Jet Propulsion Laboratory
California Institute of Technology

Estimation of Mangrove Forest Vertical Structure With UAVSAR and Lidar Data Fusion

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Introduction

- A Surface Topography and Vegetation (STV) mission was recommended in “Thriving on Our Changing Planet: A Decadal Strategy for Earth Observations from Space,” released by the National Academies of Sciences, Engineering, and Medicine in 2018.
- Multi-sensor and multi-platform approaches were highlighted as no single sensor can meet accuracy, resolution, and coverage goals.
- We are exploring data fusion of SAR and lidar data to estimate forest canopy height and vertical structure.
- Mangrove forests are vitally important coastal ecosystems. Despite their small coverage area, they are extremely productive, carbon rich ecosystems which are inherently vulnerable to sea level rise as well as human activities.
- Mangroves also have a distinct structure (e.g., above-ground root systems) and would not necessarily conform to the same model used for other forest types.

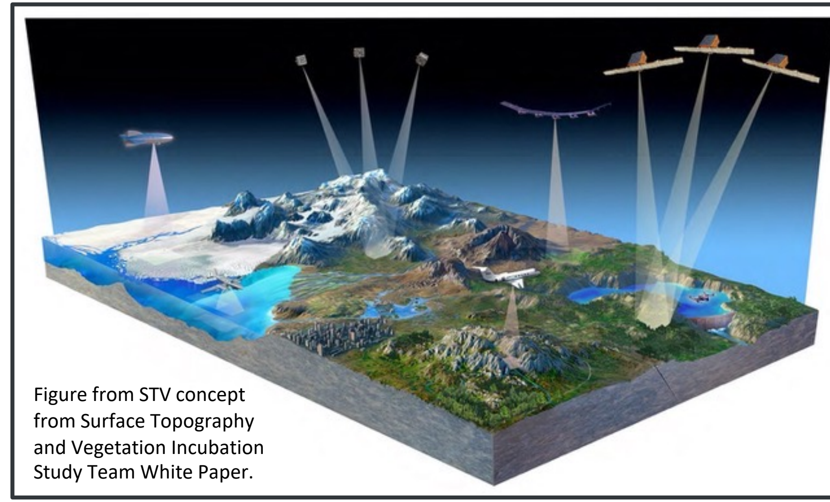
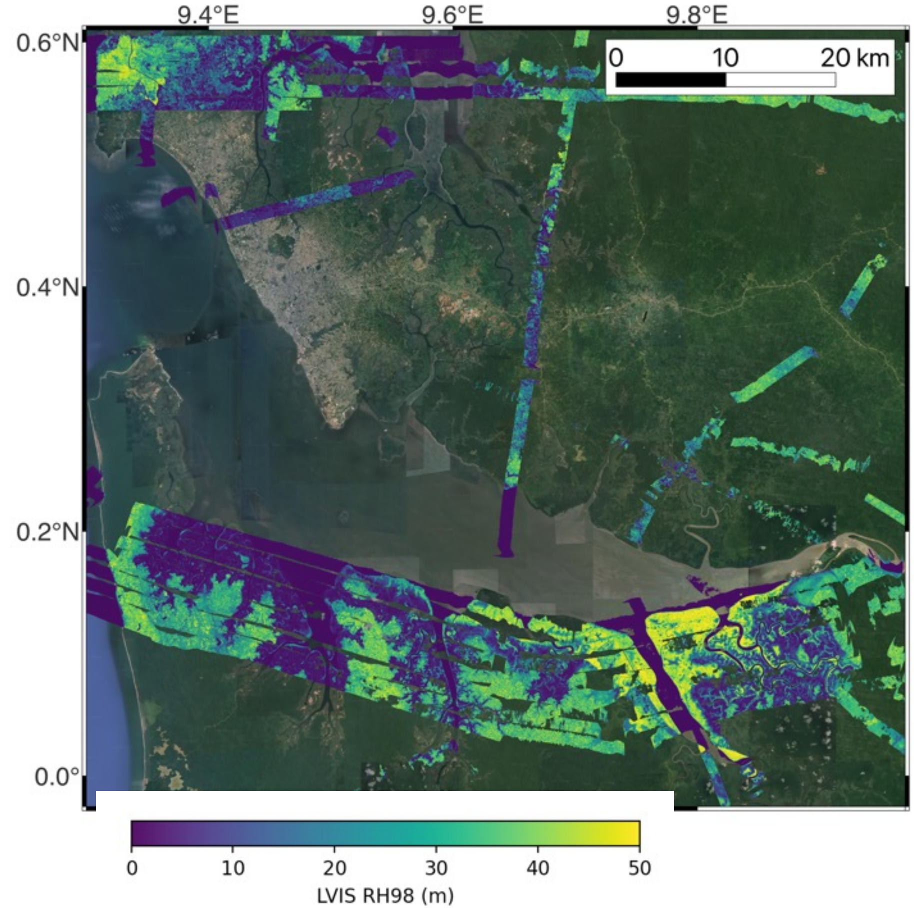


Figure from STV concept from Surface Topography and Vegetation Incubation Study Team White Paper.

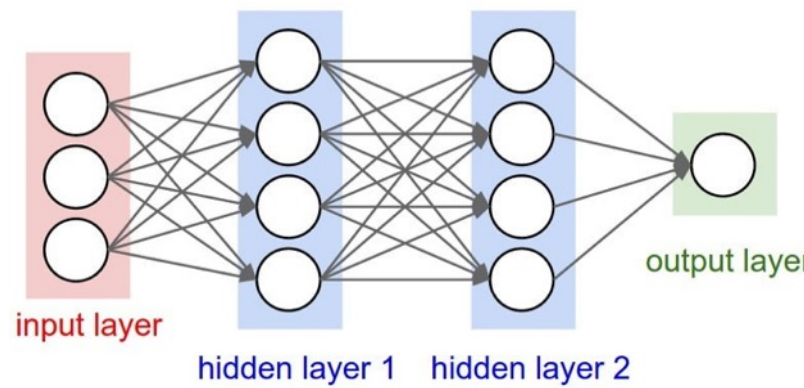
Data Overview & Study Area

- Using UAVSAR (https://uavsar.jpl.nasa.gov/) and Land, Vegetation, and Ice Sensor lidar (LVIS; https://lvis.gsfc.nasa.gov) data collected during the 2016 AfriSAR campaign.
  - Fatoyinbo, T., et al. The NASA AfriSAR campaign: Airborne SAR and lidar measurements of tropical forest structure and biomass in support of current and future space missions. Remote Sens. Environ., 264 (2021), Article 112533
- Mangrove extent from Global Mangrove Watch data.
  - Bunting, P.; Rosenqvist, A.; Hilarides, L.; Lucas, R.M.; Thomas, T.; Tadono, T.; Worthington, T.A.; Spalding, M.; Murray, N.J.; Rebelo, L-M. Global Mangrove Extent Change 1996 – 2020: Global Mangrove Watch Version 3.0. Remote Sensing. 2022



Summary of Network Configuration

- Used deep neural networks consisting of an input layer (given UAVSAR PolInSAR features as input), multiple hidden layers, and then an output layer (trained to estimate canopy height, or both canopy height and canopy height uncertainty).
- The results in these slides use four hidden layers with sizes (10, 10, 10, 5).
- Tested larger networks but with negligible improvement in performance.
- Different network configurations to accommodate different numbers of baselines:
  - Single-Baseline Network (only features from one baseline given; however, baselines can be merged using uncertainty estimated by network)
  - Triple-Baseline Network (three baselines given as input, each with kz information so network can differentiate short and long baselines)



PolInSAR Features Used as Input to Network

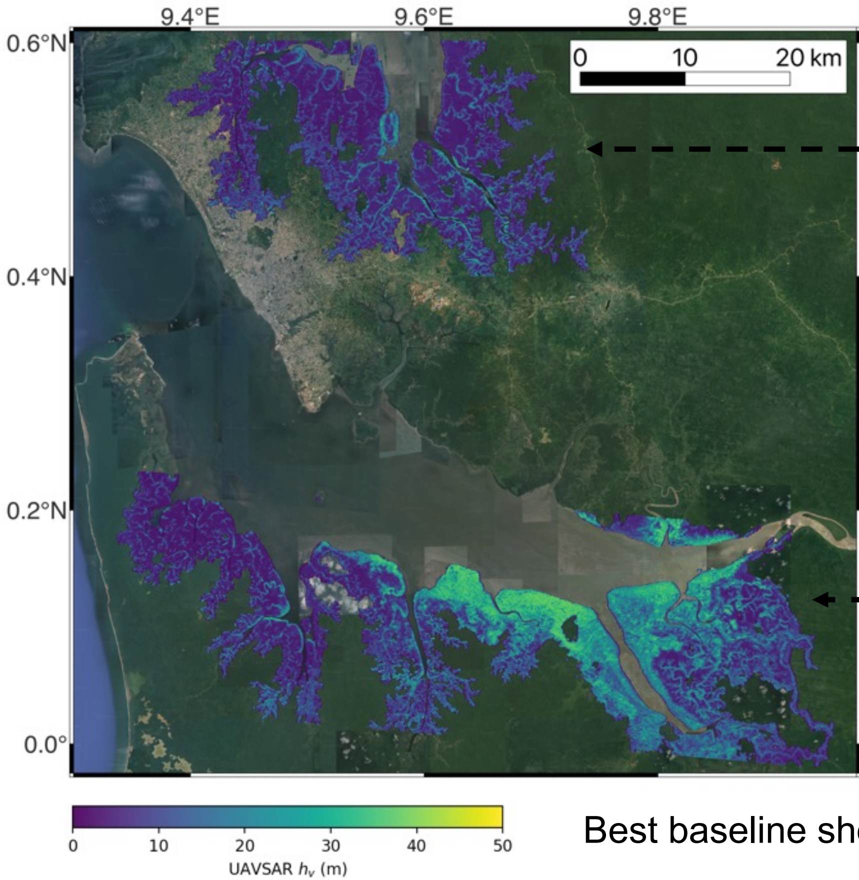
- **Backscatter** (HH, HV, VV in linear units, 3 total features).
- **Interferometric Covariance Matrix** (for each baseline, 3 complex values split into real and imaginary components, 6 total features).
- **k_z (for each baseline)**
- **High and Low Coherence Magnitude (for each baseline)**
- **High and Low Coherence Phase Center Height Above Estimated Ground (for each baseline)**
- **Coherence Separation (for each baseline)**
  - abs(high - low)
  - abs(high - ground)
- All input features are scaled (mean subtracted, then divided by standard deviation, based on training data) before training and prediction.

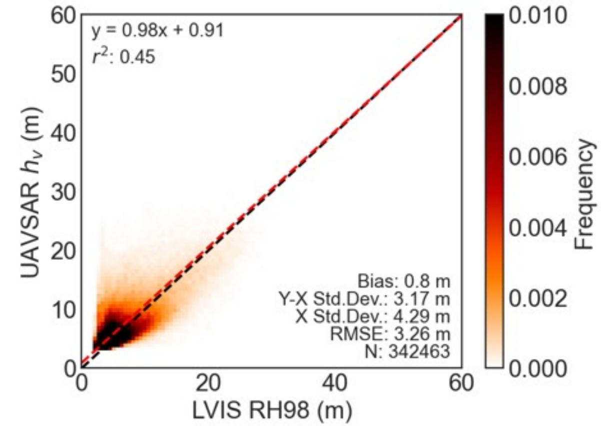
Summary of Network Training

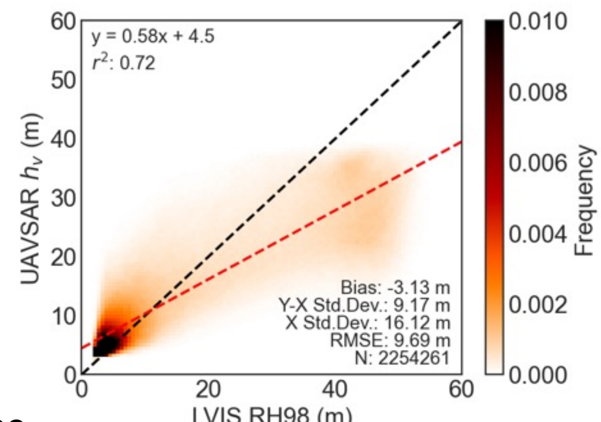
- Trained on 0.1% of the LVIS data, randomly chosen from each scene.
- Remaining LVIS data used for testing.
- Two networks, one trained on only mangrove samples within Pongara and Mondah scenes (selected using Global Mangrove Watch extents).
- Another generalized network trained on both mangrove and non-mangrove pixels within five UAVSAR scenes where we have coincident LVIS data.
  - Pongara, Mondah, Lope, Rabi (AfriSAR Scenes).
  - Boreal Ecosystem Research and Monitoring Sites (BERMS) in Saskatchewan, Canada.
- One set of networks configured to have one output, trained using square error between output and LVIS RH98 as loss function.
- Another set of networks were designed to provide two outputs: an estimate and an uncertainty. In this case, the loss function was the mean square error weighted by the uncertainty ($w = 1 / \sigma^2$) provided by the network. To avoid the network choosing high uncertainty for all samples, the loss function is regularized by the mean σ^2.

Single Baseline Network

Trained on Mangroves Only, Tested on Mangroves Only



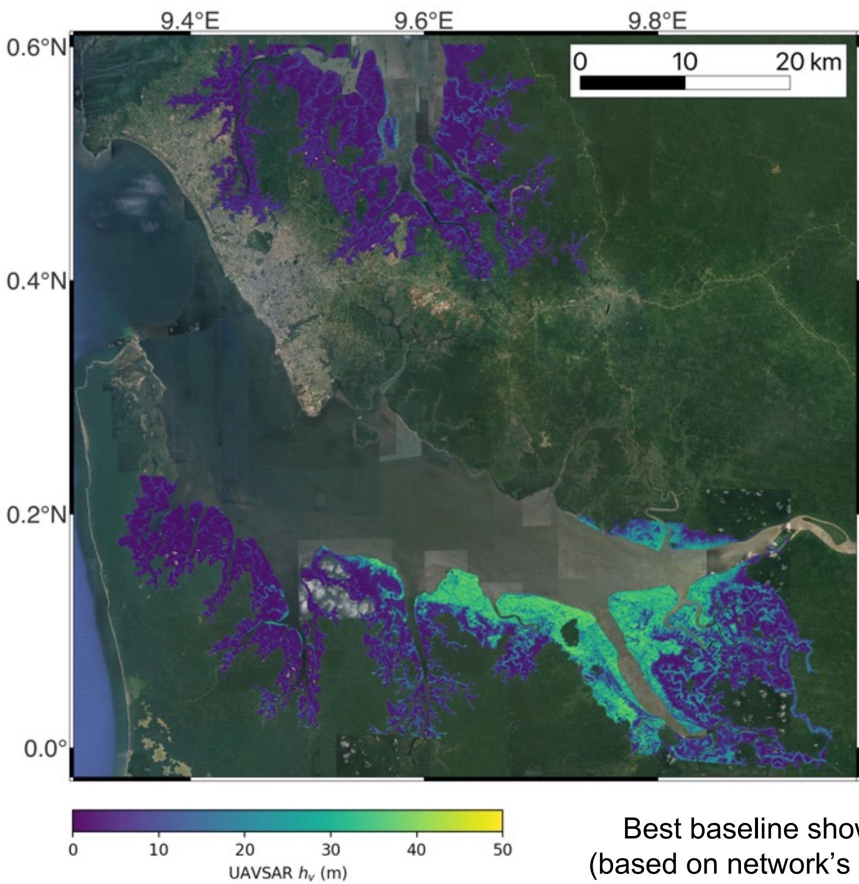




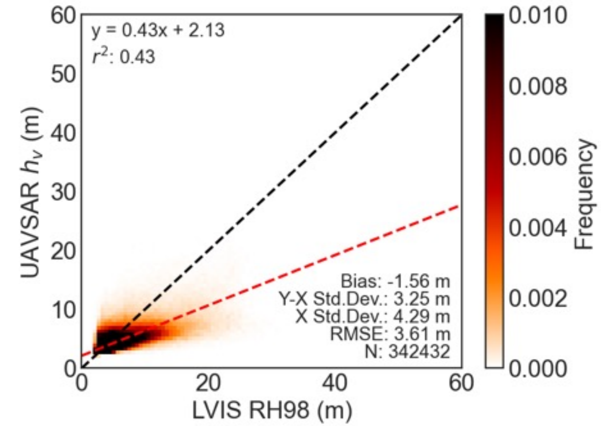
Best baseline shown for each scene.

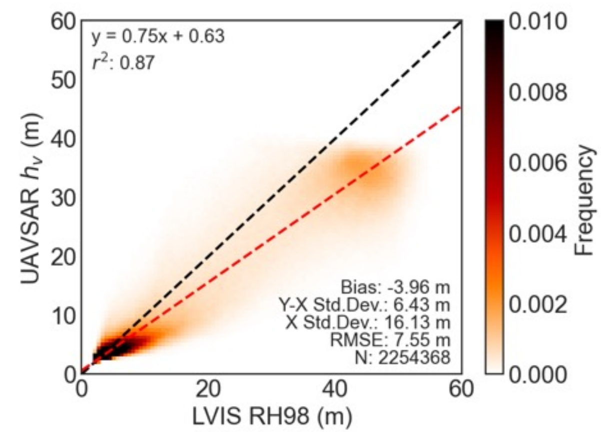
Single Baseline Network with Uncertainty Output

Trained on Mangroves Only, Tested on Mangroves Only



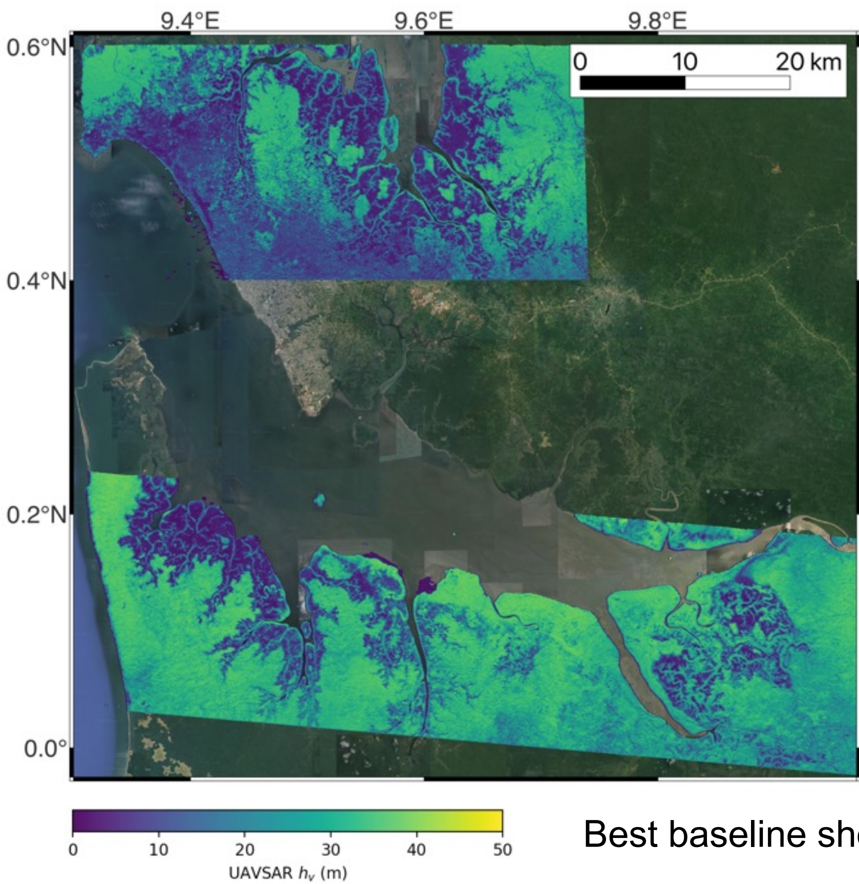
Best baseline shown for each pixel
(based on network's uncertainty output).

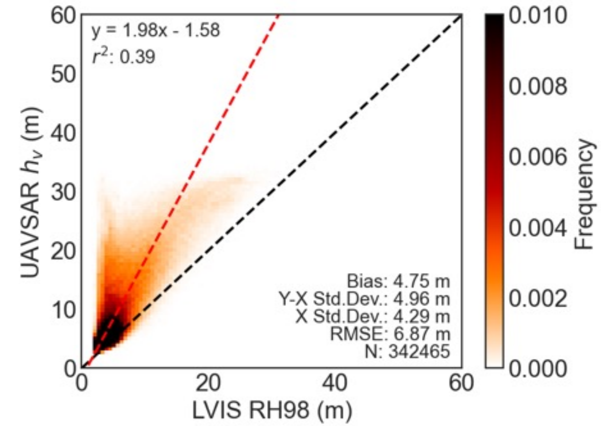


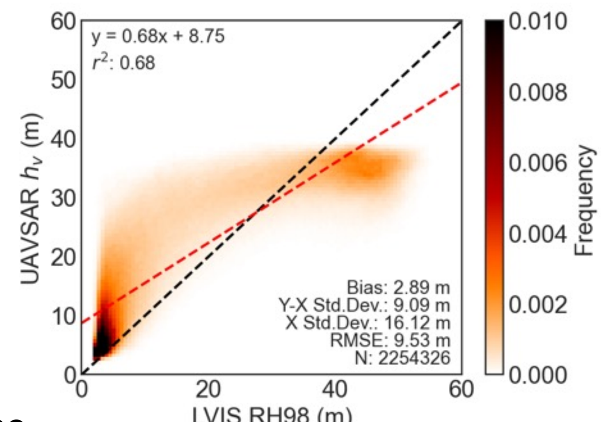


Single Baseline Network

General Model Trained on a Variety of Forest Types, Tested on Mangroves Only



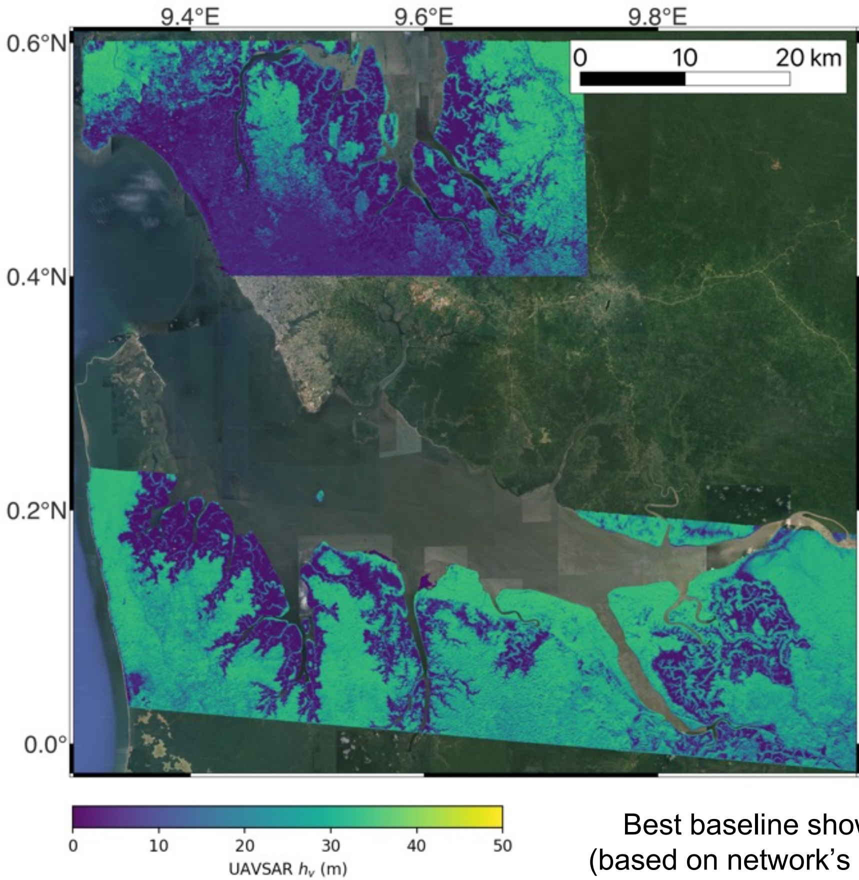




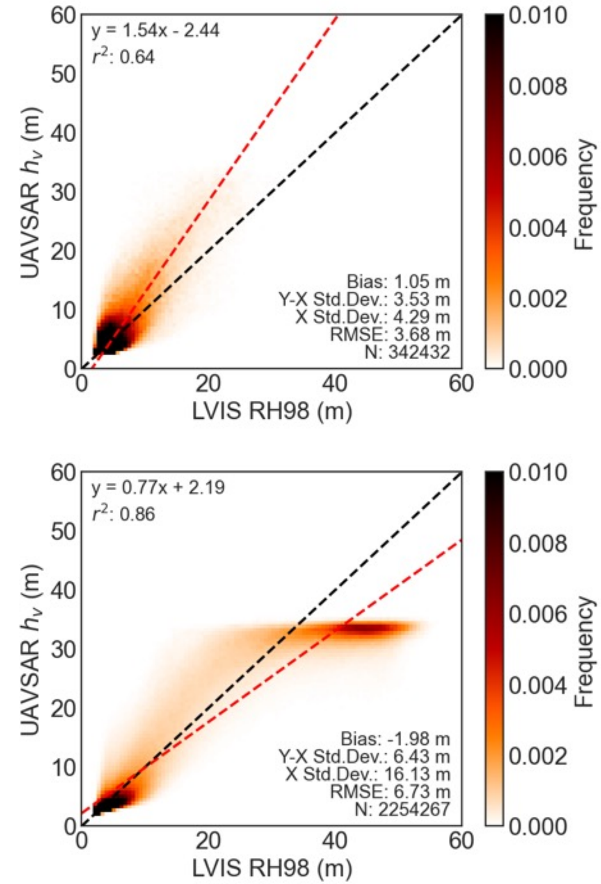
Best baseline shown for each scene.

Single Baseline Network with Uncertainty Output

General Model Trained on a Variety of Forest Types, Tested on Mangroves Only

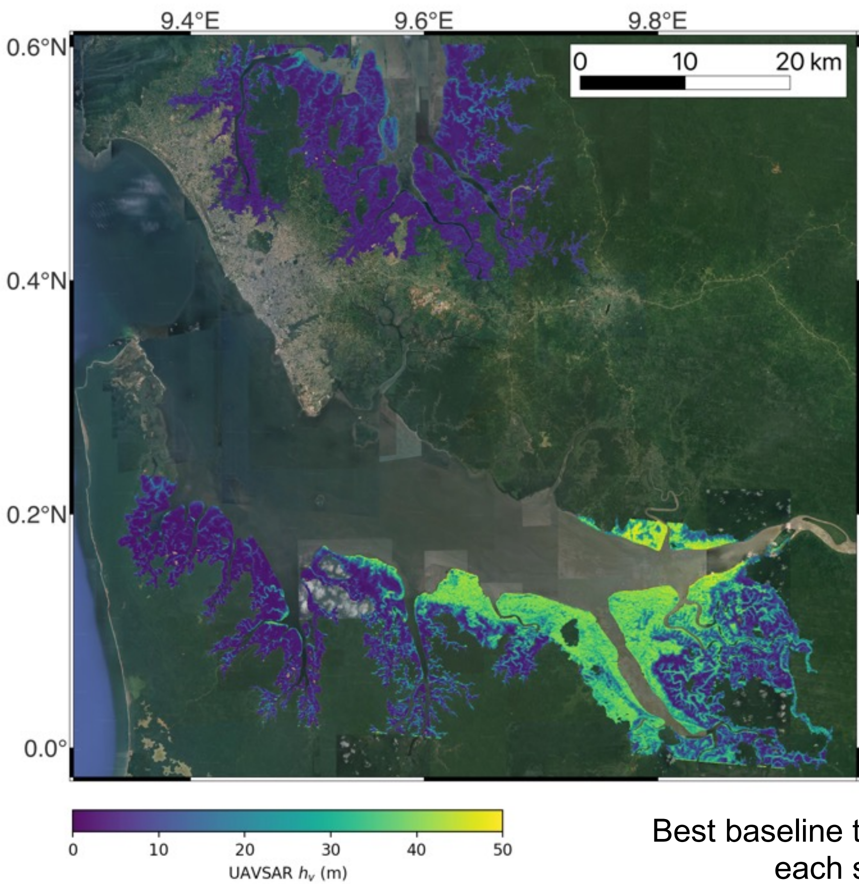


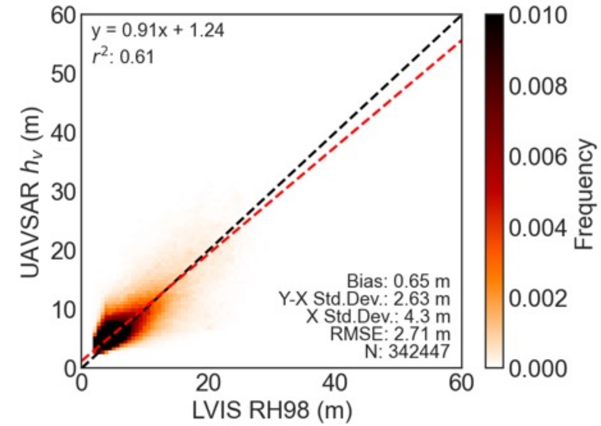
Best baseline shown for each pixel
(based on network's uncertainty output).

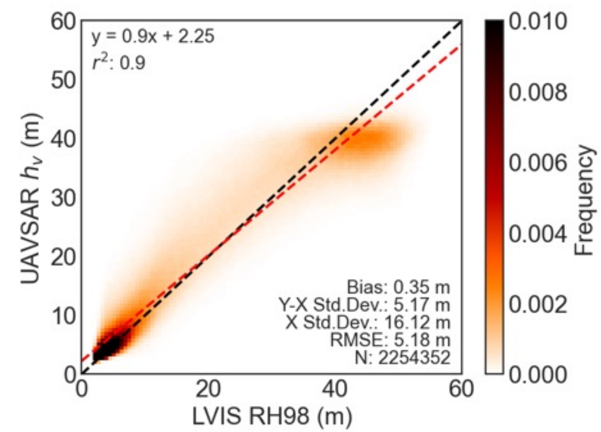


Triple Baseline Network

Trained on Mangroves Only, Tested on Mangroves Only



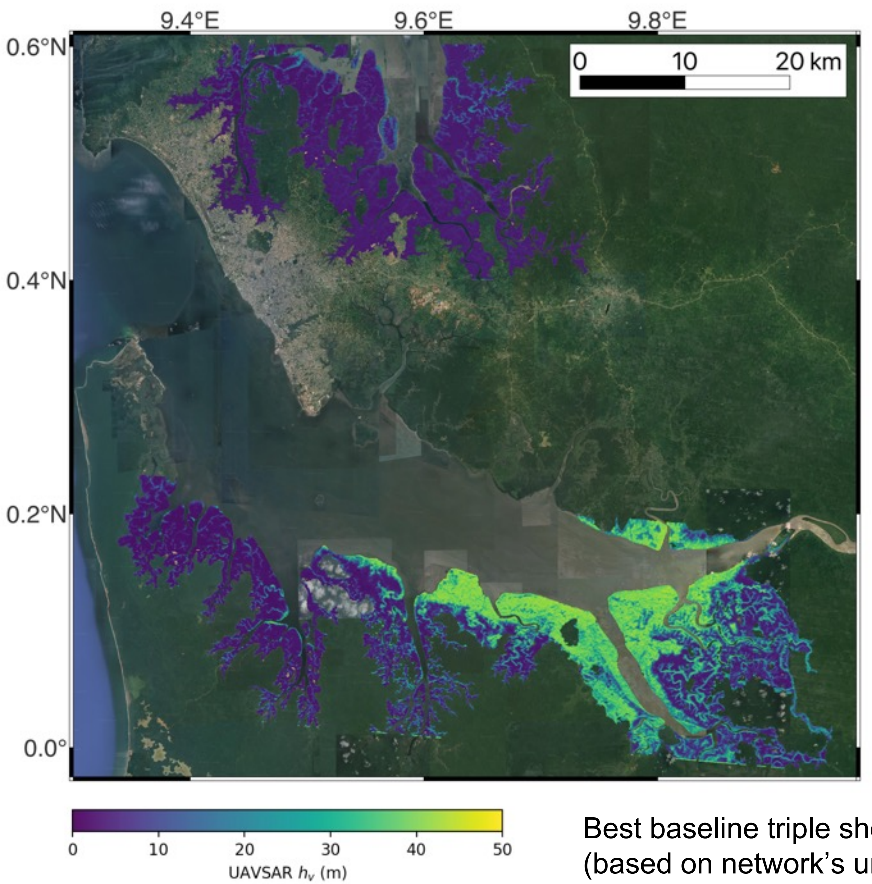


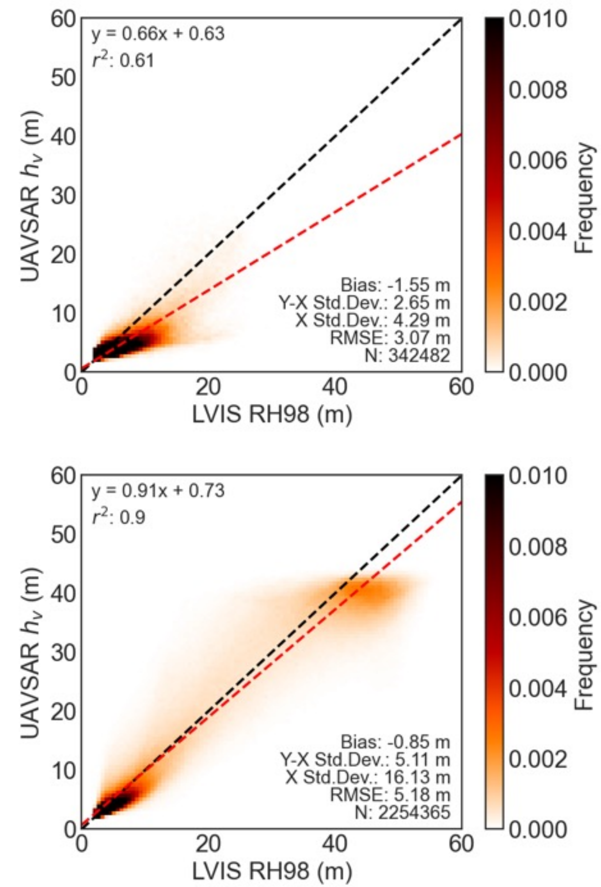


Best baseline triple shown for each scene.

Triple Baseline Network with Uncertainty Output

Trained on Mangroves Only, Tested on Mangroves Only

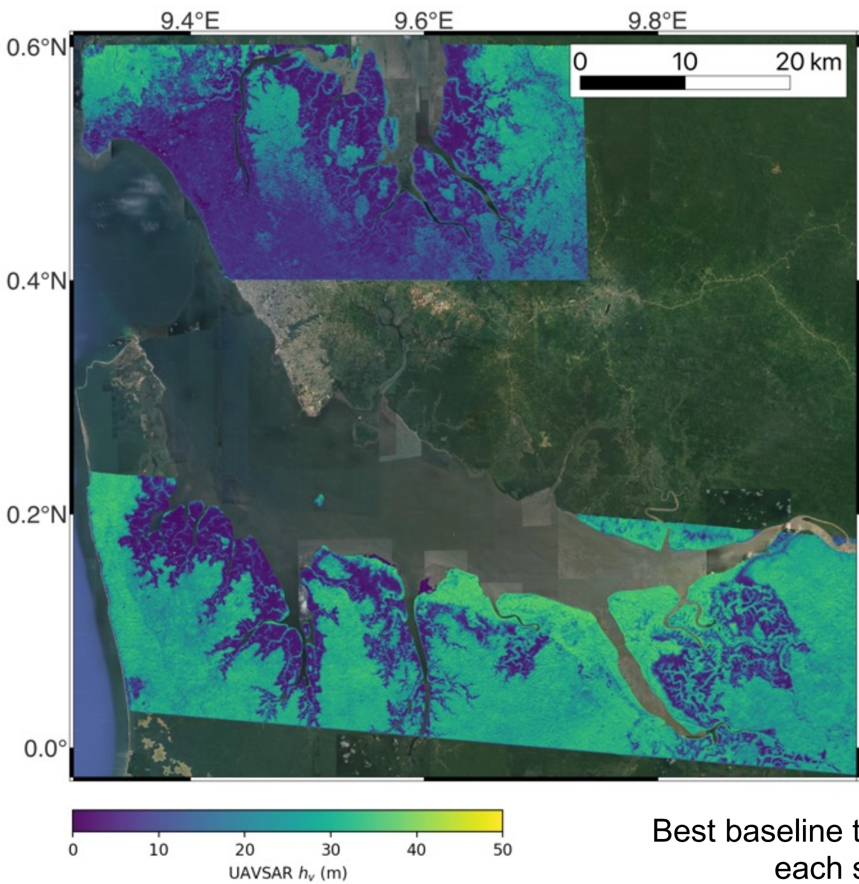


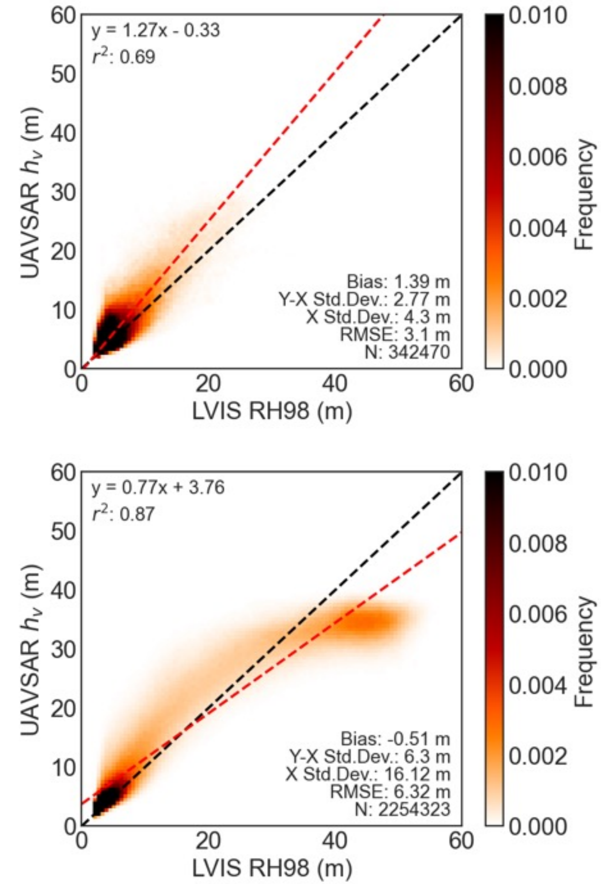


Best baseline triple shown for each pixel
(based on network's uncertainty output).

Triple Baseline Network

General Model Trained on a Variety of Forest Types, Tested on Mangroves Only

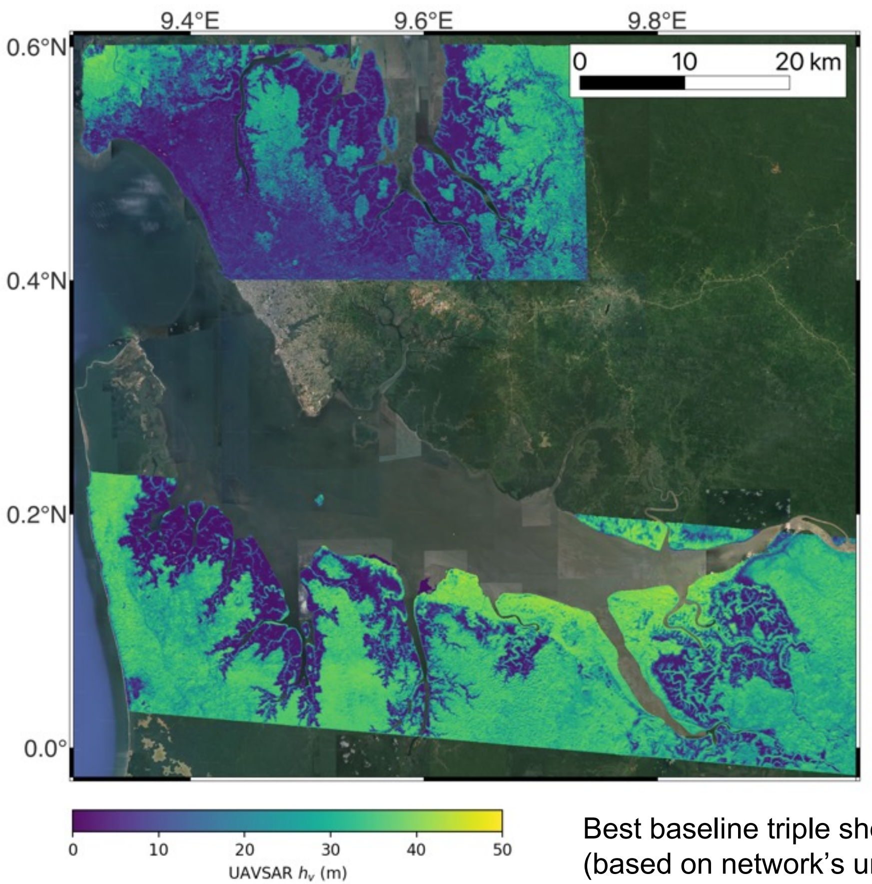


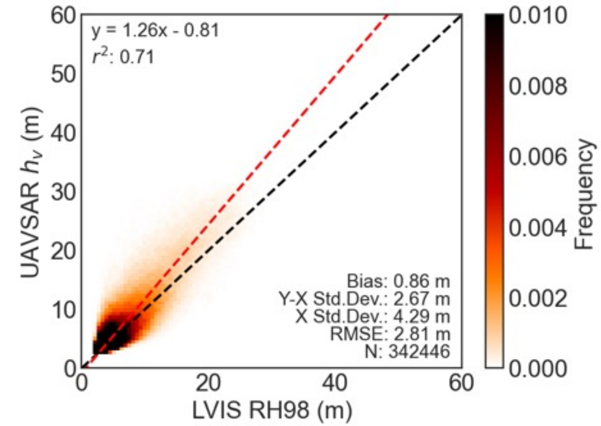


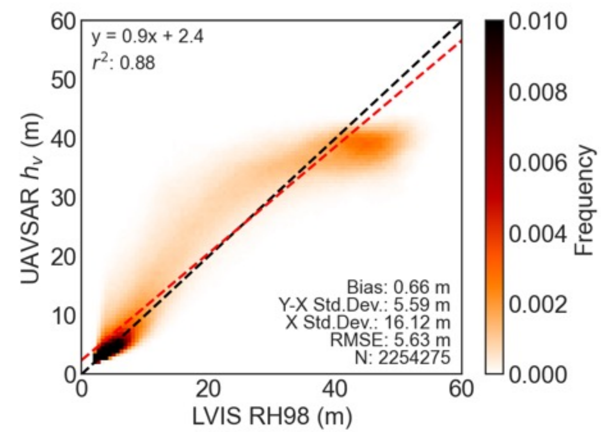
Best baseline triple shown for each scene.

Triple Baseline Network with Uncertainty Output

General Model Trained on a Variety of Forest Types, Tested on Mangroves Only



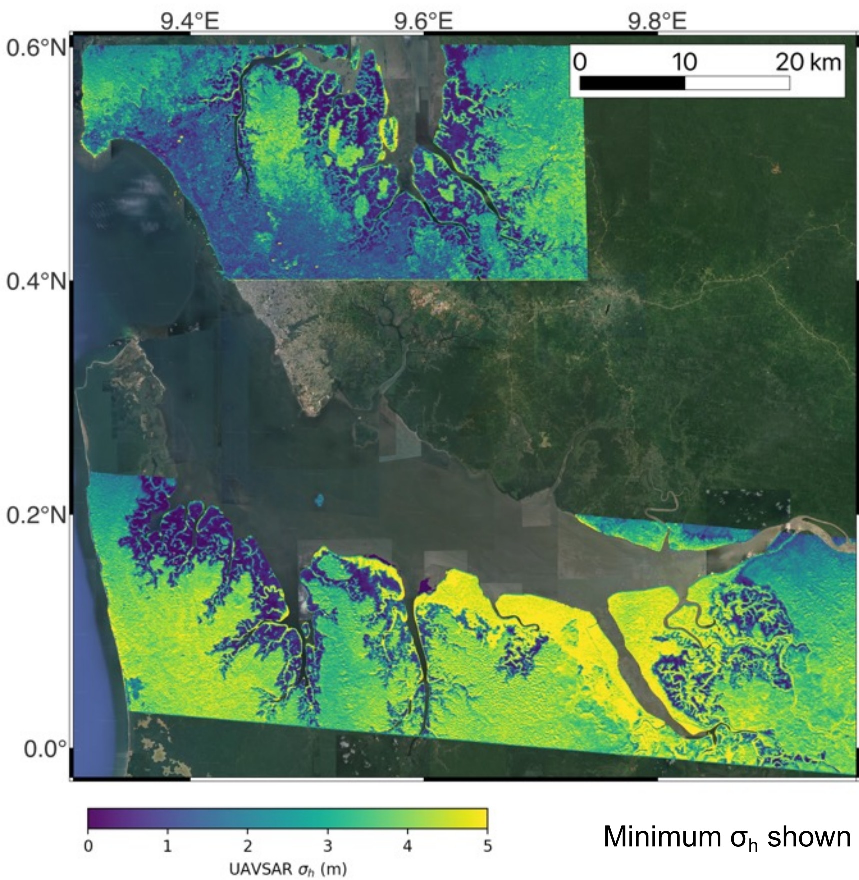


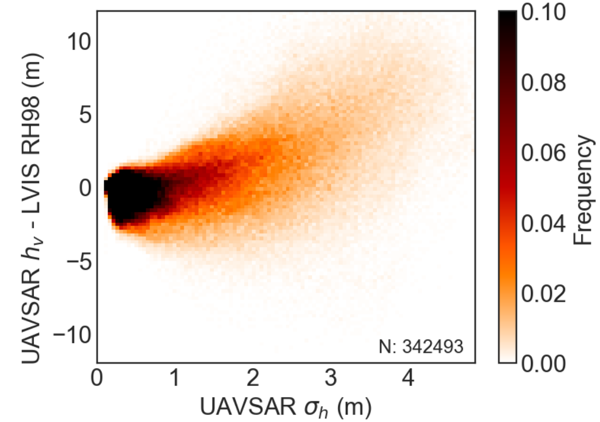


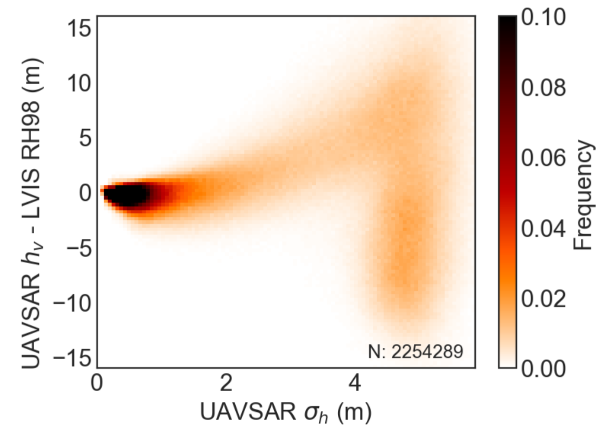
Best baseline triple shown for each pixel (based on network's uncertainty output).

Triple Baseline Network with Uncertainty Output

Are the uncertainty estimates correlated to the actual errors?



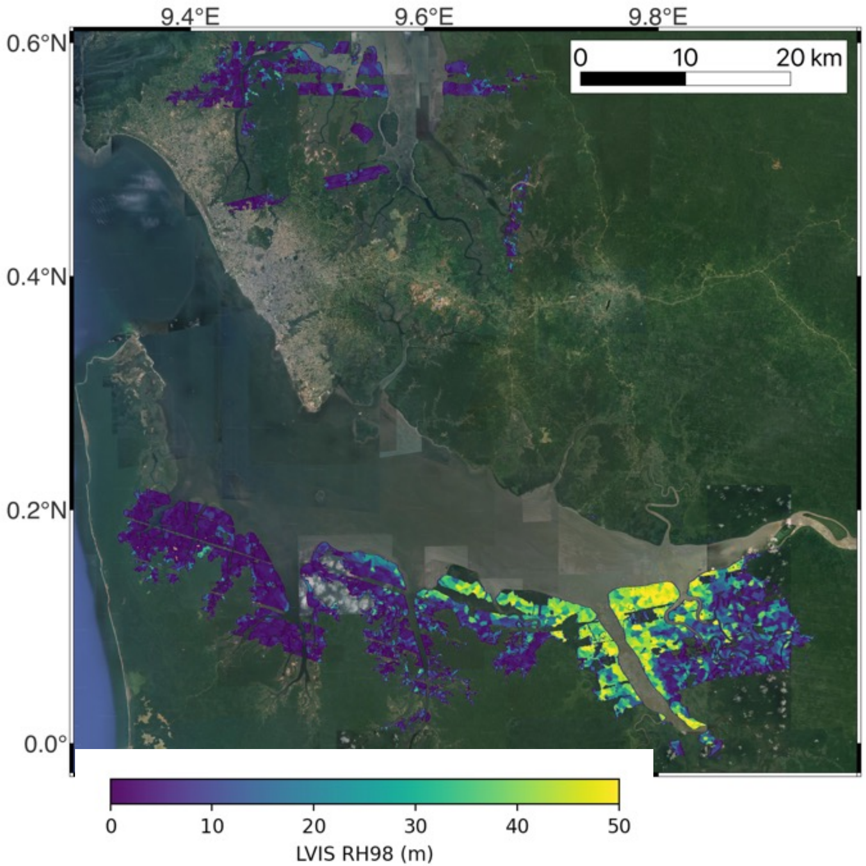


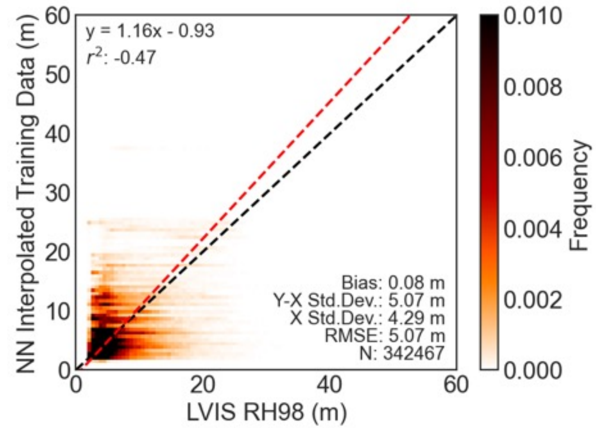


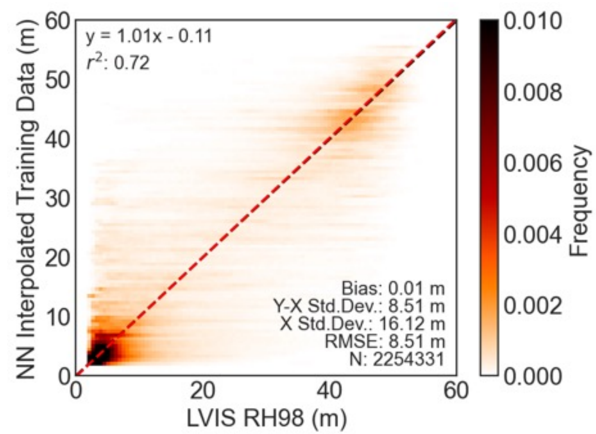
Minimum σ_h shown for each pixel.

Results Compared to Interpolated Training Data

Do the trained networks out-perform the interpolated training data?







Conclusions & Future Work

- Testing data fusion approaches using deep neural networks trained on lidar canopy height data with PolInSAR input features.
  - Networks which use multiple baselines as input produce smaller errors than single-baseline data.
  - Networks trained on mangrove data alone can outperform a generalized network. Other species-specific networks could be developed.
  - Networks can be trained to estimate uncertainty. This can improve estimation of canopy heights from multiple baselines or sets of baselines by allowing different estimates to be combined based on their uncertainty. This had a more significant improvement for the generalized network than the mangrove-specific network. Adding uncertainty estimation to a network does not make it a better estimator but can make the network more robust to a wider variety of inputs.
- In the future, we will expand the training datasets to include data from the forthcoming 2023 AfriSAR-2 campaign and other data collections, and to compare L-band and P-band data.
- Explore fusion of PolInSAR/TomoSAR with lidar data using convolutional neural networks which account for spatial structure. Explore fusion of TomoSAR profiles with lidar waveform data.
- Contact: michael.w.denbina@jpl.nasa.gov.

Open Postdoc Positions at JPL

1. **Lidar and PolinSAR/TomoSAR Data Fusion in Monitoring Changes of Vegetation Structure and Surface Topography**
   – https://www.jpl.jobs/job/R2894
   – Contact: Sassan Saatchi (sasan.s.saatchi@jpl.nasa.gov)
2. **Radar Remote Sensing of Vegetation**
   – https://www.zintellect.com/Opportunity/Details/0048-NPP-JUL23-JPL-EarthSci?contractdesignation=2
   – Contact: Marc Simard (marc.simard@jpl.nasa.gov)
3. **Hydrologist Specializing in Coastal Regions with Remote Sensing Expertise**
   – https://www.jpl.jobs/job/R4250
   – Contact: Marc Simard (marc.simard@jpl.nasa.gov)

You can also contact me, I’m happy to answer questions or point you in the right direction: michael.w.denbina@jpl.nasa.gov

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