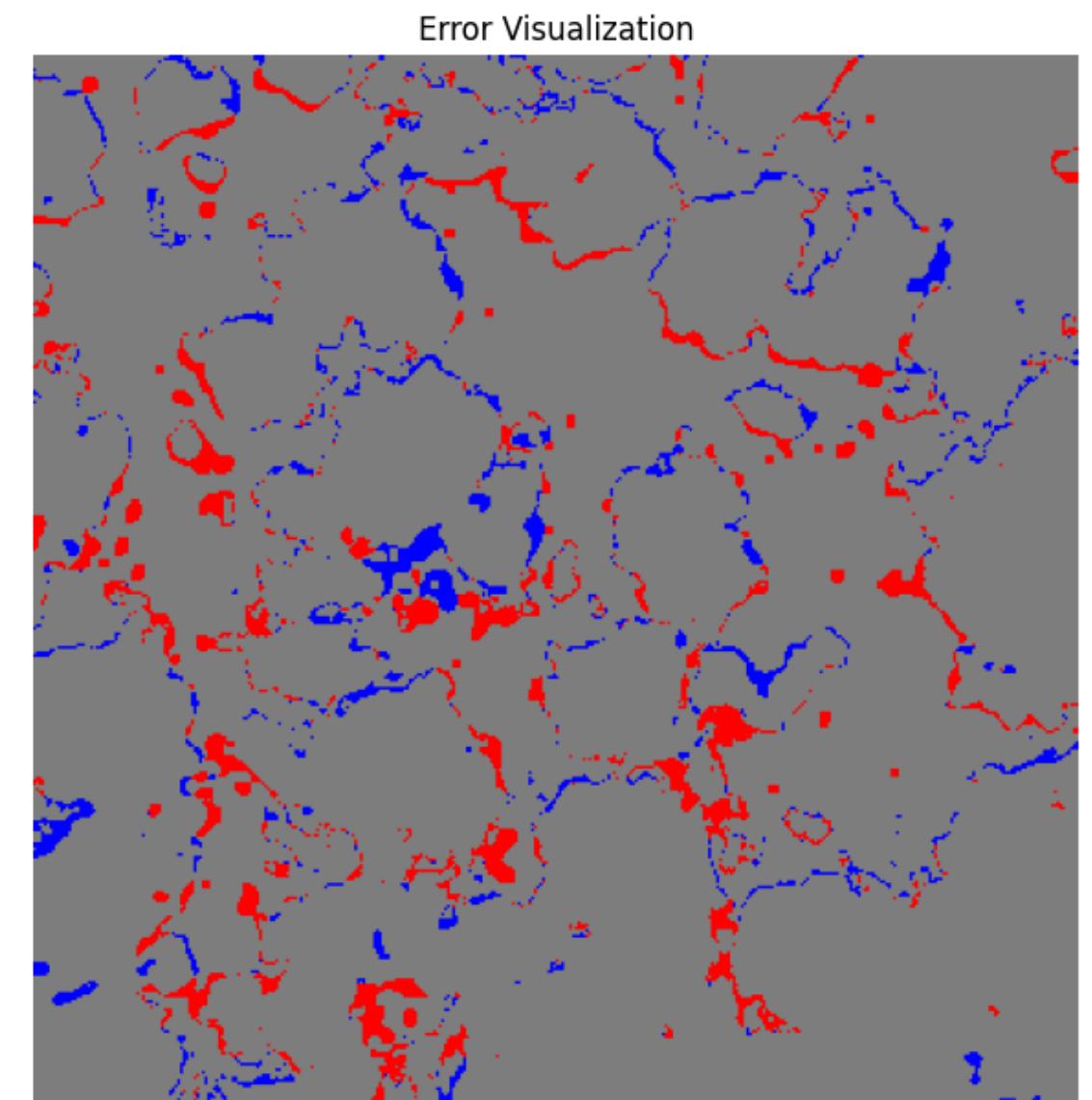
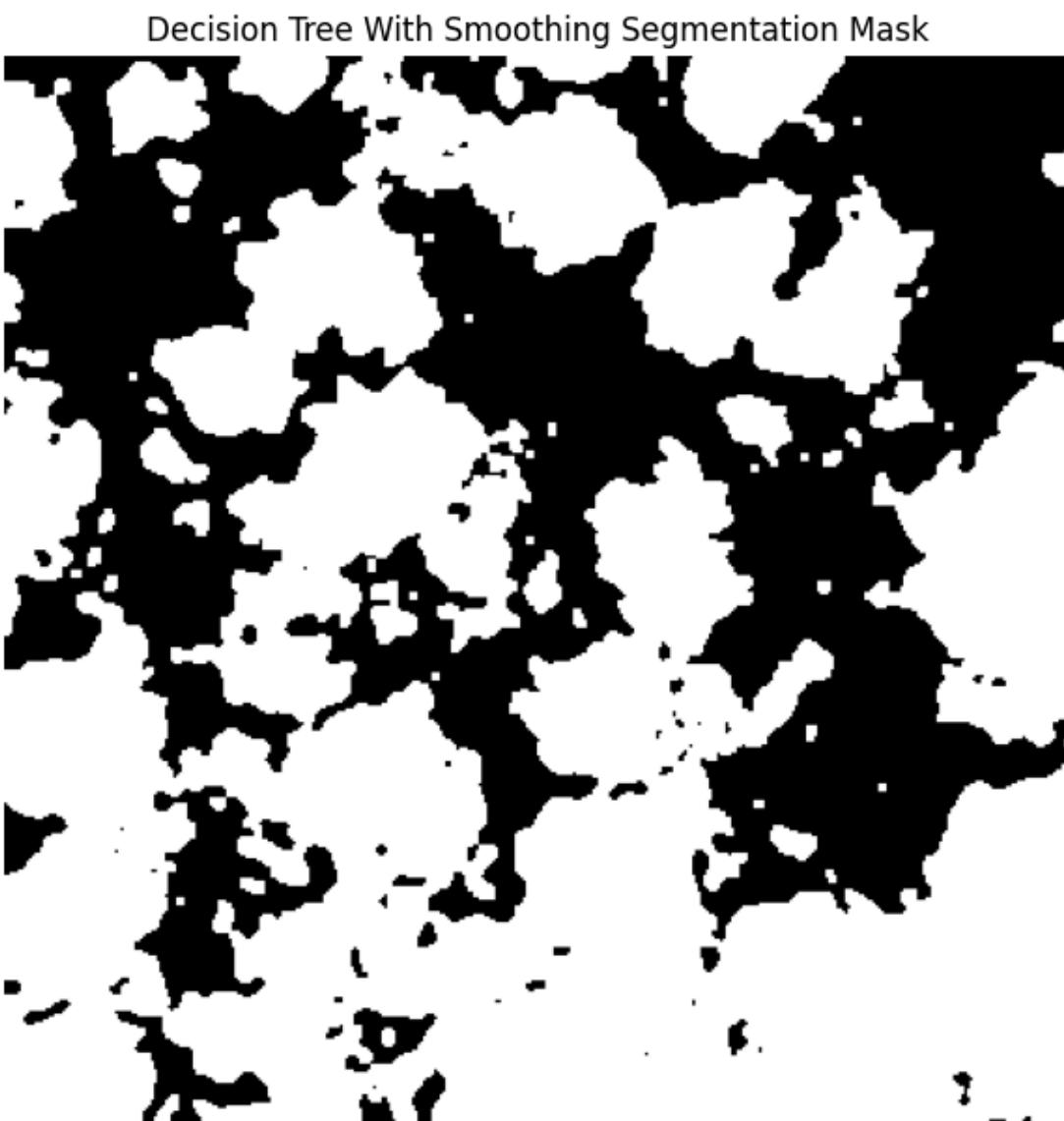
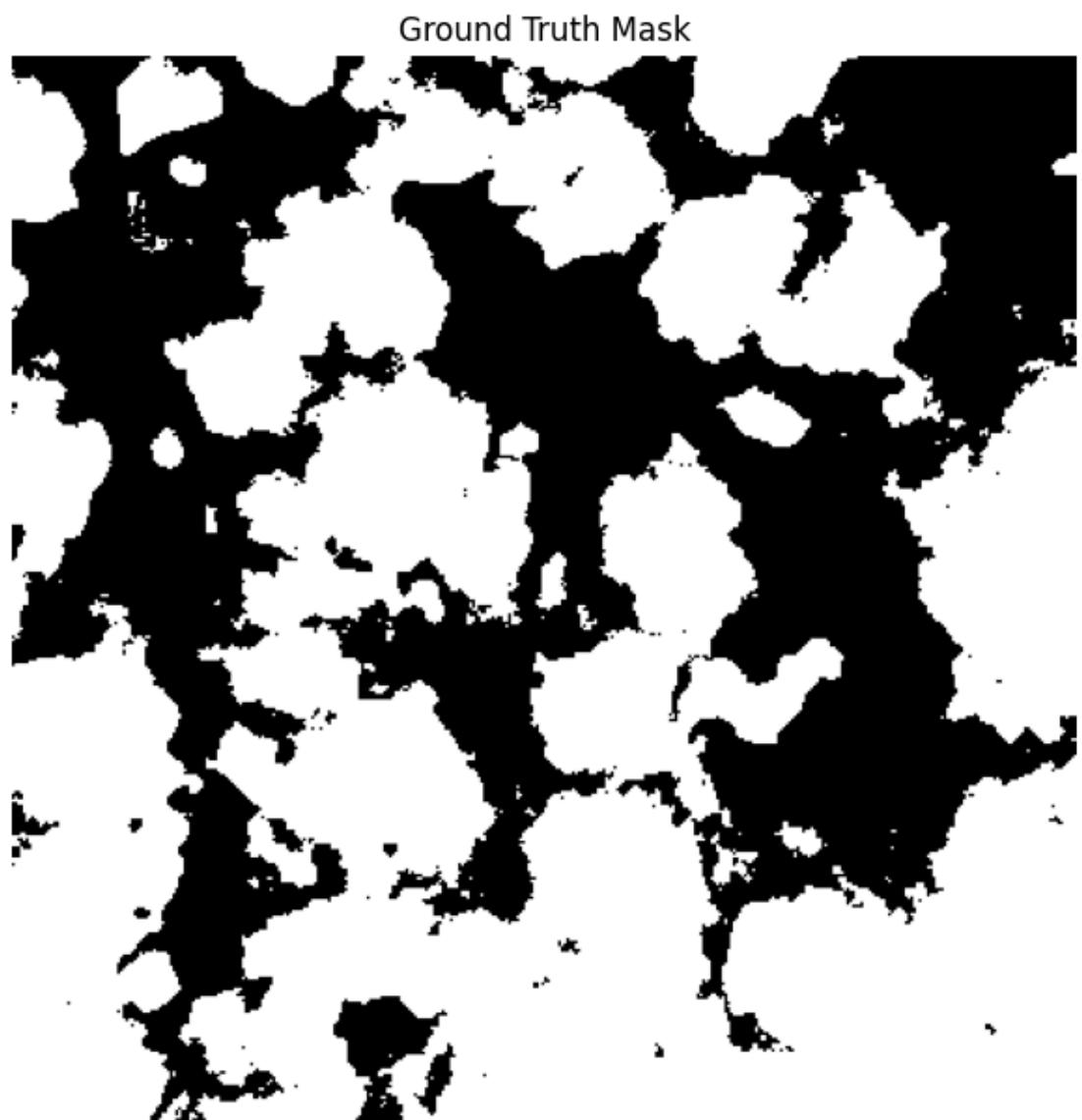
# RESULTS



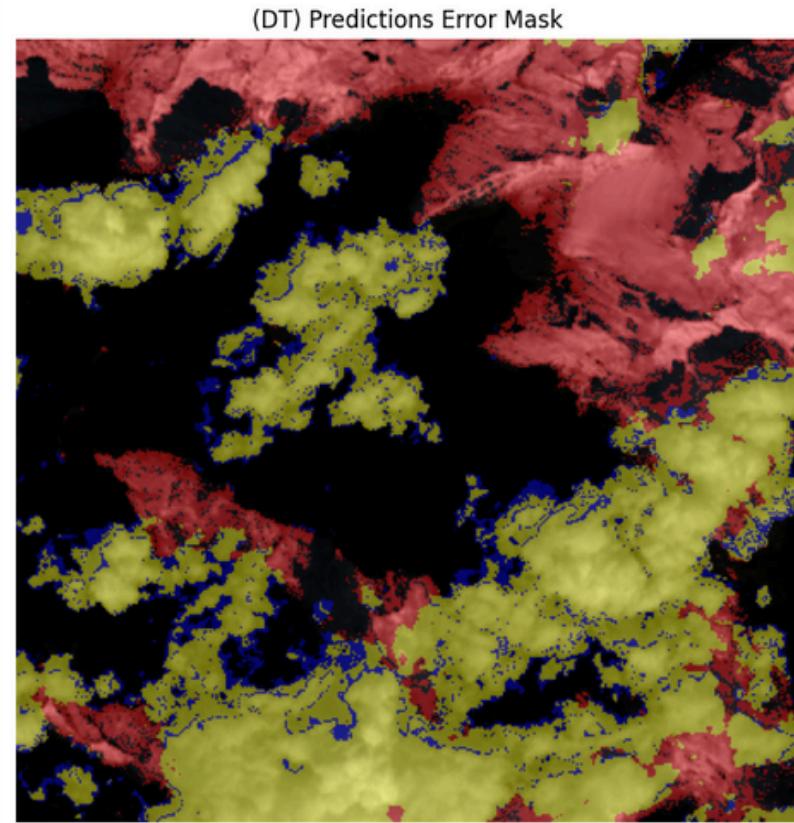
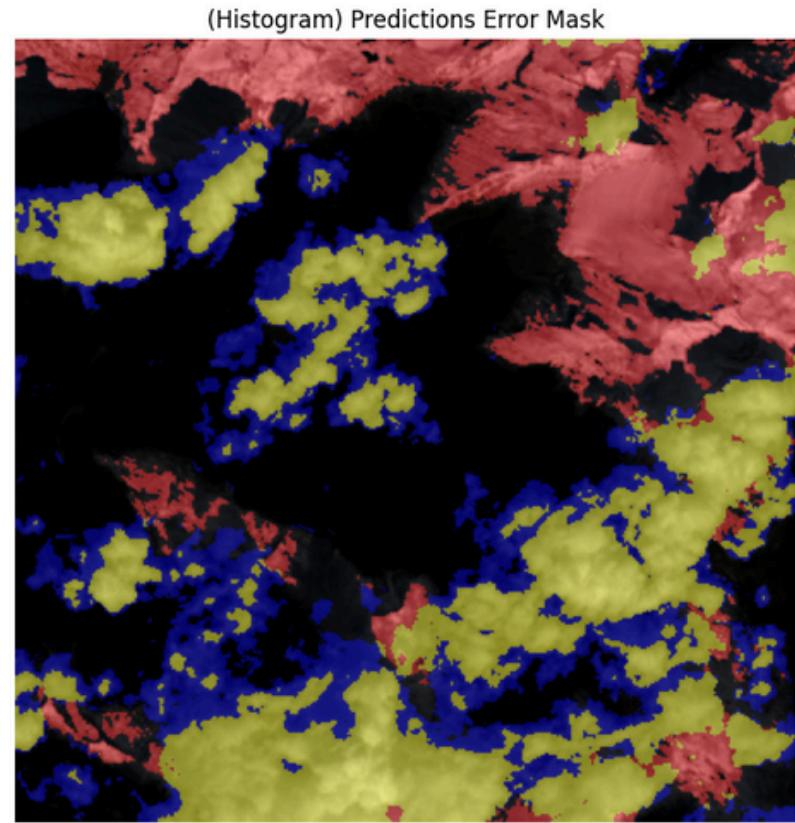
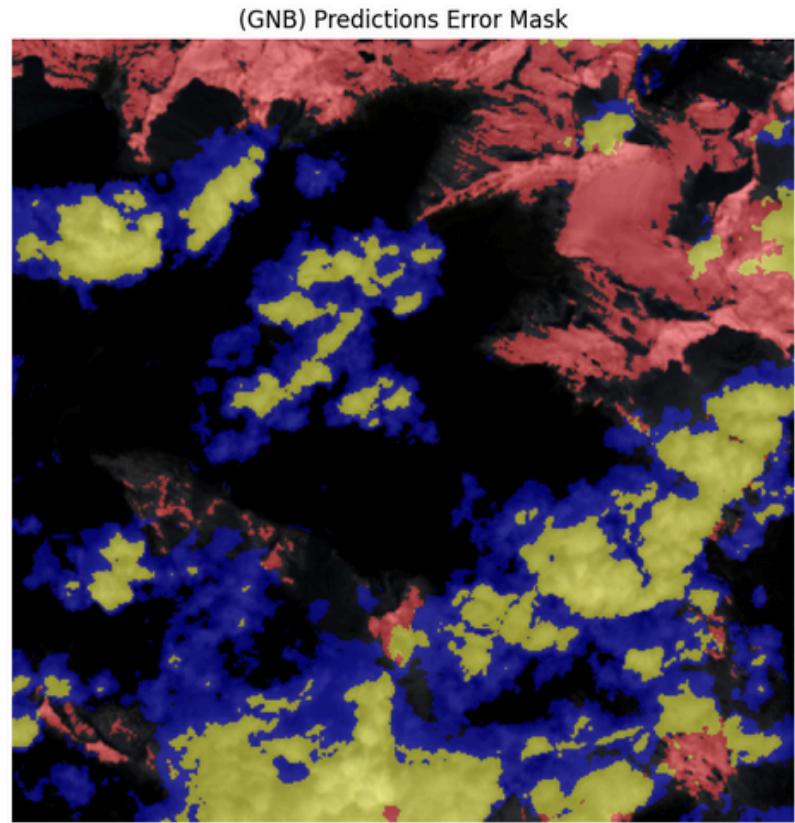
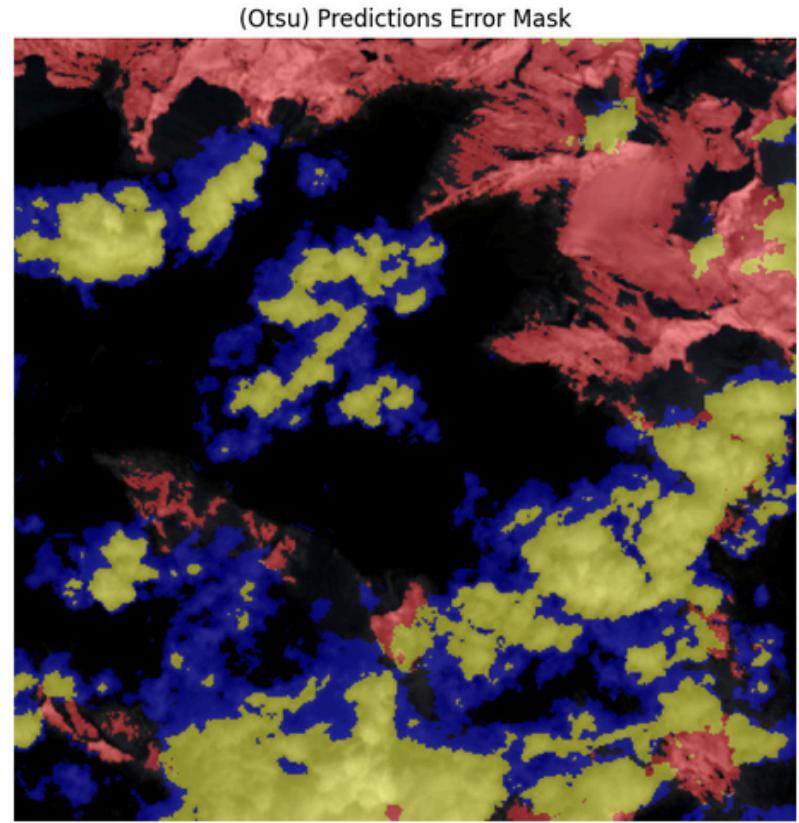
# RESULTS



# RESULTS



# RESULTS



# RESULTS

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

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

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

$$\text{Jaccard Index} = \frac{TP}{TP + FP + FN}$$

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

Method	Precision	Recall	F1 Score	Jaccard	Accuracy
GNB	0.7234	0.6199	0.6050	0.5203	0.7594
Histogram-based	0.7089	0.6899	0.6406	0.5657	0.7697
Otsu's Method	0.7148	0.5489	0.5558	0.4484	0.6926
Watershed	0.5523	0.0424	0.0662	0.0349	0.5483
Decision Tree	0.6812	0.7765	0.6775	0.6232	0.7935

Table 1: Average metrics over 1000 images for different segmentation methods.

# CONCLUSION

- Investigated classical computer vision techniques and supervised learning for cloud segmentation in satellite imagery.
- Observed differences in performance metrics across methods, with trade-offs between precision and recall.
- Explore hybrid techniques combining classical segmentation with lightweight learning-based refinements.

**THANK YOU FOR YOUR ATTENTION !**

**Any questions**

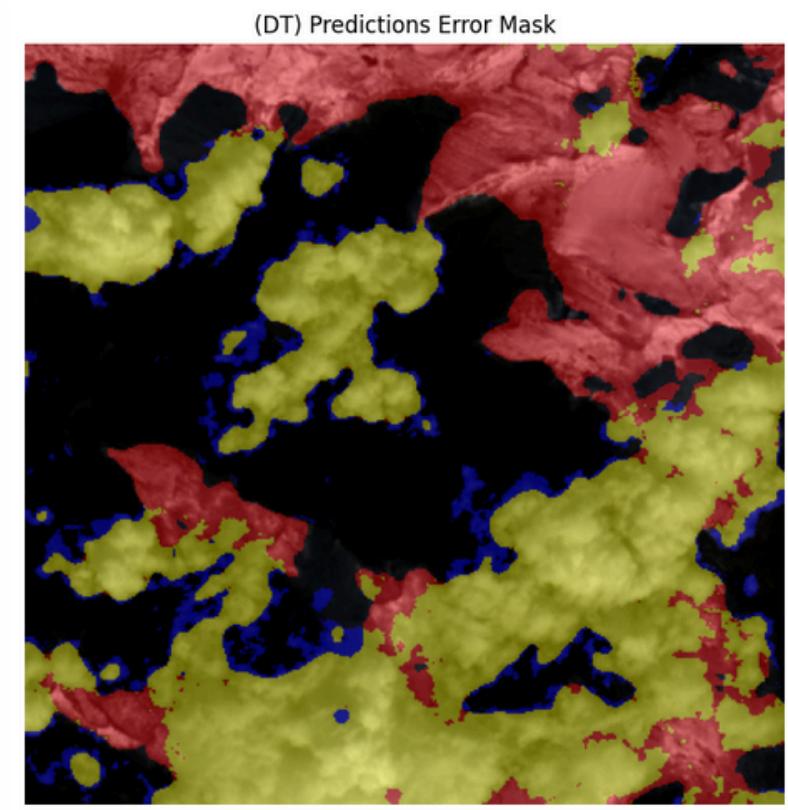
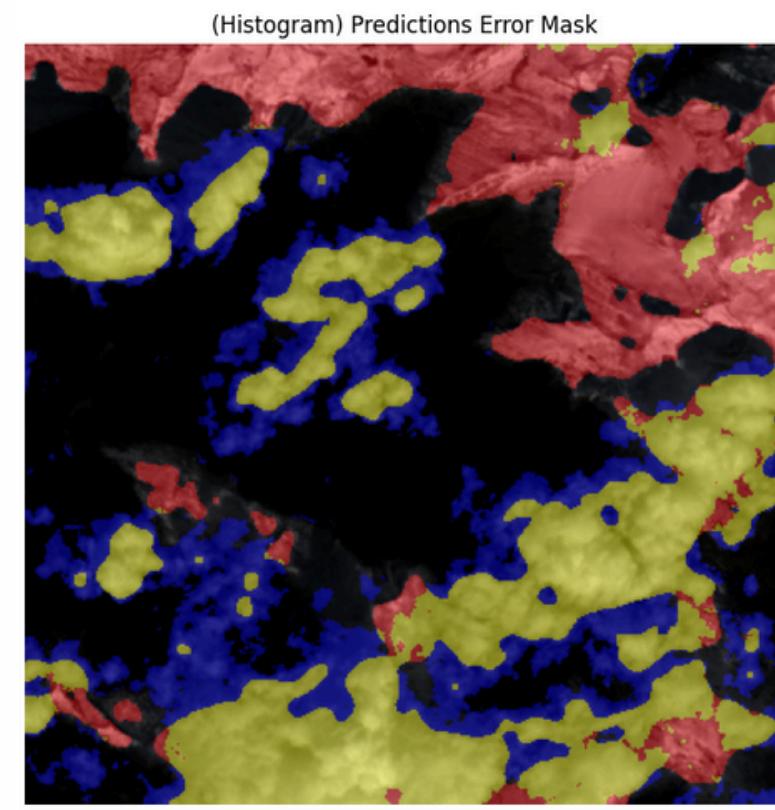
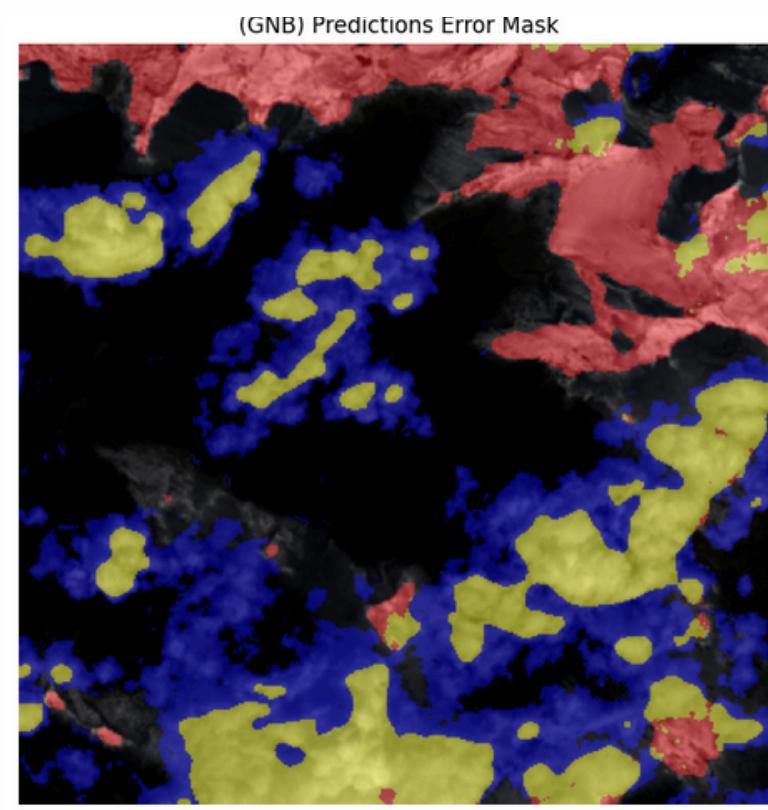
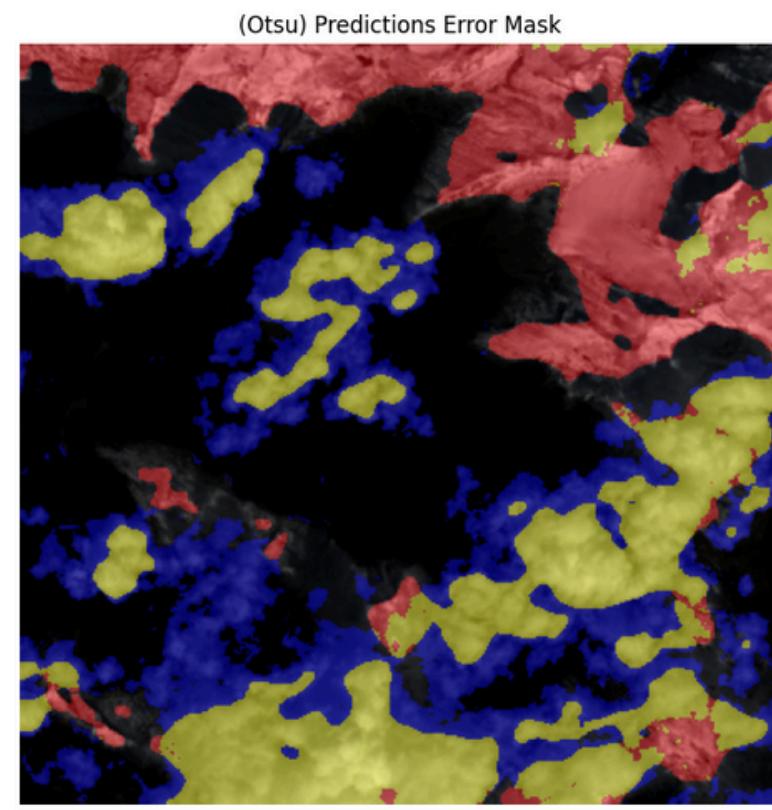


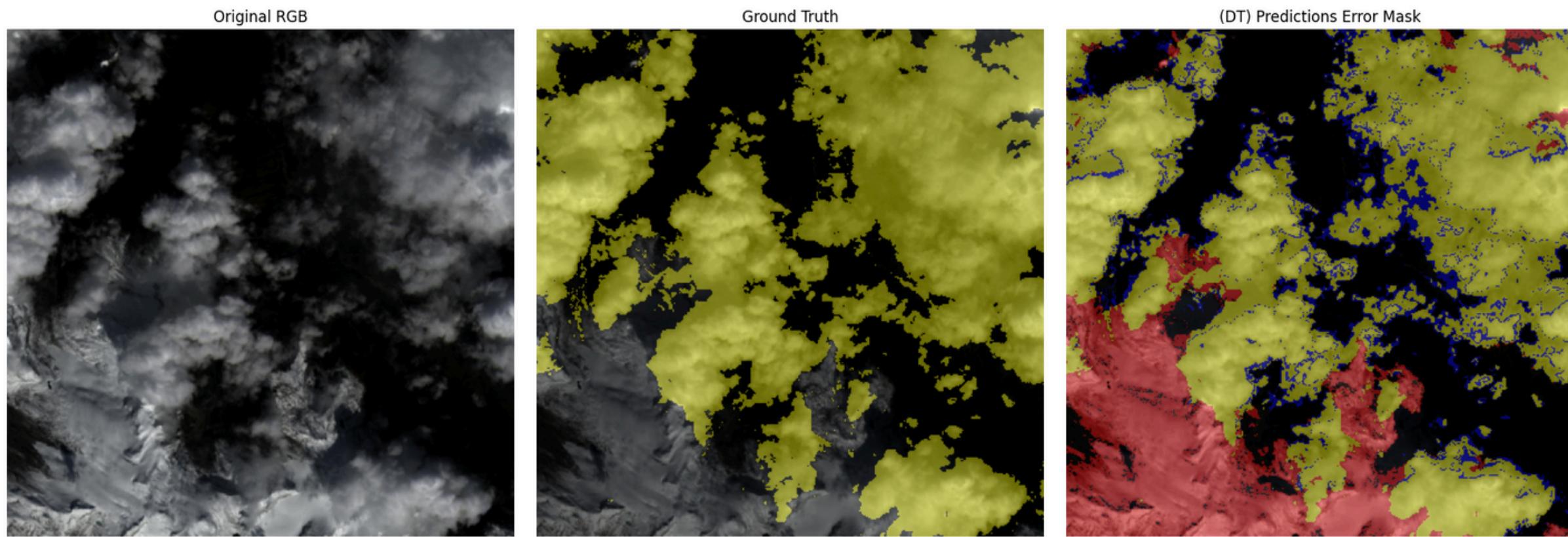
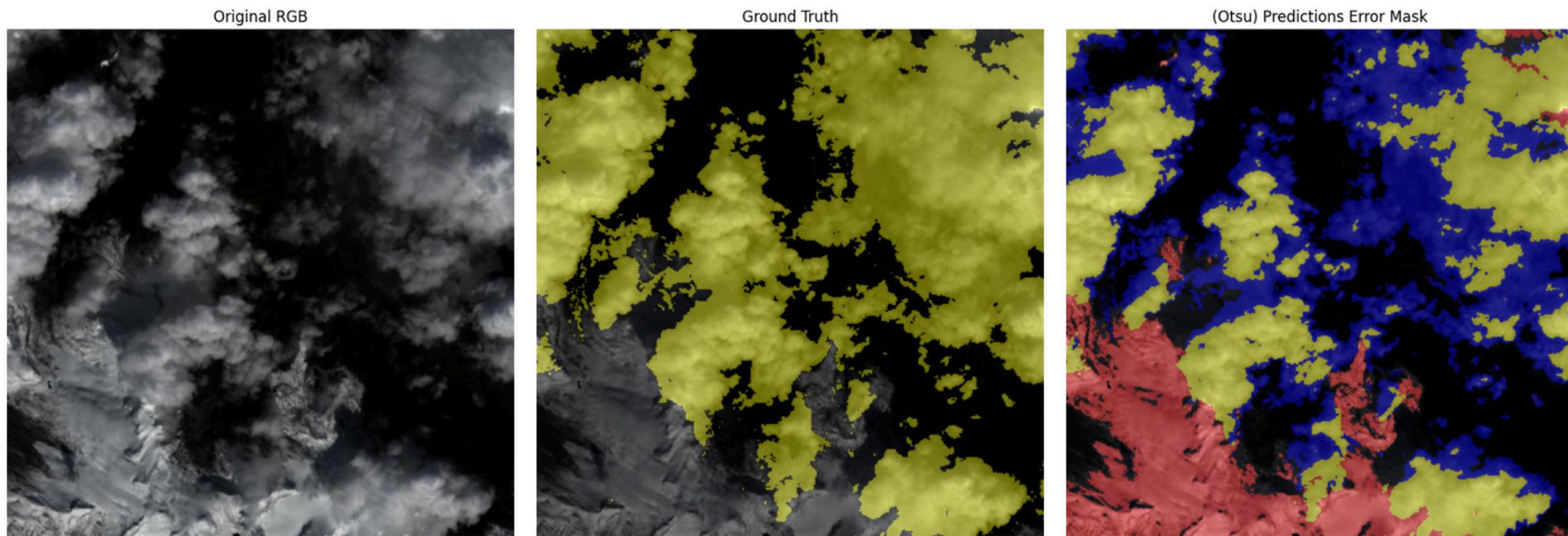
# **Appendix**

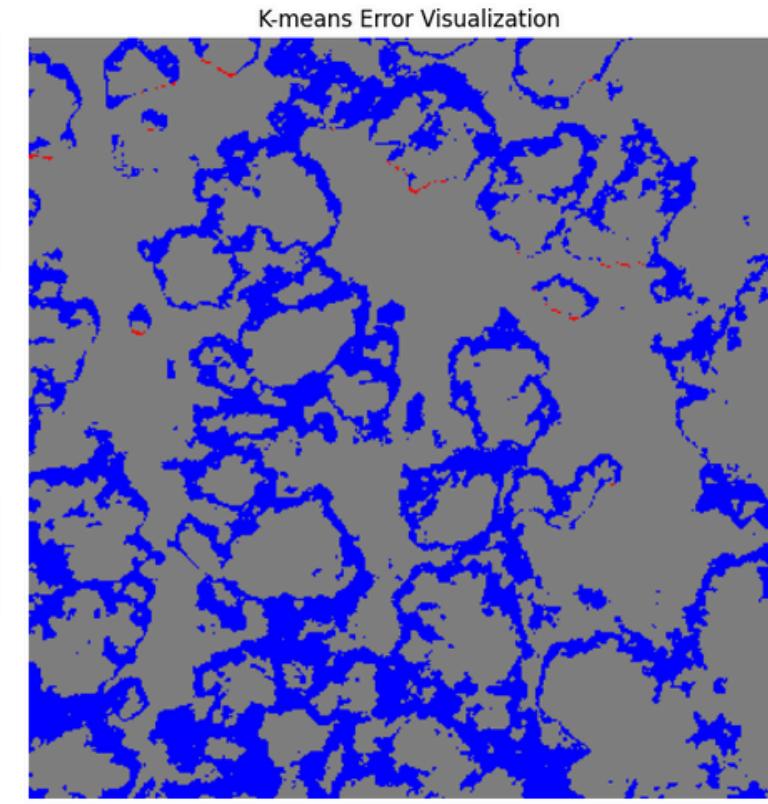
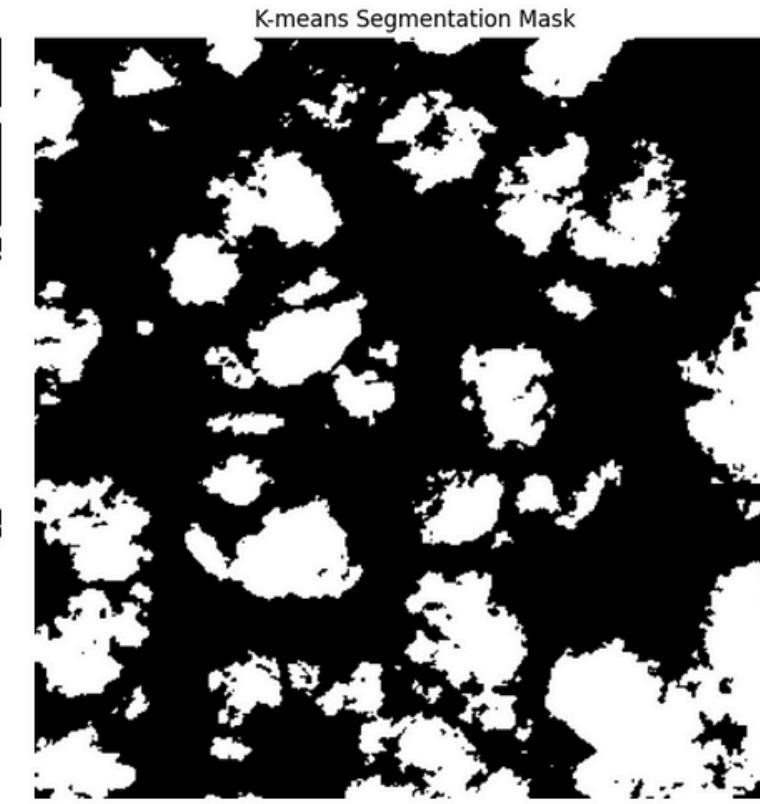
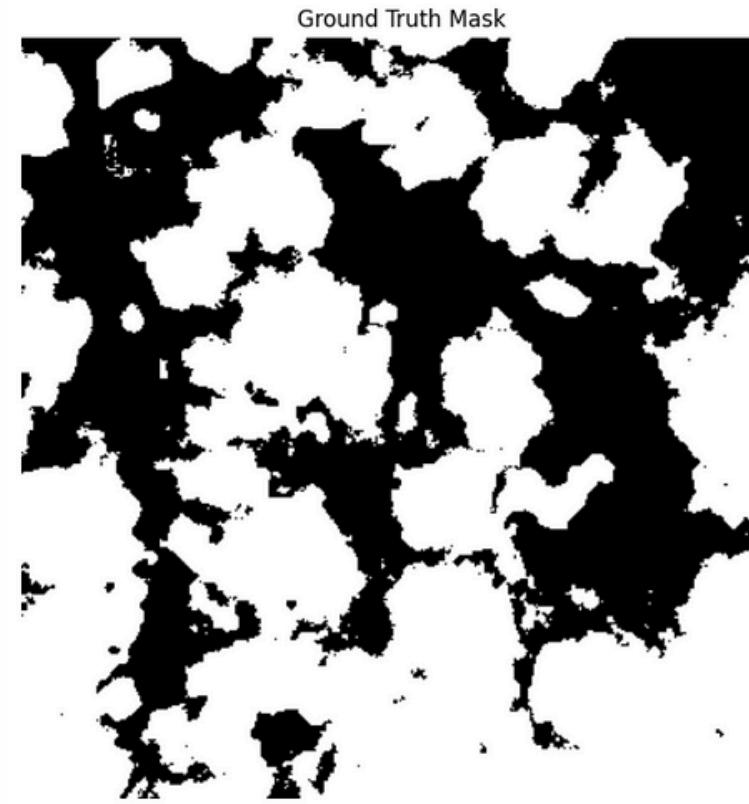
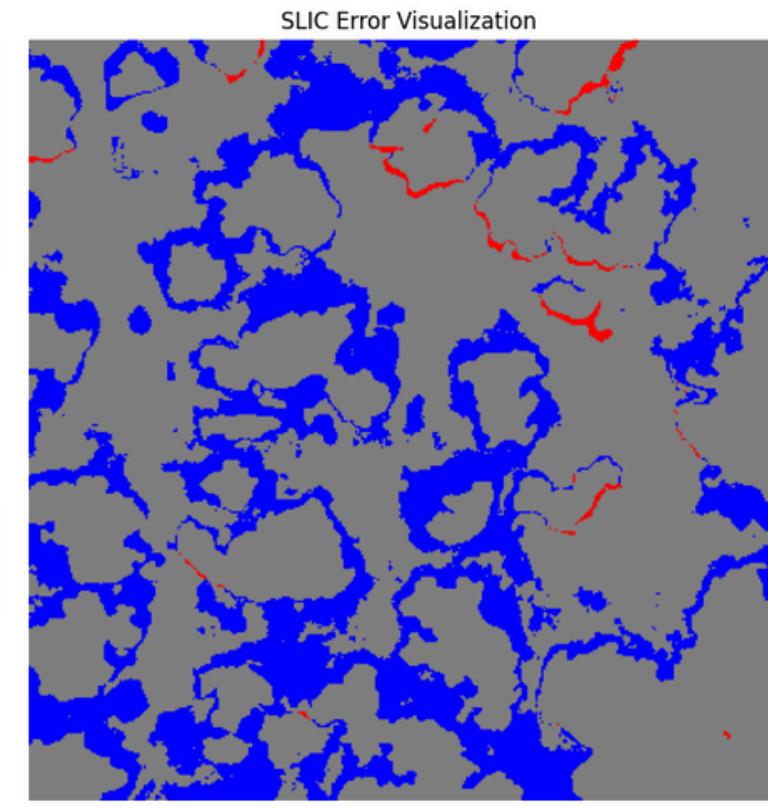
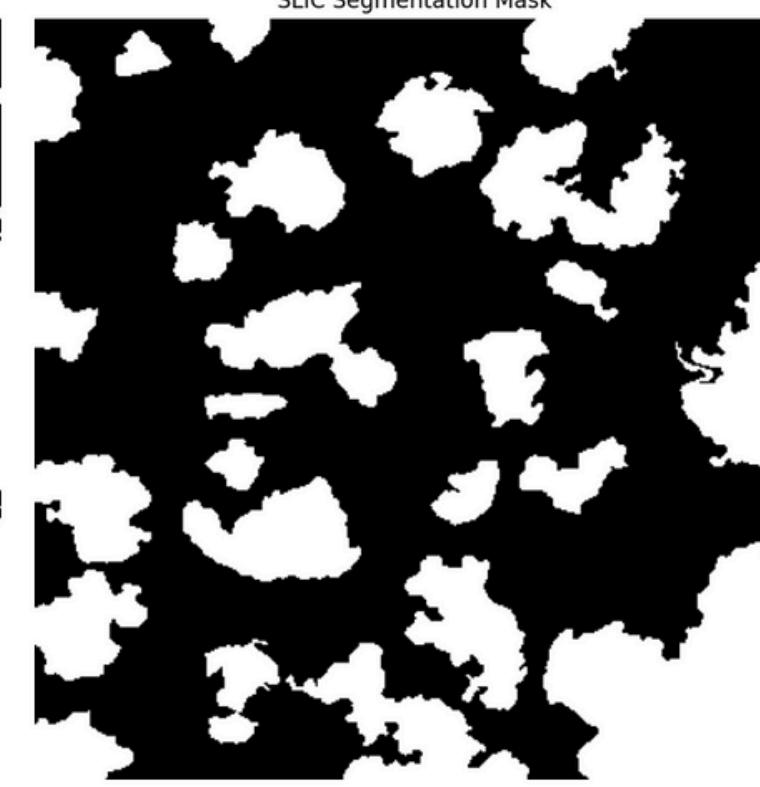
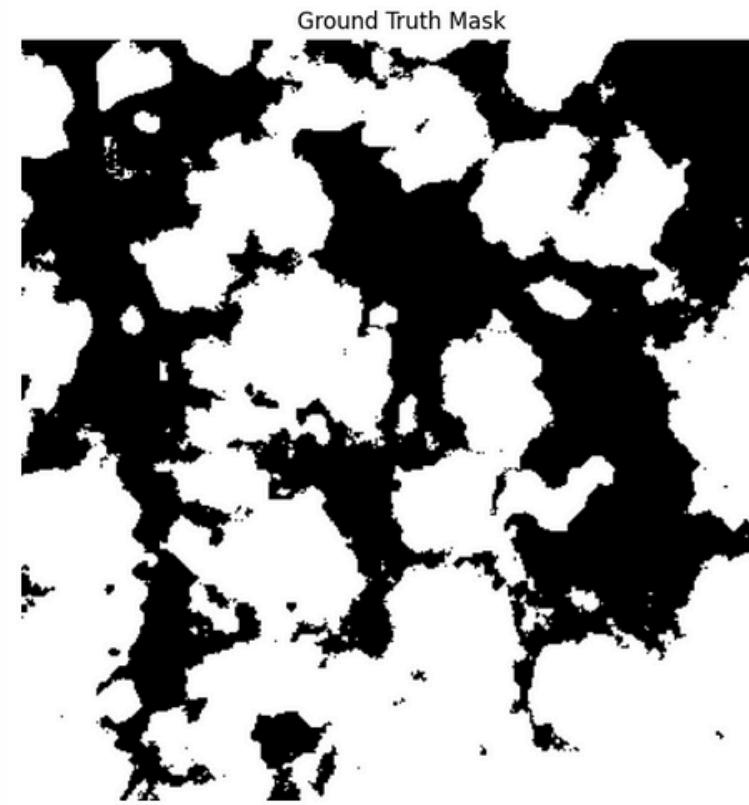
# RESULTS

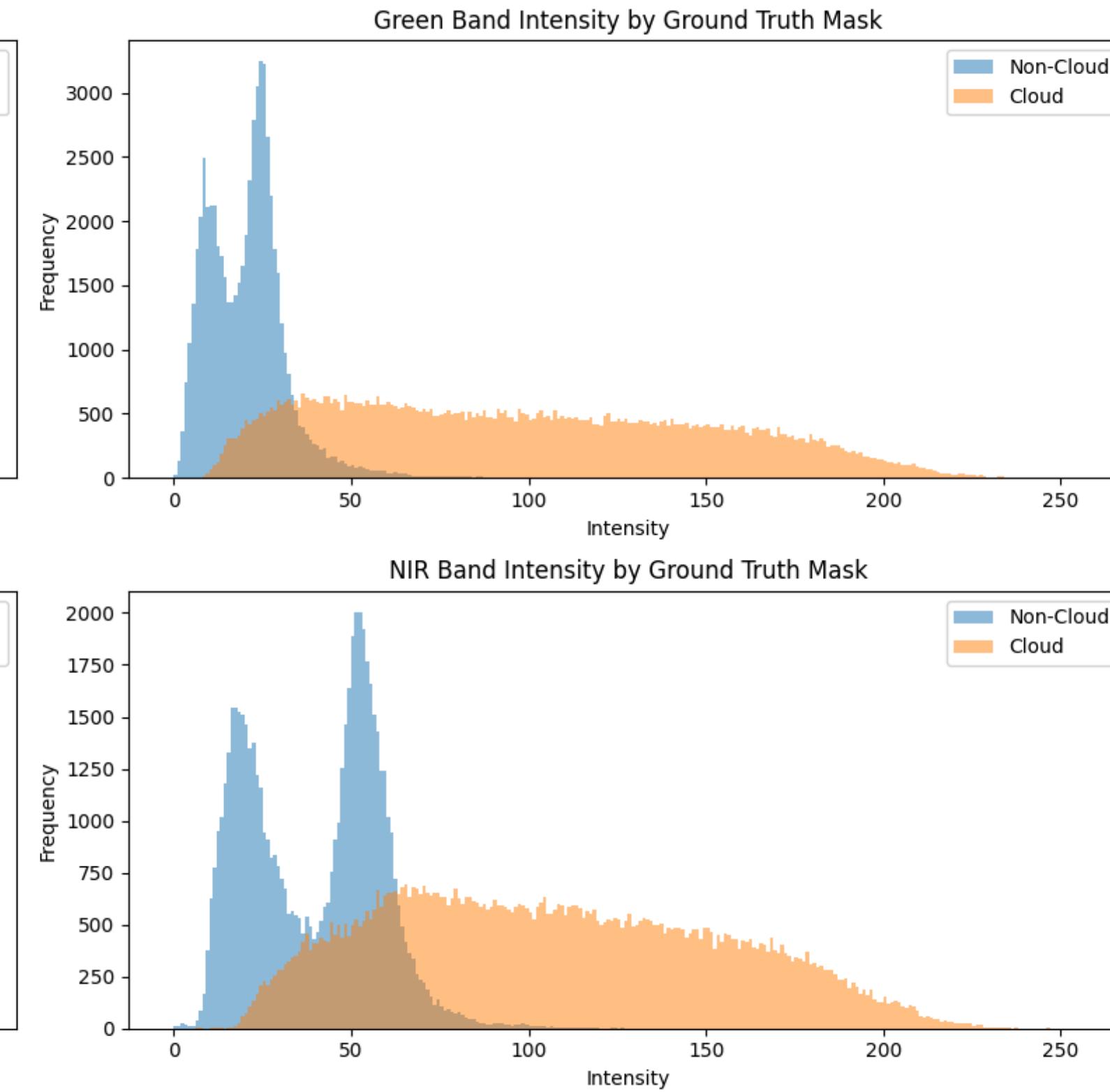
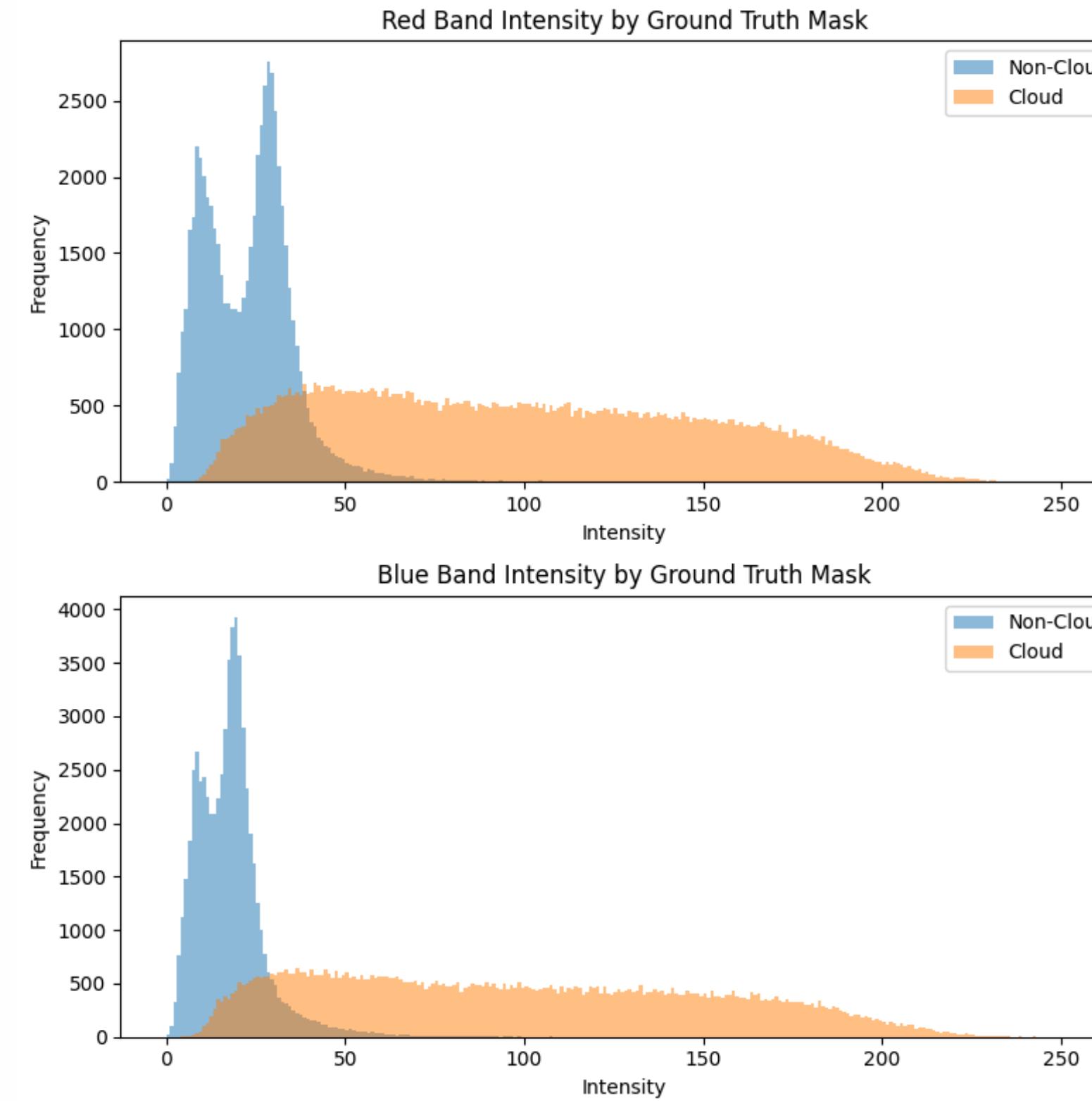
<b>Method (denoised)</b>	<b>Precision</b>	<b>Recall</b>	<b>F1</b>	<b>Jaccard</b>	<b>Accuracy</b>
GNB	0.7258	0.6374	0.6219	0.5435	0.7656
Histogram-based	0.6906	0.7425	0.6587	0.5962	0.7682
Otsu's Method	0.7142	0.5420	0.5477	0.4458	0.6796
Decision Tree	0.6909	0.7812	0.6839	0.6328	0.7961

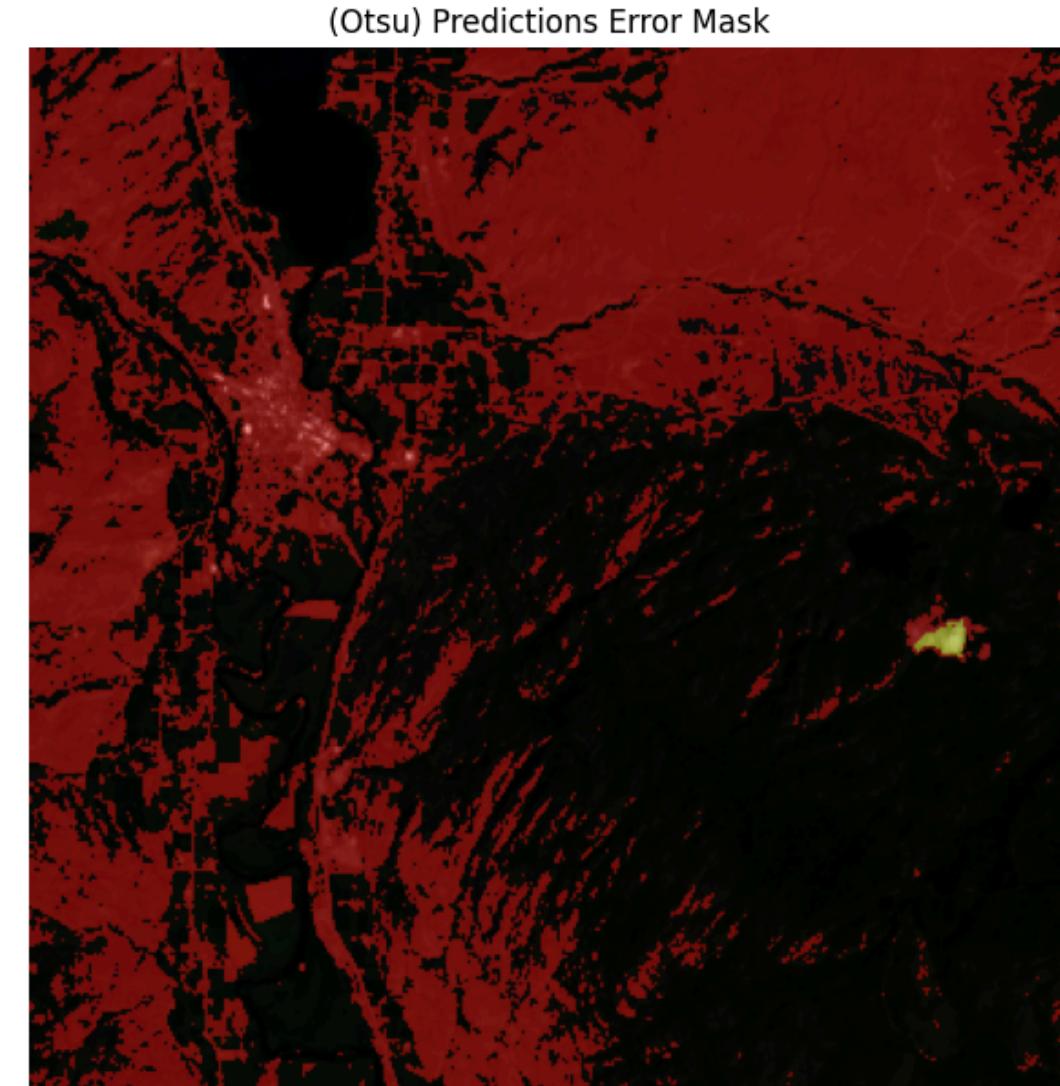
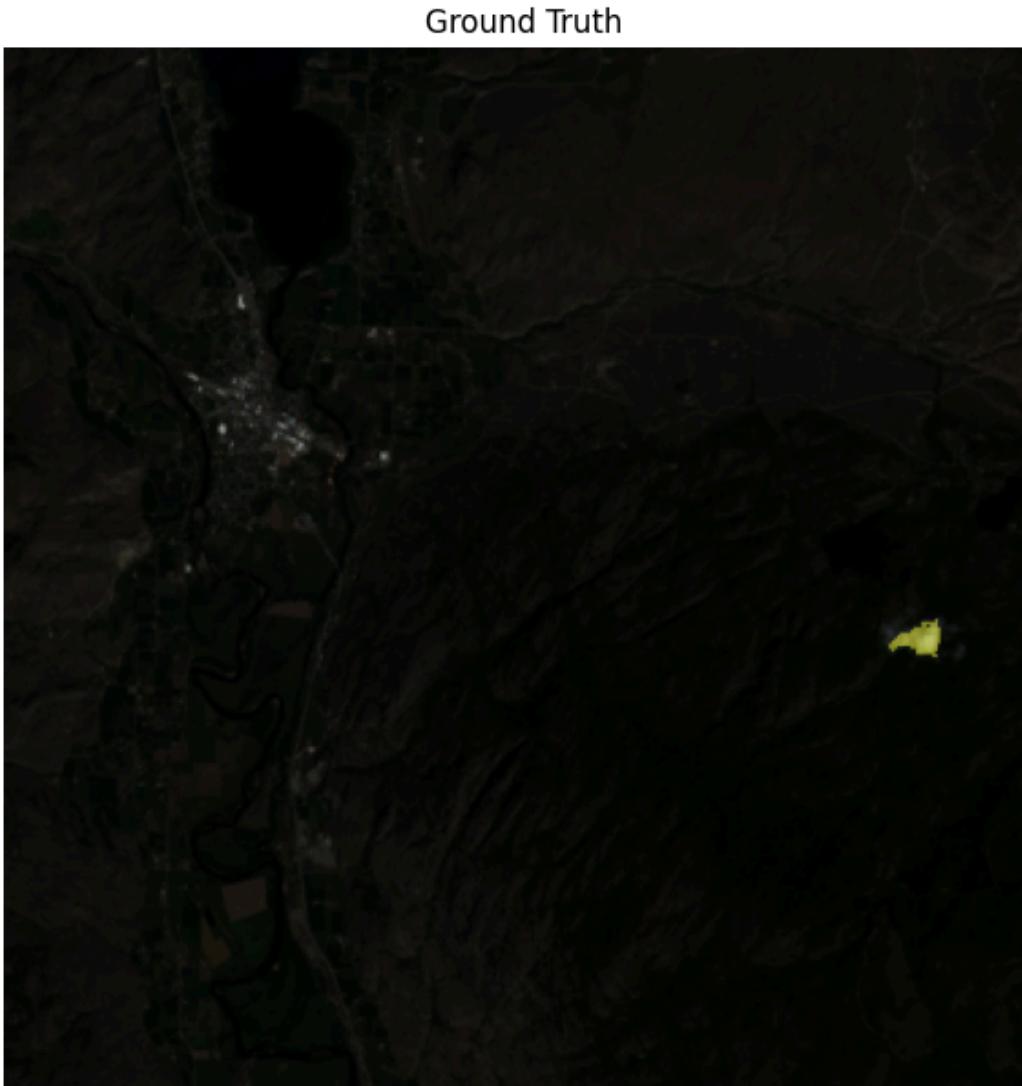
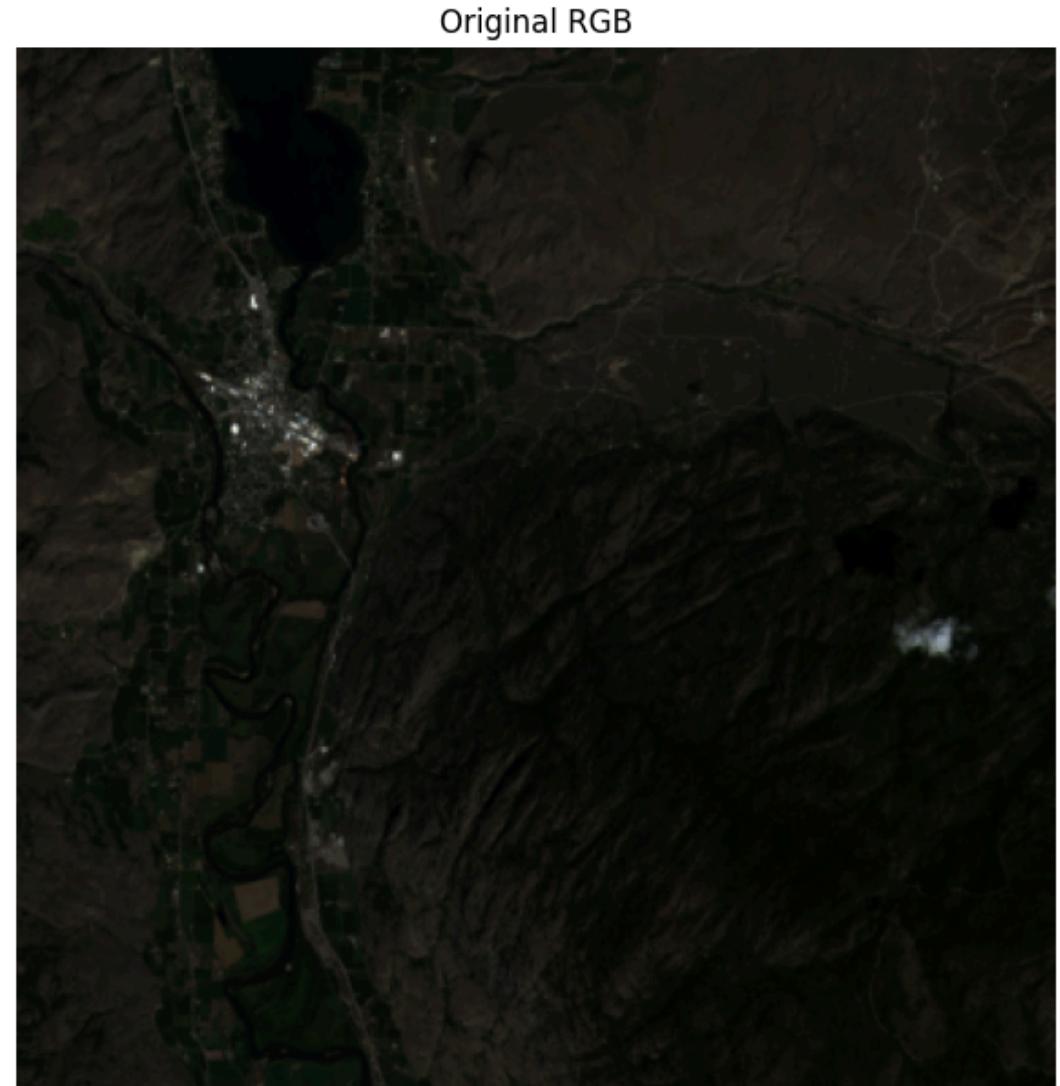
Table 2: Average Metrics with Denoising over 1000 images











# RESULTS

