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Abstract

Mangrove forests are found in intertidal zones of tropical regions around the world and provide important ecological and economic benefits – they are considered carbon sequesters, habitats for flora and fauna, and natural barriers to hurricanes and tsunamis. Wood from mangrove forests are used as fuel and building materials in surrounding coastal communities, therefore promoting local livelihoods. Despite the importance of these ecosystems, mangrove forests have historically been degraded in natural processes such as severe weather, and anthropogenic factors like conversion to agriculture and aquaculture.

This study assesses change in mangrove forests in Nigeria and Mozambique from 2015 to 2018 using SAR and optical data fusion. Due to frequent cloud cover over the study area, SAR and optical data is fused to obtain gap-free imagery without clouds. Landsat-8 OLI and Sentinel-1 imagery is fused with TensorFlow, an open source platform used in developing machine learning models. The resulting images are classified to discriminate mangrove forest cover from other land cover types, and change is estimated using image differencing. Understanding the rates and magnitude of mangrove change across space and time can aid in identifying priority areas for forest regeneration, and can help construct sustainable management practices for the future.

Study Area



The Niger Delta contains a significant amount of Nigeria's mangrove forests. Additionally, Nigeria hosts the 5th largest mangrove forest in the world.

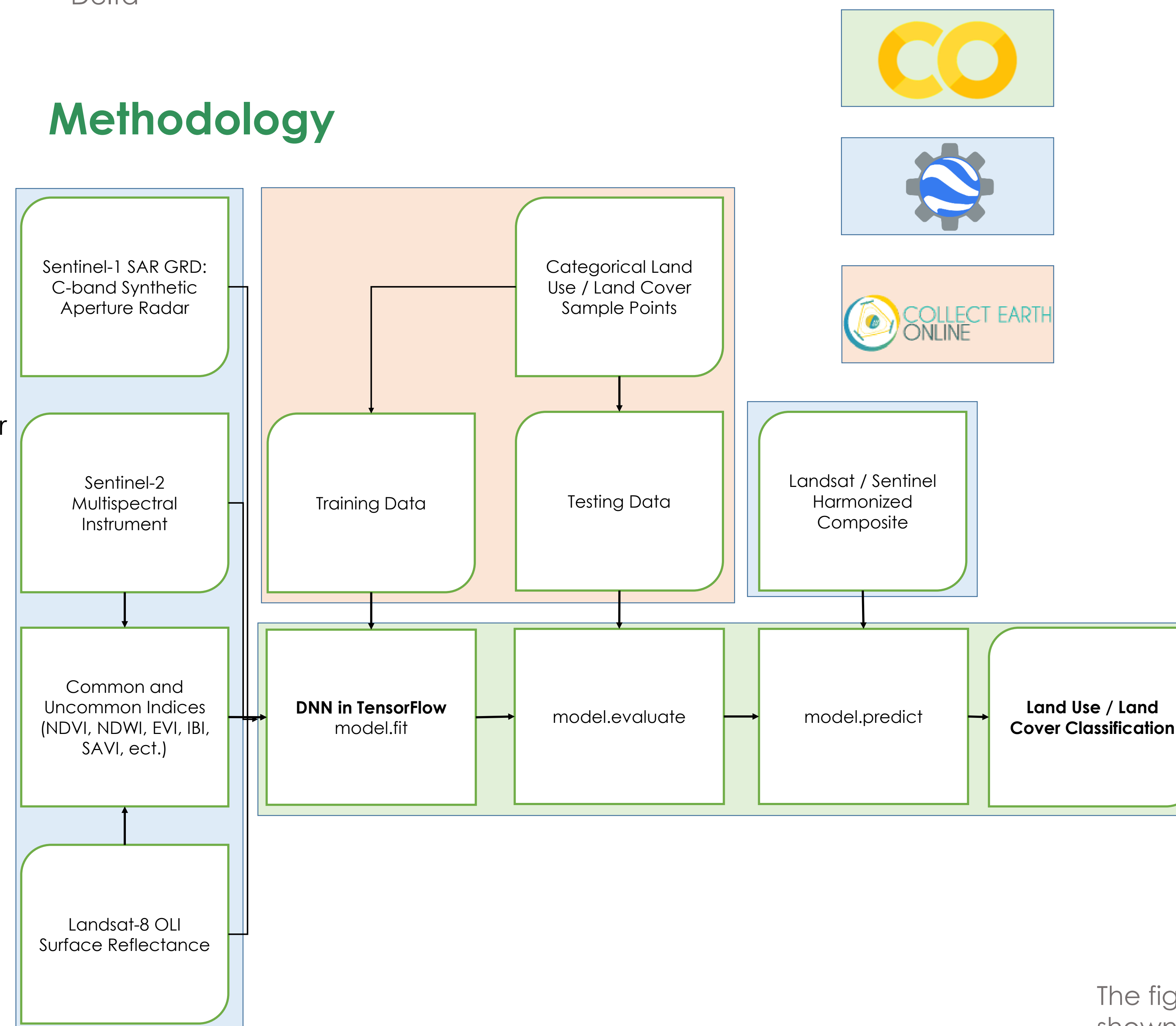
Earth Observations



Objectives

- ▶ Map mangrove forests in the Niger Delta in 2018
- ▶ Harmonize SAR and optical satellite imagery in order to obtain cloud-free data over the study area
- ▶ Assess the use of TensorFlow for mangrove forest mapping in the Niger Delta

Methodology



▶ Common and Uncommon Indices

19 indices are calculated using the normalized difference and ratio's of various bands.

▶ Training and Testing data

5000 sample points are collected in the Niger Delta using Collect Earth Online and DigitalGlobe recent imagery (WorldView) to represent 5 land use / land cover classes (mangrove forest, non-mangrove forest, agriculture, urban, and water). The points are split into training and testing data.

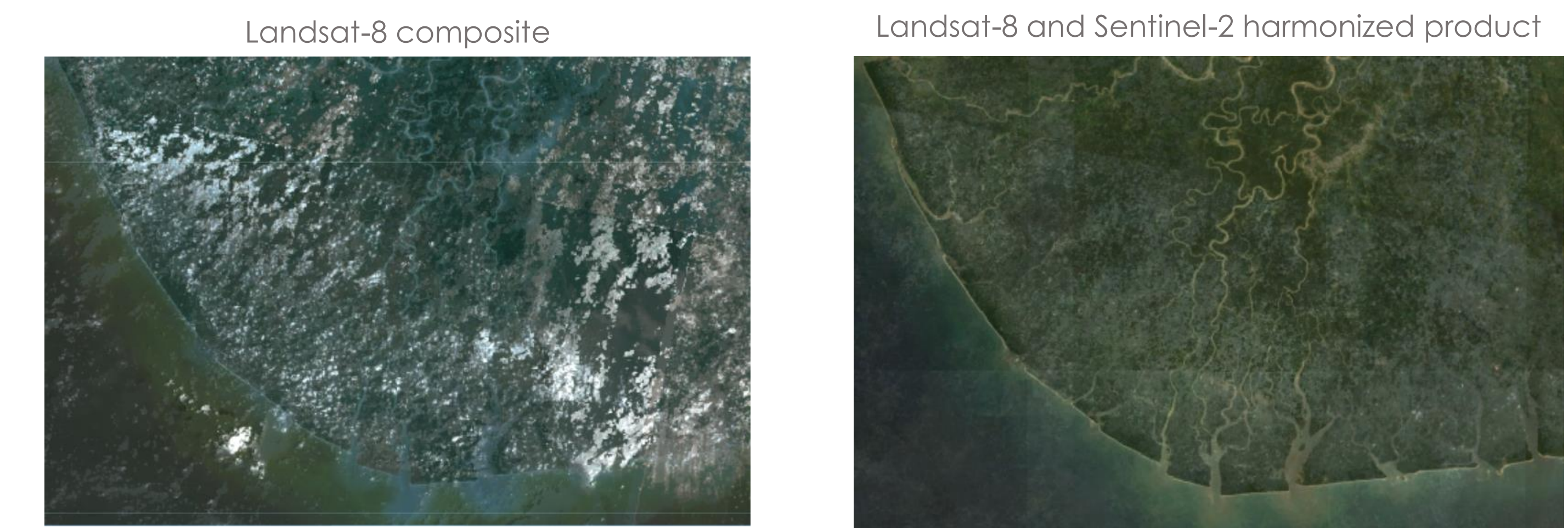
▶ DNN in TensorFlow

A DNN is built using TensorFlow in Google Colaboratory. The model shows a 76% accuracy on the testing dataset.

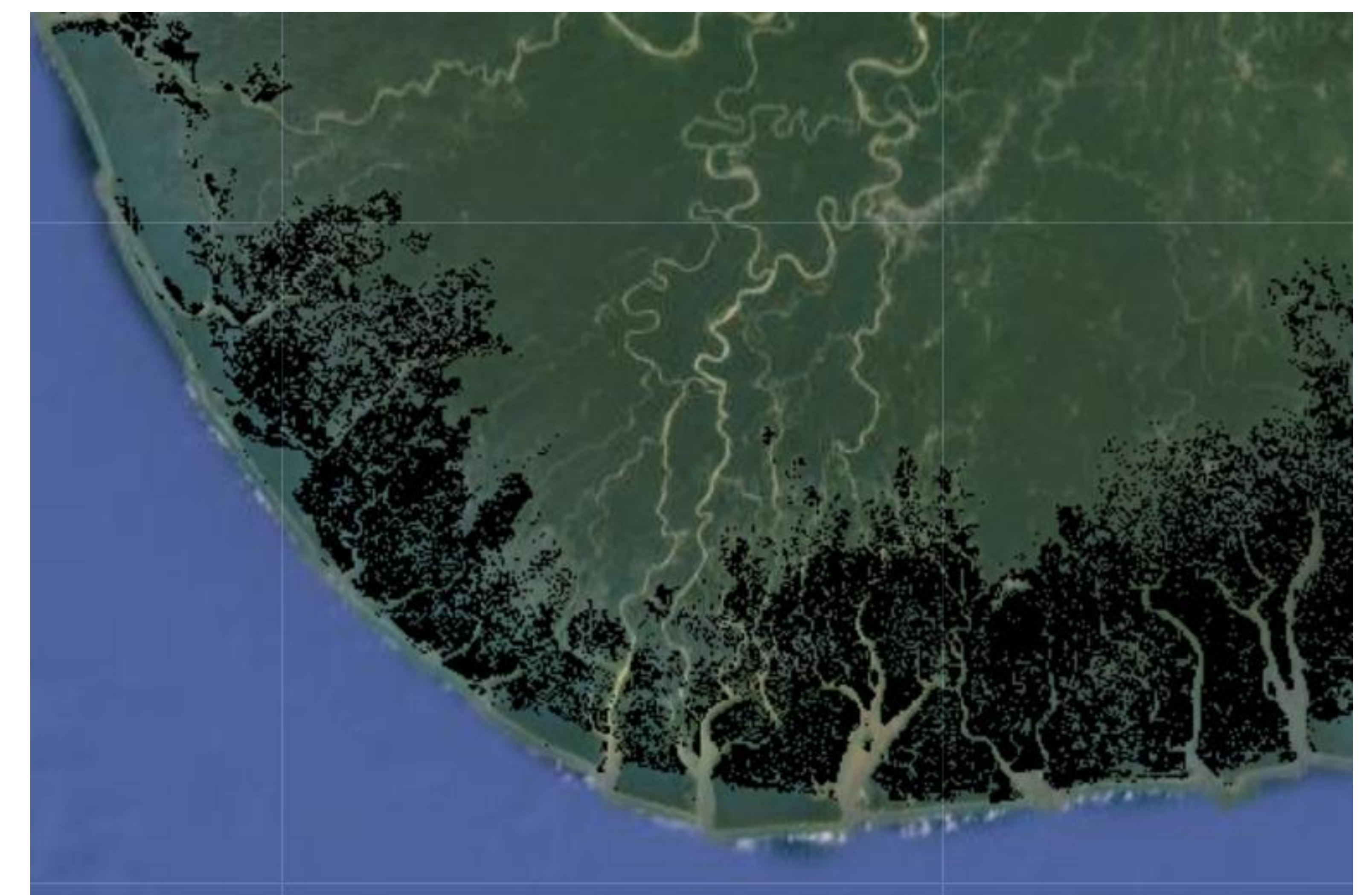
▶ Landsat / Sentinel composites

The trained model is used to predict land use / land cover for a 2018 Landsat and Sentinel composite. The output includes the prediction of land use / land cover, as well as the probability of each class at the pixel scale.

Harmonized Imagery



Results & Discussion



The figure above shows the results of the mangrove forest cover prediction from the DNN in TensorFlow, shown in black. SAR-only classifications cannot distinguish mangroves from non-mangrove forests in C-band, but methods that utilize SAR and optical imagery benefit from complimentary information.

Conclusions and Future Work

- ▶ TensorFlow is a useful and practical tool for large-scale land use / land cover analyses
- ▶ The harmonization of Landsat and Sentinel imagery is necessary in order to obtain gap-free and cloud-free imagery in tropical regions such as the Niger Delta
- ▶ This project will be scaled up to map mangrove forests along the entire coast of Nigeria and well as Mozambique. Nigeria and Mozambique contain significant mangrove forest cover, but are located on opposite sides of Africa and therefore have differing climatic regimes. Understanding how TensorFlow can be used to detect mangroves across time and space will be important information to SERVIR and our partners as we continue to utilize machine learning in future research

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