

EGU24-8930, updated on 18 Jun 2024

<https://doi.org/10.5194/egusphere-egu24-8930>

EGU General Assembly 2024

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## Exploring the importance of auxiliary datasets for soil moisture retrieval based on GNSS Reflectometry

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Various remote sensing satellites can be used for extracting soil moisture (SM), each characterized by unique spatial and temporal resolutions. Missions such as Soil Moisture Active Passive (SMAP) have provided fresh insights into the storage of near-surface soil moisture through L-band radiometry, achieving a spatial resolution of 30–50 km and the full Earth coverage in 2-3 days. The demonstrated sensitivity of the L-band electromagnetic signal to the water content of observed targets and its significant penetration depth underscores the potential of Global Navigation Satellite System-Reflectometry (GNSS-R) techniques in diverse land applications. An illustrative example of this advancing application is evident in missions like the NASA's Cyclone GNSS (CyGNSS), originally designed to detect wind speed at sea in tropical cyclones measuring the Earth surface reflections of GNSS signals of opportunity.

Within this context, the capability to retrieve soil moisture through the exploitation of GNSS-R reflections by Artificial Neural Networks has been confirmed in the literature (e.g., see [1] and [2]). In this paper, a sophisticated Artificial Neural Network (ANN) algorithm is used to explore the impact of additional auxiliary data able to account for other factors affecting the GNSS-R signal. They include topography, Above Ground Biomass (AGB), land use, roughness, soil texture, soil porosity, and dynamic variables like Vegetation Water Content (VWC) and Vegetation Optical Depth (VOD) from Soil Moisture Active Passive (SMAP). It also considers data such as Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Solar Induced Fluorescence (SIF) from Moderate Resolution Imaging Spectroradiometer (MODIS). Moreover, the effect of using latitude/longitude as input on the performances of the algorithm is assessed. The study also aims at evaluating the impact of different stratification approaches, setting up different ANN's in different geographical and landcover-based stratifications. To assess how these variables contribute to improving the accuracy of soil moisture retrieval, the datasets are collocated in space and time and resampled onto the EASE grid v2.0 projection at 25km resolution. The algorithm is subsequently trained and validated using target soil moisture values derived from SMAP L3 global daily products and in-situ measurements from the International Soil Moisture Network (ISMN). The work has been carried out in the framework of the ESA Scout 2 HydroGNSS mission development, expected to be

launched at the end of 2024.

#### Reference

[1] E. Santi *et al.*, "Combining Cygnss and Machine Learning for Soil Moisture and Forest Biomass Retrieval in View of the ESA Scout Hydrognss Mission," Sep. 2022, doi: 10.1109/IGARSS46834.2022.9884738.

[2] O. Eroglu, M. Kurum, D. Boyd, and A. C. Gurbuz, "High Spatio-Temporal Resolution CYGNSS Soil Moisture Estimates Using Artificial Neural Networks," *Remote Sensing 2019*, Sep. 2019, doi: 10.3390/RS11192272.