Diagnosis and improvement of land surface models based on remote sensing

Hui Lu
Tsinghua University
luhui@tsinghua.edu.cn

Qing He
The University of Tokyo
heq16@tsinghua.org.cn

2023/09/27

Outlines

- Background
- Research targets
- Data and methods
- Diagnosis results
- Parameter optimization results
- Final remarks

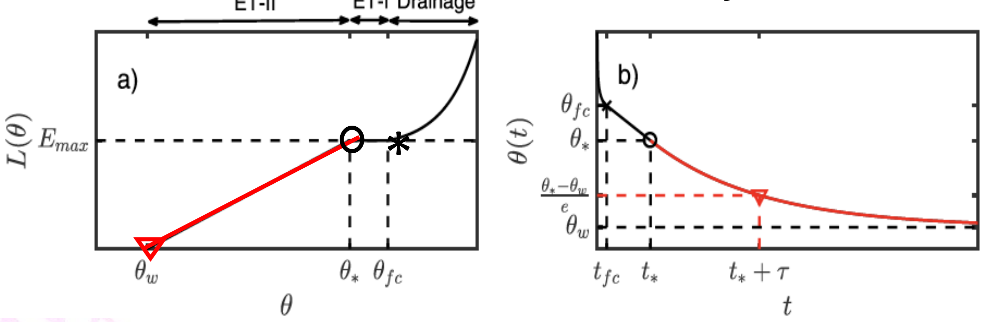
Background

What is Soil Moisture Memory and Why is it important?

- **Soil Moisture Memory (SMM):**
  - The time SM returns to its equilibrium when anomaly occurs
  - Transformation of **EF-SM coupling regimes** in the time domain
    - Energy-limited regime → High frequency
    - Water-limited regime → Low frequency

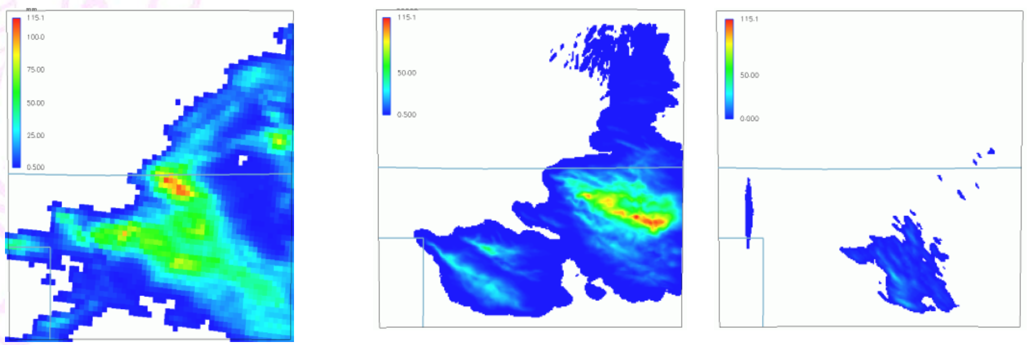
- **Why is SMM important?**
  - **SMM reflects the temporal variations (fluctuations) of soil moisture**
  - **For climate characterization:** a useful proxy for diagnosing near-surface hydrometeorological behaviors
  - **For model development:** determining the boundary conditions for atmosphere model within the Earth System Model (ESM) framework

Loss Function of SM | SM drydown curve



(McColl et al., 2017)

Observed Rainfall | Simulated rainfall With LIS | Simulated rainfall Without LIS

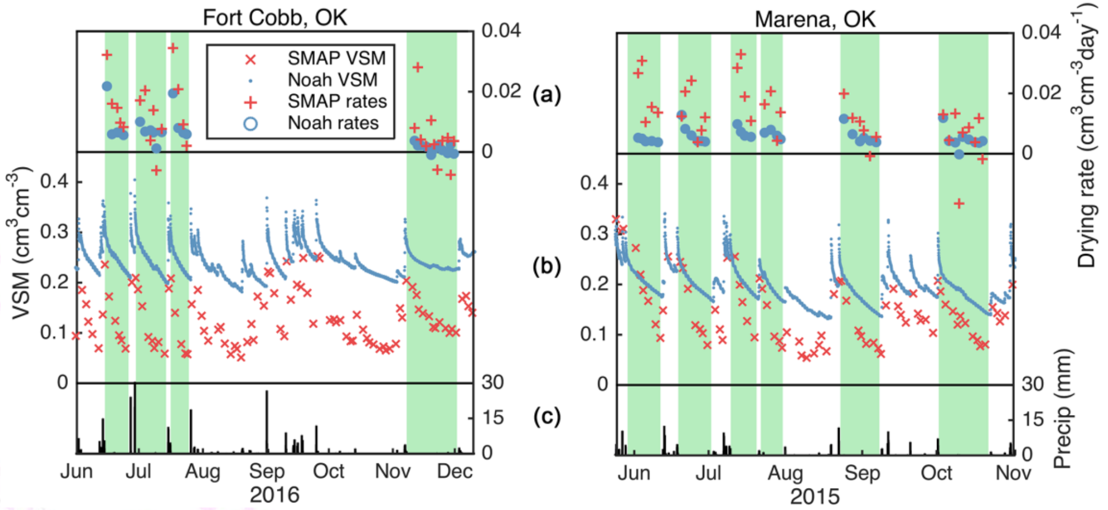


（Peters-Lidard, et al, 2006）

Background

- **How do LSMs perform in characterizing SMM?**
  - Generally, substantial differences exist between models and observations. Examples:
    - Noah vs. SMAP
    - Catchment vs. SMAP

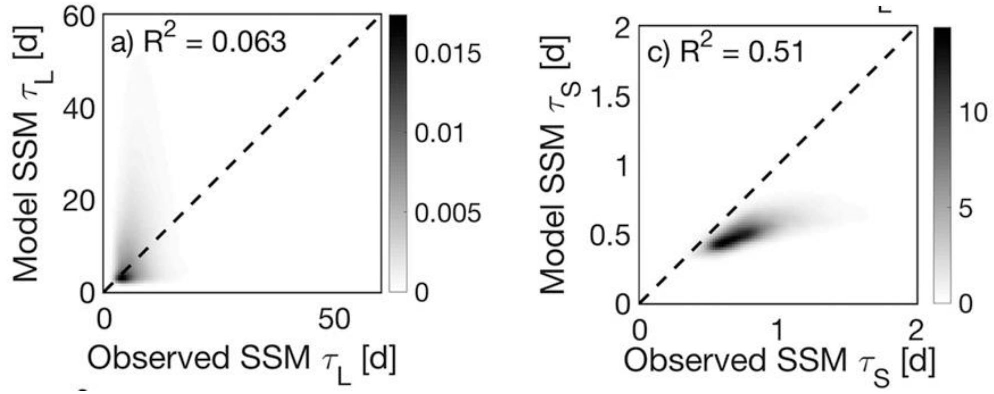
Noah vs SMAP: comparison considering only the water-limited regime



（Shellito et al, 2018）

- **What's the research gap?**
  - **Seldom attention has been paid to SMM evaluation on different regimes** →New methods needed
  - Soil moisture simulation is model dependent, **does the SMM bias commonly exist in all LSMs**?
  - **Does the SMM bias have temporal variabilities** since the observation data with longer spans available now?
  - **It is not clear how to improve the model based on these evaluations**

Catchment vs SMAP: comparison considering both water-limited and energy-limited regimes



（McColl, He et al, 2019）

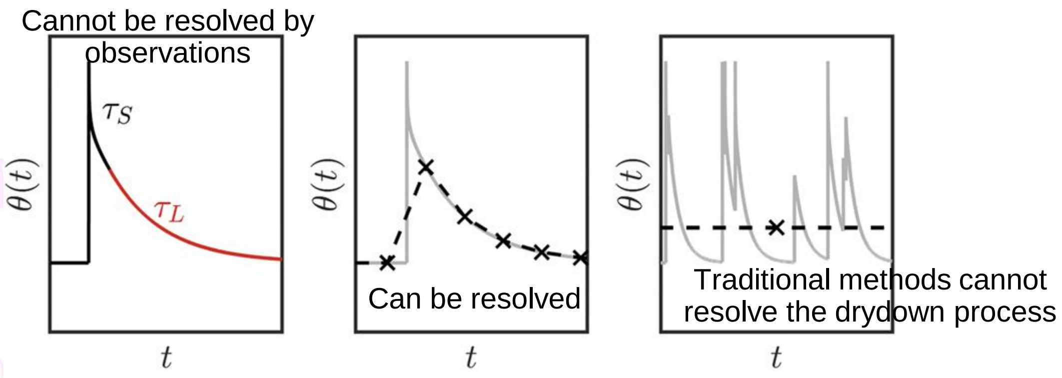
Research Aim

- **Using 5-year satellite soil moisture data to evaluate SMM performance of LSMs utilized in 6 major Reanalyses (i.e., GLDAS-Noah, GLDAS-Catchment, MERRA2, NCEP-FNL, ERA5 and JRA55)**
  - Compared to large-scale satellite observations, how do LSMs perform in simulating near-surface hydrometeorological characteristics under different soil moisture regimes?
  - Despite the models' spreads, do LSMs show common biases in their hydrometeorological behaviors? What might be the essential factors that contribute to them?

- **By answering the above questions, this study could:**
  - Provide useful information on data quality for data users, and provide feedbacks for the data producers to guide their development
  - Provide implications for LSM development in terms of SMM and soil moisture simulation

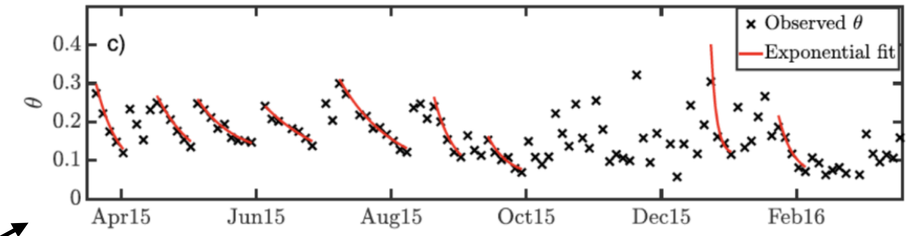
Data and Methods

- **A Hybrid Model to Quantify SMM at Different regimes**



a) Fully-resolved drydowns b) Partially-resolved drydowns c) Unresolved drydowns

- Hybrid model for different stages of SMM process
  - **Using the empirical model for water-limited process** as it can be resolved by the temporal resolution of current satellite observations
  - **Using the stochastic model for energy-limited process**: as it cannot be resolved by the time interval of observations; also it is dominated by the precipitation events (noises)



$$\frac{d\theta(t)}{dt} = \begin{cases} -\dfrac{\theta(t)-\theta_w}{\tau_L}, & \text{if} \quad P=0 \\ -\dfrac{\theta(t)-\bar{\theta}}{\tau_S} + \varepsilon(t), & \text{if} \quad P>0 \end{cases}$$

$$\theta(t) = \Delta\theta \exp\left(-\frac{t-\Delta t_P}{\tau_L}\right) + \theta_w .$$

$$\tau_S = -\frac{\frac{\Delta t}{2}}{\log\left(\frac{\Delta z \overline{\Delta\theta}_+}{\alpha}\right)} = -\frac{\frac{\Delta t}{2}}{\log(F_P)}$$

$$\boxed{\theta(t)} = \Delta\theta \exp\left(-\frac{t-\Delta t_P}{\boxed{\tau_L}}\right) + \boxed{\theta_w} .$$

Wilting point

SM timeseries, known

Water-limited SMM τ_L

Energy-limited SMM τ_S (Details for the derivation are in supplementary materials)

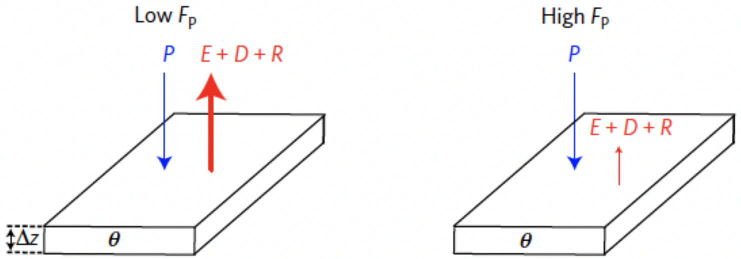
（McColl, He et al, 2019）

Data and Methods

- **Proxies for diagnosing possible reasons contributing to model biases**
  - **Precipitation fraction (F_p) related to τ_S**

    $$F_P(f) = \frac{\Delta z \sum_{i=1}^{fT} \Delta\theta_{i+}}{\int_0^T P(t)dt},$$

    - **Definition: how much precipitation can be stored in soil layer**
    - **Reflecting the terrestrial water cycle rate:** Higher F_p → more water stored in soil, less into runoff



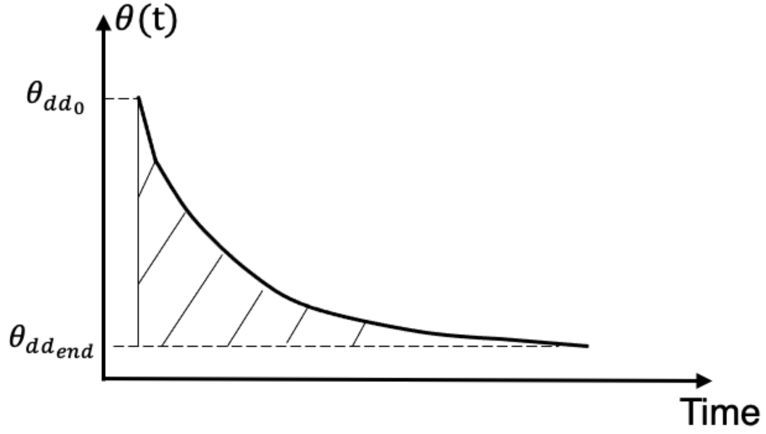
（McColl et al, 2017）

  - **Stage-II ET (ET_{II}) related to τ_L**

    $$ET_{II} = \sum_{i=1}^{n} \Delta z \theta_{dd_{0,i}} (1 - \exp(-\frac{\Delta t_{dd_i}}{\tau_L}))$$

    - A proxy for measuring ET flux limited by surface water availability
    - Also serve as an application for ET estimation over bare soil areas

  - **Soil moisture thresholds: important parameters in LSMs**
    - **Wilting point θ_w:** taken as multi-year mean $\theta_{dd_{end}}$
    - **Critical point θ_c:** taken as multi-year mean θ_{dd_0}



Data and Methods

- **Surface soil moisture and precipitation data from satellite observation and six reanalyses are used**
  - **Satellite observation**
    - **Surface soil moisture from SMAP**
      - 2015.4.1 – 2020. 3.31, 5 annual cycles, 3 day, 36km
    - **Precipitation from GPM**
      - 2015.4.1 – 2020. 3.31, 5 annual cycles, hourly, 36km
- **Reanalyses Dataset**

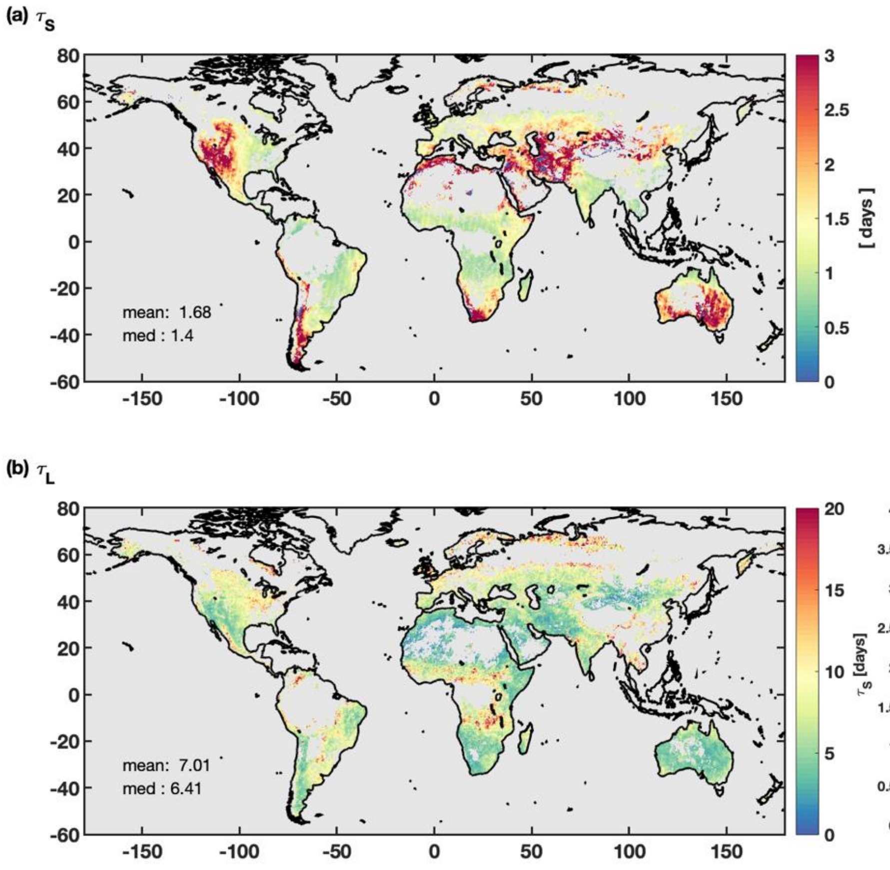
All data are aggregated to 36km, 3-day resolution

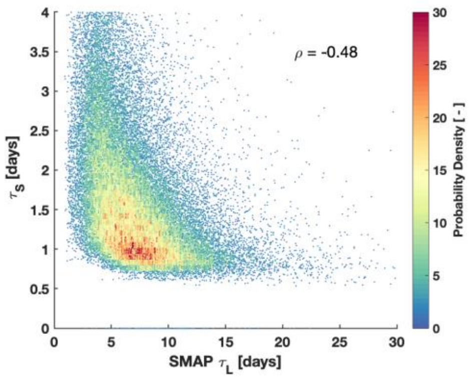
Dataset	Agency	LSMs	Online/Offline schemes	Surface Soil Layer Depth	Spatial Resolution	Temporal Resolution
GLDAS-CLSMv2.2	NASA GES DISC	Catchment	Offline	0-2cm	0.25° ×0.25°	1 day
GLDAS-Noahv2.1	NASA GES DISC	Noah	Offline	0-10cm	0.25° ×0.25°	3 hours
MERRA2	NASA GMAO	Catchment	Coupled	0-5cm	0.625° ×0.5°	1hour
NCEP-FNL	NCAR	Noah	Coupled	0-10cm	1° ×1°	6 hours
ERA5	ECMWF	(H)TESSEL	Coupled	0-10cm	0.25° ×0.25°	1 hour
JRA55	JMA	SiB/SiB2	Coupled	0-2cm	0.5° ×0.5°	3hours

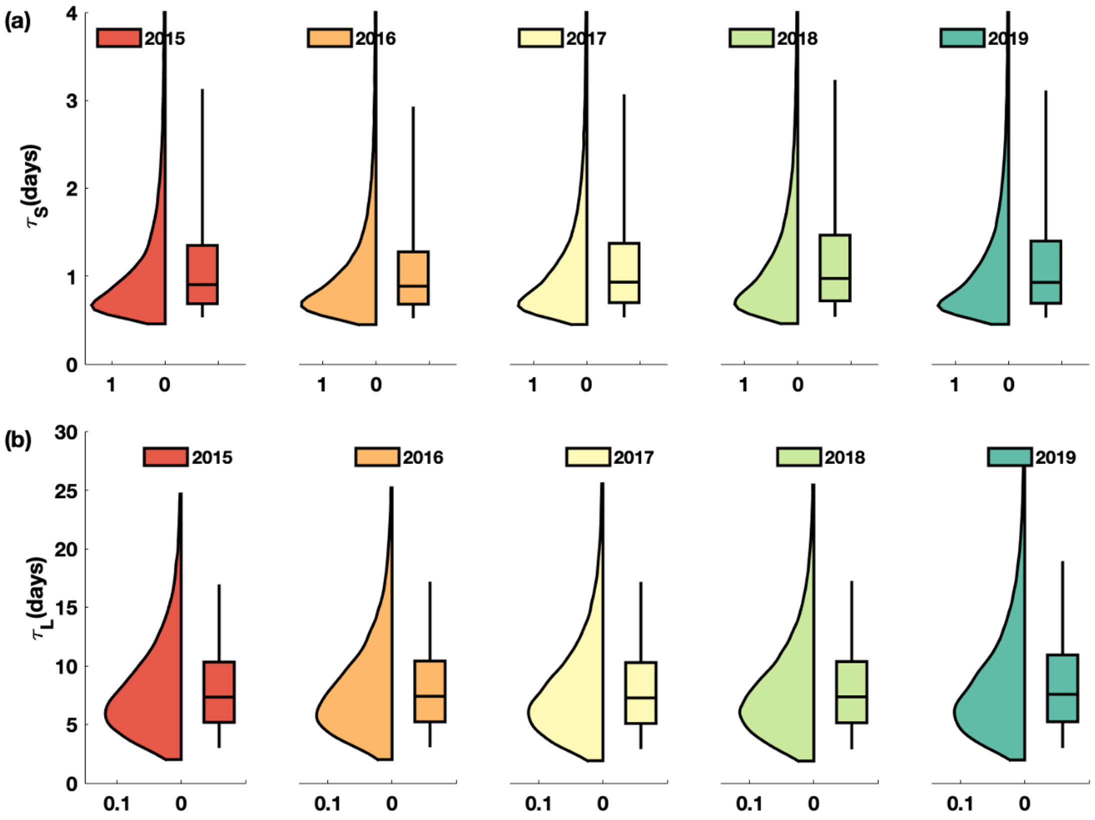
Results —— SMM from 5-year SMAP data

- **Spatial pattern**
  - τ_S : longer in arid areas
  - τ_L : longer in humid areas
  - τ_S and τ_L are spatially anti-correlated, consistent to our previous studies

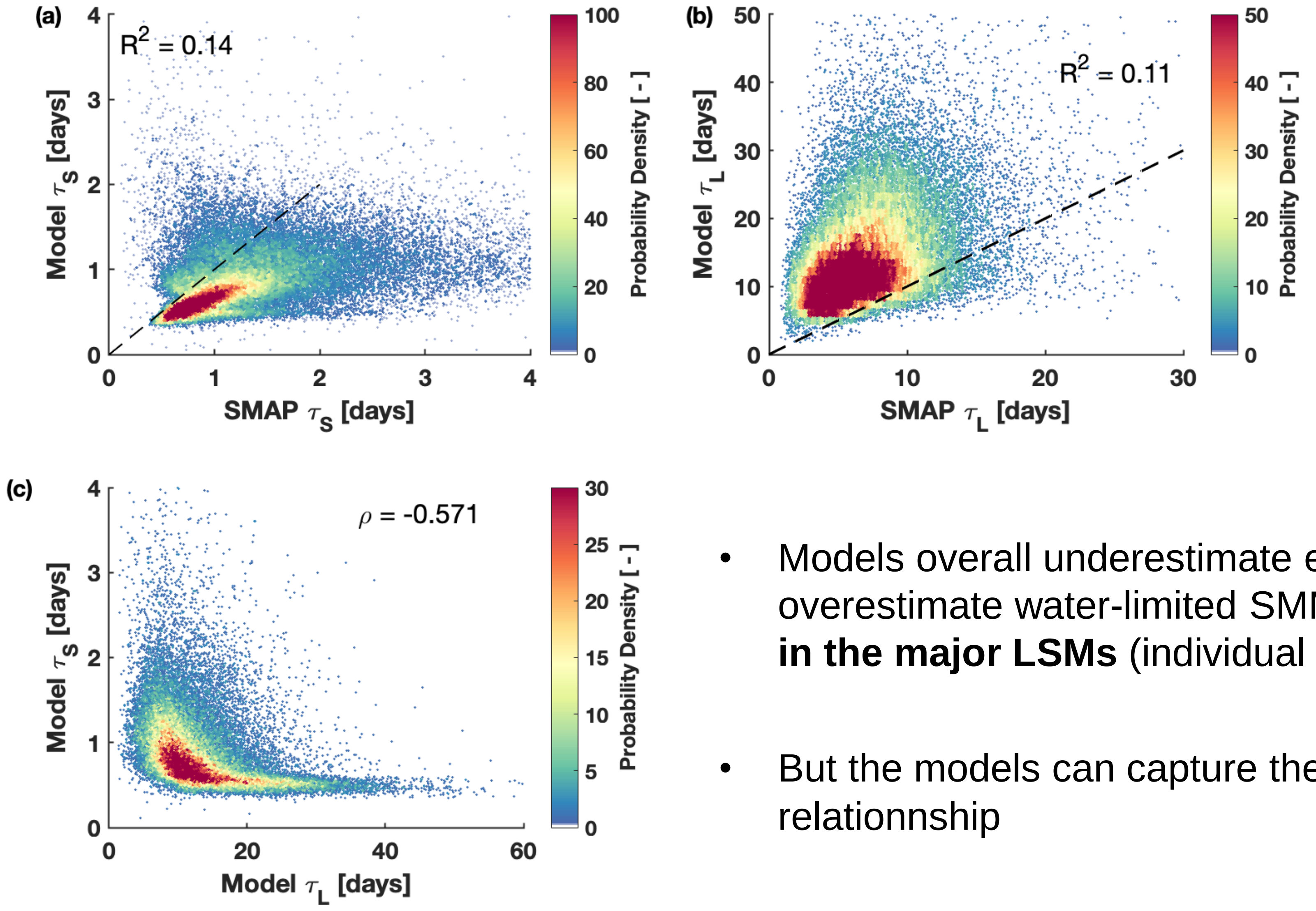
- **Temporal variability**
  - SMM from SMAP is robust within 5 annual cycles both globally (below) and regionally (supplementary materials)







Results ——SMM Comparison of multi-model mean and SMAP



- Models overall underestimate energy-limited SMM, while overestimate water-limited SMM →**SMM biases commonly exist in the major LSMs** (individual comparison will be shown later)

- But the models can capture the overall anti-correlated τ_S- τ_L relationnship

Results —— Intercomparison between models

- Both τ_S and τ_L biases are model dependent, but the magnitude of biases are similar across 5 annual cycles
- ERA5 performs the closest estimation of both τ_S and τ_L to those from SMAP

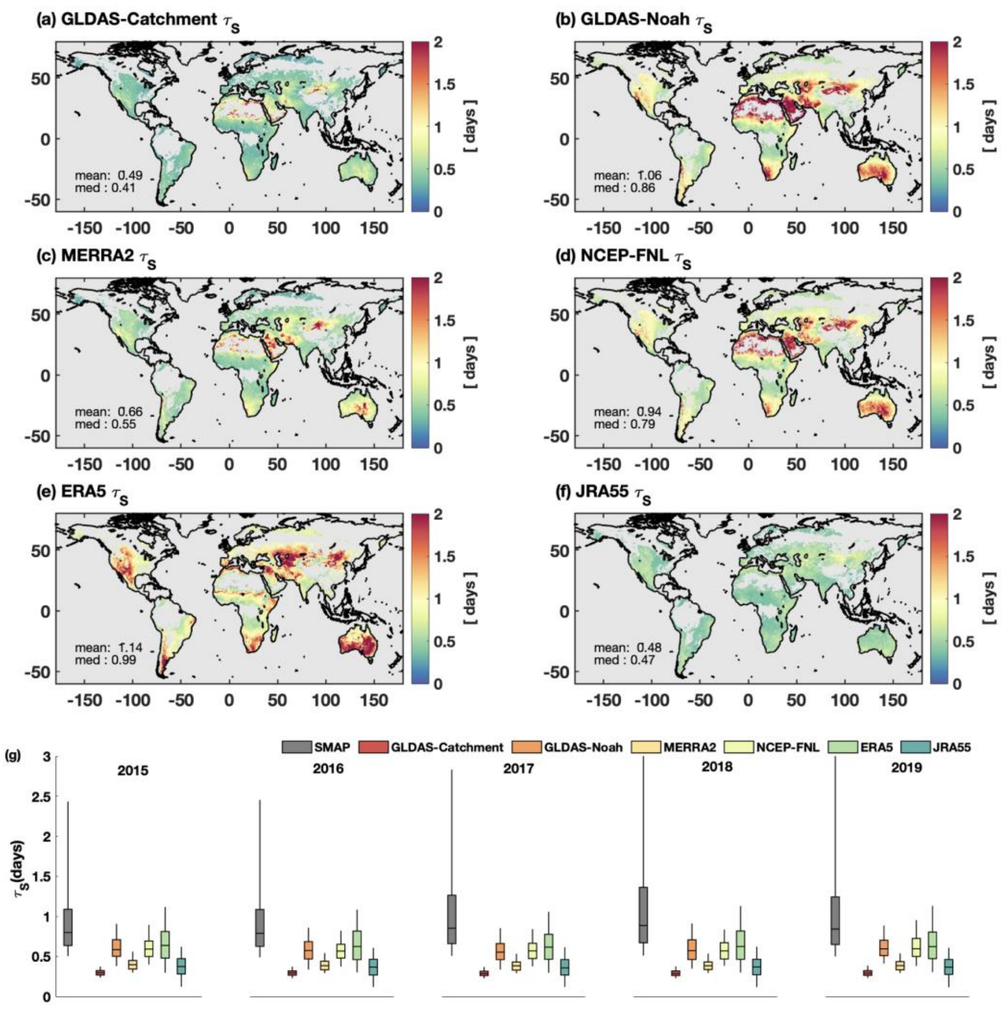
- τ_S : Sensitive to soil layer depth but no significant sensitivity to coupled/offline schemes

- τ_L : insensitive to either soil layer depth or coupled/offline schemes

2cm

5cm

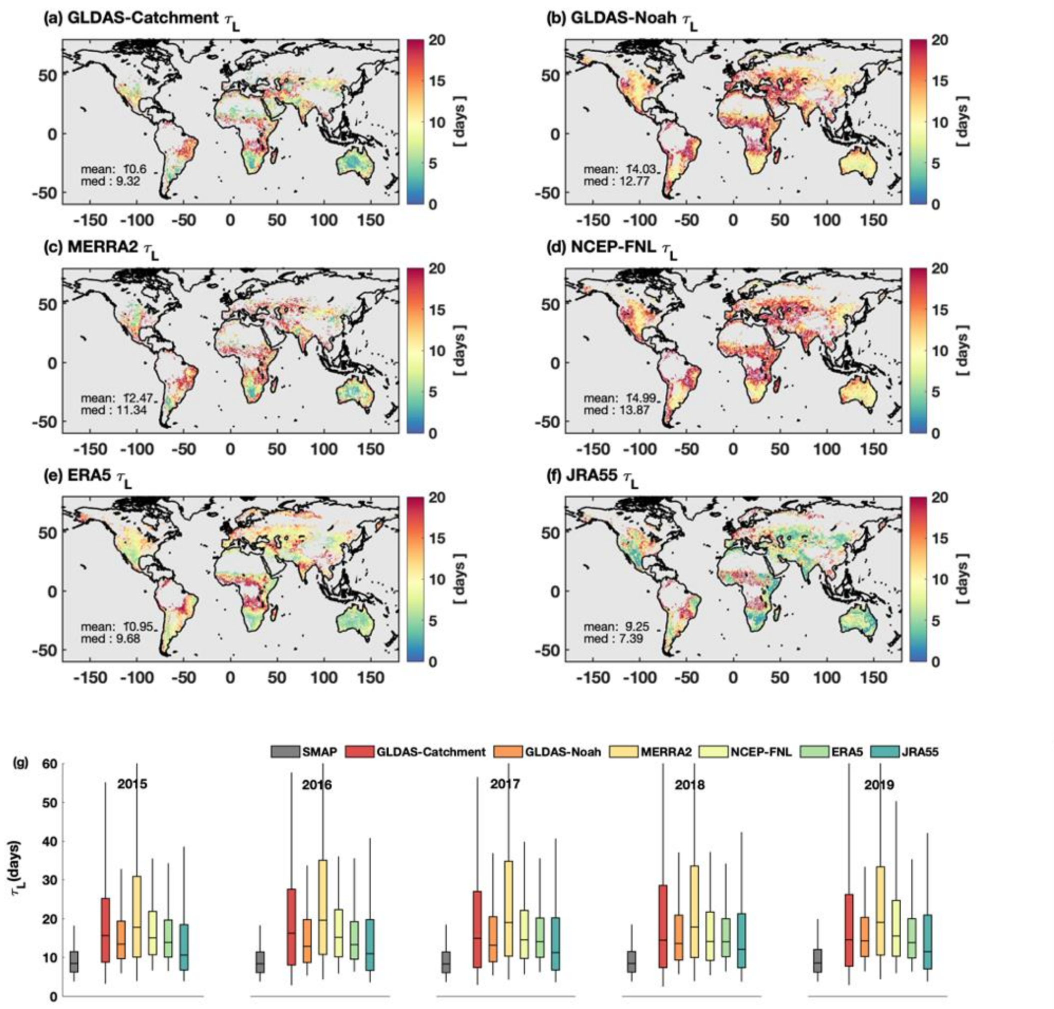
2cm



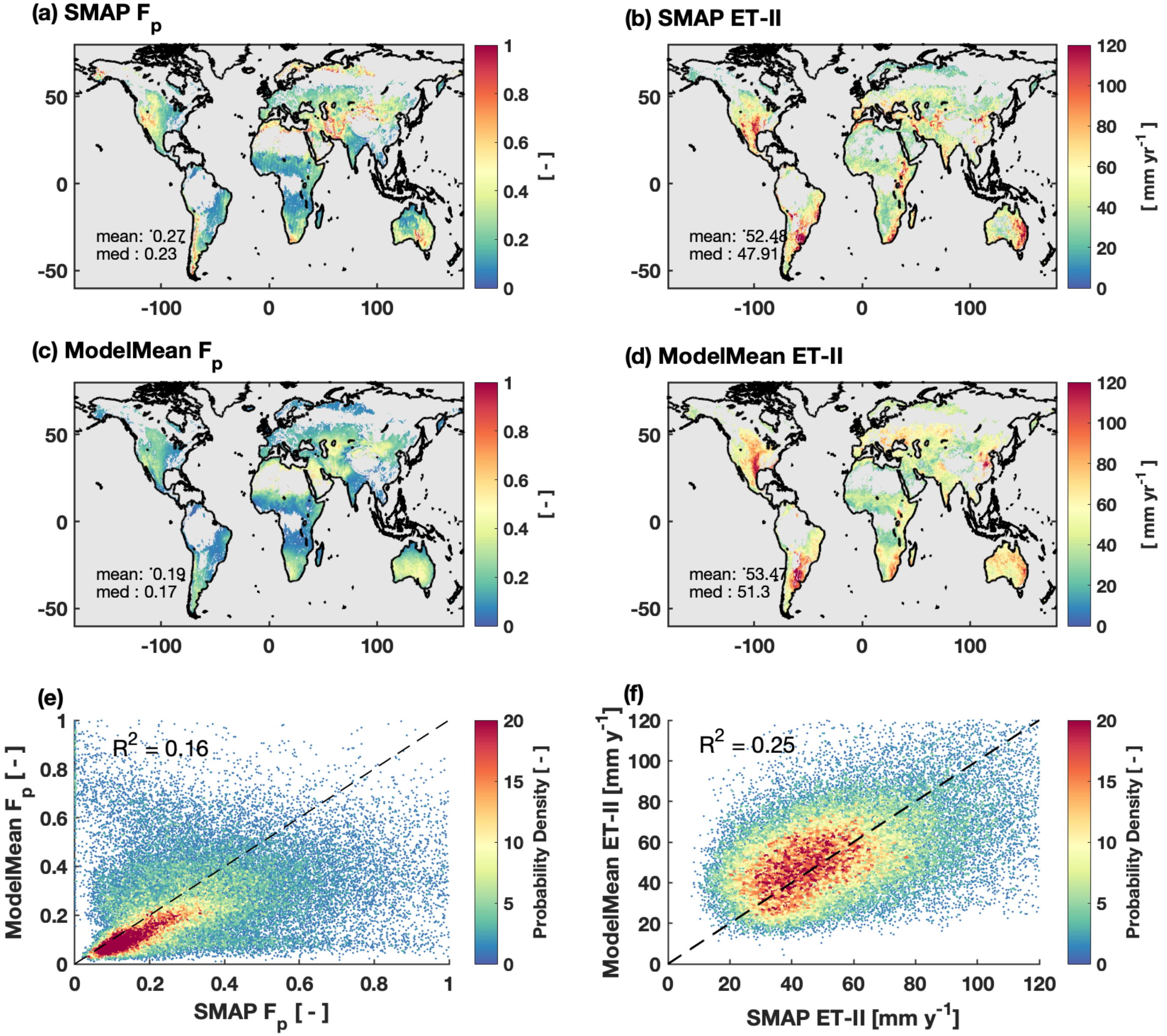
2cm

5cm

2cm

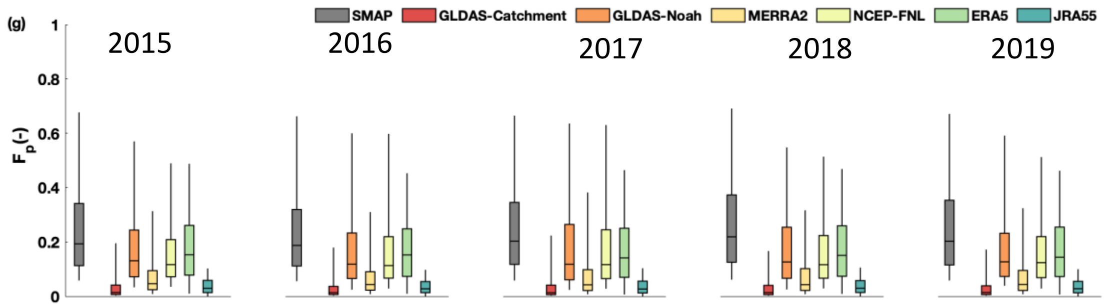


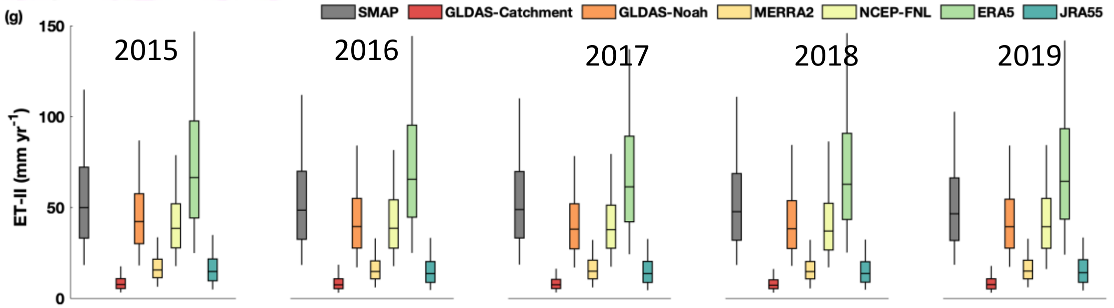
Results —— F_p and ET_{II} comparison of multi-model mean and SMAP



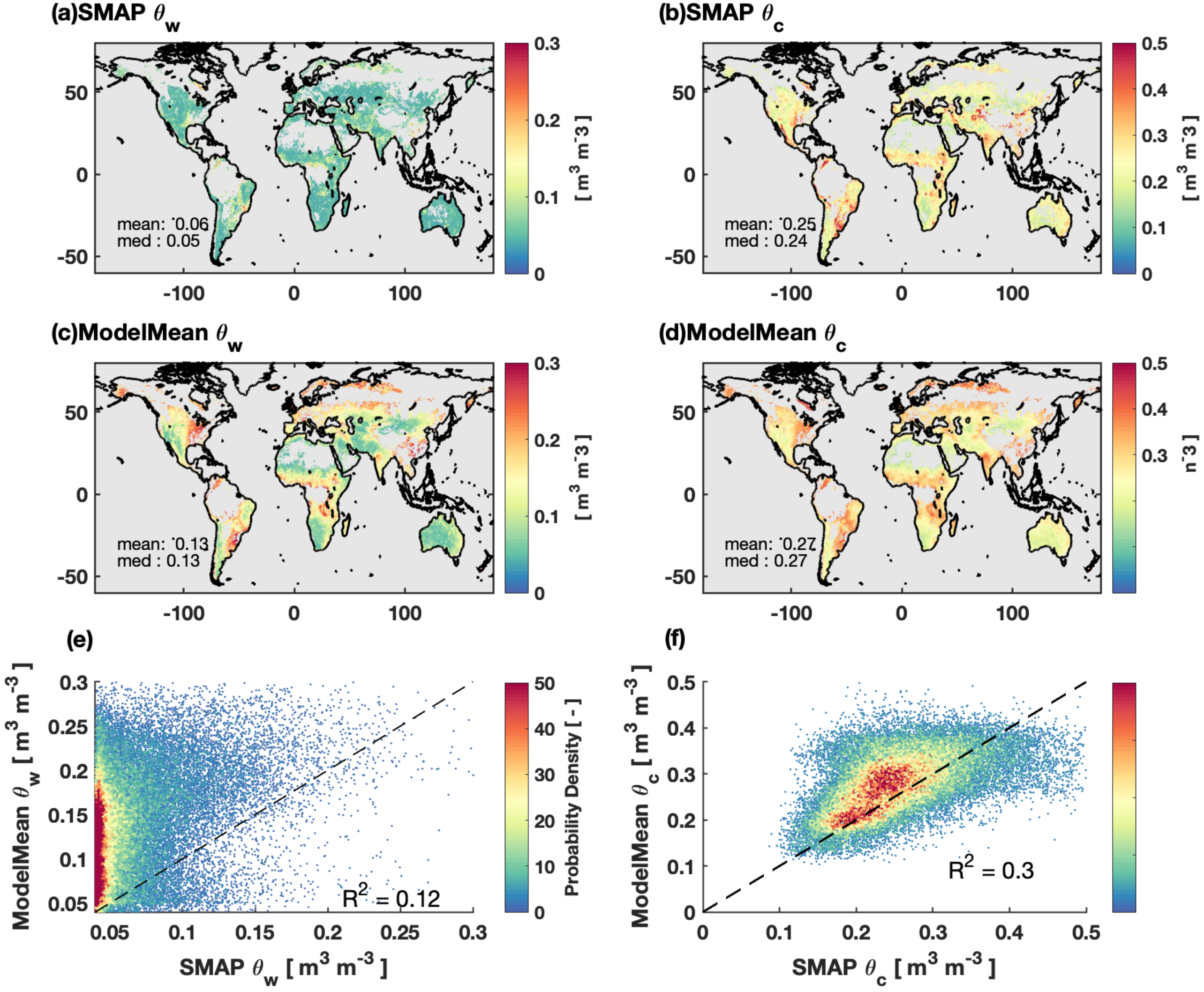
Only results from GLDAS-Noah, NCEP-FNL and ERA5 are aggregated here (same soil layer depth)

- F_p : Models overall underestimate water cycle rate
- ET_{II}: Models overestimate it in arid regions, while underestimate it in humid regions
- Biases are similar across years

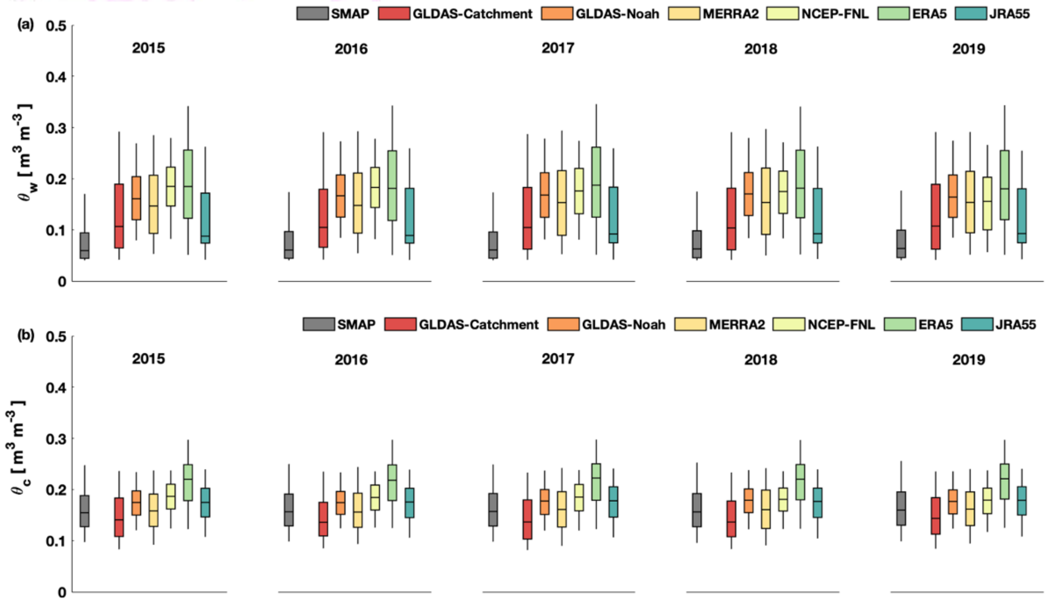




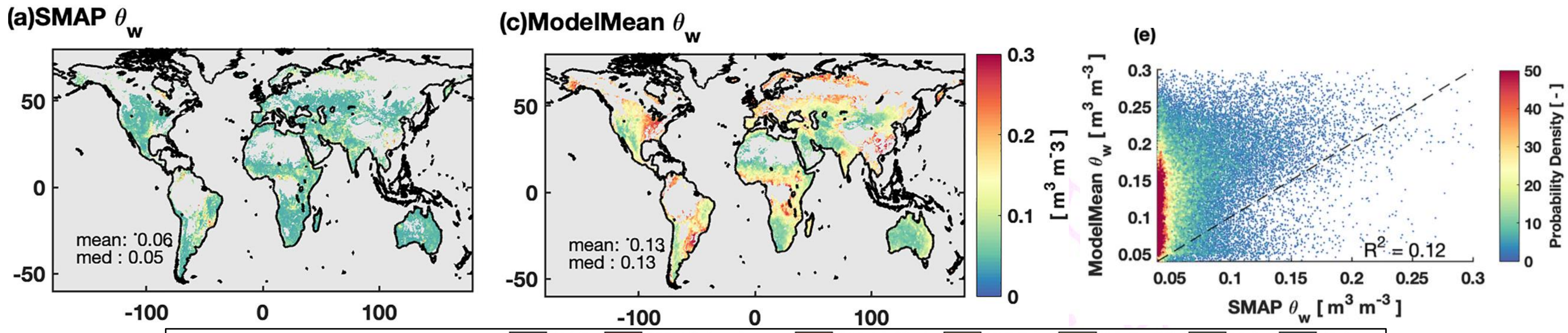
Results —— θ_w and θ_c comparison of multi-model mean and SMAP

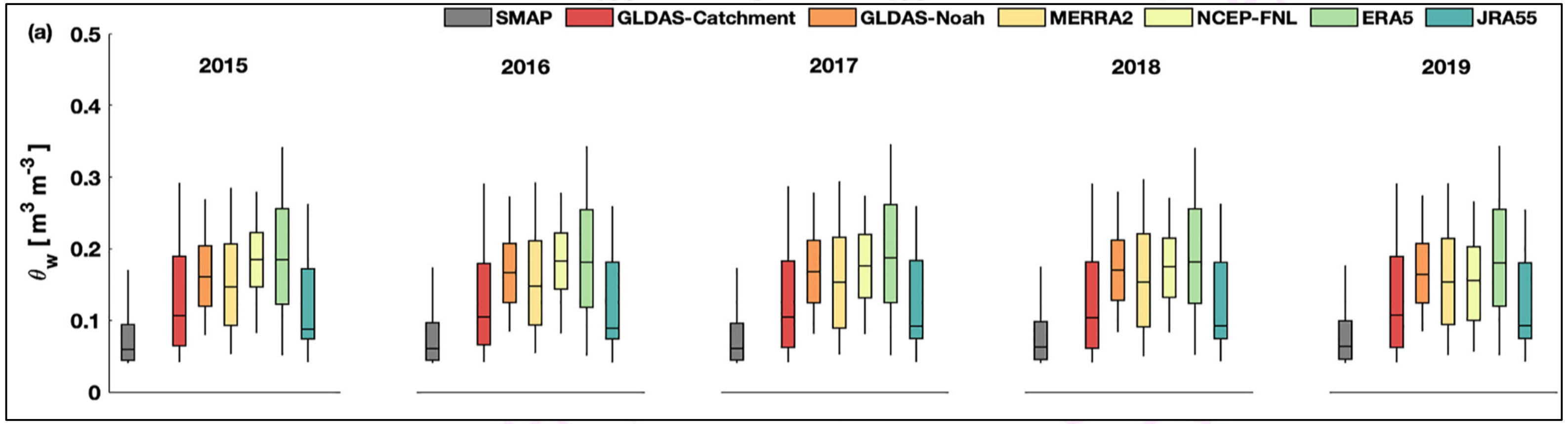


- Significant biases of θ_w and θ_c between models and SMAP
  - Models underestimate θ_w, overestimate θ_c
  - Biases are consistent over the years
- θ_w and θ_c are two critical parameters prescribed in LSMs → **need to be corrected in LSMs!**



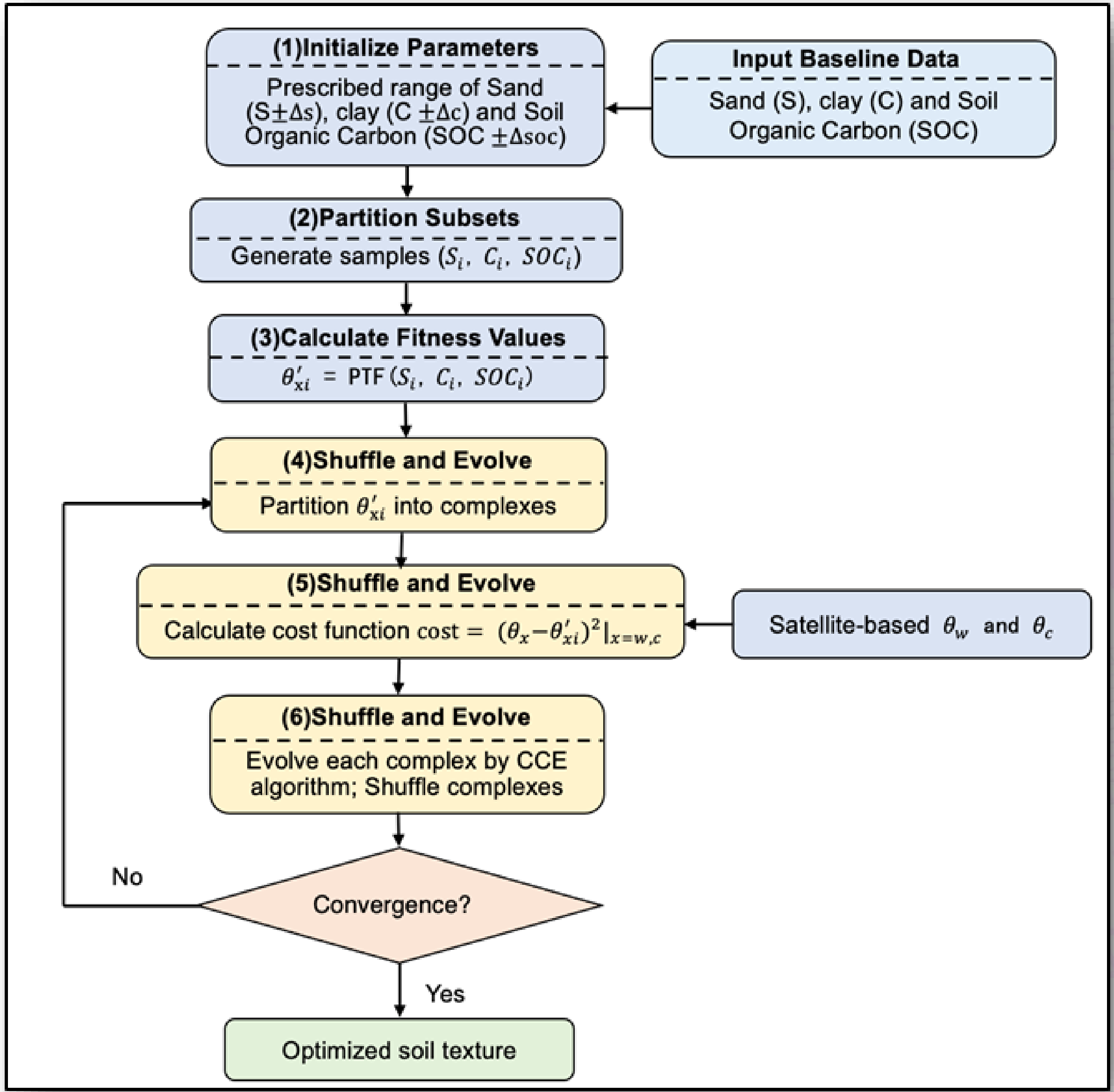
Possible causes of bias– soil parameters





- The models present a substantial overestimation of wilting point—the multi-model mean shows a global median of 0.13 versus 0.05 of SMAP.
- The model wilting point has much greater heterogeneity, a wide range of values.

Improving LSM by optimizing soil parameters



- Optimizing soil texture using satellite observed θ_w and θ_c
- Perturbing the baseline soil texture data set and then optimizing it using SCE_UA
- Baseline soil texture data sets
  - GSDE
  - HWSD
- Different PedoTransfer functions

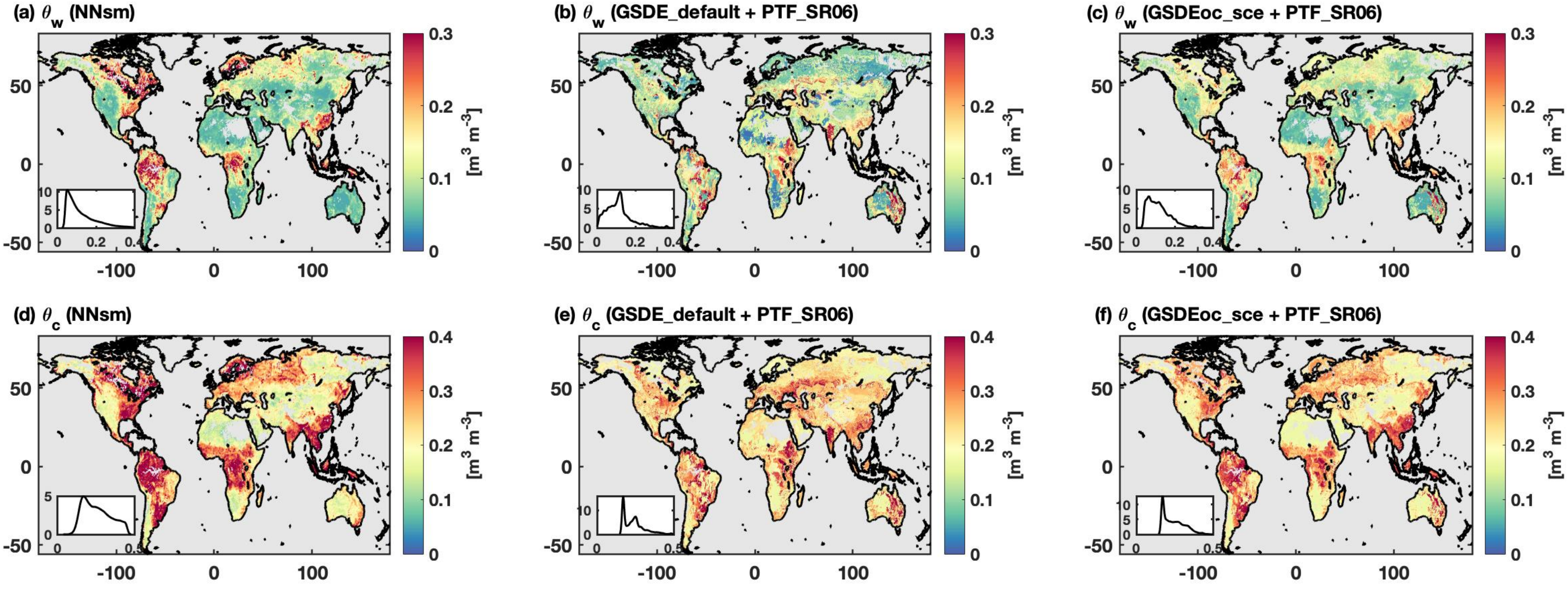
Experiment Designs for Global Soil Texture Optimization

Experiment Name	Baseline Soil Data Name	PTF Scheme	Optimized Soil Data Name	Prescribed Ranges†
Opti_exp1	GSDE_default	SR06	GSDEoc_sce	ΔSand: ±20% ΔClay: ±10% ΔSOC: ±5% Iteration: 3000 steps
Opti_exp2	GSDE_default	CH78	GSDEnoc_sce	
Opti_exp3	HWSD_default	CH78	HWSDnoc_sce	

†The lower and upper bound for Sand, Clay and SOC are 6% to 98%, 3% to 58%, 0 to 15% respectively. Optimization results exceed this range is regarded as ineffective and will be masked out. The analysis in the main context is conducted on 3000 iteration steps, i.e., for each experiment there are 3000 suits of soil sand, clay (and SOC) combinations.

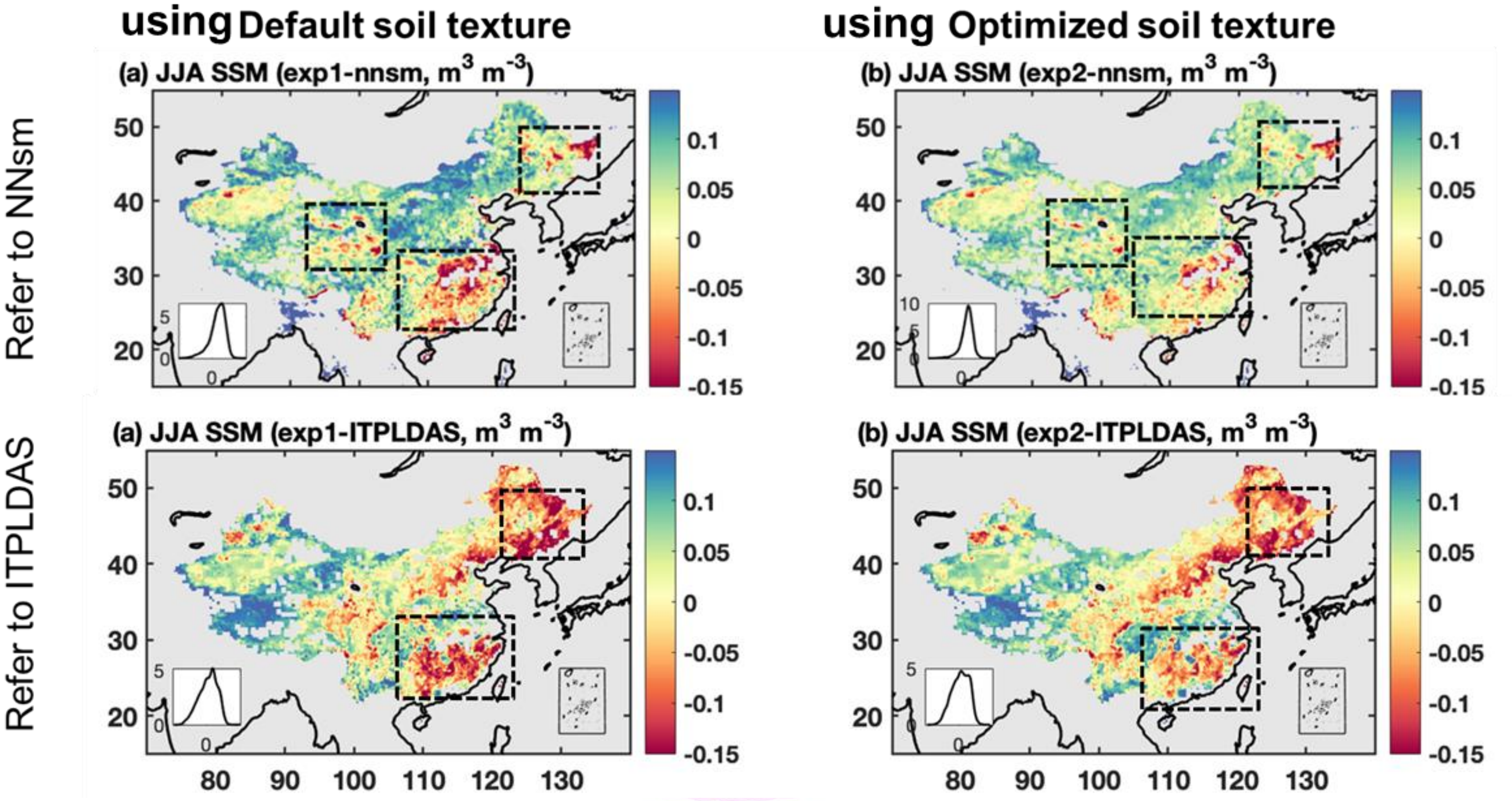
The opitimization result will then be chosen as the one combination that can produce the closest θw and θc to the satellite estimations.

Optimized Results: θ_w and θ_c



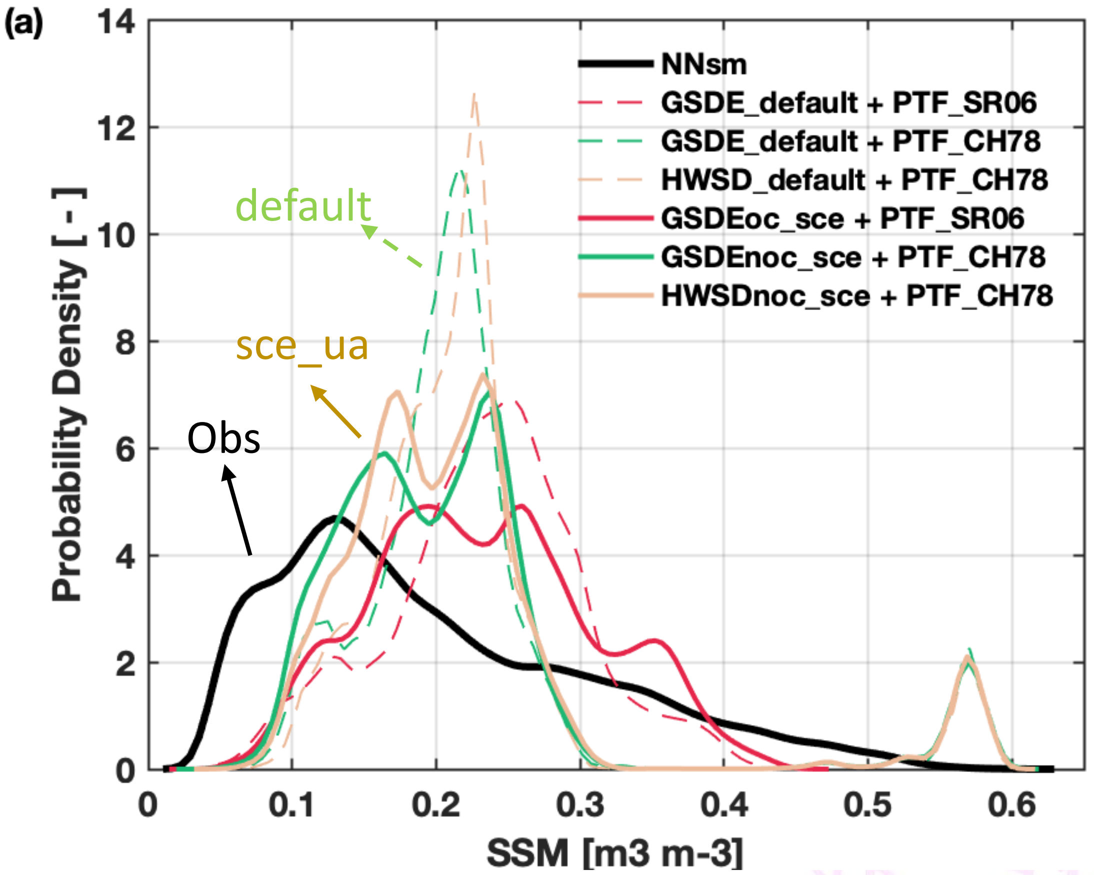
- The wilting point and critical soil moisture content of GSDE can be partially improved by optimizing soil texture

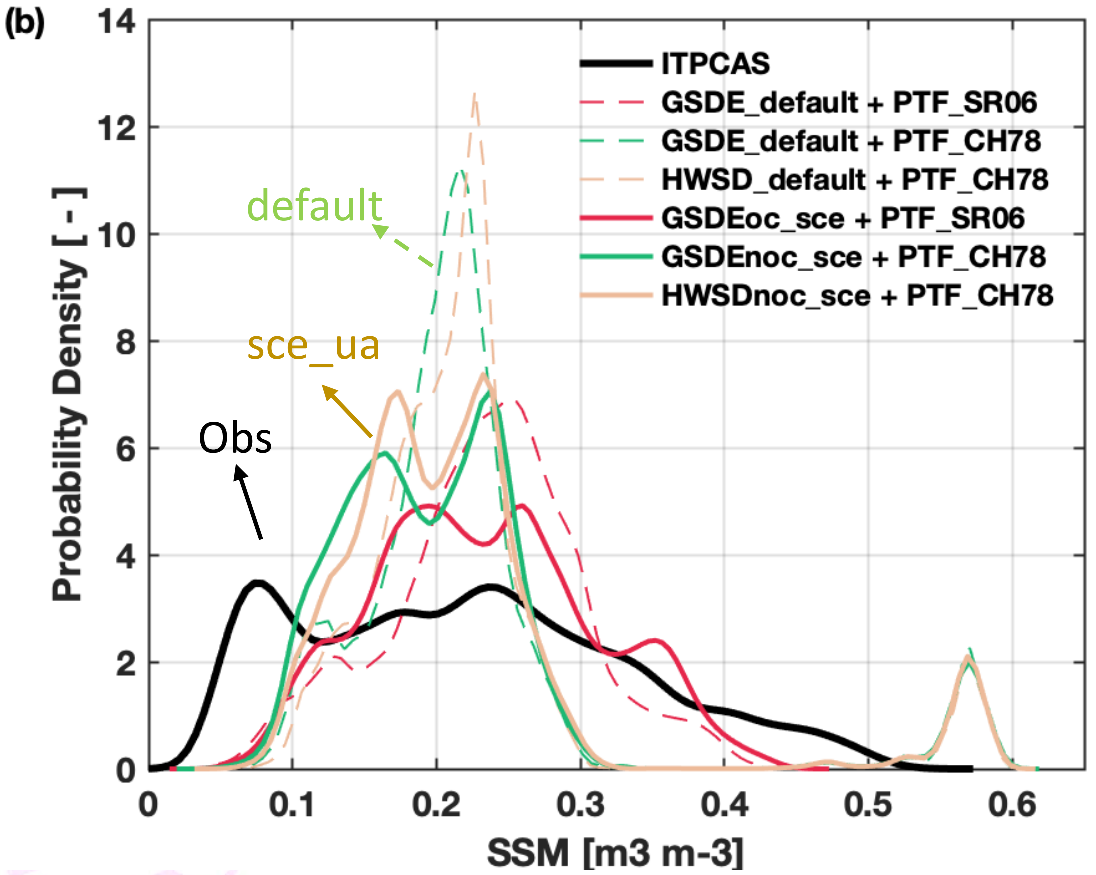
Optimized Results: SSM over China



- Optimized soil texture can partly improve the NoaH performance

Results: Histogram of soil moisture in China





- The histograms of optimized cases are closer to the observation (both NNsm and ITPCAS)

Results – Validation at In-situ stations

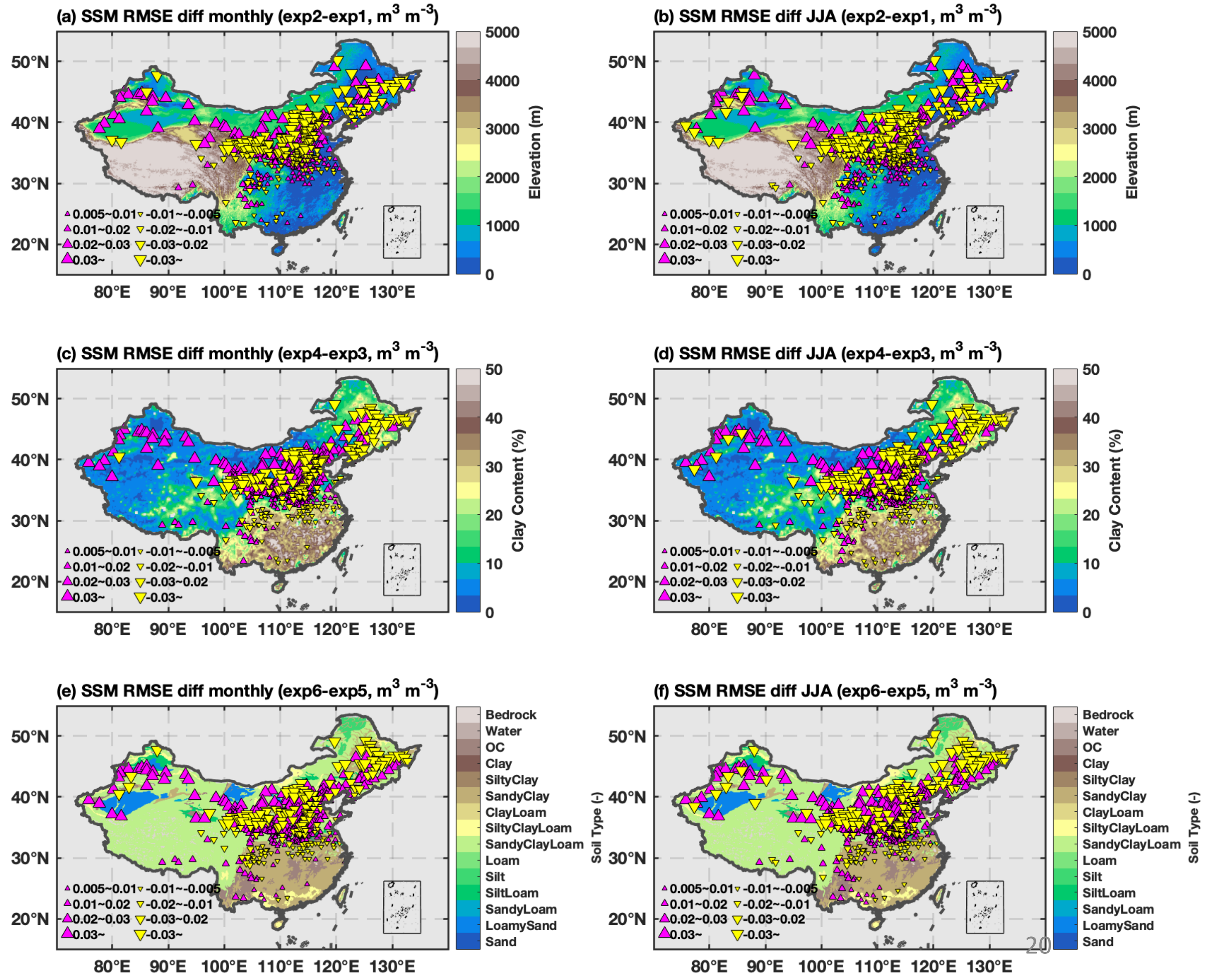
- RMSEs are improved over half of the stations at both monthly and JJA-mean time scale
- More stations are improved at JJA-mean scale
- Stations with RMSEs increased
  - Influence of elevation (slope)
  - Soil clay content
  - Soil types

Monthly | JJA-mean

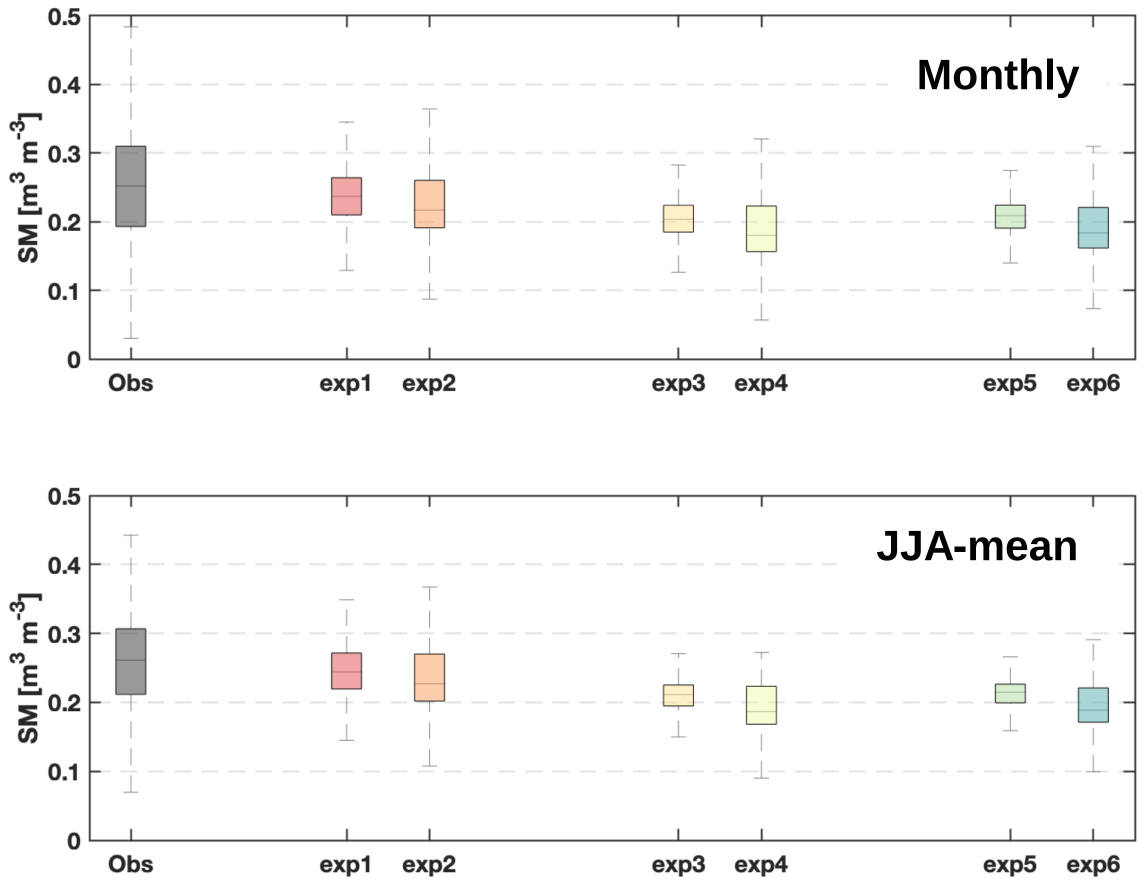
GSDE w SOM

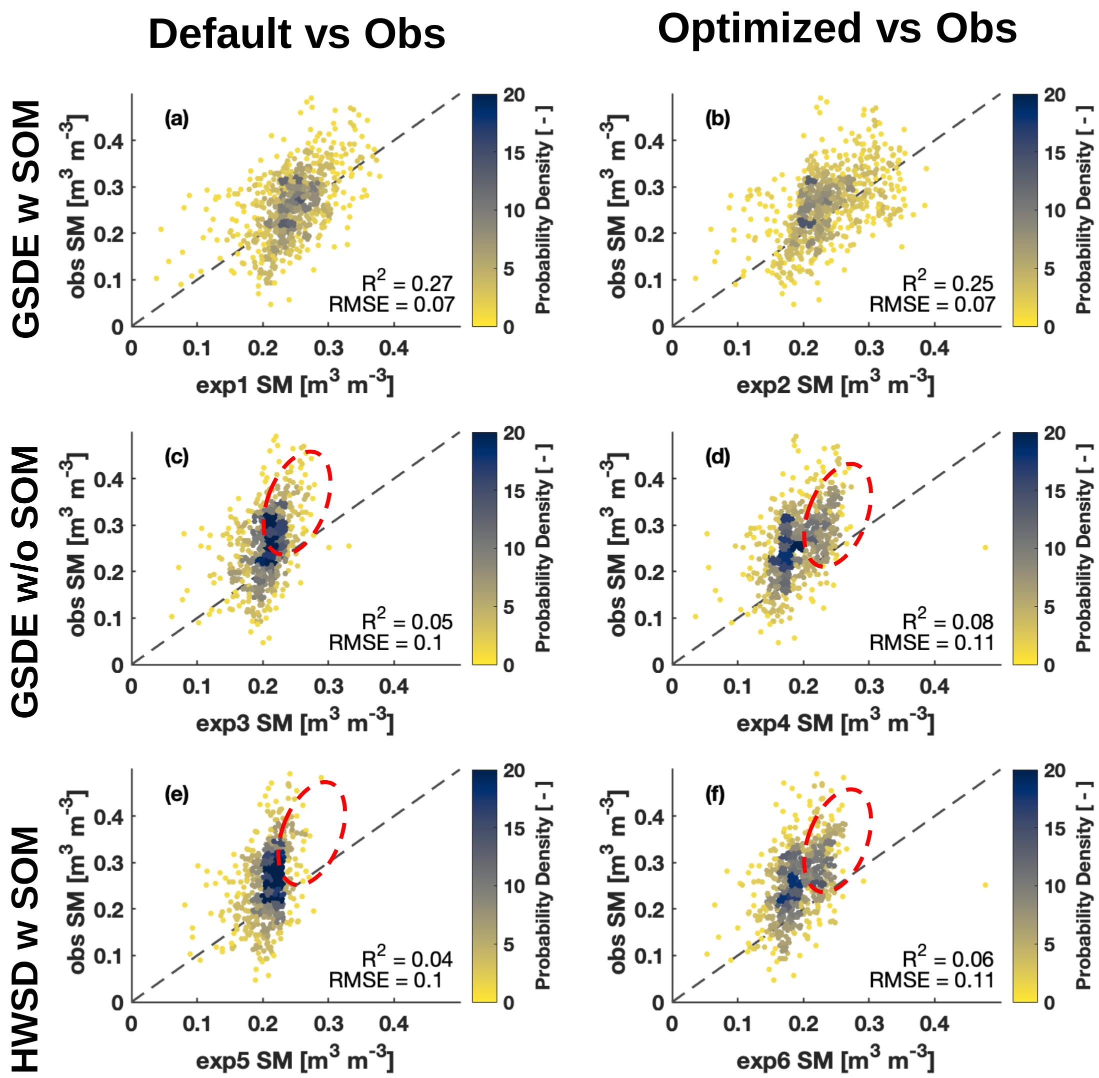
GSDE w/o SOM

HWSD w SOM



Results – Validation at In-situ stations





- The spatial variability across stations is improved with consistent RMSE accuracy (both Monthly and JJA-mean scales)

Conclusions

- Current major LSMs tend to show common SMM biases globally, **with underestimation of the energy-limited SMM and overestimation of water-limited SMM**.
- Inter-model comparison shows **ERA5 performs the best in characterizing SMM** in terms of both energy-limited and water-limited regimes
- **The SMM biases may be highly related to the misrepresentation of soil moisture thresholds (θ_w and θ_c)**
- Remote-sensing retrieved soil thresholds are proven to show unique benefits for calibrating the state-of-art soil texture maps, with clear improvement of SM simulations in terms of accuracy and spatial variability.

The way forward

- **For model evaluation:**
  - While we indeed evaluate major LSMs in this study, **what about behaviors of SMM in fully coupled ESMs**? → Evaluation using outputs from CMIP6 data
- **For model improvement:**
  - Which soil parameters play the most major role in determining SM simulation in LSMs? →Sensitivity analyses
  - How to retrieve them from satellite products and incorporate them in LSM improvement?

Thank you for your attention!