National Aeronautics and Space Administration

Harmonizing SAR and optical data to map surface water extent: a deep learning approach

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OPERA

1. Introduction

Surface water is a highly dynamic component of the water cycle. Time varying information on the location and extent of surface water is critical for hydrologic science, water resource management and disaster response.

The JPL Observational Products for End-Users from Remote Sensing Analysis (**OPERA**) project will develop and provide two near-global Dynamic Surface Water Extent (**DSWx**) products, one each using synthetic aperture radar (SAR) data (Sentine-1, NISAR), and optical data (Sentinel-2, Landsat).

2. Harmonizing SAR and optical data

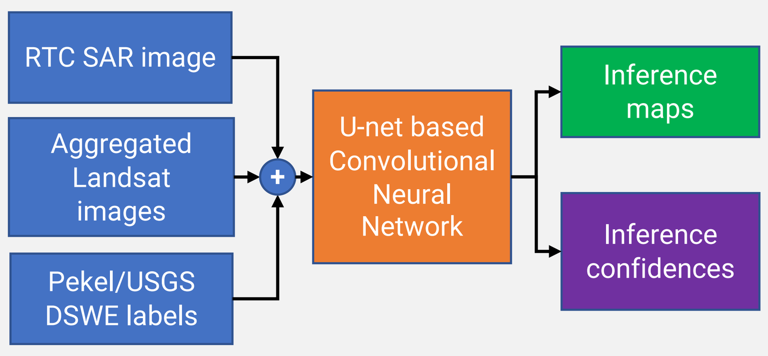
The ability of SAR to penetrate through cloud cover gives it an advantage over optical measurements, but the data also requires careful interpretation in order to avoid false positive detections of water surfaces. Harmonized SAR and optical datasets provide the advantages of both sensor types and are valuable for generating time series maps of water extent.

3. Using machine learning to detect open water

While expert-determined thresholds are typically determined on a per-scene basis to generate water maps, it is possible to combine the large corpus of available satellite imagery with machine learning techniques to produce inferences more accurately and efficiently.

Here, we demonstrate the ability of neural networks to ingest harmonized SAR and optical imagery and detect open water surfaces for a number of different scenes at the spatial resolution of SAR images, with the eventual goal of generating accurate global open surface water and inundation maps.

We train a convolutional neural network on a large number of 512x512 pixel image stacks, containing SAR, optical, and terrain elevation information. Ground truth labels for the models are derived from Landsat imagery, either in the form of water occurrence data or publicly available data products such as the USGS Dynamic Surface Water Extent maps.



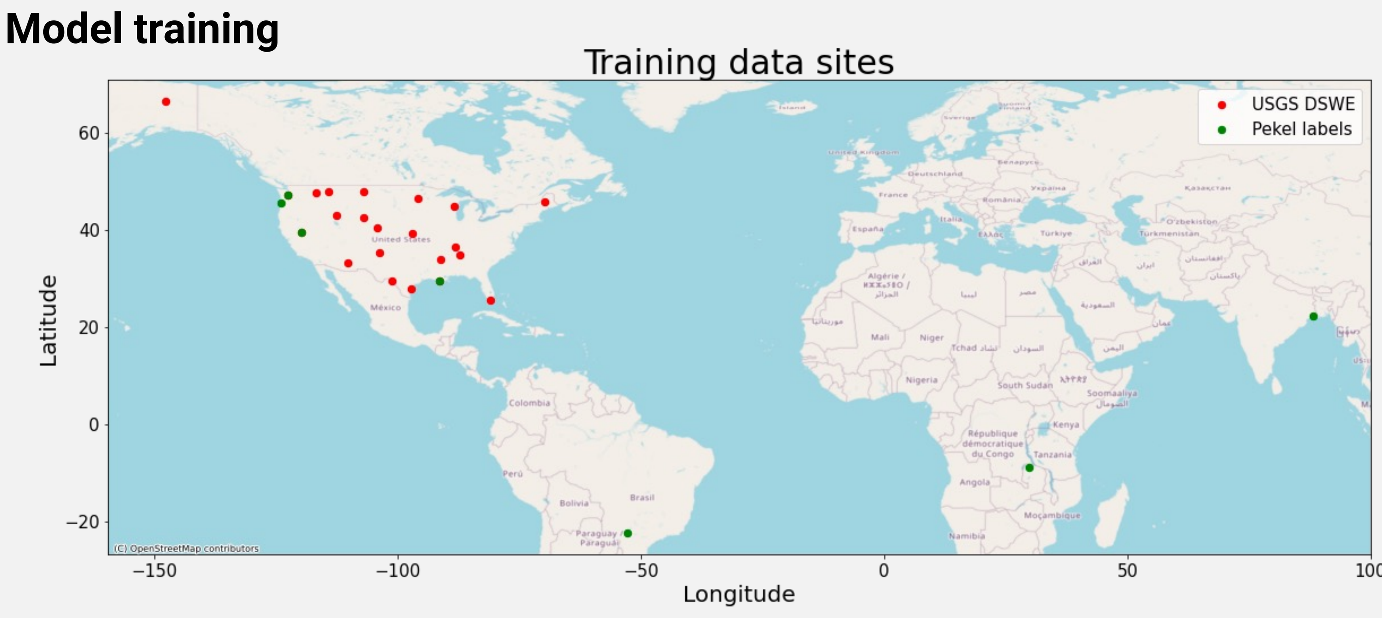
Generating confidence maps

Along with inference maps, model confidences can be derived by applying a softmax function to the model out

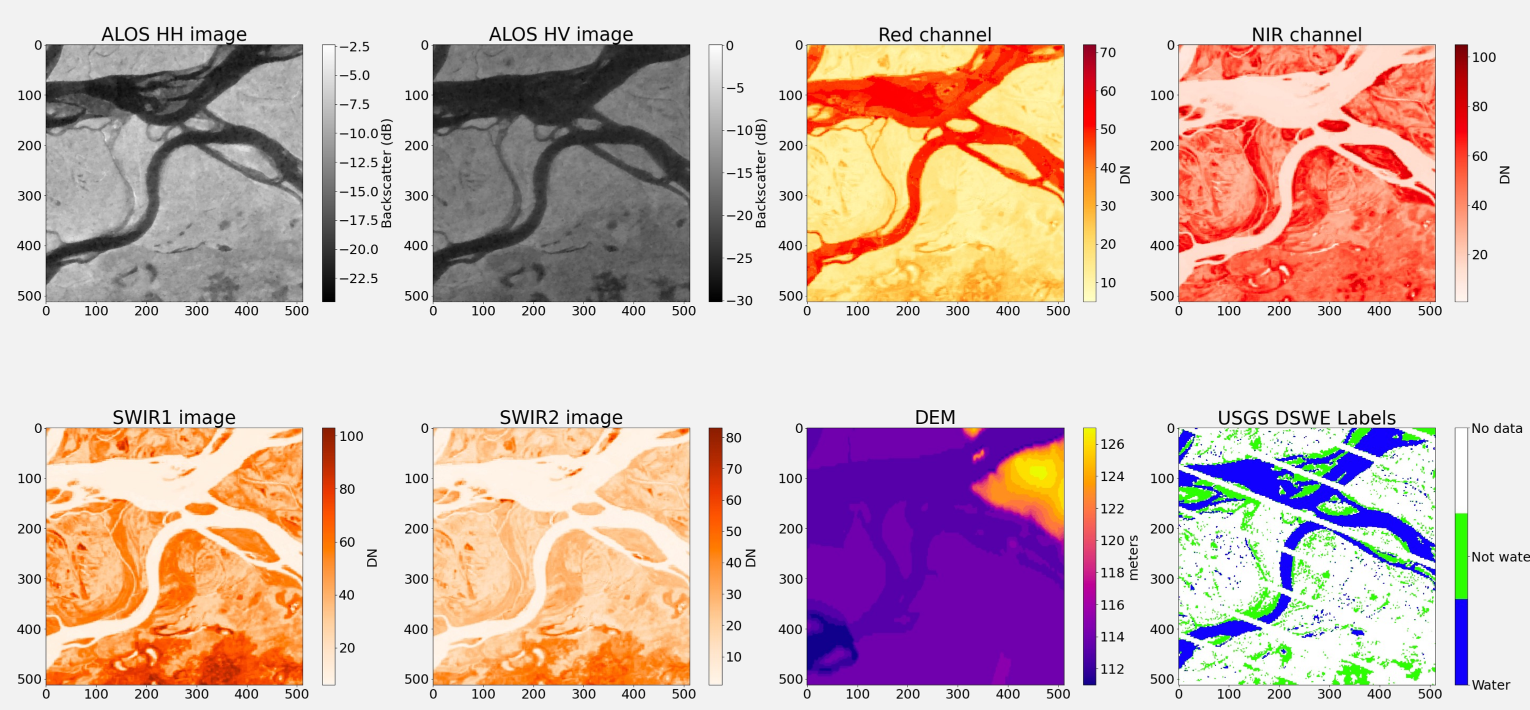
$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Model Parameters	Value
Network architecture	U-net + ResNet50
Model inputs	HH, HV, Red, NIR, SWIR1, SWIR2, DEM
Ground Truth	USGS DSWE/Pekel water occurrence
Loss function	Categorical Cross-Entropy
Initialization weights	imagenet
Data transforms	Denoise SAR, image augmentation

4. Model training

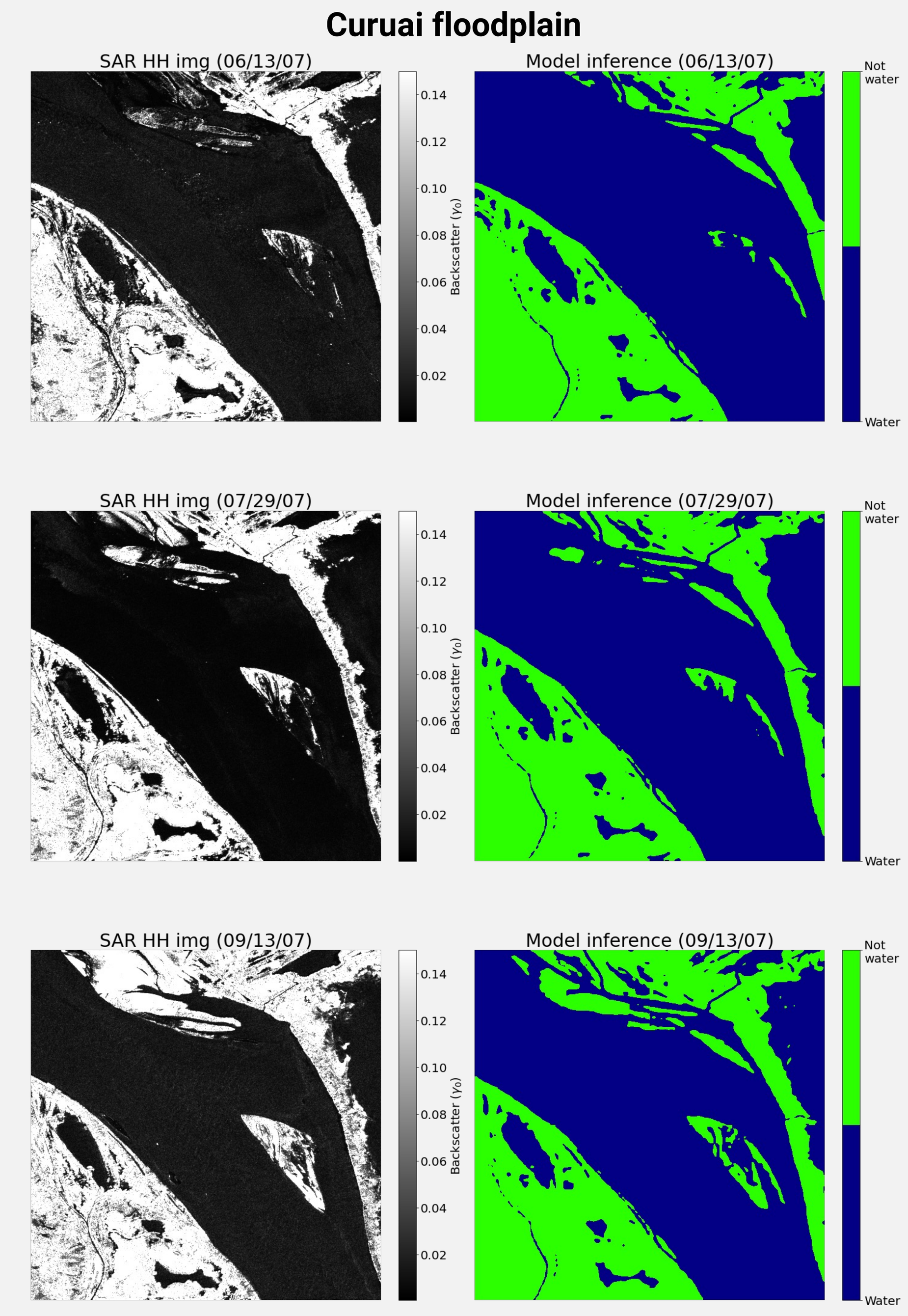


Sample input image stack and training labels

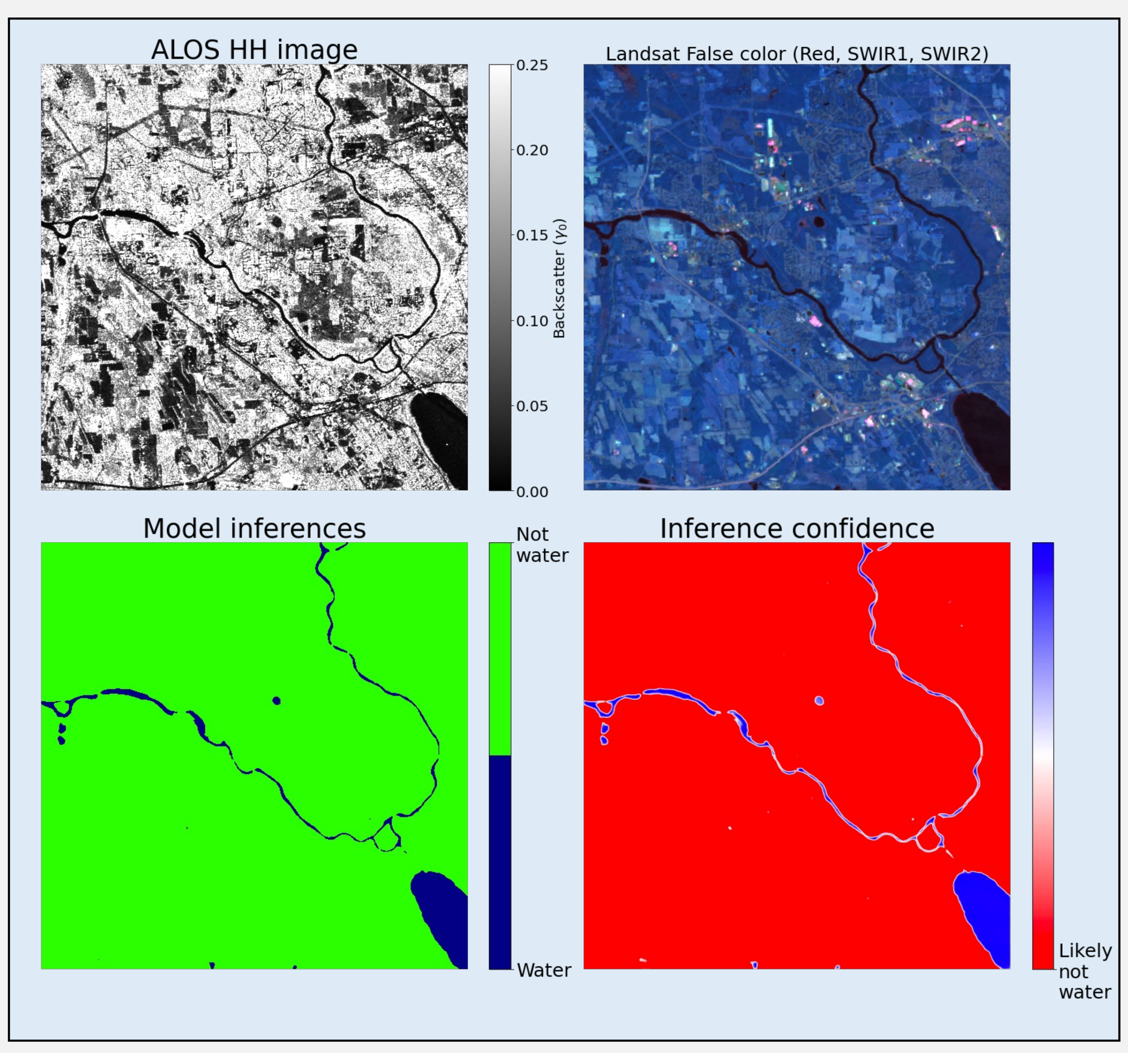


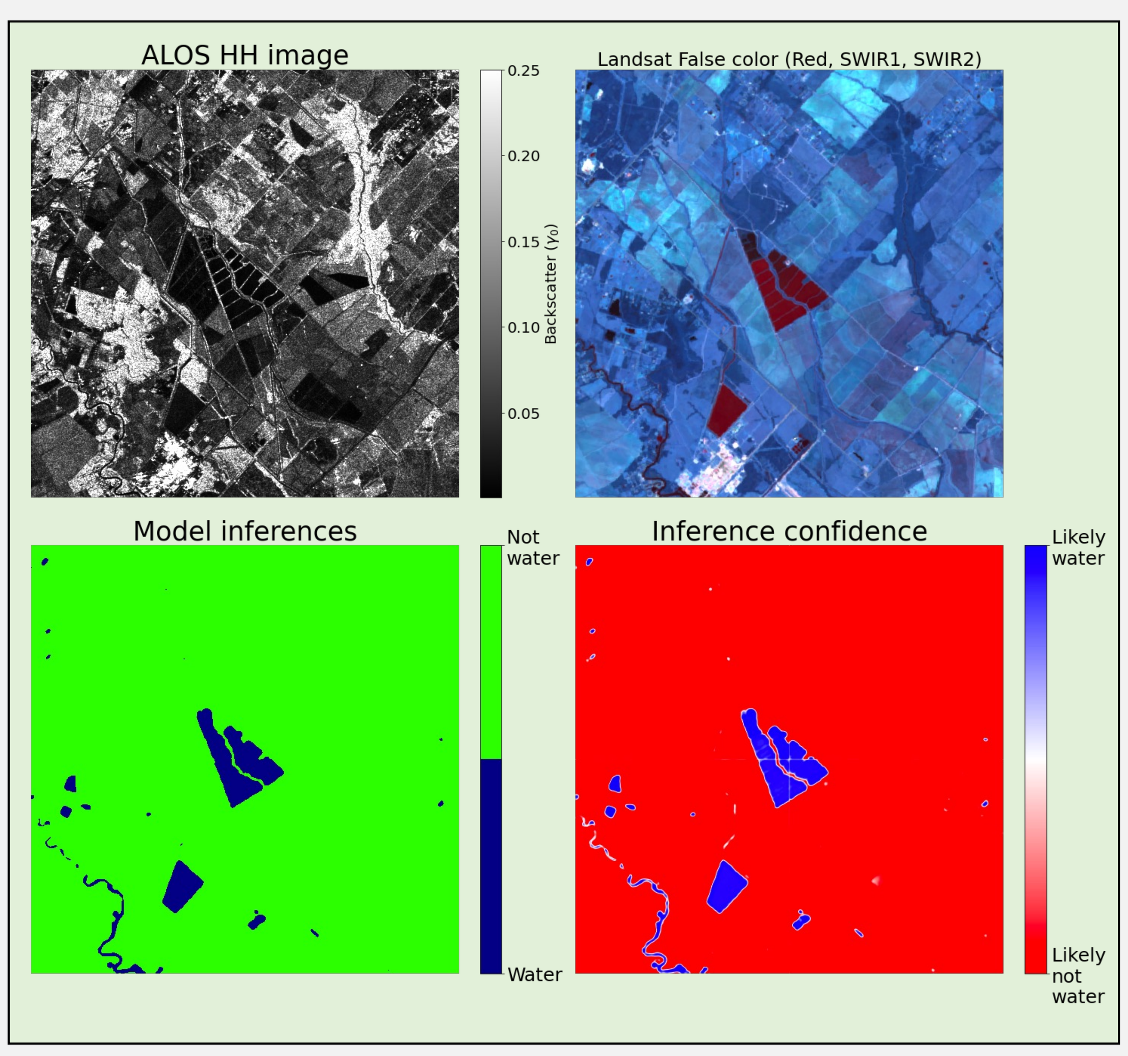
5. Time series inferences

Curuai floodplain

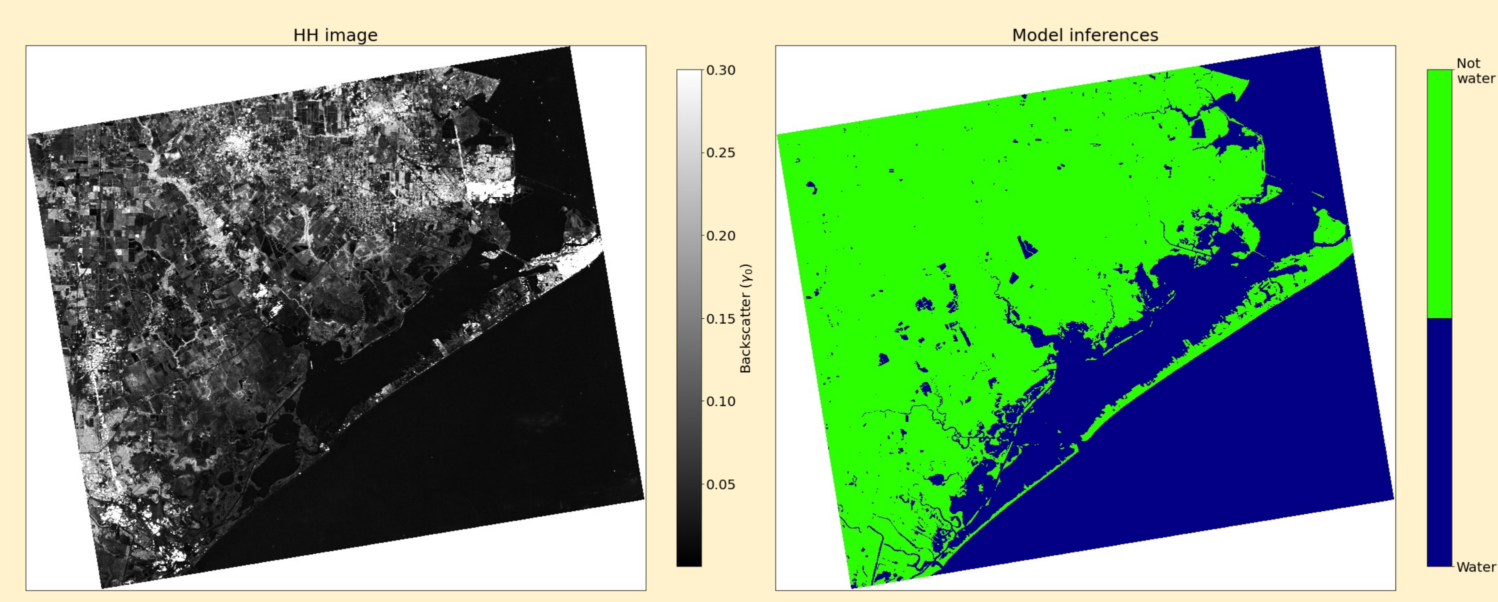


6. Sample inferences

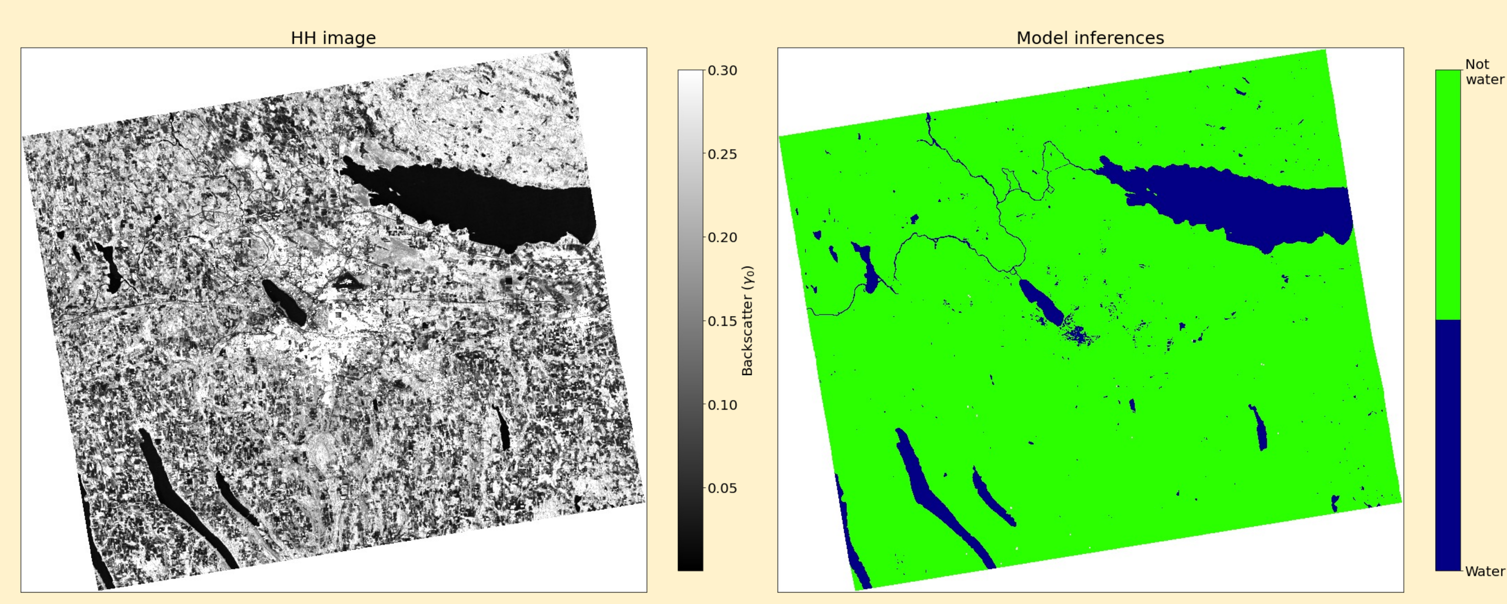




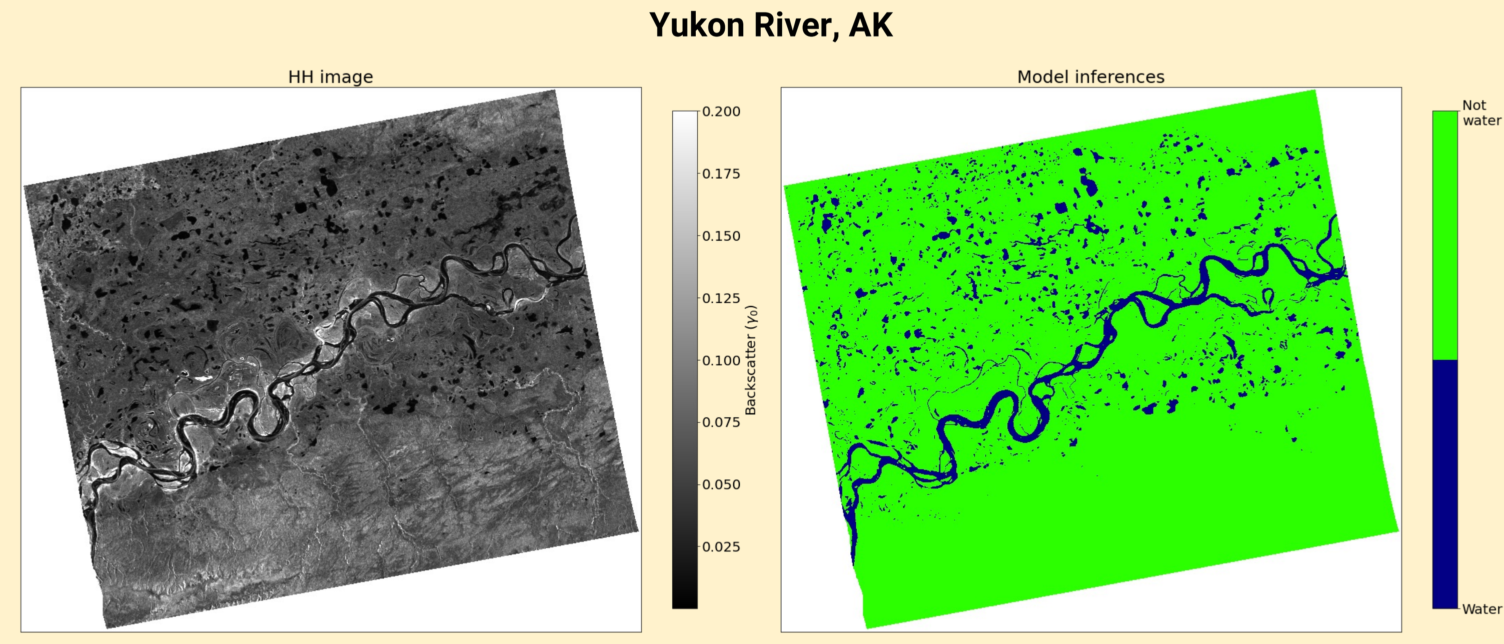
Galveston, TX



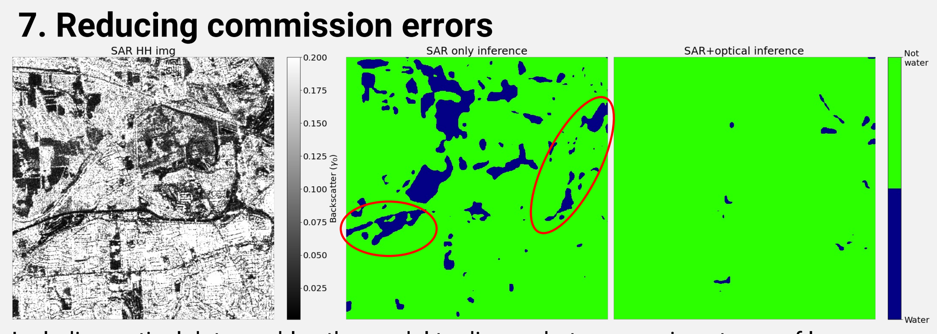
Lake Oneida, NY



Yukon River, AK



7. Reducing commission errors



Including optical data enables the model to discern between various types of low-backscatter regions in the SAR data, thus helping reduce false positive detections of water surfaces.

8. Future work

1. Incorporate additional classes (inundated vegetation, partial water)
2. Extend to additional SAR and optical sensors (Sentinel 1/2, UAVSAR, NISAR)

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Poster Number: **PRD-EB#011**