Development of CYGNSS Soil Moisture using a Machine Learning Model

Thomas Huitema (UMD/Computer Science)
Mentor: Dr. Jifu Yin (STAR/SMCD/LVB)

Cooperative Institute for Satellite Earth System Studies

Introduction & Objectives

- Satellite reflectivity is known to be influenced by soil moisture
- Current global SM products (SMAP) have a temporal frequency of 2-3 days
- CYGNSS collects data at low cost and higher frequency

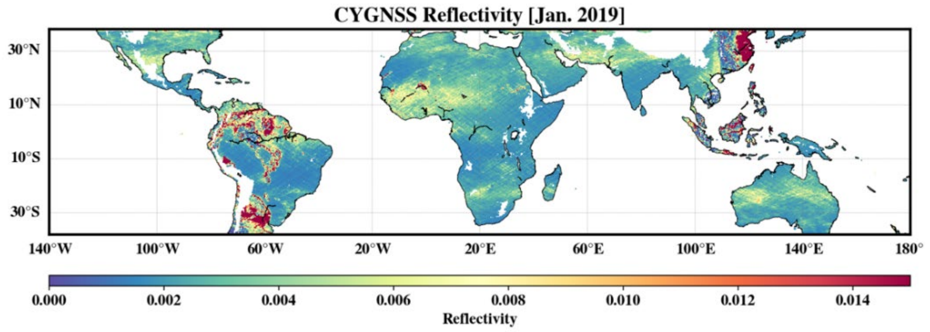
[1] Collected CYGNSS reflectivity, SMAP soil moisture (SM), and ancillary data
[2] Developed a machine learning model to retrieve CYGNSS soil moisture
[3] Evaluated CYGNSS SM retrievals using reference data SMAP
[4] Validated CYGNSS SM retrievals with in-situ observations

Machine Learning Framework

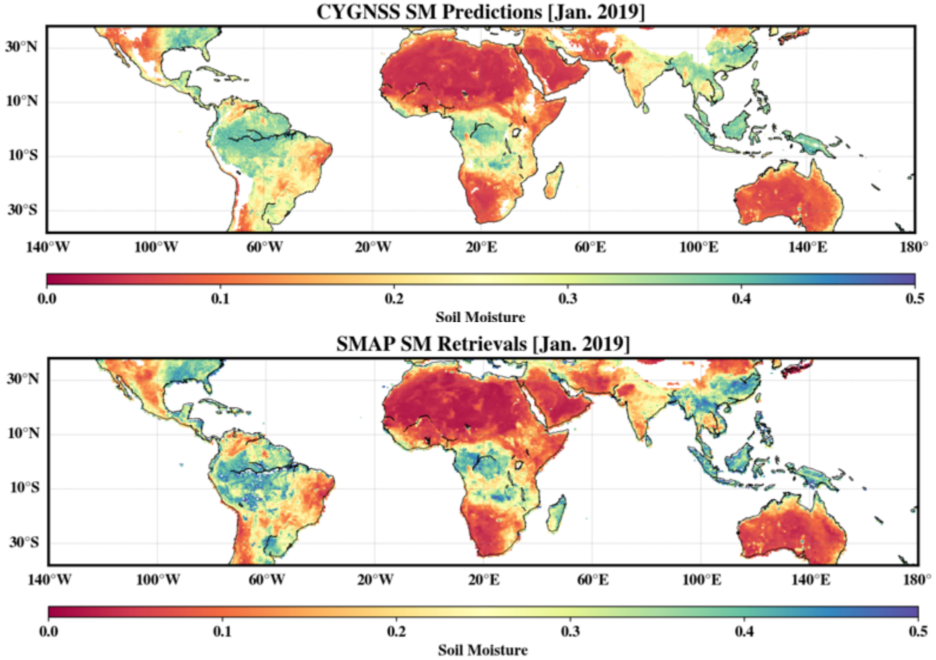
- XGBoost ML model has better behavior than other popular models
- Input: CYGNSS reflectivity and signal-to-noise ratio, elevation, clay & sand ratios, soil texture, VIIRS land cover, MODIS NDVI, month
- Reference: SMAP SM retrievals
- Cluster data into 4 geographical quadrants, train 1 model on each
- Train period: 2019 to 2022
- Test period: Jan. 2023 to Sep. 2023
- Metrics: RMSE, ubRMSE, MAE, R

Training [2019 - 2023]				Testing [Jan. 2023 - Sep. 2023]			
RMSE	ubRMSE	MAE	R	RMSE	ubRMSE	MAE	R
0.0502	0.0502	0.0343	0.8962	0.0588	0.0586	0.0404	0.8587

Average performance metrics of each cluster model in the train & test periods between CYGNSS and SMAP SM



Monthly example of the 25 km CYGNSS reflectivity for January 2019

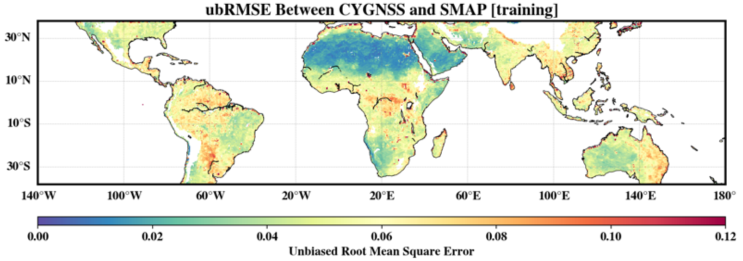


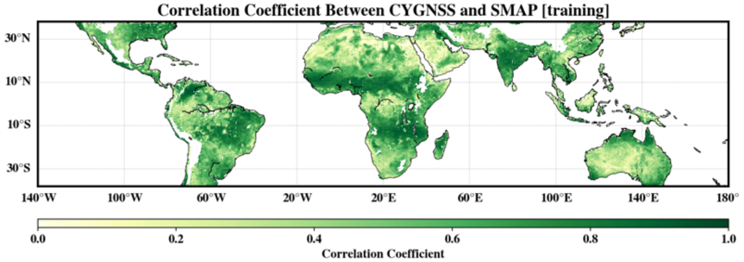
Spatial maps of CYGNSS SM predictions and SMAP intra-month mean SM (m^3/m^3) for January 2019

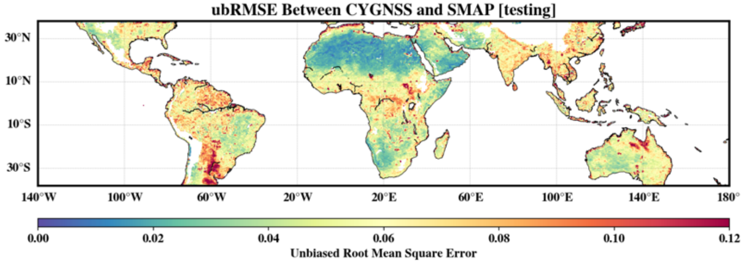
Development of CYGNSS Soil Moisture using a Machine Learning Model

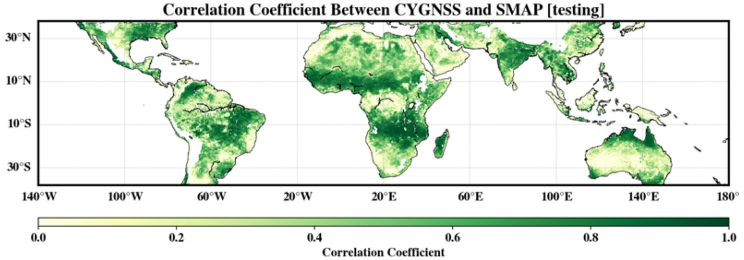
Thomas Huitema (UMD/Computer Science)
Mentor: Dr. Jifu Yin (STAR/SMCD/LVB)

Evaluation against SMAP SM



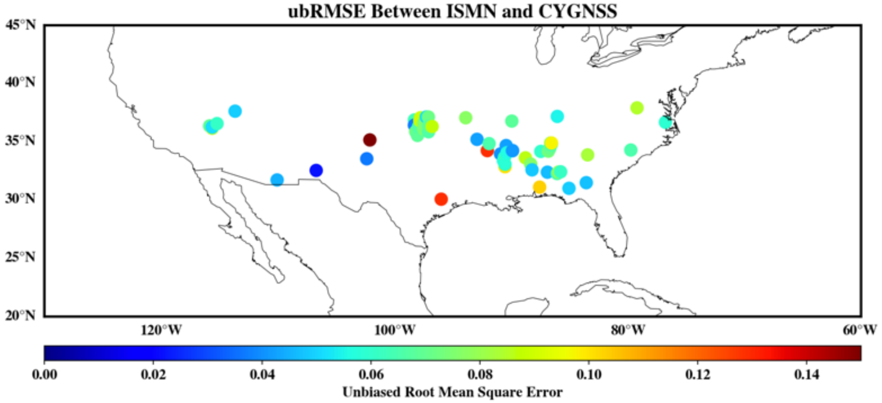






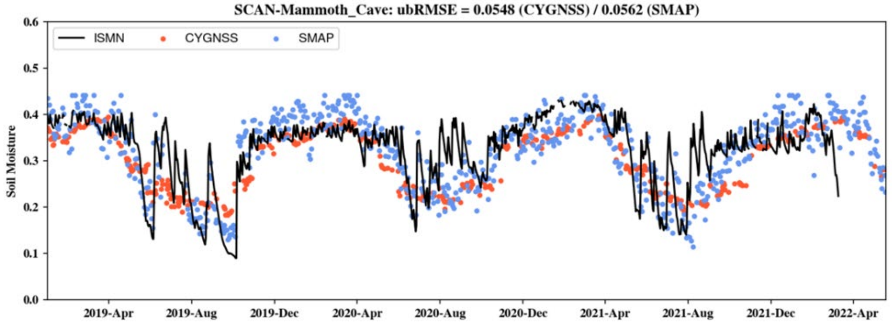
With respect to SMAP SM, ubRMSE (m^3/m^3) and Correlation Coefficient (R) for CYGNSS SM over train & test periods

Validation with 88 ISMN in-situ sites



With respect to in-situ SM, ubRMSE (m^3/m^3) for CYGNSS SM predictions

	RMSE	ubRMSE	R	SD
CYGNSS	0.0959	0.0716	0.3432	0.0450
SMAP	0.0996	0.0741	0.4500	0.0705



SM (m^3/m^3) time series from in-situ, CYGNSS, and SMAP at SCAN-Mammoth_Cave (Mammoth Cave, KY) from 2019 to 2022

Results & Future Work

- CYGNSS SM overall performs well with retrieving and forecasting SM
- Retrievals are less accurate in forest regions (e.g. Amazon rainforest)
- When validated with in-situ, CYGNSS is similar to SMAP but has low temporal variation
- CYGNSS SM captures general trends but day-to-day predictions are less accurate
- Improvements for spatial & temporal performance: clustering technique, spatial resolution, ancillary data, increasing training period data
- Applications: weather forecasting, drought monitoring, irrigation strategy