Adapting and Evaluating CyGNSSnet: A Deep Learning Approach to estimate Global Soil Moisture using GNSS Reflectometry

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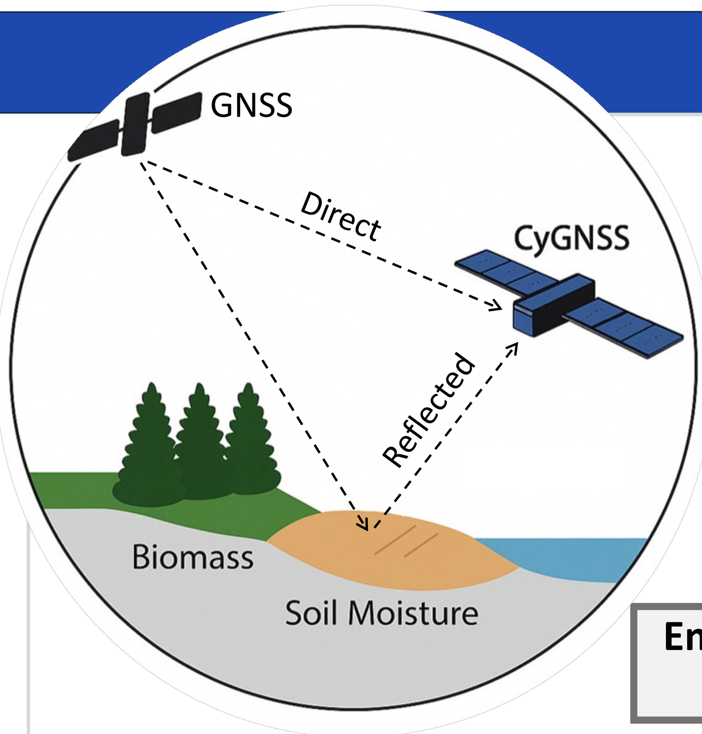
Introduction

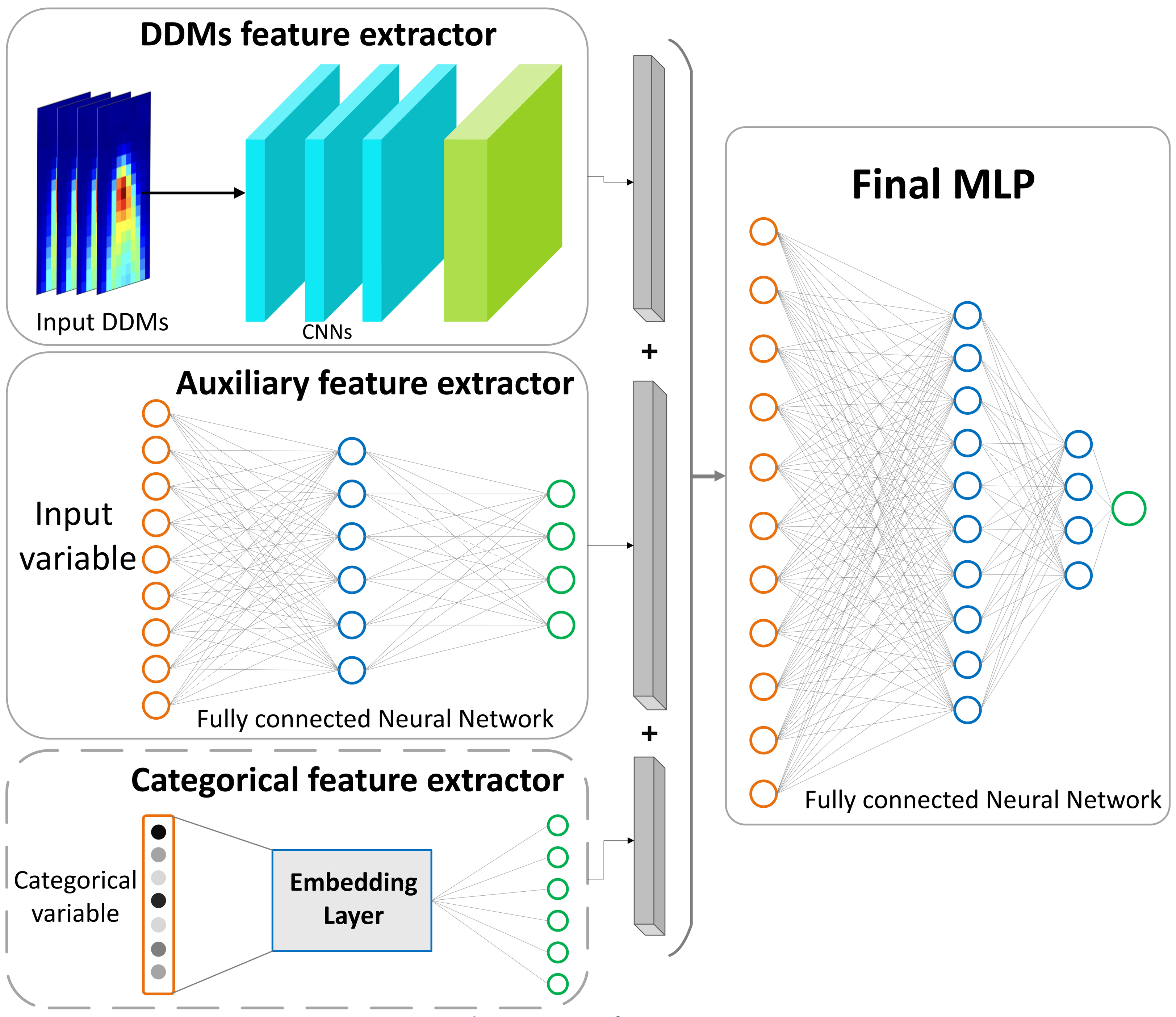
Following the 2016 launch of NASA's Cyclone GNSS (CYGNSS) mission, GNSS-R data with high spatiotemporal resolution have become available. The capability of Deep Learning models to retrieve soil moisture using GNSS-R proved by studies like [1] and [2].

This study adapts CyGNSSnet [3], a deep convolutional neural network, for soil moisture retrieval from CyGNSS Delay Doppler Maps (DDMs). The model ingests raw DDM observables and auxiliary variables. Moreover, an embedding layer employed to transform categorical variable to a dense vector. Training is conducted with PyTorch Lightning on HAICORE compute resources.



Model Description

CNN	3 × Conv2D (32 filters, 3×3, ReLU) + BatchNorm AdaptiveAvgPool2D → output size: (1, 2) 1024-D feature vector
MLP	2 fully connected layers (512 → 128 units) BatchNorm + ReLU + Dropout
Embedding Layer	Integer class ID → Embedding Layer → Dense vector
Final MLP	3 fully connected layers (512 → 256 → 128 → 1 units) BatchNorm + ReLU + Dropout



Architecture of CyGNSSnet

Datasets and Pre-processing

CYGNSS Level 1 V3.2 Delay Doppler Maps (DDMs) and associated engineering measurement parameters, along with auxiliary data from 2019 to 2021 (three years) were used.

All the auxiliary datasets and target SMAP soil moisture are matched with individual specular points from CyGNSS dataset by the nearest neighbour method. Table 1, summarizes the variables.

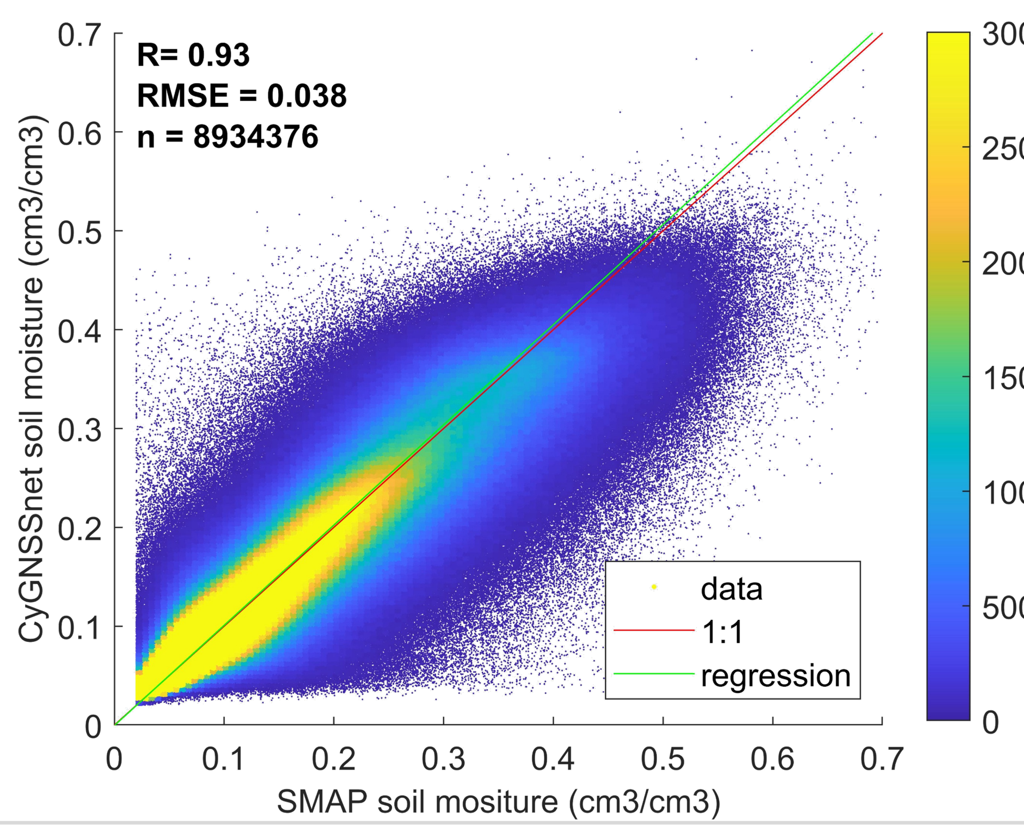
Type of data	Variables
CyGNSS Measurements	2D DDM (raw counts, power analog, brcs, eff scatter) - ddm snr - sp_inc_angle - gps_eirp - p_rx_gain - inst_gain -latitide - longitude
CyGNSS-Derived	Reflectivity (dB) - Trailing Edge Width - Coherency Index - Range scale factor - Kurtosis
SMAP	Vegetation Water Content (VWC) - Vegetation Optical Depth (VOD)
MODIS	Normalized Difference Vegetation/Water Index (NDVI and NDWI) Land Surface Temperature
Static Auxiliary	DEM-derived variables (Elevation - Slope - rms_height - rms_slope) - AGB
Categorical variable	Intersection of CCI Land Cover Classification - Global Temperature Regime GAEZ v4 (FAO)

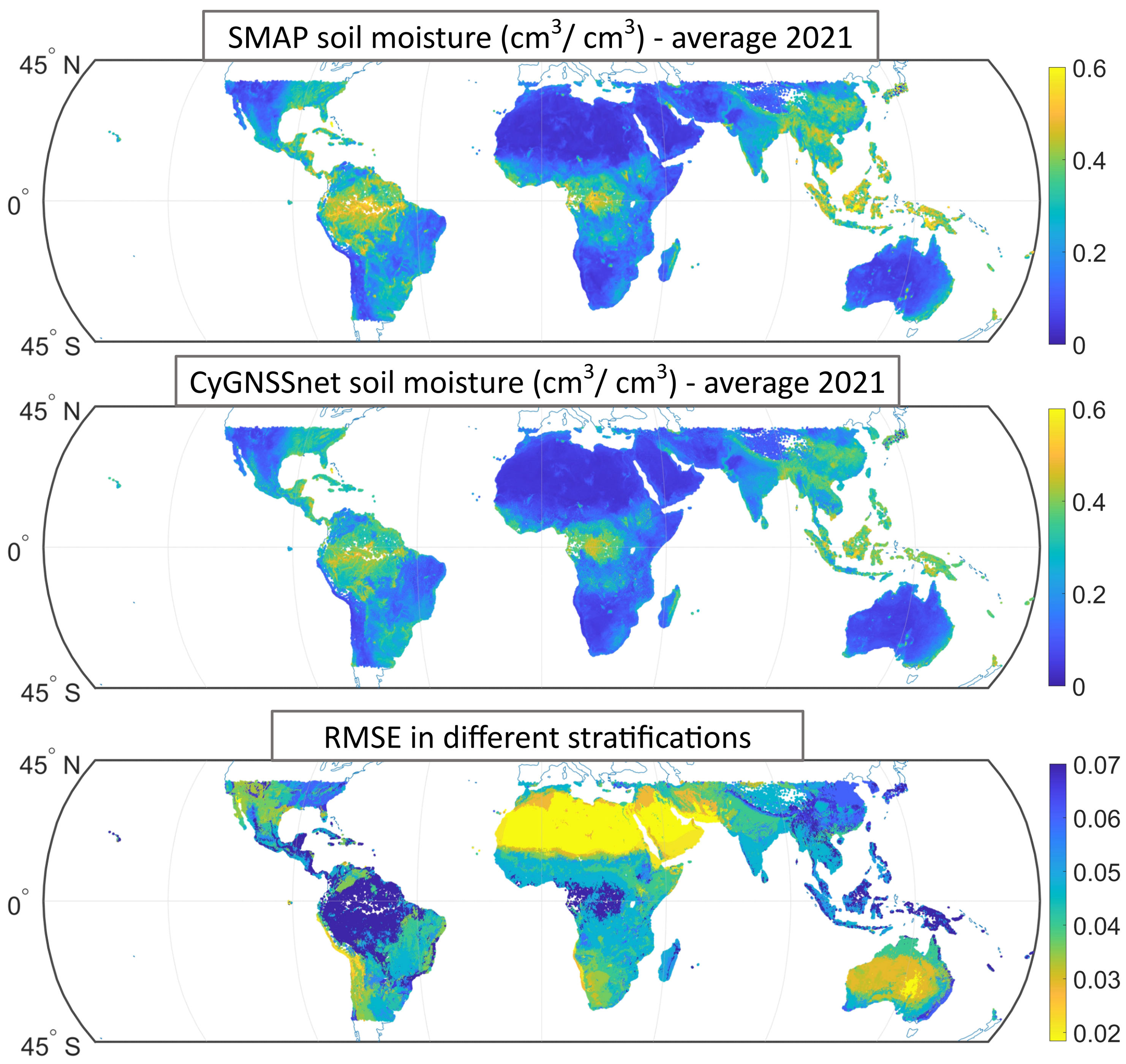
Table. 1. Variables used in training the model

Results and Performance Evaluation

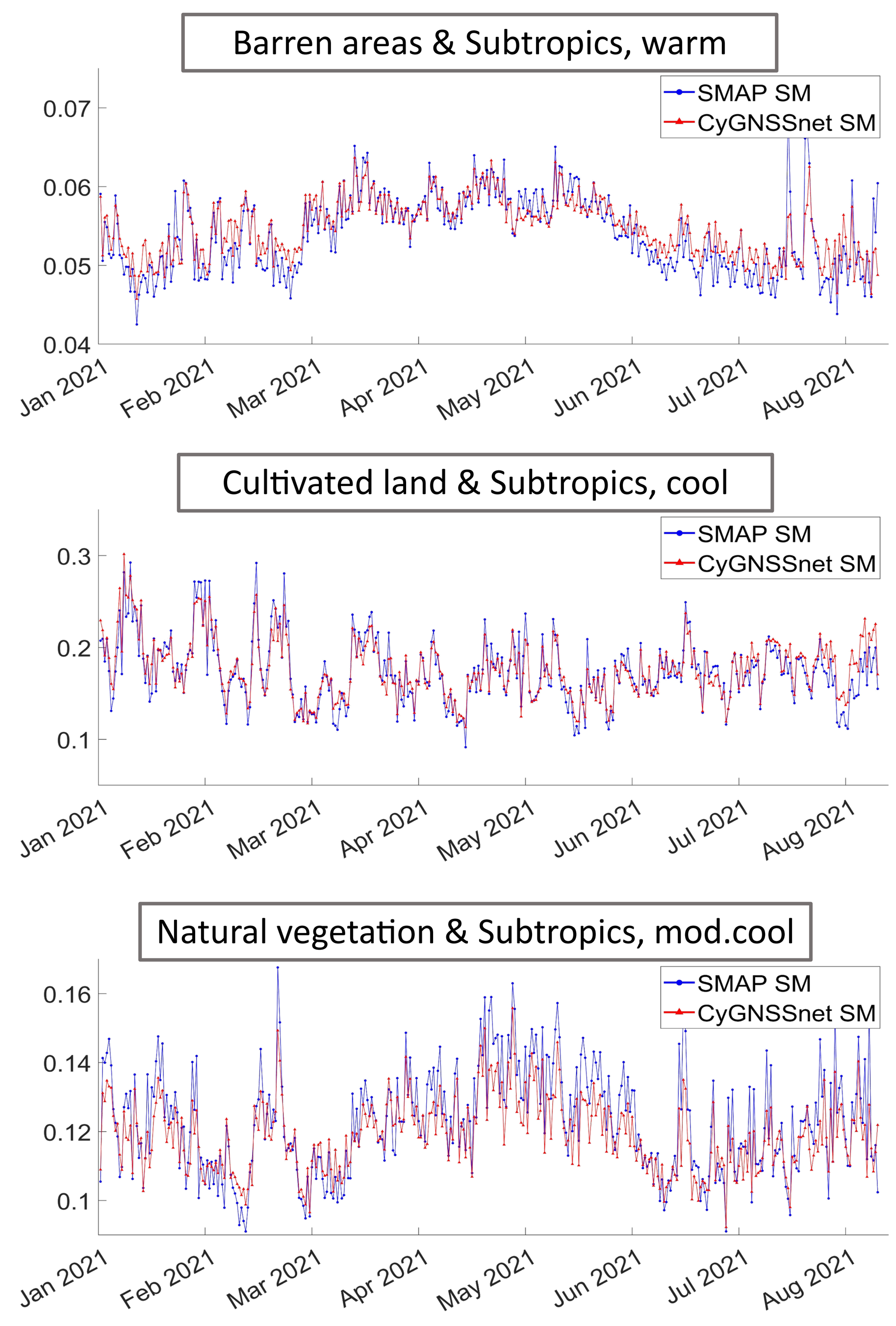
Inputs	RMSE
CyGNSS (Measurements + CyGNSS-Derived)	0.097
CyGNSS + Vegetation indices (SMAP & MODIS) + AGB	0.053
CyGNSS + Vegetation indices + AGB + Dem-Derived variables	0.045
CyGNSS + Vegetation indices + AGB + Dem-Derived variables + Latitude + Longitude	0.039
CyGNSS + Vegetation indices + AGB + Dem-Derived variables + Latitude + Longitude + Categorical variables	0.038

Table. 2. Summary of performances with different input combinations





Map of SMAP soil mositure, CyGNSSnet soil moisture, RMSE (instratifications)



Examples of daily averaged SMAP-SM and CyGNSS-SM for 2021, comparison in some strattifications

Conclusion

The adapted CyGNSSnet model achieved excellent performance, with an RMSE of 0.038 cm^3/cm^3 and a correlation coefficient of 0.93. The results demonstrate the model's strong ability to retrieve soil moisture across diverse land cover and climate zones. Incorporating stratification embeddings improved generalization by providing eco-climatic context, allowing the model to maintain high accuracy across heterogeneous environments.

References

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