AGU Fall Meeting 2022
GC15F-03

Addressing Underestimation in Global Forest Structure Mapping

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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

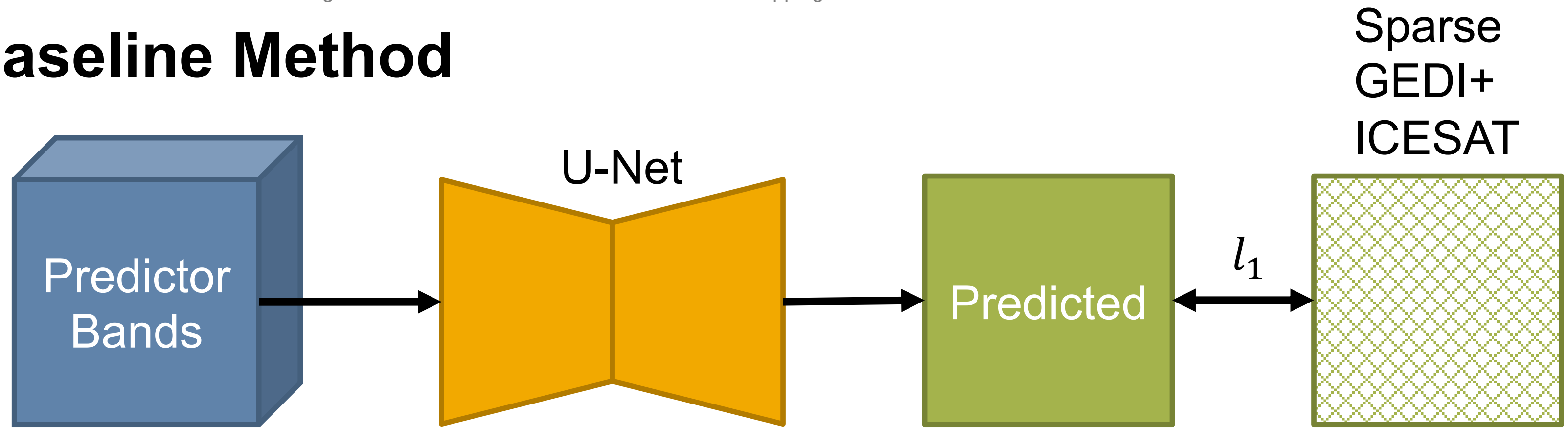
- GEDI L2A relative height metrics
  - Focus on RH98, most notable underestimation
  - Shots filtered and binned to 100m pixels
  - More detail (Favrichon, et al., GC15F-08)
- ICESAT-2
  - Cross-calibrated to provide data at higher latitudes
  - More detail (Yang, et al., INV21A-05)

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

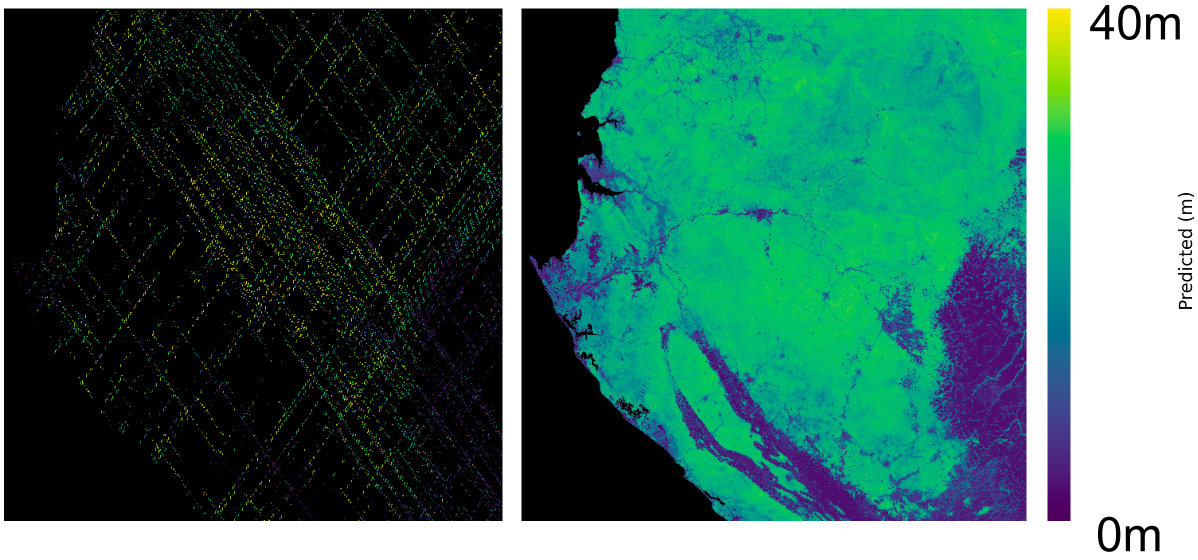
Baseline Method

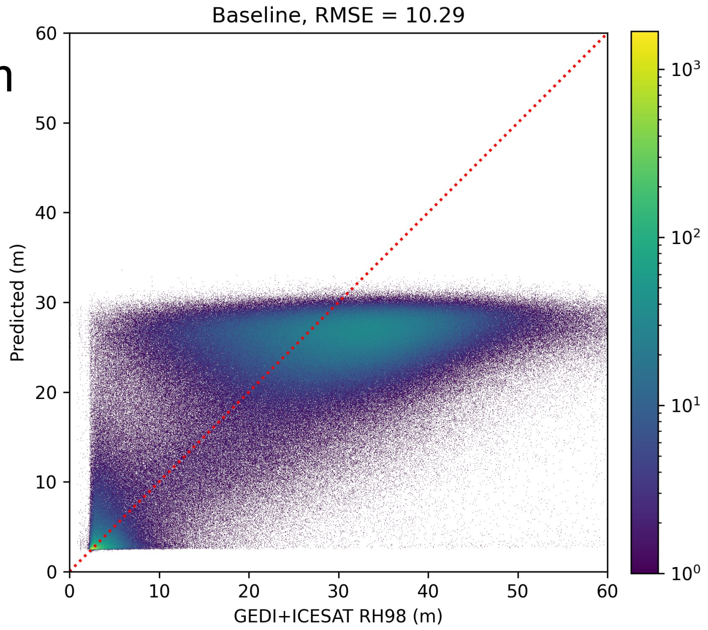


- Predictor rasters tiled into 256x256 with 32px overlap
- Multi-GPU model training pipeline trains a complete 100m global model within a day (~40 epochs), complete map prediction in an hour

Baseline Method Results

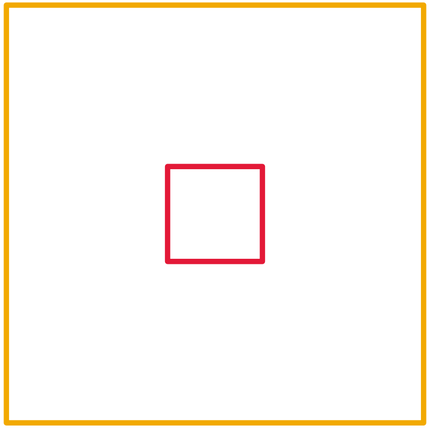
GEDI+ICESAT





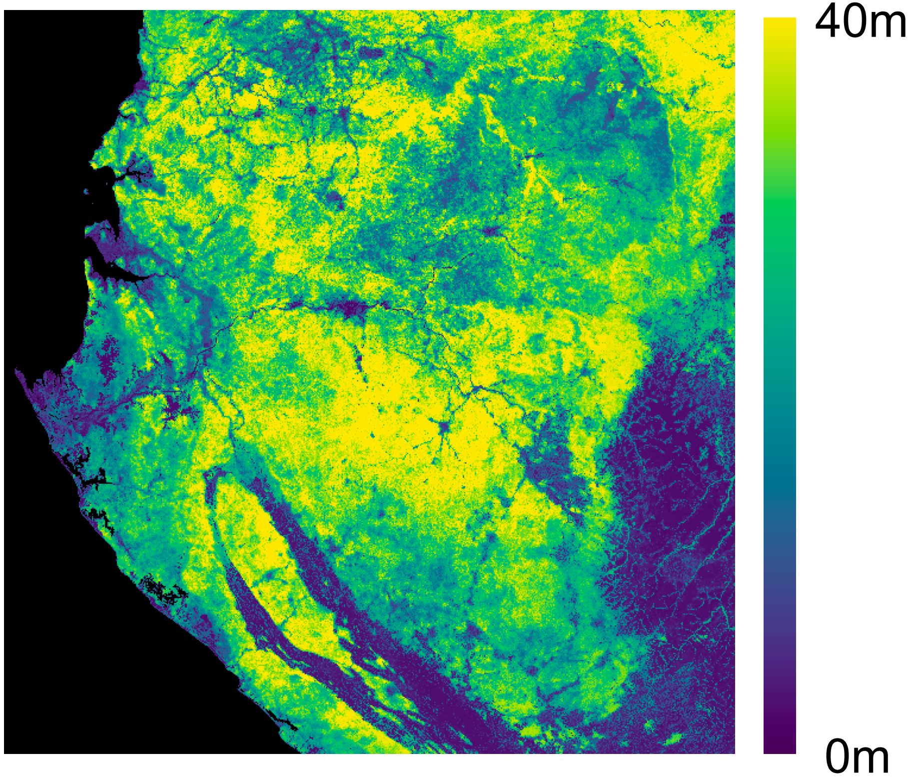
Consistent underestimation of tall forests

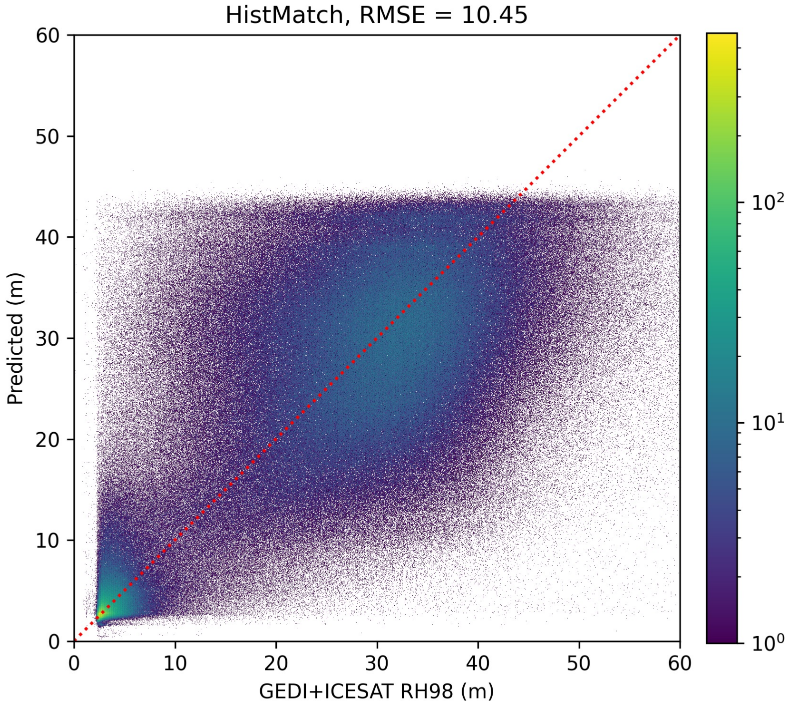
Histogram Matching



- 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

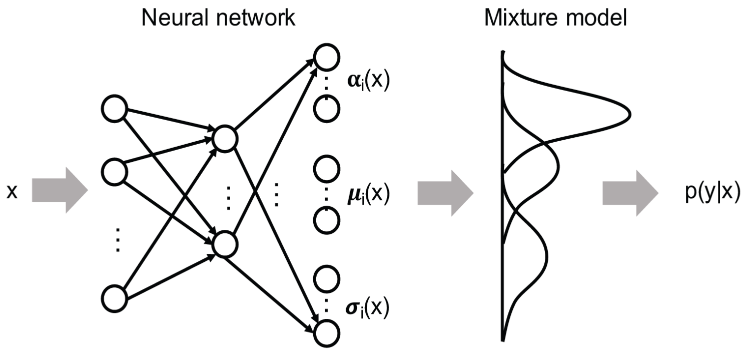
Histogram Matching Results

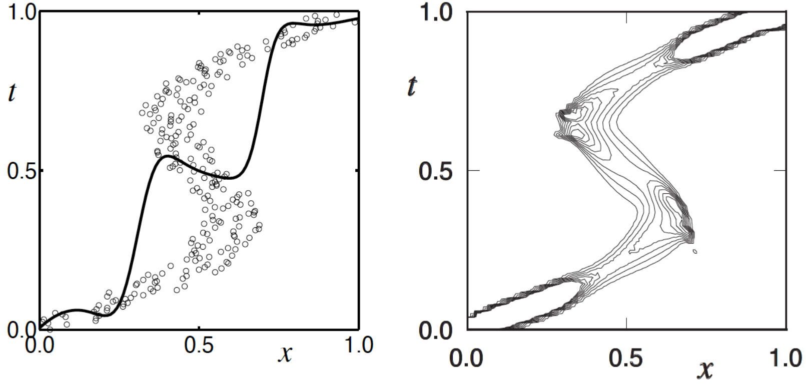




Mixed Density Network

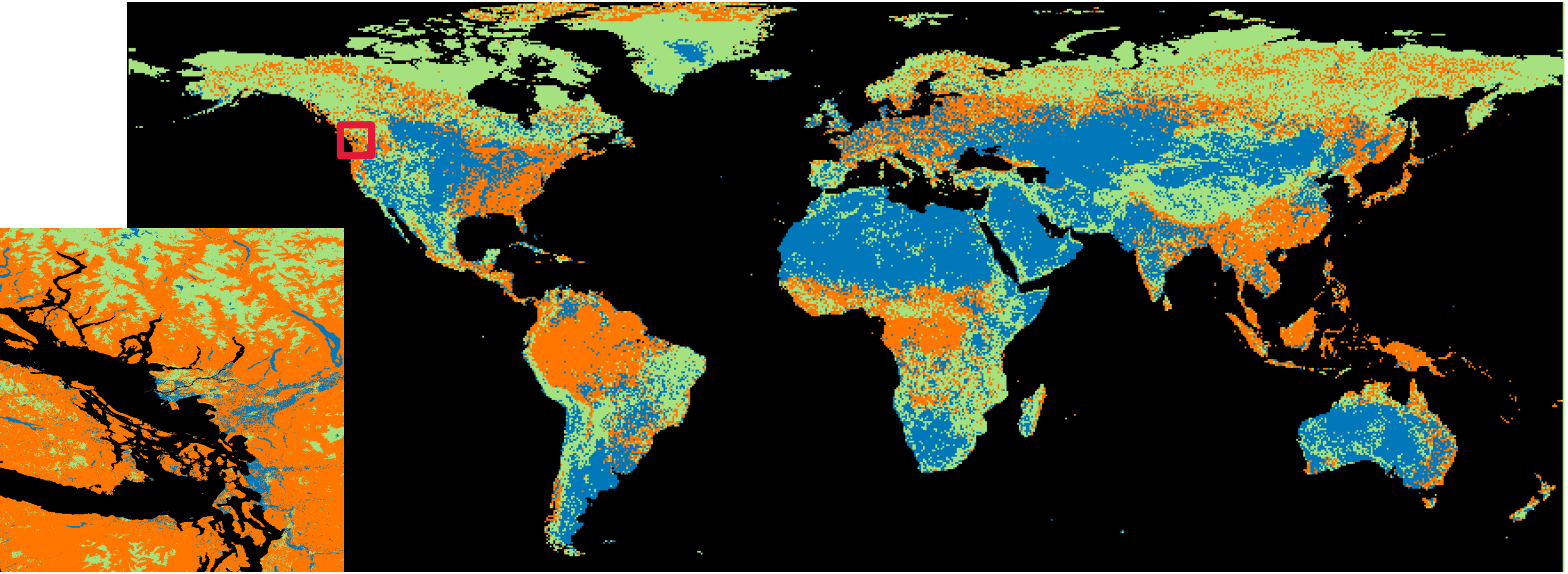
- Prior models (e.g. Lang et al., 2022) predict the mean and variance for each pixel, minimizing the Gaussian negative log likelihood
- Mixed Density Networks predict **multiple** Gaussian distributions
  - Model also predicts a **weight** for each distribution
  - 4 distributions → 12 output channels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





(Bishop, 1994)

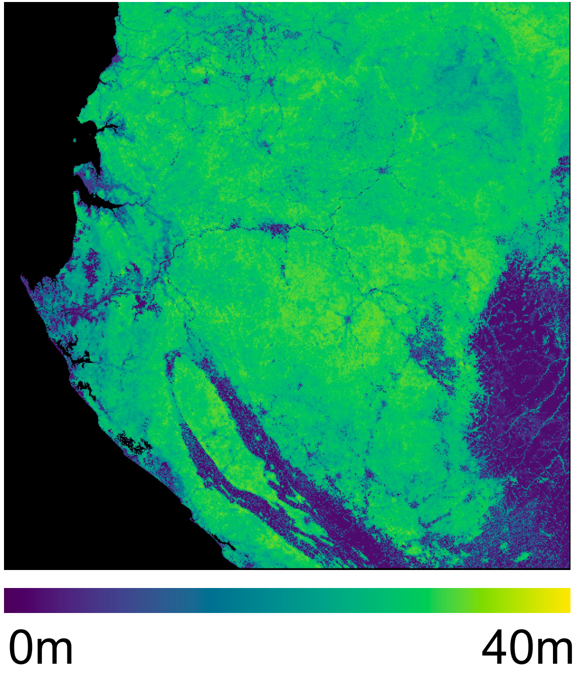
Mixed Density Network Results



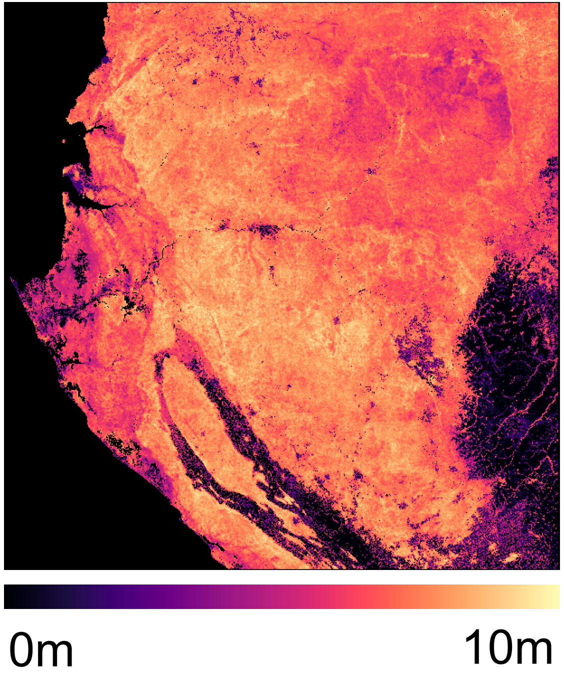
- Each color represents different dominant distribution
- Model specializes each distribution for a different vegetation type
  - **Unsupervised!**

Mixed Density Network Results

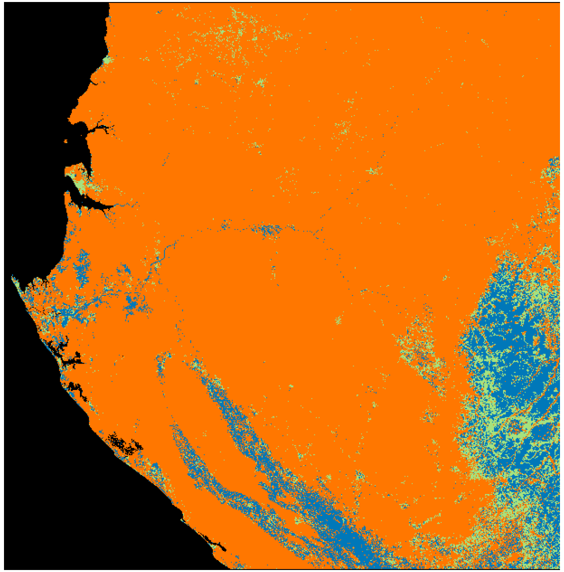
Dominant Mean



Dominant Variance

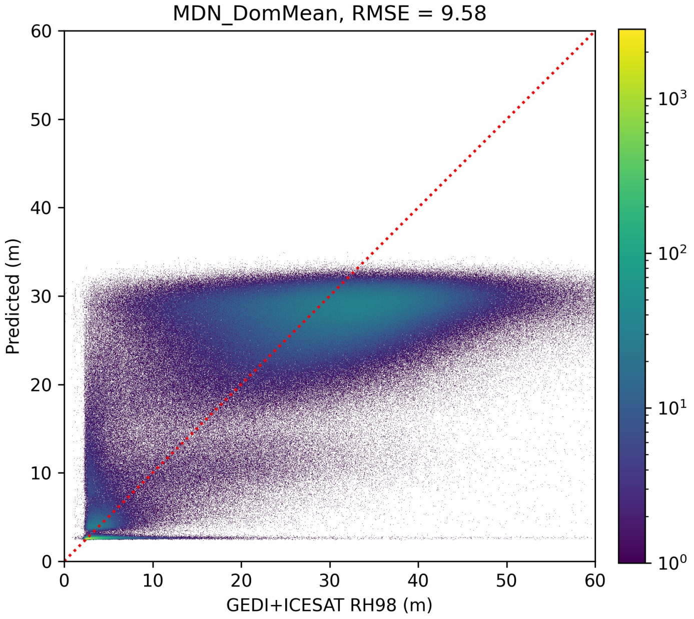


Dominant Distribution

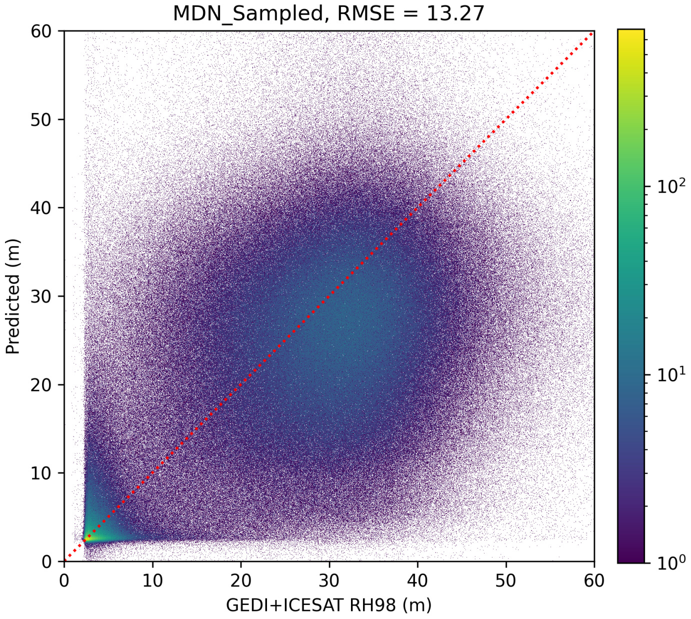


Mixed Density Network Results

Dominant Means Only

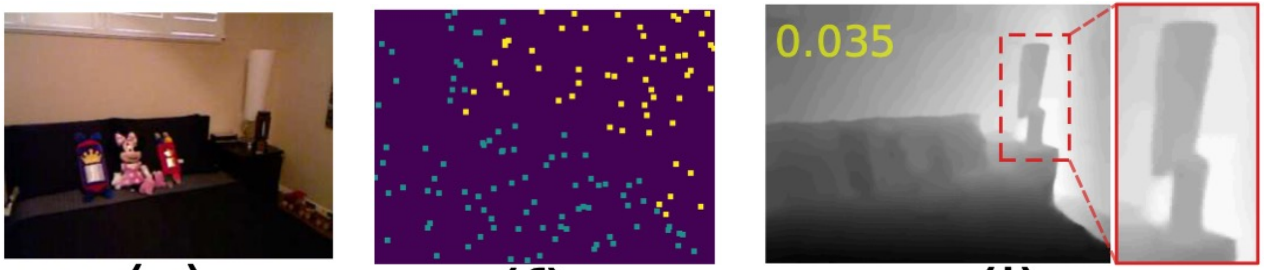


Values Sampled from Distribution



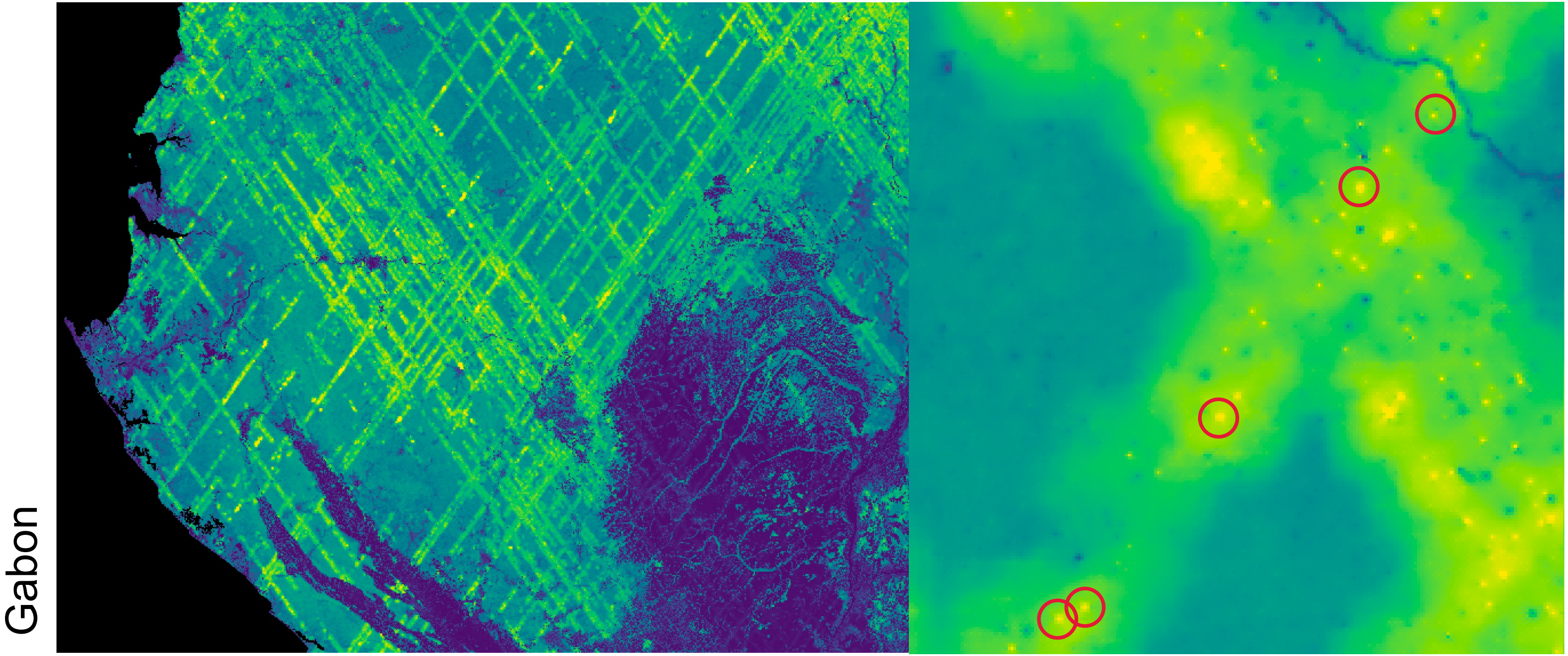
Monocular Depth Completion

- 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



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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