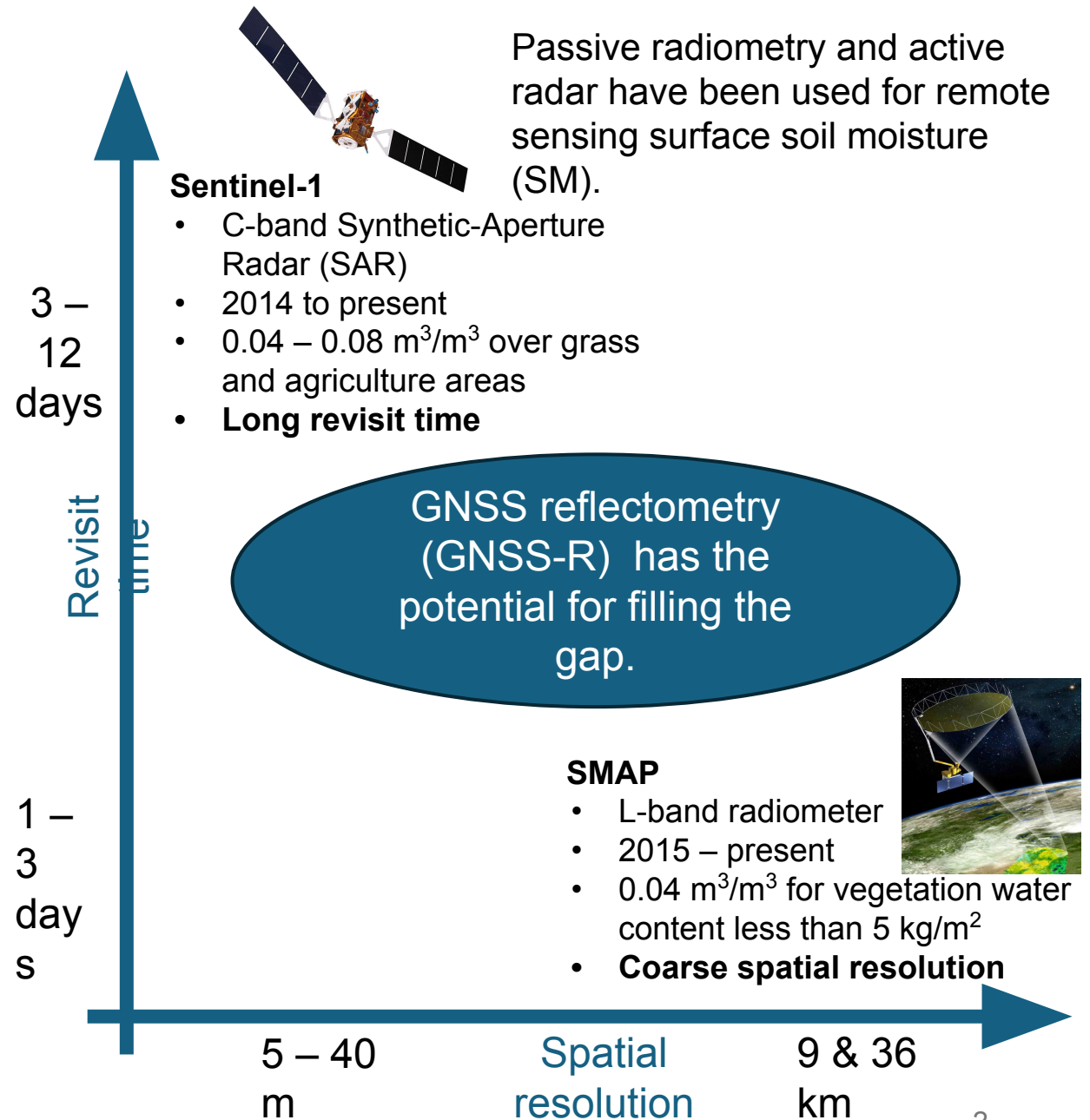
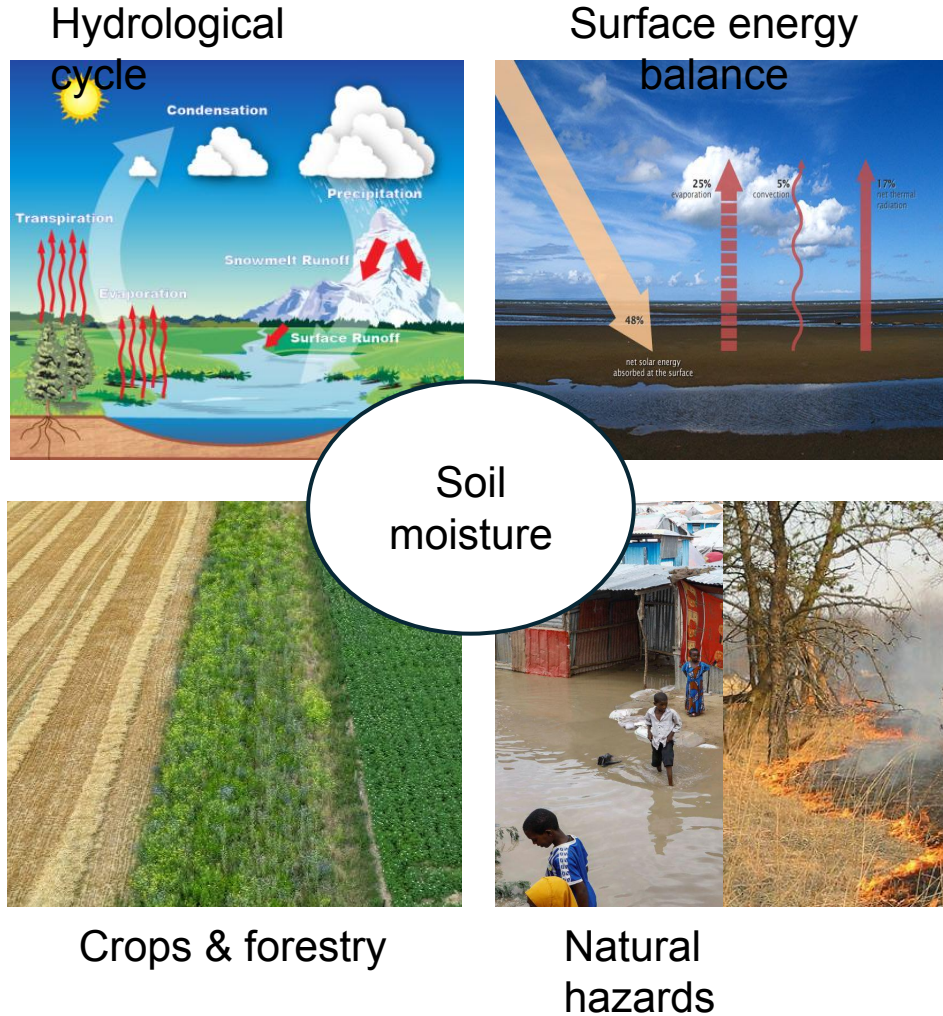


# Mapping Soil Moisture Using Spire GNSS-R reflectivity Observations

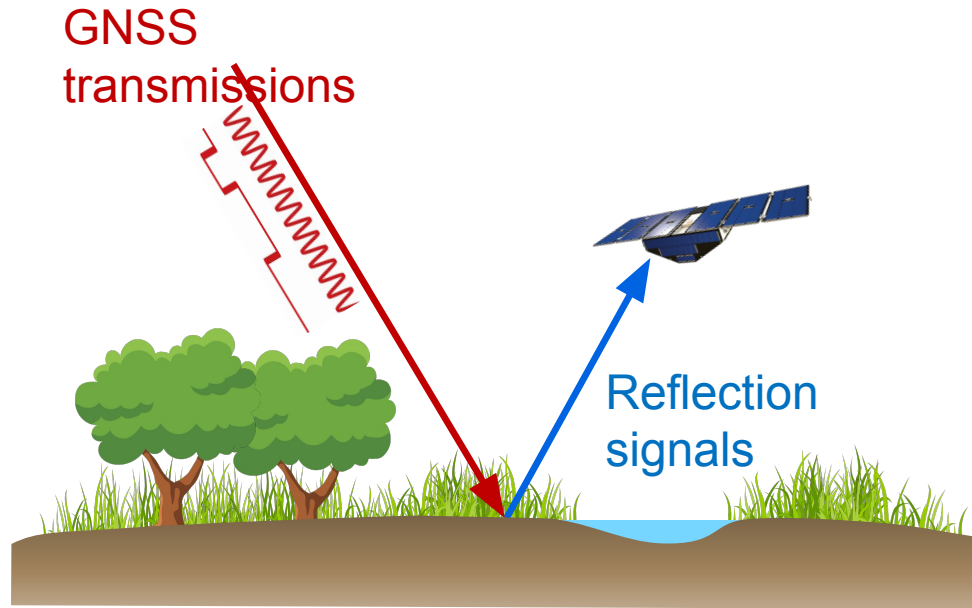
Jiahua Zhang, William Gullotta, Ming Li,  
Jan-Peter Weiss, John Braun, Maggie Sleziak

UCAR, COSMIC

# Soil moisture (SM)

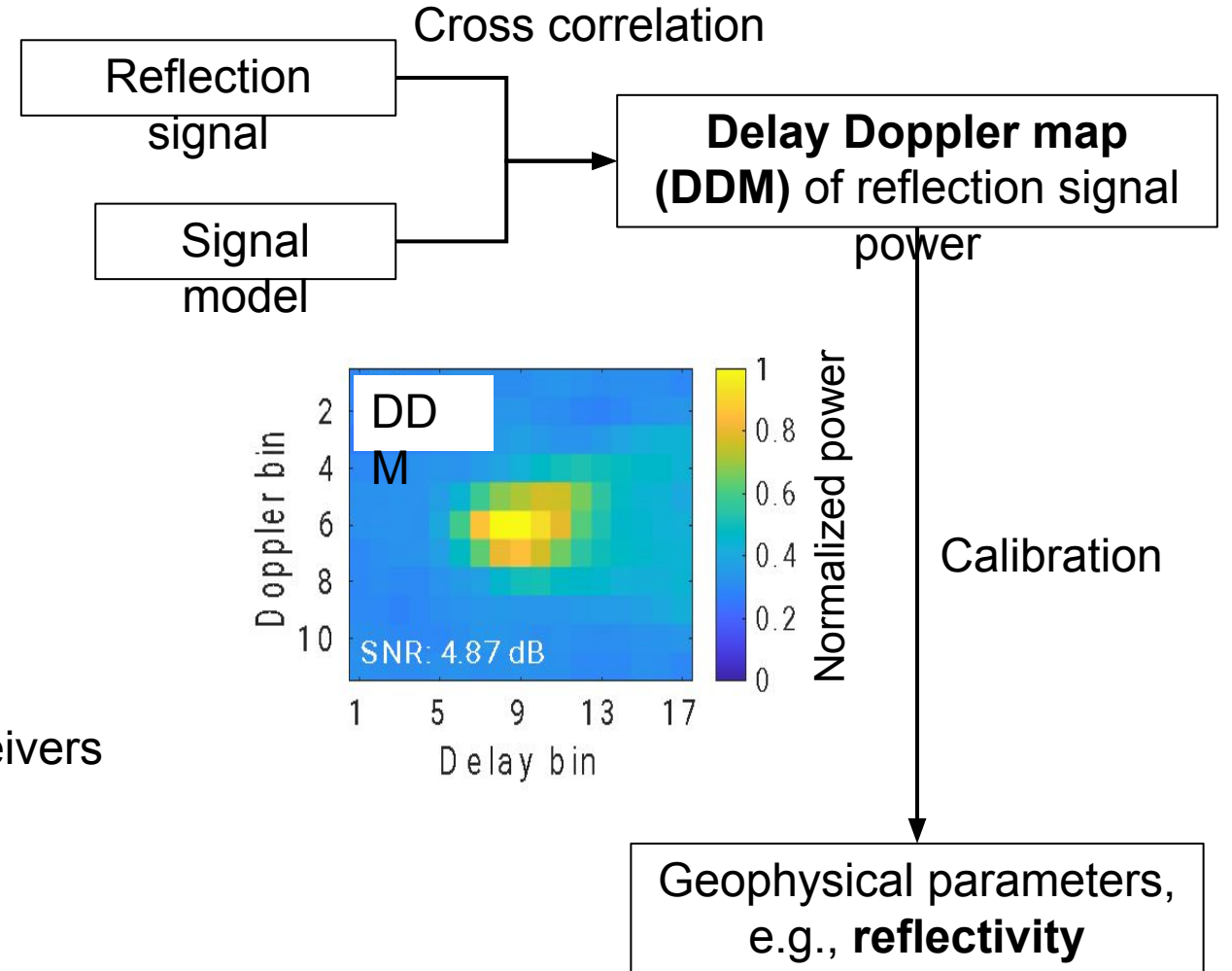


# GNSS Reflectometry (GNSS-R)



## GNSS-R as a passive bistatic radar:

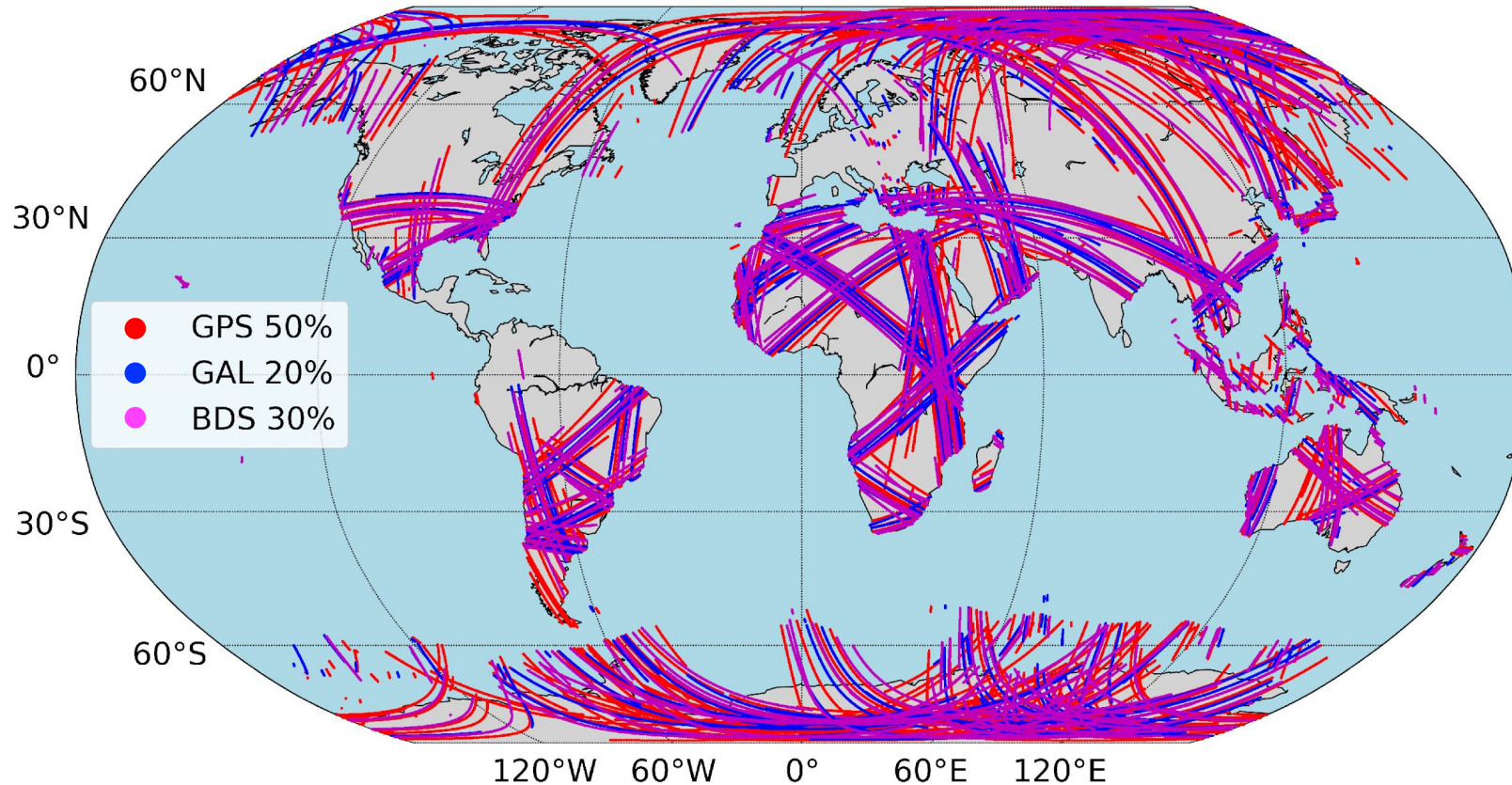
- Facilitate building constellations of LEO receivers
  - A large volume of reflection data
  - Short revisit time
- Other features:
  - Footprint size: hm–km
  - Penetrate relatively dense vegetation
  - All-weather, day and night operations



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 ( $\Gamma$ ) 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

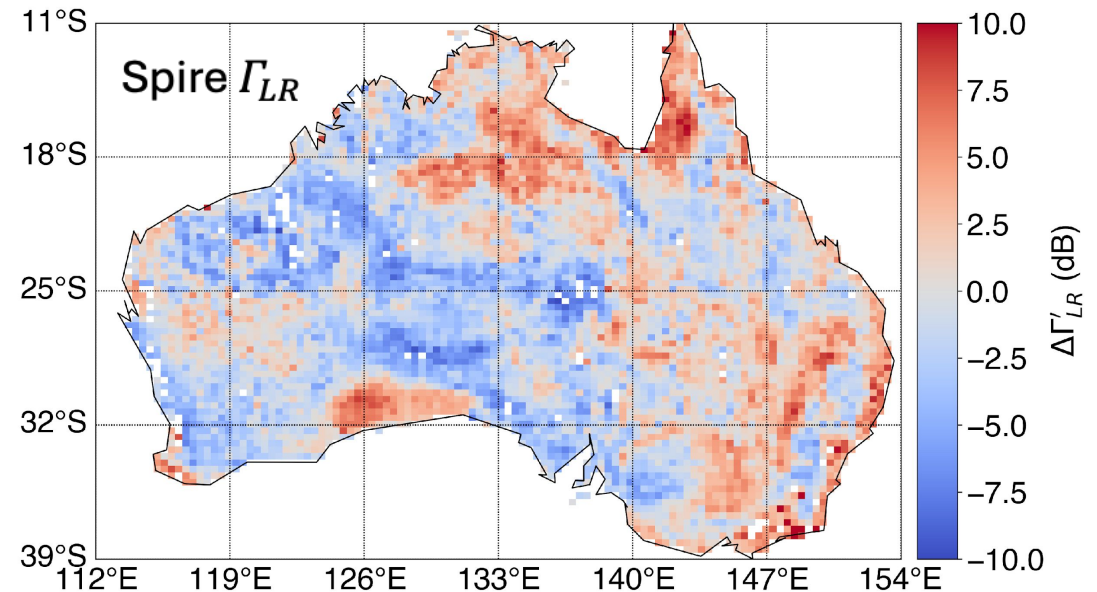
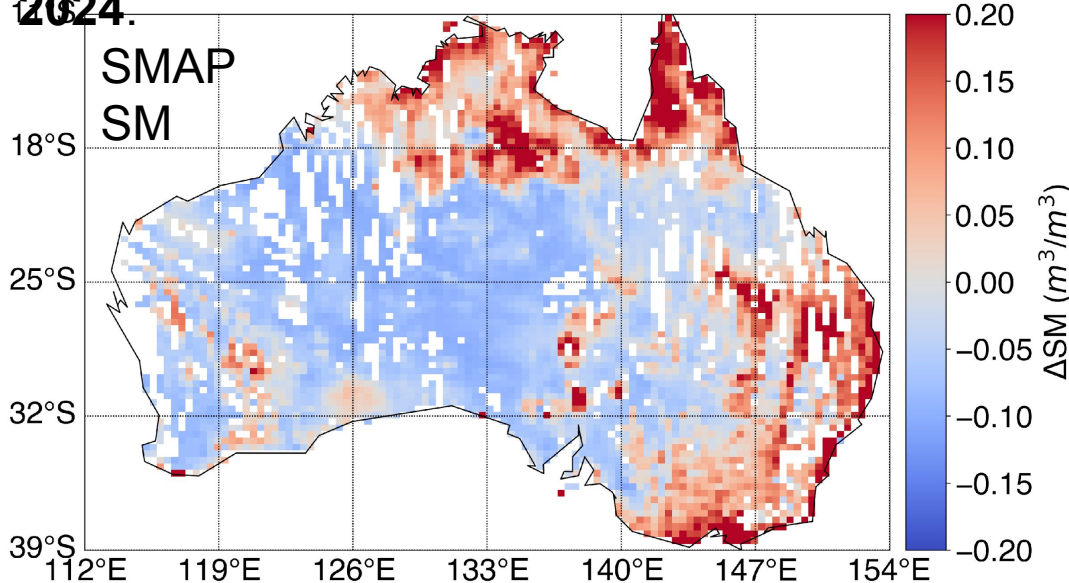
Soil dielectric constant  $\epsilon_{soil}$

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

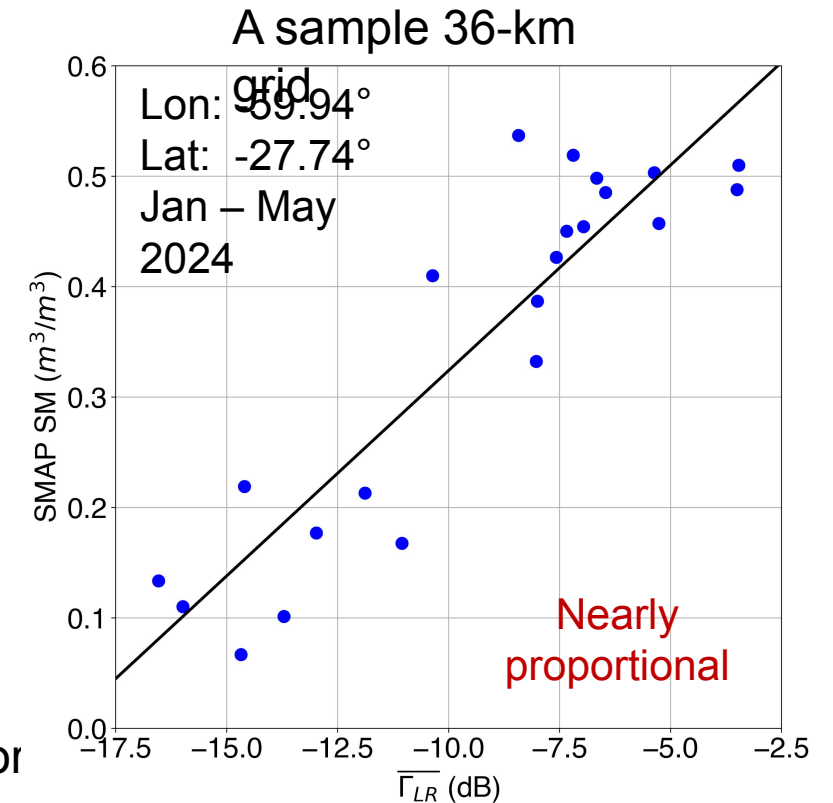
## 1. Empirical algorithm: linear regression method

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

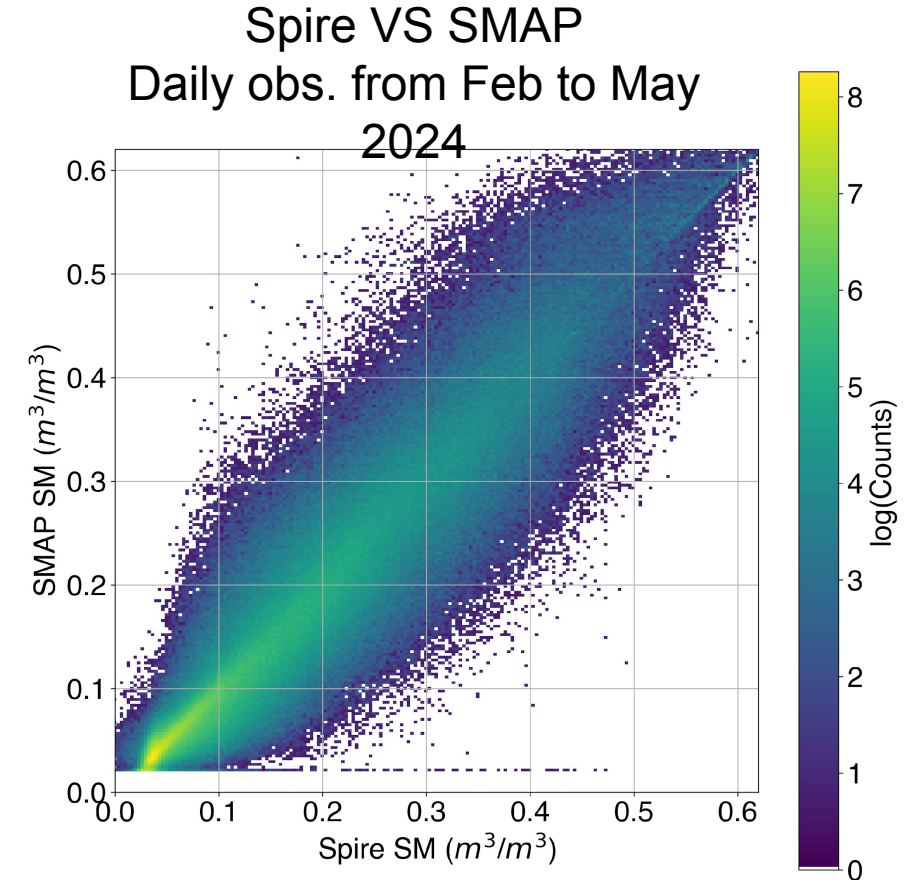
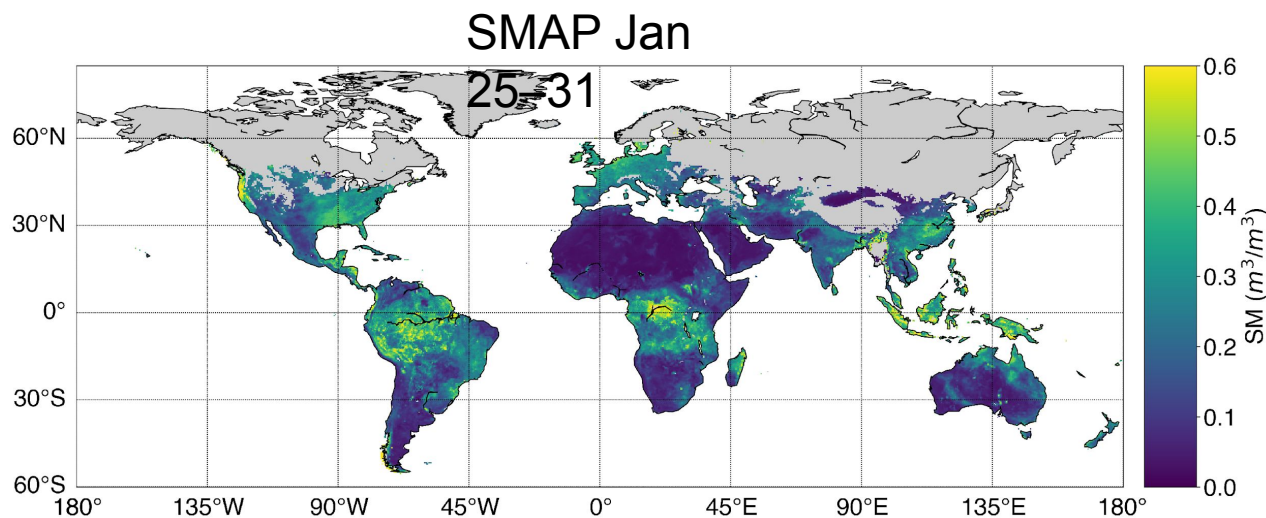
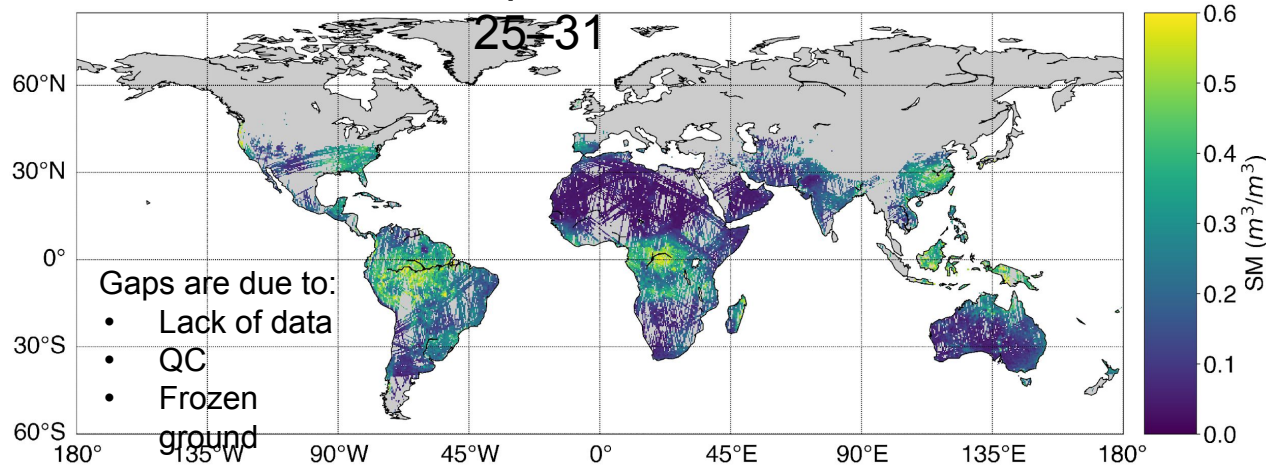
1. Based on the forward model of reflectivity
2. Providing independent SM observations
3. Challenging to realize as it requires accurate corrections for surface roughness and vegetation

## 3. Machine learning & deep learning methods



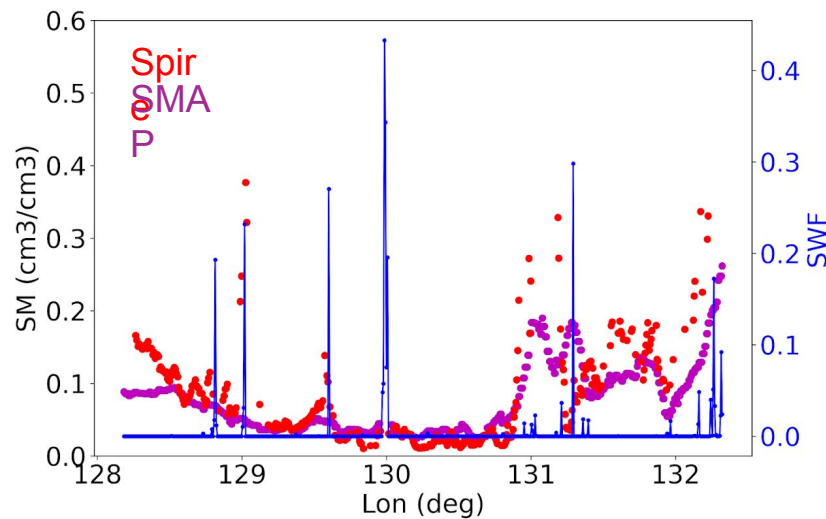
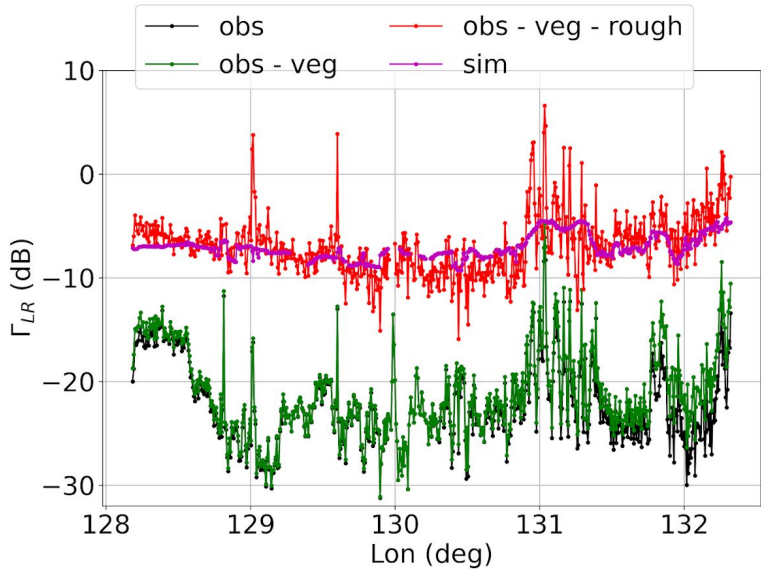
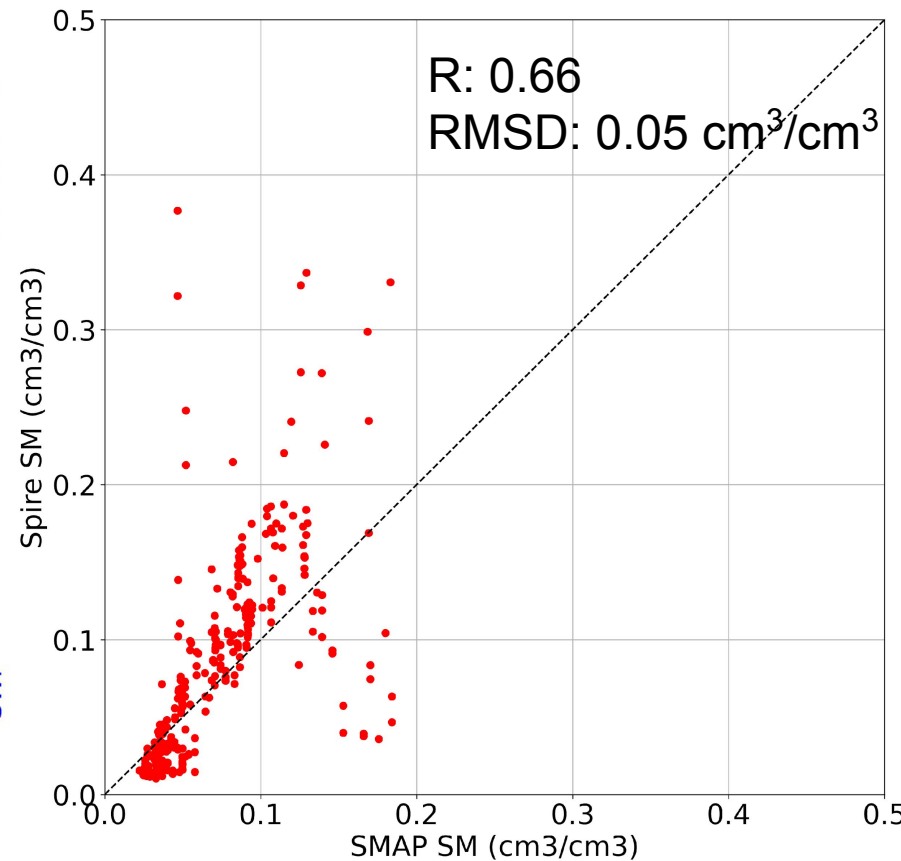
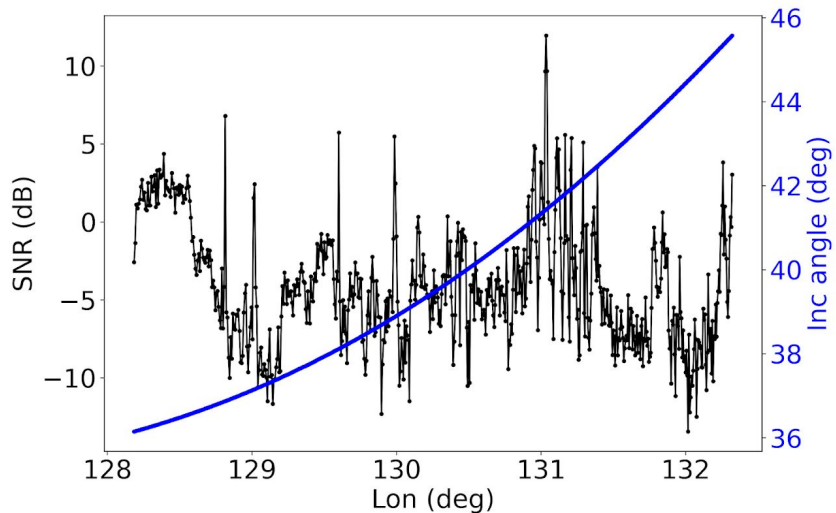
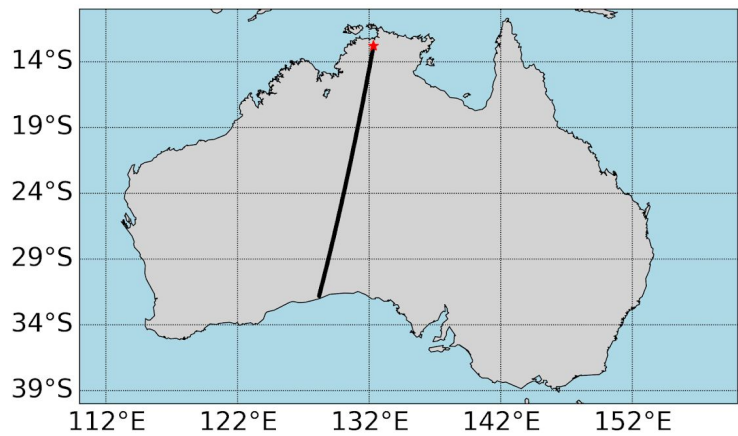
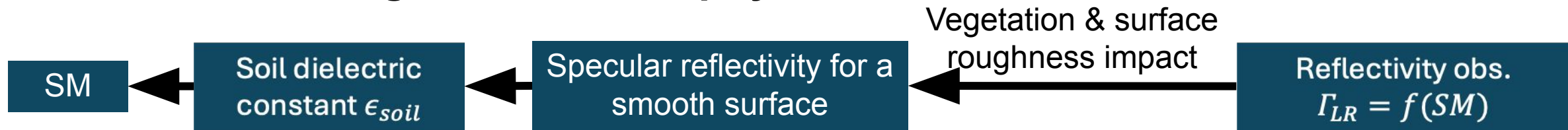
# SM inversion algorithms: linear regression method & results

- 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



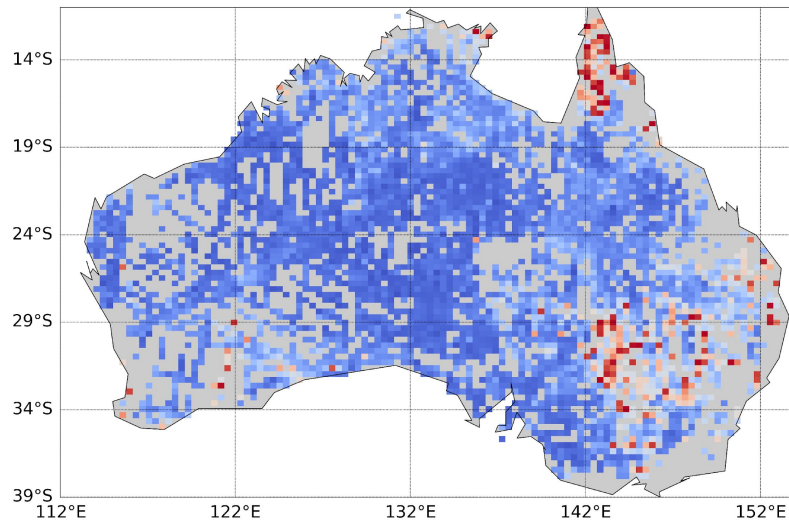


# SM inversion algorithms: semi-physical method & results

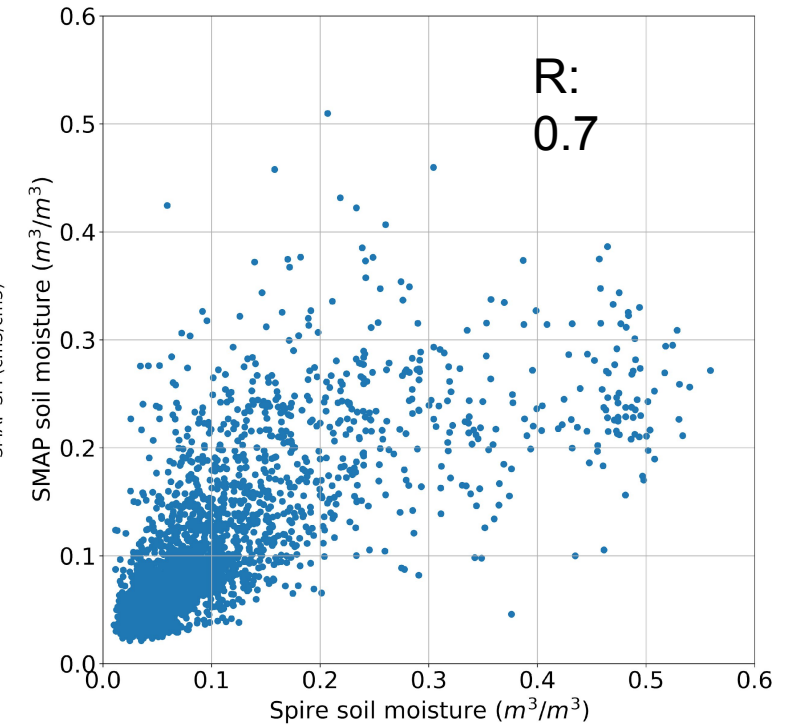
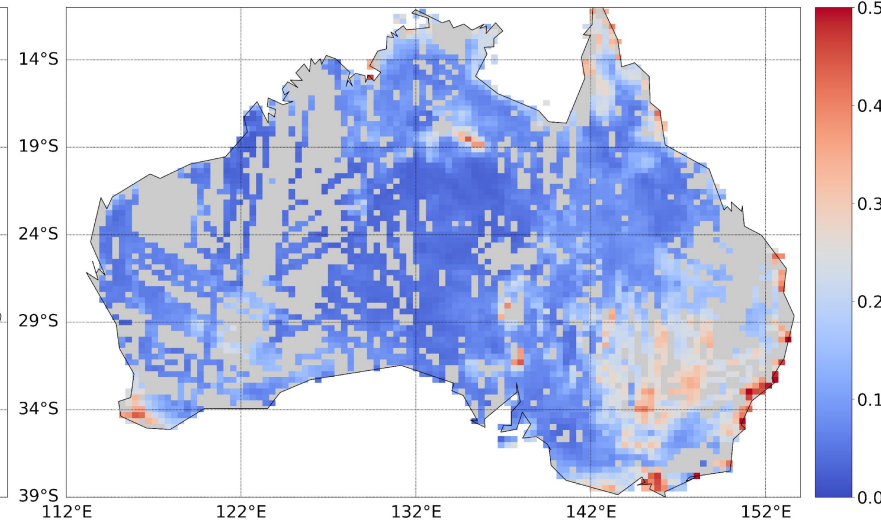
In practice, we use the mean value of corrected  $\Gamma_{LR}$  observations in grids with a size of 36 km to suppress noise.

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

Spire



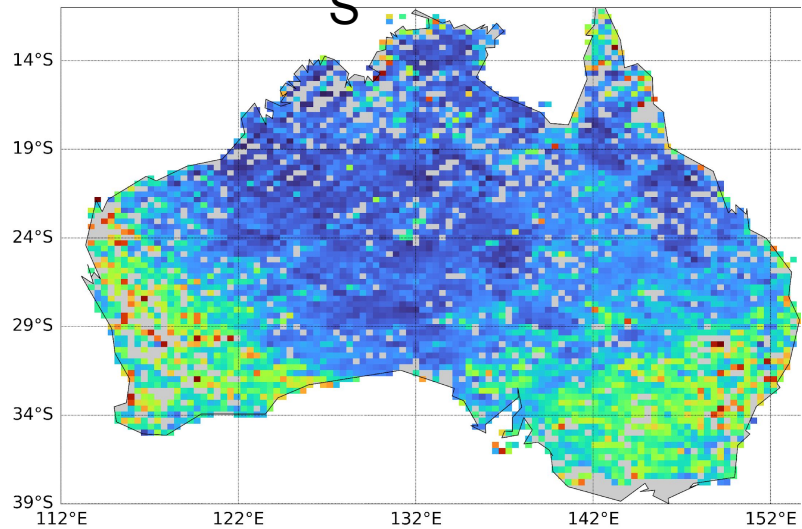
SMA



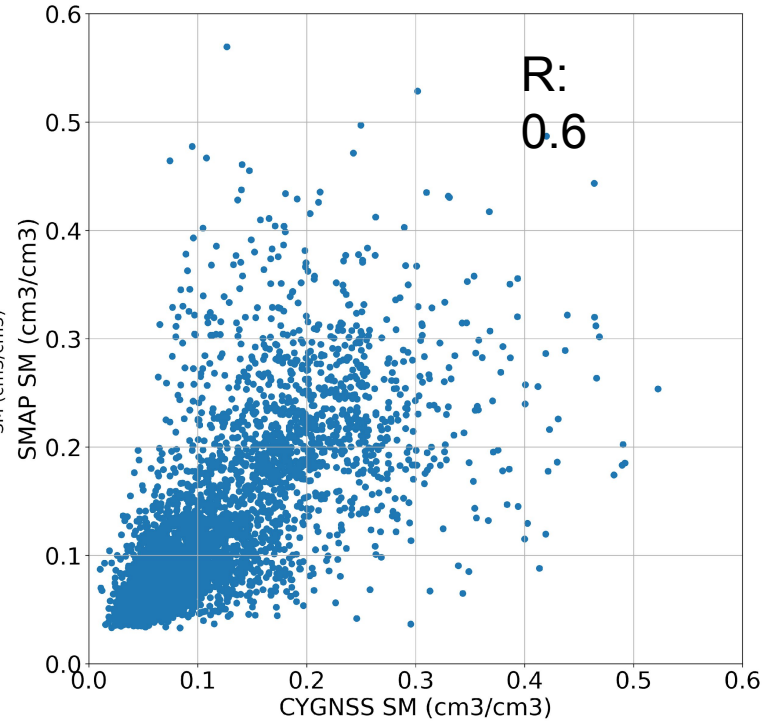
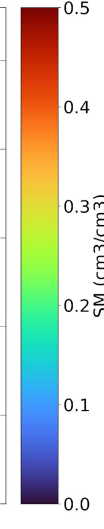
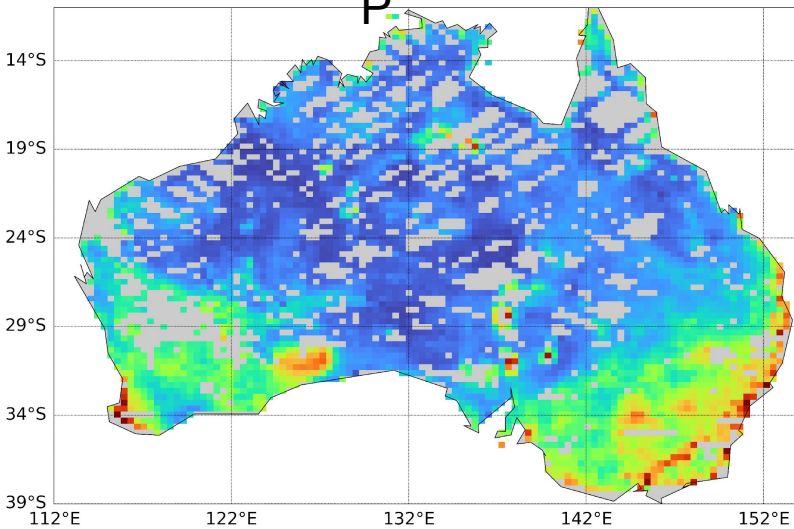
# SM inversion algorithms: semi-physical method & results

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