Developing a Multimodal AI Framework for Wetlands Mapping with Multi-Sensor Earth Observation Data

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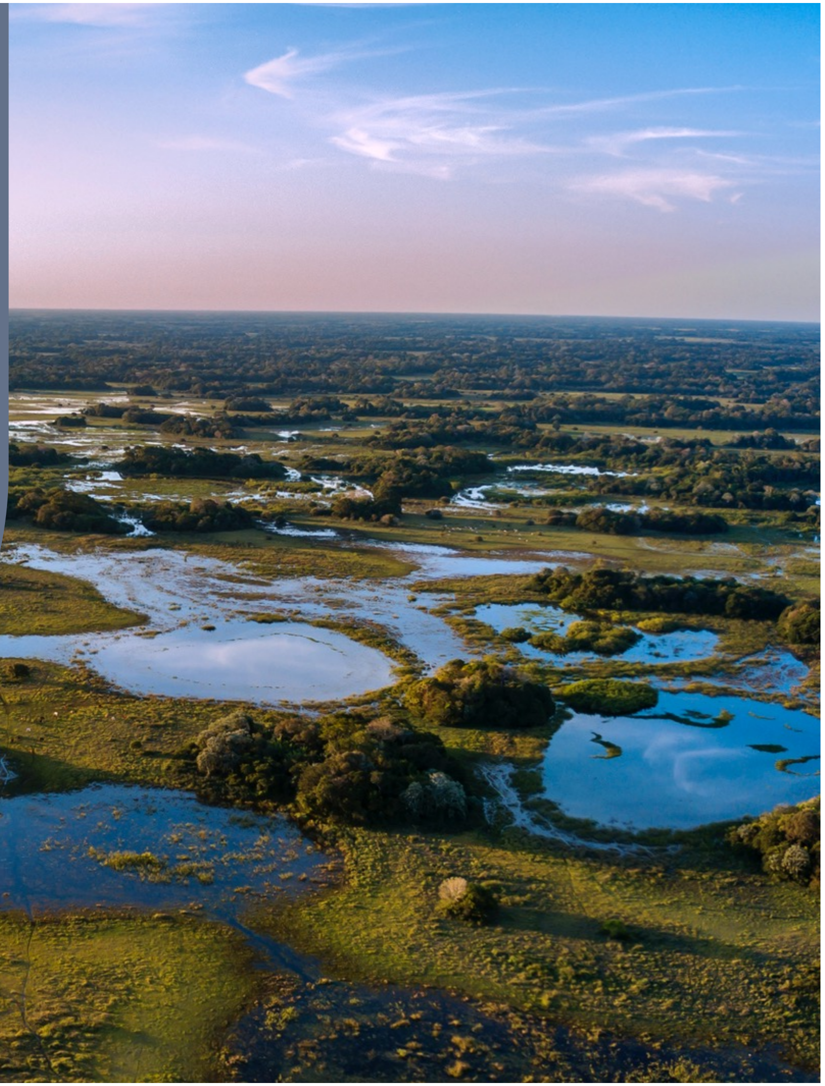
2 NEODAAS

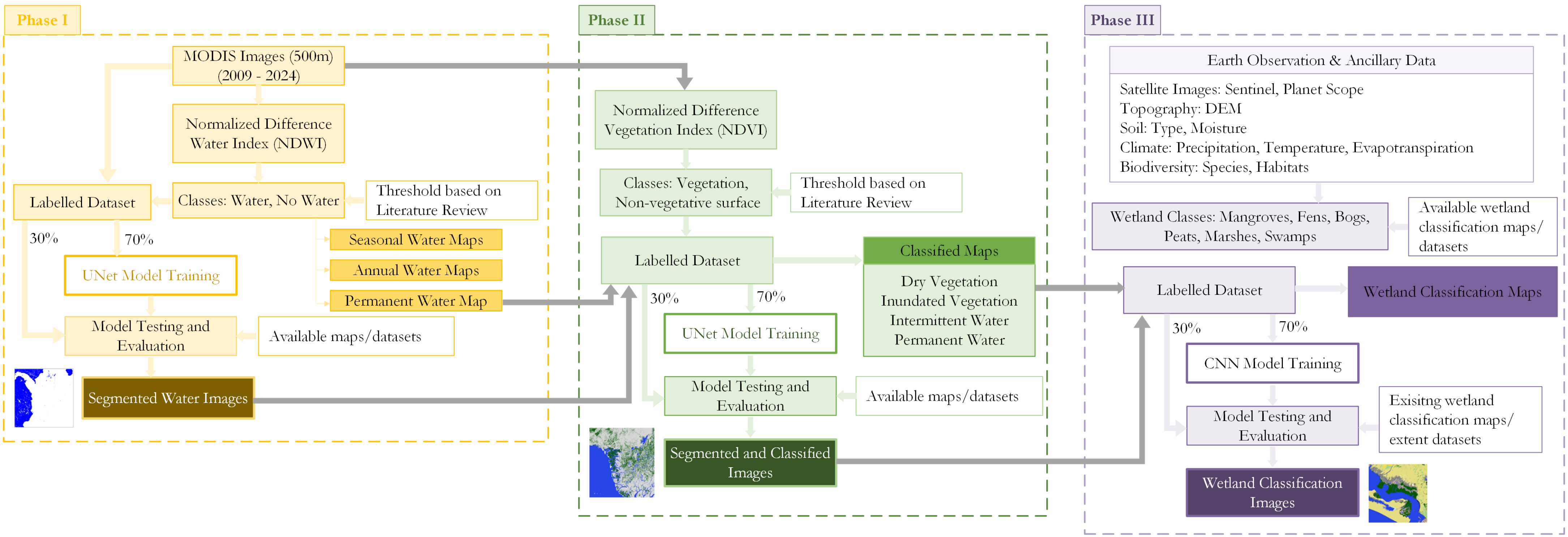


Introduction

- Methane is a greenhouse gas that traps heat in the atmosphere with over 25 times the warming power of CO_2 over a 100-year period, making it a major driver of climate change.
- Wetlands cover just 6% of Earth's Surface. However, they are the largest natural resource of methane.
- Despite their essential roles in carbon storage, water filtration, and climate regulation, ~ 2/3rd of these ecosystems have disappeared since the early 20th century.
- Loss of wetlands introduces significant uncertainties in global methane flux models, which rely on accurate, high-resolution wetland data.
- Accurate mapping of wetlands is challenging as they are spatially complex and temporally dynamic, permanent or seasonal, and support diverse vegetation that varies with topography, temperature, and climate.
- Traditional mapping approaches struggle to capture these fine-scale variations, yet such detail is crucial for understanding methane emissions accurately.
- We are developing an AI-based framework to address this gap by using multi-source Earth Observation data to segment and classify wetlands.

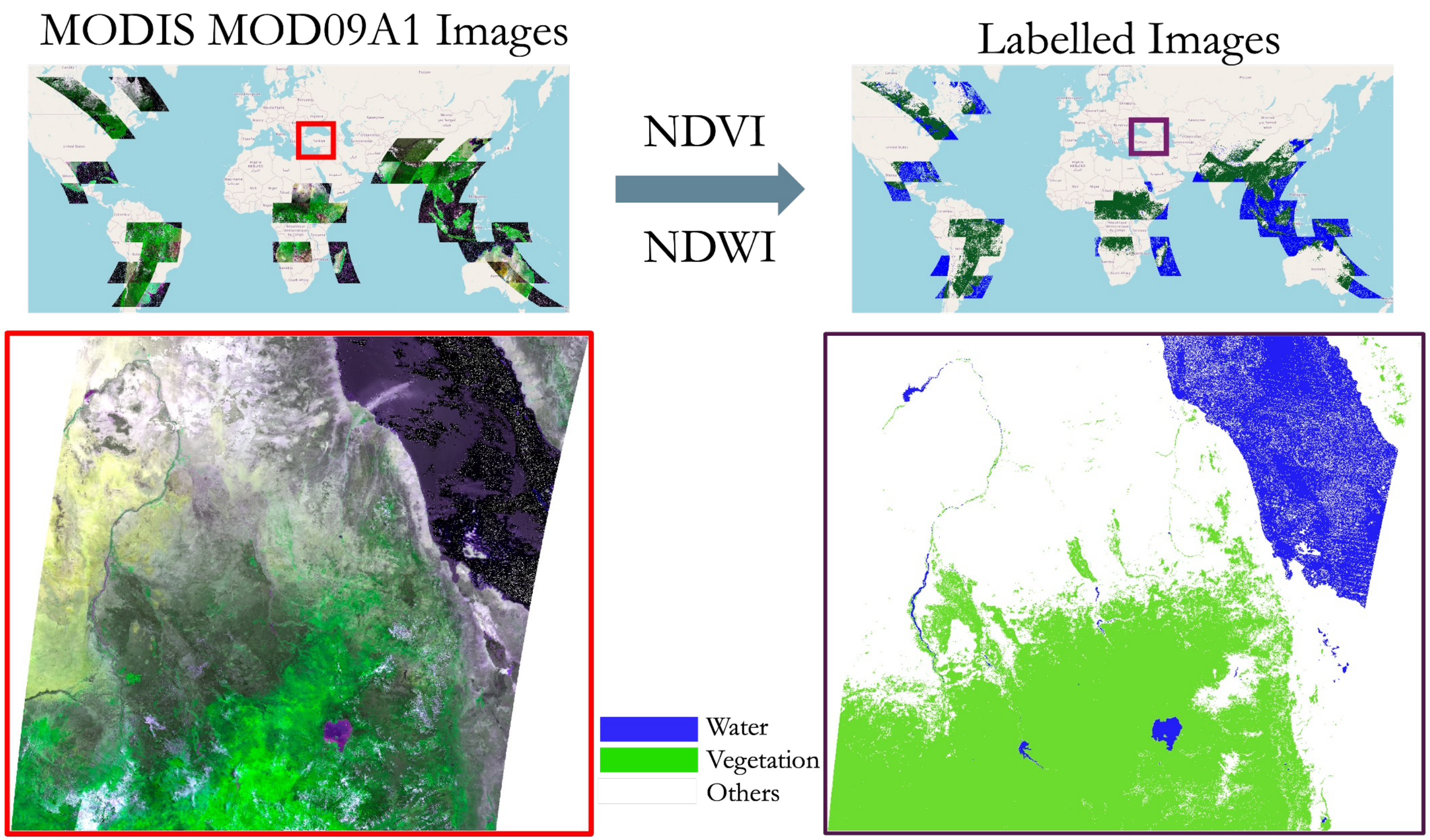
Planned Workflow

- We developed a three-phase AI workflow to segment and classify wetlands
- Current focus is on mapping water and vegetation to produce seasonal, annual, and permanent water maps, along with water-vegetation maps.
- The final phase will cover detailed wetland classification using high-resolution earth observation data.



Preprocessing

- Spectral indices (NDVI and NDWI) derived from MODIS MOD09A1 were used to classify pixels as water and vegetation based on histogram thresholding technique.



Bands: G, R, NIR, SWIR

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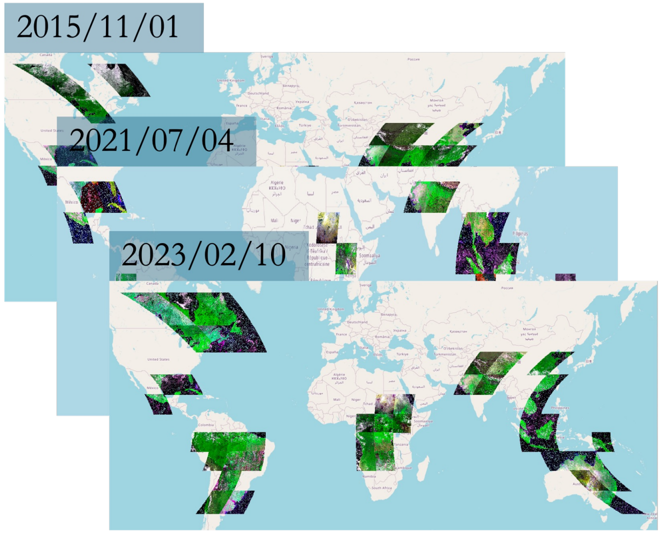
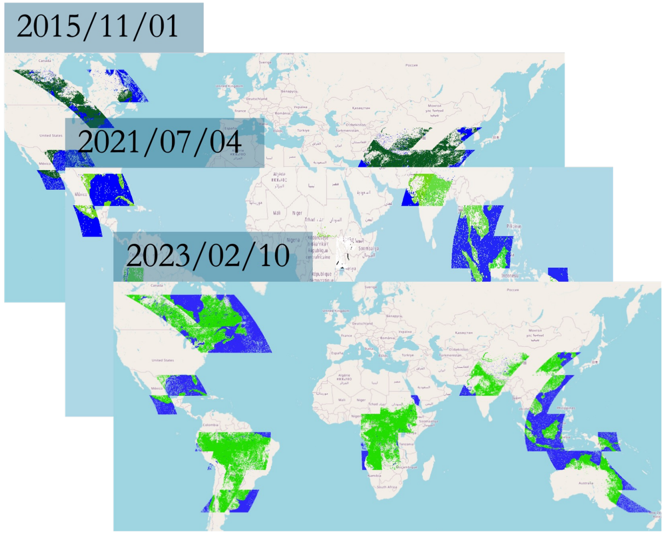
Model Training

The labelled data were tiled into 256 x 256 pixels patches, augmented, and was used to train six deep learning models.



MODIS MOD09A1 Images



Labelled Images

Trained Models

- UNet
- UNet++
- DeepLabV3+
- SegNet
- PSPNet
- FPN

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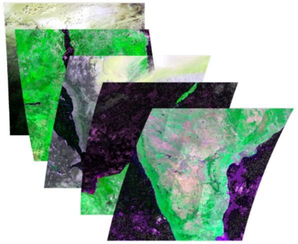
Model Evaluation

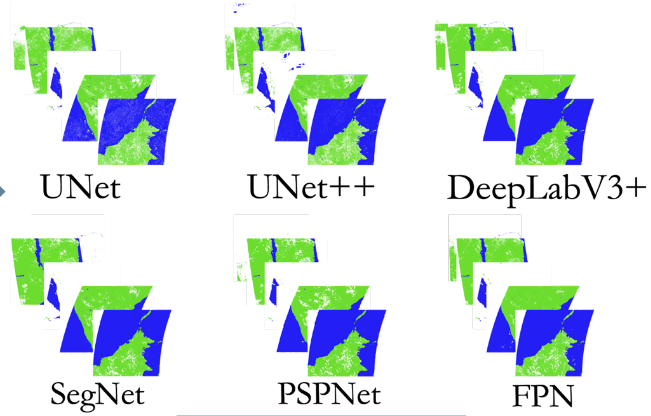
UNet model performed best with the highest overall accuracy and highest confidence scores for individual classes.



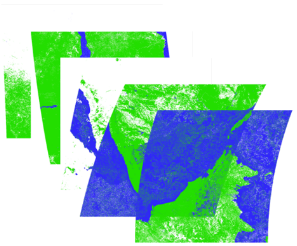
Test Images

Trained Models

- UNet
- UNet++
- DeepLabV3+
- SegNet
- PSPNet
- FPN



Predictions



Ground Truth

Model	Overall Accuracy	Confidence Score		
		Water	Vegetation	Other
UNet	0.92	0.87	0.76	0.92
UNet++	0.90	0.82	0.74	0.89
DeepLabV3+	0.87	0.81	0.68	0.85
FPN	0.89	0.82	0.71	0.86
PSPNet	0.87	0.74	0.58	0.86
SegNet	0.90	0.80	0.72	0.87

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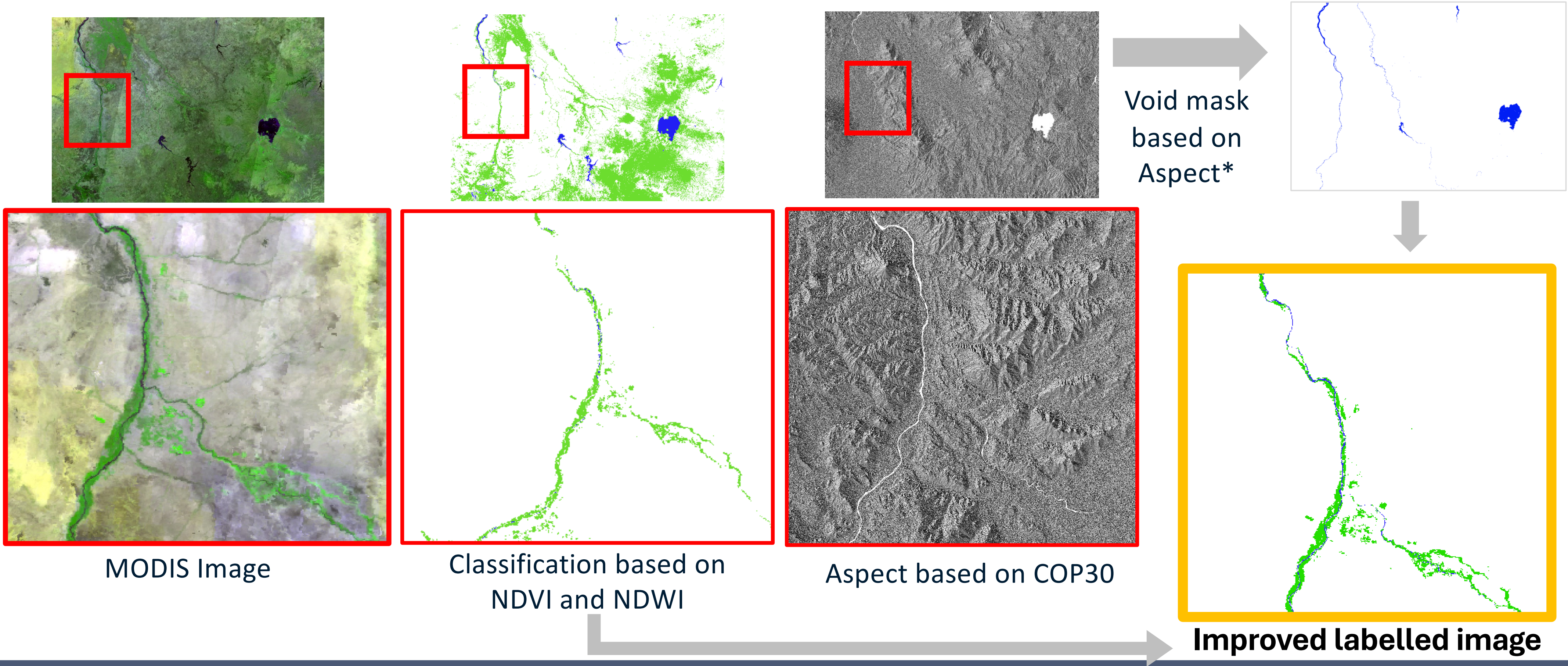
Labels Refinement

Despite good overall performance, models struggled to identify thin water channels and smaller water bodies. Aspect (topographic gradient) derived from Copernicus GLO-30 DEM was used to improved the labelled data



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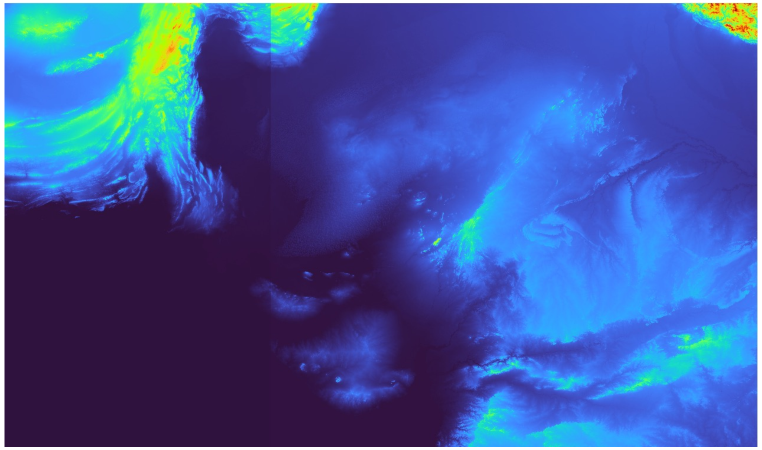
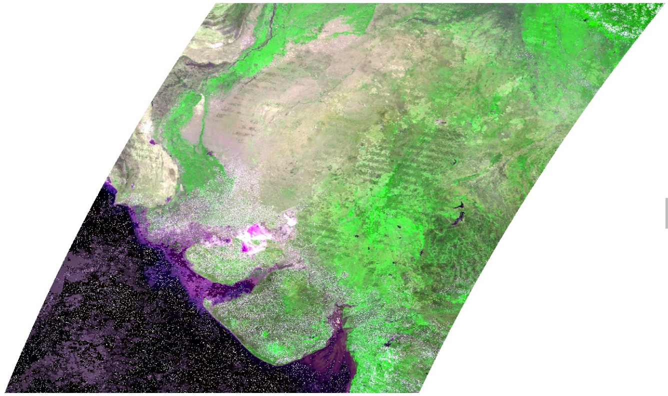
DEM Resampling

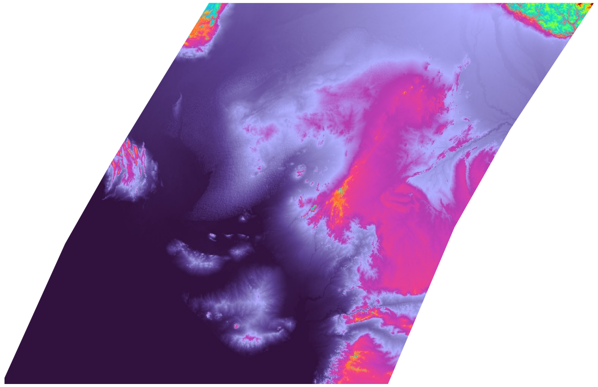
DEM based on COP30m was resampled to 500m resolution using averaging technique.



COP 30m DEM



Reference MODIS Image



DEM resampled to 500m

Model Re-Training

To improve models' prediction capabilities, DEM was included as an additional channel along with the MODIS 4 bands and improved labelled images to train the model

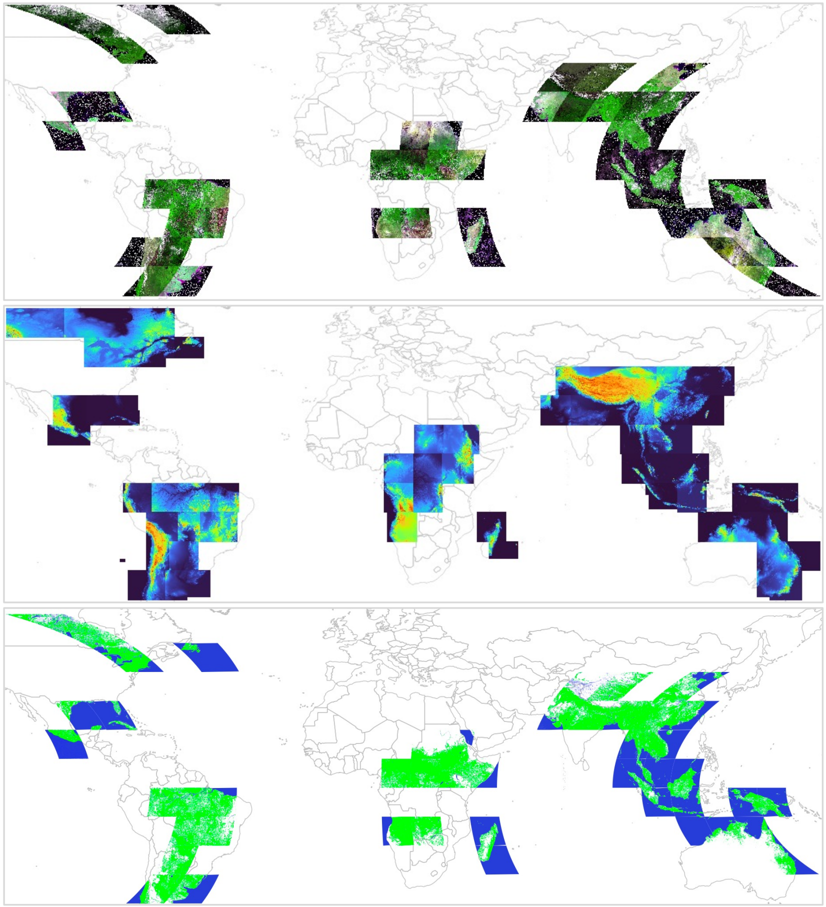
MODIS 4 bands

+

DEM

+

Improved Labelled Images



Trained Models

- UNet
- UNet++
- DeepLabV3+
- SegNet
- PSPNet
- FPN

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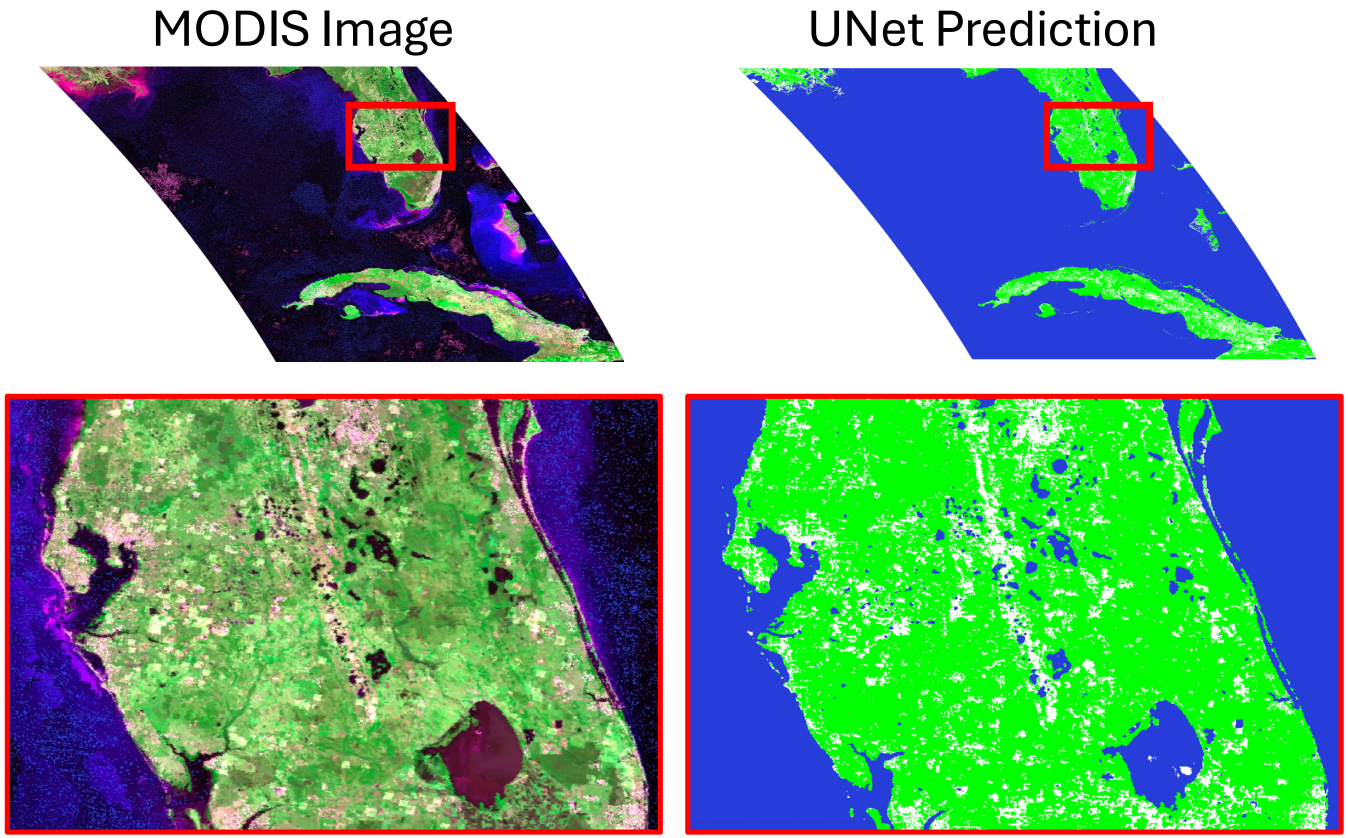
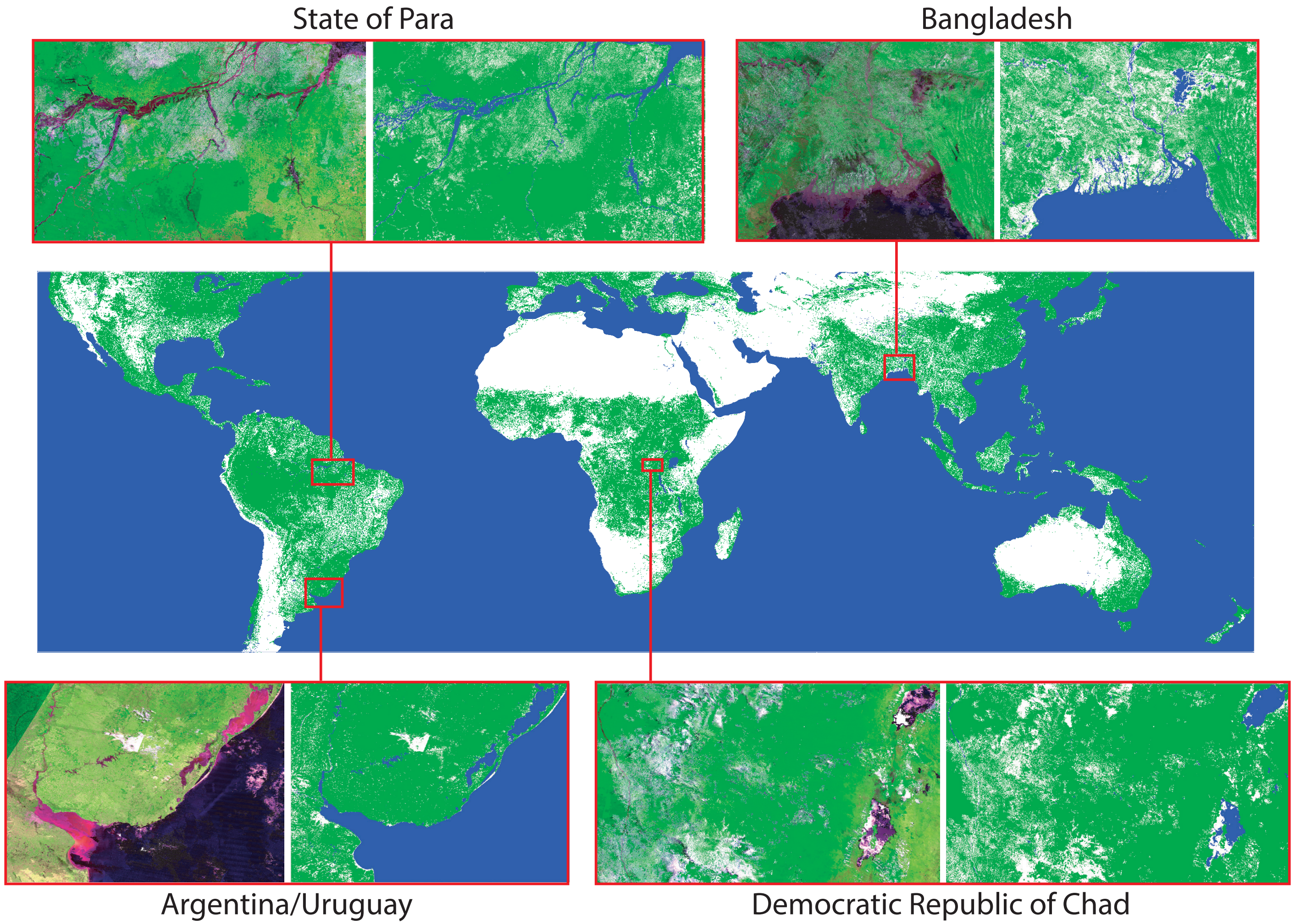
Model Evaluation

Models exhibited improved prediction performance, especially UNet in identifying smaller and isolated water bodies and thin water channels

Model	Overall Accuracy	Confidence Score	
		Water	Vegetation
UNet	0.94	0.93	0.87
UNet++	0.93	0.91	0.88
PSPNet	0.91	0.88	0.85
SegNet	0.90	0.88	0.82
FPN	0.93	0.91	0.88
DeepLabV3 +	0.92	0.90	0.87



Predictions based on Trained UNet



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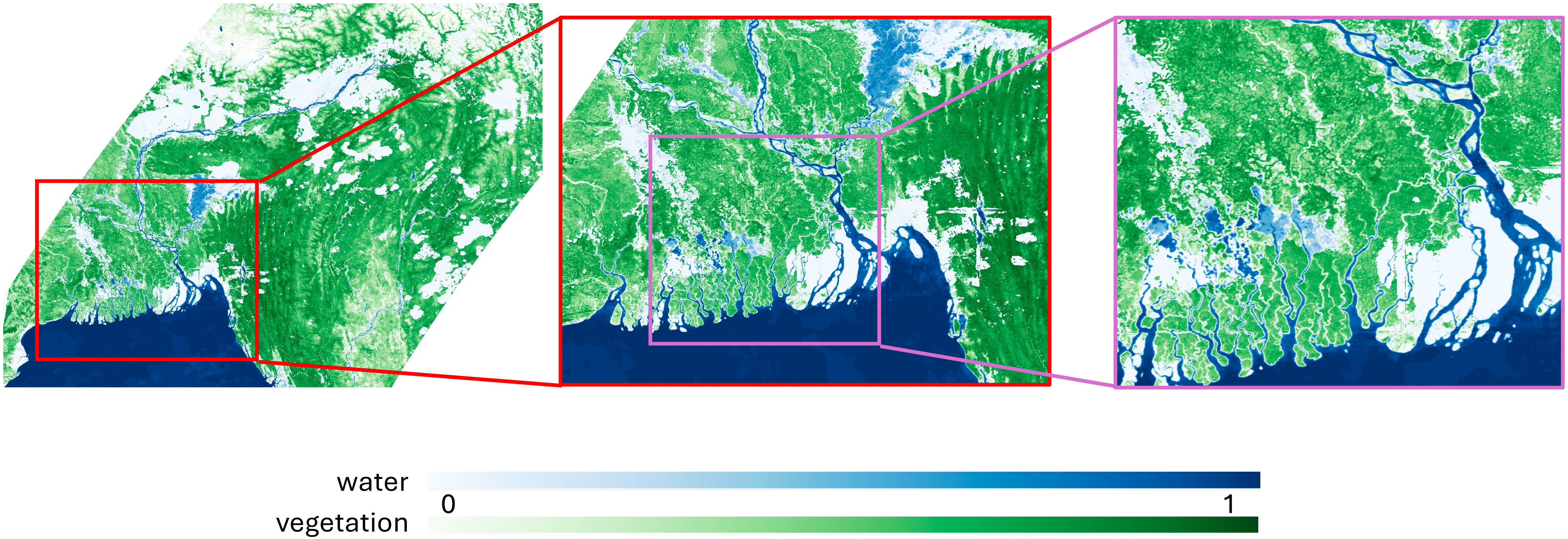
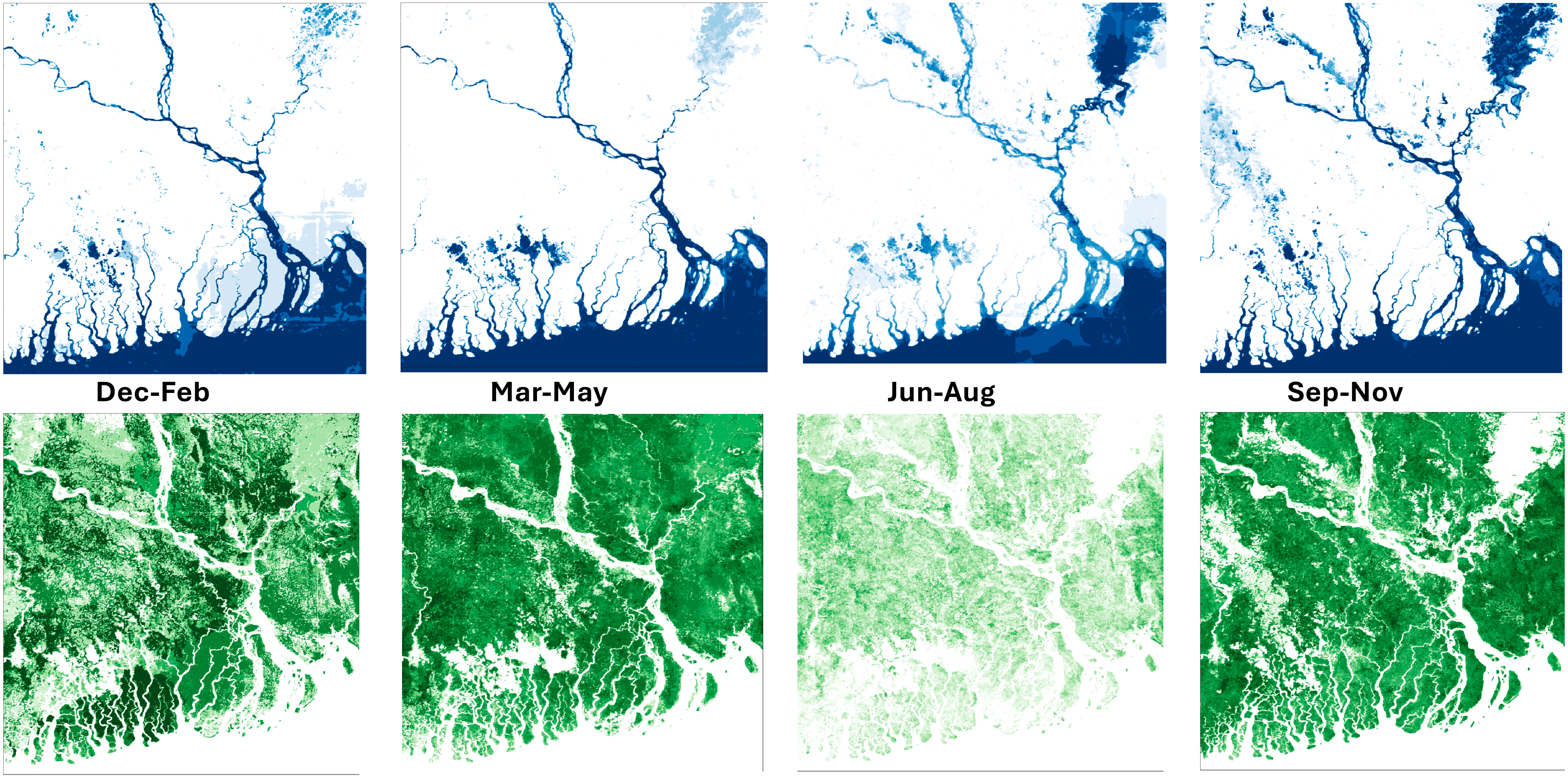
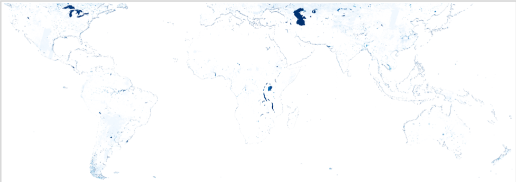
Annual Frequency Map 2001





Seasonal Frequency Maps 2001

Annual Water Frequency Maps



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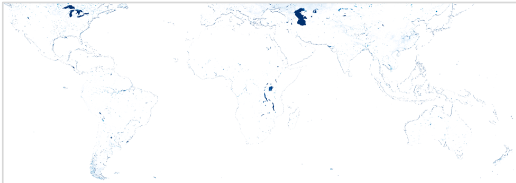

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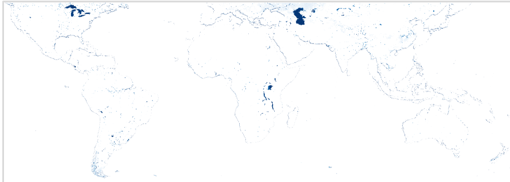

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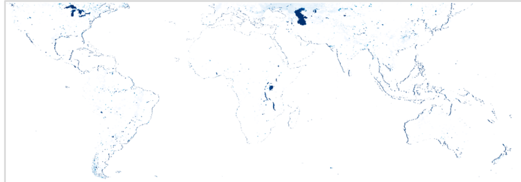

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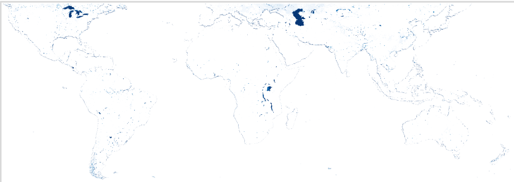

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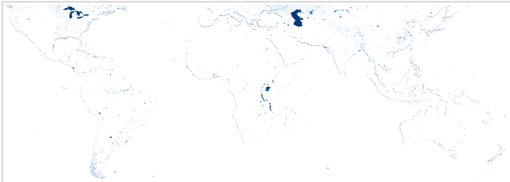

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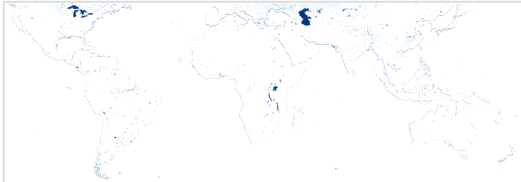

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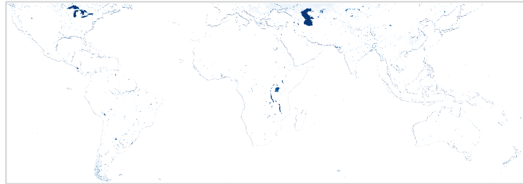

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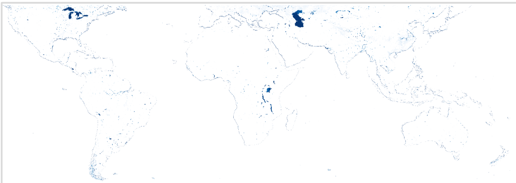

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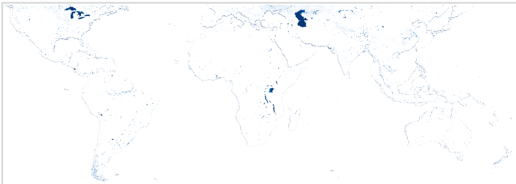

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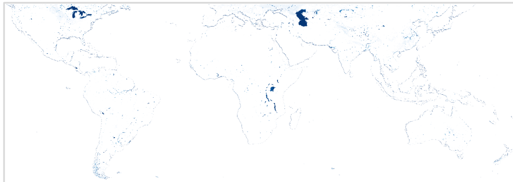

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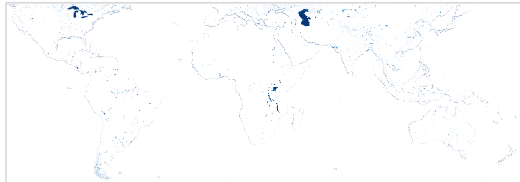

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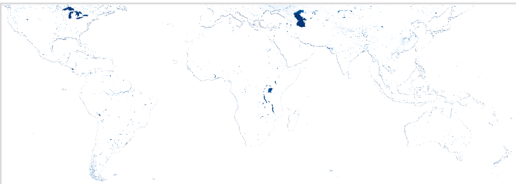

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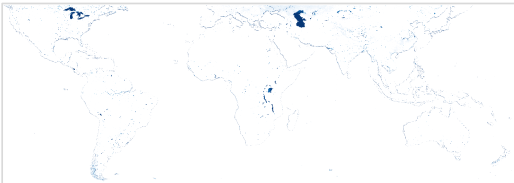

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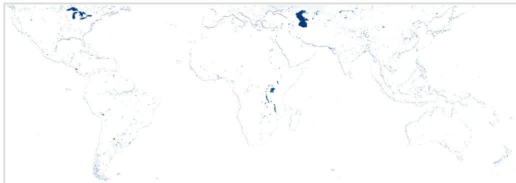
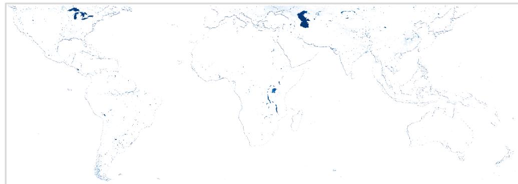


2017



2018

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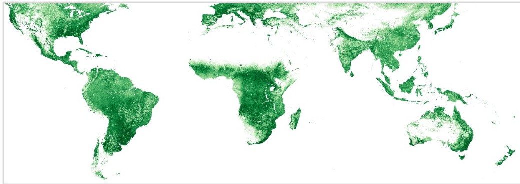
Annual Vegetation Frequency Maps



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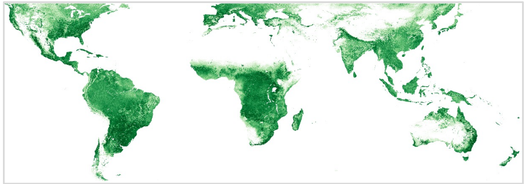

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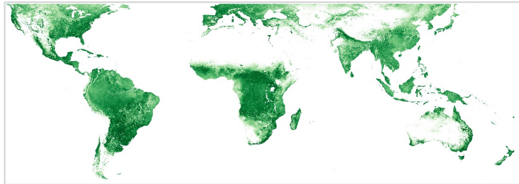

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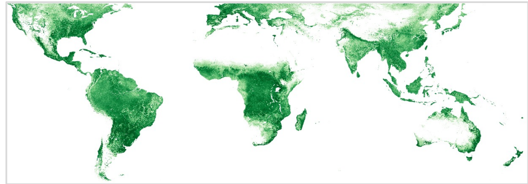

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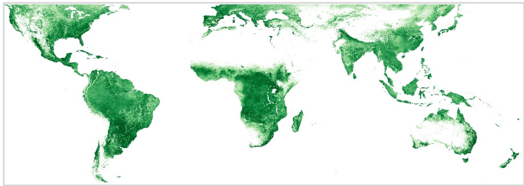

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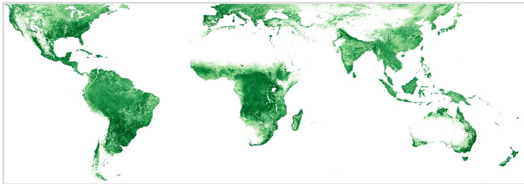

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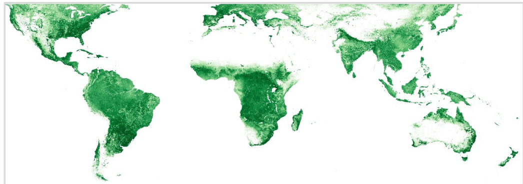

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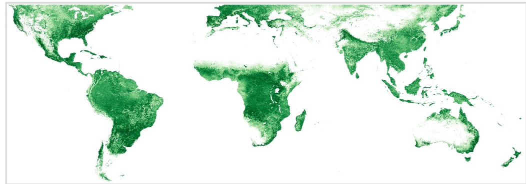

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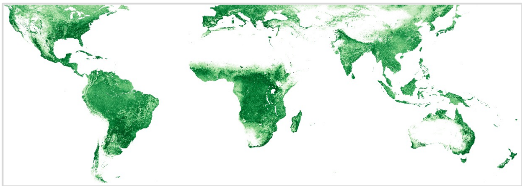

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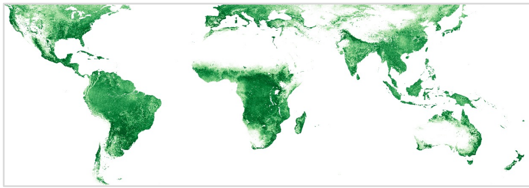

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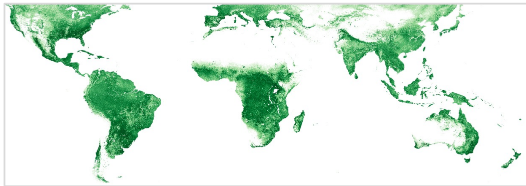

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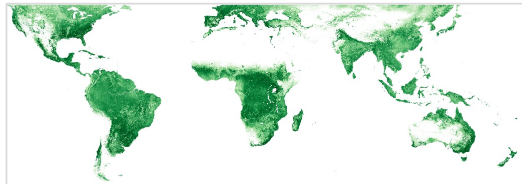

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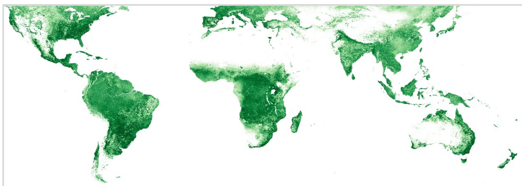

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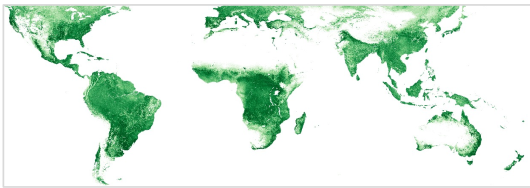

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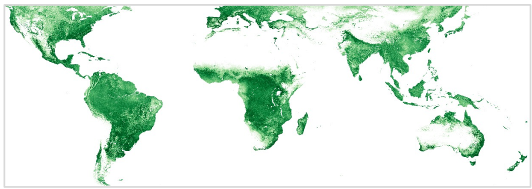

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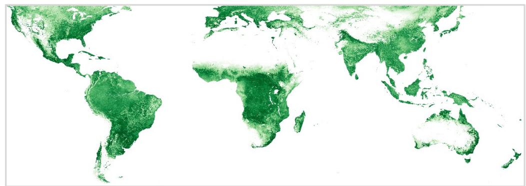

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Next Steps…

- Perform time series analysis to create seasonal, annual, and permanent water maps
- Integrate Sentinel and PlanetScope data for detailed wetland classification
- Generate comprehensive wetland maps validated against existing global datasets
- Use observed wetland extent to drive Digital Twin wetland methane modelling