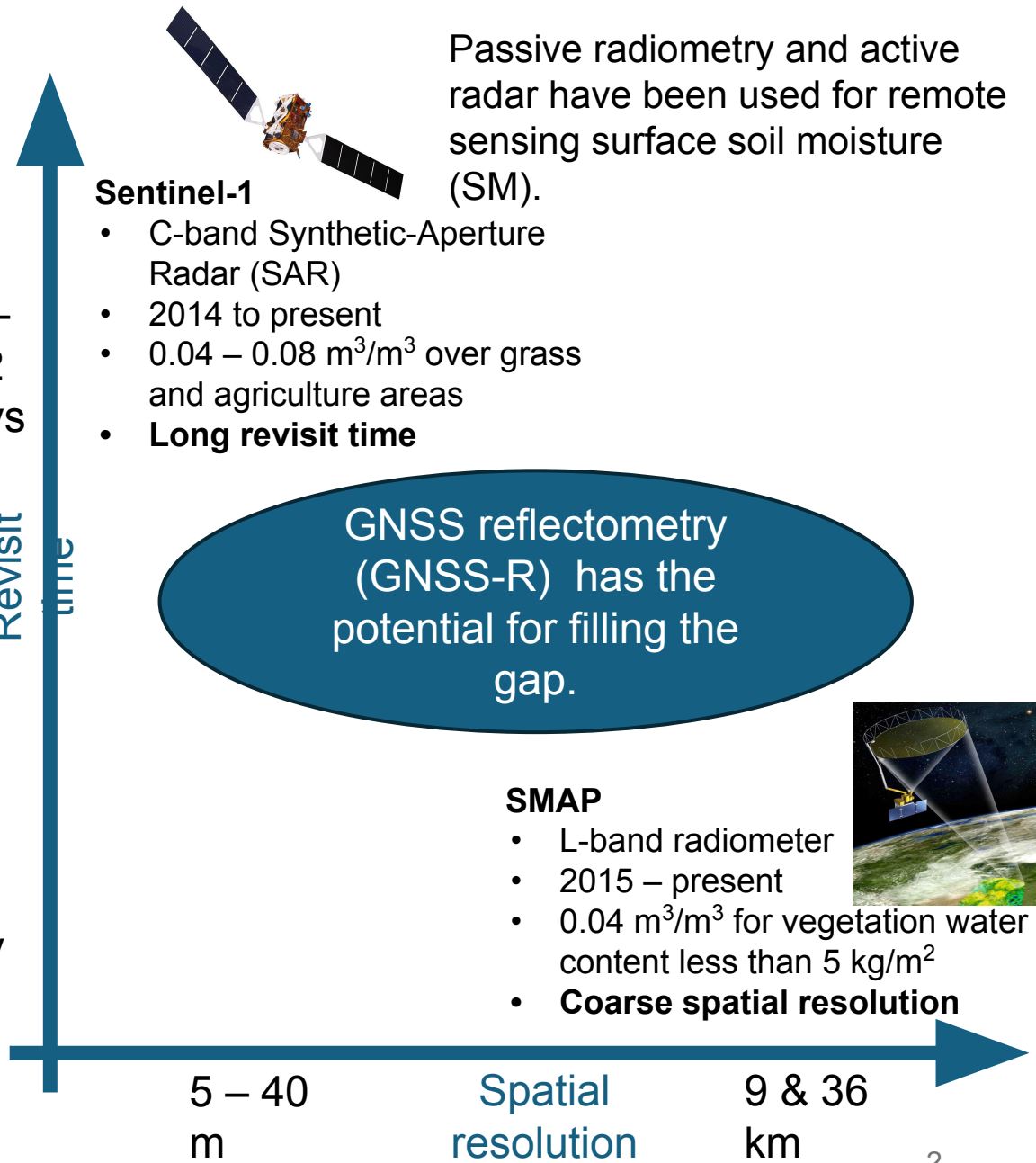
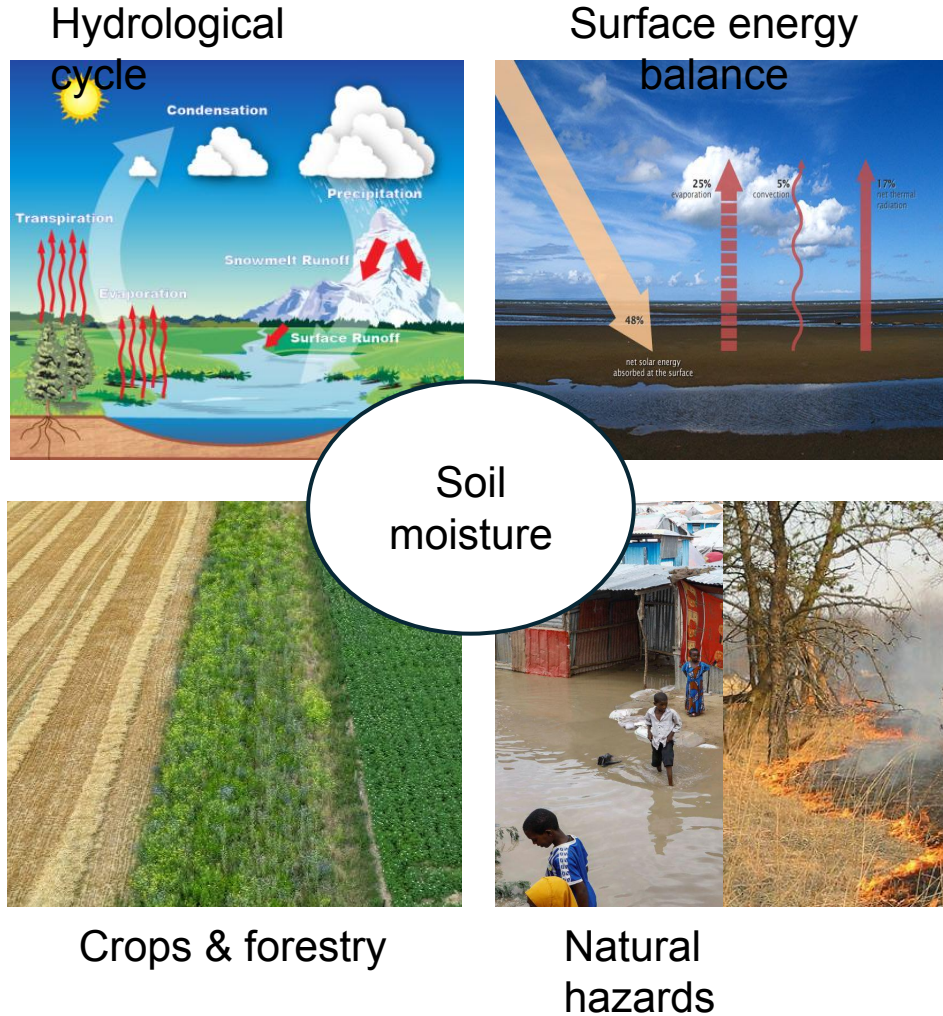


Mapping Soil Moisture Using Spire GNSS-R reflectivity Observations

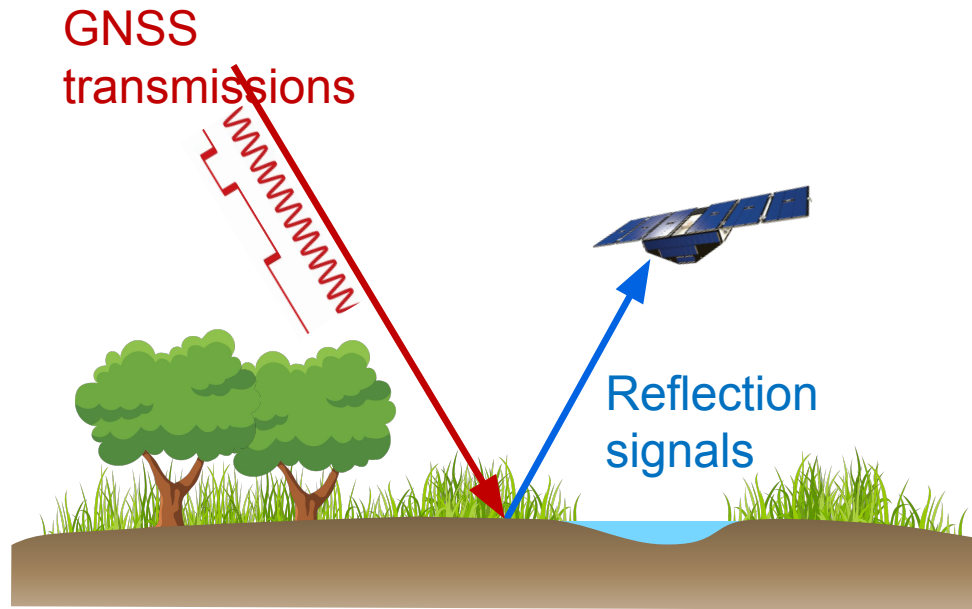
Jiahua Zhang, William Gullotta, Ming Li,
Jan-Peter Weiss, John Braun, Maggie Sleziak

UCAR, COSMIC

Soil moisture (SM)

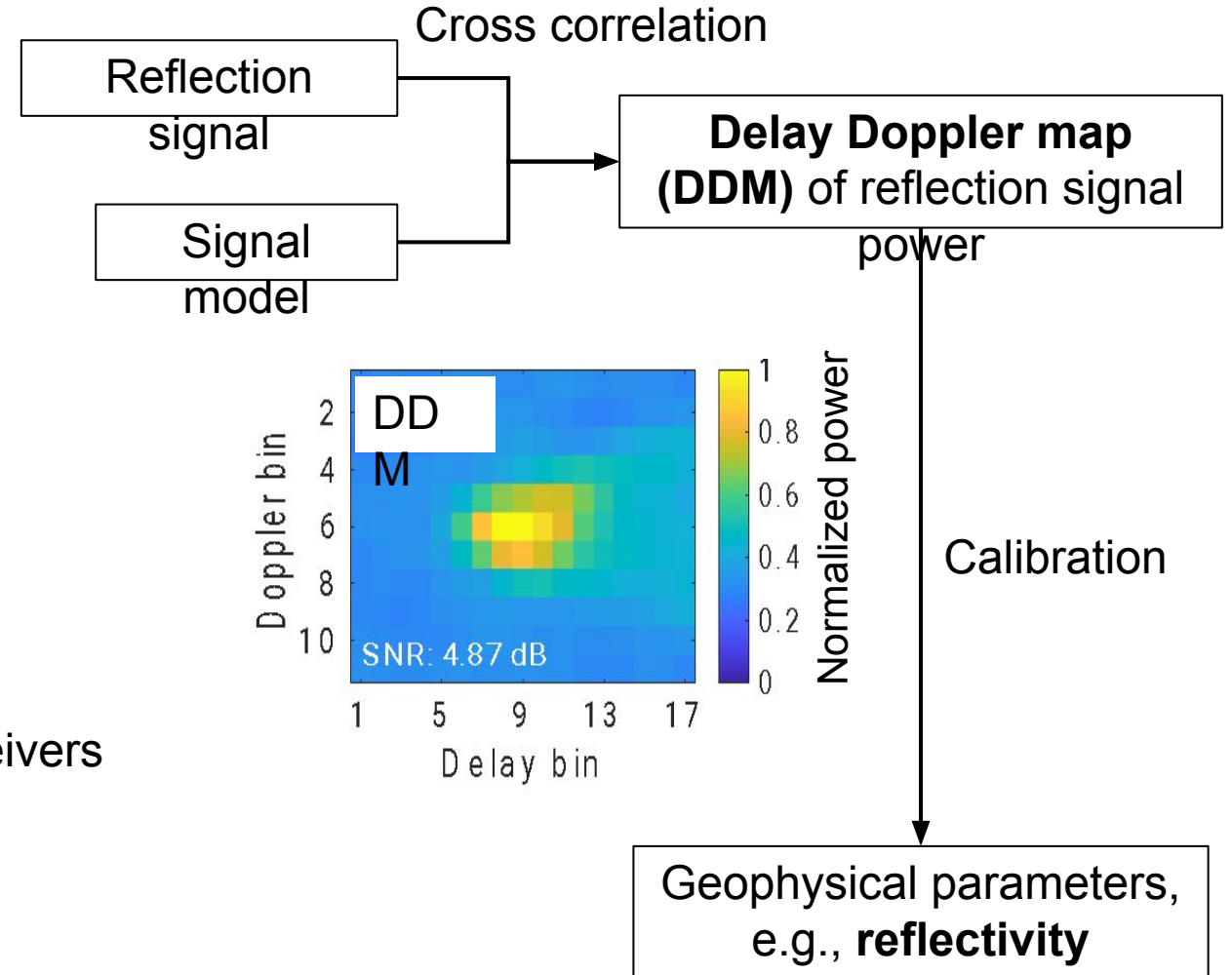


GNSS Reflectometry (GNSS-R)



GNSS-R as a passive bistatic radar:

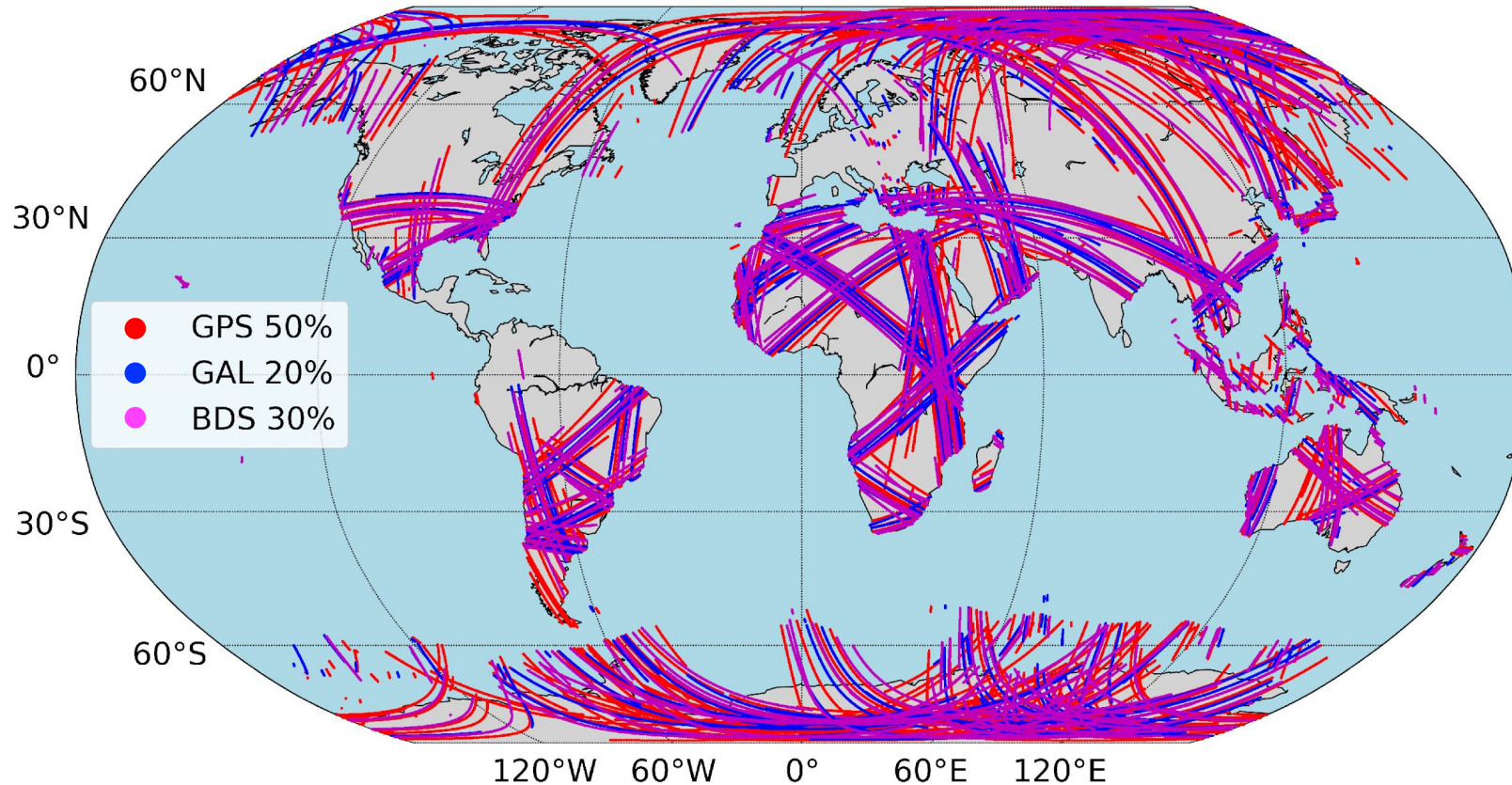
- Facilitate building constellations of LEO receivers
 - A large volume of reflection data
 - Short revisit time
- Other features:
 - Footprint size: hm–km
 - Penetrate relatively dense vegetation
 - All-weather, day and night operations



We use **Spire reflectivity data** for mapping **soil moisture** under a NOAA pilot study.

Spire reflectivity data

- FM110 (low-inclination orbit) & FM 146, 147, and 172 (near-polar orbit)
- L1 band signals from multi-GNSS, e.g., GPS, Galileo, and Beidou
- DDMs and **calibrated reflectivity at 2 Hz**. Along-track sampling spacing is ~3 km.
- ~30% of the 36 km land grid is covered by quality-controlled observations
- Observations in polar regions: permafrost freeze/thaw detection sea/land ice



Ground tracks of reflection data over land and sea ice on Feb 1, 2024

Principles of using reflectivity to measure SM

Reflectivity (Γ) refers to the ratio between reflected signal power and incidence signal power.

Mechanism of how SM affects

reflectivity:

Soil properties

- SM
- Soil texture
- Soil temperature

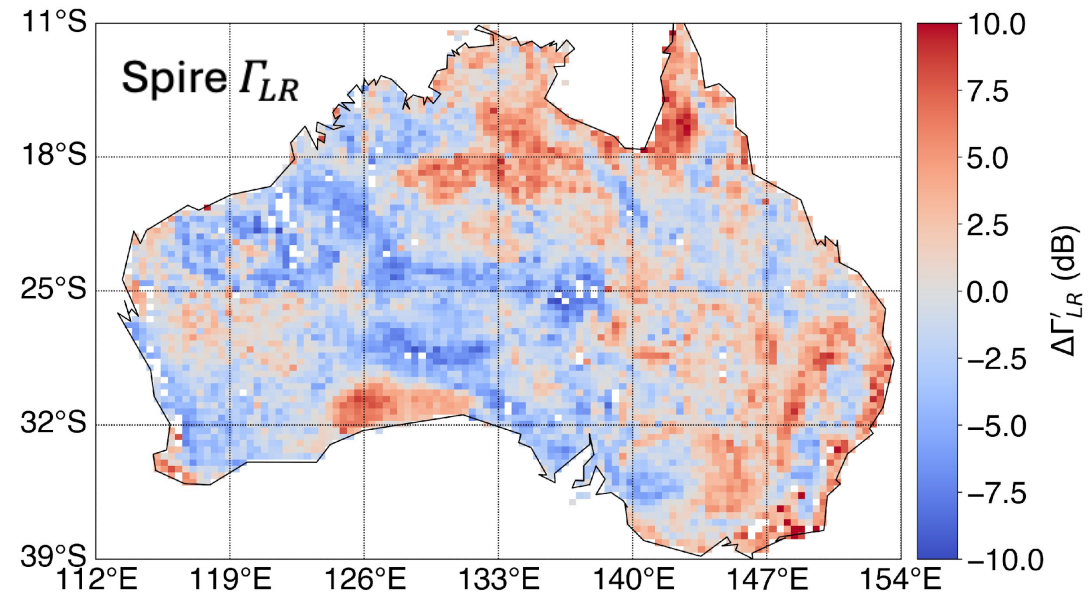
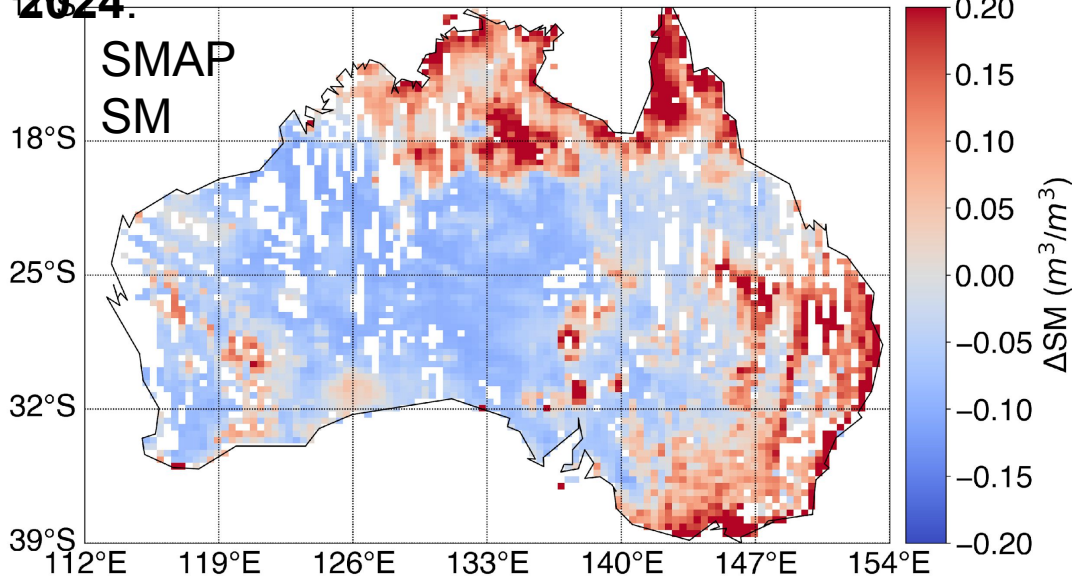
Soil dielectric constant ϵ_{soil}

Specular reflectivity for a smooth surface

Vegetation & surface roughness impact

Reflectivity obs.
 $\Gamma_{LR} = f(SM)$

Difference in the mean of SMAP SM/Spire reflectivity between April 1–15 and March 16–31, 2024.



SM inversion algorithms

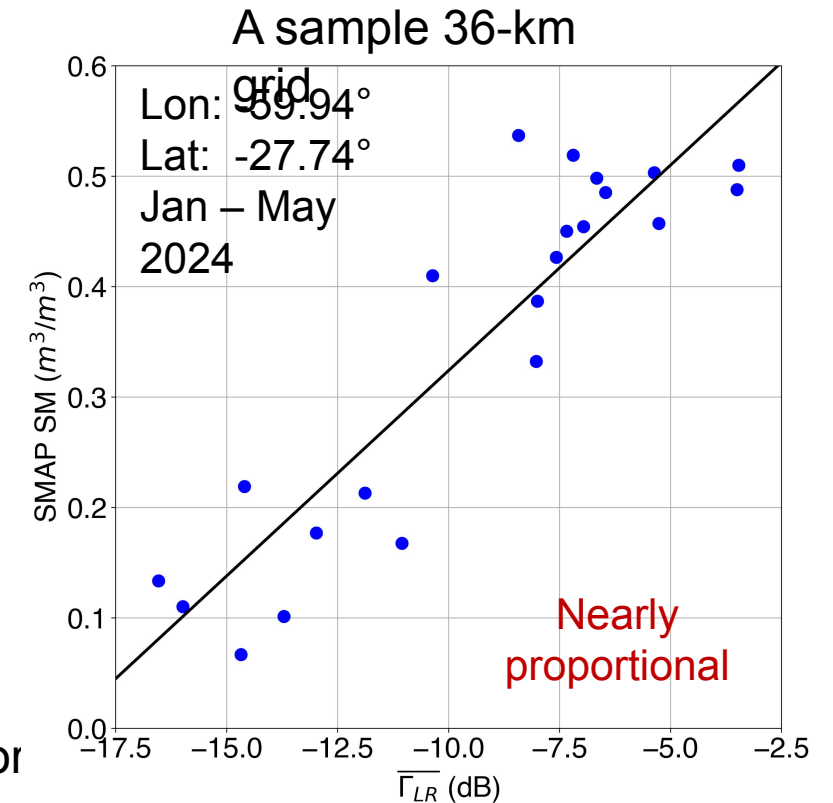
1. Empirical algorithm: linear regression method

1. The general basis: corrected reflectivity is nearly proportional to soil moisture content.
2. Easy to implement
3. Dependent on external SM data

2. Semi-empirical inversion algorithm

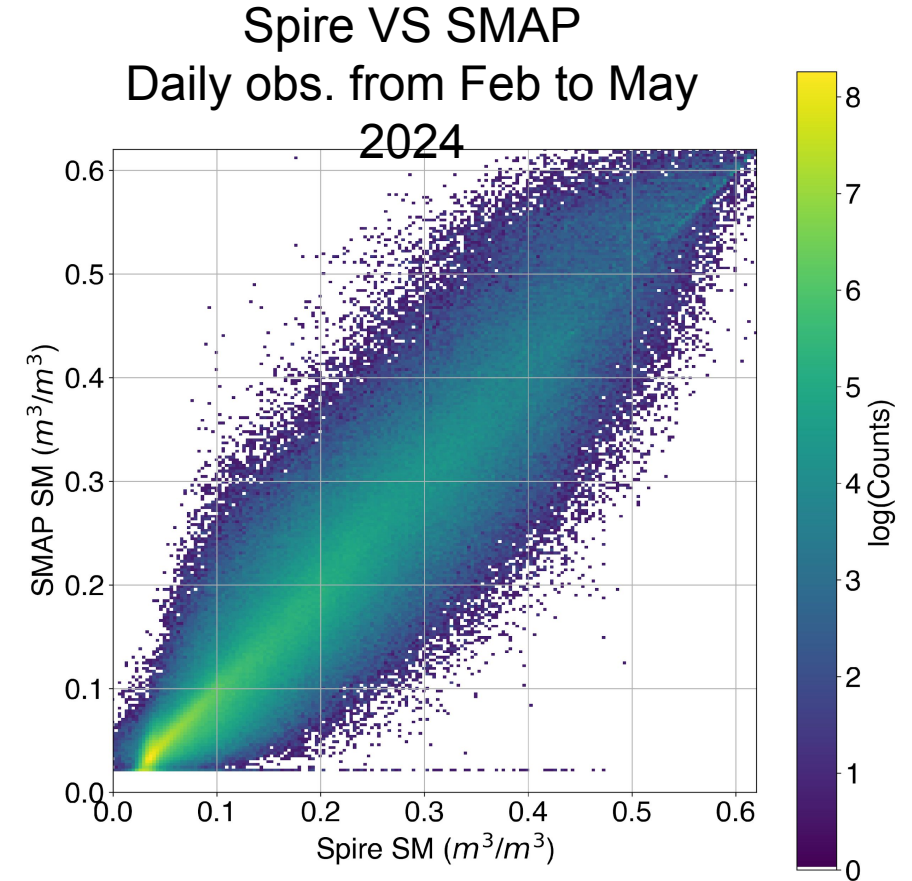
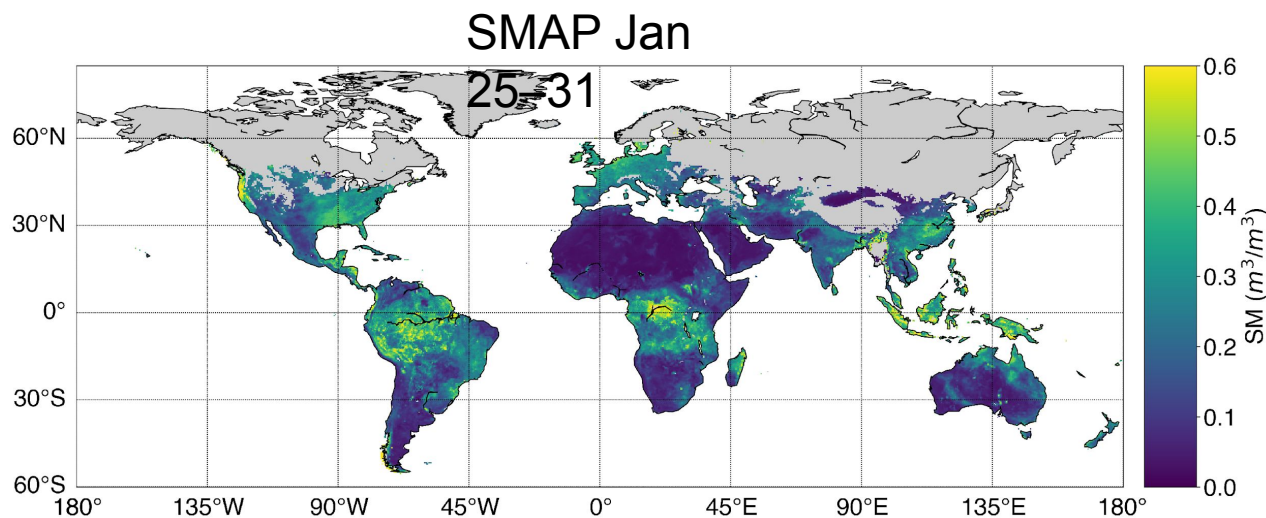
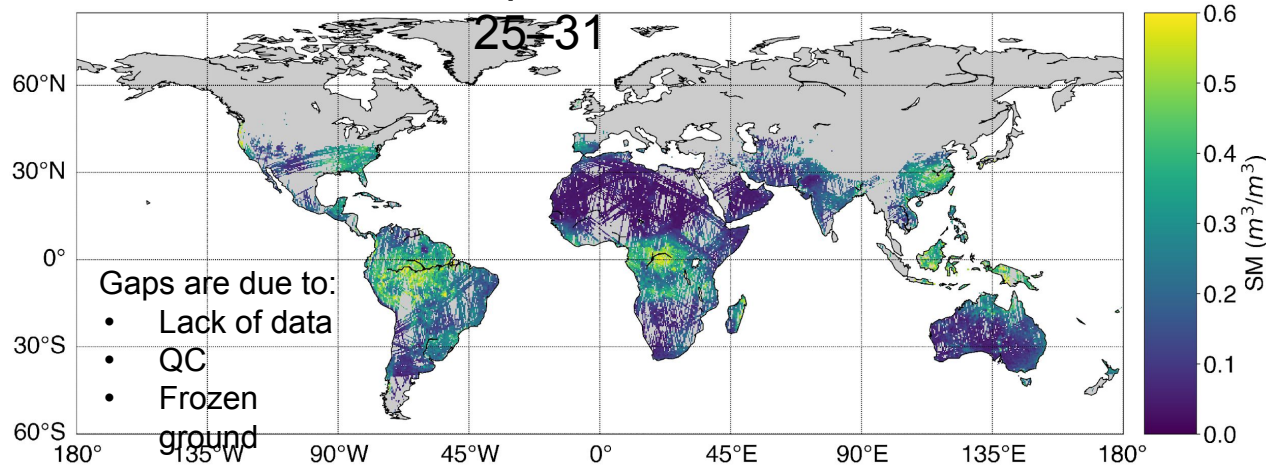
1. Based on the forward model of reflectivity
2. Providing independent SM observations
3. Challenging to realize as it requires accurate corrections for surface roughness and vegetation

3. Machine learning & deep learning methods



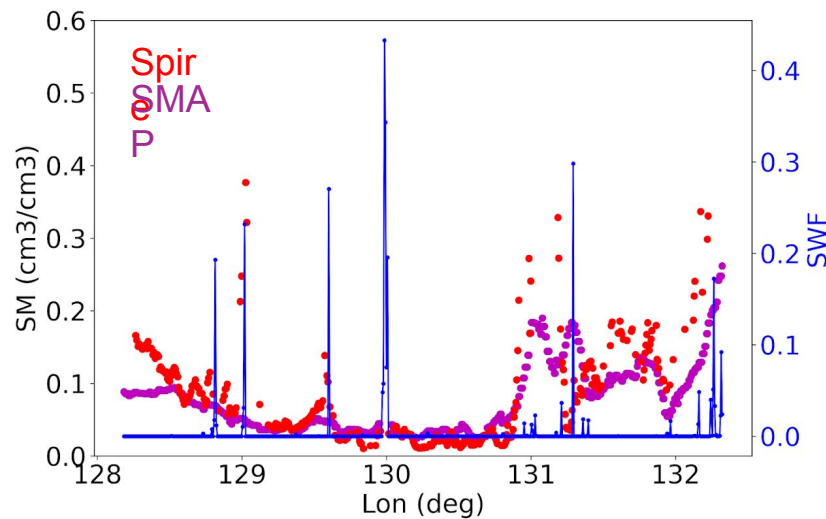
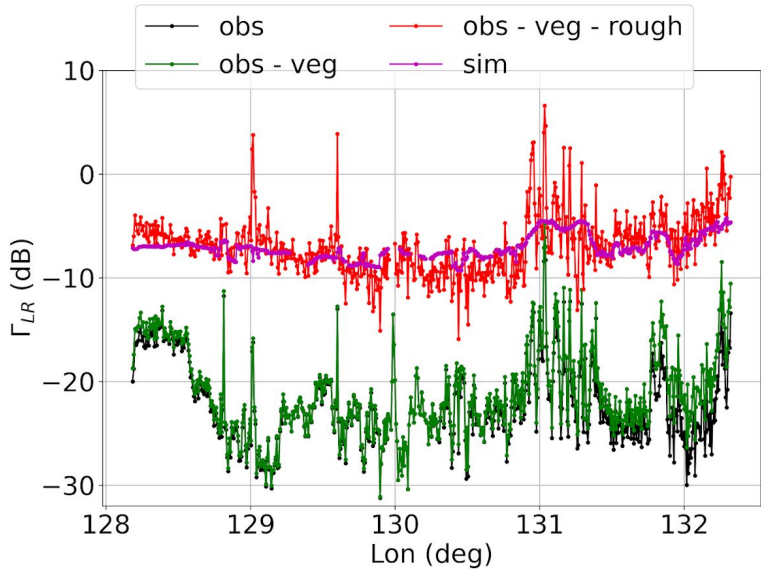
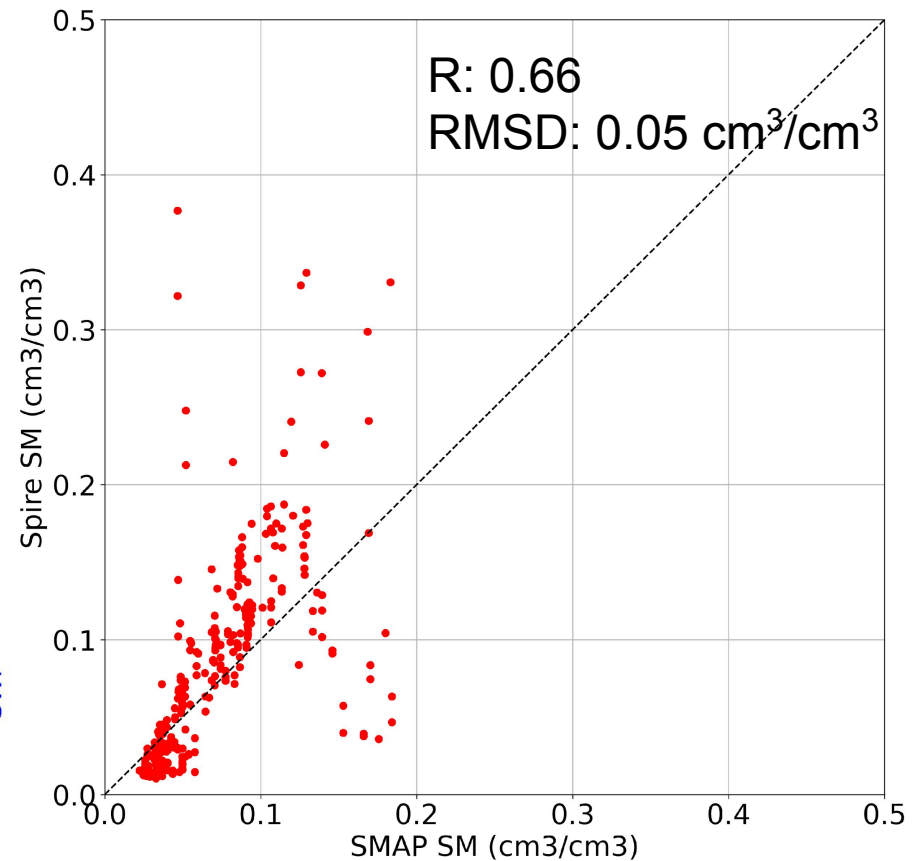
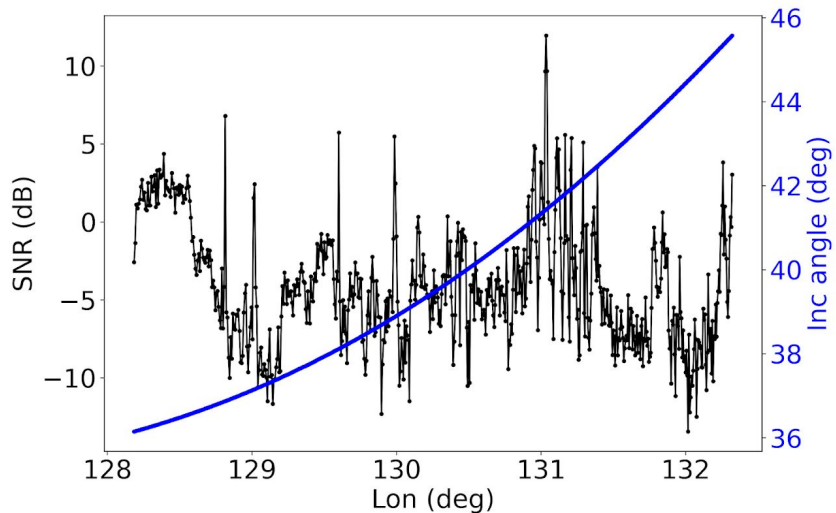
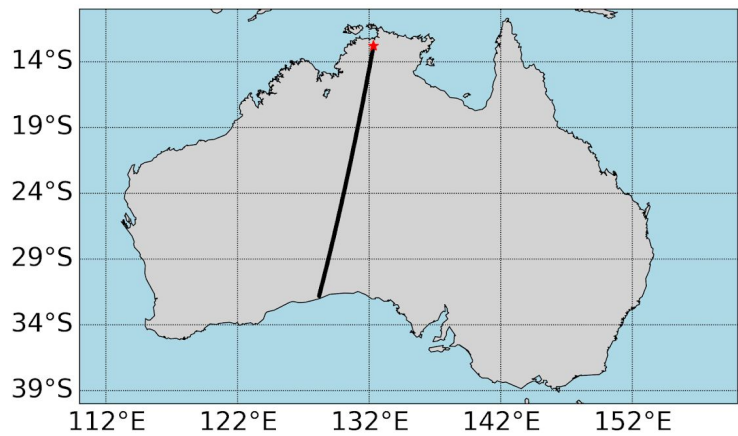
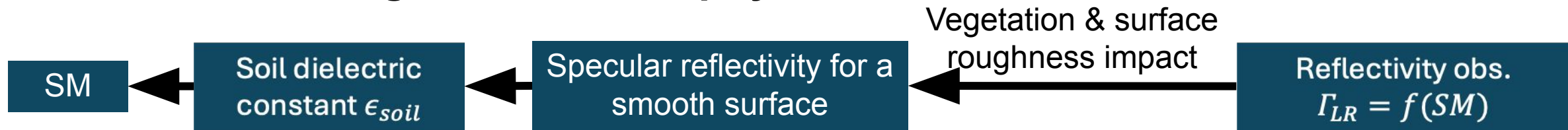
SM inversion algorithms: linear regression method & results

- Fit gridded maps of **Spire reflectivity** observations to **SMAP SM data** to derive the best linear fit model.
- The grid size is 36 km



Overall RMSD: $0.05 m^3/m^3$
Comparable to other studies using
GNSS-R reflectivity observations.

SM inversion algorithms: semi-physical method & results

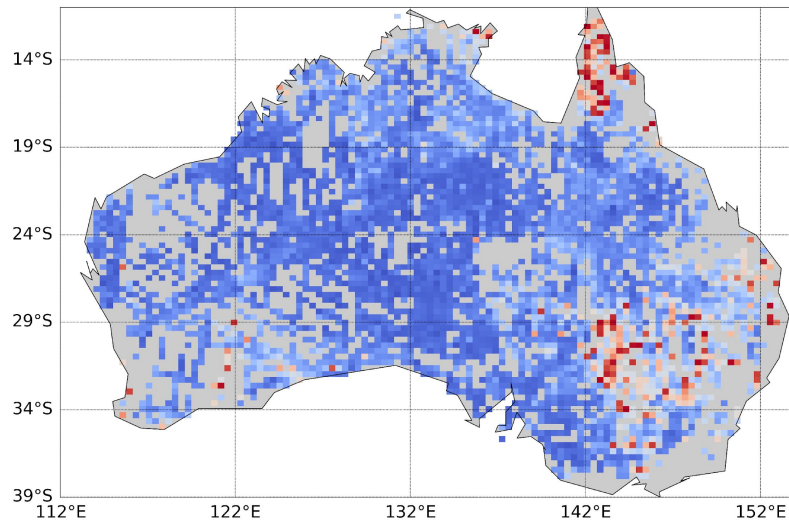


SM inversion algorithms: semi-physical method & results

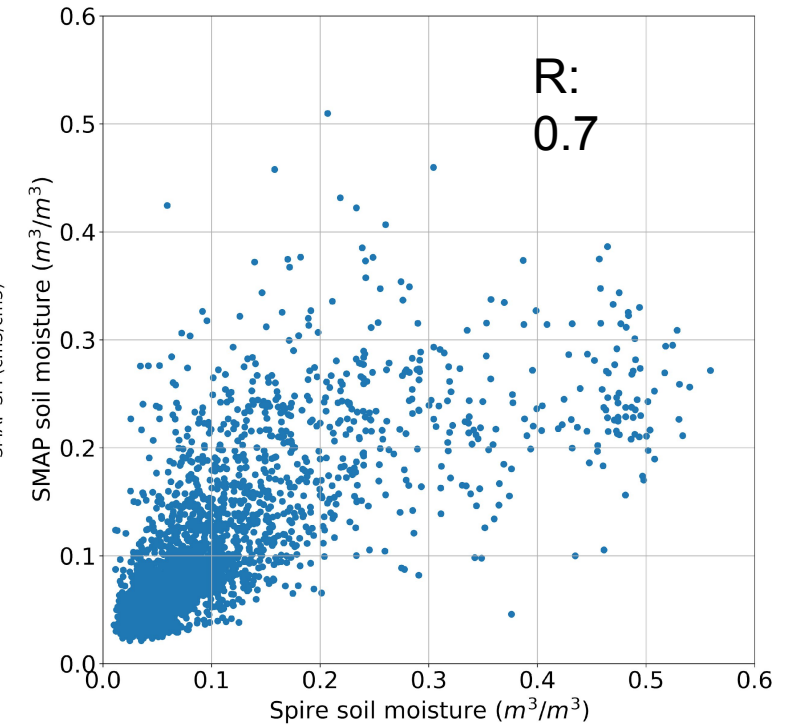
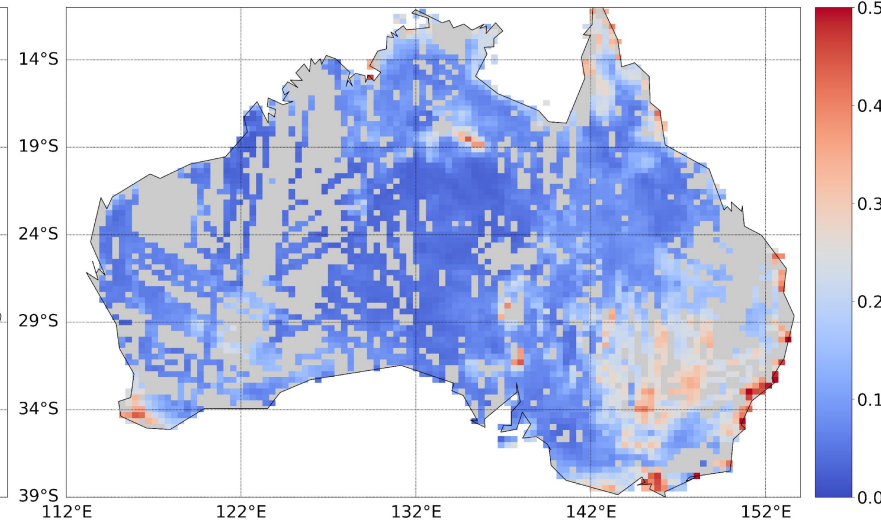
In practice, we use the mean value of corrected Γ_{LR} observations in grids with a size of 36 km to suppress noise.

Averaged Spire/SMAP SM during May 1-14, 2024

Spire



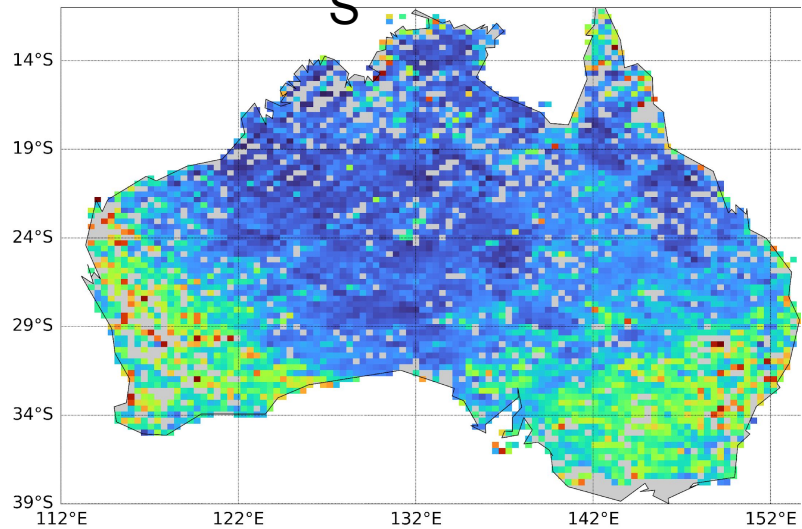
SMA



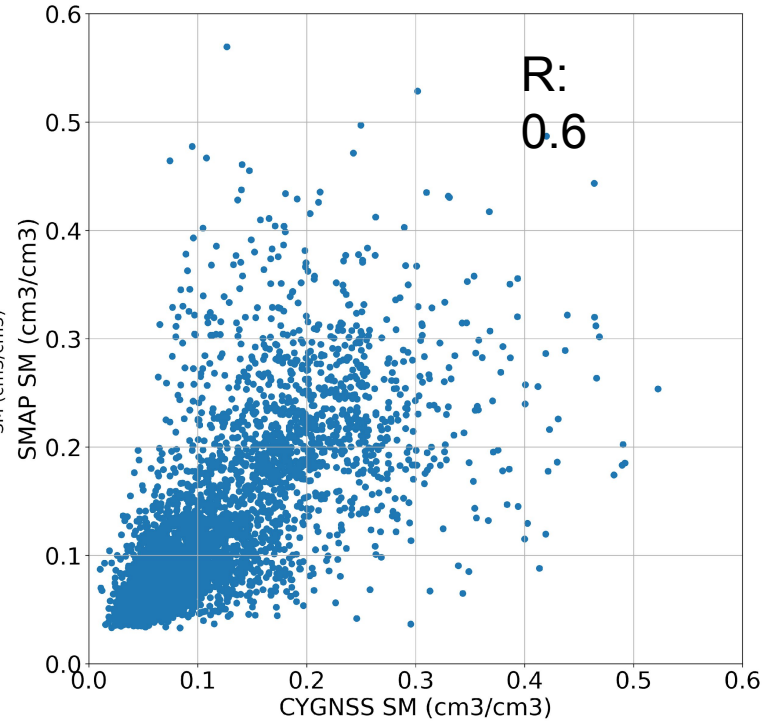
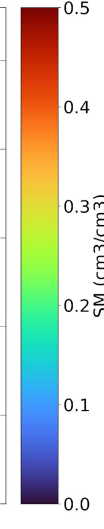
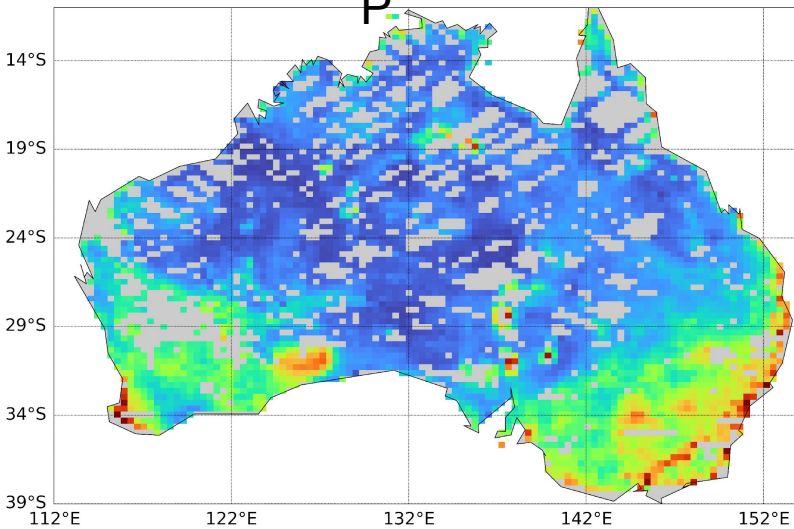
SM inversion algorithms: semi-physical method & results

Averaged CYGNSS/SMAP SM during Jun 5-7, 2024

CYGNSS
S



SMA
P



Summary

- Implement linear regression method and semi-empirical method for inverting SM
- Linear regression method:
 - Retrieve daily & weekly Spire soil moisture observations at 36 km
 - Overall RMSD is $0.05 \text{ cm}^3/\text{cm}^3$ compared to SMAP data
- Semi-empirical method:
 - Initial experiments over Australia with promising results