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Sensing Water: First estimates of soil moisture from the Rongowai airborne remote sensing mission for GNSS-Reflectometry

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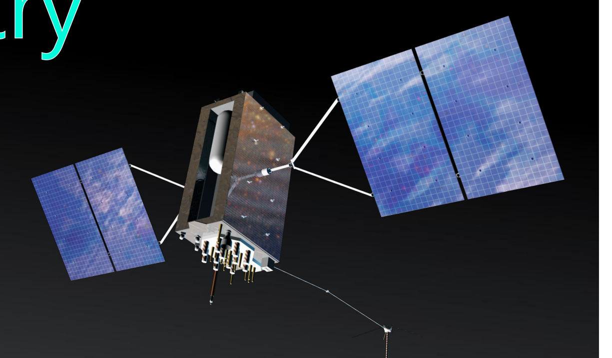
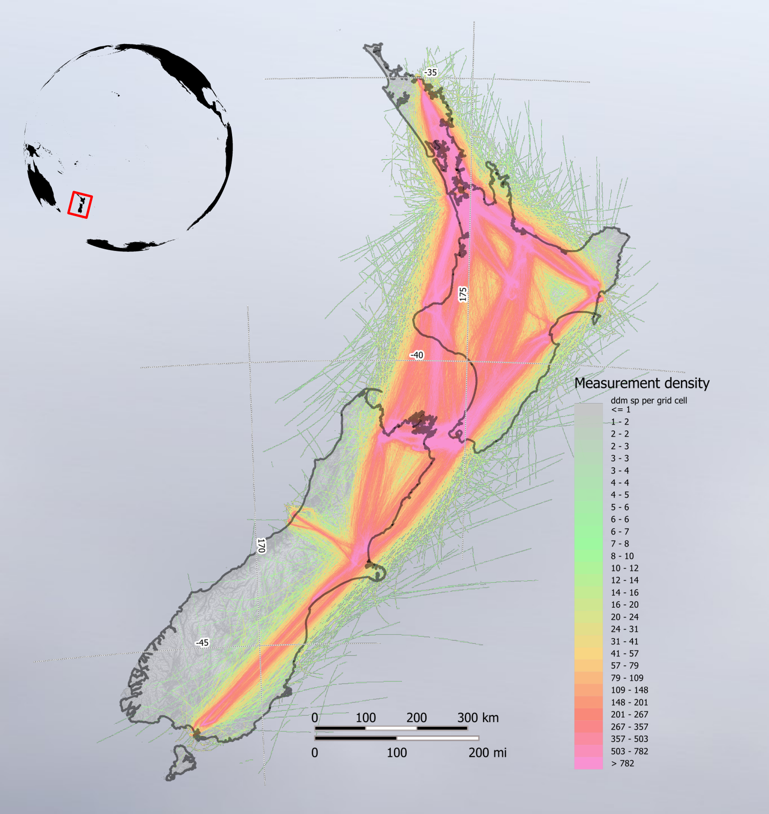
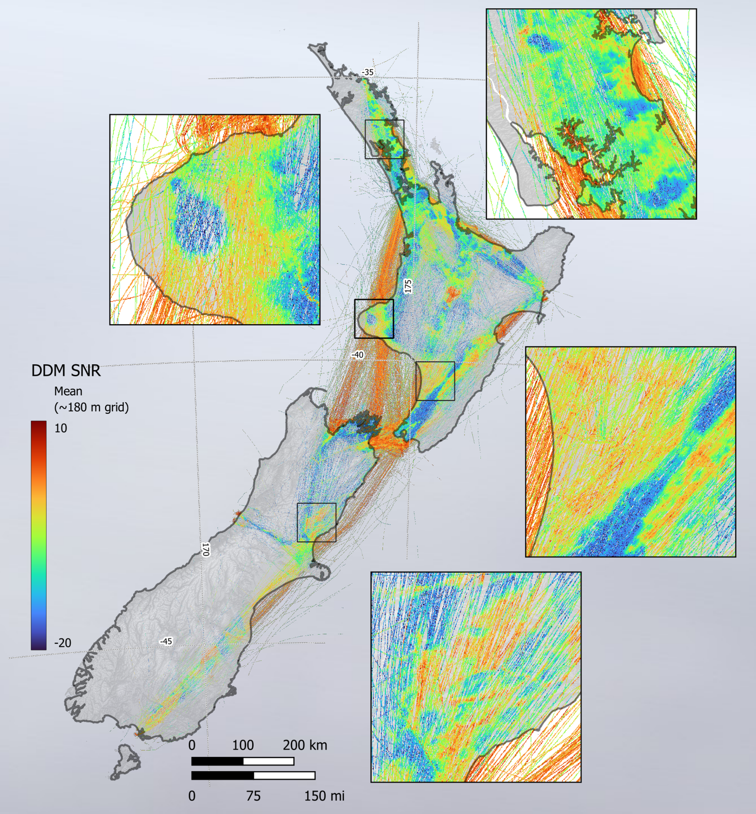


In a unique partnership, the Rongowai ("sensing water" in te reo Māori) airborne remote sensing mission comprises of a next-generation Global Navigation Satellite System Reflectometry (GNSS-R) receiver (NGRx) mounted on a domestic Air New Zealand Q300 aircraft. The sensor captures reflected GNSS "signals of opportunity", building on the legacy of novel space borne missions such as CyGNSS (Ruf et al. 2012), and providing valuable data for the development of future missions such as HydroGNSS. During the aircraft's routine scheduled operations, Rongowai autonomously records reflected GNSS signals, then transmits data via a cellular connection once the aircraft has landed. The L-band GNSS radio signals which are reflected from the land surface are sensitive to soil moisture (Kim and Lakshmi, 2018) and surface water (Gerlein-Safdi & Ruf, 2019), providing a valuable additional source of data for the terrestrial hydrosphere. Rongowai is enabling unprecedented high spatiotemporal resolution surface water and soil moisture estimates across New Zealand's diverse landscapes. Here we present our progress towards the development of algorithms for soil moisture estimation using Rongowai data.

Building from our previous work using CyGNSS data at a near-global scale (Datta et al. 2022), we developed a machine learning framework for the rapid processing of Rongowai science data (L1), with the aim of producing soil moisture data products. The framework assimilates multiple sources of satellite or airborne remote sensing data as predictors, with soil moisture measurements from in-situ gauges used for training and testing. A random forest algorithm is used with predictor variables including terrain indices based on high resolution LiDAR (slope, topographic wetness index and height above nearest drainage), forest heights derived from NASA GEDI, vegetation greenness using NDVI from MODIS, Copernicus Global Land Cover, antecedent weather conditions using precipitation observations from GPM, surface soil mineralogy from FAO SoilGrids, and soil saturated hydraulic conductivity. Predictor variables are used along with polarimetric delay Doppler map data to predict soil moisture for each observation location at high resolution. In further work, a multi-temporal gridded data product will be created to facilitate use by stakeholders.

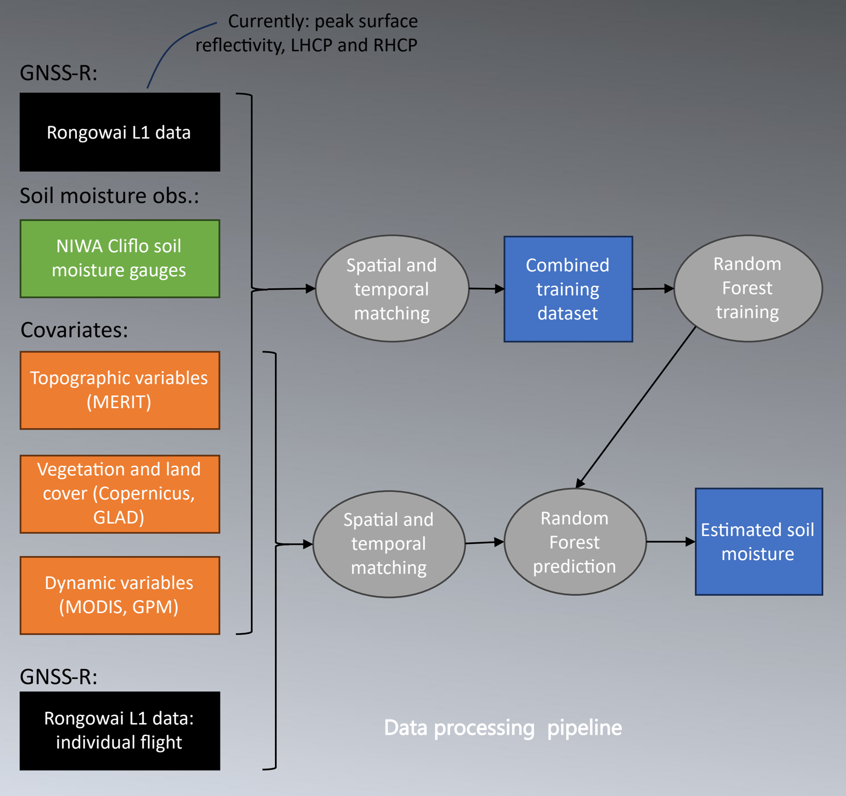


The highest density of coverage is obtained close to routine flight tracks for the Q300 aircraft

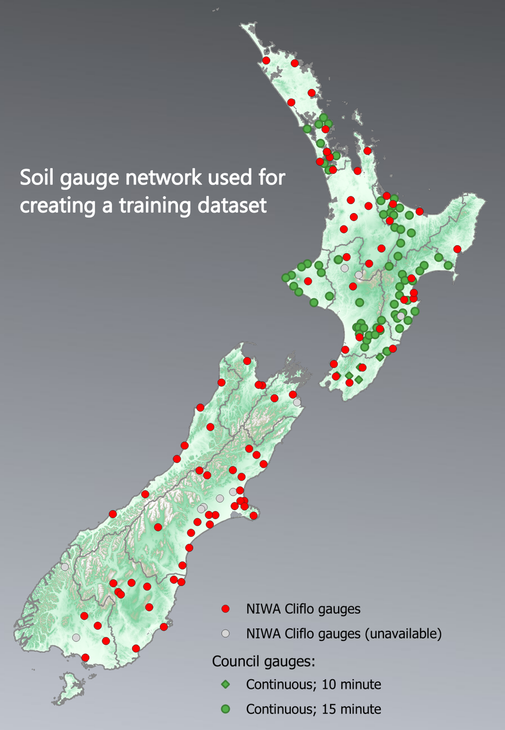


Good signal strength is recieved from agricultural areas which tend to be have low topographic relief

Rongowai is installed on a Q300, ZK-NFA, operated by Air New Zealand domestically



Data processing pipeline

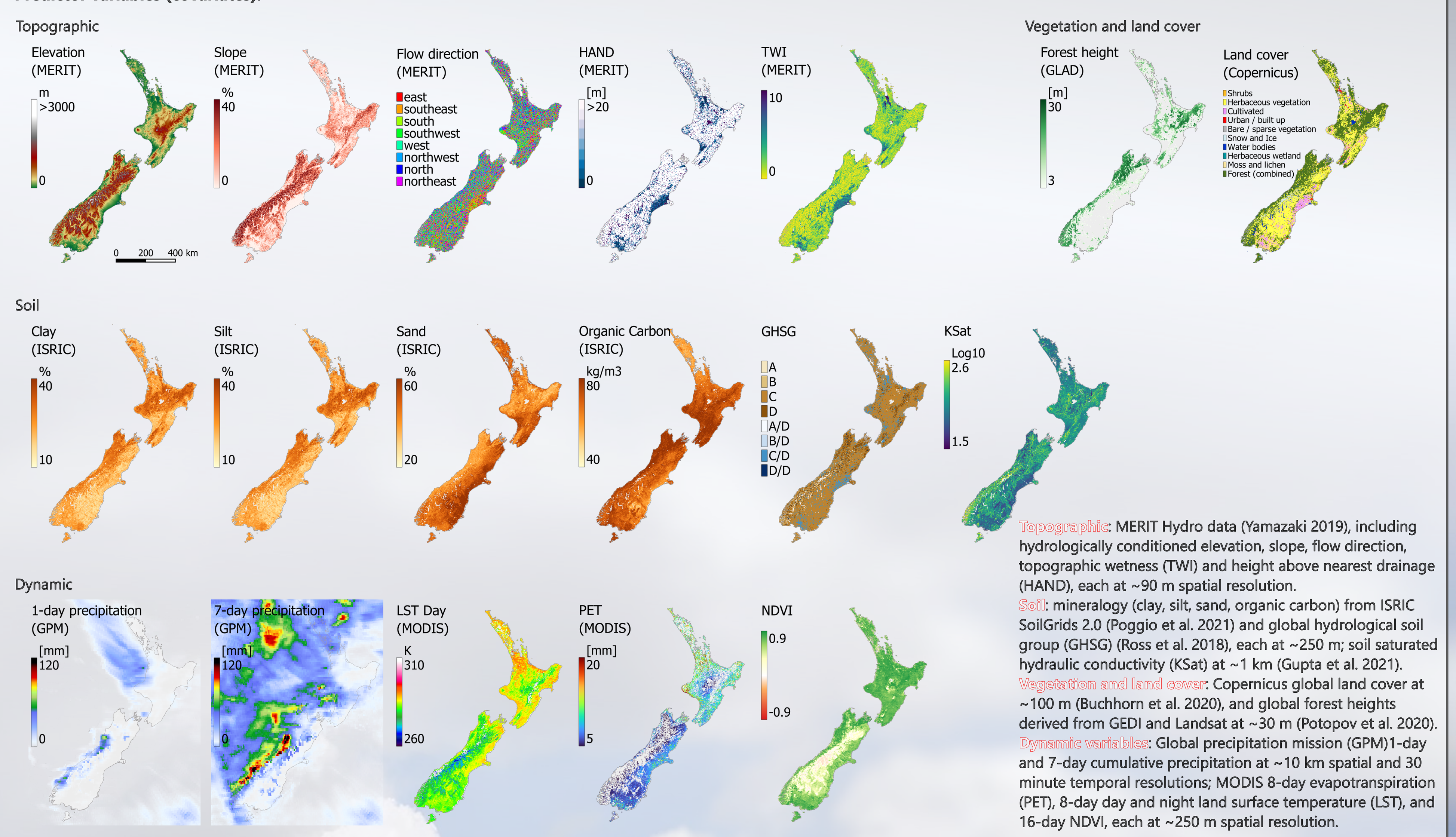


Soil gauge network used for creating a training dataset

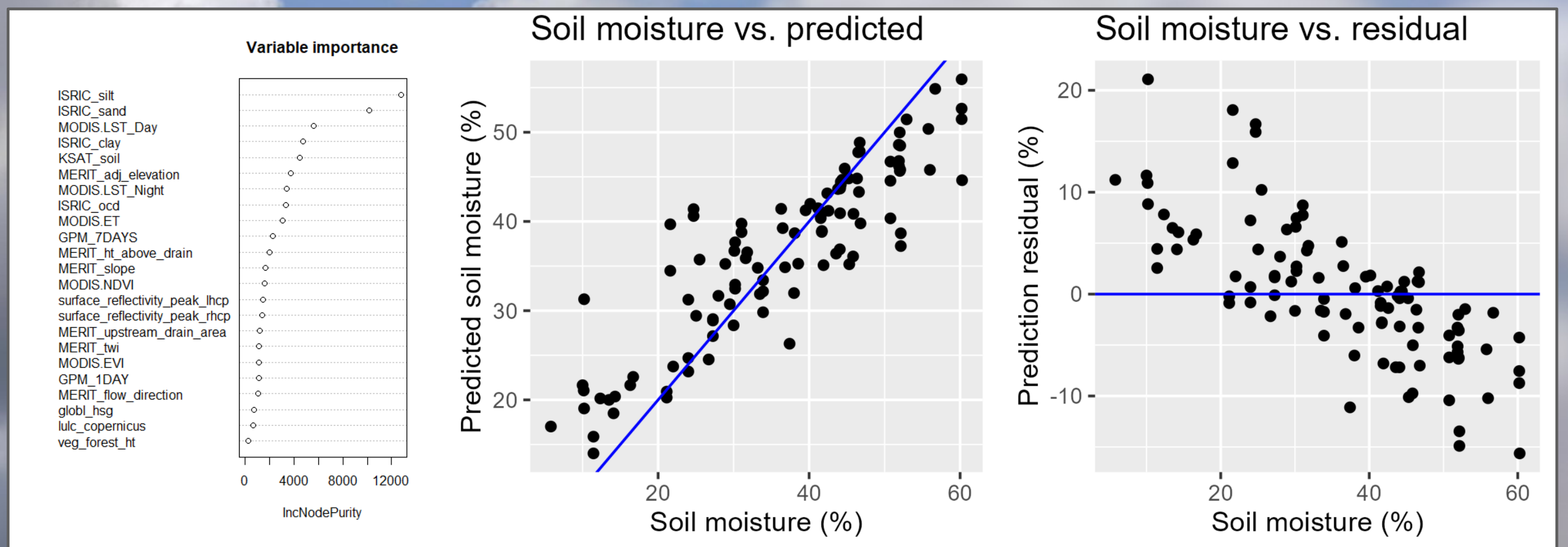
Methods:
We built on the work of Datta et al. (2022) to develop a data assimilation framework for the processing of Rongowai Level 1 data (Lin et al. 2022a) into higher level data products such as soil moisture. To develop a training dataset for machine learning, we first combined Rongowai data (for all flights, 26 Oct. 2022 to 27 Sep. 2023) with soil moisture gauge observations from NIWA's Cliflo network (left). Observations were paired if the gauge location was contained within the estimated Rongowai Fresnel zone (Lin et al. 2022b), and with observations within 1 hour of the recorded signal. A total of 1302 matched Rongowai and soil gauge observations were found.

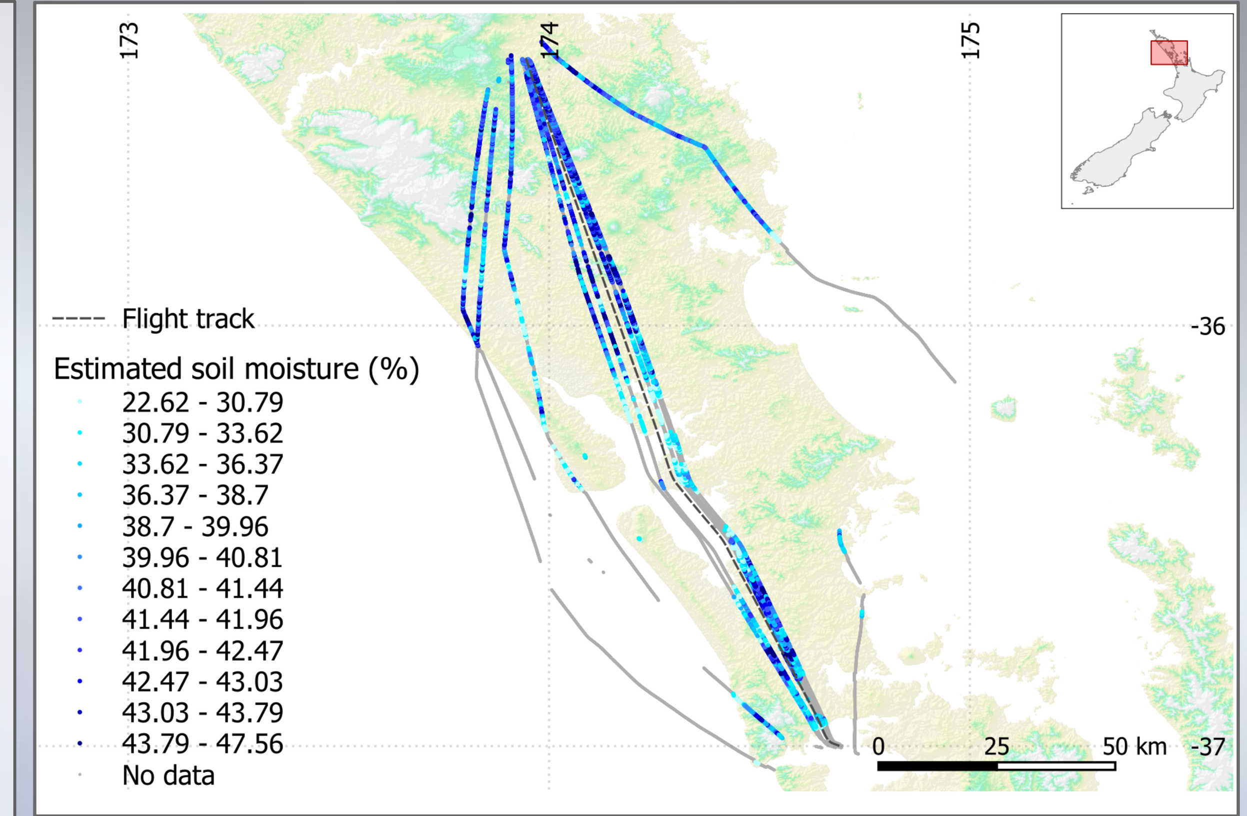
The locations of the Rongowai specular points (and observation times for dynamic variables) were used to extract values from predictor variables (below) for the pixels containing them, and the full dataset (1302 matches) was filtered to remove rows with missing values, leaving complete data in 514 rows. These were split into 80% training (411 rows) and 20% testing (103 rows), and used in a random forest model with 500 trees.

Predictor variables (covariates):



Topographic: MERIT Hydro data (Yamazaki 2019), including hydrologically conditioned elevation, slope, flow direction, topographic wetness (TWI) and height above nearest drainage (HAND), each at ~90 m spatial resolution.
Soil: mineralogy (clay, silt, sand, organic carbon) from ISRIC SoilGrids 2.0 (Poggio et al. 2021) and global hydrological soil group (GHSG) (Ross et al. 2018), each at ~250 m; soil saturated hydraulic conductivity (KSat) at ~1 km (Gupta et al. 2021).
Vegetation and land cover: Copernicus global land cover at ~100 m (Buchhorn et al. 2020), and global forest heights derived from GEDI and Landsat at ~30 m (Potopov et al. 2020).
Dynamic variables: Global precipitation mission (GPM)1-day and 7-day cumulative precipitation at ~10 km spatial and 30 minute temporal resolutions; MODIS 8-day evapotranspiration (PET), 8-day day and night land surface temperature (LST), and 16-day NDVI, each at ~250 m spatial resolution.





Results:
The mean r^2 of random forest models with training data was 0.72, and mean square of residuals was 46.4. In predicting soil moisture for the 20% data reserved for testing, the r2 achieved was 0.75, and 6.7% RMSE. There is a positive bias of ~10% in predicted soil moisture for lower values, and a similar negative bias in high values. The variables with the highest importance for predictions were those related to soil properties. An example prediction of soil moisture for a single flight is shown in above. Specular points without predictor variables are no data (e.g., open water). While these early results show reasonable accuracy, there is likely good scope for improvement. The number of training data will increase with additional flights, and additional gauges will give a greater chance of matches (e.g., regional council and SoilScape (Melebari et al. 2023) sites are to be added). Some predictor variables had a large number of missing data (e.g. MODIS PET), and alternatives should be considered.

Summary:
We have demonstrated a data assimilation framework for generating estimates of soil moisture from Rongowai GNSS-R data combined with data representing topography, soil, vegetation and weather conditions. A random forest model was able to predict soil moisture with reasonable accuracy, but can be improved through additional observational and predictor variable data.

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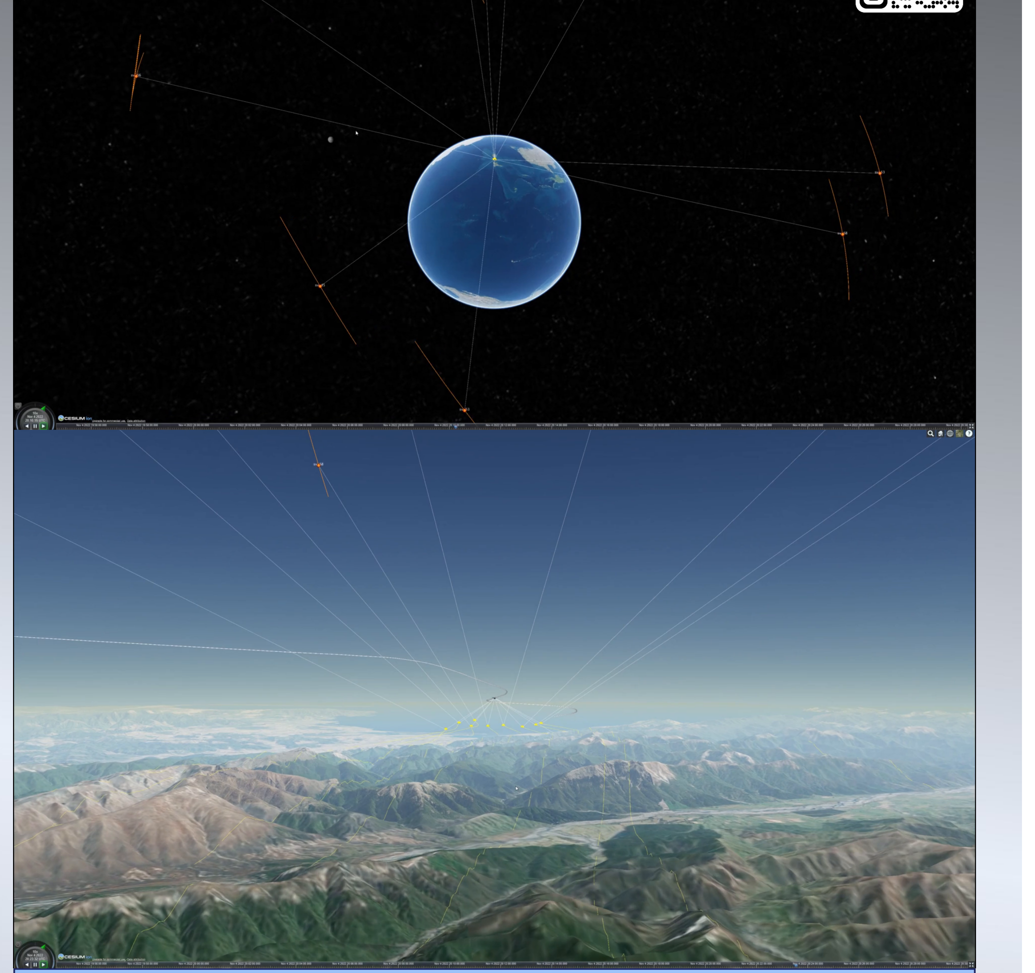
See an animation of a Rongowai flight here:
https://youtu.be/eS9OYEfJKcA



Data:
Rongowai L1 data are availabile on PODAAC!
https://podaac.jpl.nasa.gov/dataset/RONGOWAI_L1_SDR_V1.0

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