A new satellite derived irradiance algorithm for the GOES-R generation

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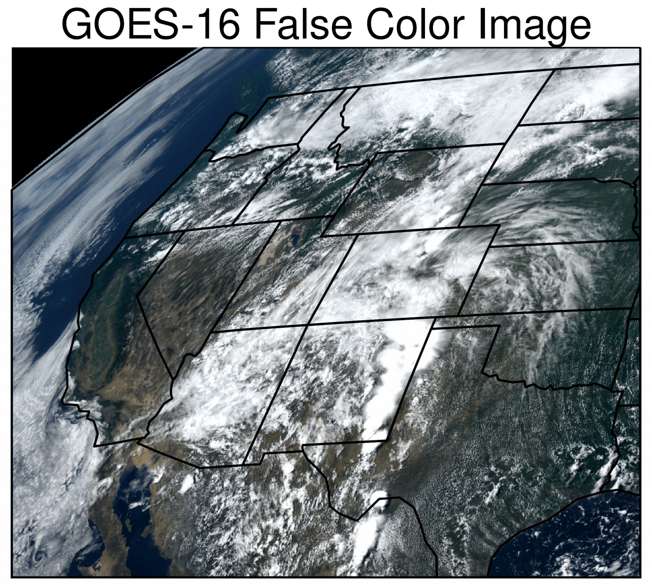
Summary

- Ultimate goal is to create an empirical model that uses only GOES-R imager data without exogenous inputs (e.g. NWP model data) to predict GHI
- Try to leverage CALIPSO active LIDAR data to estimate cloud properties from GOES-R imager data to improve GHI prediction
- GHI model compares favorably to current methods
- No further improvement yet using predicted cloud properties
- Training time for each model ~1 min on a modern 4 core desktop

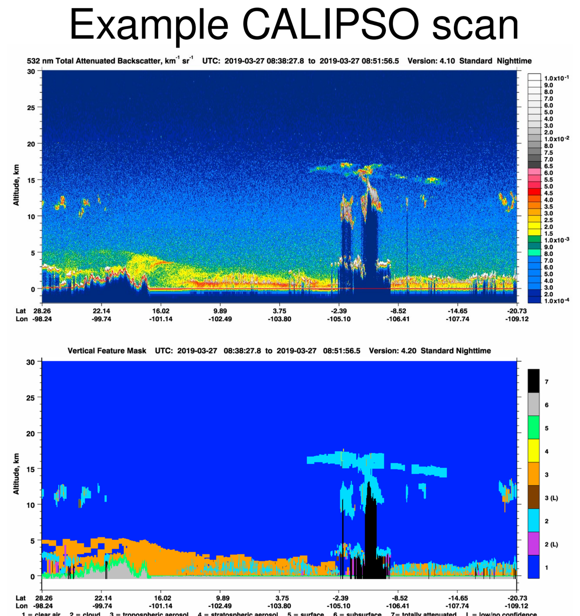
Data

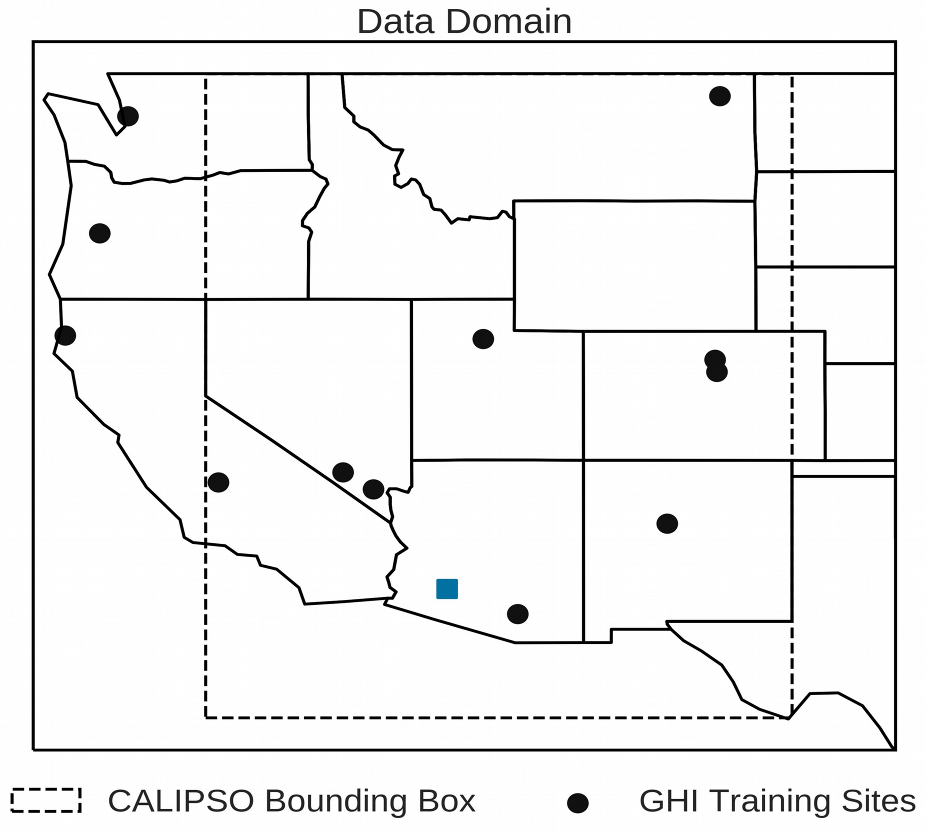
- Time period: 03/2018 to 06/2019
- GOES-16 Level 2 Cloud and Moisture Imagery for all 16 bands up/downsampled to 1km as primary predictors
- CALIPSO v4.20 1km Cloud Layer product as signal for cloud mask, cloud type, and cloud height. One daytime scan over the US at ~20Z
- GOES pixel data co-located with CALIPSO data after correcting for parallax; shifts within GOES image collection time likely an issue
- GHI signal from sensors in NOAA SURFRAD, NOAA SOLRAD, NREL MIDC networks, and proprietary out of sample test site

GOES-16 False Color Image



Example CALIPSO scan



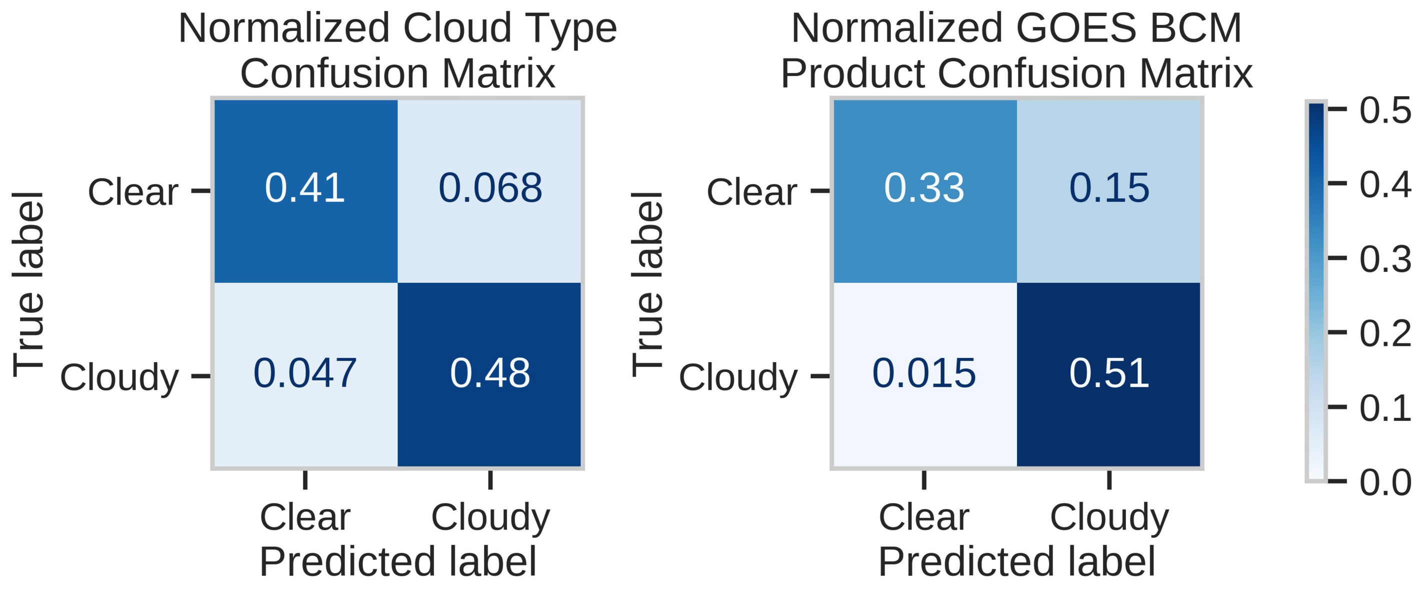


Data domain with CALIPSO data bounding box, locations of training sites for GHI regression, and location of the out of sample site for GHI regression

Estimating Cloud Properties

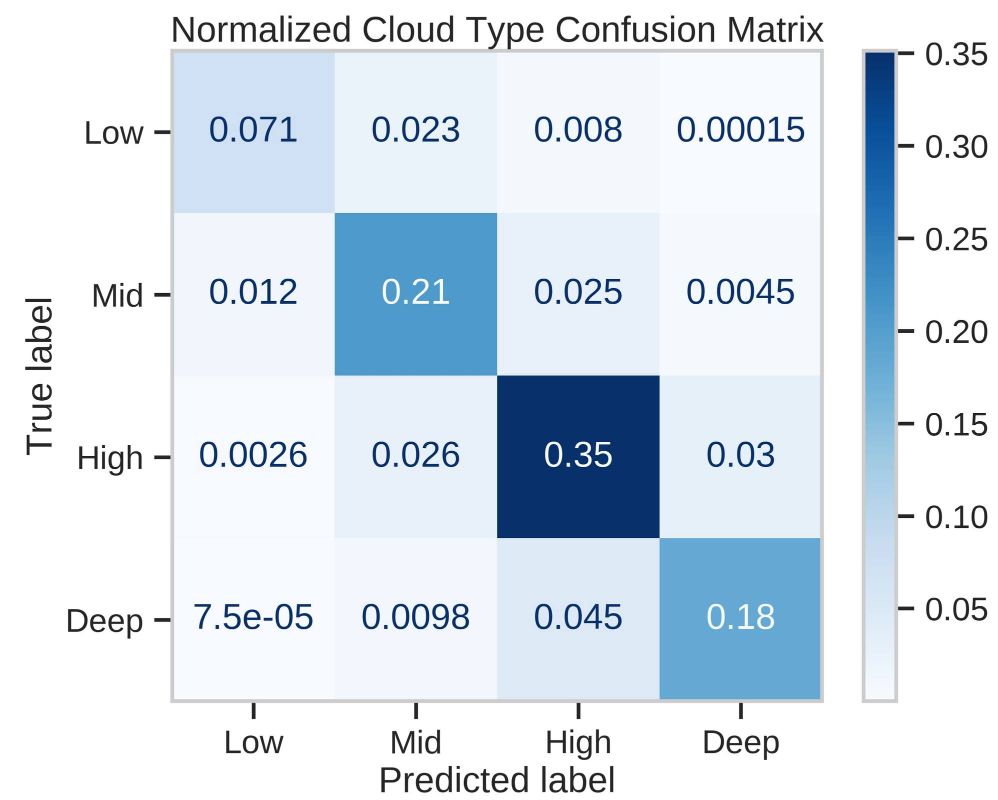
Cloud Mask

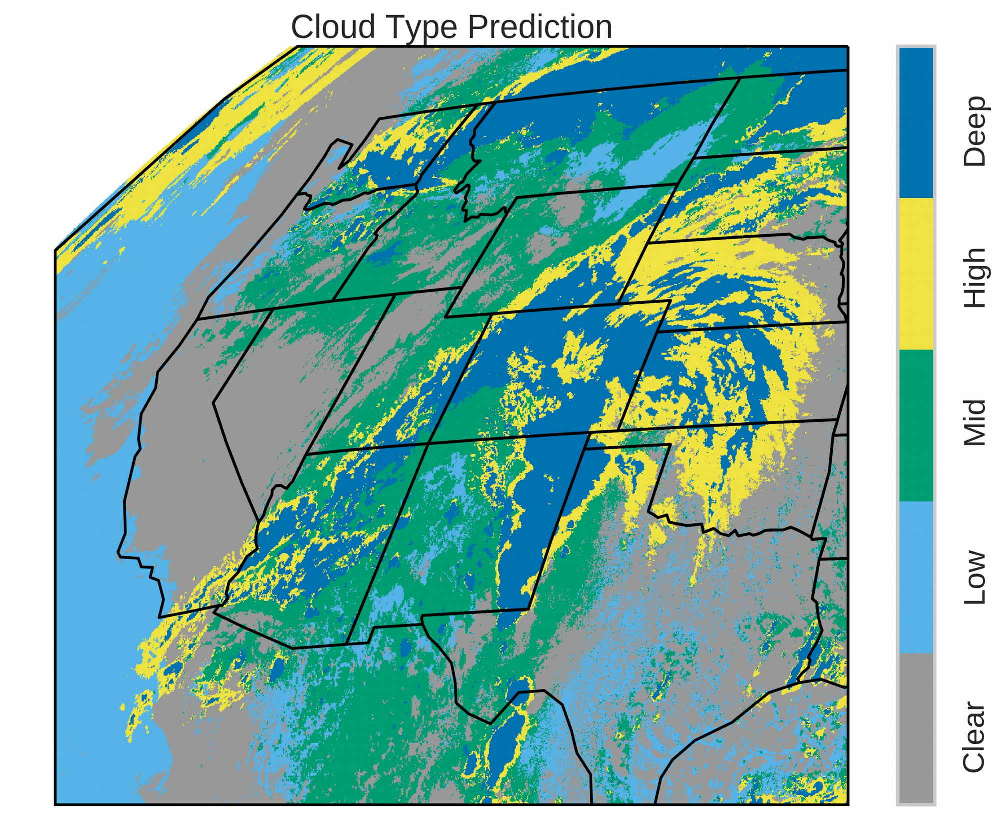
- Two layer multilayer perceptron classifier
- Better co-location between CALIPSO and GOES pixels likely to improve result
- Different failure distribution from GOES Binary Cloud Mask product



Cloud Type

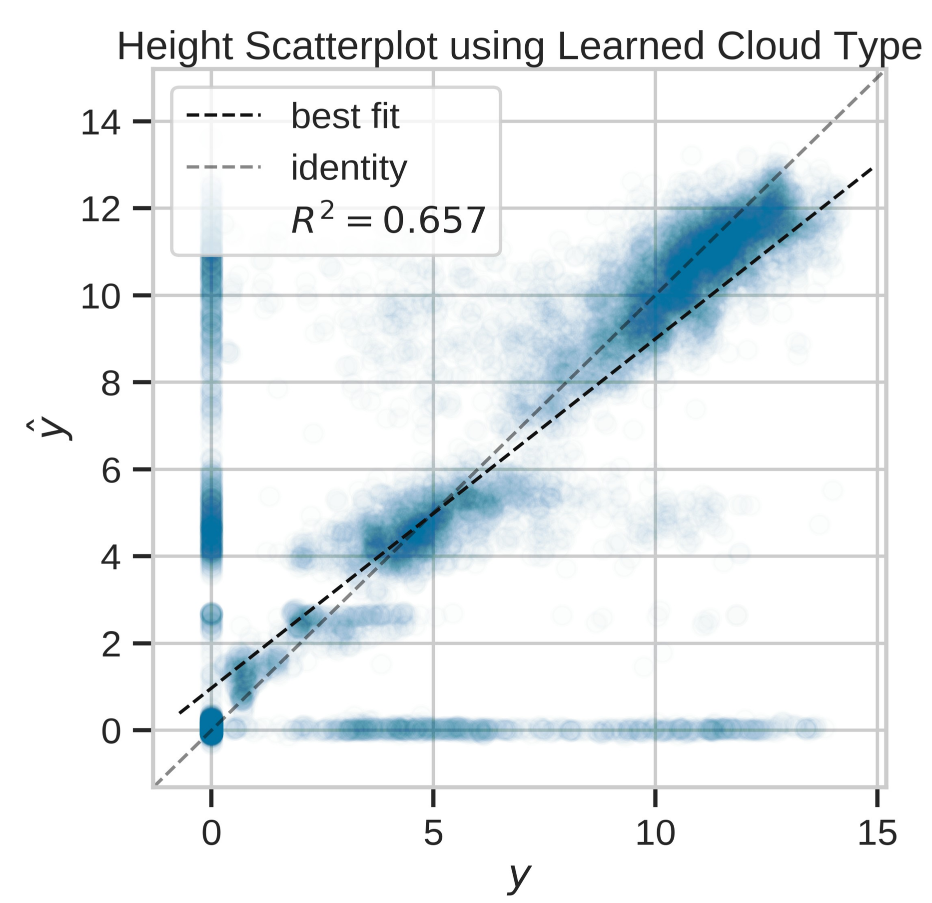
- Single layer multilayer perceptron one -vs-many classifier
- Only trained on points reported as cloudy by CALPISO
- Low clouds most difficult with few examples in training data

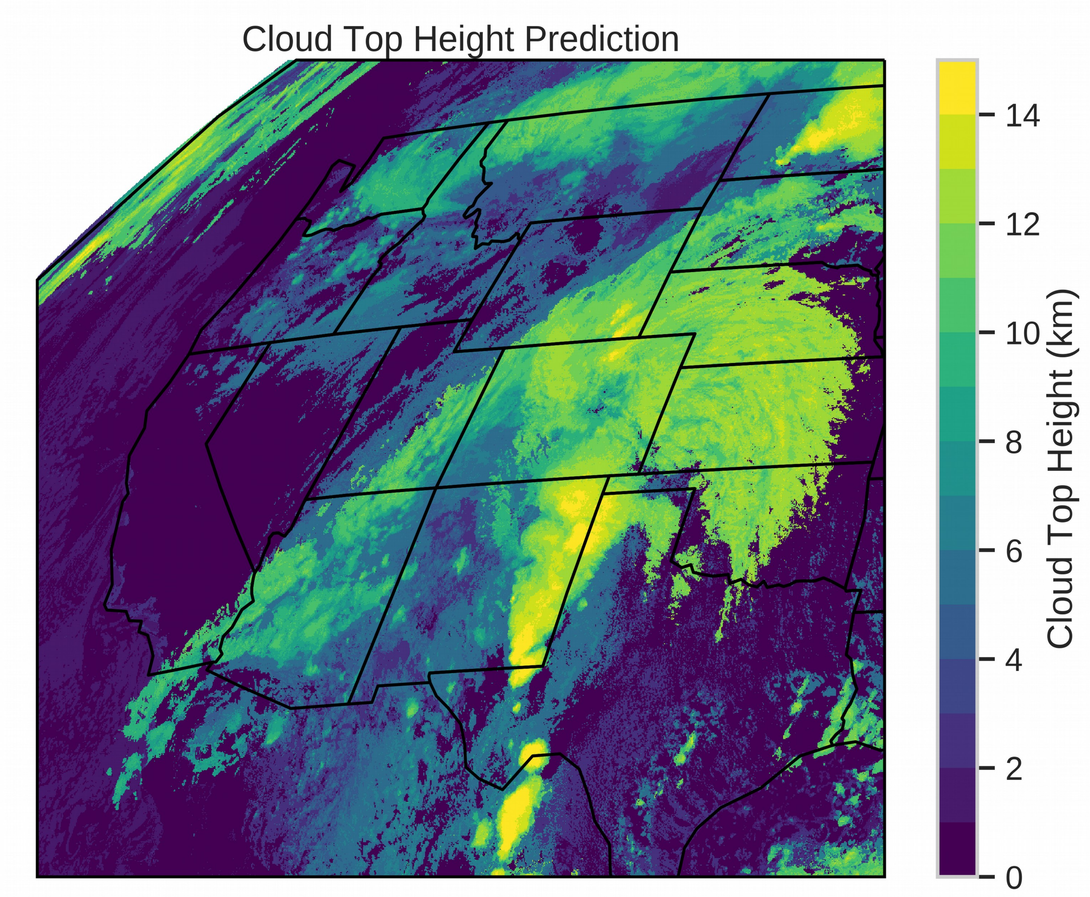




Cloud Top Height

- Single layer multilayer perceptron regression
- Also use cloud type as a predictor
- Best fit by using CALIPSO cloud type ($R^2 > 0.9$)
- Cloud type classify error evident
- Training without cloud type predictor still shows error in determining cloud mask



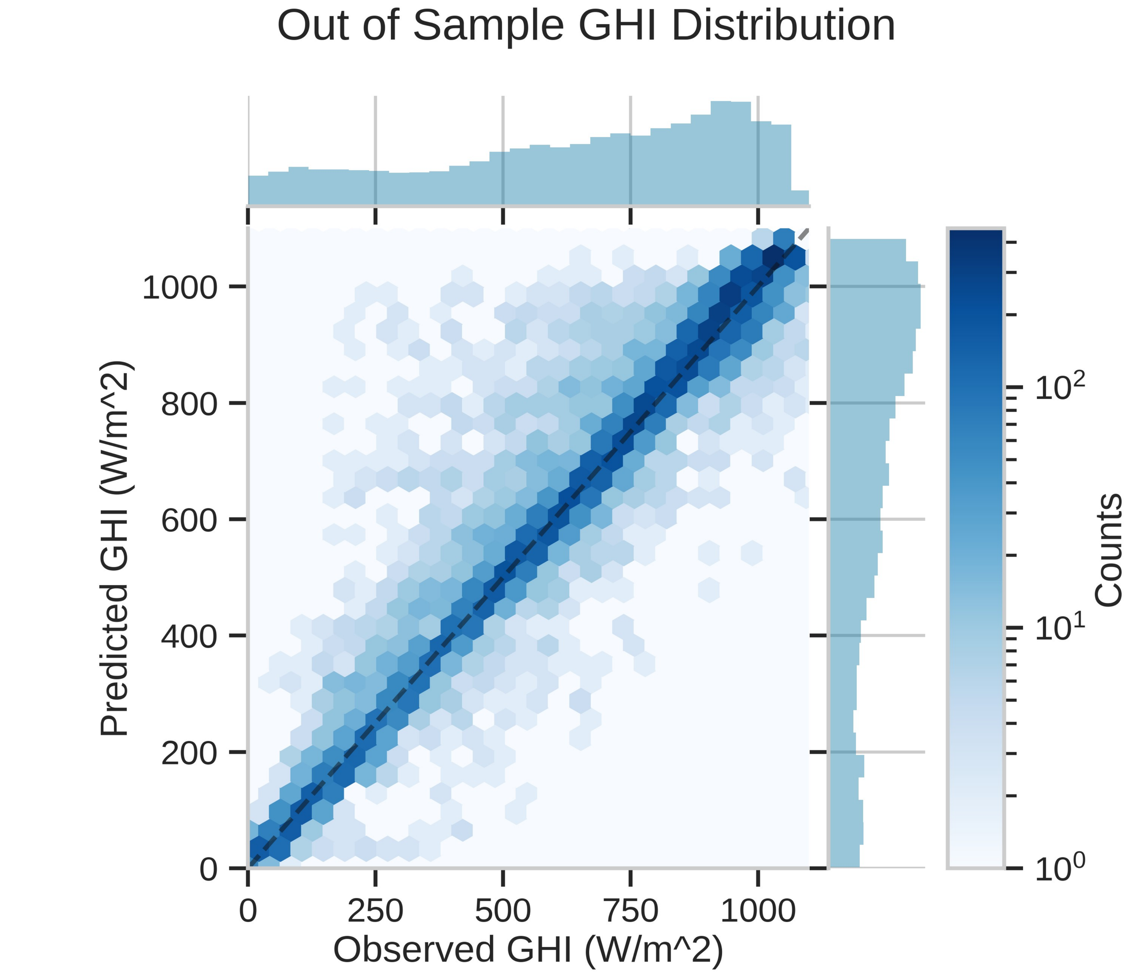


Estimating Irradiance

- A model to predict GHI was trained on one year of data from:
  - 16 channels from the GOES-16 MCMIP CONUS product (~2km resolution, every 5 min)
  - Solar zenith angle (<90°), azimuth angle, and extra radiation
  - Site latitude, longitude, and elevation
- Used a gradient boosted regression tree model (LightGBM) which generalized better than multilayer perceptron
- A second model using the predicted cloud height to adjust for parallax, along with cloud mask, type, and height as predictors, led to no difference in the final results indicating that information from CALIPSO did not propagate to the GHI model
- Future work will include improving cloud property models and GHI prediction using those models

Table 1. Error metrics for the GHI model predictions for the training dataset, the testing dataset, and the out of sample dataset. The errors are consistent between training and testing, and the model generalized to locations that it was not trained on. The GOES-15 Physical Model refers to the model describe in [1] as applied to GOES-15 data and evaluated in [2]. This data is from a separate time period and satellite, but it illustrates that the new GHI model performs at least as well.

	RMSE	MAE	MBE
Train Set	83.2	47.1	-4.18
Test Set	91.4	50.4	-4.09
Out of Sample	76.4	40.9	12.9
GOES-15 Physical Model*	98.8	38.8	20.7



References

[1] Kim, C.K., et al. Toward Improved Solar Irradiance Forecasts: Comparison of Downwelling Surface Shortwave Radiation in Arizona Derived from Satellite with the Gridded Datasets. Pure Appl. Geophys. 173, 2929–2943 (2016) doi:10.1007/s00024-016-1307-y

[2] Lorenzo, A. T., et al. Optimal interpolation of satellite and ground data for irradiance nowcasting at city scales. Solar Energy 144, 466-474 (2017) doi: 10.1016/j.solener.2017.01.038

Data & Code: https://github.com/uarenforecasting/erebos