Remote Sensing of Surface Soil Moisture from FengYun MicroWave Radiation Imager (MWRI) Data Using a Machine Learning Technique

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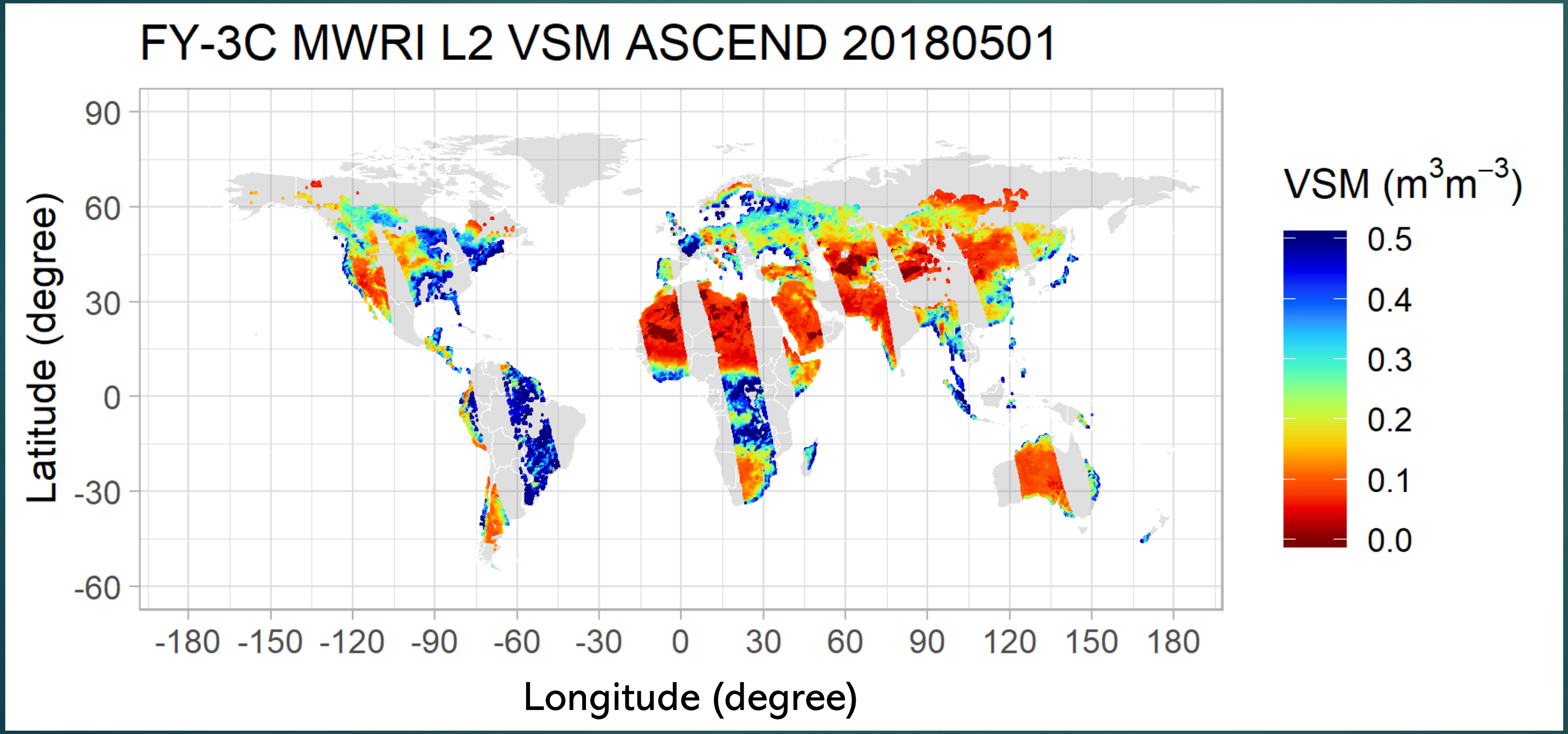
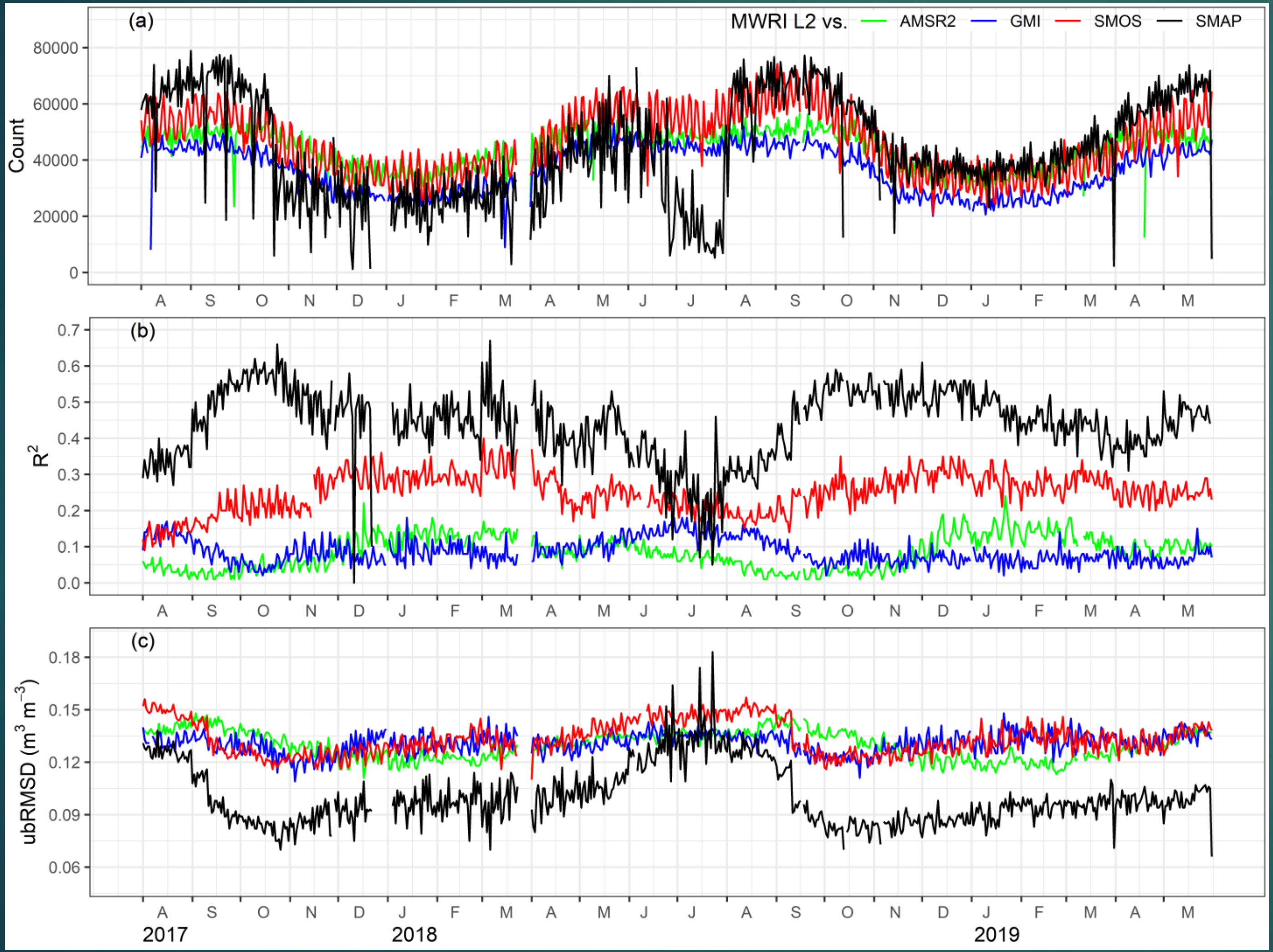
Situation of Study

- Soil moisture can be retrieved from microwave imager over most of land conditions. However, the algorithm performances over Tibetan Plateau and northwestern China vary greatly from one to another due to frozen soils and surface volumetric scattering.



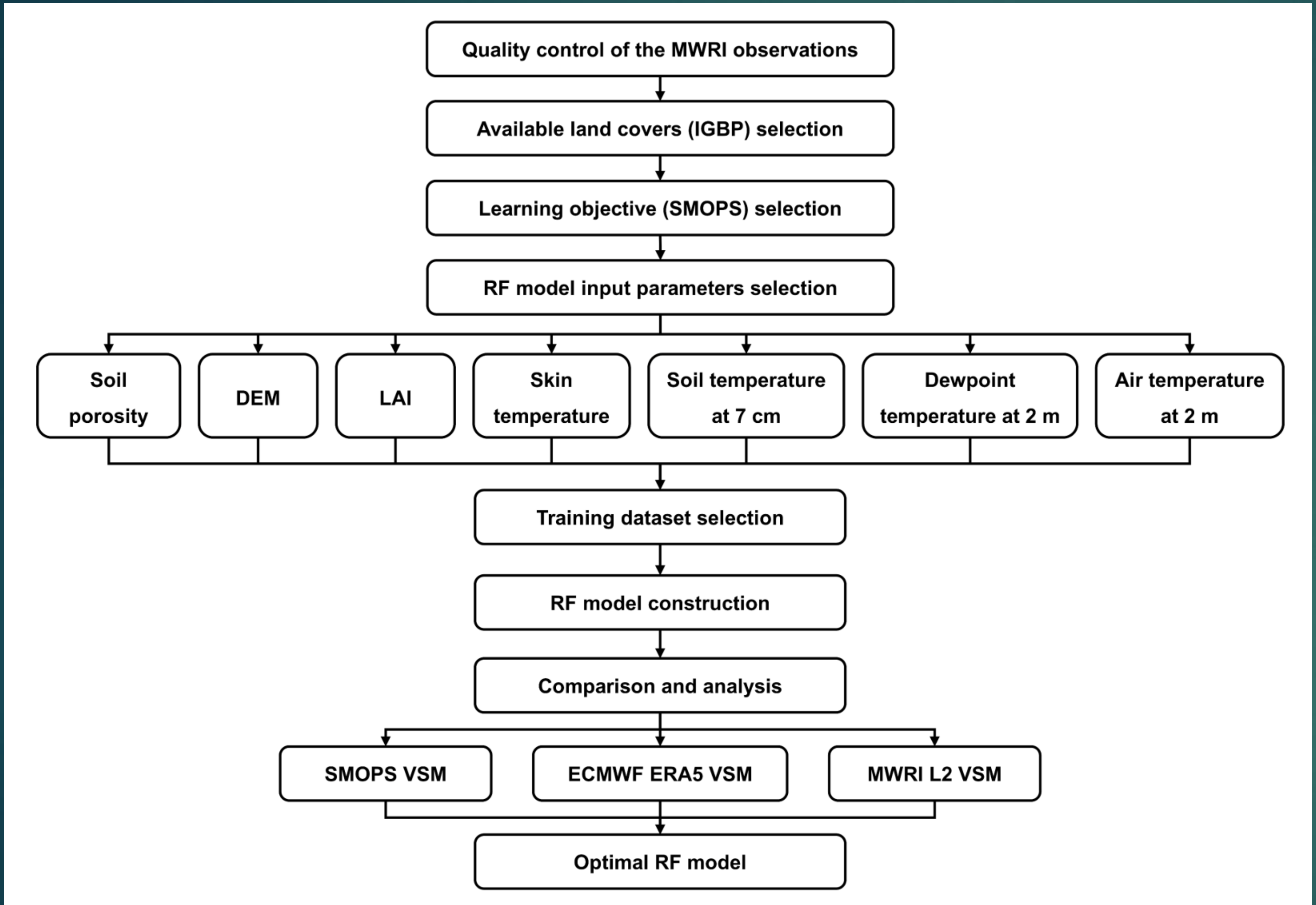
MWRI L2:
operational VSM products from National Satellite Meteorological Center (NSMC) of China Meteorological Administration (CMA)

Performance of the MWRI L2 VSM products



	R^2	ubRMSD (m^3 m^{-3})
MWRI L2 vs. AMSR2	0.09	0.13
MWRI L2 vs. GMI	0.09	0.13
MWRI L2 vs. SMOS	0.25	0.13
MWRI L2 vs. SMAP	0.44	0.10

Random forest training model experiments



Flowchart for the optimal random forest (RF) model decision

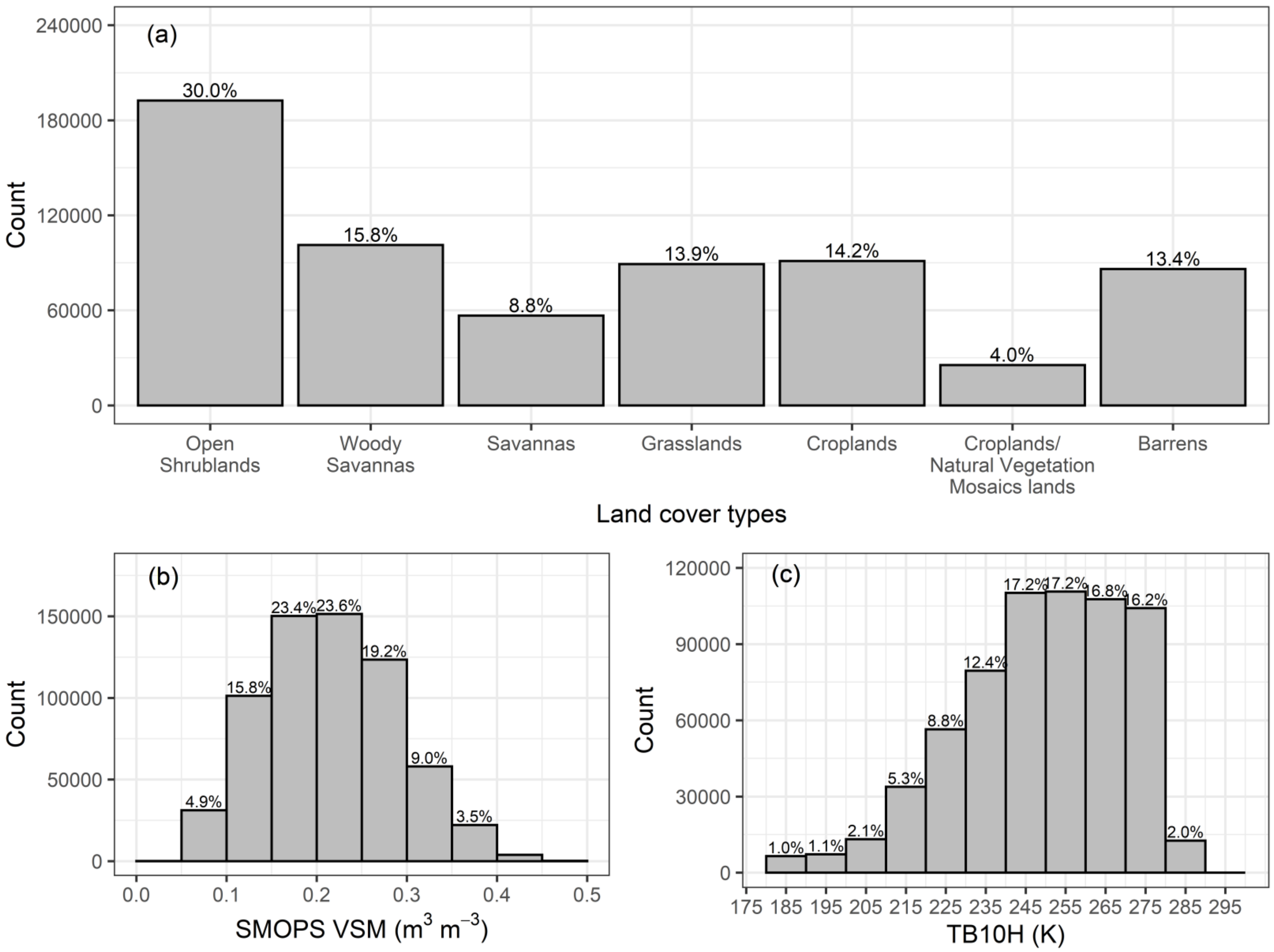
Random forest training models

- Four RF models are trained, using the same training dataset and the same number of decision trees (480) but various model inputs. EXP1 is a dependent experiment containing all available 22 parameters: 17 independent parameters from MWRI (multifrequency TBs, PRs, and DEM) and the statistical soil porosity map, and 5 dependent parameters from ECMWF ERA5 reanalysis (low vegetation LAI, dewpoint temperature and air temperature at a height of 2 m, skin temperature, and soil temperature for the top 7 cm).
- EXP3 are also dependent, while EXP2 and EXP4 are independent.

	EXP1	EXP2	EXP3	EXP4
DEM	√	√	√	√
Porosity	√	√	√	√
Tsoil	√		√	
Tskin	√			
Tdew	√			
Tair	√			
TB10H	√	√	√	√
TB10V	√	√	√	√
LAI	√		√	
PR10	√	√	√	√
TB18H	√	√	√	√
TB89V	√	√	√	√
TB89H	√	√	√	√
TB36H	√	√	√	√
TB23H	√	√	√	√
PR23	√	√	√	√
PR18	√	√	√	√
TB36V	√	√	√	√
PR36	√	√		
TB18V	√	√	√	√
TB23V	√	√	√	√
PR89	√	√		

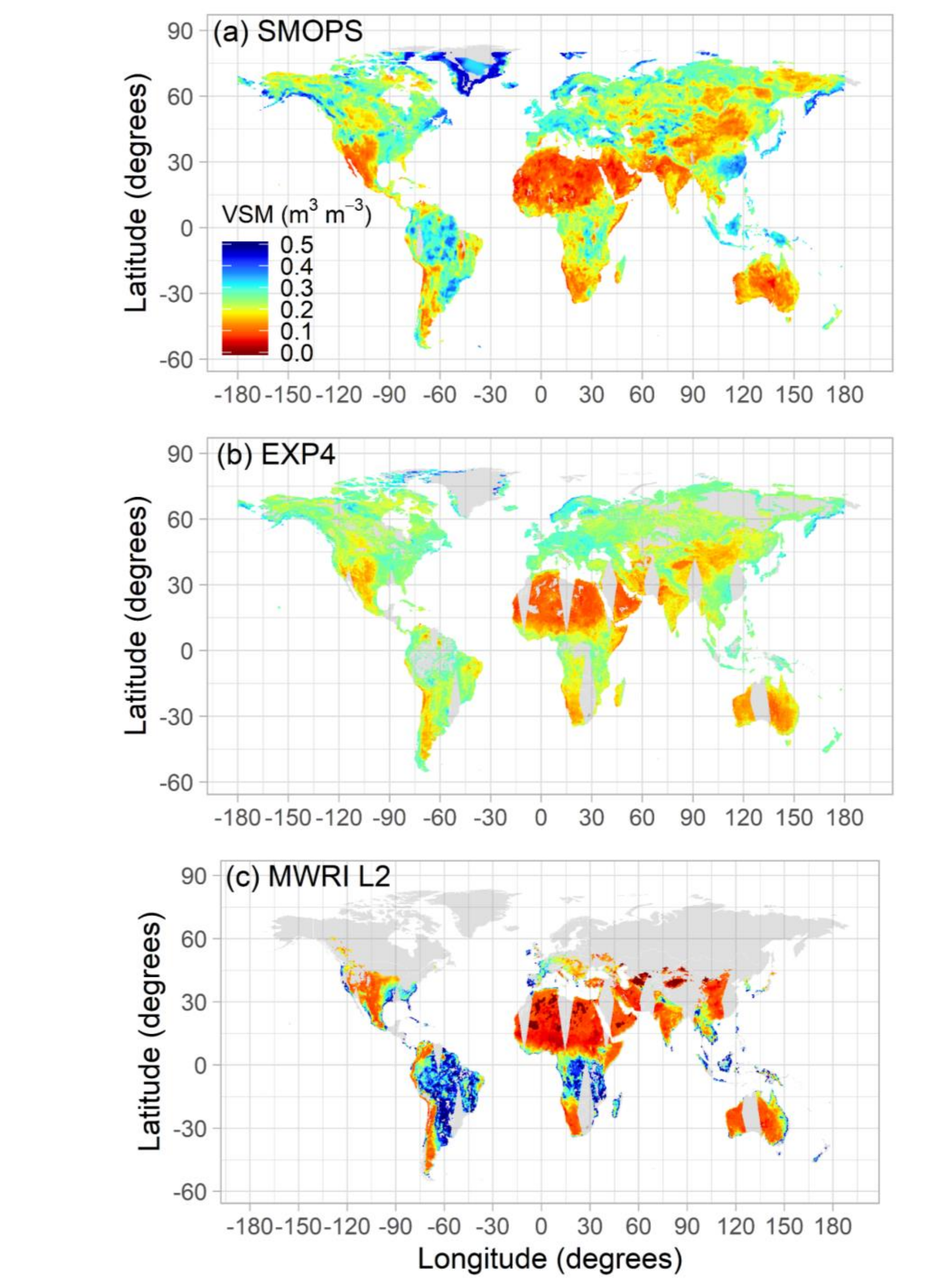
Random forest training dataset

▶The training dataset used in this work is simply selected from **four random days to represent the four seasons in a year, but it includes the variations** in global soil texture and land cover using **a high-density spatial sampling (0.25 degree).**



Soil moisture retrieval (1)

- Surface volumetric soil moisture (VSM) distributions from (a) SMOPS products, (b) EXP4 VSM estimates and (c) MWRI L2 VSM products on 15 March 2018.
- Soil Moisture Operational Products System (SMOPS) products disseminated from NOAA , which are our learning objectives.

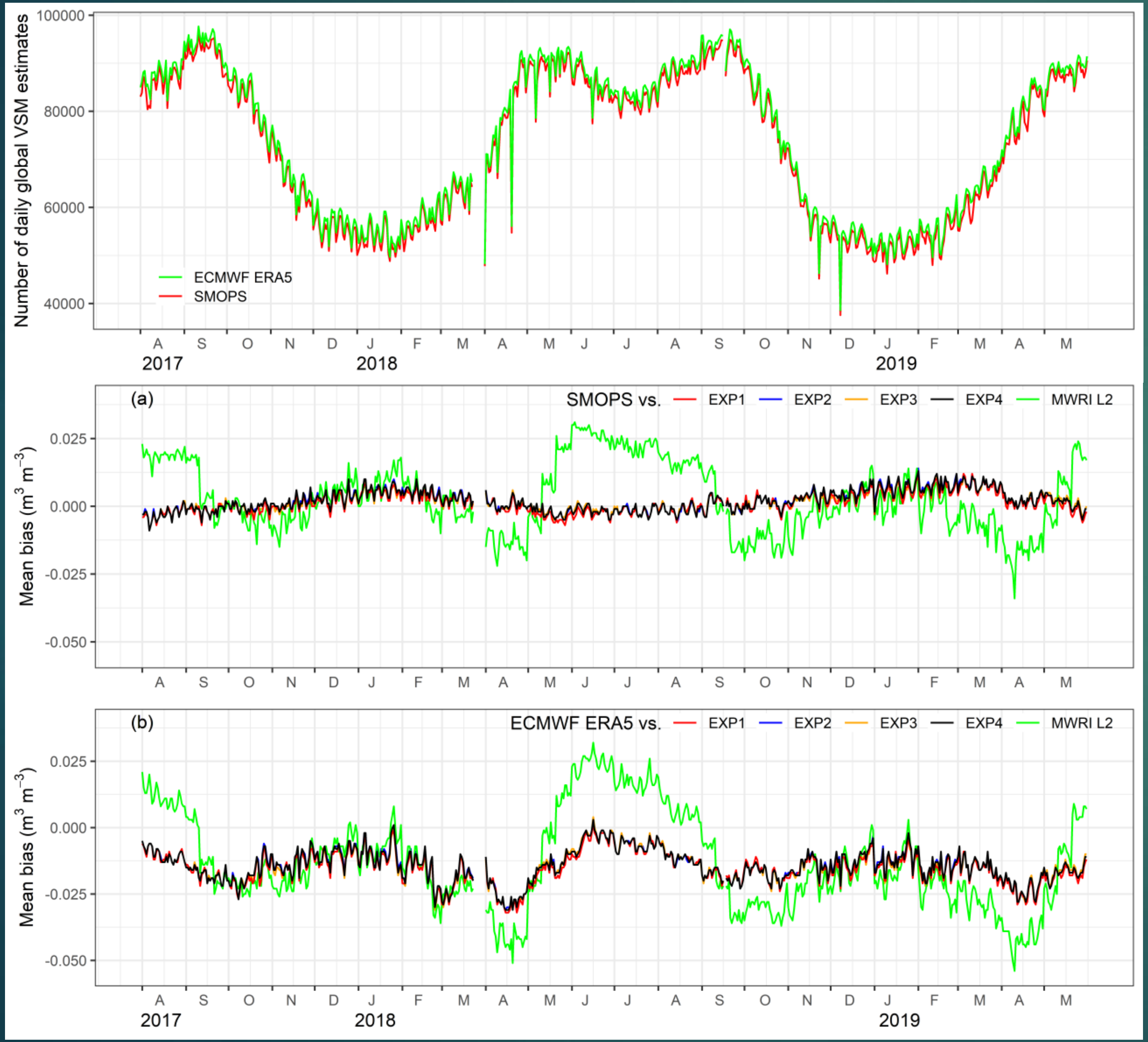


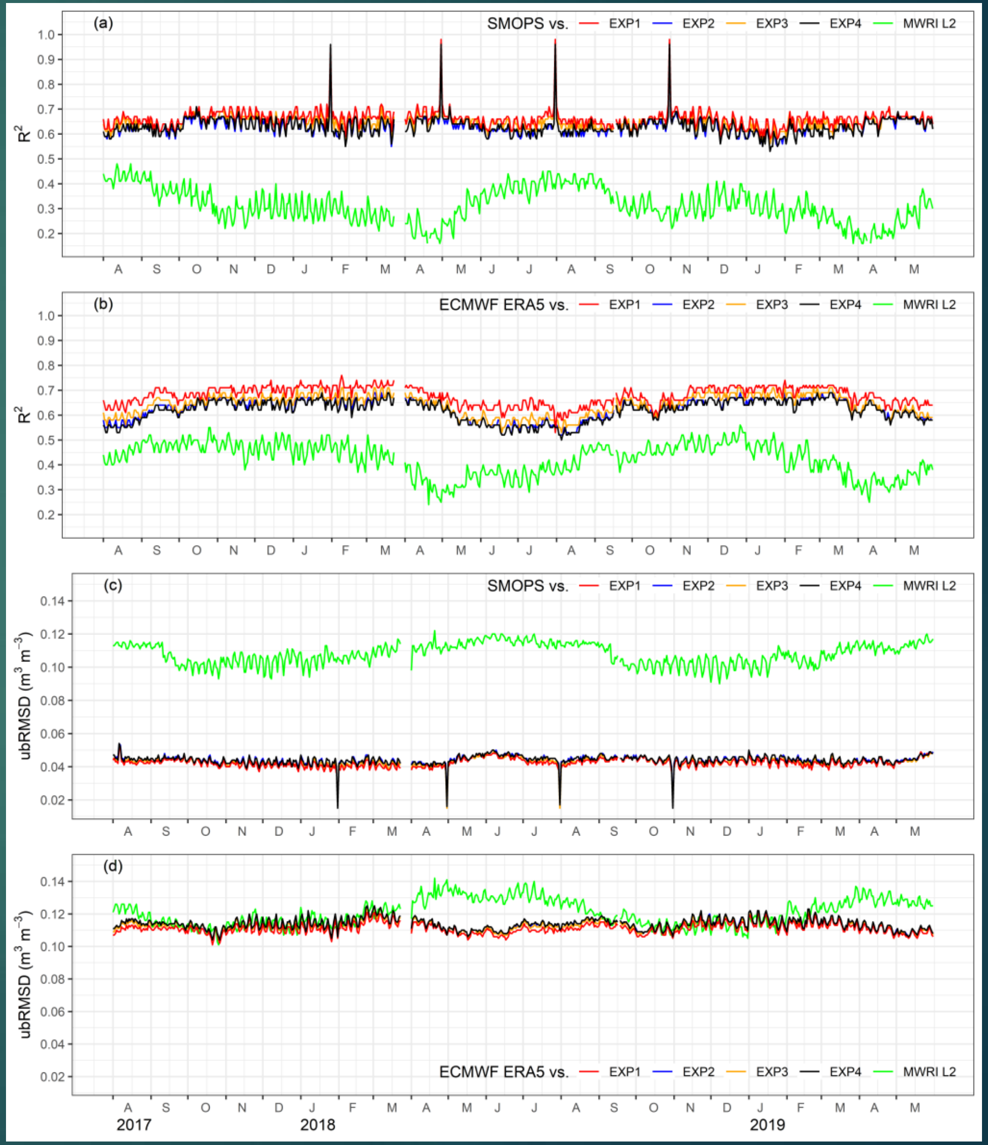
NOAA

This study

CMA

Soil moisture retrieval (2)



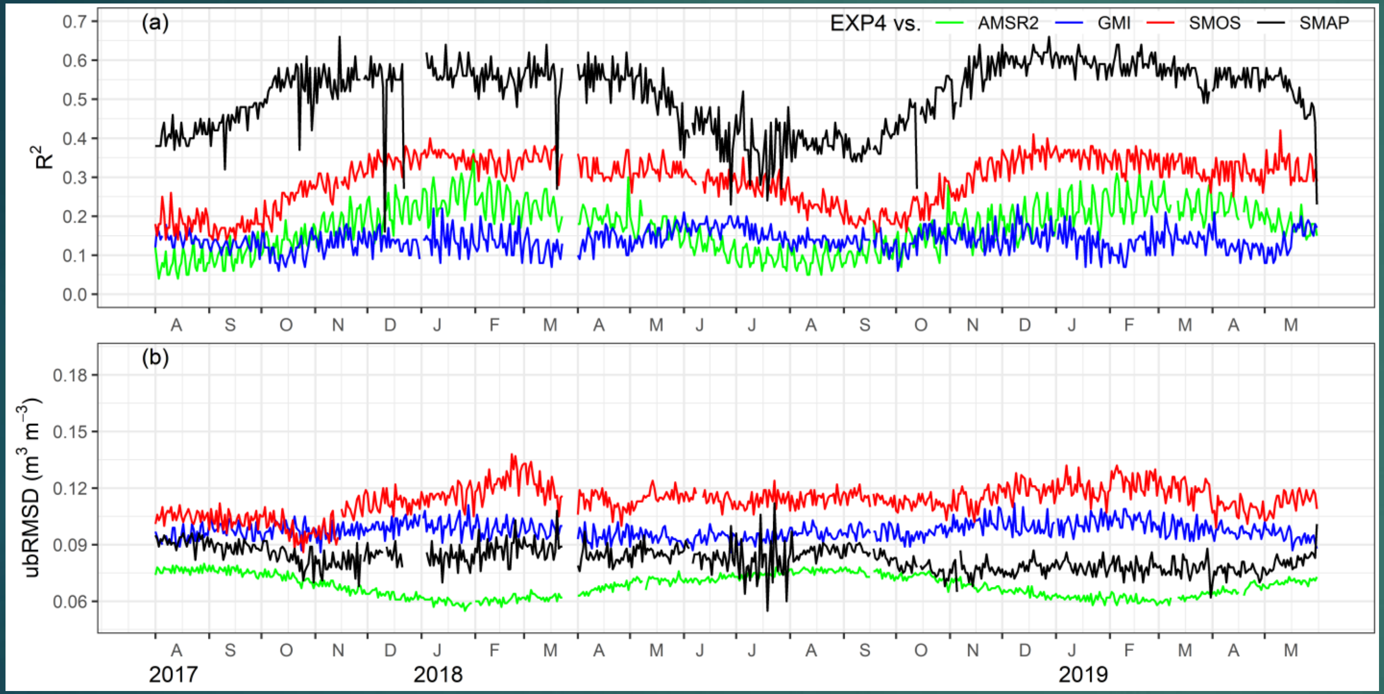


Soil moisture retrieval (3)

IGBP types	N	R^2 between SMOPS and					Bias ($m^3\ m^{-3}$) between SMOPS and					ubRMSD ($m^3\ m^{-3}$) between SMOPS and				
		EXP1	EXP2	EXP3	EXP4	L2	EXP1	EXP2	EXP3	EXP4	L2	EXP1	EXP2	EXP3	EXP4	L2
All	72645	0.66	0.63	0.65	**0.63**	**0.31**	0.0013	0.0021	0.0015	0.0020	0.0032	0.0423	0.0442	0.0429	**0.0440**	**0.1079**
IGBP 7	14849	0.57	0.53	0.55	0.53	0.26	0.0008	0.0019	0.0014	0.0018	-0.0250	0.0386	0.0403	0.0392	0.0402	0.0801
IGBP 8	10876	0.51	0.45	0.48	0.46	0.10	0.0012	0.0033	0.0019	0.0030	0.0521	0.0478	0.0505	0.0490	**0.0501**	**0.1283**
IGBP 9	9689	0.53	0.46	0.50	0.47	0.21	0.0014	0.0017	0.0014	0.0016	0.0410	0.0452	0.0480	0.0465	0.0477	0.1173
IGBP 10	10616	0.58	0.56	0.57	0.56	0.26	0.0030	0.0025	0.0027	0.0023	-0.0125	0.0425	0.0437	0.0430	0.0435	0.1013
IGBP 12	10425	0.49	0.46	0.49	0.46	0.09	0.0042	0.0047	0.0046	0.0046	0.0139	0.0465	0.0478	0.0466	0.0476	0.1155
IGBP 14	2776	0.43	0.39	0.42	0.39	0.07	-0.0085	-0.0086	-0.0070	-0.0084	0.0478	0.0456	0.0472	0.0461	0.0469	0.1240
IGBP 16	12406	0.48	0.42	0.48	0.42	0.10	0.0025	0.0036	0.0021	0.0035	-0.0419	0.0305	0.0326	0.0306	**0.0326**	**0.0472**

Comparisons of volumetric soil moisture (VSM) between MWRI estimates (from EXP1, EXP2, EXP3, EXP4, and L2) and SMOPS products at a depth of 5 cm from 1 August 2017 to 31 May 2019. IGBP numbers 7, 8, 9, 10, 12, 14 and 16 are related with open shrublands, woody savannas, savannas, grasslands, croplands, croplands/natural vegetation mosaic lands and barrens, respectively.

Performance of our EXP4 VSM estimates (1)



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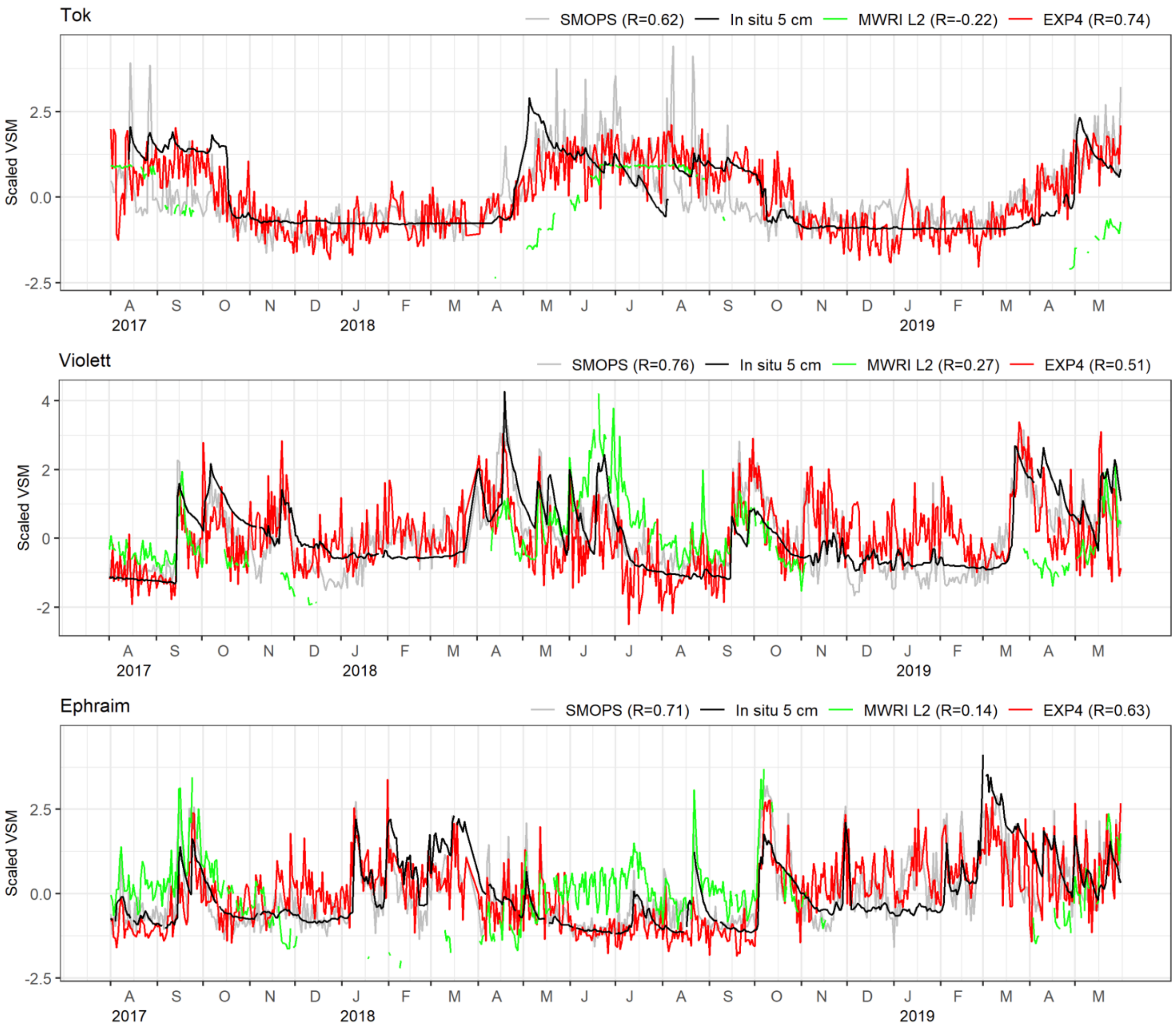
	R^2	ubRMSD ($m^3\ m^{-3}$)
EXP4 vs. AMSR2	0.17	0.07
EXP4 vs. GMI	0.14	0.10
EXP4 vs. SMOS	0.29	0.11
EXP4 vs. SMAP	0.51	0.08

Performance of our EXP4 VSM estimates (2)

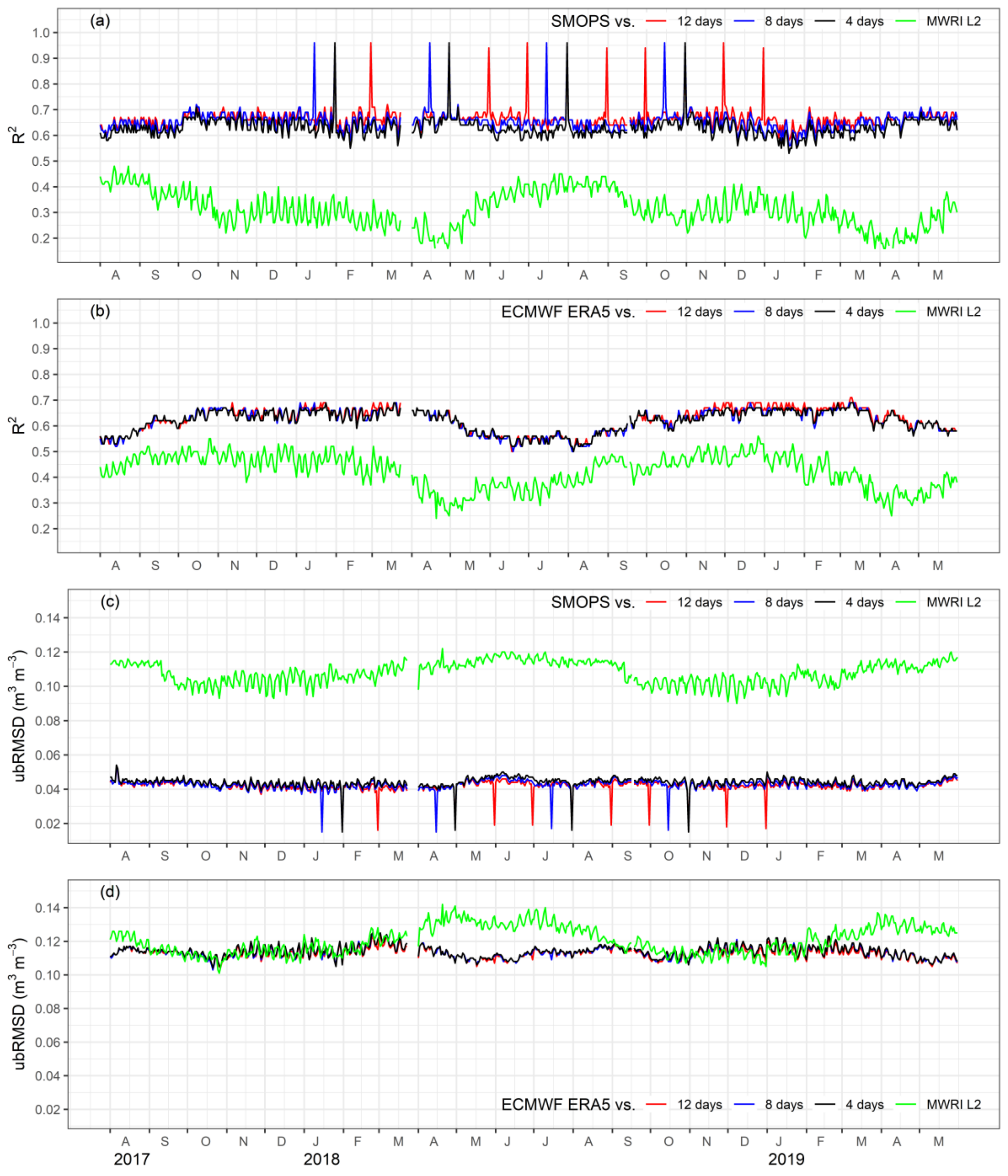
SCAN Stations	Scaled SMOPS vs. in-situ			Scaled EXP4 vs. in-situ			Scaled MWRI L2 vs. in-situ		
	N	R	ubRMSD ($m^3\ m^{-3}$)	N	R	ubRMSD ($m^3\ m^{-3}$)	N	R	ubRMSD ($m^3\ m^{-3}$)
Tok	637	0.62	0.870	637	**0.74**	**0.712**	163	-0.22	1.690
Ku-Nesa	618	0.46	1.051	618	0.36	1.132	190	-0.19	1.459
Conrad Ag Rc	642	0.69	0.790	642	0.43	1.064	362	**0.48**	**1.072**
Fort Assiniboine	653	0.48	1.020	653	0.53	0.964	346	-0.18	1.587
Moccasin	635	0.57	0.929	635	0.47	1.030	355	0.42	1.150
Violett	654	0.76	0.699	654	0.51	0.994	345	0.27	1.301
Sheldo	648	0.53	0.963	648	0.38	1.110	363	0.20	1.207
Chicken	621	0.58	0.906	621	0.53	0.966	-	-	-
Enterprise	630	0.53	0.973	630	0.45	1.049	455	0.06	1.341
Ephraim	642	0.71	0.762	642	0.63	0.862	361	0.14	1.227
Grouse	655	**0.77**	**0.685**	655	0.59	0.910	4	0.47	1.287
Park	653	0.70	0.770	653	0.55	0.945	212	-0.19	1.546



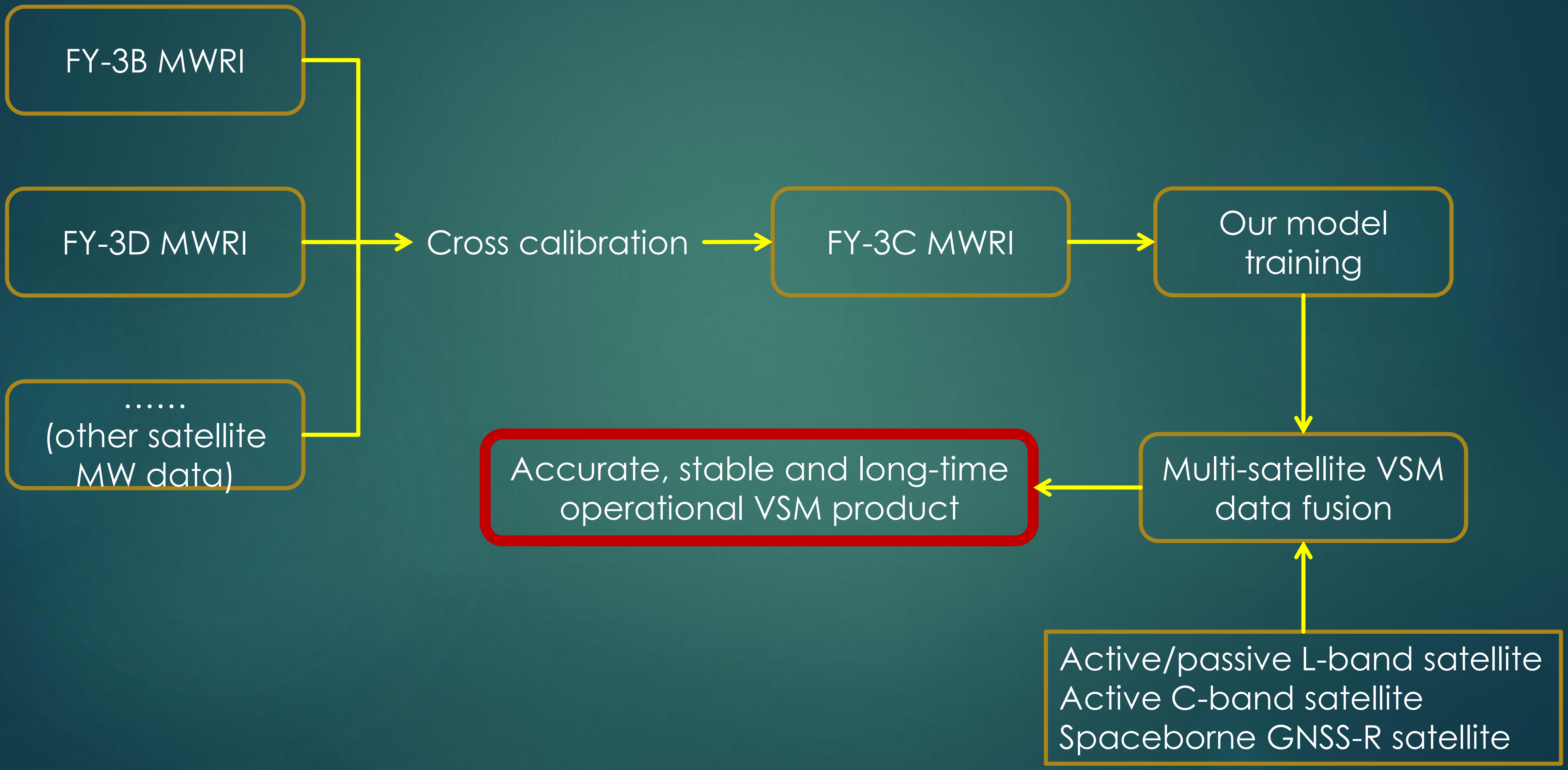
Performance of our EXP4 VSM estimates (3)

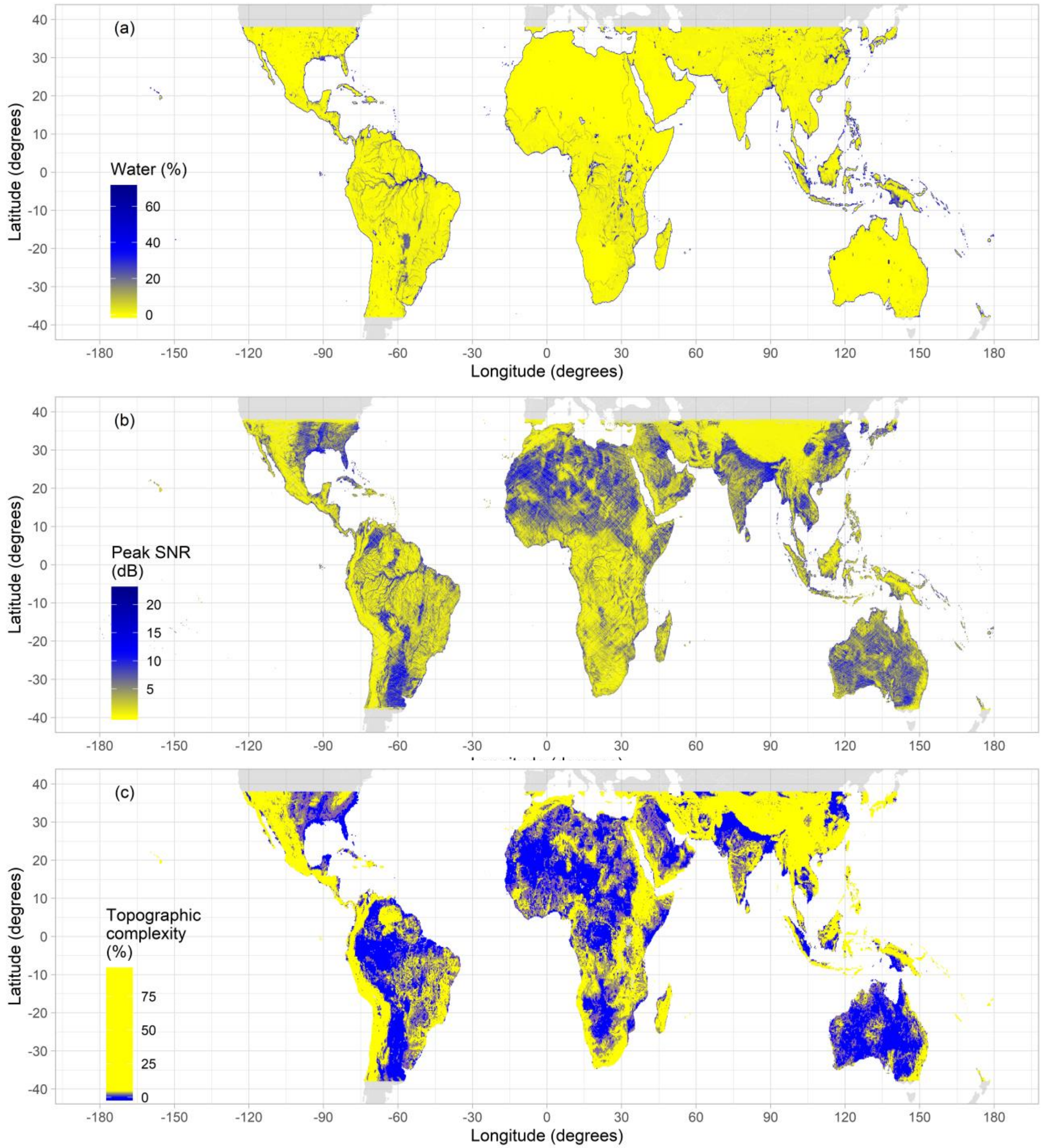
Discussion

It is clearly shown that more random days cannot significantly improve the scores. However, using more days of MWRI data in the training can consume huge computing resources.



Future plans





New spaceborne GNSS-R remote sensing technique

Summary

- The quality of MWRI VSM product is improved significantly; (R^2 = 0.63, ubRMSD = 0.044 m^3 m^{-3} and mean bias = 0.002 m^3 m^{-3} for a global scale)
- The spatial coverage is better, especially over the western part of China;
- The training process is very efficient, only four days of data are used.

Product address: https://pan.baidu.com/s/1M0Opt3Cp_kxbuCLbhcxrEA

password: fi77

Thanks !