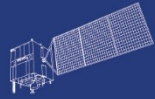


HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



Sentinel-5p



Aeolus

2023 DRAGON 5 SYMPOSIUM  
3<sup>rd</sup> YEAR RESULTS REPORTING  
11-15 SEPTEMBER 2023

[PROJECT ID. 59312]

[MULTI-FREQUENCY MICROWAVE RS OF GLOBAL WATER  
CYCLE AND ITS CONTINUITY FROM SPACE]

**ID. 59312**

**PROJECT TITLE: Multi-Frequency Microwave RS of Global Water Cycle and Its Continuity From Space**

**PRINCIPAL INVESTIGATORS: Yann Kerr & Jiancheng Shi**

**CO-AUTHORS:**

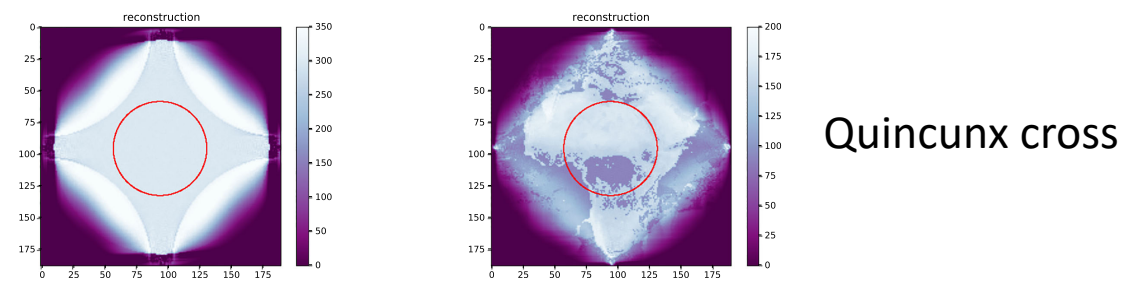
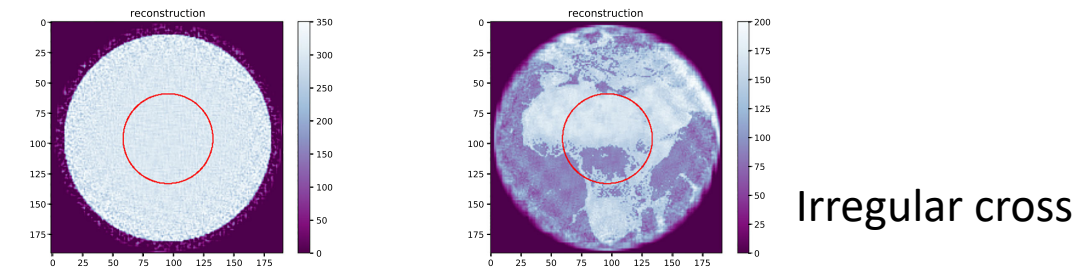
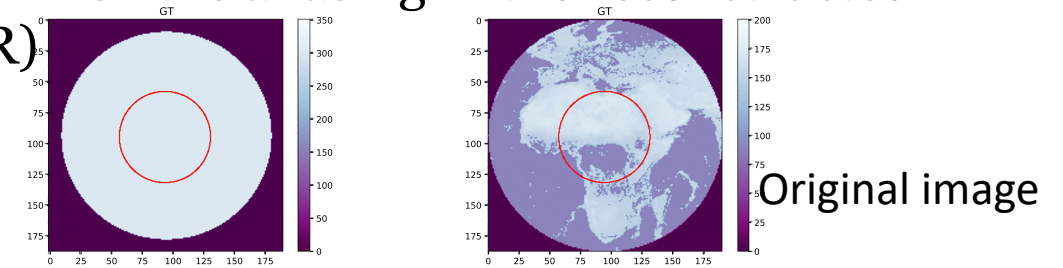
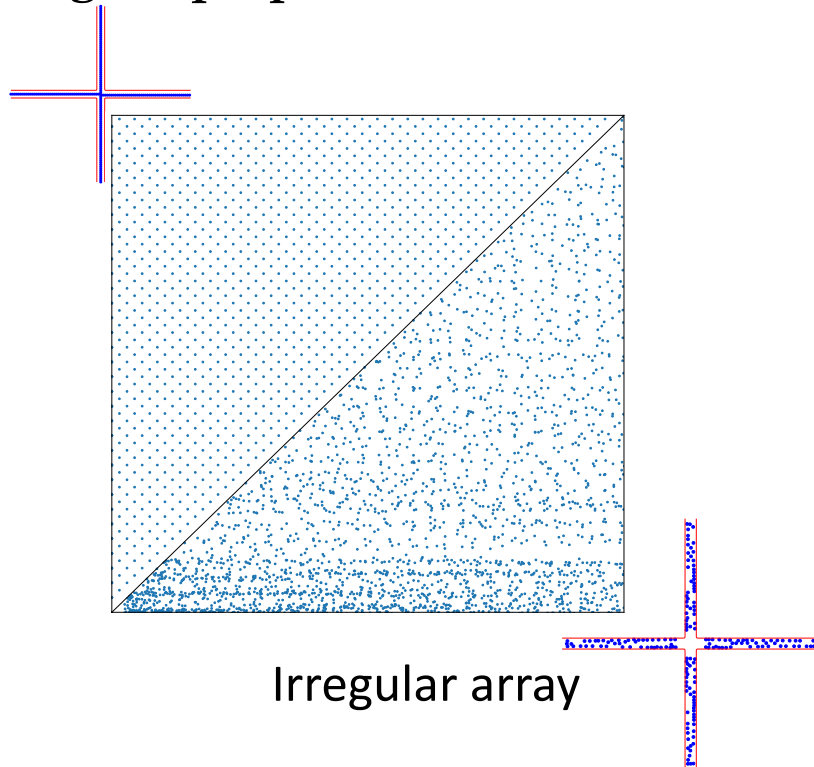
**Nemesio Rodriguez, François Cabot, Eric Anterrieu, Tianjie Zhao, Hao Liu, Zhiqing Peng, Jingyao Zheng, Pan Duan, Panpan Yao**

**PRESENTED BY: Panpan Yao**

- **Objectives:** To strengthen the ability of microwave remote sensing in global water cycle studies and seek for new opportunities of satellite missions.
  - **Task 1:** Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques
  - **Task 2:** New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions
  - **Task 3:** Enhancement of the spatial-temporal resolution of remote sensing products by combine use of multi-source satellites
  - **Task 4:** Applications of multiple microwave and optical remote sensing products for eco-hydrological modelling in the Luan river basin
  - Academic exchanges

## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

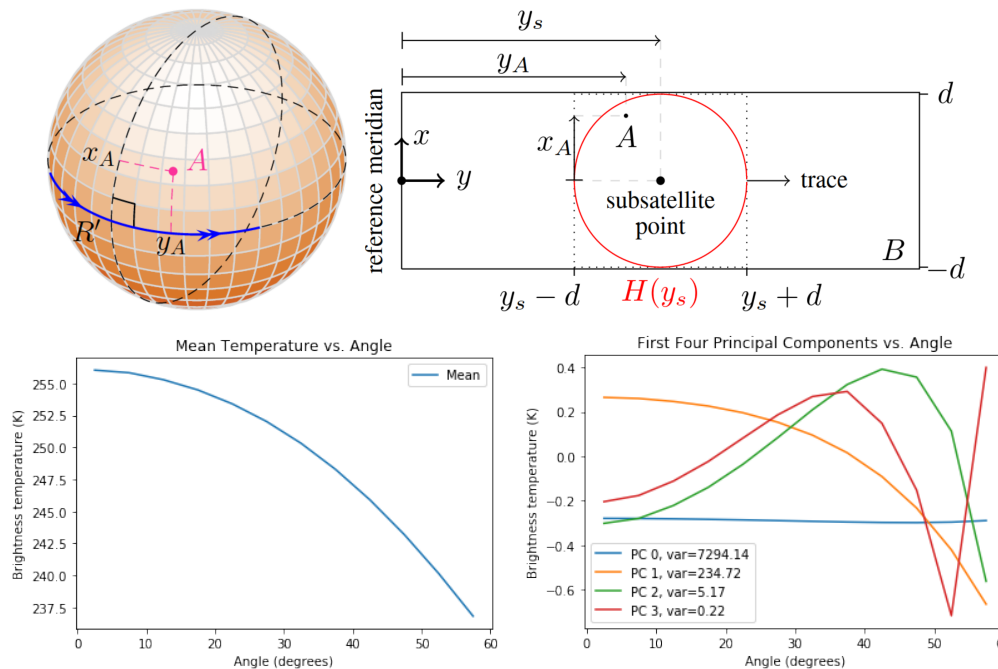
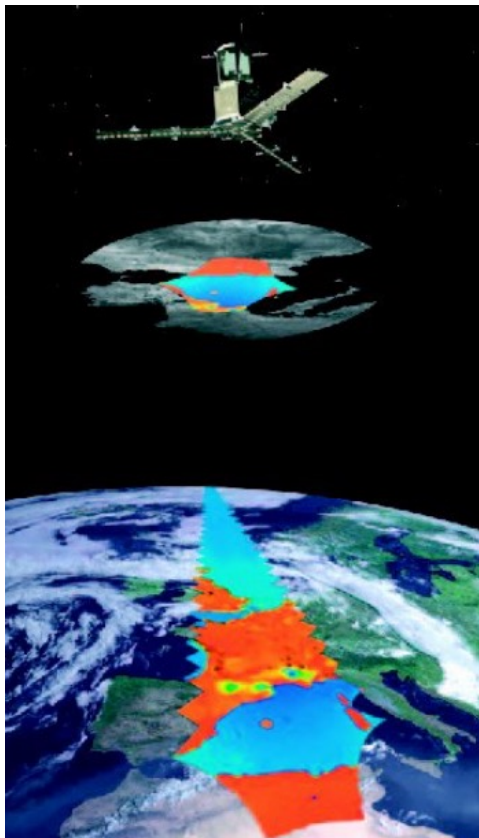
- Irregular antenna arrays have been studied to diminish the aliasing in the reconstructed images (preparation of new missions—SMOS-HR)



(Krzakala et al. 2021, IEEE JSTARS)

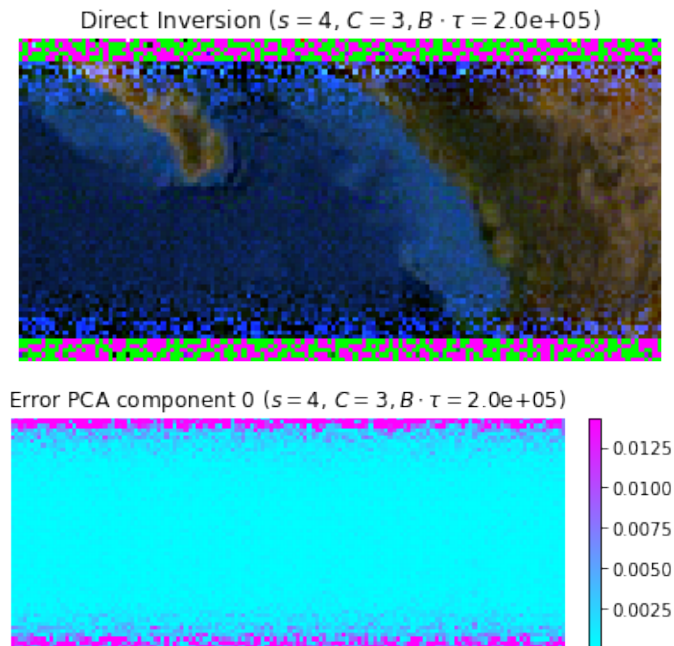
## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- Simultaneous reconstruction of subsequent snapshots can impose more constraints on the TB images and reduce noise.



Reconstruction d'image multi-snapshot

(Dunitz et al. 2021, IEEE CAMA)



## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- Digital beam forming shows promising results as an alternative to aperture synthesis. Less noise in the TB versus incidence angle curves due to less sensitivity to disparities in the antenna power patterns



Technical Note

### An Algebraic Comparison of Synthetic Aperture Interferometry and Digital Beam Forming in Imaging Radiometry

Eric Anterrieu<sup>1\*</sup>, Pierre Lafuma<sup>2</sup> and Nicolas Jeannin<sup>3</sup>

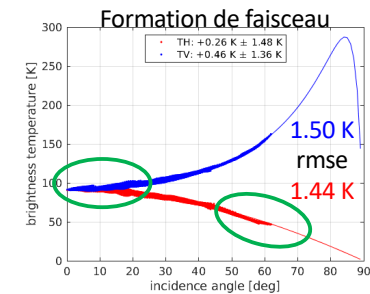
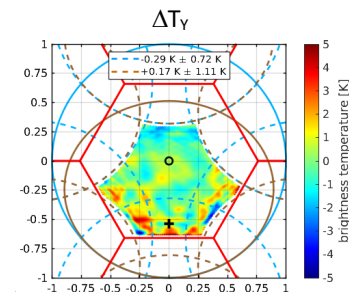
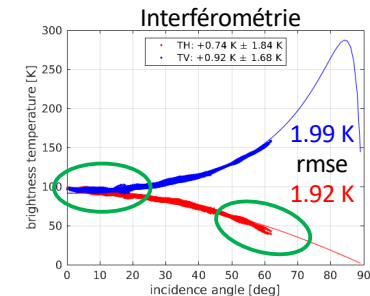
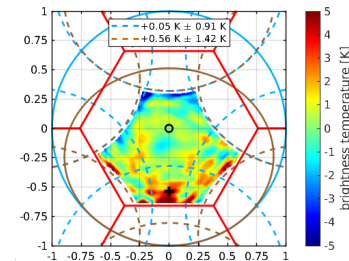
<sup>1</sup> Centre d'Études Spatiales de la Biosphère (CESBIO), 13 Avenue Colonel Roche, 31400 Toulouse, France

<sup>2</sup> Centre National d'Études Spatiales (CNES), 18 Avenue Edouard Belin, 31400 Toulouse, France

<sup>3</sup> Airbus Defence and Space (ADS), 31 Rue des Cosmonautes, 31400 Toulouse, France

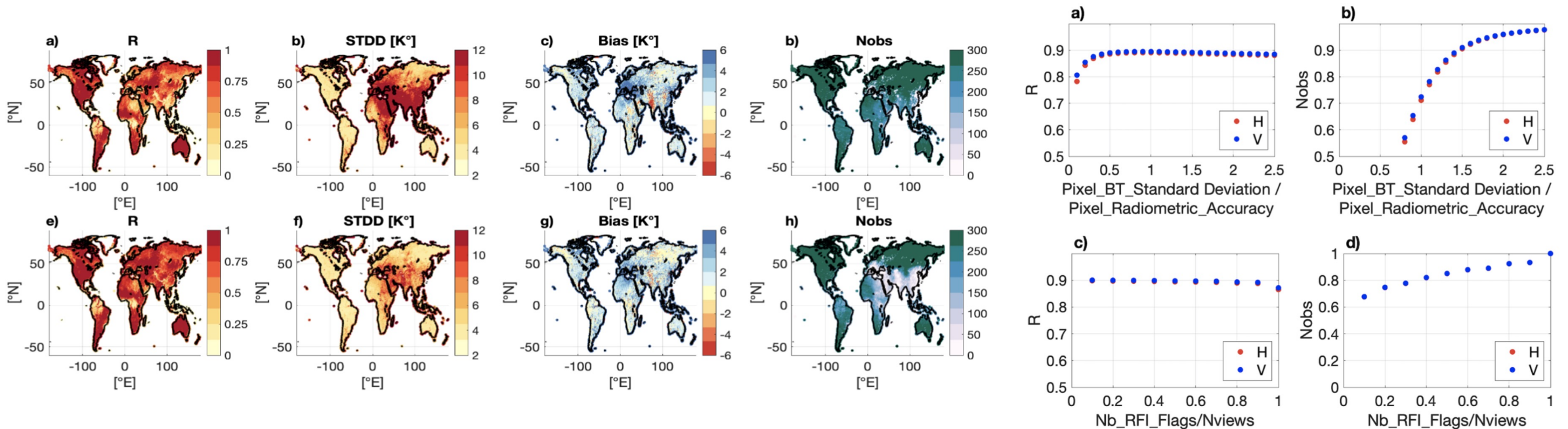
\* Correspondence: eric.anterrieu@cesbio.cnes.fr

**Abstract:** Digital beam forming (DBF) and synthetic aperture interferometry (SAI) are signal processing techniques that mix the signals collected by an antenna array to obtain high-resolution images with the aid of a computer. This note aims at comparing these two approaches from an algebraic perspective with the illustrations of simulations conducted at microwaves frequencies within the frame of the Soil Moisture and Ocean Salinity (SMOS) mission. Although the two techniques are using the same signals and sharing the same goal, there are several differences that deserve attention. From the algebraic point of view, it is the case for the singular values distributions of the respective modeling matrices which are both rank-deficient but do not have the same sensitivity to the diversity of the array's elementary antennas radiation patterns. As a consequence of this difference, the level and the angular signature of the reconstruction floor error are significantly lower with the DBF paradigm than with the SAI one.



## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

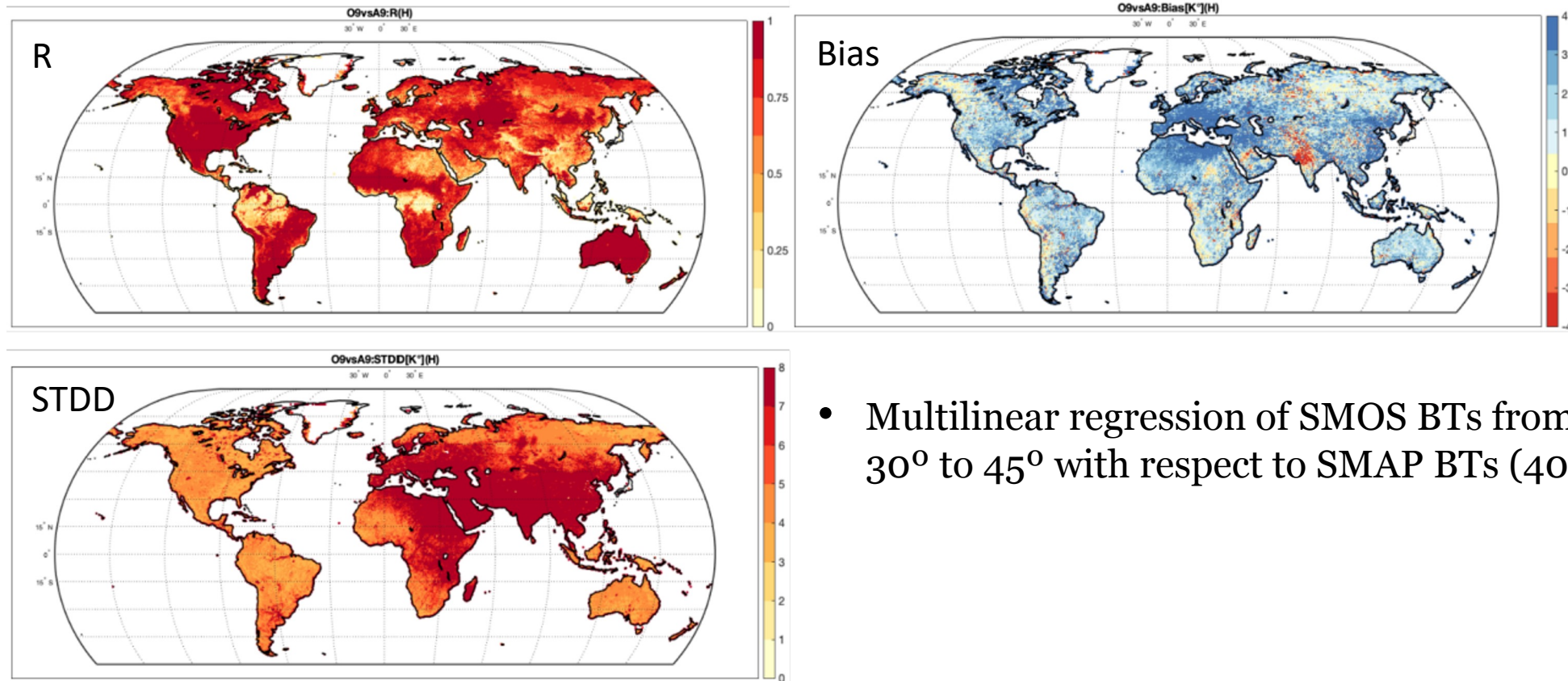
- Using SMAP Tbs to define thresholds to filter SMOS Tbs in regions affected by RFI
- Comparison to SMAP allow to define thresholds using RFI\_flags/Nviews and BT\_std/BT\_accuracy



Madelon, Rodriguez-Fernandez et al.

## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- After applying those filters it is possible to reduce bias in SMOS and SMAP BTs



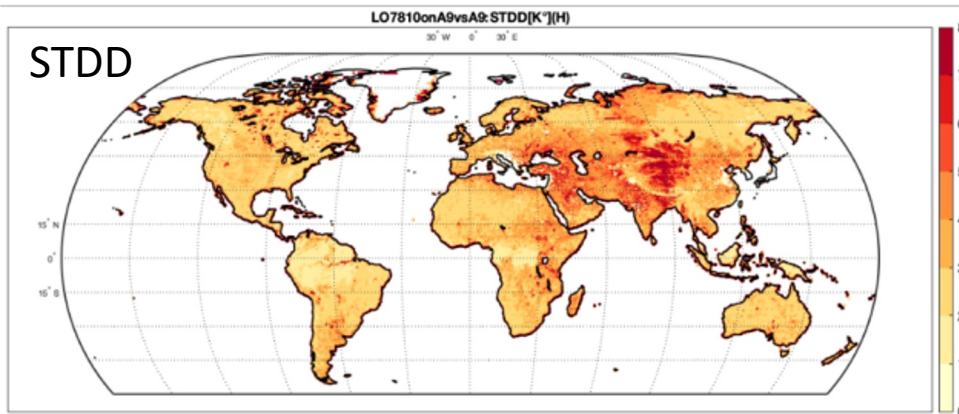
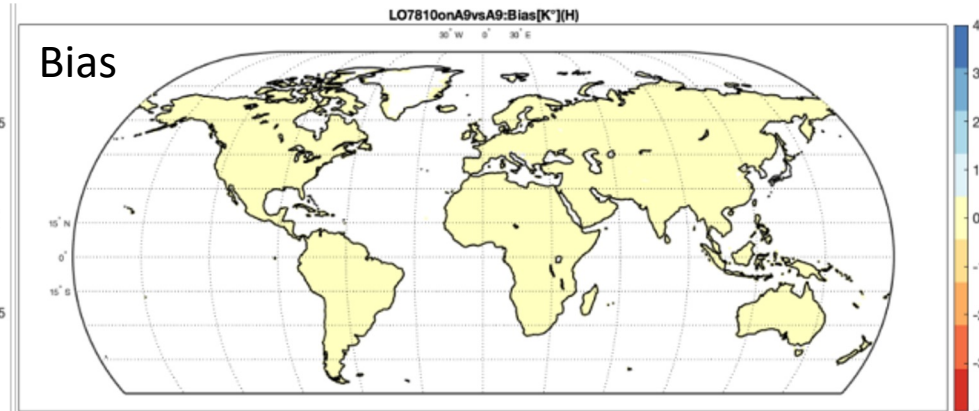
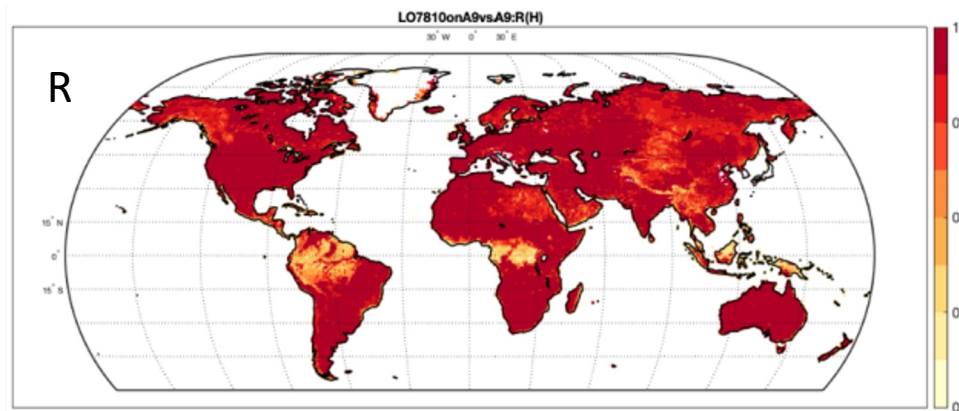
- Multilinear regression of SMOS BTs from  $30^\circ$  to  $45^\circ$  with respect to SMAP BTs ( $40^\circ$ )

Madelon, Rodriguez-Fernandez et al.



## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- After applying those filters it is possible to reduce bias in SMOS and SMAP BTs

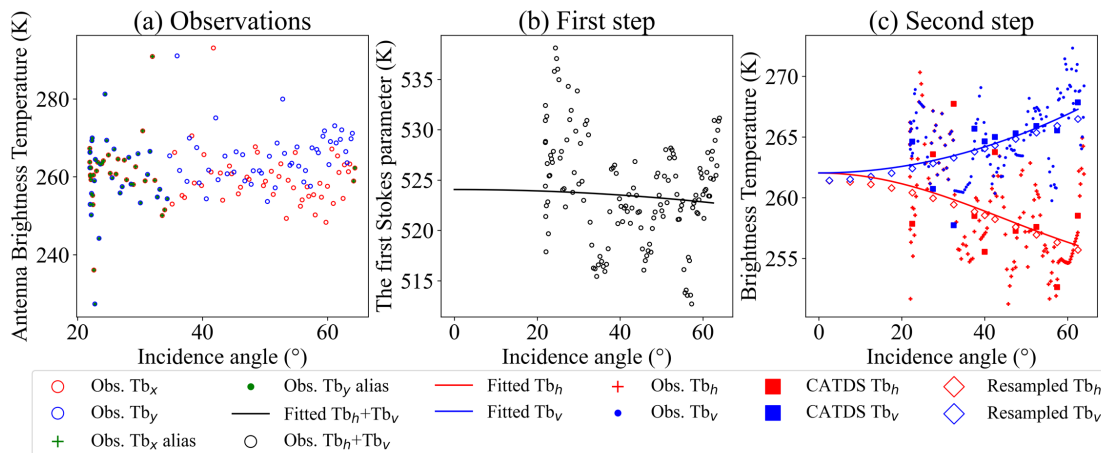


- Multilinear regression of SMOS BTs from  $30^\circ$  to  $45^\circ$  with respect to SMAP BTs ( $40^\circ$ )
- Important to have a common L-band time series to be used to rescale time series of other sensors for climate data records

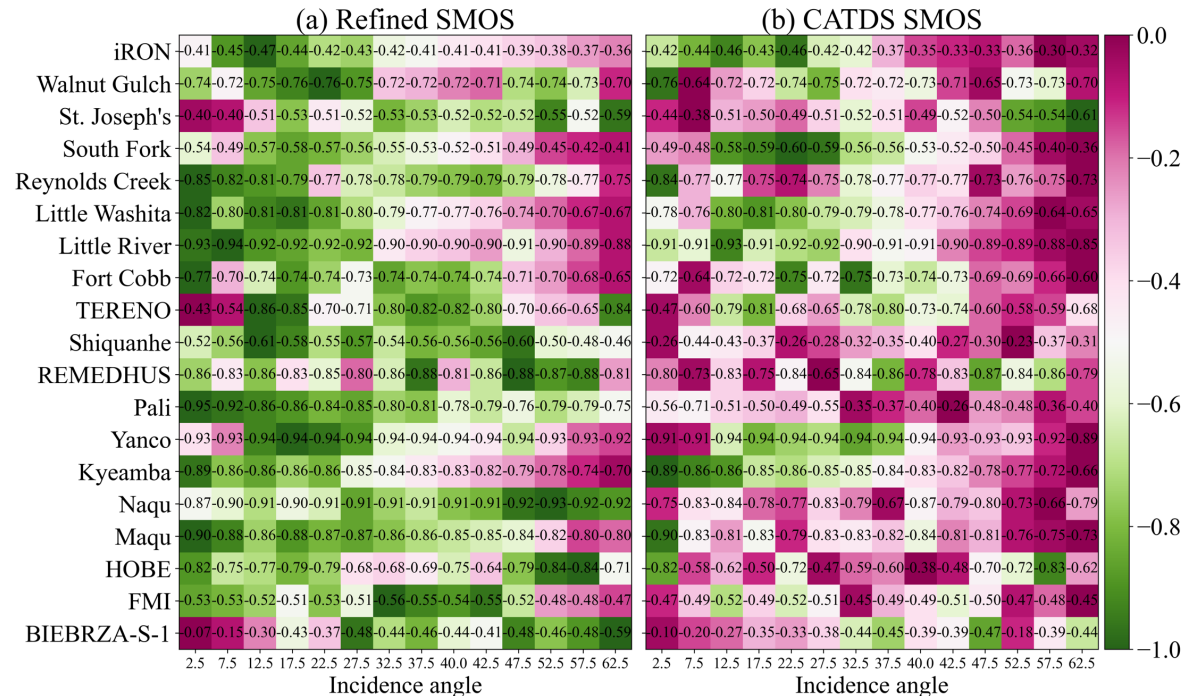
Madelon, Rodriguez-Fernandez et al.

## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- An RFI-suppressed SMOS L-band multi-angular TB dataset (since 2010) was generated by the two-step regression approach.
- The two-step regression refined SMOS TB has better R values (negative) between emissivity and *in situ* soil moisture.



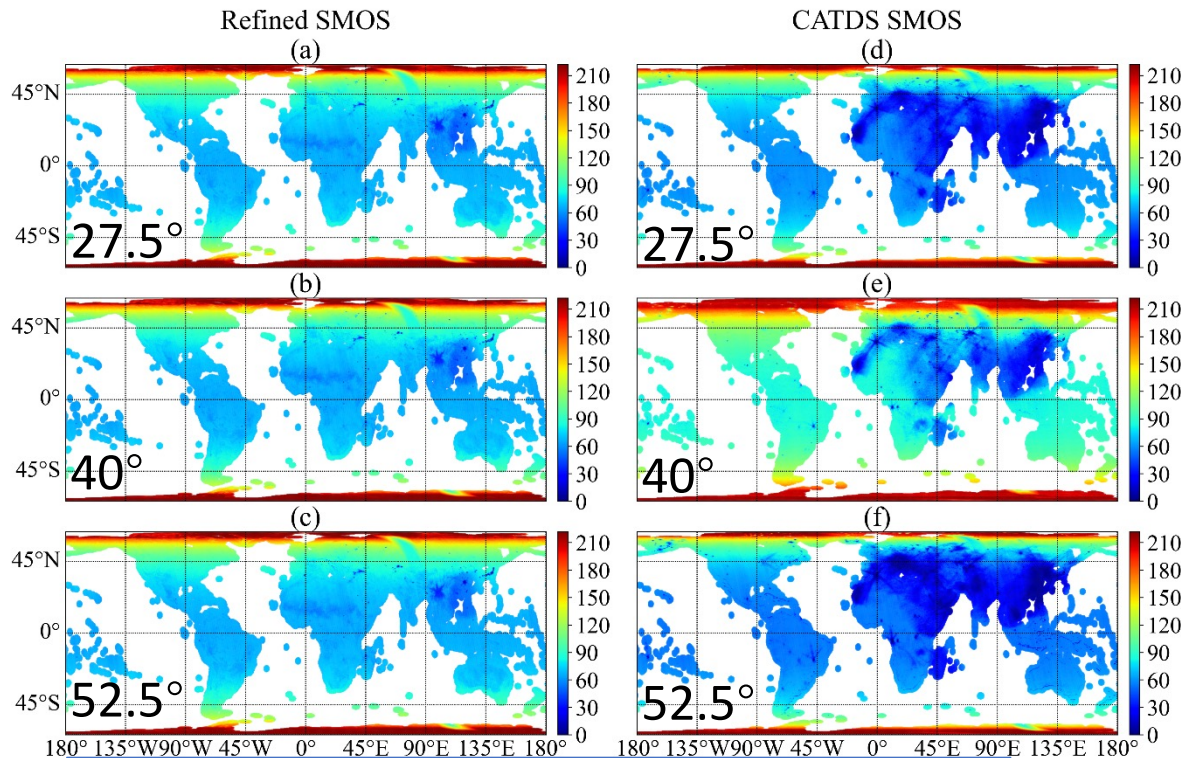
DOI: 10.11888/Terre.tpdc.300406



(Peng, Zhao, Shi et al. 2023, Scientific Data)

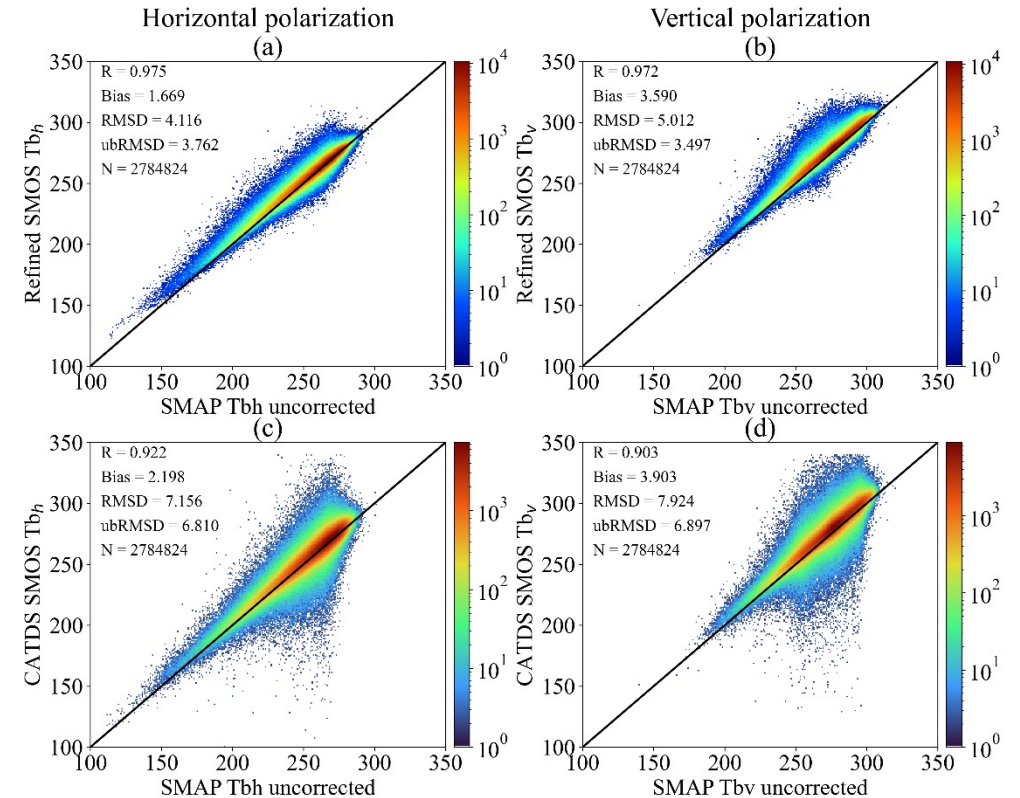
## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- Refined SMOS TB has consistent spatiotemporal coverage at different incidence angles, which is beneficial for algorithms rely on multi-angular TB.



(Peng, Zhao, Shi et al. 2023, Scientific Data)

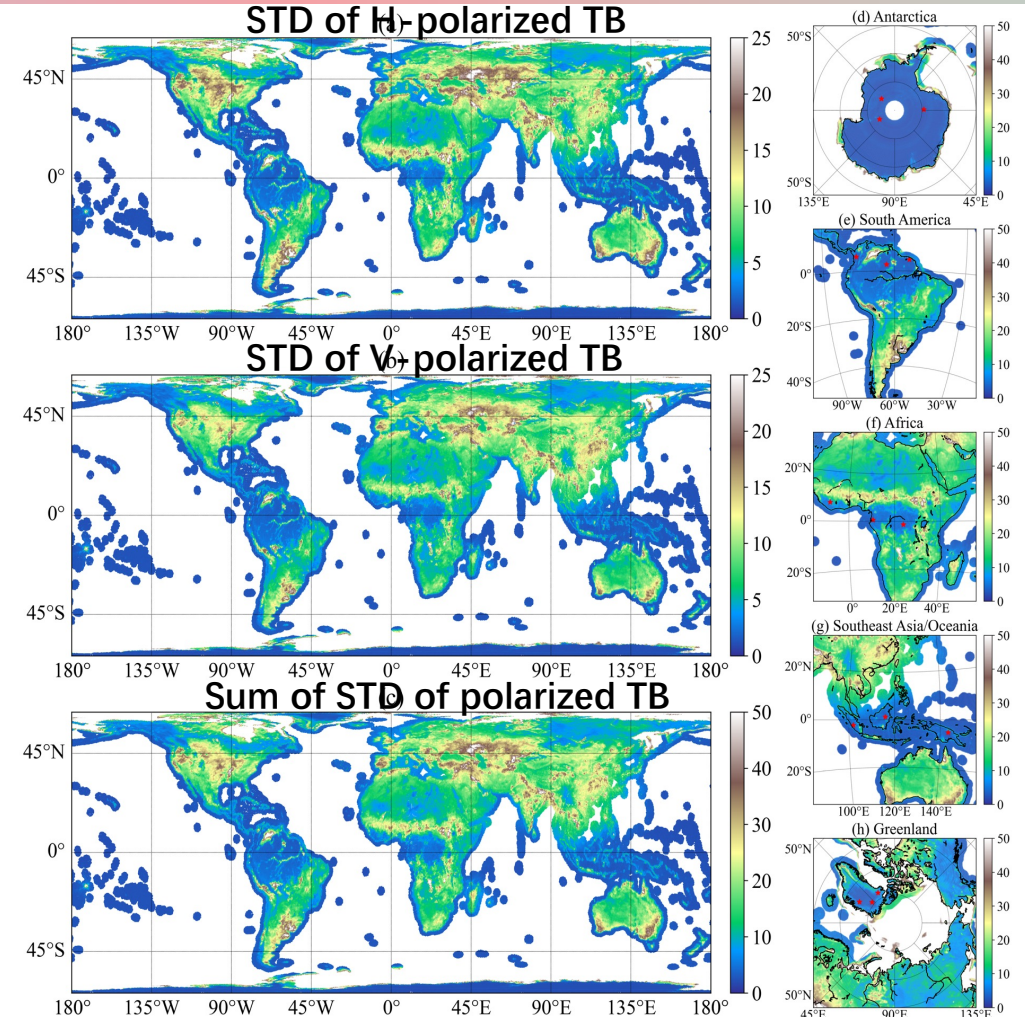
- Refined TB at 40° has good relationship with SMAP TB, SMOS TB are warmer than SMAP TB.



## Task 1: Brightness-temperature retrieval techniques for synthetic aperture interferometric radiometers and RFI mitigation techniques

- SMOS instruments are functioning well, small STDs of TBs are predominantly observed in high-latitude areas, as well as densely vegetated regions.
- These selected reference targets (right column of the figure) may serve as “warm” and “cold” targets for the calibration of the future Terrestrial Water Resources Satellite (TWRS) over the land area.

DGG ID	Longitude	Latitude	Mean of TBh	STD of TBh	Mean of TBv	STD of TBv	Fig. 8
6249545	-139.533	-83.642	189.722	0.893	221.863	0.919	(d)
6252745	-1.713	-79.373	201.231	0.791	222.165	1.032	(d)
7158754	150.772	-83.700	194.764	0.744	221.250	0.956	(d)
1112149	-76.255	5.986	271.502	1.190	275.522	1.201	(e)
1152189	-63.473	2.700	276.502	1.398	280.326	1.355	(e)
1166606	-53.745	4.752	276.248	1.408	280.799	1.235	(e)
2037509	-8.083	7.631	271.963	2.029	279.377	2.123	(f)
2126717	10.423	0.619	274.977	1.806	279.303	1.432	(f)
2185183	23.861	-1.378	278.022	1.856	282.437	1.801	(f)
8002802	101.870	-2.224	272.918	1.279	277.274	1.149	(g)
8061254	115.869	1.225	275.716	1.259	279.840	1.579	(g)
8183696	143.350	-5.151	271.729	1.152	274.839	1.027	(g)
48463	-60.257	77.767	170.519	1.823	207.350	1.807	(h)
36185	-41.228	79.036	191.604	1.126	222.506	1.046	(h)
39808	-29.860	75.202	195.219	1.435	224.356	1.191	(h)



(Peng, Zhao, Shi et al. 2023, Scientific Data)

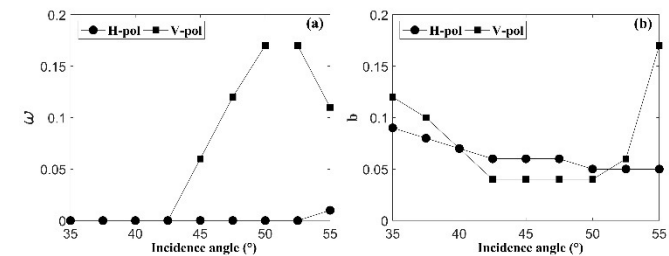
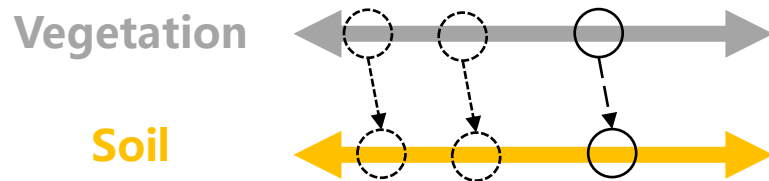
Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

■ A general soil moisture retrieval algorithm (multi-channel collaborative algorithm, MCCA) that could be applied to various satellites was developed.

- (1) Self-constraint relationship between soil and vegetation parameters is used as constraints
- (2) Vegetation tau (VOD) is dependent on frequency, polarization and incidence angle

$$F_{\omega-\tau}^{-1}: \tau_{ch} = -\log\left(\frac{-b' - \sqrt{b'^2 - 4 \cdot a' \cdot c'}}{2 \cdot a'}\right) \cdot \cos \theta$$

$$F_{asm}: \frac{\tau_{ch(1)}}{\tau_{ch(2)}} = \left(\frac{f_1}{f_2}\right)^{C_f} \cdot \frac{\sin^2 \theta_1 \cdot C_{P_1} + \cos^2 \theta_1}{\sin^2 \theta_2 \cdot C_{P_2} + \cos^2 \theta_2}$$



- (3) for a given Tb and corresponding soil and vegetation parameters, the Tb at another channel can be predicted

$$F_{cond}: Tb_{ch(2)}^{total} = V_{ch(2)}^e - S_r V_r \cdot V_{ch(1)}^e + S_r V_r \cdot Tb_{ch(1)}^{total}$$

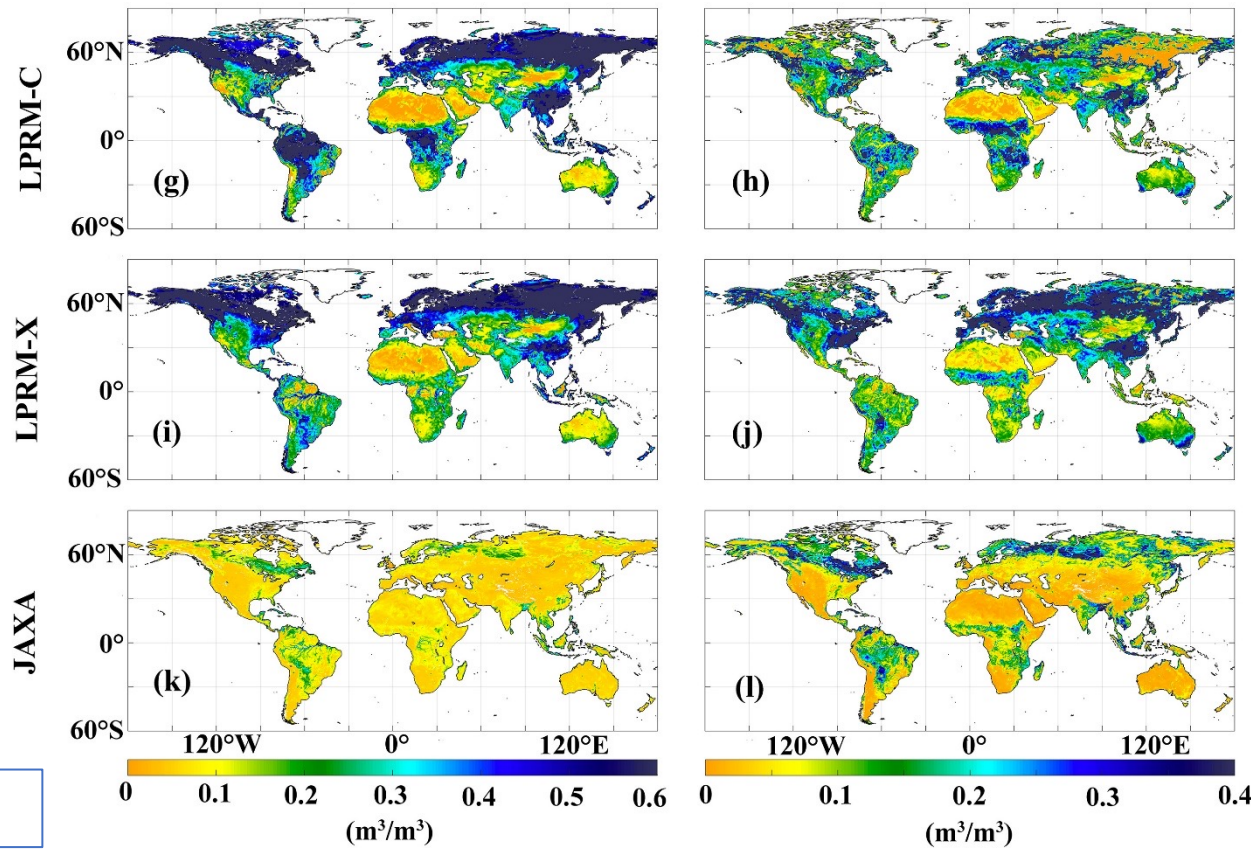
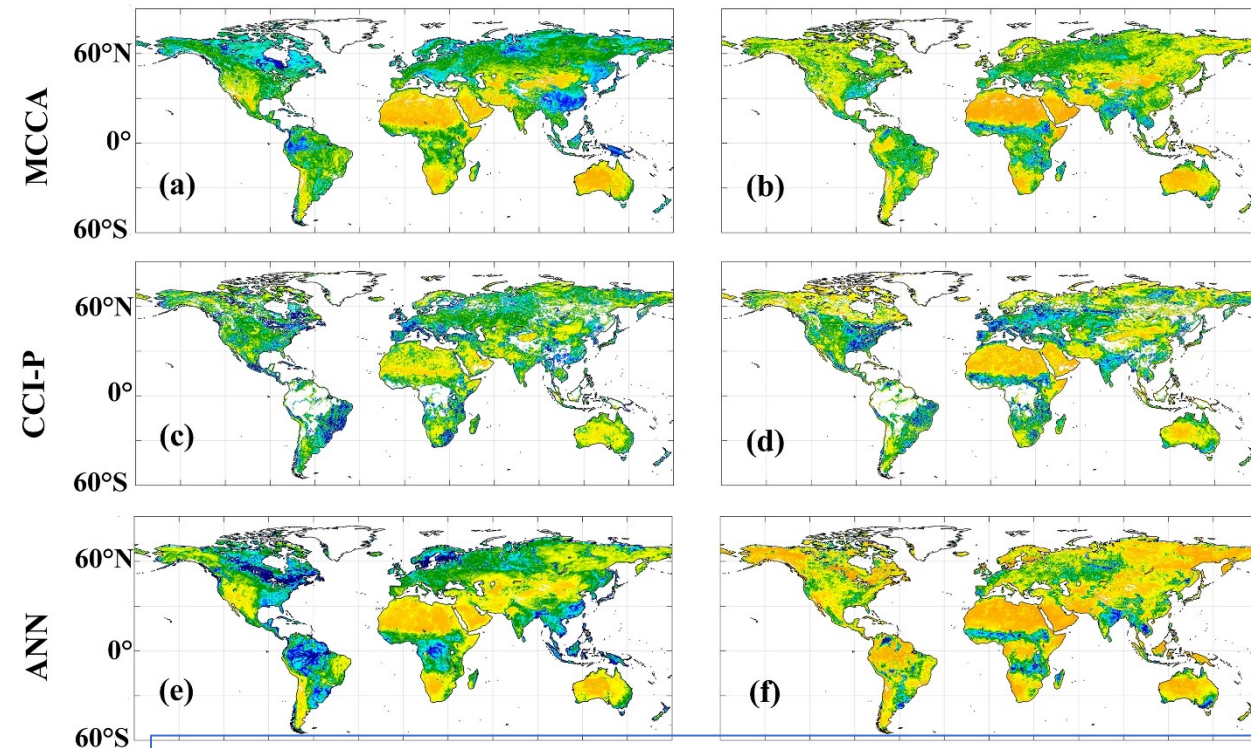
Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

- The global spatial distribution is more reasonable (LPRM products tend to be wet; JAXA products tend to be dry; CCI products have incomplete spatial coverage).

### Implementation for AMSR

Annual average

Seasonal amplitude

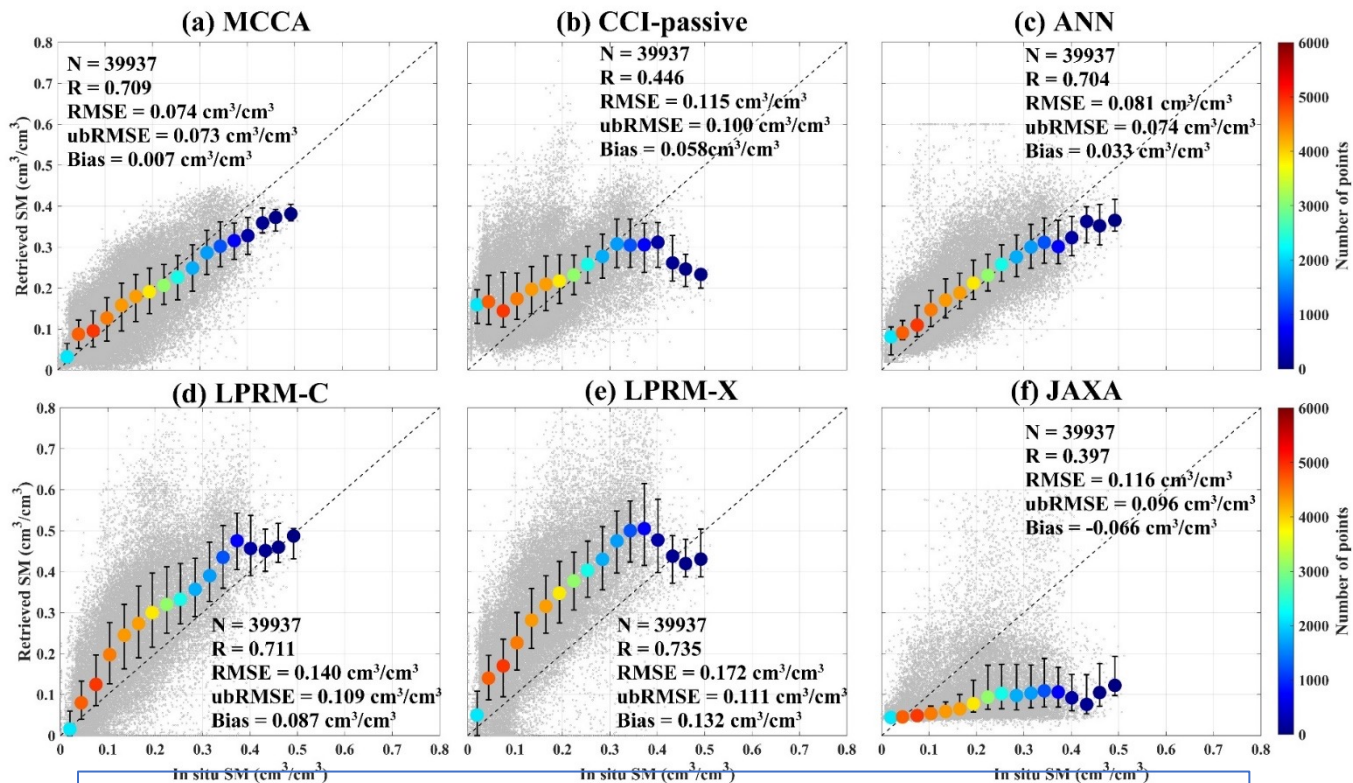


(Hu, Zhao et al. 2023, Remote Sensing of Environment)

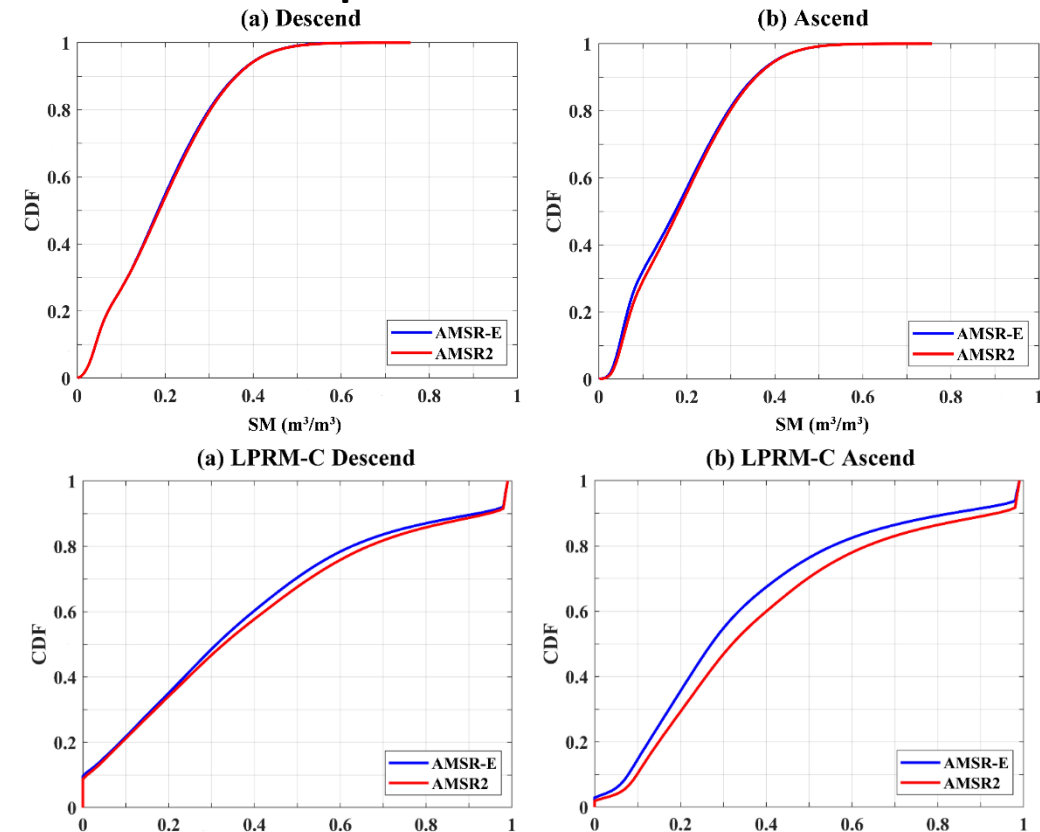
Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

- The accuracy of soil moisture is improved compared with other soil moisture products through validation at 25 ground SM val networks.

- Consistency between AMSR-E and AMSR2 retrievals.

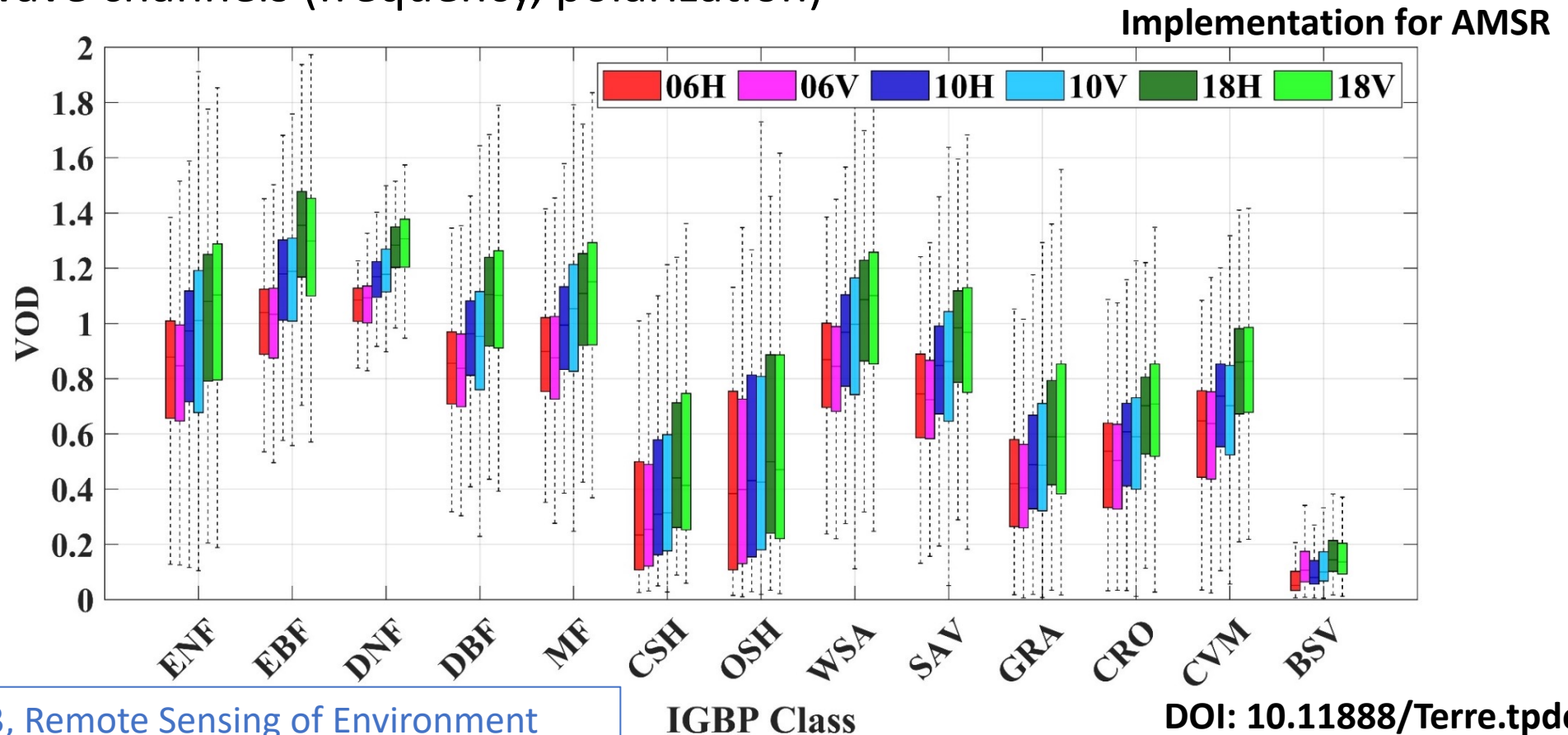


## Implementation for AMSR



Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

- The demonstration of the variation pattern of vegetation optical depth with microwave channels (frequency, polarization)





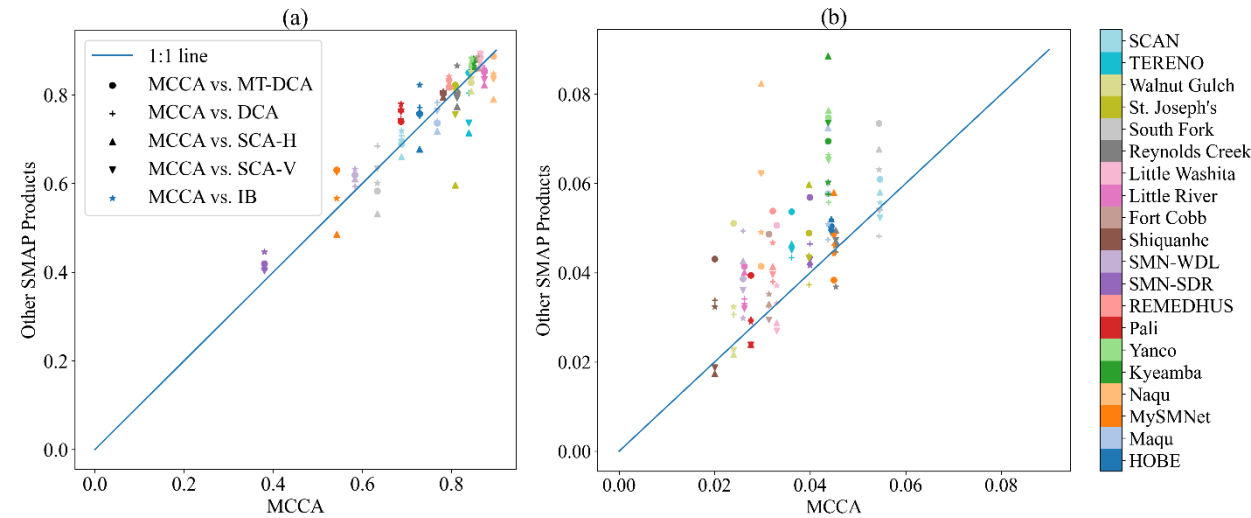
Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

- The MCCA retrieved soil moisture generally has a comparable correlation (R) with other SMAP products, while the ubRMSE of MCCA soil moisture is generally lower than that from other SMAP products.

## Implementation for SMAP

### Correlation

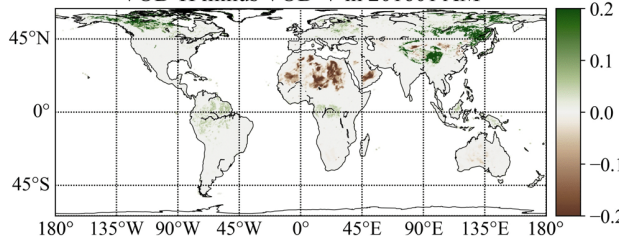
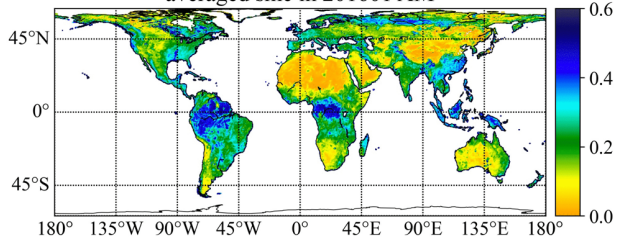
### ubRMSD



Peng, Zhao, Shi et al. 2023,  
Remote Sensing of Environment (under revision)

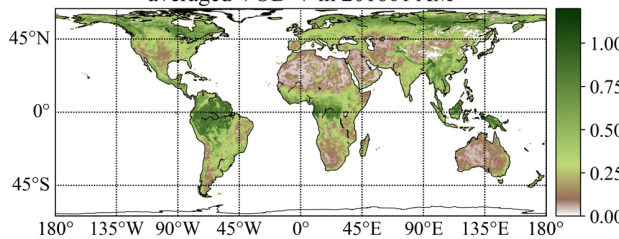
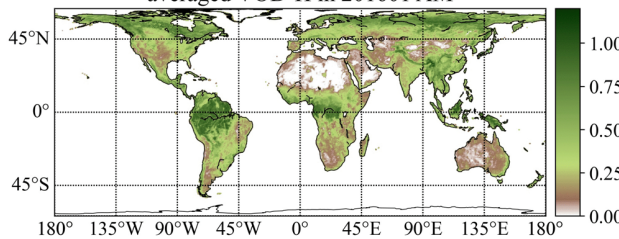
averaged smc in 201601 AM

VOD-H minus VOD-V in 201601 AM



averaged VOD-H in 201601 AM

averaged VOD-V in 201601 AM



**Vegetation optical depth  
VOD (H-pol)**

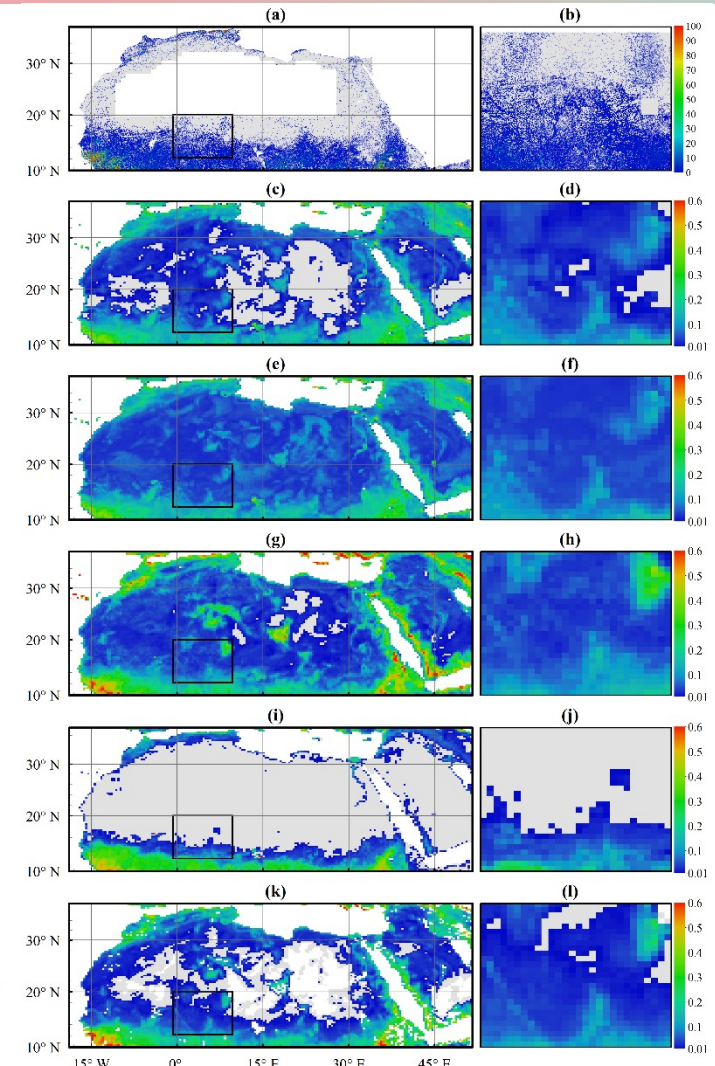
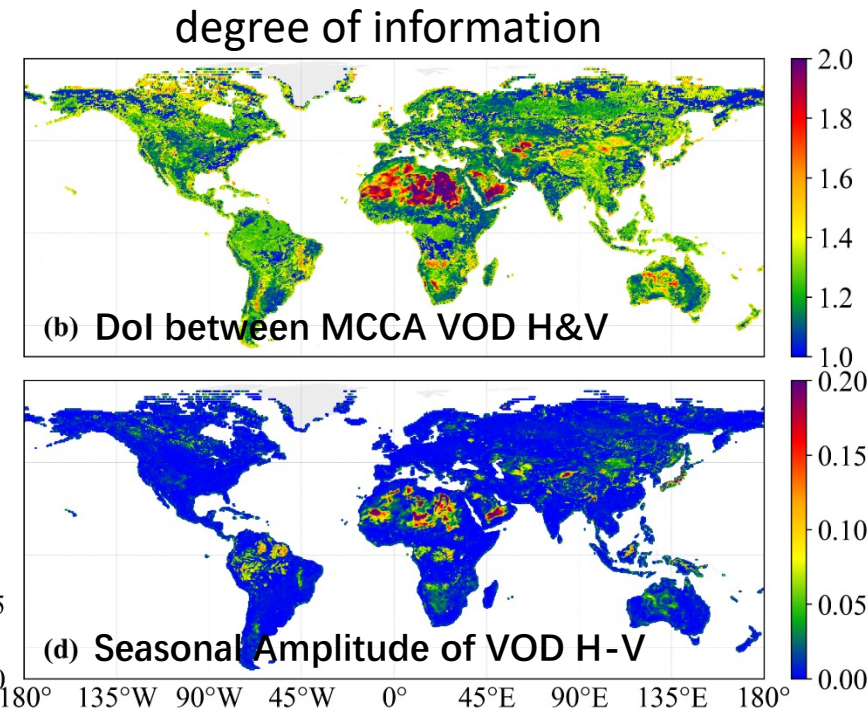
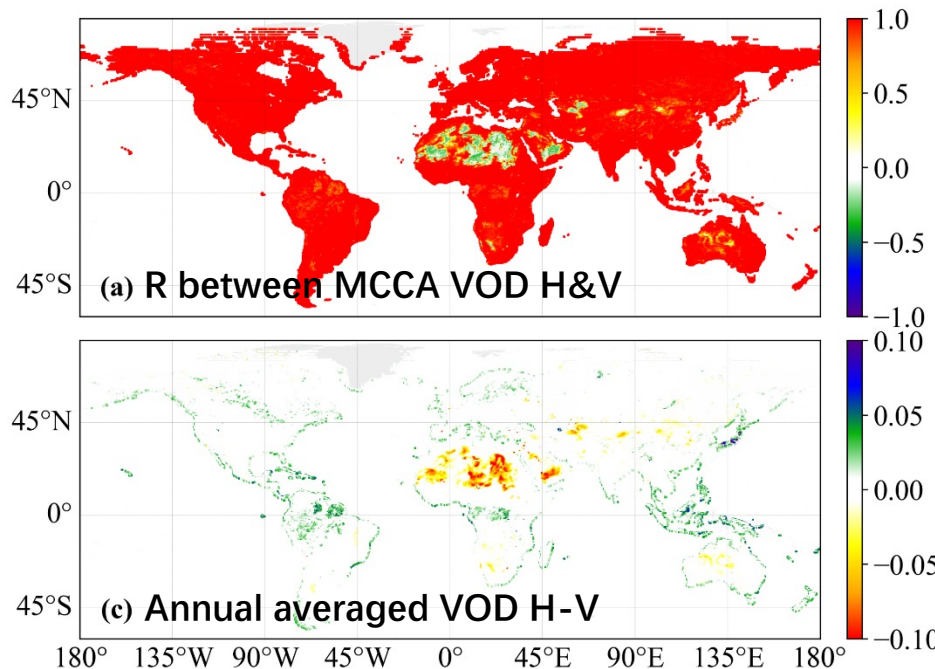
**VOD (V-pol)**

DOI: 10.11888/Terre.tpdc.272088.

## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite

### missions

- Polarized VODs provide more information compared to one VOD.
- Lower V-polarized VOD in densely vegetated area may attribute to the plant canopies with a structure dominated by vertical stalks in forest.
- Higher V-polarized VOD than H-polarized VOD in Sahara needs more studies to explore.





## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

□ A new soil moisture dataset was derived from Chinese FengYun-3 series satellite(NNsm-FY), using Machine learning technology and SMAP L band soil moisture.

• Data:

Data	Source	Time Period
FY-3B MWRI L1 TB	provided by NSMC	2010-2019
SMAP L3 soil moisture	<a href="https://nsidc.org/data/smap">https://nsidc.org/data/smap</a>	2015-2017

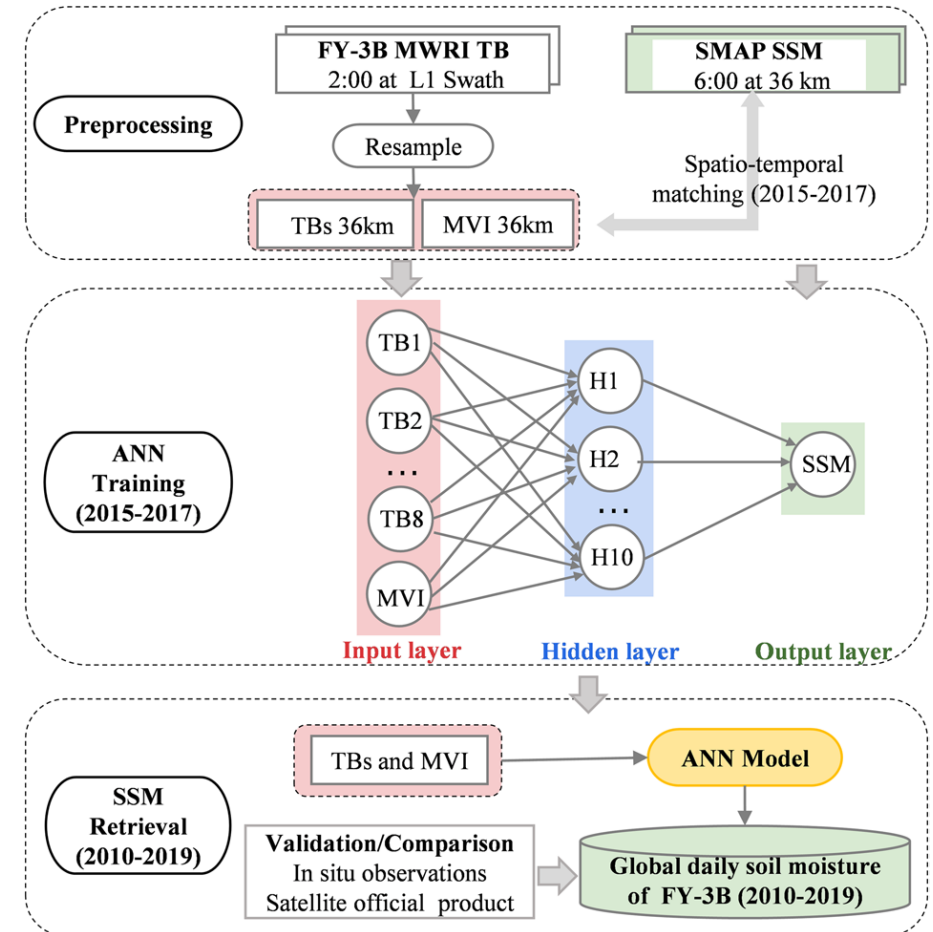
• In situ Soil moisture :

----14 Dense validation networks

(a) 7 USDA watershed networks, (b) 2 Tibetan Plateau networks (c) 2 OZNet networks, (d) the REMEDHUS network, and (e) 2 AMMA networks.

----5 flux datasets(258 sites)

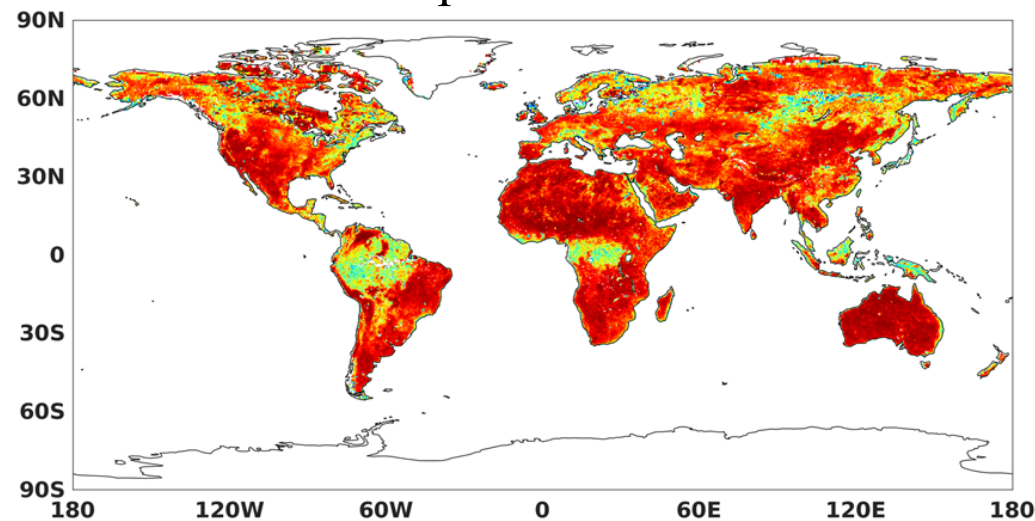
(a) FLUXNET2015, (b) ICOS2020, (c) ICOSETC2022, (d)AmeriFlux Network (e) TERN



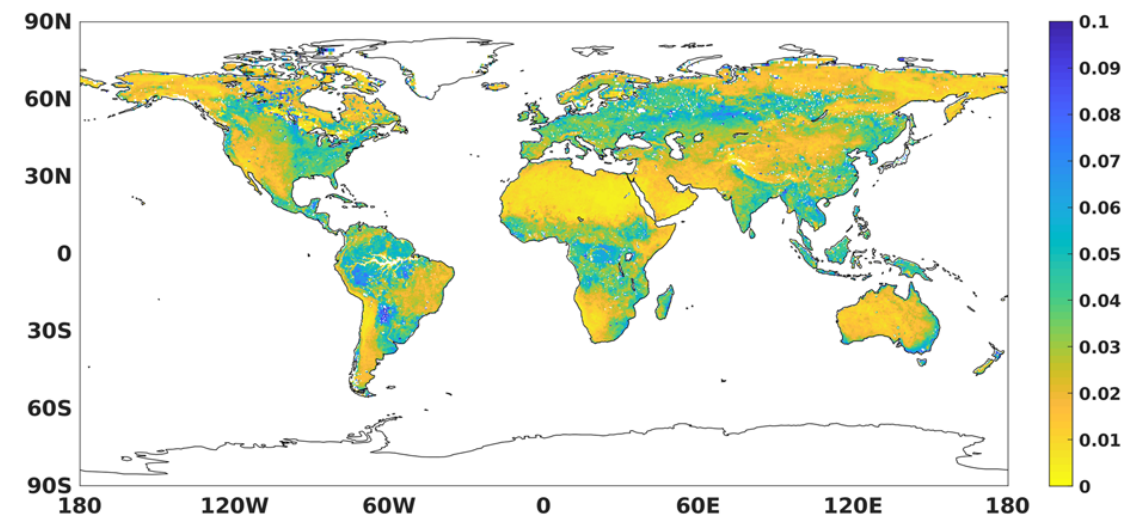
## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

### ☐ Training result (2015-2017)

- high CC (>0.8) with the target SMAPL3sm globally, except for regions of equatorial rainforest and forest at high latitude such as part of Russia.
- Statistically, 60 percent of RMSE over global land are below  $0.03 \text{ m}^3/\text{m}^3$ , and 30 percent of RMSE is between  $0.03 \text{ m}^3/\text{m}^3$  and  $0.05 \text{ m}^3/\text{m}^3$ .



(a) CC



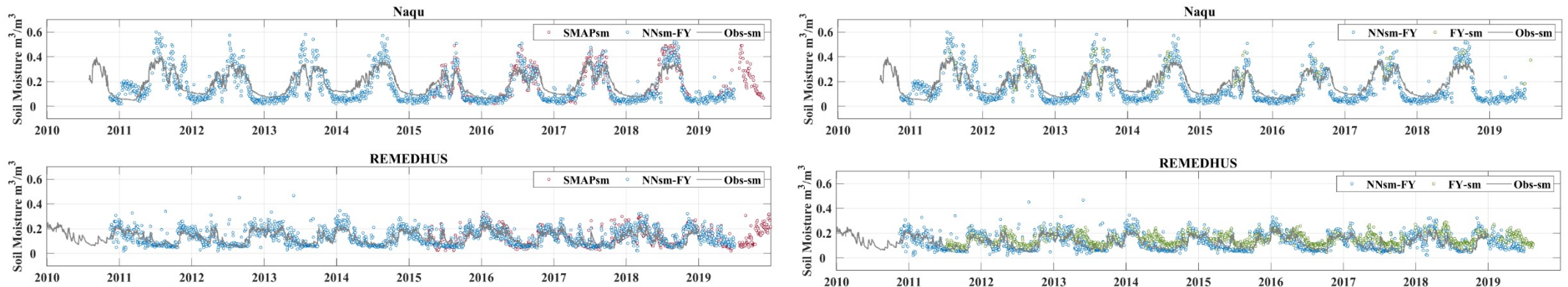
(b) RMSE(m<sup>3</sup>/m<sup>3</sup>)

statistical result of FYNNsm and SMAPL3sm

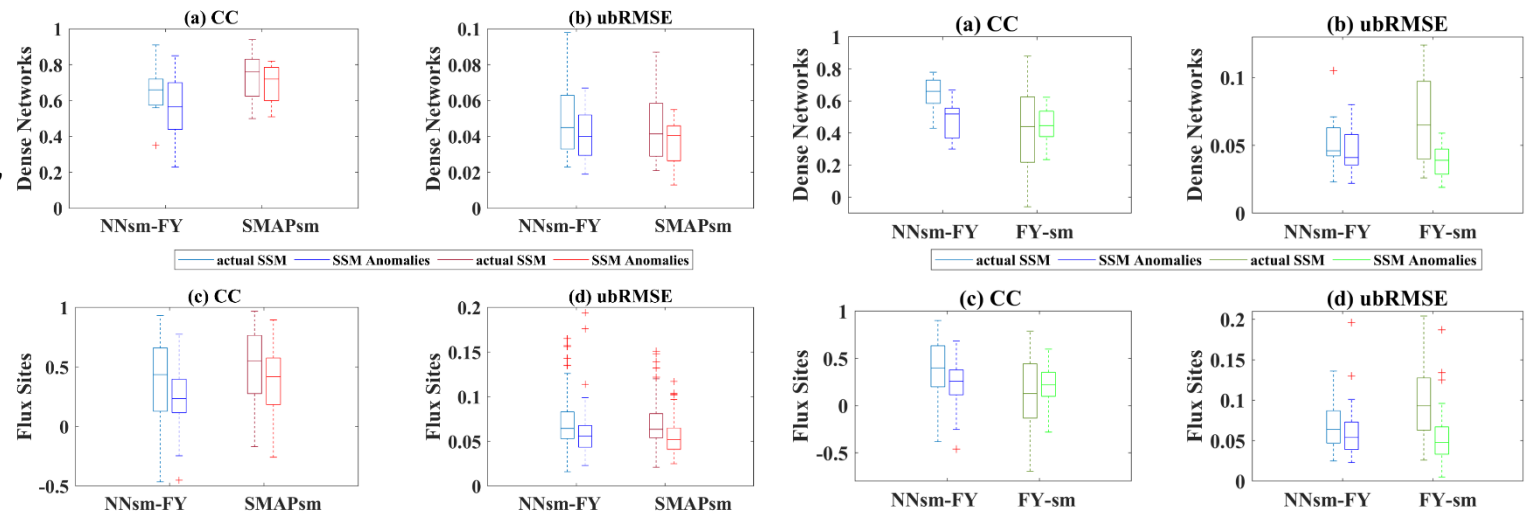
## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

### Validation and Comparison

at dense networks



- NNsm-FY agrees well with SMAPsm and in situ, while FY-sm shows overestimation over REMEDHUS network; At Naqu network, FY-sm has very few retrievals only in Northern summer



- From boxplot both at dense networks and flux sites, NNsm-FY performs poor than SMAP and better than FY-sm

## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

□ A new soil moisture dataset was obtained from the China-France Ocean Satellite (CFOSAT) using an improved change detection algorithm (Ku-band scatterometer)

- Change detection algorithms for vegetation cover

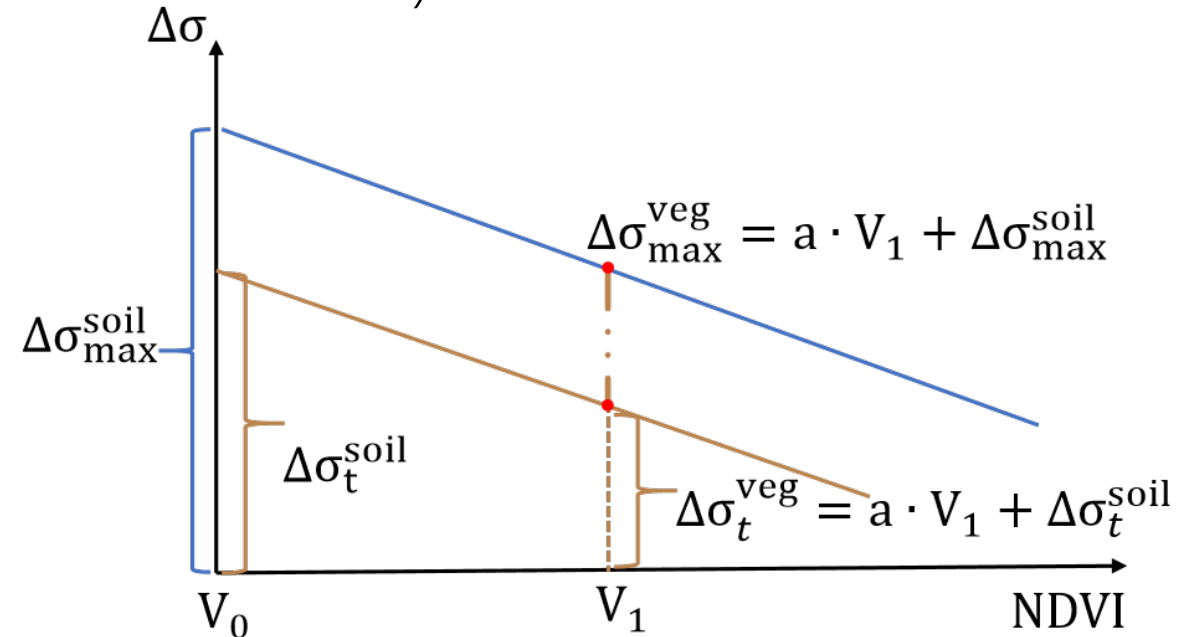
The total backscatter change is expressed as the sum of the change in backscatter under bare soil conditions and the portion of the change in backscatter influenced by vegetation.

$$\Delta\sigma_t^{\text{veg}} = a \cdot V + \Delta\sigma_t^{\text{soil}} = \sigma_t^{\text{veg}} - \sigma_{\text{min}}^{\text{veg}}$$

$$\Delta\sigma_{t,V_1}^{\text{veg,(i,j)}} = a \cdot V_1 + \Delta\sigma_t^{\text{soil}} = \sigma_{t,V_1}^{\text{veg,(i,j)}} - \sigma_{\text{min},V_1}^{\text{veg,(i,j)}}$$

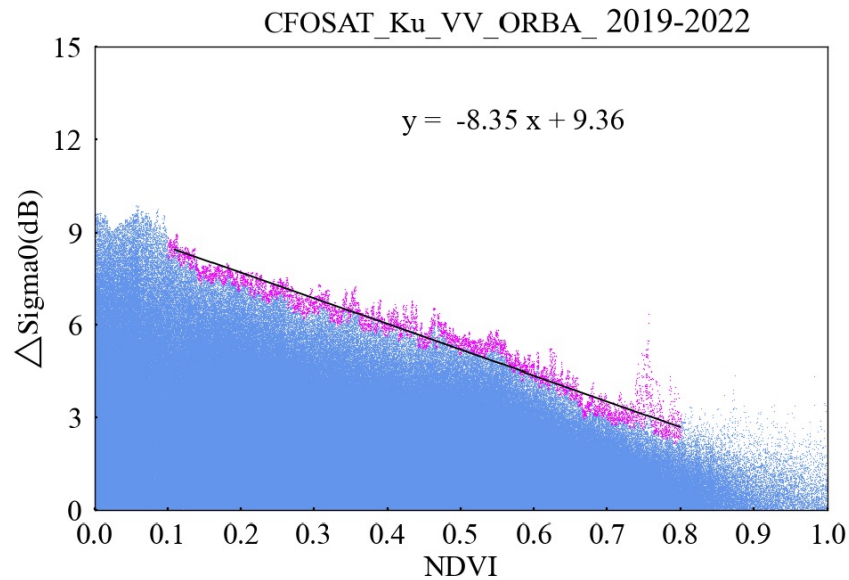
$$\Delta\sigma_{\text{max},V_1}^{\text{veg,(i,j)}} = a \cdot V_1 + \Delta\sigma_{\text{max}}^{\text{soil}} = \sigma_{\text{max},V_1}^{\text{veg,(i,j)}} - \sigma_{\text{min},V_1}^{\text{veg,(i,j)}}$$

$$SM = \exp\left(\frac{\Delta\sigma_{t,V_1}^{\text{veg,(i,j)}} - a \cdot V_1}{\Delta\sigma_{\text{max},V_1}^{\text{veg,(i,j)}} - a \cdot V_1}\right) [\ln(SM_{\text{max}} + k) - \ln(SM_{\text{min}} + k)] + \ln(SM_{\text{min}} + k) - k$$



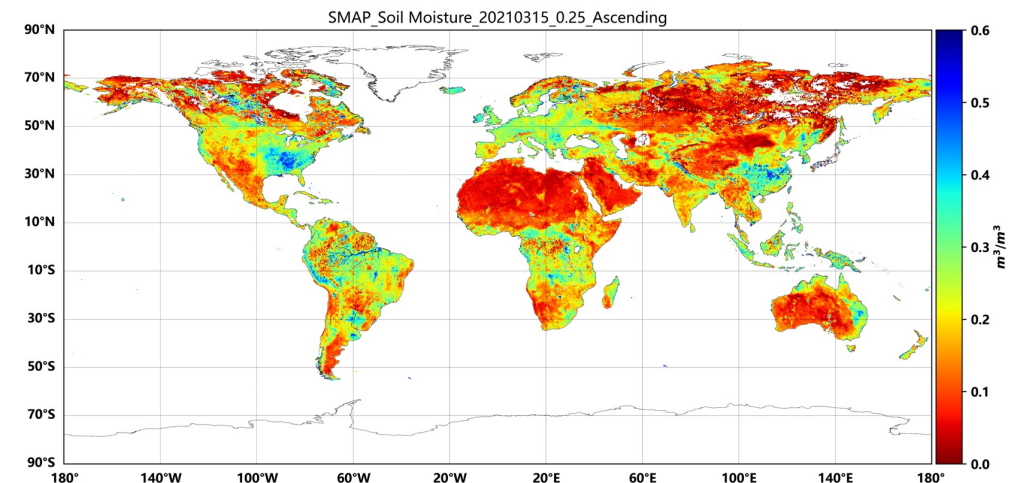
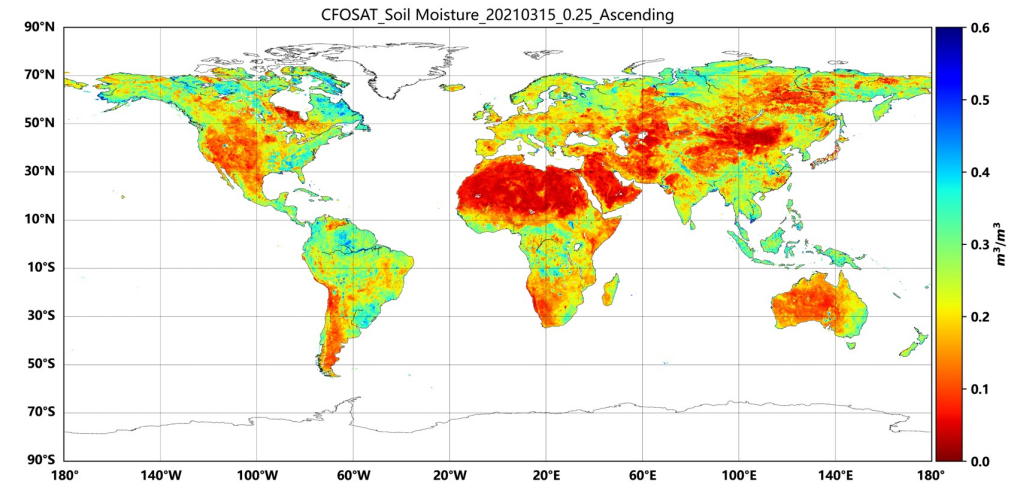
## Task 2: New retrieval algorithm development and long-term data record development and validation for soil moisture based on current and future satellite missions

### CFOSAT Global Soil Moisture Retrieval Results



- Establish a fitting function between the CFOSAT backscatter coefficient and NDVI from 2019 to 2022 to create a change detection algorithm for soil moisture retrieval.

(Duan, Zhao et al. Under review)

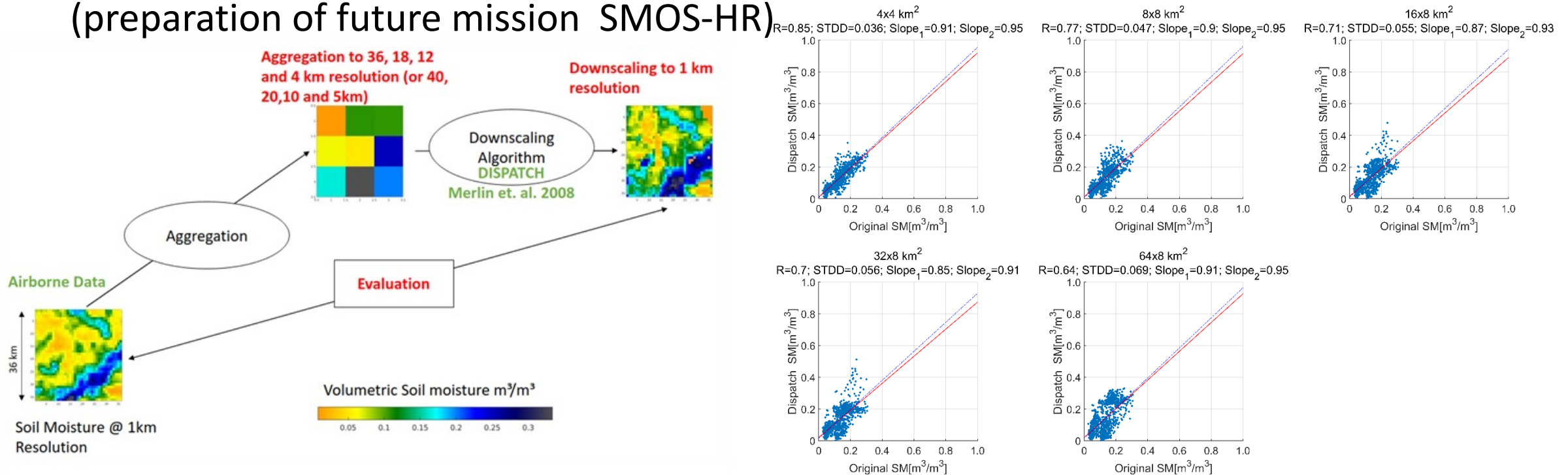


Global Soil Moisture Comparison between CFOSAT and SMAP



## Task 3: Enhancement of the spatial-temporal resolution of remote sensing products by combine use of multi-source satellites

- Using Luan-river Basin airborne data, NAFE' 06, SMAPVEX15, and SMAPVEX16 to evaluate the impact of the initial resolution on the downscaling results (preparation of future mission SMOS-HR)



(Rodriguez-Fernandez, Zhao, Colliander et al. (Preparing)

- Downscaling results in the Luan River Basin
- Better soil moisture estimation can be performed with higher initial resolution (the higher correlation, and the lower STDD)

## Task 3: Enhancement of the spatial-temporal resolution of remote sensing products by combine use of multi-source satellites

- Multi-scale evaluation of different soil moisture data sets with respect to *in situ* measurements
  - Interpolated products (SMAP 9km) give the same results as the original SMAP 36km.
  - Downscaled SMAP+S1 gives less good results. When aggregated to 25 km the performances increase significantly

Products	$R$	$R^a$	Bias	SDD
Sentinel-only high-resolution data				
$S^2MP_{S1S2}$	0.59	0.36	-0.06	0.05
$S^2MP_{S1S3}$	0.56	0.37	-0.06	0.06
CoperSSM	0.53	0.18	0.04	0.08
Merged high-resolution data				
CoperSWI	0.74	0.46	0.05	0.05
SMAPS1	0.64	0.35	-0.03	0.06
Coarse-resolution data				
SMAPL3	0.76	0.58	-0.04	0.05
SMAPL3E	0.77	0.59	-0.04	0.05
SMOSL3	0.67	0.47	-0.03	0.07
SMOSNRT	0.68	0.46	-0.03	0.05
CCISM	0.71	0.50	0.03	0.05
High-resolution data aggregated to coarse resolution				
$S^2MP^*_{S1S2}$	0.58	0.38	-0.06	0.06
$S^2MP^*_{S1S3}$	0.56	0.38	-0.05	0.06
CoperSSM*	0.53	0.20	0.05	0.07
CoperSWI*	0.73	0.47	0.05	0.05
SMAPS1*	0.79	0.44	-0.02	0.04

(Madelon, Rodriguez-Fernandez et al. 2022, HESS)

## Task 3: Enhancement of the spatial-temporal resolution of remote sensing products by combine use of multi-source satellites

Comprehensive analyses of alternative downscaling soil moisture products to give clear guidance on the performance differences between current downscaling techniques

### Downscaling factors

Downscaling factors	STR	NSDSI-1/2/3	ATI	DTA	SEE	TVDI	VTCI
Full name	shortwave infrared transformed reflectance	normalized shortwave-infrared (SWIR) difference bare soil moisture indices	Apparent thermal inertia	Diurnal temperature amplitude	soil evaporative efficiency	Temperature and Vegetation Dryness Index	vegetation temperature condition index
Why it can be used as a proxy for soil moisture	water absorption difference between shortwave-infrared bands, greater amounts of water in the soil result in a more significant difference in soil reflectance		Variations in surface thermal inertia—the resistance to temperature variations—can be indicative for variations in soil moisture		LST-VI triangular feature space		
References	Babaeian et al., 2018, RSE	Yue et al., 2019, ISPRS	Van doninck et al. 2011, IJAEOG	Fang et al., 2022, Vadose Zone Journal	Merlin et al., 2012, TGRS	Tagesson et al., 2018, RSE	Peng et al., 2016, TGRS

### Downscaling methods

- ✓ Daily model

$$SM_{HR} = SM_{LR} + \frac{SM_{LR}}{factor_{LR}} * (factor_{HR} - factor_{LR})$$

Molero et al., 2016, RSE
- ✓ Yearly model

$$SM_{HR} = SM_{LR} + \frac{1}{N} \sum_{i=1}^N \frac{SM_{LR,i}}{factor_{LR,i}} * (factor_{HR} - factor_{LR})$$

Merlin et al., 2013, RSE
- ✓ Linear Regression model

$$SM_{HR} = SM_{LR} + \left( \frac{\partial SM}{\partial factor} \right)_{LR} * (factor_{HR} - factor_{LR})$$

Das et al., 2011, TGRS
- ✓ Change detection algorithm

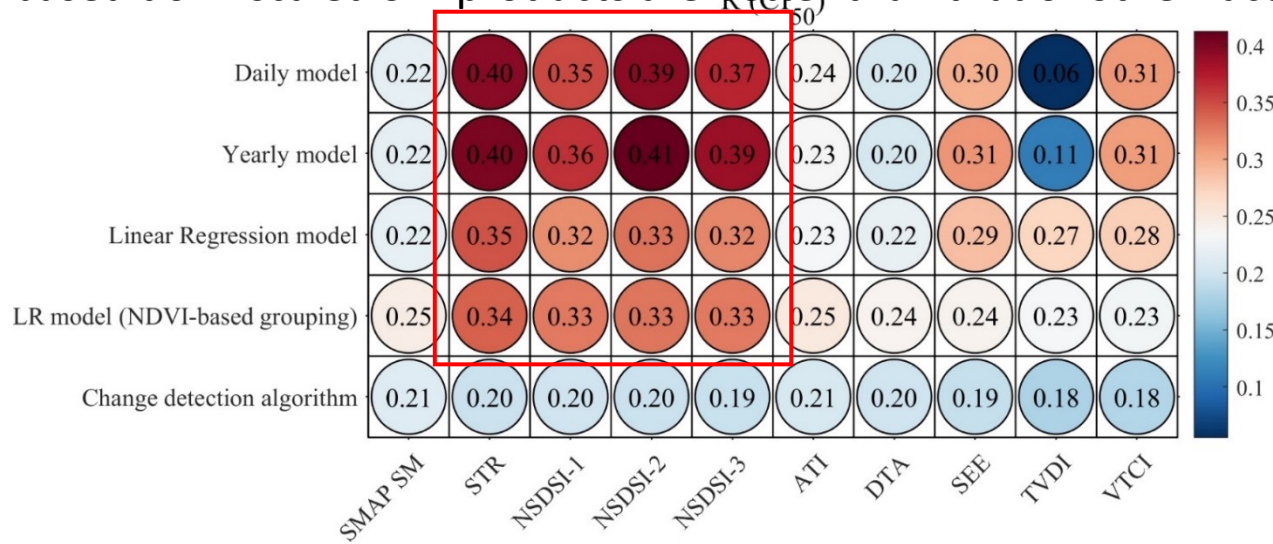
$$SM_{HR,t} = SM_{LR,t-t_R} + \left( \frac{\partial SM}{\partial factor} \right)_{LR} * (factor_{HR} - factor_{HR,t-t_R})$$

Piles et al., 2009, TGRS

## Task 3: Enhancement of the spatial-temporal resolution of remote sensing products by combine use of multi-source satellites

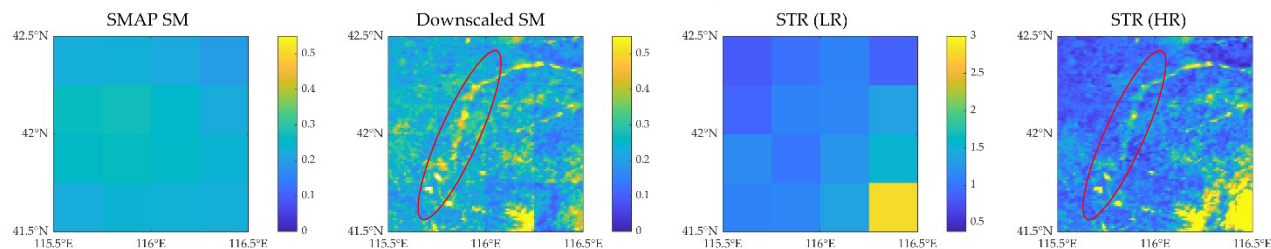
### Downscaling results in the Luan River Basin

- The spatio-temporal downscaled R values of reflectance-based downscaled SM products are better than that of other factors

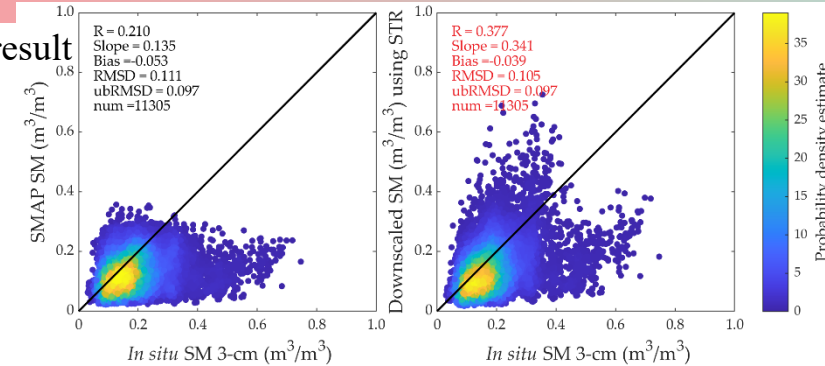


### SM spatial maps can clearly reveal water bodies

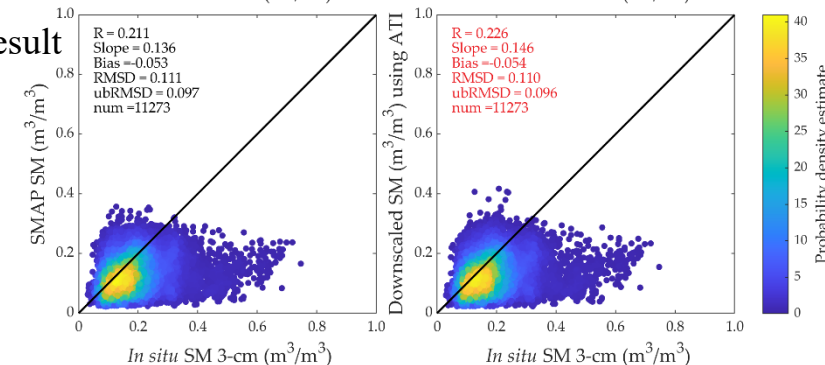
SMN-SDR 2019167



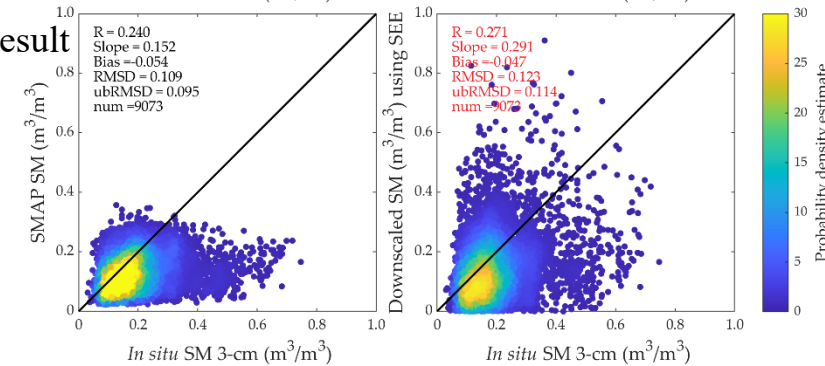
### STR-based result



### ATI-based result



### SEE-based result



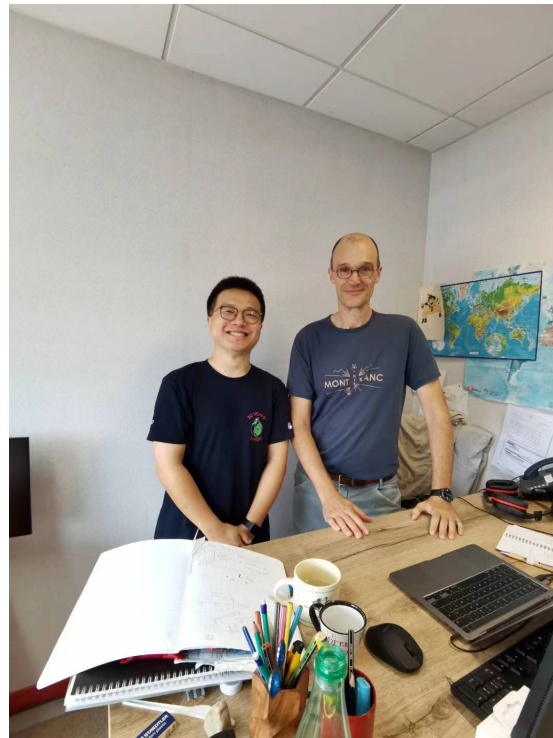
Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert “ftp”

ESA /Copernicus Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. ESA SMOS SCLF1C (ftp)	137,224	1.		1. FY-3 B,C,D	835
1. ESA SMOS AUX_ECMWF (ftp)	137,249	2.		2.CFOSAT	8915
2. CATDS SMOS L3TB (ftp)	8582	3.		1.	
2. CATDS SMOS AUX (ftp)	729	4.		2.	
5.		5.		3.	
6.		6.		6.	
Total:		Total:		Total:	
Issues:		Issues:		Issues:	

Name	Institution	Poster title	Contribution including period of research
Panpan Yao	AIRCAS	A global daily soil moisture dataset derived from Chinese FengYun-3 MWRI	A new soil moisture dataset was derived from Chinese FengYun-3 series satellite(NNsm-FY), using Machine learning technology and SMAP L band soil moisture.
Jiaqi Zhang	AIRCAS	Characterizing the Channel Dependence of Vegetation Effects on Microwave Emissions from Soils	Investigating the channel dependence of vegetation effects on microwave emissions from soils using a higher-order vegetation radiative transfer model.
Xiaowen Gao	AIRCAS	Snow density retrieval in Quebec using space-borne SMOS observations	This research established a method to retrieve snow density below vegetation canopy using L-band SMOS observations and achieved a bias of 9.4 kg/m <sup>3</sup> and an RMSE of 83 kg/m <sup>3</sup> at 43 stations located in Quebec, Canada.

## Academic exchanges

- Chinese PhD student Zheng Jingyao visited CESBIO SMOS team for one year (2022.9-2023.9)



- Collaboration on two articles



Soil moisture downscaling using multiple modes of the DISPATCH algorithm in a semi-humid/humid region

Jingyao Zheng<sup>a</sup>, Haishen Lü<sup>a,\*</sup>, Wenhui Gao<sup>b</sup>, Tianjie Zhao<sup>c</sup>, Chaojie Yang<sup>d</sup>, Nemesio Rodriguez-Fernandez<sup>d</sup>, Jiancheng Shi<sup>e</sup>, Yonghua Zhu<sup>f</sup>, Jianping Shi<sup>g</sup>, Chuen Siang Kang<sup>g</sup>, Xiaoyi Wang<sup>h</sup>, **Zheng, Zhao, Rodriguez-Fernandez, Merlin et al. JAG, 2021**

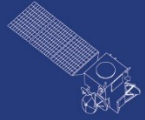
Manuscript

[Click here to access/download;Manuscript;Manuscript\\_WDL-SM-FT-Val\\_RSE2023.docx](#)

[Click here to view linked References](#)

1 Use of a new Tibetan Plateau network for permafrost to  
2 characterize satellite-based products errors: an application to soil  
3 moisture and freeze/thaw

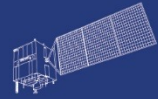
4 Jingyao Zheng<sup>a,b</sup>, Tianjie Zhao<sup>b\*</sup>, Haishen Lü<sup>a</sup>, Defu Zou<sup>c</sup>, Nemesio Rodriguez-  
5 Fernandez<sup>d</sup>, Arnaud Mialon<sup>d</sup>, Philippe Richaume<sup>d</sup>, Jianshe Xiao<sup>e</sup>, Jun Ma<sup>f</sup>, Lei Fan<sup>g</sup>,  
6 Peilin Song<sup>h</sup>, Yonghua Zhu<sup>a</sup>, Rui Li<sup>b</sup>, Panpan Yao<sup>b</sup>, Qingqing Yang<sup>d</sup>, Shaojie Du<sup>i</sup>, Zhen  
7 Wang<sup>b</sup>, Zhiqing Peng<sup>b</sup>, Yuyang Xiong<sup>g</sup>, Lanpin Xing<sup>g</sup>, Lin Zhao<sup>h</sup>, John Kerr<sup>d</sup>, and  
8 Jiancheng Shi<sup>m</sup> **Zheng, Zhao, Rodriguez-Fernandez, Kerr et al. RSE, under Revision**



HY



HJ-1AB



CBERS



Gaofen



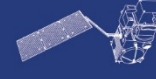
Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



Sentinel-5p



Aeolus

Thanks for your attention!

谢谢!