

# Addressing Underestimation in Global Forest Structure Mapping

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## Abstract

Mapping global vertical vegetation structure (VS) is critical for the quantification of global carbon stocks. While orbital LIDAR measurements of NASA's Global Ecosystem Dynamics Investigation (GEDI) mission provide direct estimates of vertical VS, they only cover 4% of the global land surface. Recent works have produced global contiguous maps of canopy height using convolutional neural network (CNN) models and satellite imagery. However, these models faced some challenges estimating high canopy heights (>30 m) and identified some tiling artifacts (Lang et al., 2022; Potapov et al., 2020).

We present various methods to address these limitations. First, we remove tiling artifacts by using overlapping tiles when producing maps and removing zero-padding from CNN architectures. Second, we compare the benefits and limitations of a few different methods to improve high canopy height estimation. Among the methods is histogram matching predicted heights to nearby LIDAR measurements. Another is learning a calibration model to correct each pixel based on similar known measurements nearby. Finally, we borrow recent advances in deep depth completion from the autonomous driving field to create an integrated model that uses known values to improve the prediction map.

To demonstrate these methods, we map global vertical VS with a CNN model at 1km resolution using observations from Landsat, L-band synthetic aperture radar observations from the Advanced Land Observing Satellite (ALOS) PALSAR-2, and surface topography. For model training, GEDI relative height metrics are filtered and aggregated into 1km grids. We also use measurements from the Ice, Cloud and land Elevation Satellite 2 (ICESat-2), inter-calibrated with GEDI using co-located measurements. Finally, we apply the aforementioned corrective methods to the product, reporting global RMSE and MAE metrics, as well as visual qualitative observations. These results open the path for unsaturated global vertical VS products at higher 500 m, 200 m, and 100 m resolutions.

Abstract content goes here



AGU Fall Meeting 2022  
GC15F-03

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This document has been reviewed and determined not to contain  
export controlled technical data.

# Motivation

- GEDI provides sparse measurements of vegetation vertical profile
- Other optical and radar sensors provide dense indirect measurements
- Deep learning to generate a wall-to-wall global map
- **Prior work suffers from underestimation of >25m heights**

# Outline

- Predictor & Target Data
- Methods & Results
  - Baseline Product
  - Histogram Matching
  - Mixed Density Networks
  - Monocular Depth Completion
- Conclusion & Future Work

# Target Data

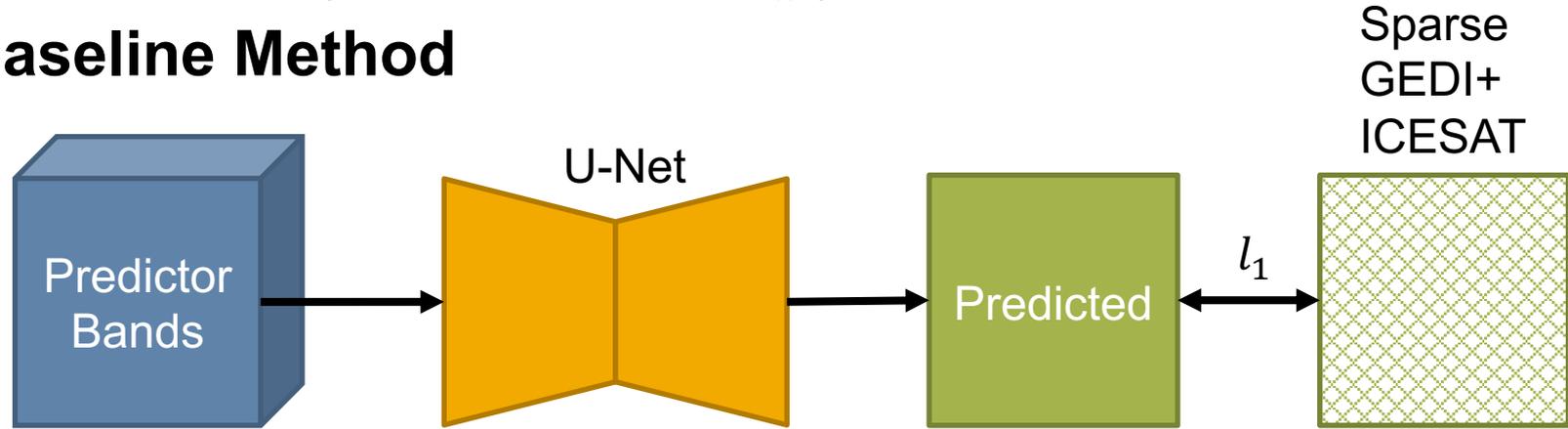
- GEDI L2A relative height metrics
  - Focus on RH98, most notable underestimation
  - Shots filtered and binned to 100m pixels
  - More detail (Favrichon, et al., GC15F-08)
- ICESAT-2
  - Cross-calibrated to provide data at higher latitudes
  - More detail (Yang, et al., INV21A-05)

# Predictor Data

18 bands total

Data	Bands	Provider
ALOS PALSAR 2	HH, HV	JAXA
MODIS LST	Day, Night averages	NASA
MODIS NBAR	1~7	NASA
Landsat 8	Veg Idx, Red, NIR, SWIR1, SWIR2	USGS
Copernicus DEM	(Elevation)	ESA
CGLS VCF	(Forest Cover)	ESA

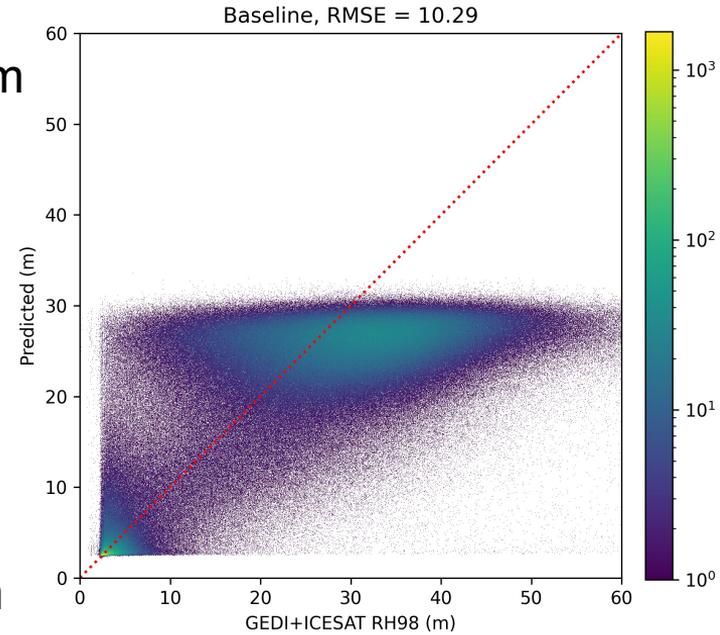
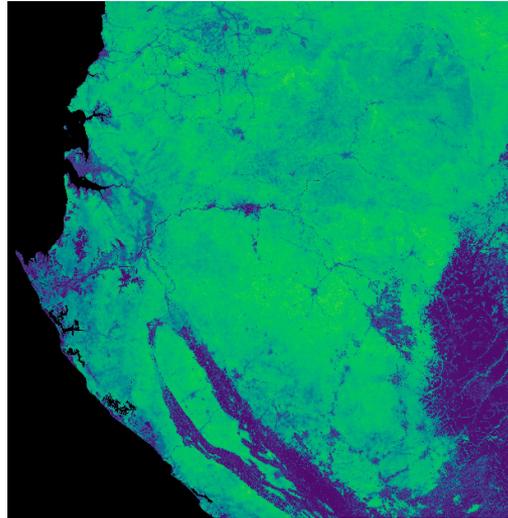
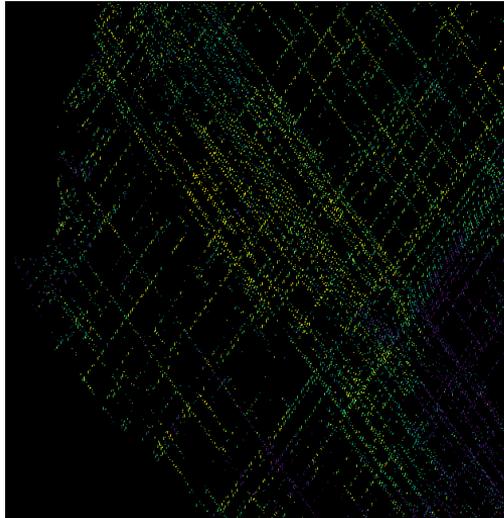
# Baseline Method



- Predictor rasters tiled into 256x256 with 32px overlap
- Multi-GPU model training pipeline trains a complete 100m global model within a day (~40 epochs), complete map prediction in an hour

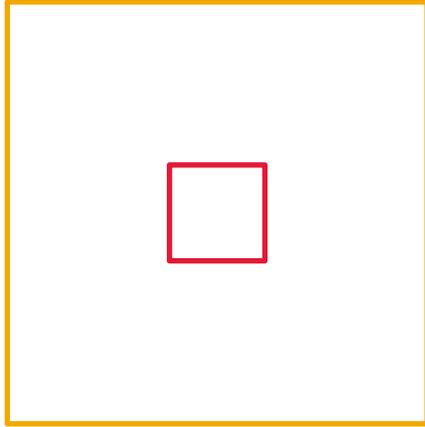
# Baseline Method Results

## GEDI+ICESAT



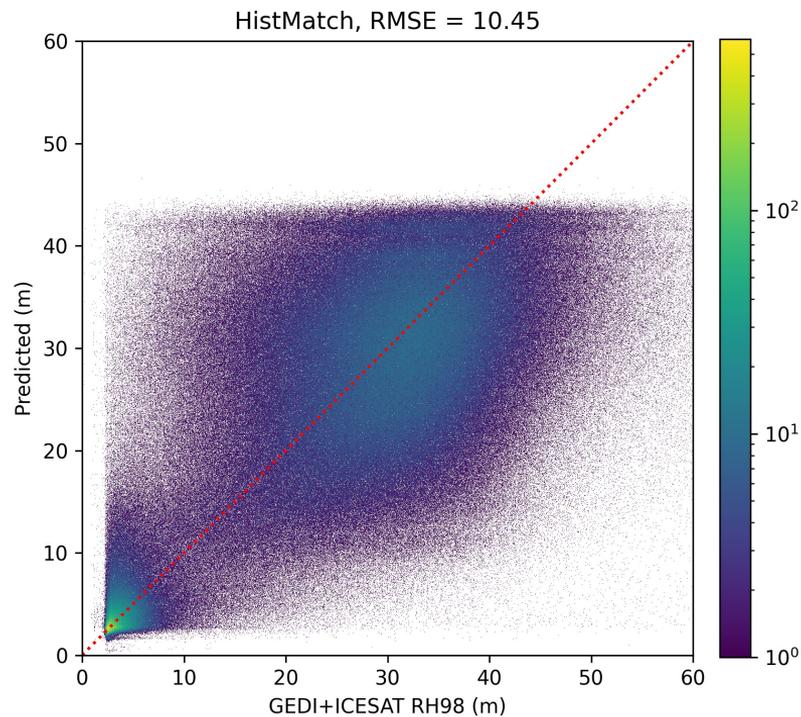
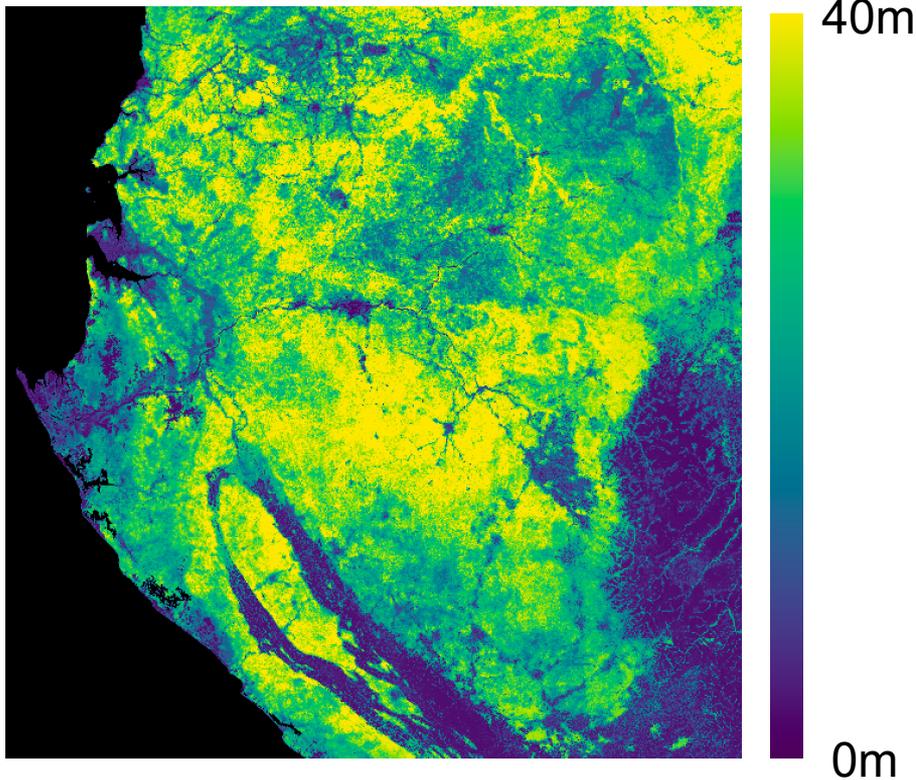
Consistent underestimation of tall forests

# Histogram Matching



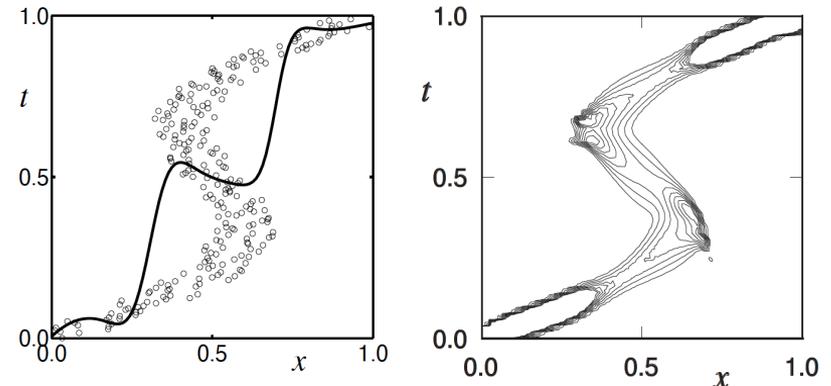
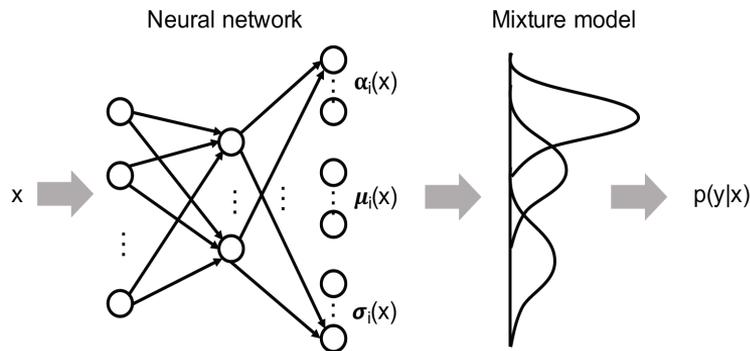
- Match the distribution of the **inner predicted values** to the distribution of the **outer GEDI+ICESAT values**
- Post hoc correction step, no changes to the model
- Assumes sufficient known values in the outer region
- Possibly brittle on edges of regions

# Histogram Matching Results



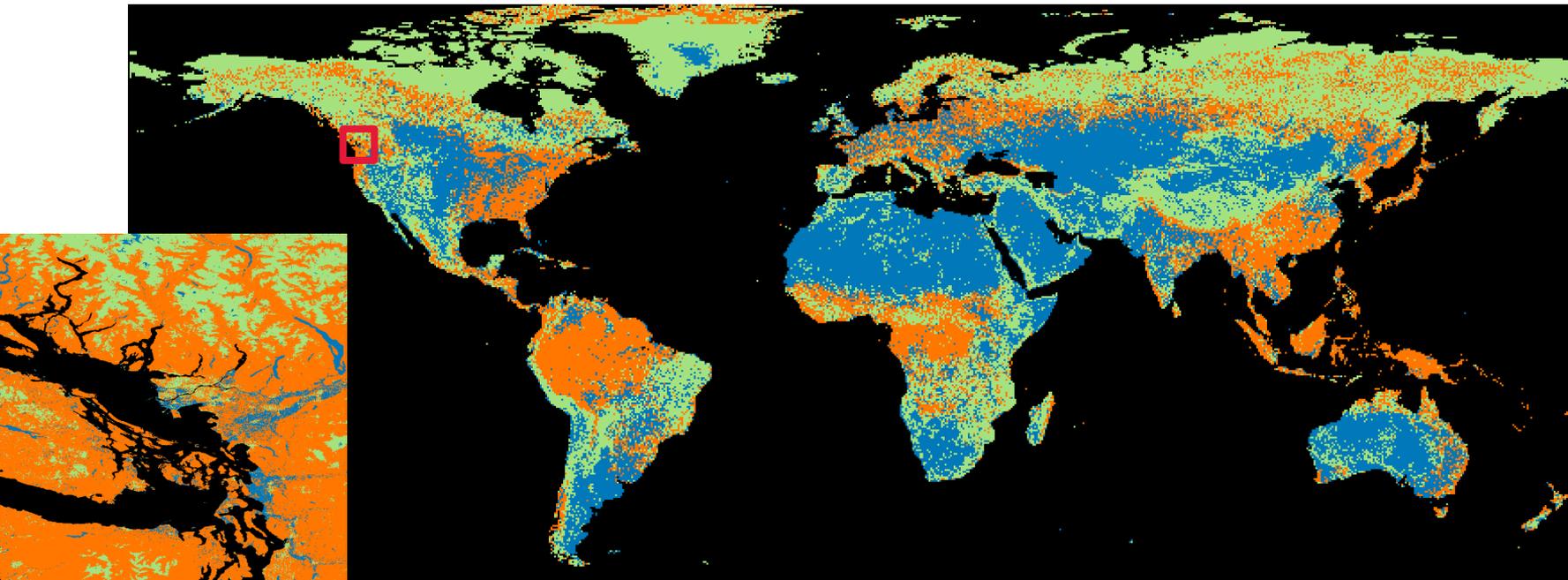
# Mixed Density Network

- Prior models (e.g. Lang et al., 2022) predict the mean and variance for each pixel, minimizing the Gaussian negative log likelihood
- Mixed Density Networks predict **multiple** Gaussian distributions
  - Model also predicts a **weight** for each distribution
  - 4 distributions  $\rightarrow$  12 output channels (mean, variance, weight)
- Useful when multiple targets exist for the same predictor



(Bishop, 1994)

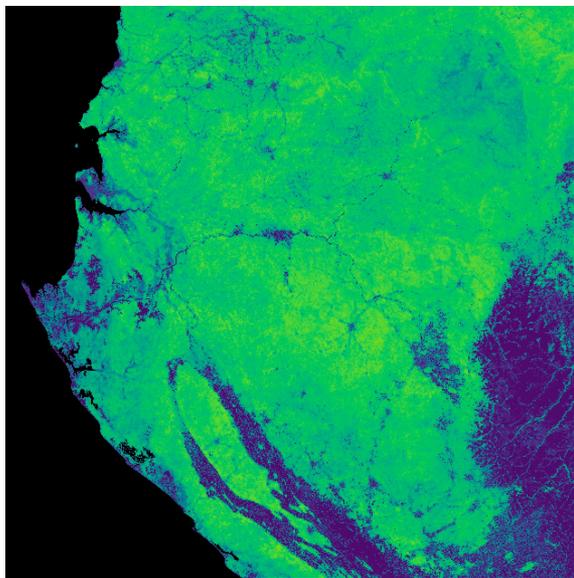
# Mixed Density Network Results



- Each color represents different dominant distribution
- Model specializes each distribution for a different vegetation type
  - **Unsupervised!**

# Mixed Density Network Results

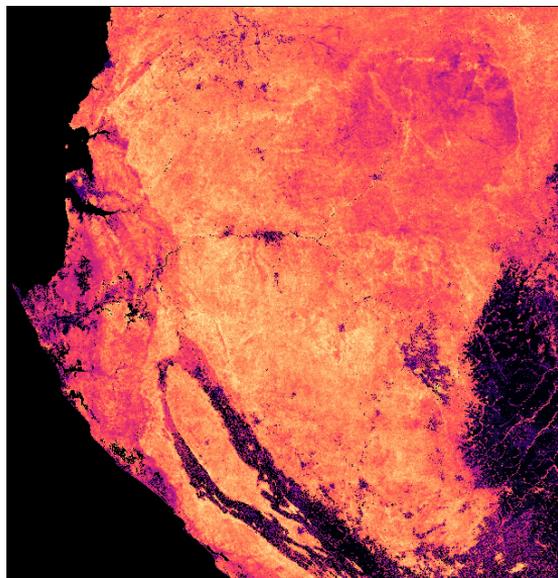
Dominant Mean



0m

40m

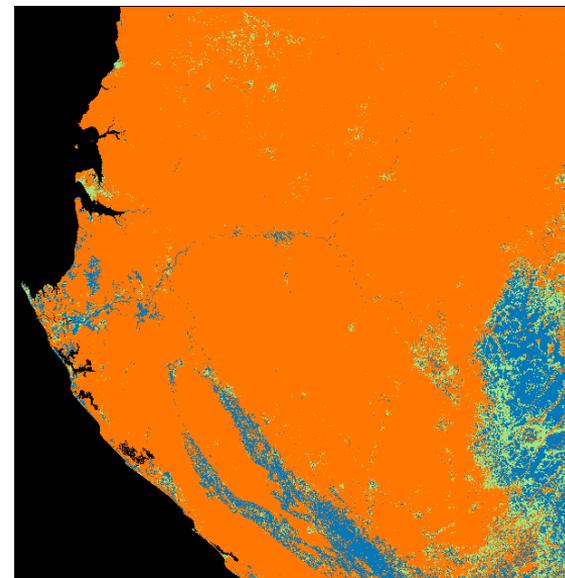
Dominant Variance



0m

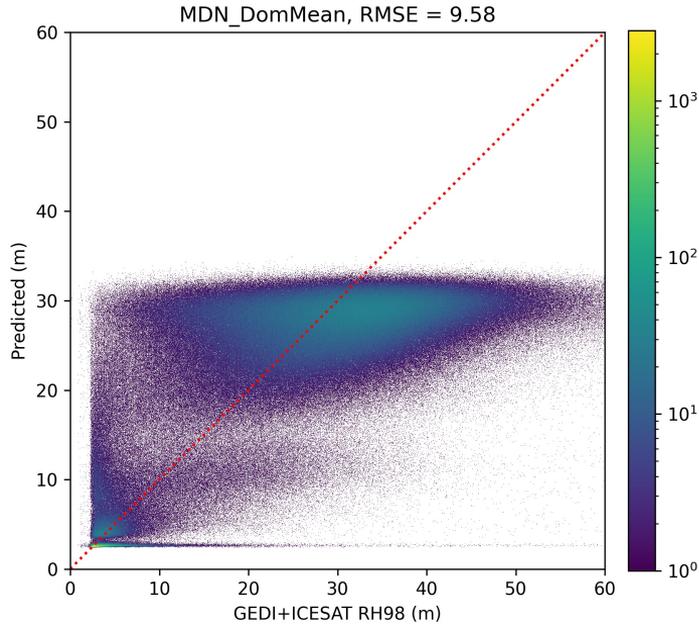
10m

Dominant Distribution

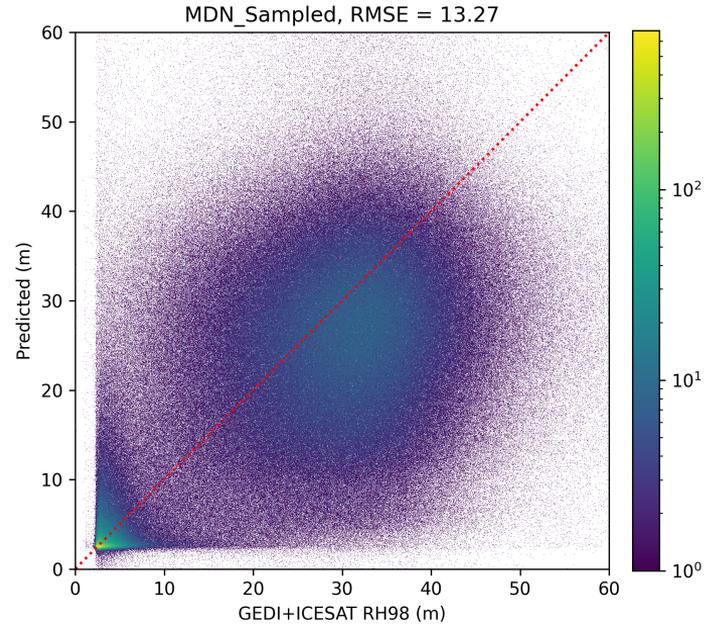


# Mixed Density Network Results

## Dominant Means Only



## Values Sampled from Distribution

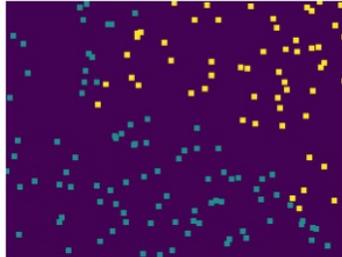


# Monocular Depth Completion

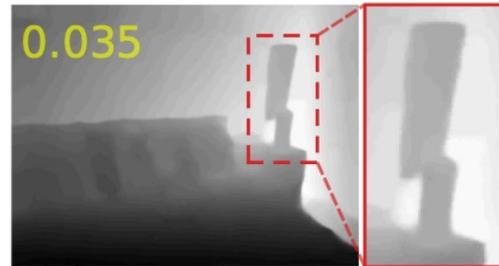
- Rapidly growing field for autonomous vehicles
- Combining Sparse LIDAR and dense RGB image to generate dense LIDAR maps
- Convolutional Spatial Propagation Networks (CSPNs) propagates sparse labels to the rest of the image
- Drawbacks:
  - Often trained on simulated dense labels, but only sparse labels available
  - Lack of open-source codebases due to a financially motivated field



(a)

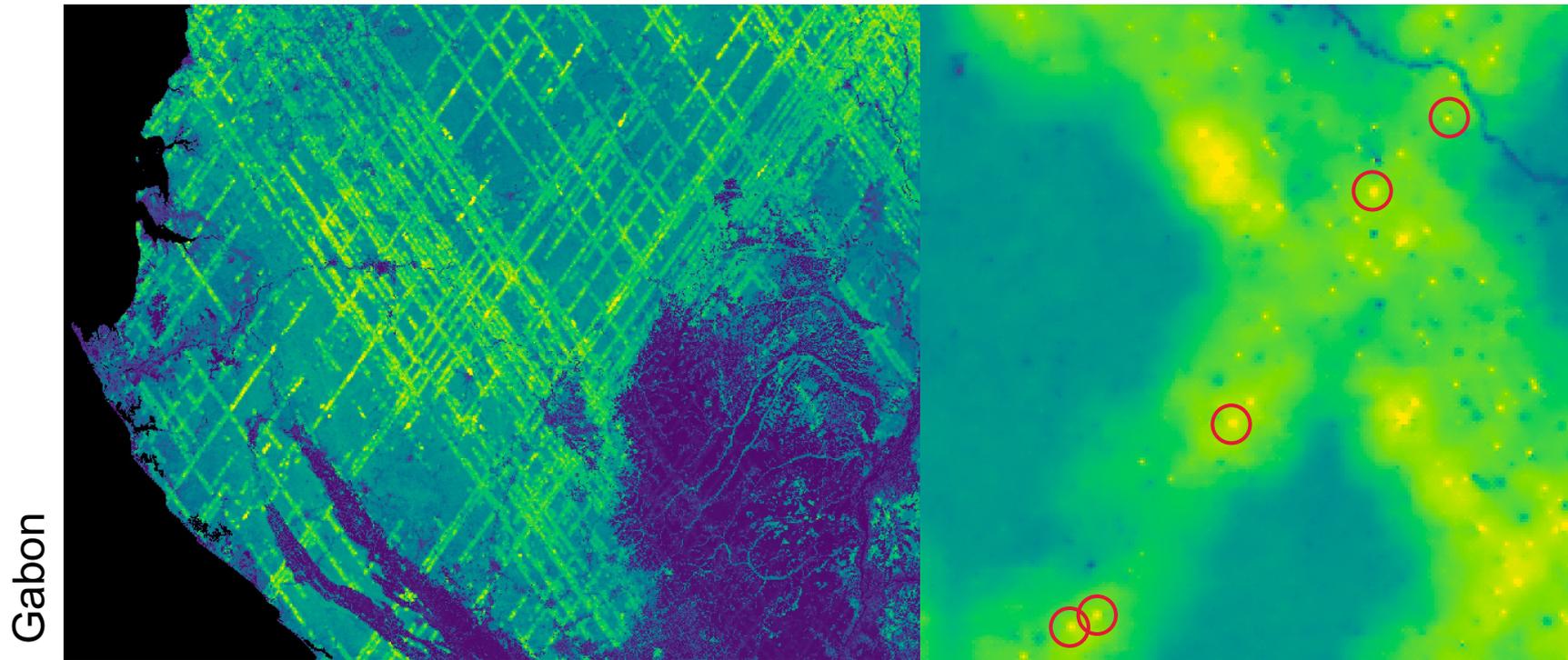


(f)



(j)

# Depth Completion Results



Gabon

Given only 5% of labeled pixels, model learns how to complete the orbital maps  
Ongoing research into sparse-to-sparse depth completion

# Conclusion

- Implemented pipeline for fast 100m global map generation
- Three different promising methods for addressing underestimation
- Future work towards a non-biased global map for multiple RH metrics



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