MASTER THESIS

U-NET AND SATELLITE IMAGES FOR HAB MONITORING

ABOUT HABS

HABs are the development of bacteria at the surface of any water shelf. They form large patches of ‘surface scum’, which is an easily identifiable visual feature. HABs are a risk for the ecosystem and its dependants.

While HABs occur naturally with good weather and abundant nutrients, this phenomenon has expanded massively due to anthropogenic action. It is hence a grand challenge, and is part of SDG 6: ensuring water quality.

... AND REMOTE SENSING

Earth Observation

Remote sensing is the act of capturing data that represents a certain environment from a distance. Earth Observation is a major contributor to the field, with its range of satellites that capture the Earth's properties with high spatiotemporal resolution.

Machine Learning

Machine learning is widely used in the context of remotely sensed EO data. It allows for the automatic detection of migrant vessels in the Mediterranean, the forecast of ice sheet dispersion for arctic cargo ships, risk assessment for the eventuality of wildfires in an area...

HAB Context

Remote sensing has been largely adopted for HAB monitoring functions. HABs can be recognized by their spectral properties which are captured by satellite imagery. Algorithms are designed to extract this information and evaluate the presence of blooms.

RESEARCH MOTIVATIONS

REDUCE COSTS

HAB monitoring practices require almost holistically the capture of in-situ measurements. Doing this for a broad range of water shelves quickly becomes an economically important venture. Thus, it is of interest to find a solution that can easily be scaled and with little associated costs.

DEVELOP ML

Solutions that use machine learning and neural networks exist, though they are resource-intensive, location-locked and very rare. More general applications of HAB monitoring are still based on CI methods.

HELP NL

Limited array of tools for the Netherlands. The ‘waterschaps’ collect measurements for certain locations over the summer, there is one algorithm-based method that monitors the coast & lastly an app that allows citizens to report HABs near them. The country could seriously benefit from a consistent means of monitoring.

RESEARCH QUESTIONS

Will a U-Net model be able to recognize HABs well enough even with using simple, relatively unprocessed satellite imagery as training data?

Is the model generalizable? Is it preferable to focus model training and application on only one specific body of water or more, for a widely scalable application or a case-wise approach?

SOLUTION

Create 3 tasks: predict HABs for new images of a lake that was seen during training, predict for a new unseen lake & predict for Zeeland.

Code 2 models: one U-Net trained on one lake only & another trained on multiple lakes

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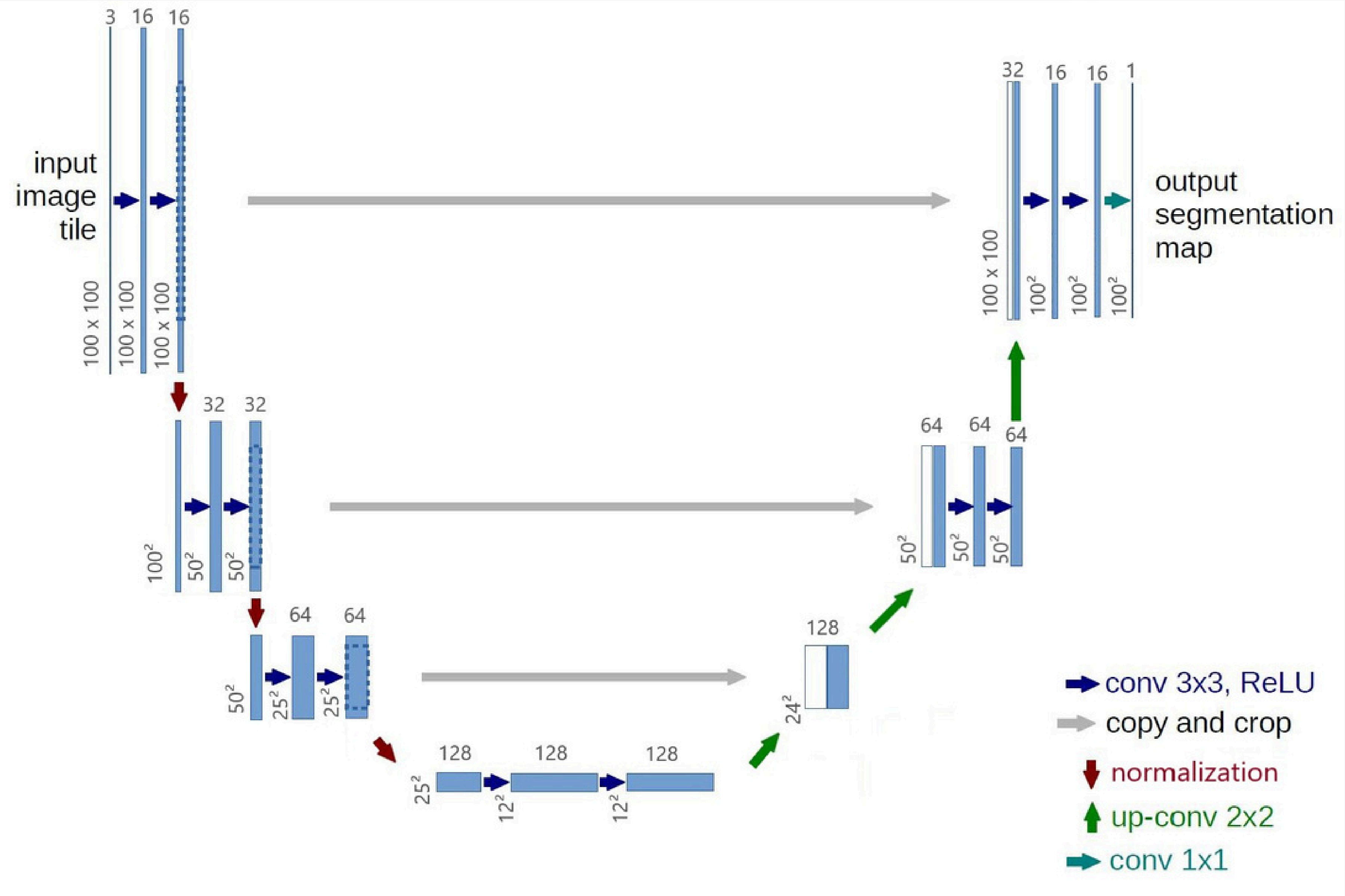
Assess performance, both qualitatively & quantitatively

MODEL

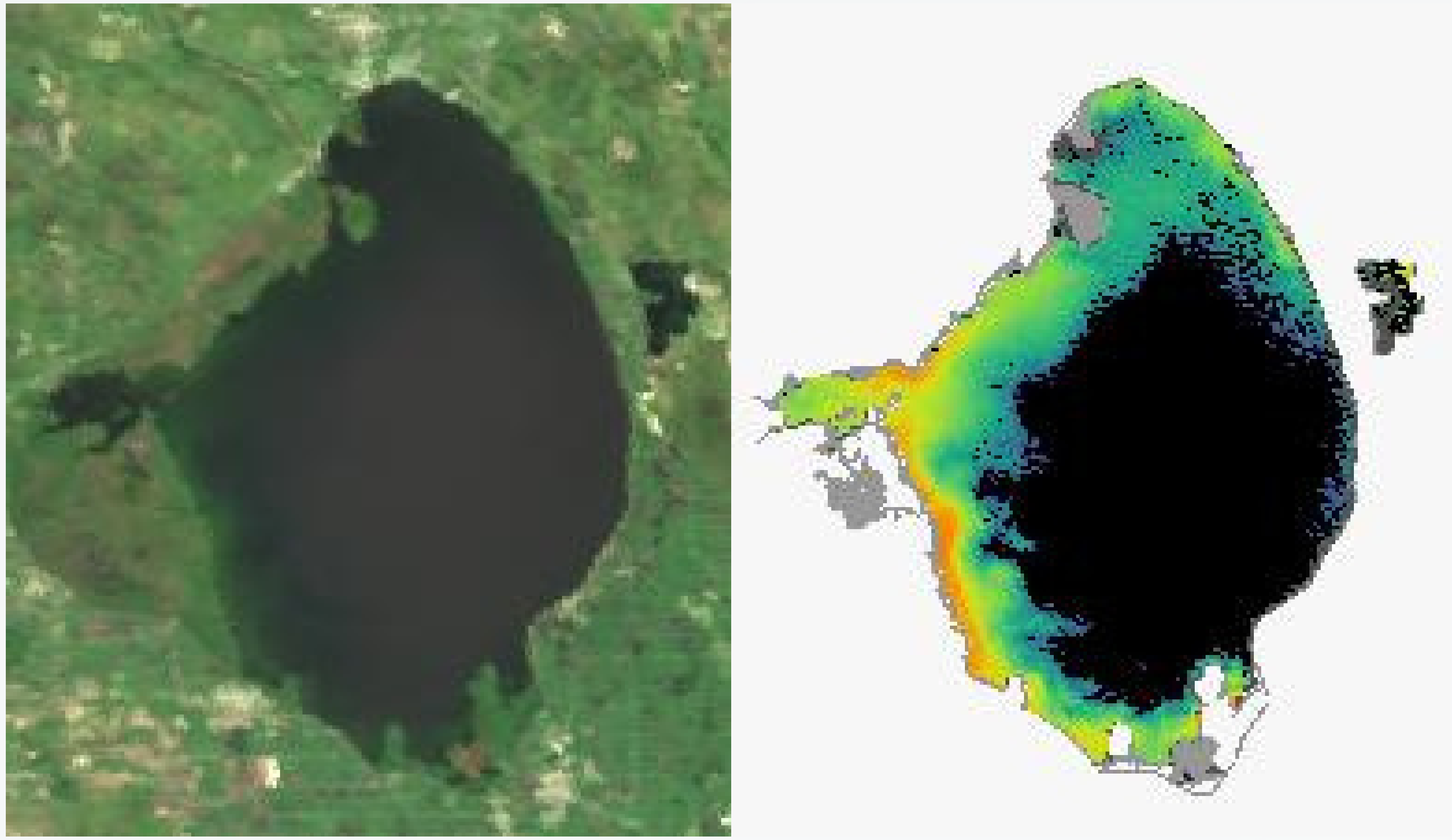


U-Net CNN

- Performs image segmentation
- Does not require extensive training dataset
- Includes skip connections
- Is assumed to be state of the art with regards to performing image segmentation, a key consideration to this study

DATA

Sentinel 3 Data

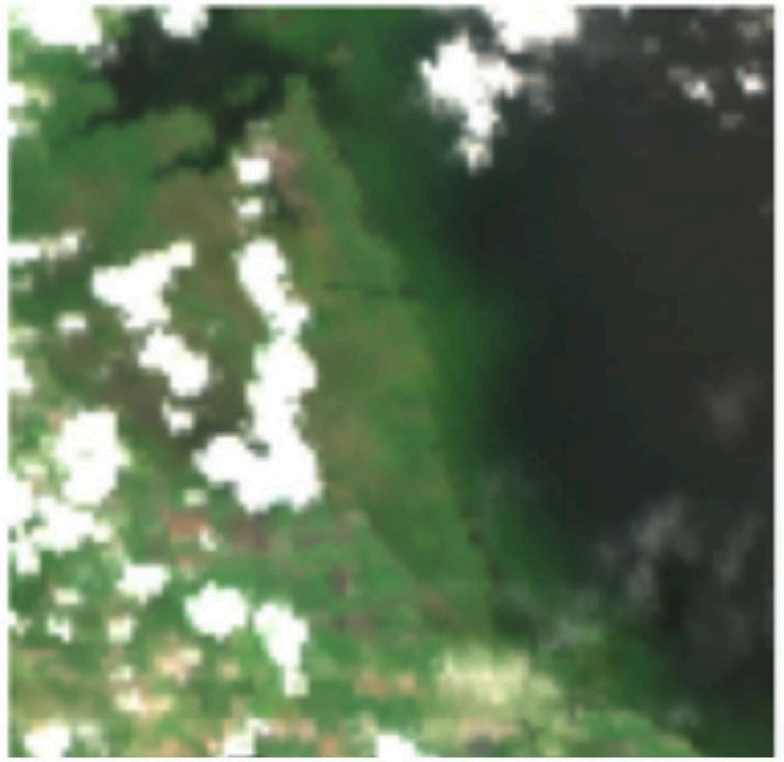


- NCCOS retrieved Sentinel 3 images
- Spatial resolution: 300m per pixel
- Temporal resolution: daily images
- Notable variance in images
- Includes segmentation mask
- Pre-processing steps included normalizing, tiling & augmenting

Region	Dimensions	N	Segmentation masks?
Lake Okeechobee 2022	196 x 225	366	Yes
Lake Okeechobee 2021	196 x 225	255	Yes
Lake Pontchartrain	650 x 323	130	Yes
Green Bay	410 x 537	83	Yes
Albemarle Sound	530 x 673	103	Yes
Anna Jacobapolder	100 x 100	8	No

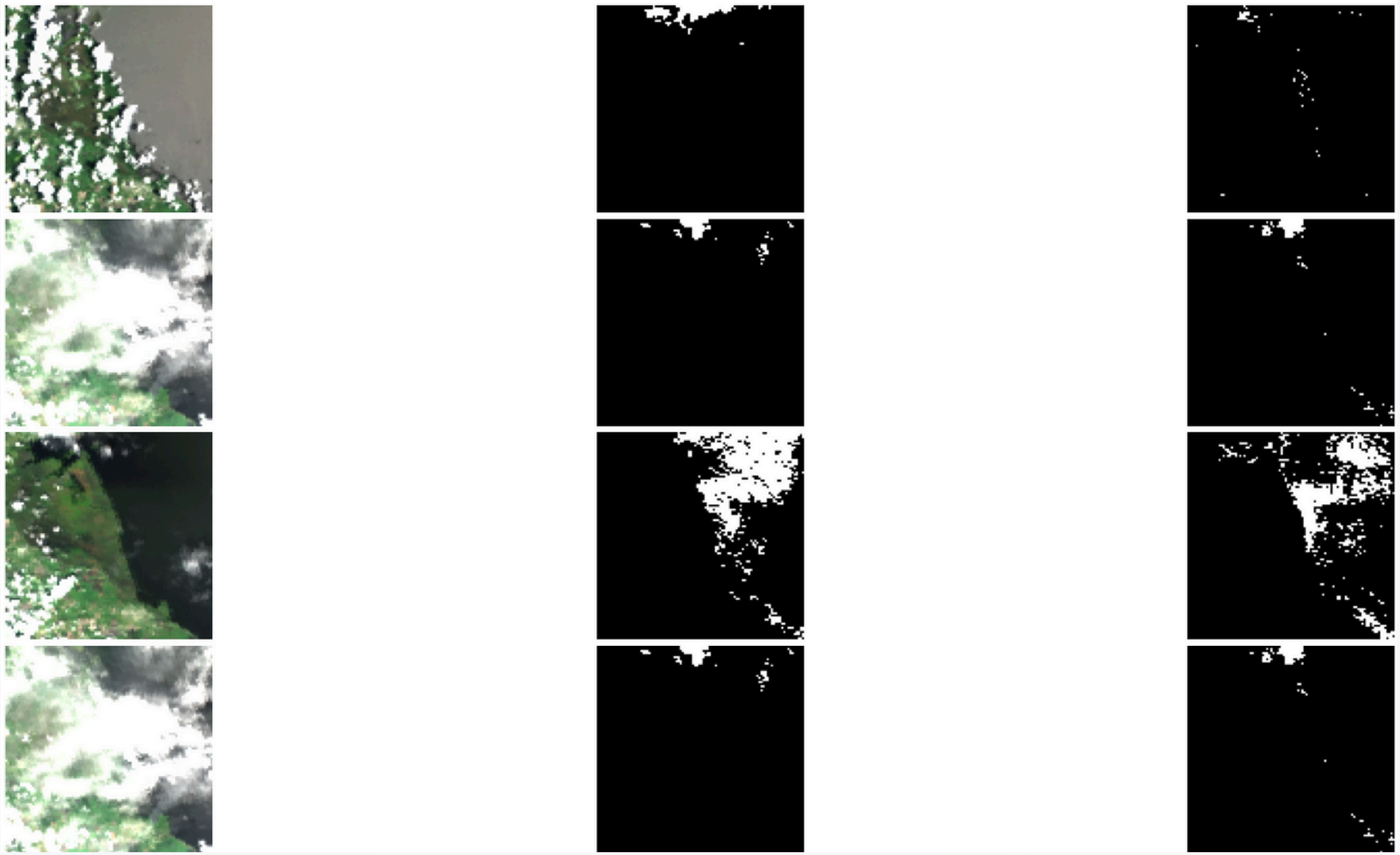
DATASETS

Processed Data



Regions	N	Training/Testing?
Okeechobee 2022	996	Training
Multi-lake	812	Training
Okeechobee 2021	273	Testing
Albemarle Sound	740	Testing
Anna Jacobapolder	8	Testing

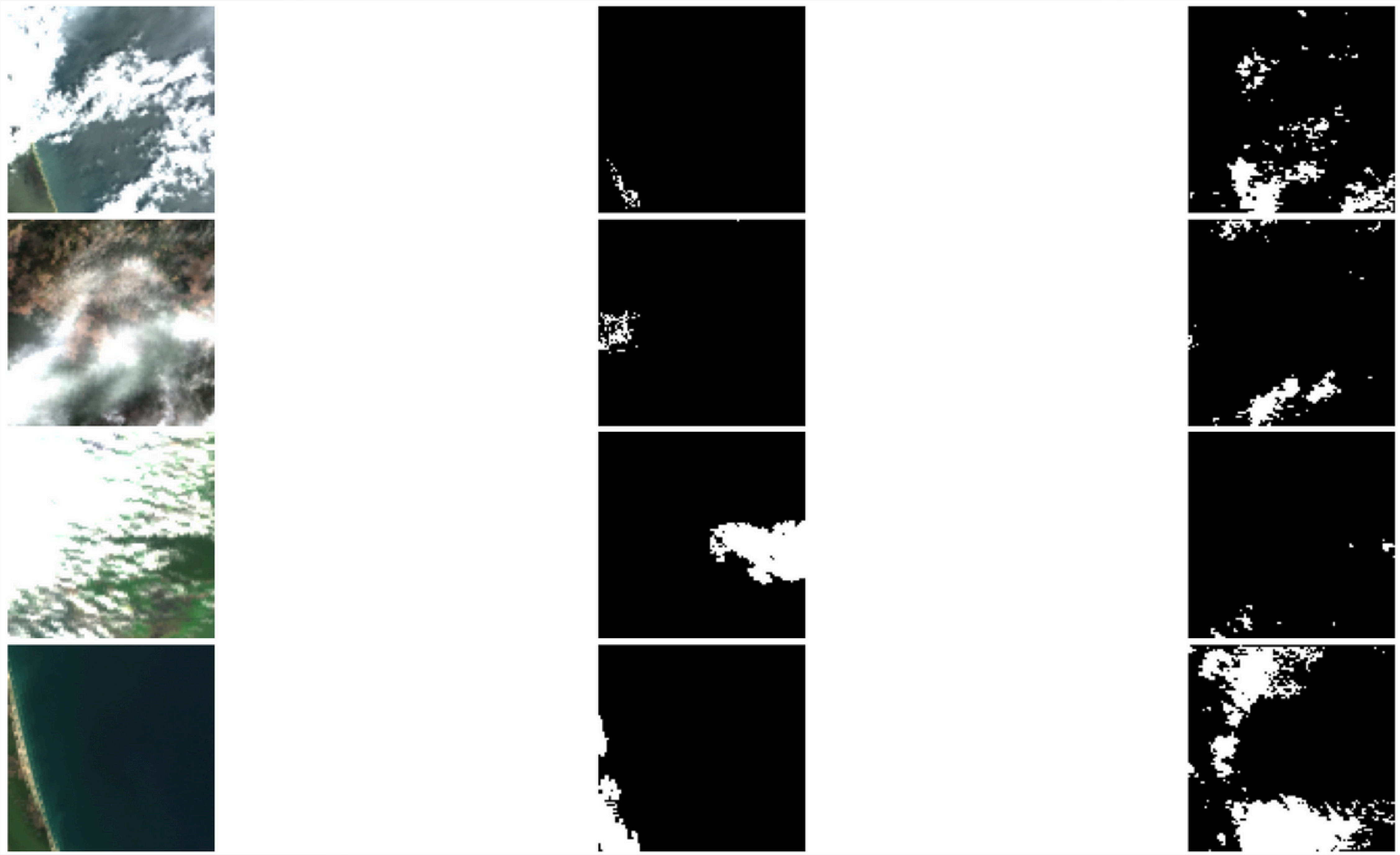
RESULTS - MODEL 1



Metric	Task 1	Task 2
Pixel Accuracy	0.951	0.869
IoU	0.941	0.963
Dice	0.387	0.053

Table 4: Model 1 Results

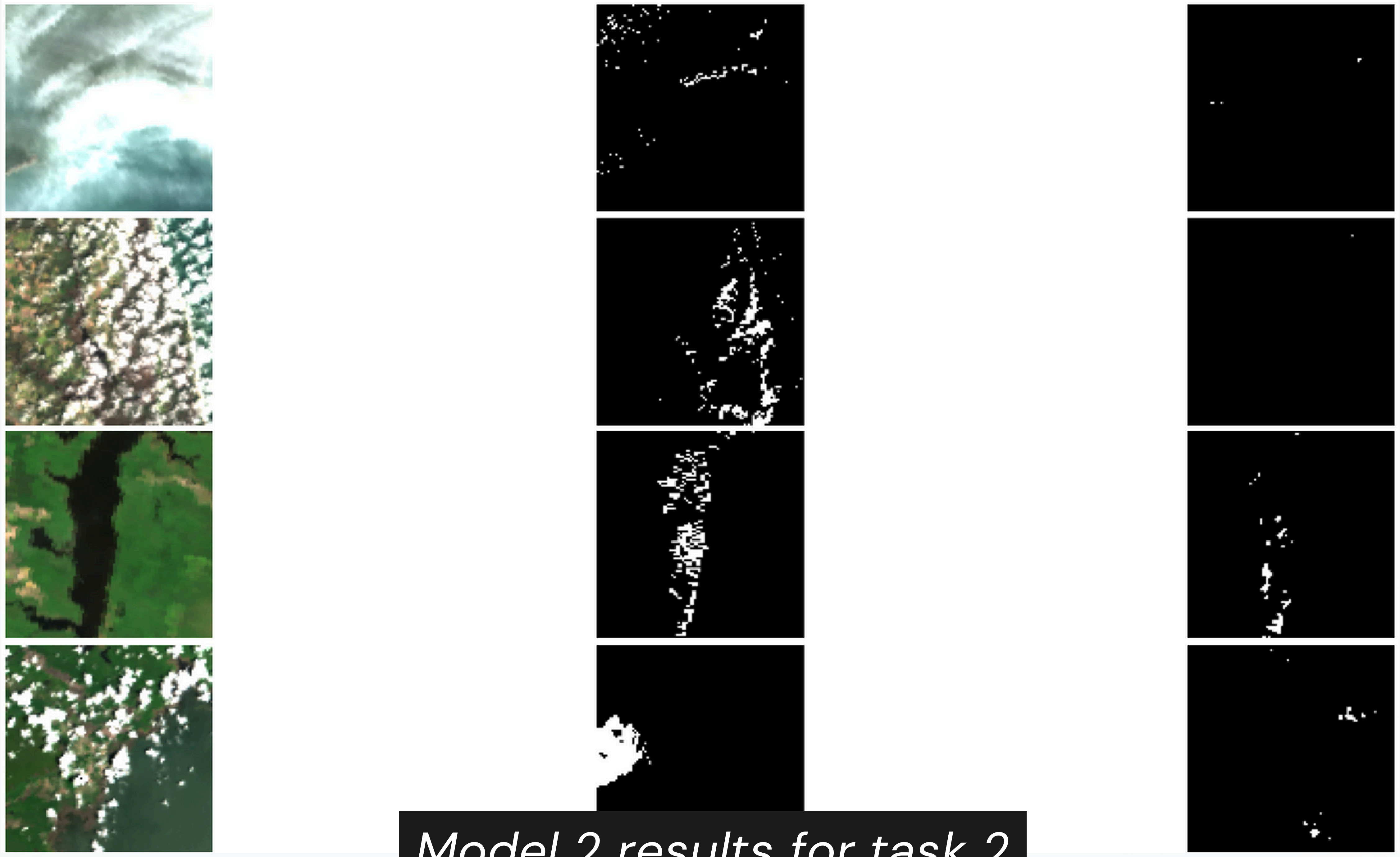
RESULTS - MODEL 1



Metric	Task 1	Task 2
Pixel Accuracy	0.951	0.869
IoU	0.941	0.963
Dice	0.387	0.053

Table 4: Model 1 Results

RESULTS - MODEL 2



Model 2 results for task 2

ANSWERS

- First, simple implementation of U-Net is indeed able to predict HABs well
- However, it cannot be said that is easily scalable in its current state
- Additionally, M1 outperforms M2, which advocates for consistency in training data aspect

Metric	Task 1	Task 2
Pixel Accuracy	0.951	0.869
IoU	0.941	0.963
Dice	0.387	0.053

Table 4: Model 1 Results

Metric	Task 1	Task 2
Pixel Accuracy	0.943	0.951
IoU	0.936	0.958
Dice	0.351	0.021

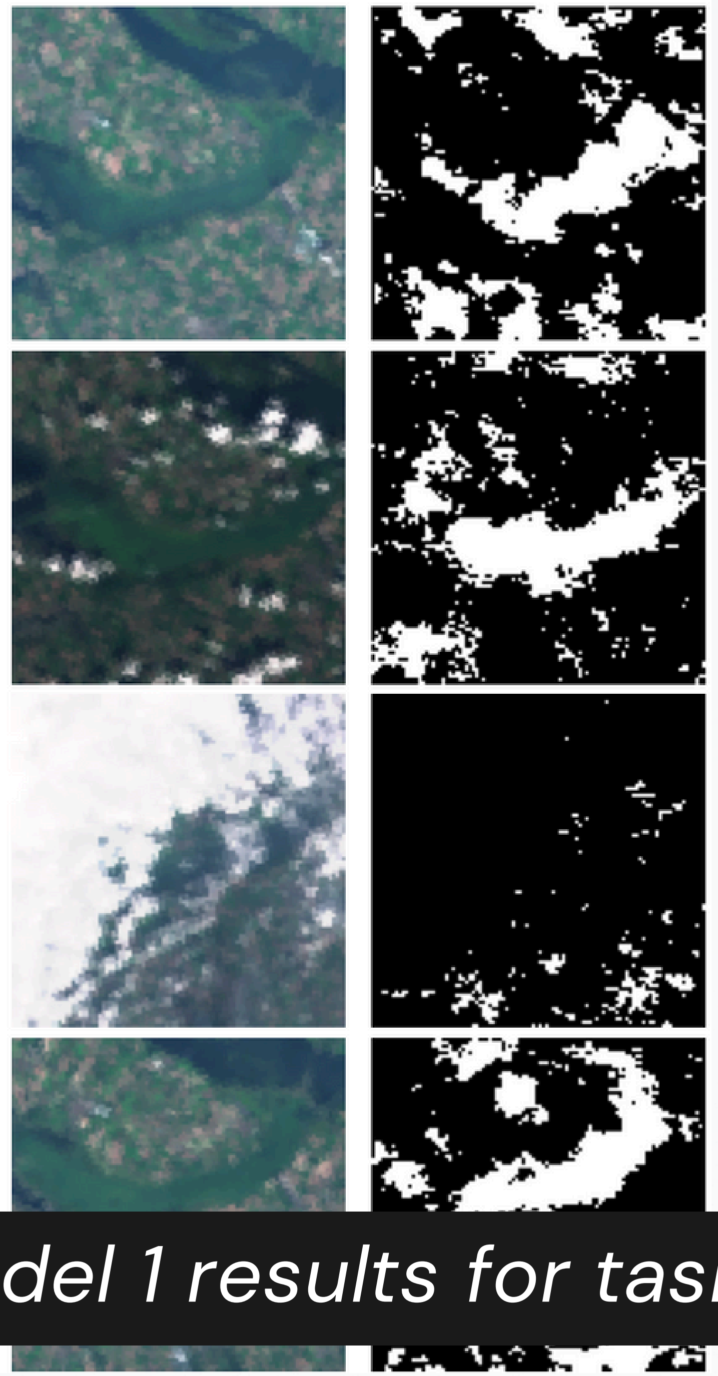
Table 5: Model 2 Results

LIMITATIONS

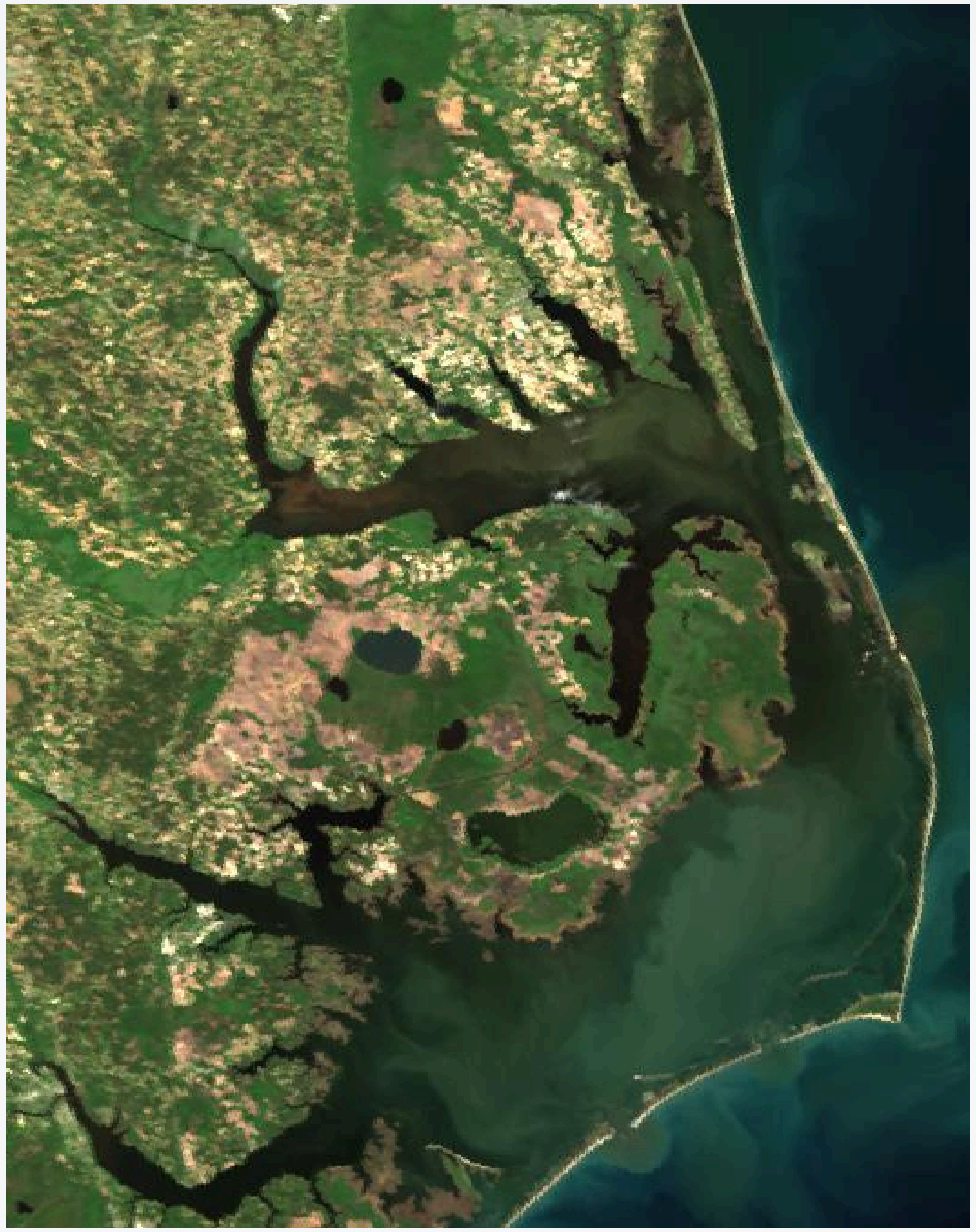
- Lack of geoscientific pre-processing
- Topography variance and tile selection
- Model sophistication
- Availability of ground truths
- Sentinel 3 resolution
- U-Net inflexibility

RECOMMENDATIONS

- Implement geoscientific pre-processing: **homogenize**. Remove cloud cover, normalize terrain etc.
- Ensure rigorous tile selection
- Deepen layers of the model, increase filters
- Use Sentinel 2, albeit would entail using a different model & methodology
- Region-wise approach
- Post-processing: Conditional Random Fields



Model 1 results for task 3



THANK YOU FOR YOUR ATTENTION!