Soil moisture and temperature measuring networks in the Tibetan Plateau and their applications

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CYWater, Beijing, 6 August 2016

Outline

- Motivation
- Soil moisture and temperature measuring networks in the Tibetan Plateau
- Data applications
  - Validation of PMV RS products
  - Validation of LDAS product
  - Satellite data-based LSM calibration
- Summary

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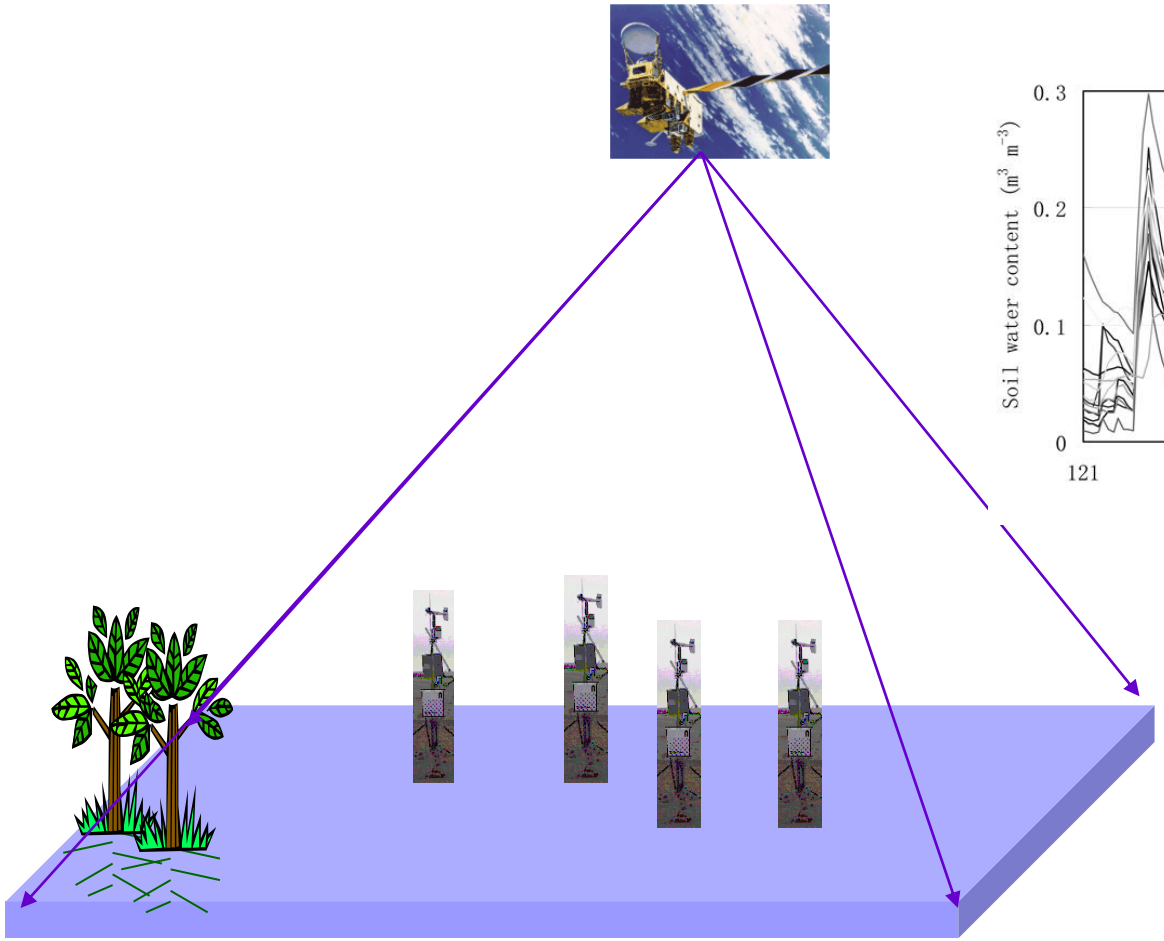
Motivation

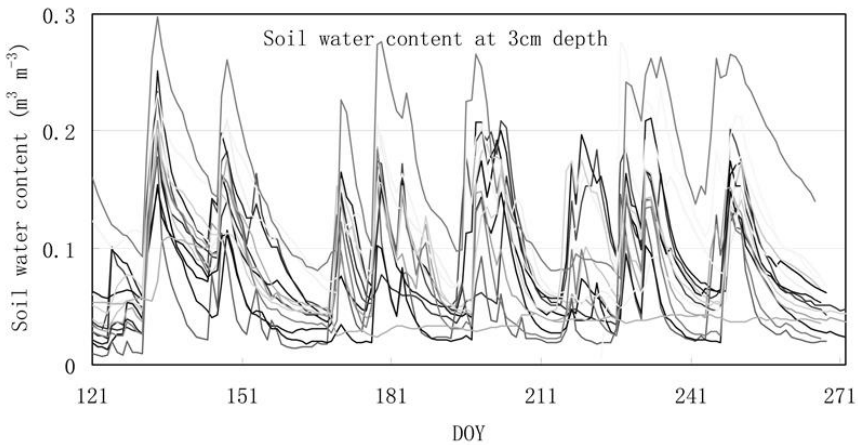
- Soil moisture modulates surface energy partitioning and plays a crucial role in land climate.

- What is the accuracy of RS soil moisture products for the Tibetan Plateau? How to improve the accuracy of soil moisture estimated from satellite data?

- LSMs without calibrations do not perform well for soil moisture simulations. How to specify soil parameter values at grid scale?

Motivation: Validations of satellite or modeled soil moisture need dense measurements, because soil moisture has high spatial variability.





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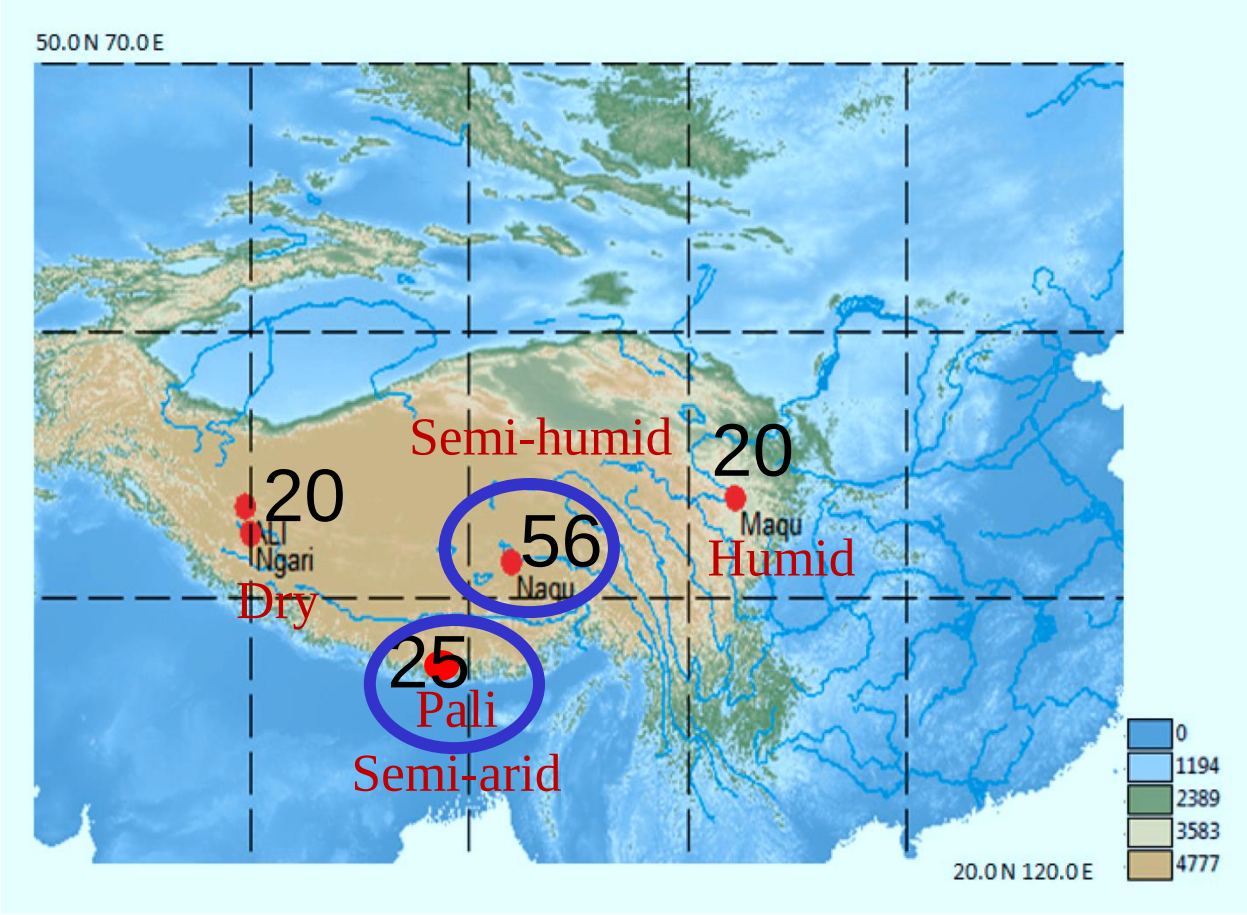
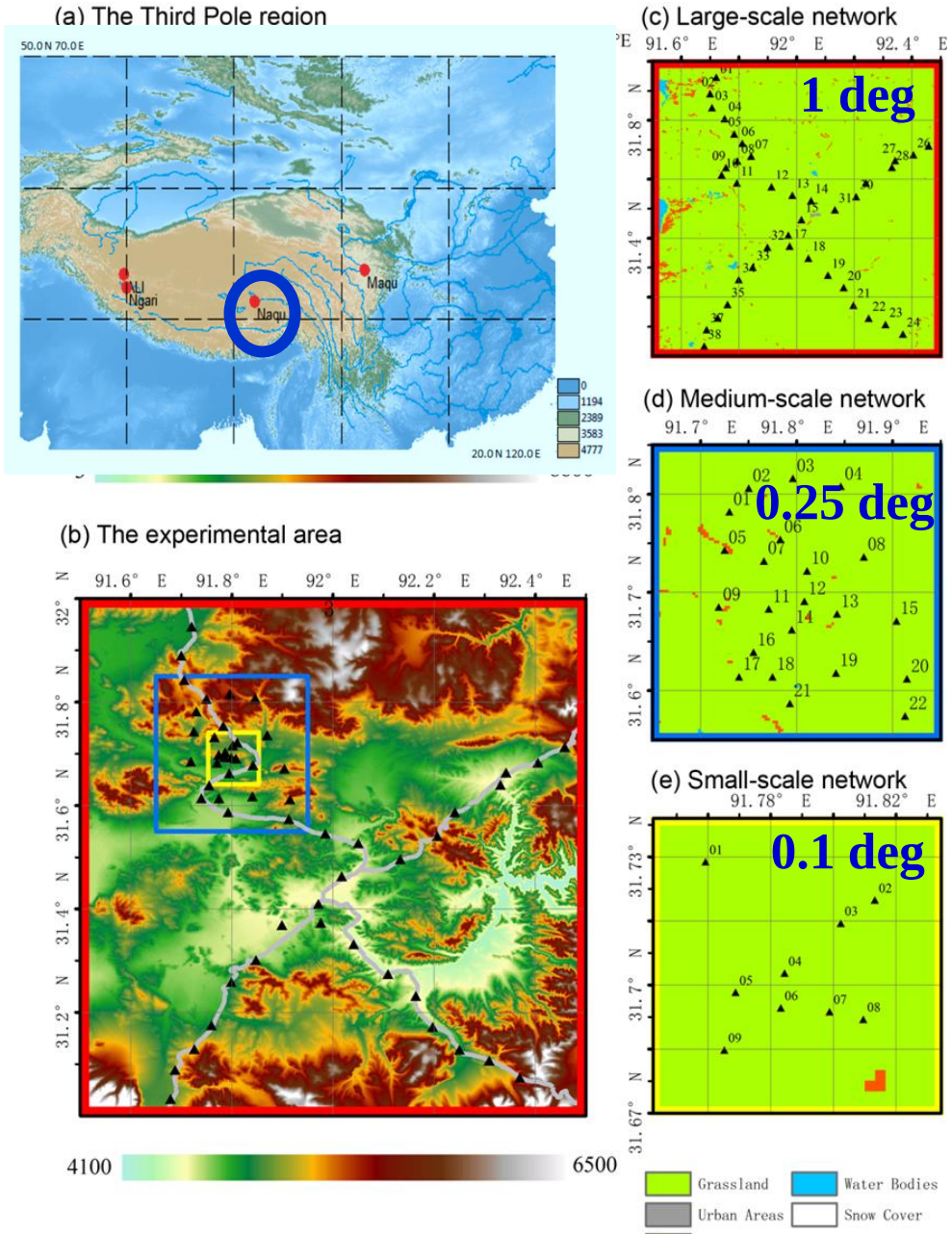
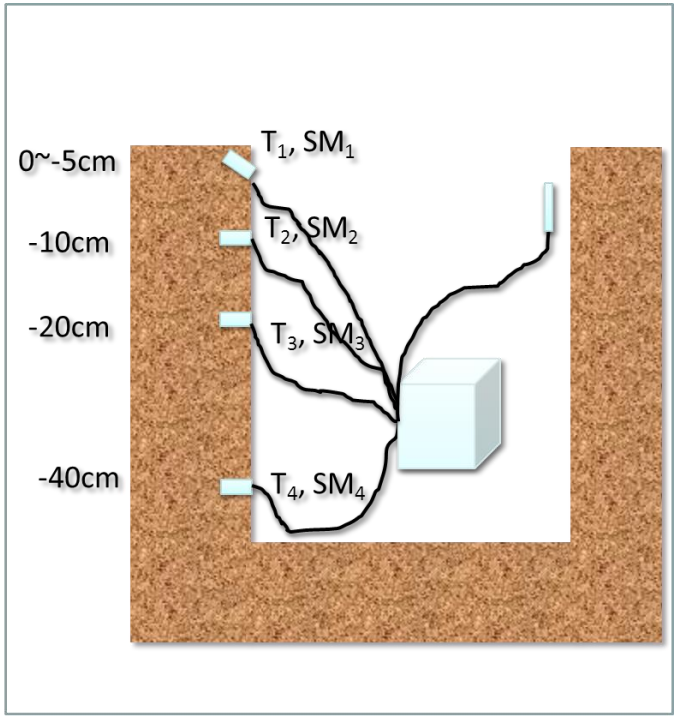
The Tibetan Plateau observatory of plateau scale soil moisture and soil temperature



(Su et al., 2011 HESS; Yang et al., 2013)

Naqu multi-scale soil moisture and temperature network in CTP



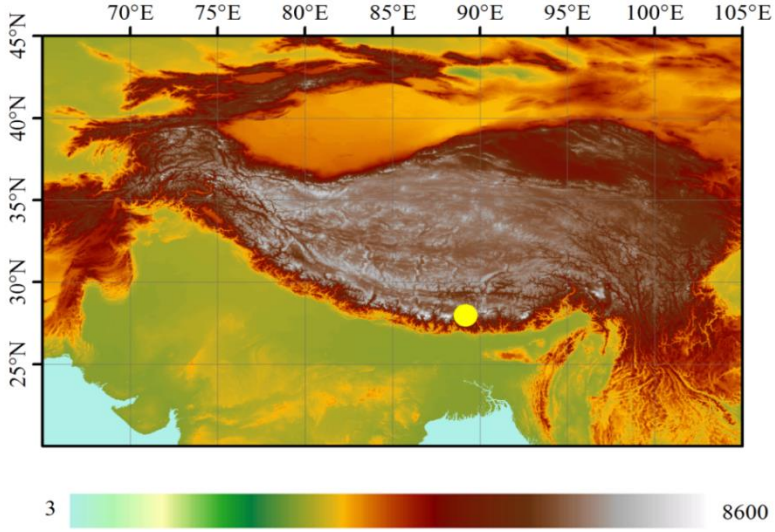


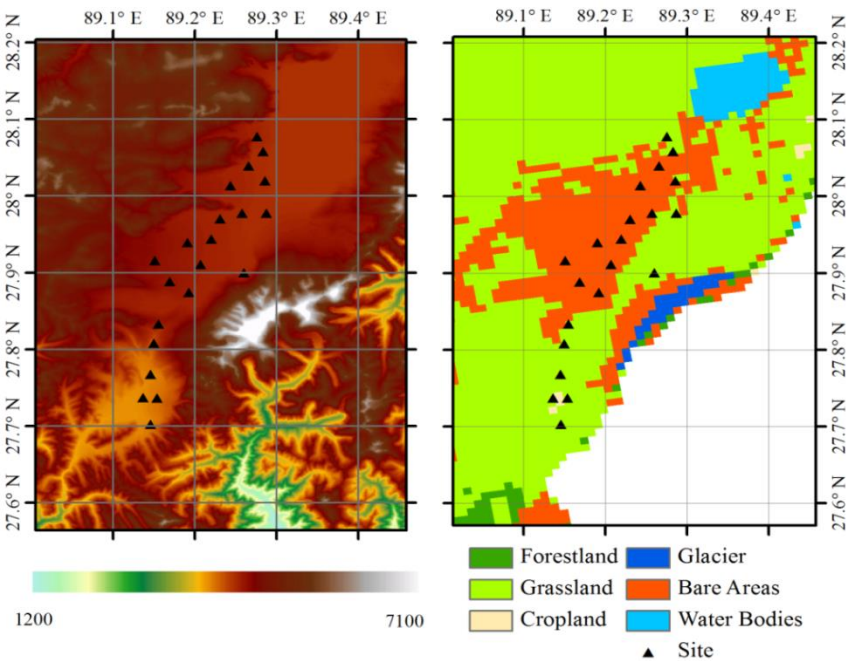
6

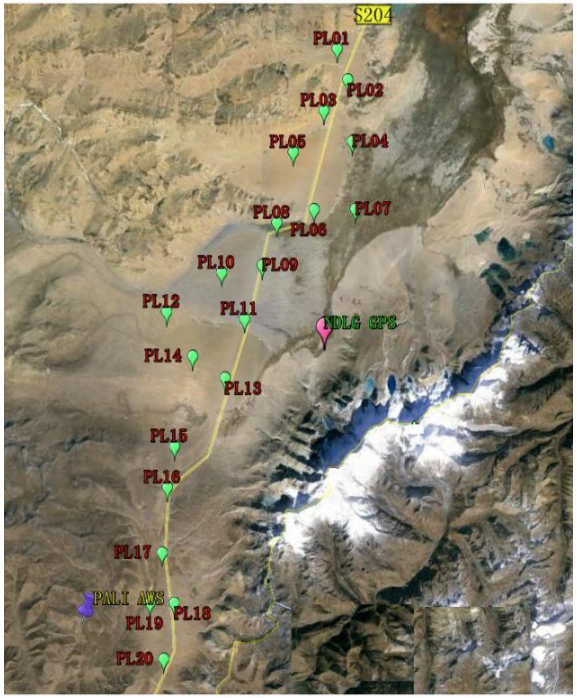
- Above 4500 m a.s.l.
- Sensor calibrated,
- Data accessible through ISMN

(Yang et al., 2013 BAMS)

Pali soil moisture and temperature network in STP



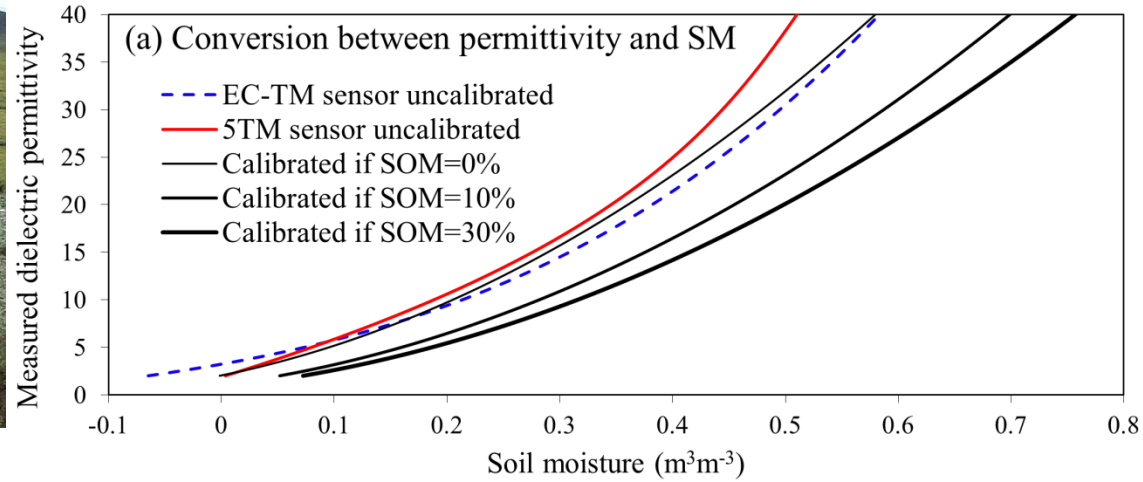


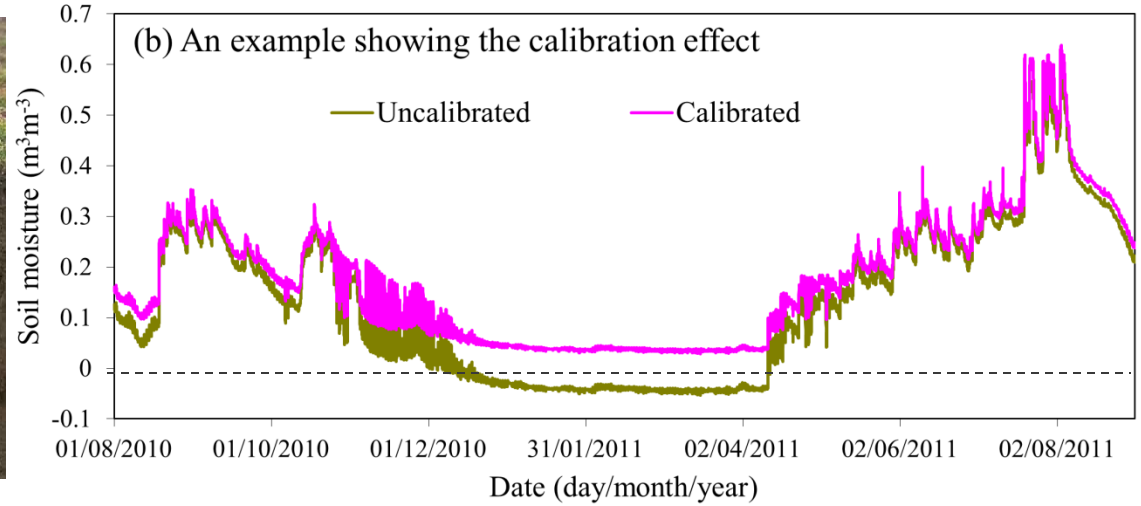


- Setup in June 2015
- 25 stations
- 4 levels at each station :

  0-5, 10, 20, 40 cm
- Soil properties are measured

Sensor calibration according to soil texture and SOC
Based on relationship established by laboratory experiments

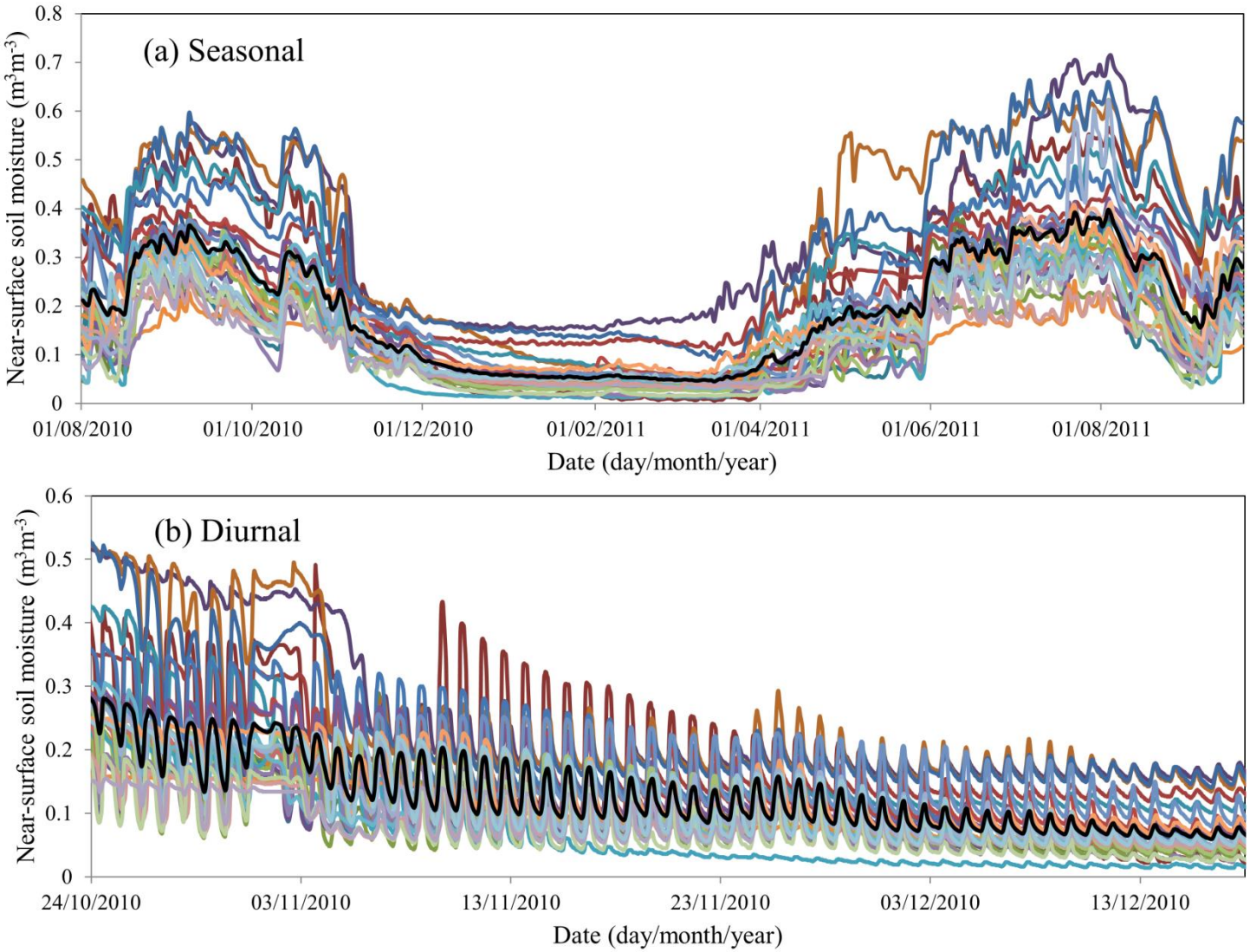




very high soil organic matters content

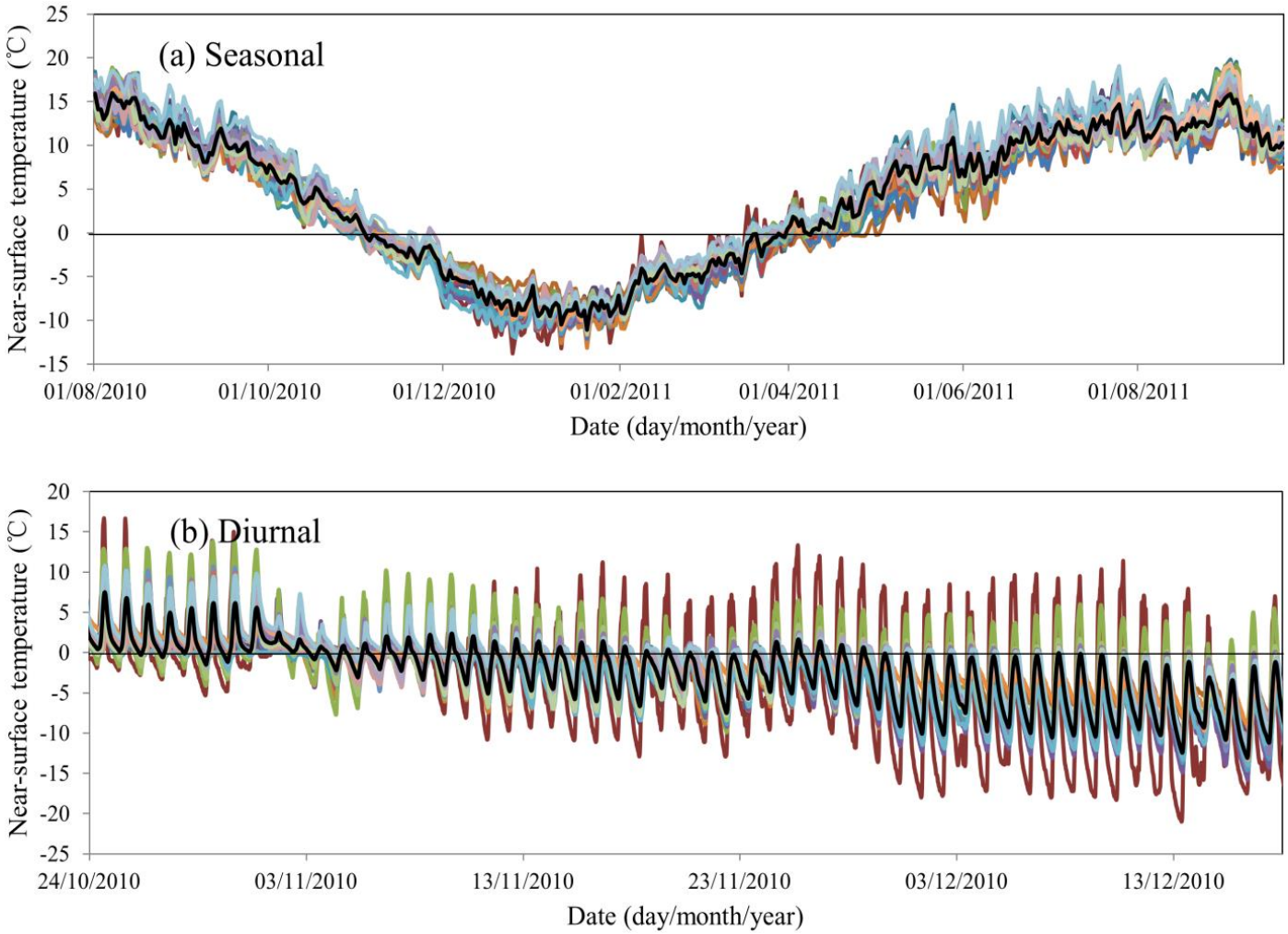
(Yang et al., 2013 BAMS)

Observed soil moisture



(Yang et al., 2013 BAMS)

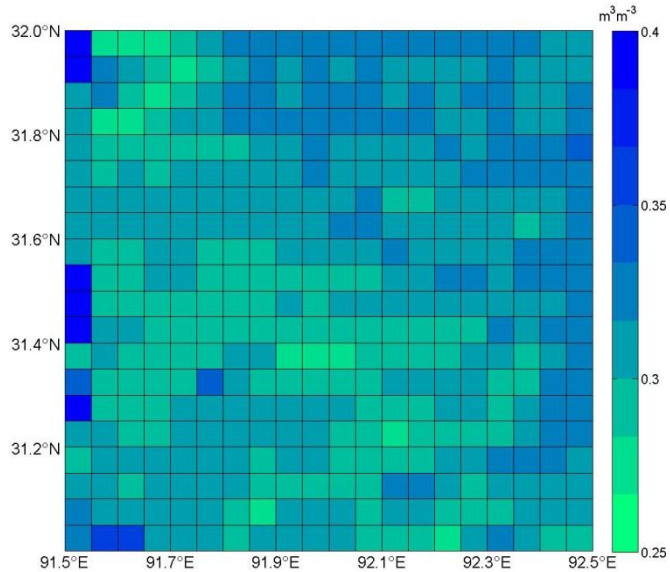
Observed soil temperature

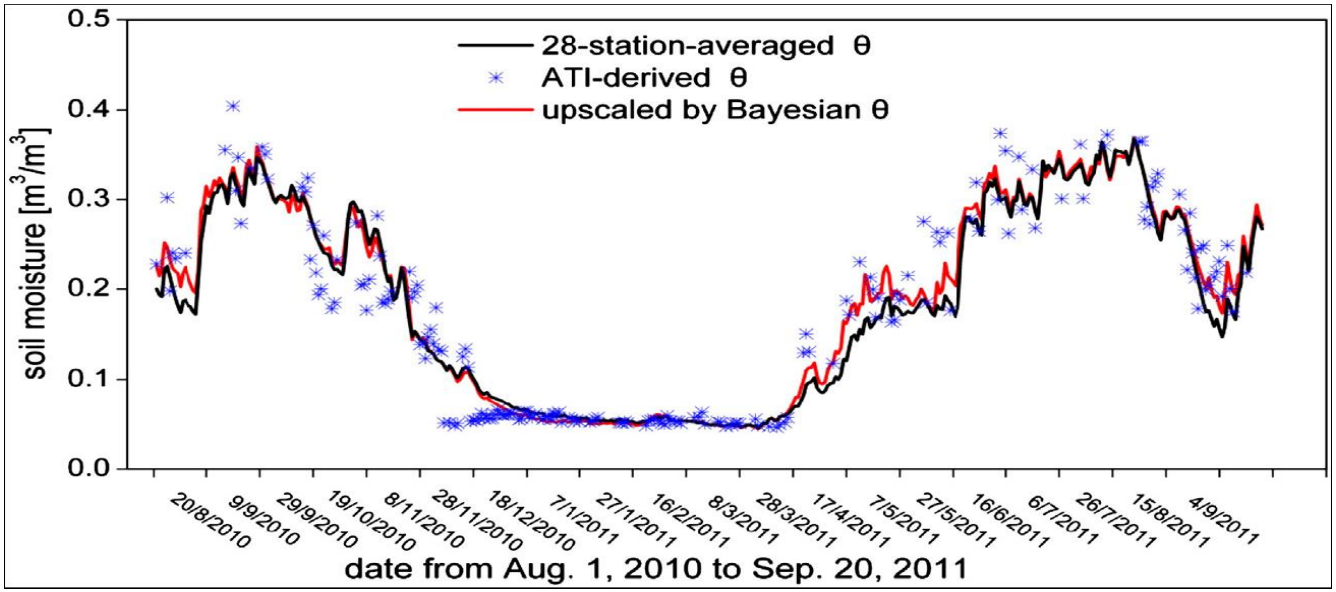


(Yang et al., 2013 BAMS)

Upscale from points to pixels by introducing MODIS LST

Soil moisture distribution obtained by upscaling





(Qin et al., 2013RSE)

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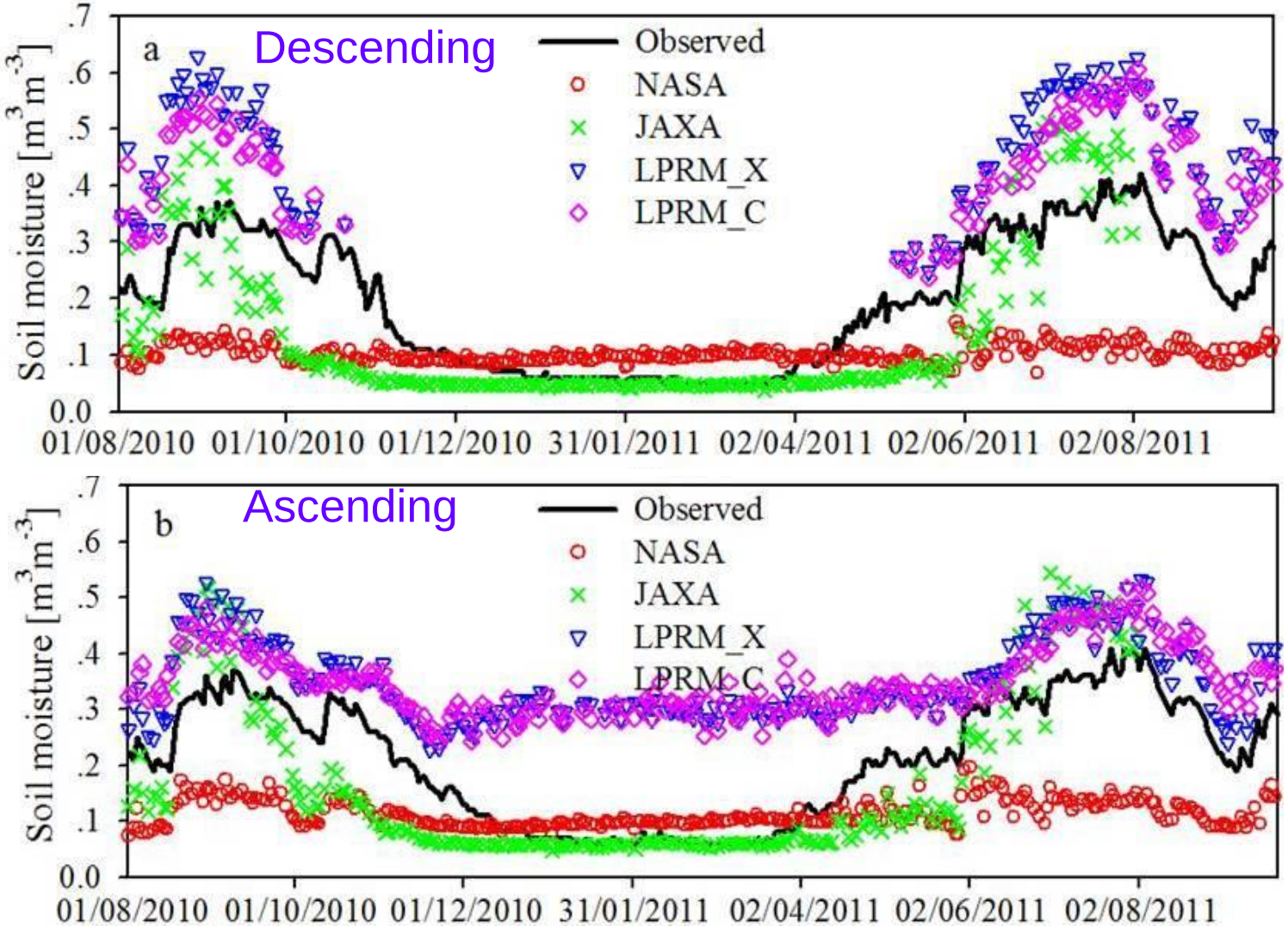
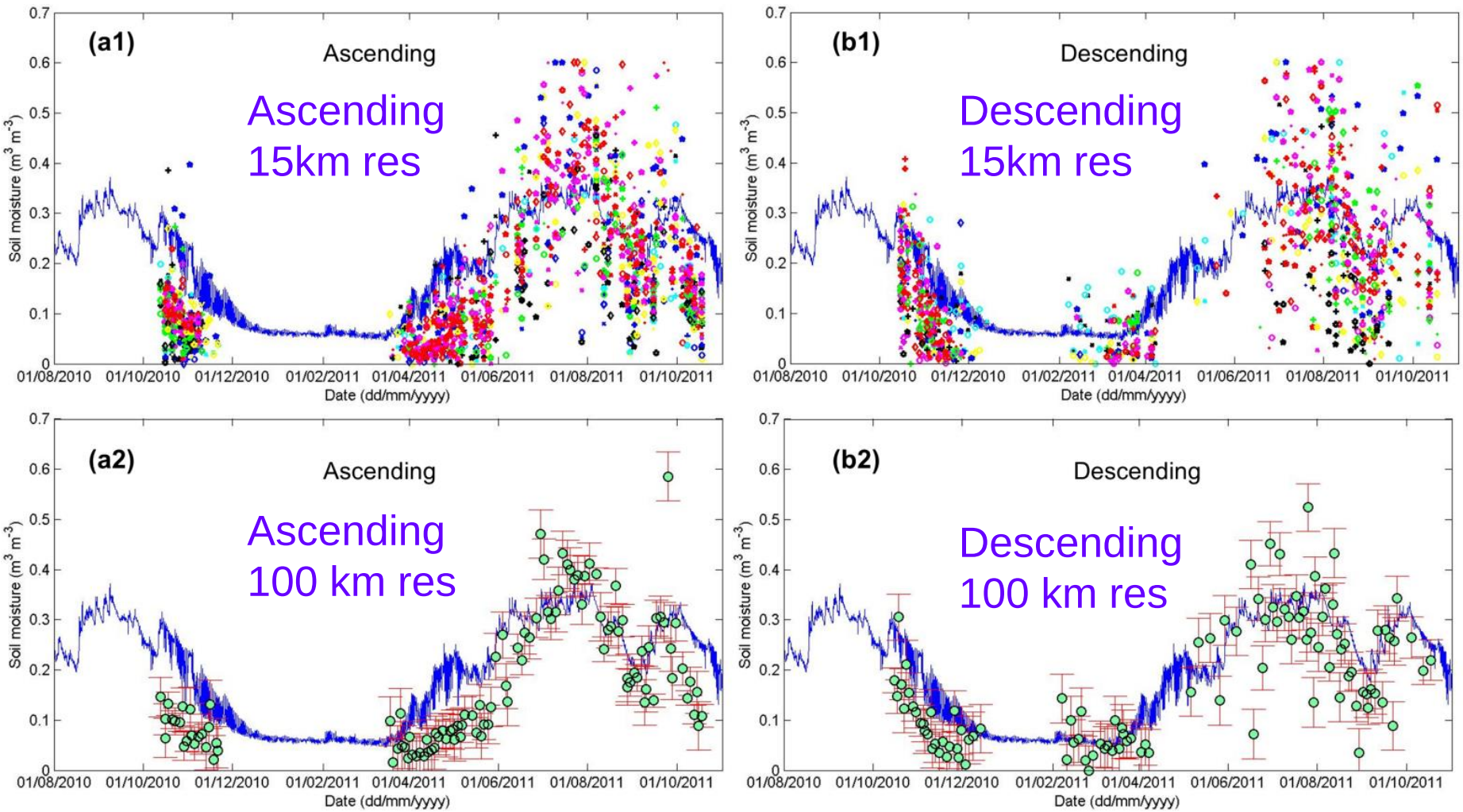
Evaluation: four AMSR-E satellite products have large biases, either underestimated or over-estimated



(Chen et al., 2013 JGR)

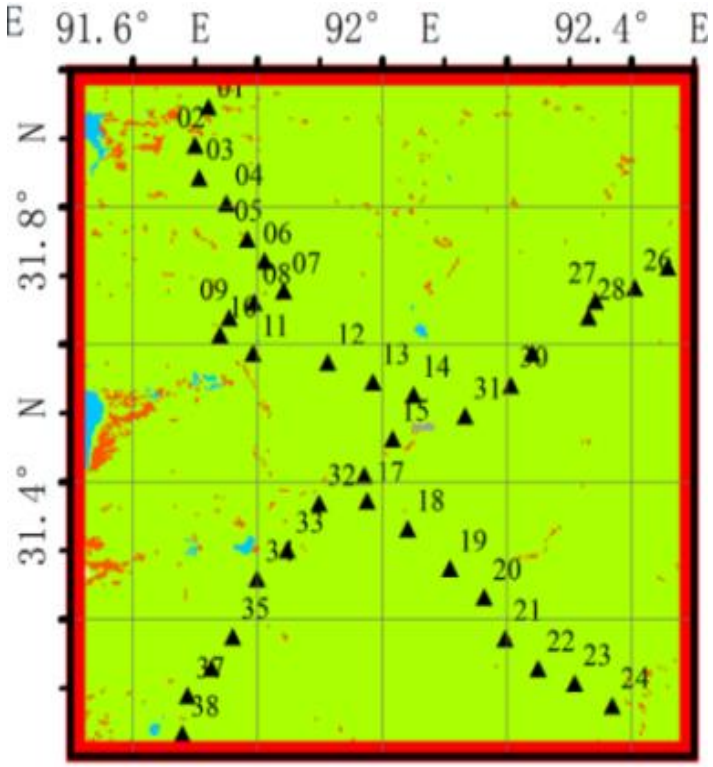
Evaluation: The accuracy of SMOS L2 SM data is scale-dependent; higher accuracy at coarser resolution



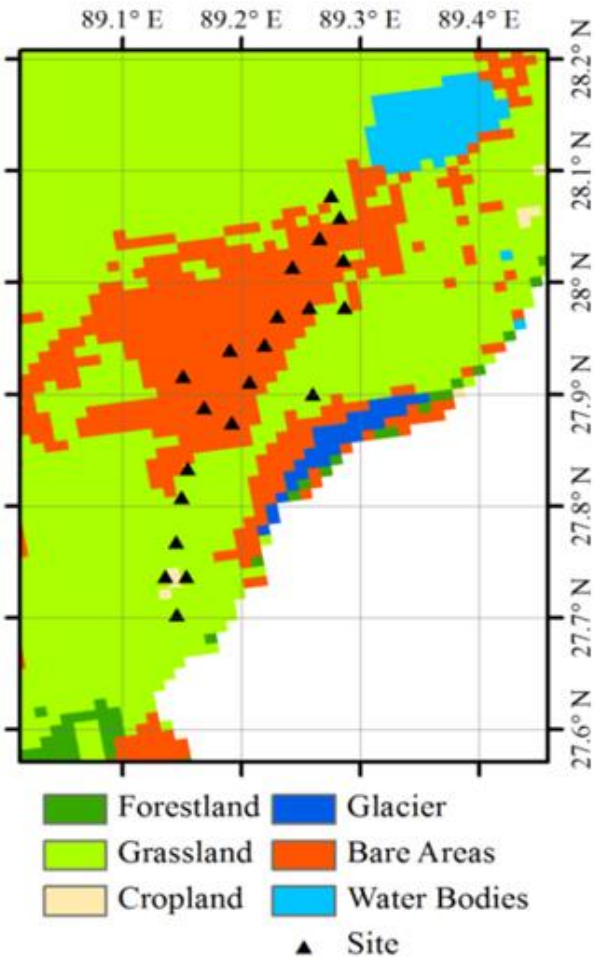
(Zhao et al., 2014 RSE)

SM Evaluation within Naqu and Pali networks, 2015

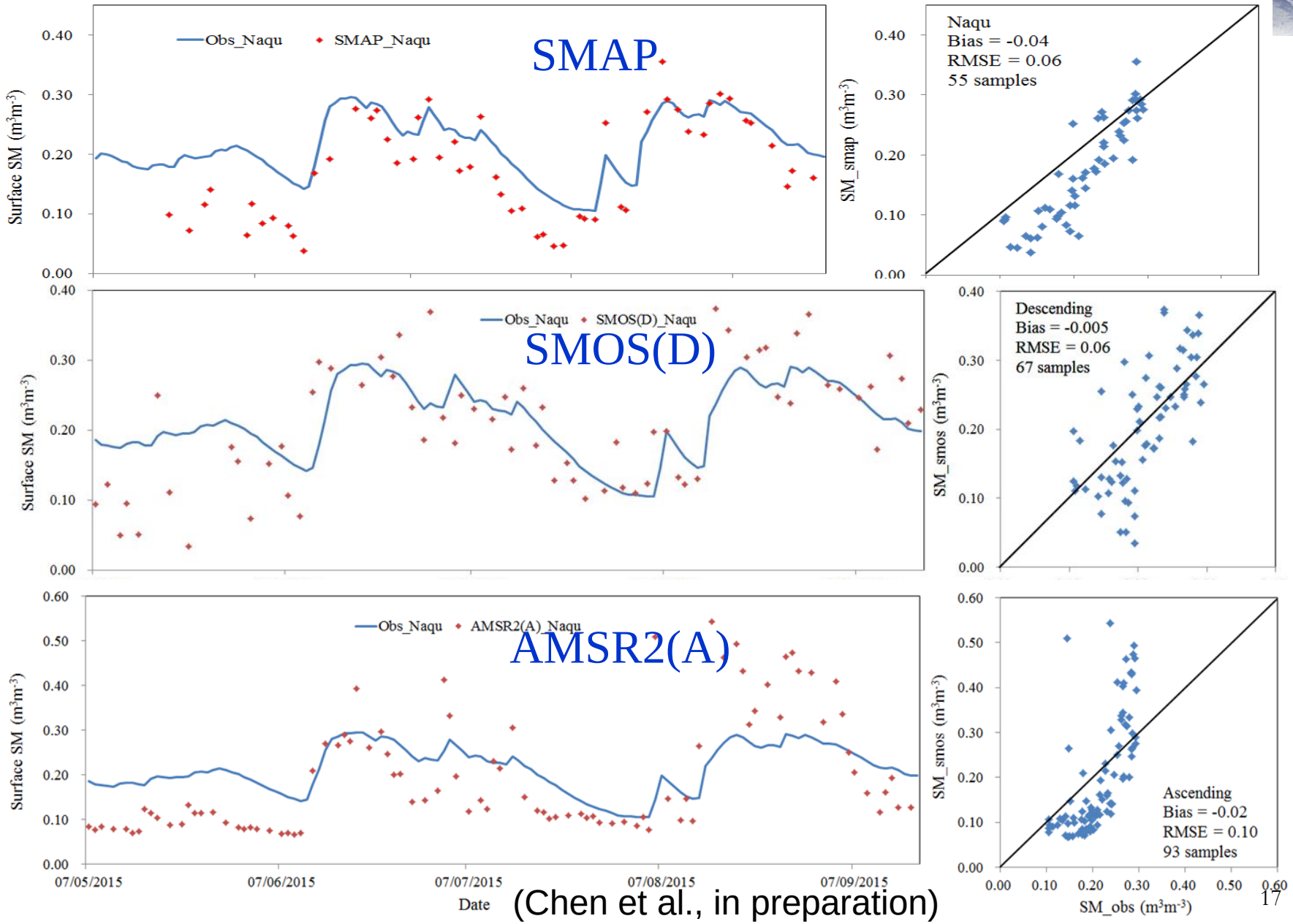
Naqu



Pali

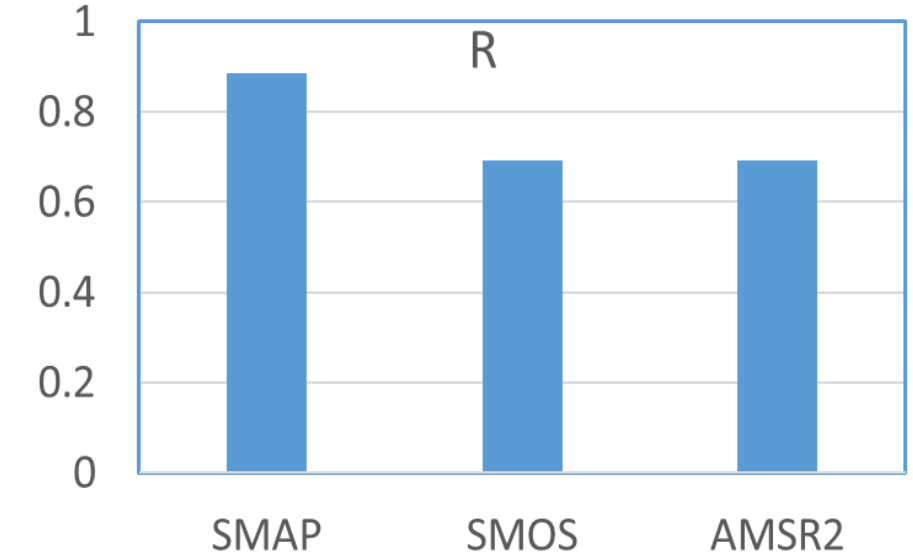


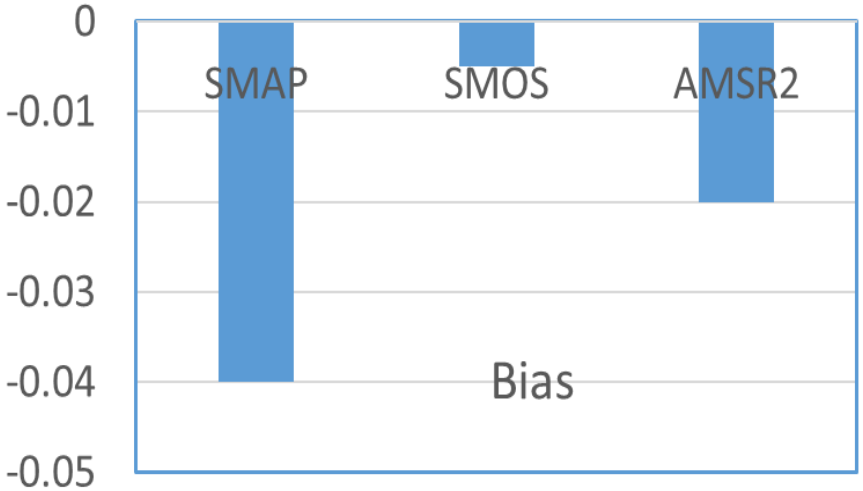
Evaluation in Naqu

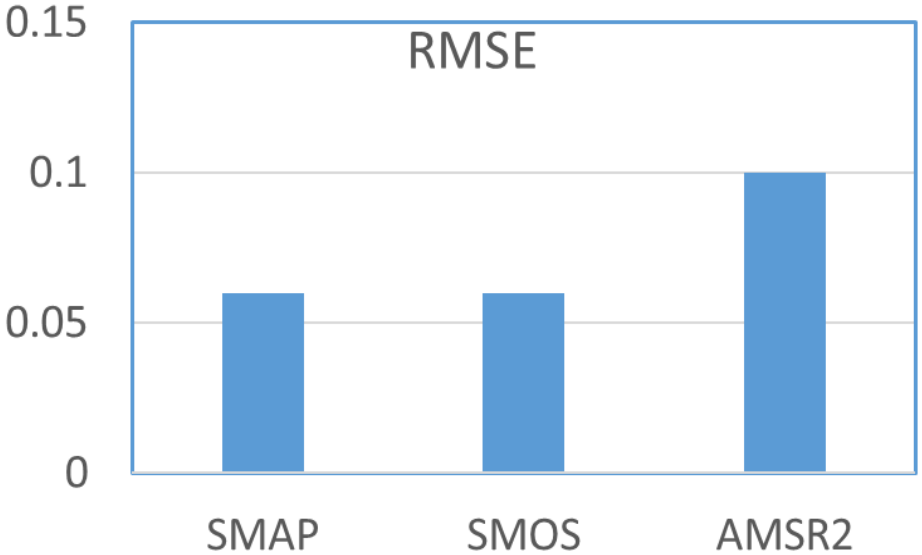


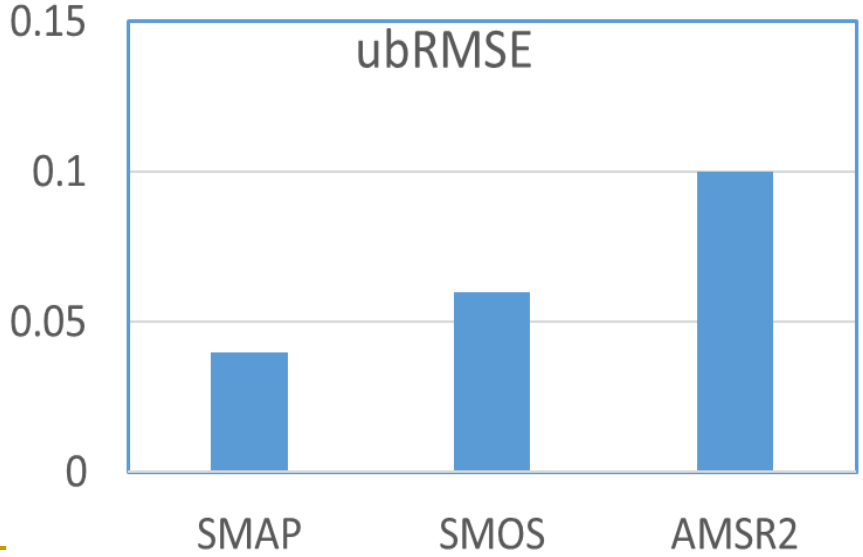
(Chen et al., in preparation)

Evaluation in Naqu



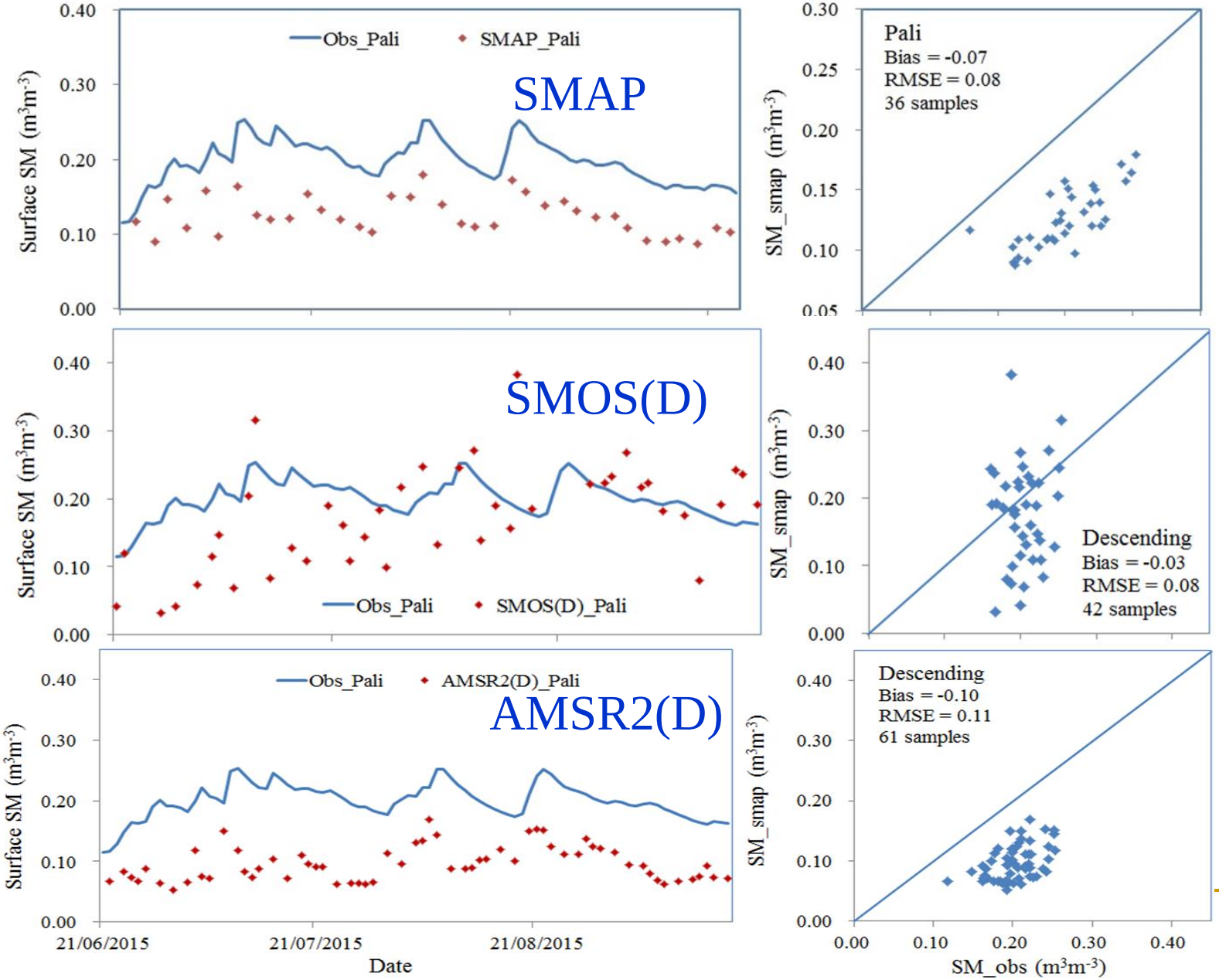




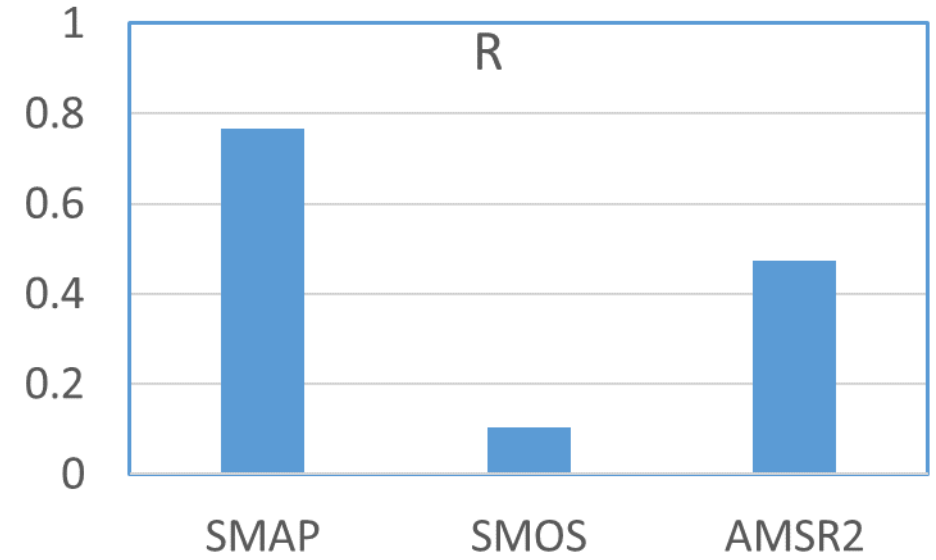


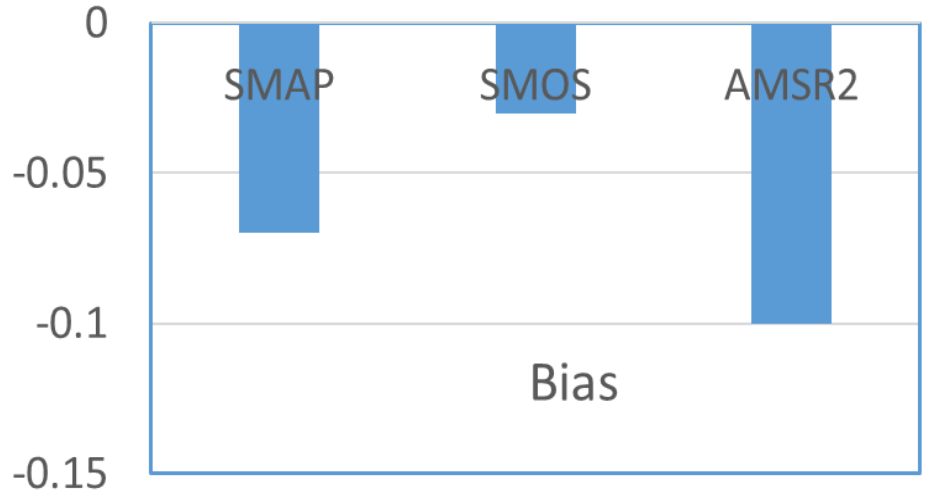
(Chen et al., in preparation)

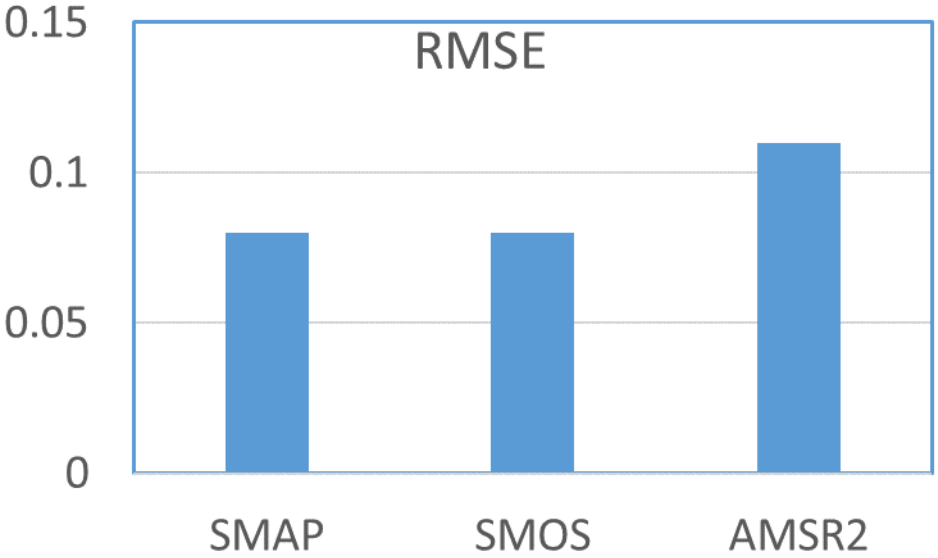
Evaluation in Pali

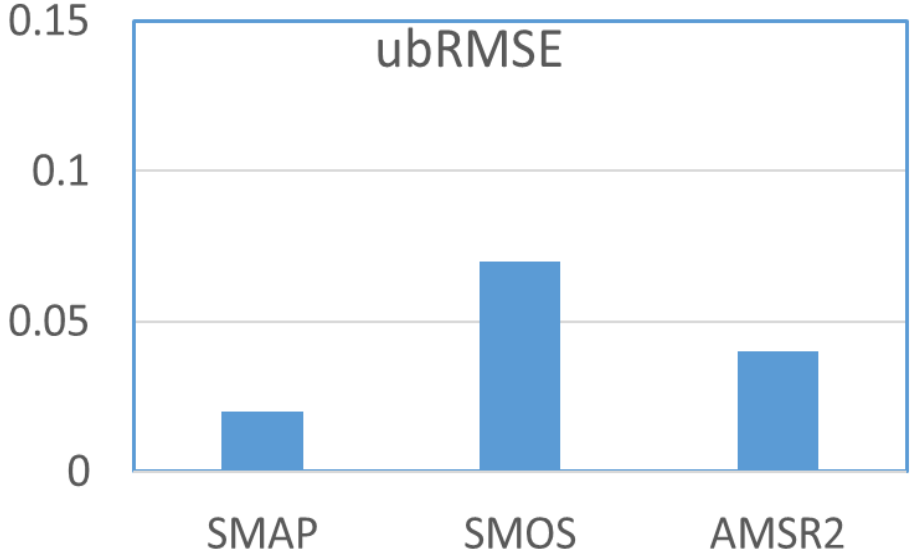


Evaluation in Pali





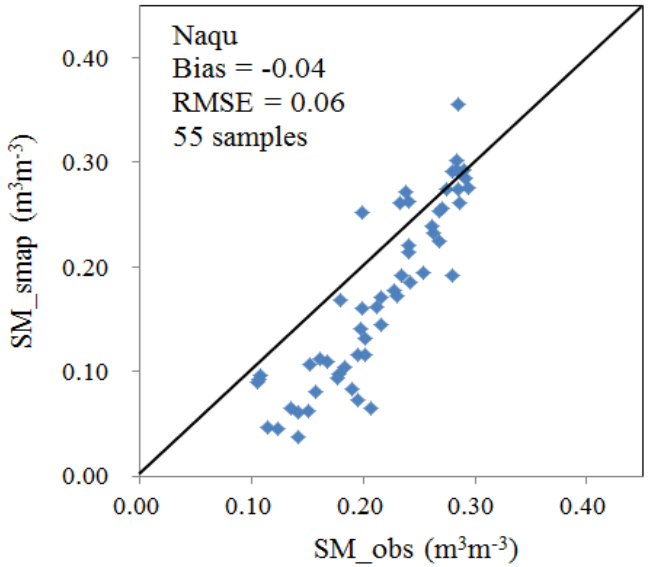


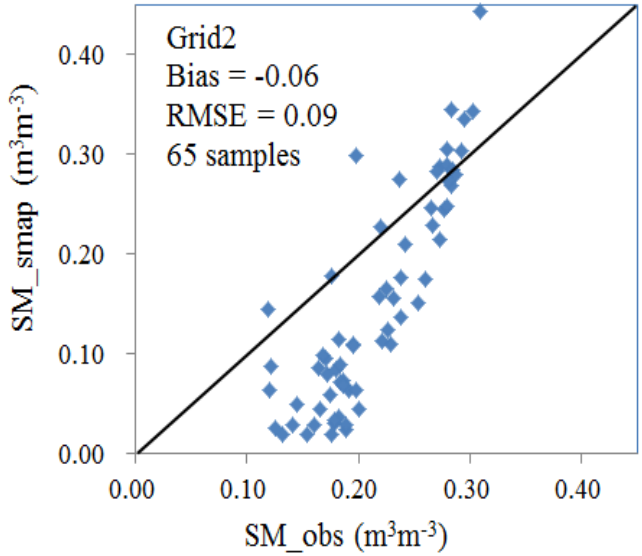


(Chen et al., in preparation)

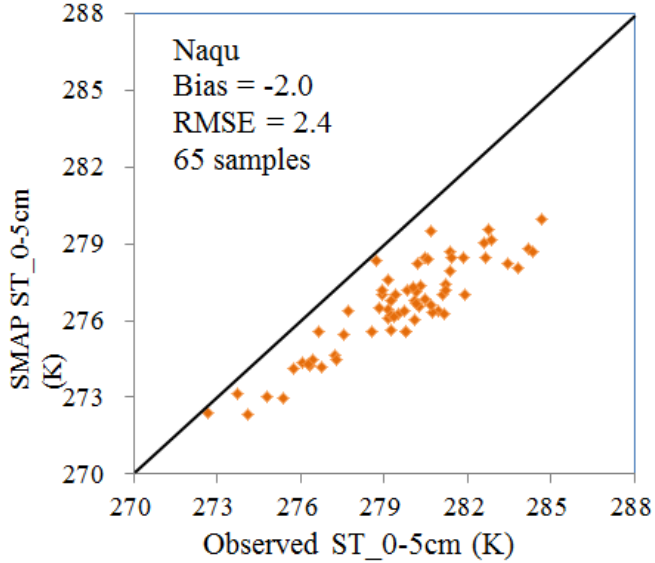
Discussion: the under-estimation of GEOS-5 effective ST leads to under-estimation of SMAP SM in Naqu area

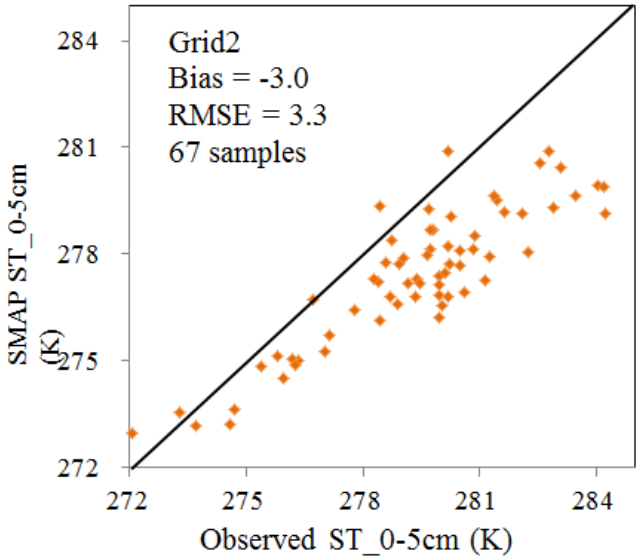
Naqu SM 0-5cm





Naqu ST 0-5cm





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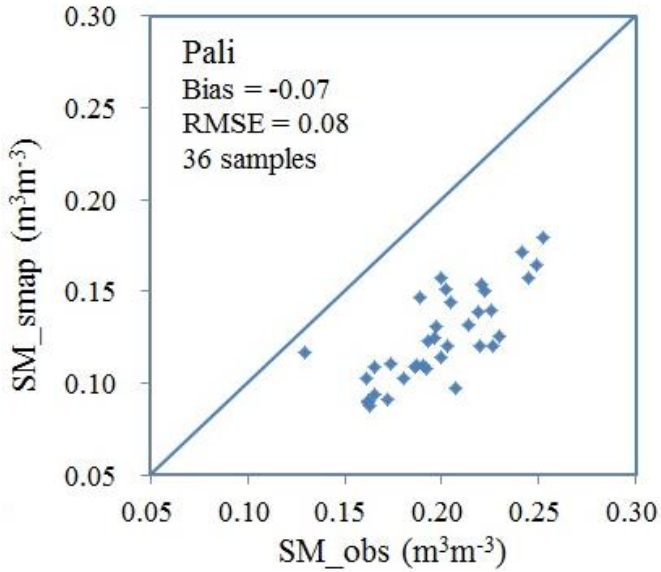
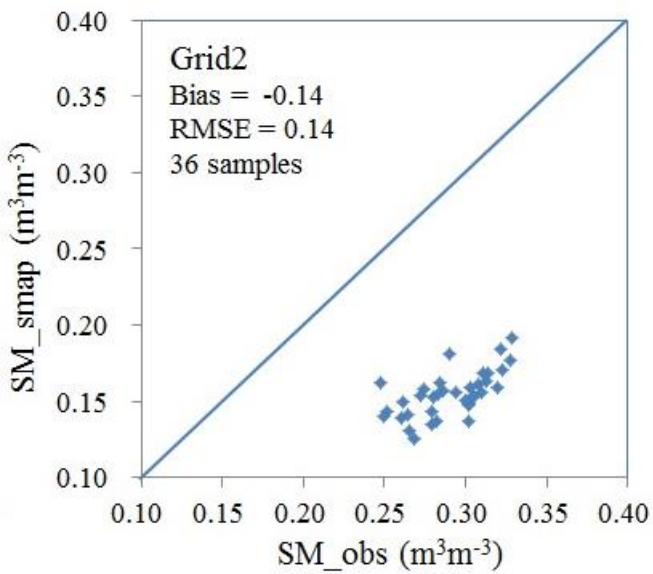
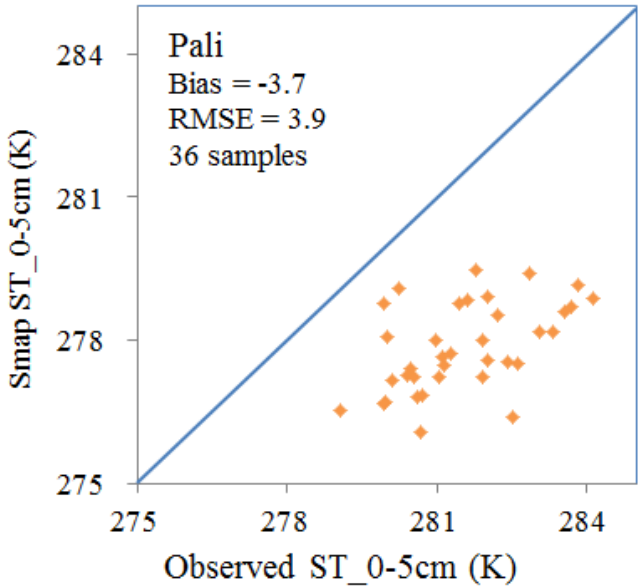
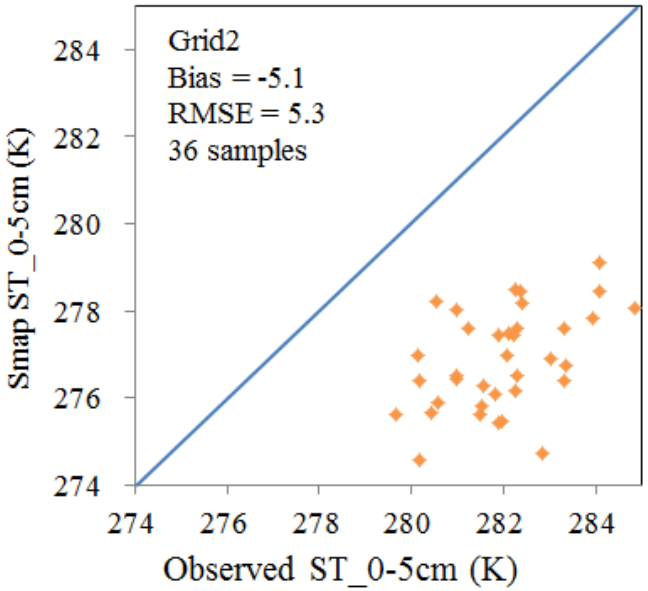
Pali SM 0-5cm





Pali ST 0-5cm





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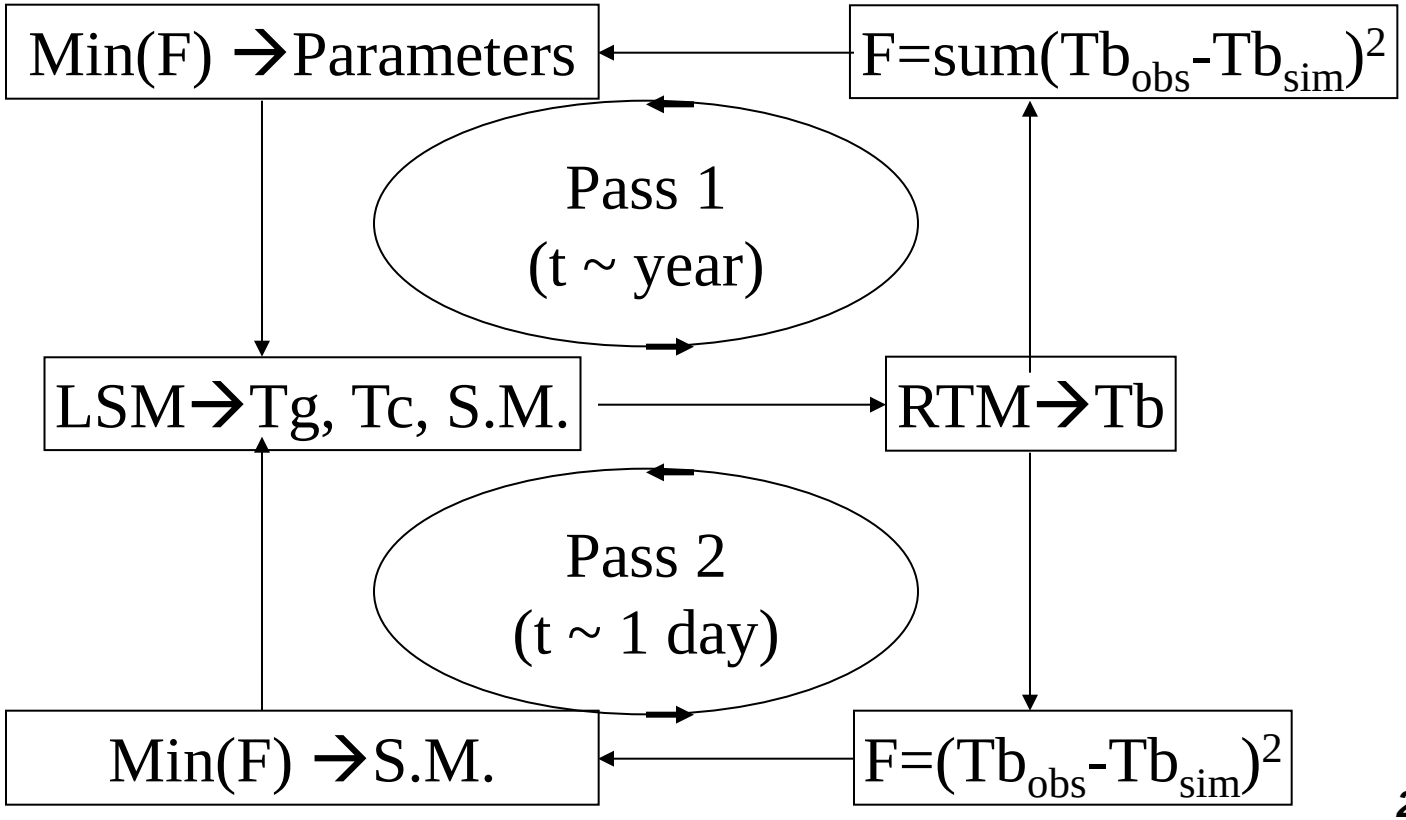
Dual-pass (calibration + assimilation) Algorithm

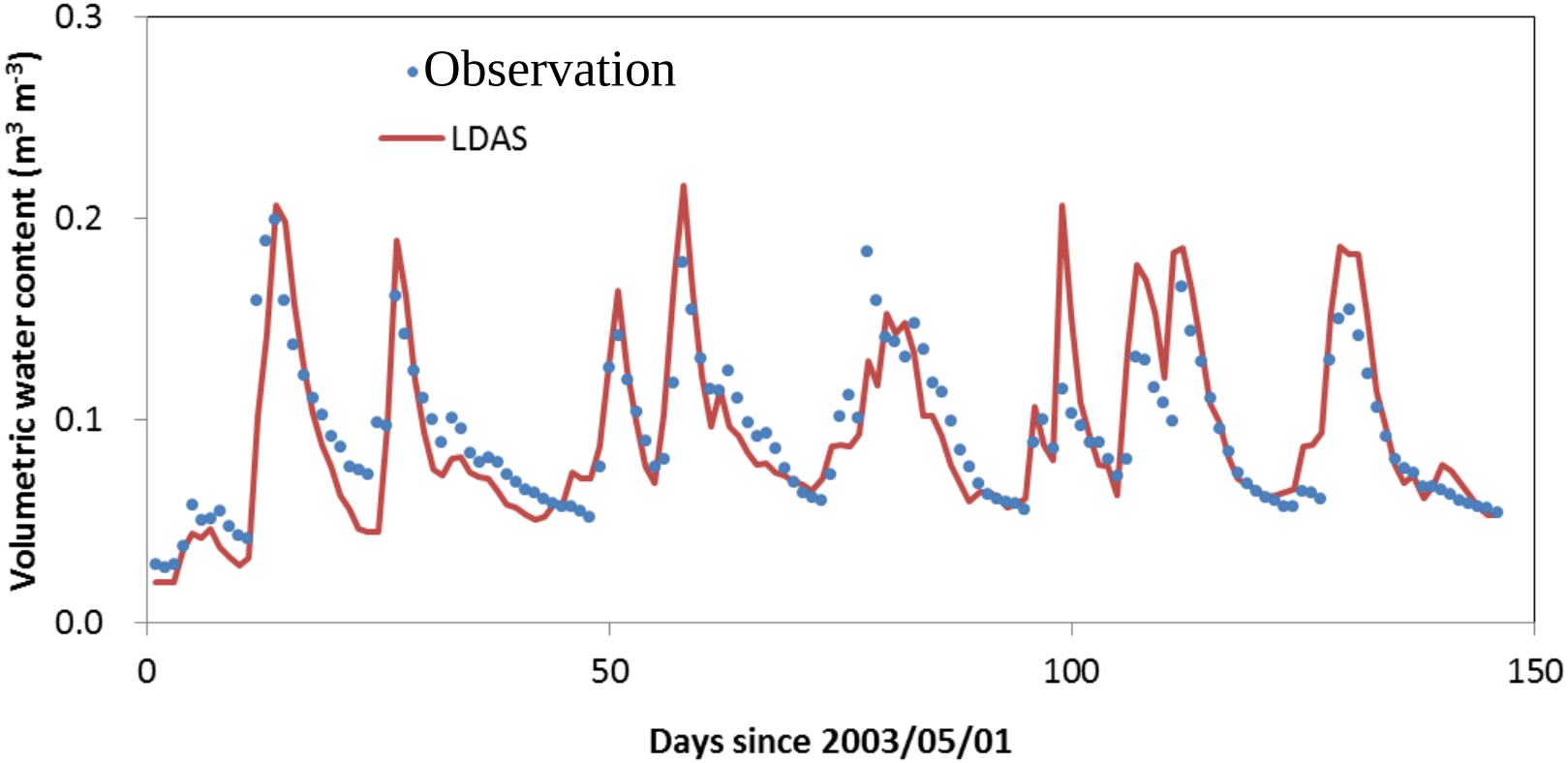
- Pass 1: Optimize parameter values in a long-term window (~year)
  - Tuning parameters with satellite data
  - time-consuming but only conduct once.
- Pass 2: Estimate land state in a short-term window (daily)



(Yang et al., 2007JMSJ; 2009 JHM)

Evaluate: LDAS output against the Mongolian network (LAI<0.5)

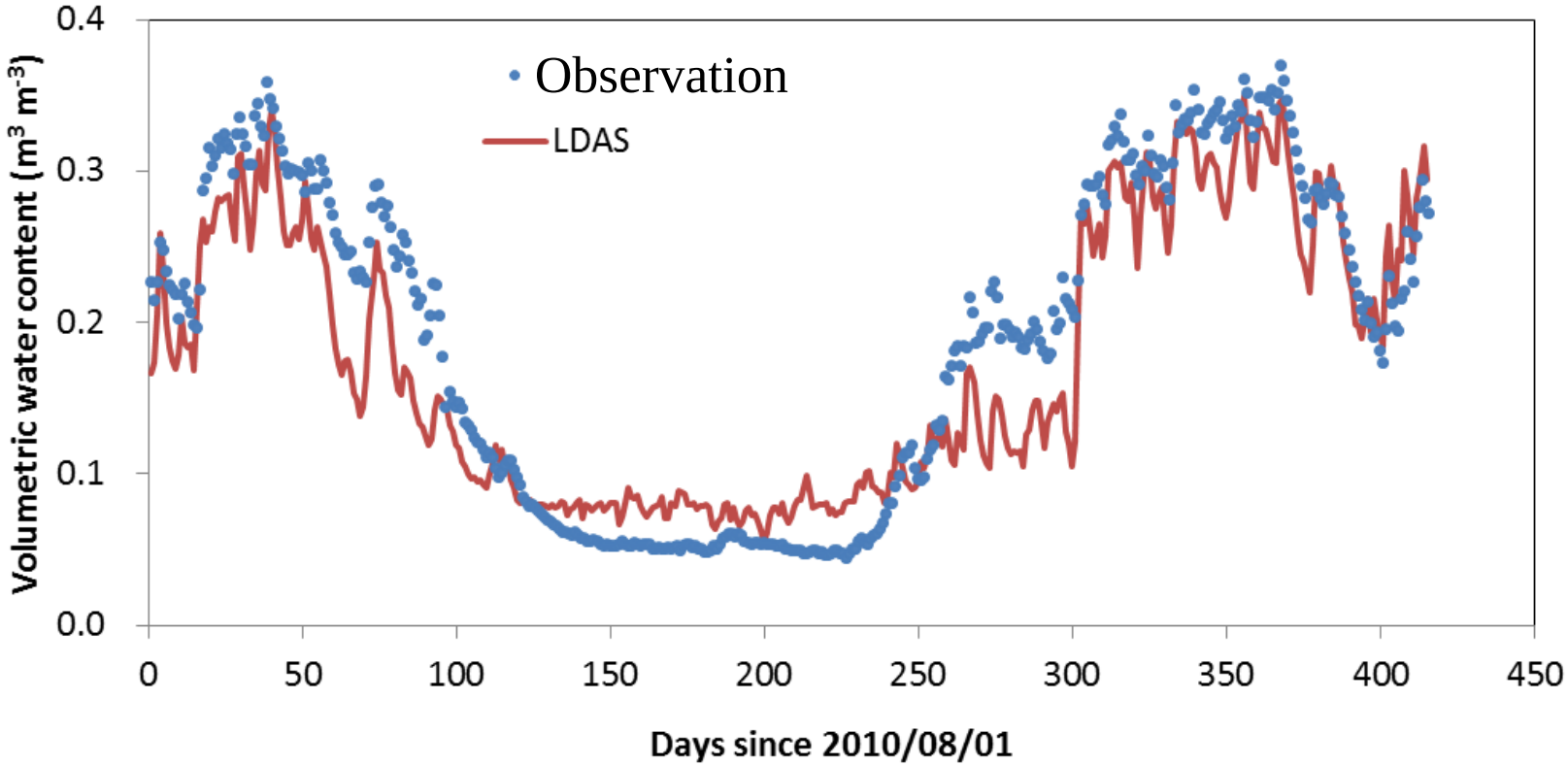
Assimilate AMSR-E TBv data (6.9, 10.7, 18.7 HGz) with TBv-based auto-calibration, driven by GLDAS forcing



(Yang et al., in preparation)

Evaluate: LDAS output against the CTP-Naqu Network (LAI<1)

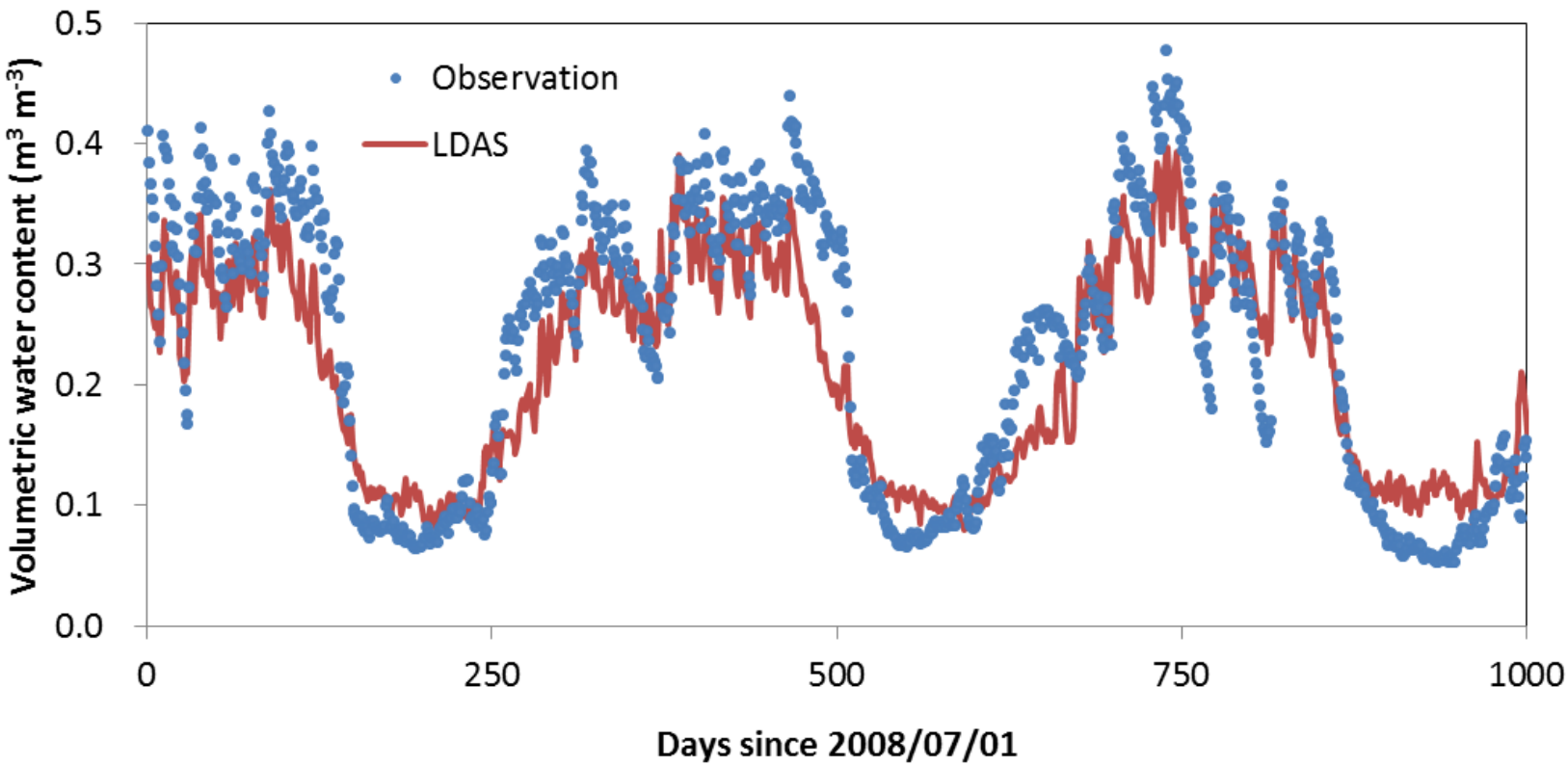
Assimilate AMSR-E TBv data (6.9, 10.7, 18.7 HGz) with TBv-based auto-calibration, driven by CMFD (China Met. Frocing data)



(Yang et al., in preparation)

Evaluate: LDAS output against the ETP-Maqu network (LAI <2.5)

Assimilate AMSR-E TBv data (6.9, 10.7, 18.7 HGz) with TBv-based auto-calibration, driven by CMFD (China Met. Frocing data)



(Yang et al., in preparation)

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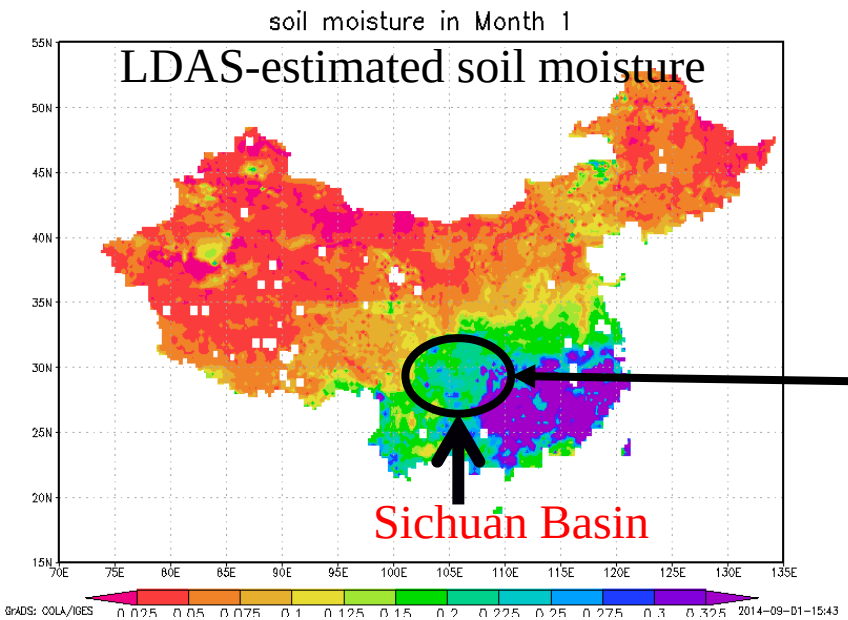
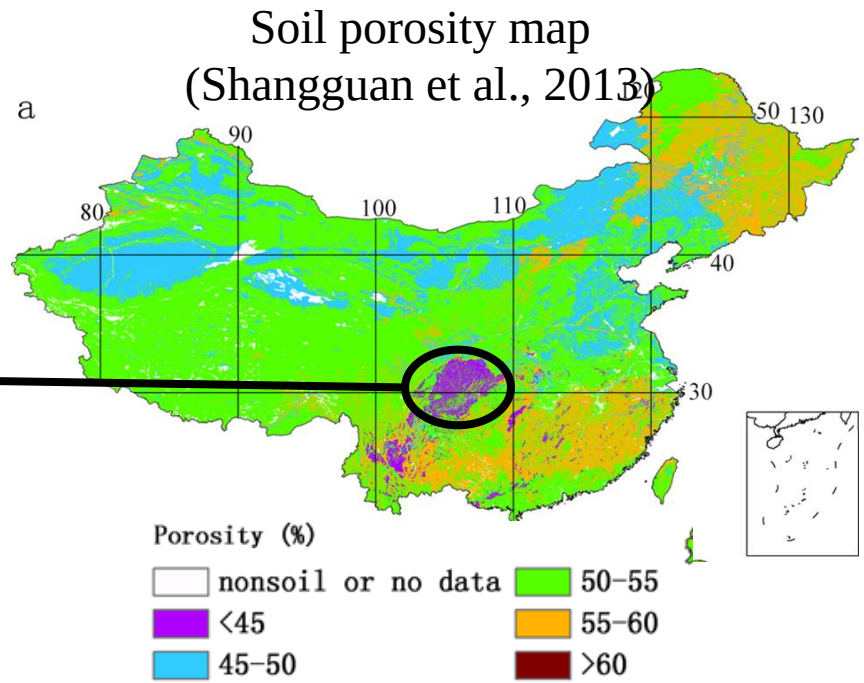
LDAS soil moisture product for China mainland (dx=0.25 deg., dt=daily, 2002-2011). The estimated soil moisture seems reasonable and produces some unique regional feature

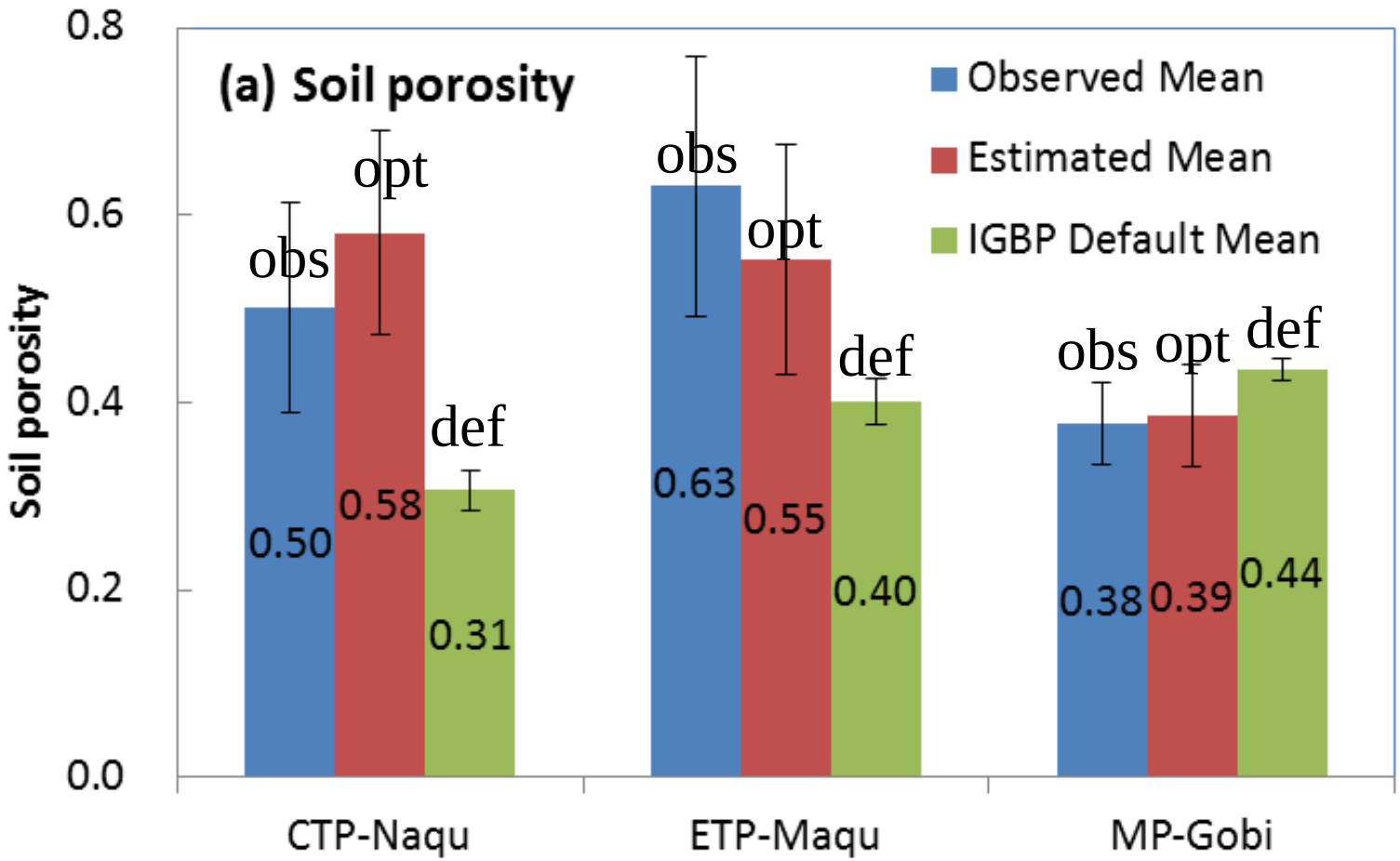




Precipitation amount is high in Sichuan Basin but LDAS yields low soil moisture values

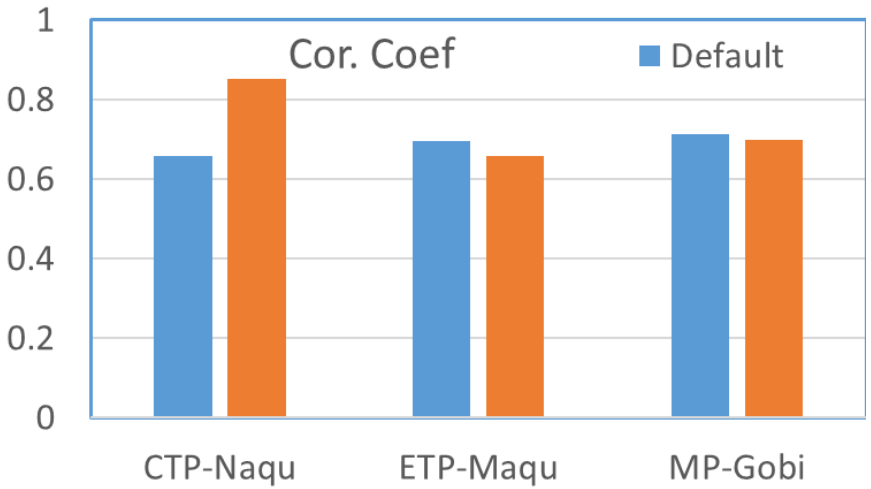
The soil in Sichuan Basin is a kind of purple soil and has low porosity.

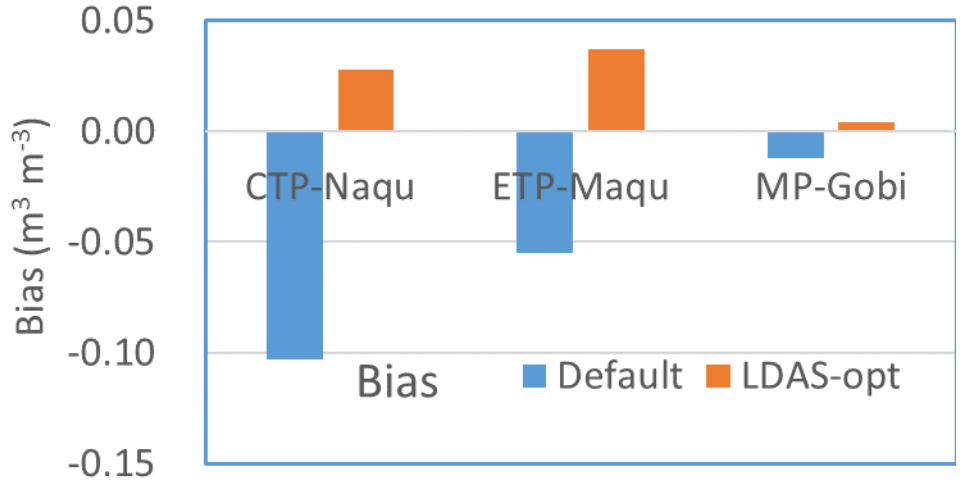
LDAS-estimated soil porosity (the most important parameter for soil moisture) is closer to observed one than IGBP global soil parameter data

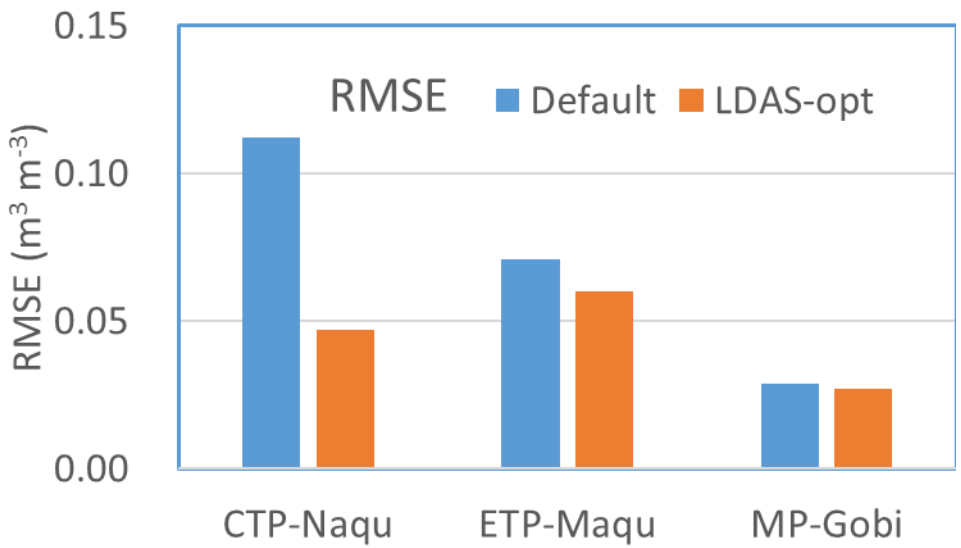


(Yang et al., 2016 JoH)

Comparison between two LSM simulations with default / LDAS-opt parameter values







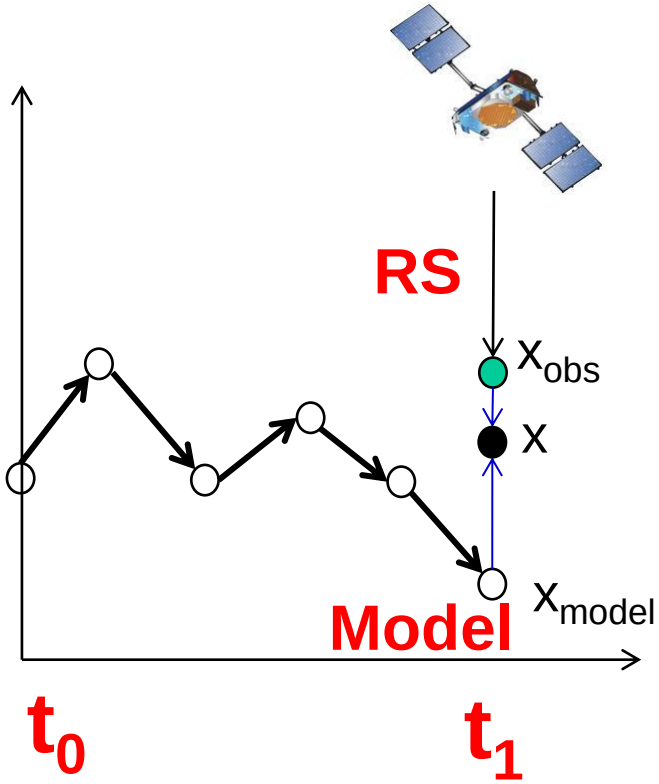
Summary

- Four soil moisture measuring networks are available on the Tibetan Plateau, covering different soil moisture regimes.
- SMAP (less ubRMSE) and SMOS (less bias) soil moisture products have better accuracy than AMSR for this region.
- Assimilating microwave data with auto-calibration can improve soil moisture estimate.
- LDAS-estimated soil parameter values can effectively improve soil moisture simulation. This provides a basis for land model calibration at grid-scale.

Thank you for your attention！

How to understand the difference between observation and model?

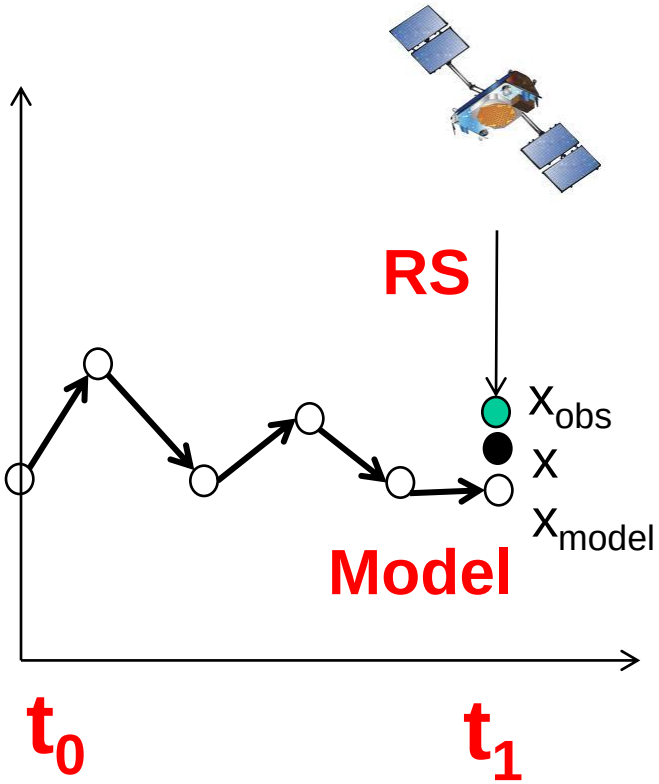
General data assimilation



$$x = x_{model} + \lambda (x_{obs} - x_{model})$$

λ depends on both model and observation error co-variances, whose estimation is very difficult and is an essential issue of DA.

Our speculation



$$x = x_{model} + \lambda (x_{obs} - x_{model})$$

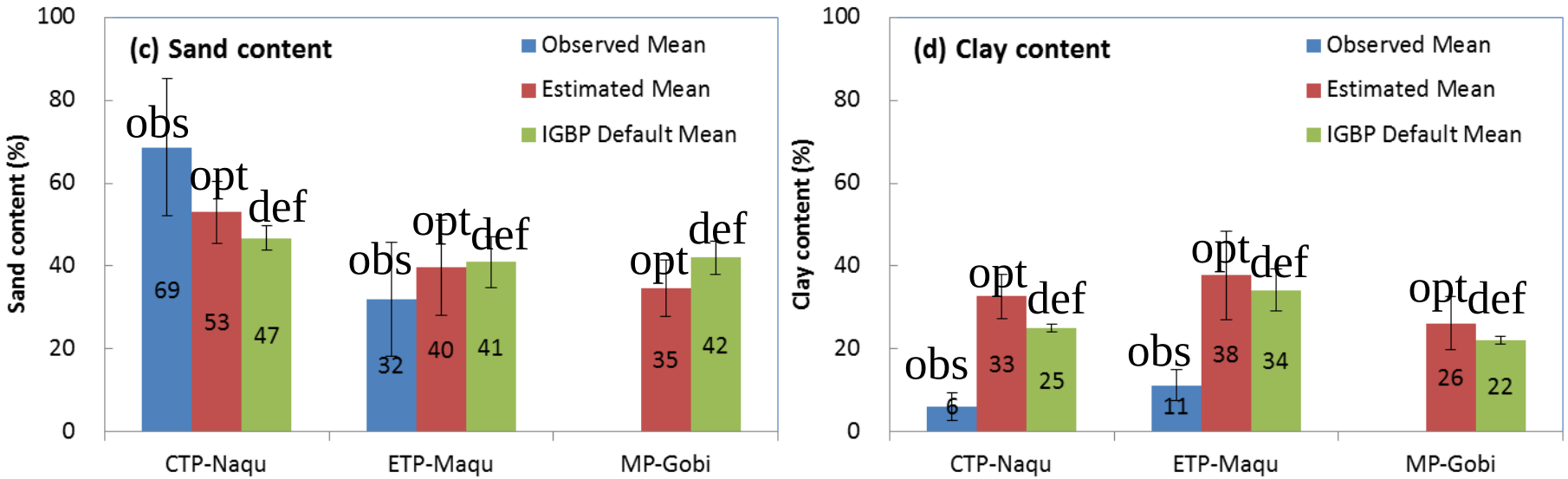
The difference is due to unsuitable parameter specification. If it is minimized through parameter tuning, λ is no more important.

In this LDAS

- AMSR-E TB (C-, X-, and Ku-band) data are assimilated into LSM through variational method, with Q-h as the observation operator and SiB2 as the model operator.

- The AMSR-E data can only provide limited land information, so we estimate sensitive soil parameters (soil porosity, soil texture) and microwave parameters (surface roughness, vegetation optical parameter)

However, the LDAS-estimated soil texture is not better than IGBP global soil parameter data.



The estimated soil texture values are effective ones instead of truth ones, because they are used for estimating soil hydraulic and thermal properties through empirical pedotransfer functions.

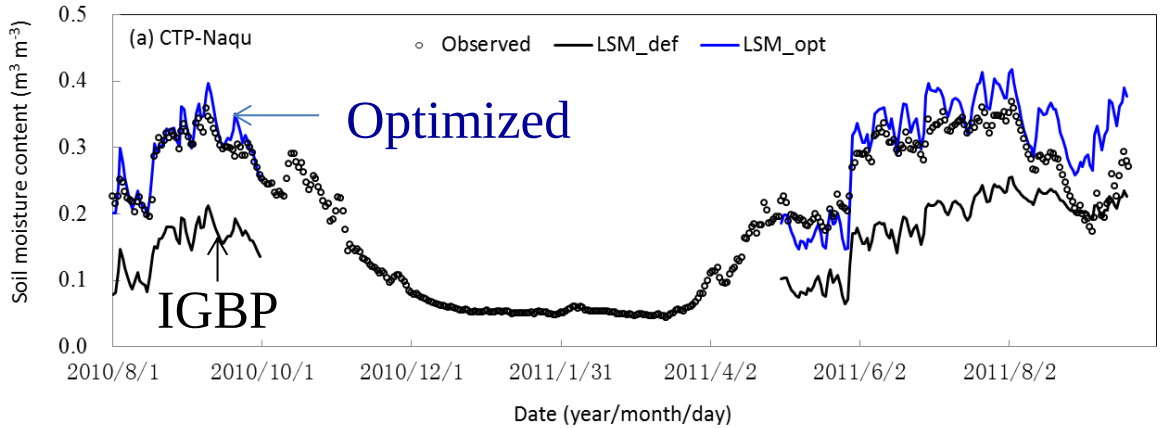
(Yang et al., 2016 JoH)

Simulated SM with IGBP data and with LDAS-optimized data

CTP-Naqu

IGBP : underestimate

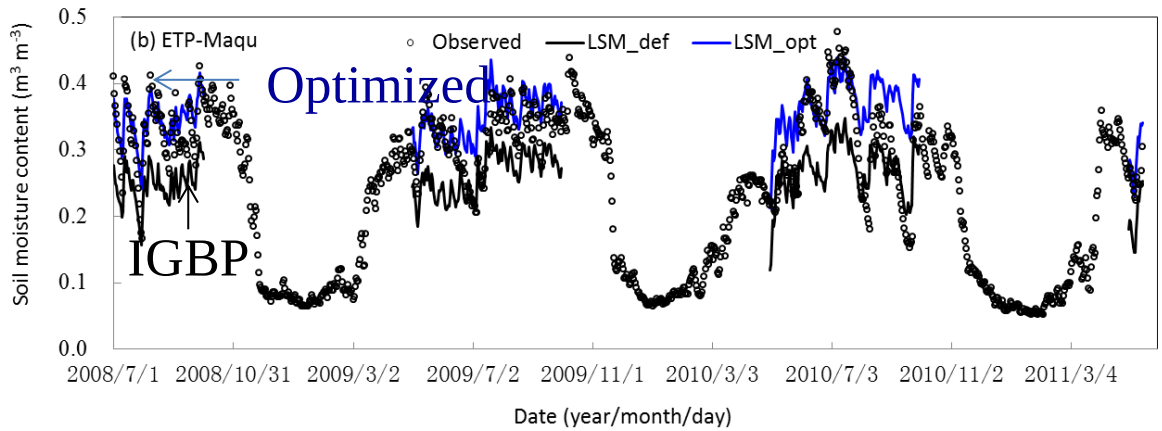
Estimated: agreeable



ETP-Maqu

IGBP : underestimate

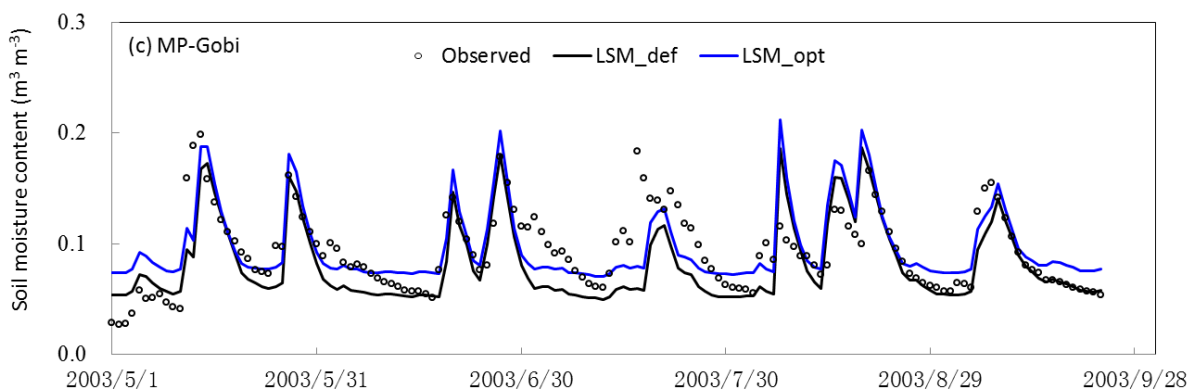
Estimated: reasonable



Mongolia

IGBP : agreeable

Estimated: agreeable



(Yang et al., 2016 JoH)