Verification of the SMAP Level-4 Soil Moisture Analysis Using Rainfall Observations in Australia

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IGARSS 2019

Yokohama, 28 July – August 2, 2019

Skill of the SMAP Level-4 Product in a Data-Sparse Region.

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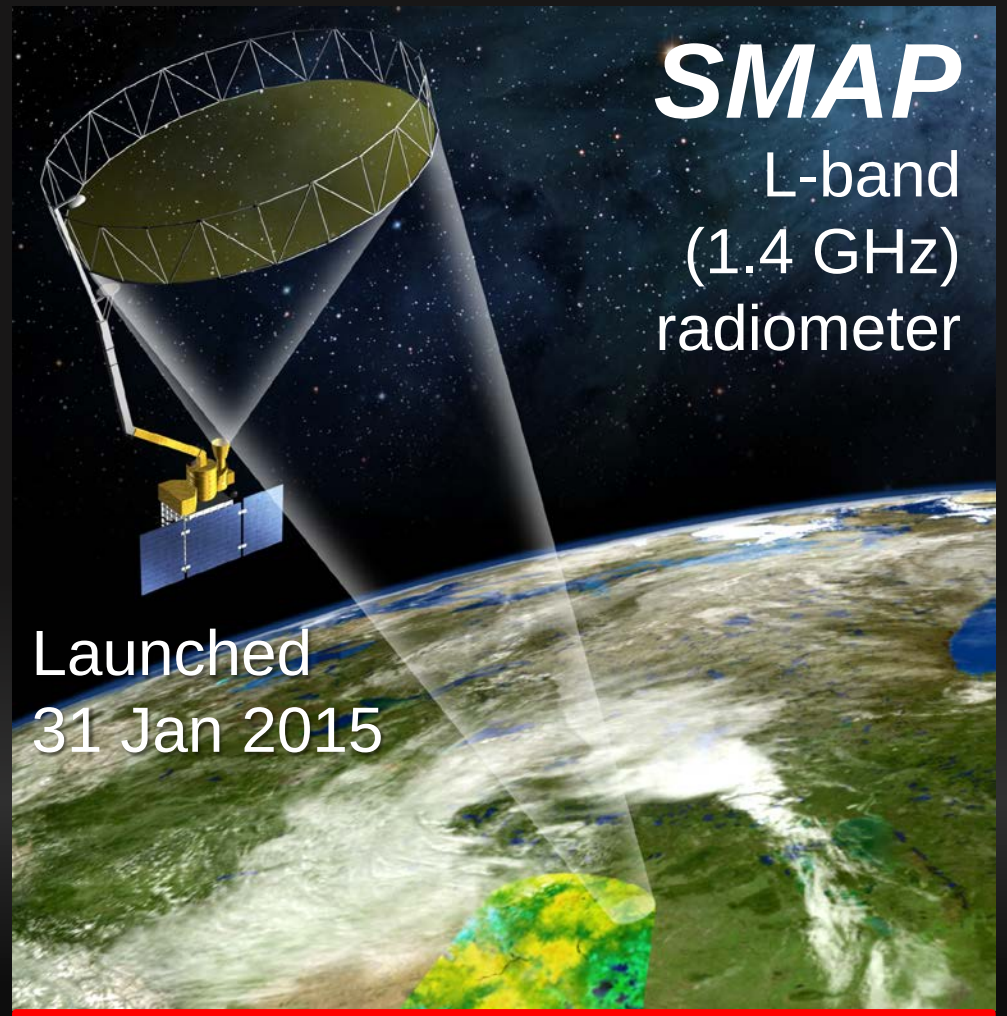
Motivation



Sensitive only to **surface** soil moisture (~0-5 cm)

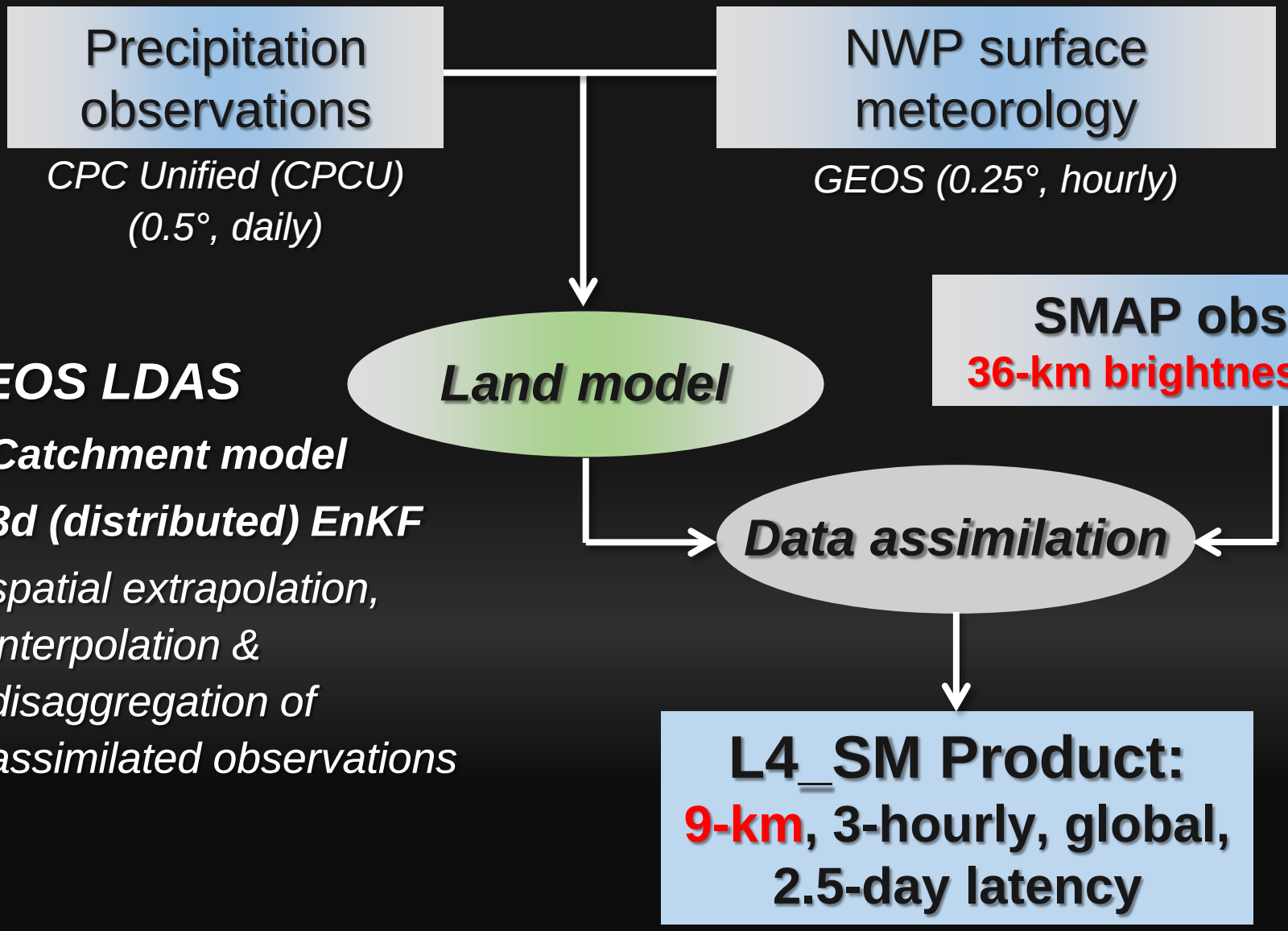
Key Objectives of the

Level 4 Surface & Root-Zone Soil Moisture

(L4_SM) product:

1. **Root-zone soil moisture (0-100 cm)**
2. **Spatially & temporally complete**

L4_SM Algorithm Overview



GEOS LDAS

- ***Catchment model***
- ***3d (distributed) EnKF***

spatial extrapolation, interpolation & disaggregation of assimilated observations

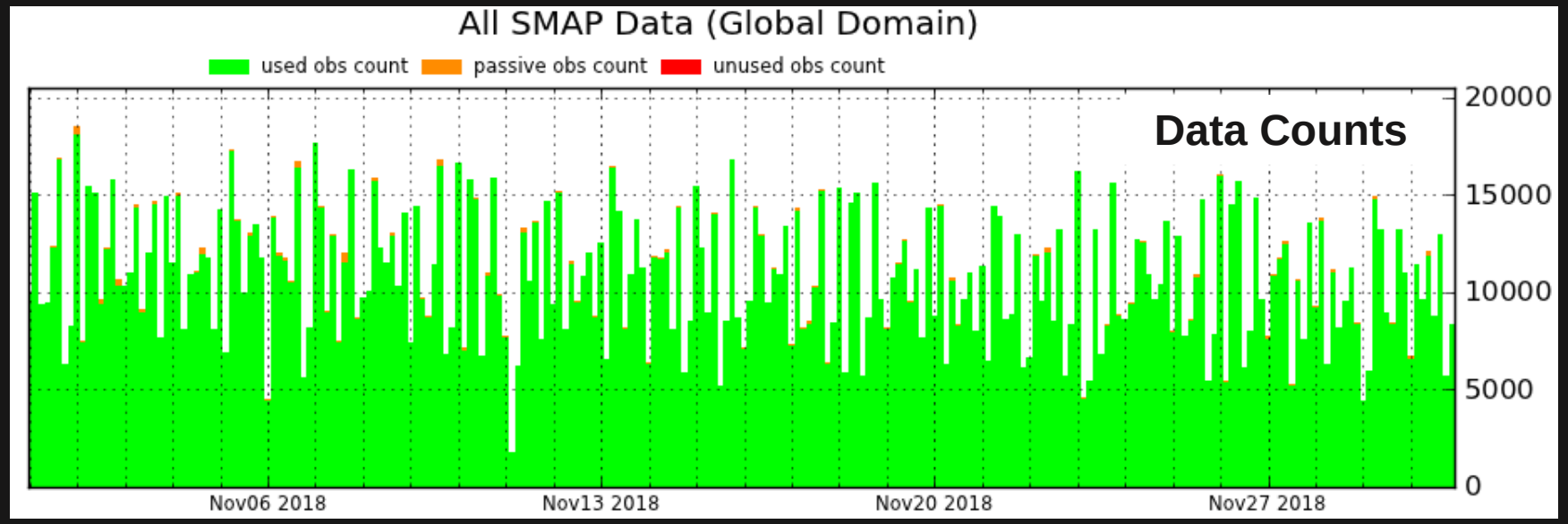
***Surface & root-zone soil moisture**, soil temperature, snow, surface fluxes, surface met. forcing.*

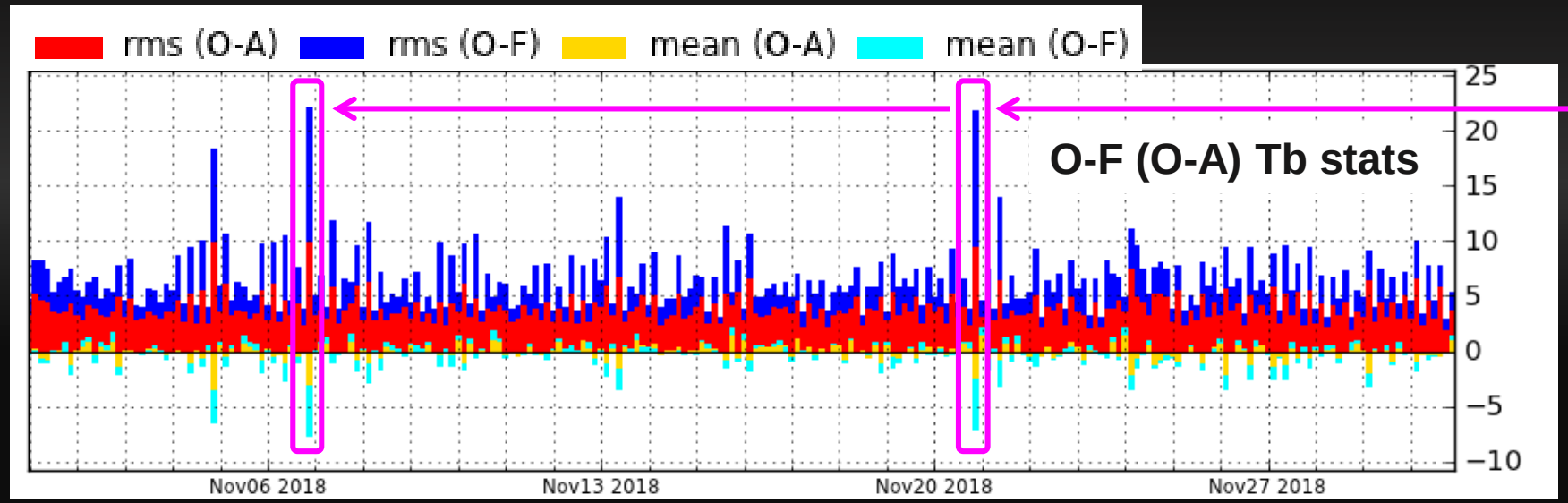
Brightness temp. (obs & modeled), assimilation diagnostics, uncertainty estimates.

Land model constants.

Reichle et al. 2017a, JHM, doi:10.1175/JHM-D-17-0063.1
Reichle et al. 2017b, JHM, doi:10.1175/JHM-D-17-0130.1

L4_SM Monitoring (Nov 2018, Vv4030)

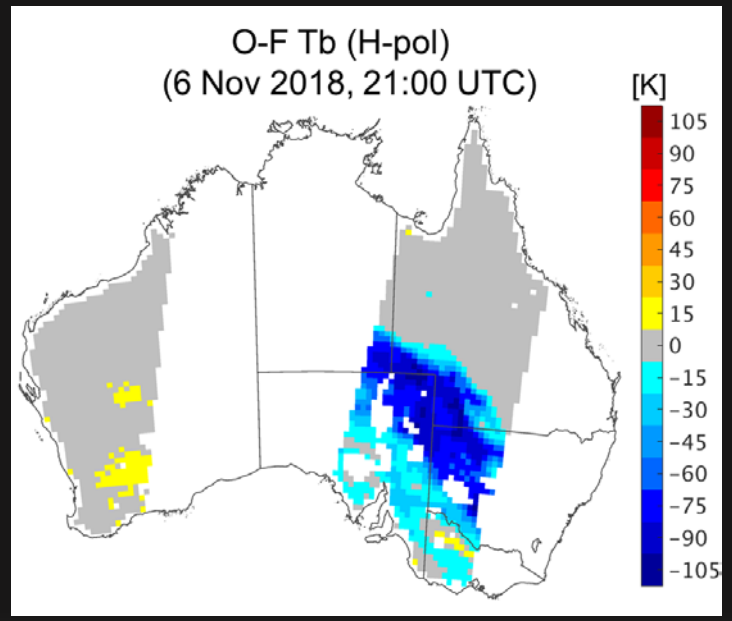


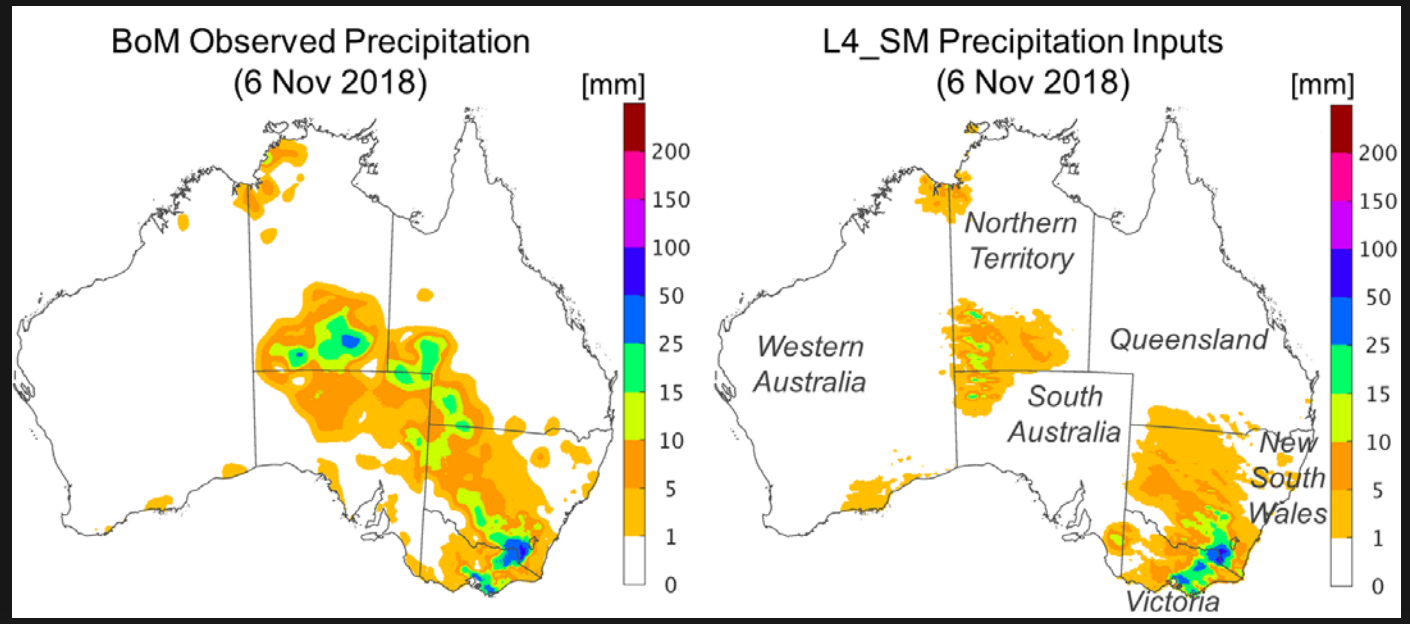


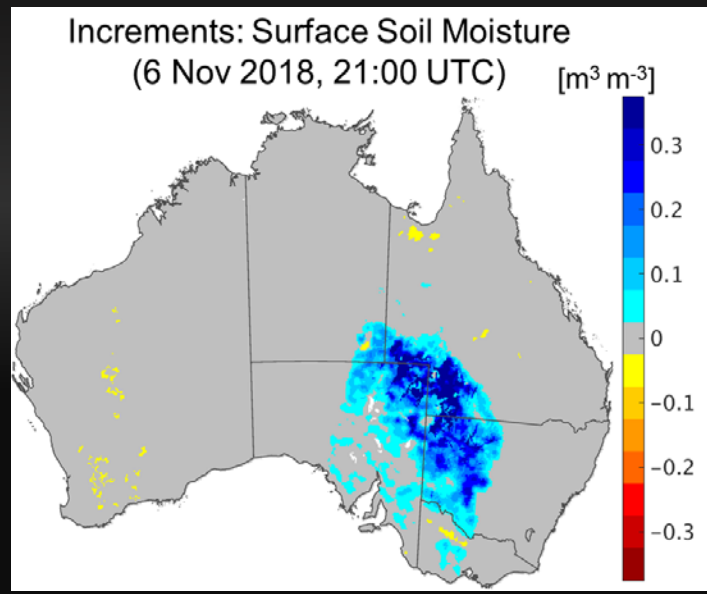
RMS(O-F) > 20 K:
21z on 6 Nov 2018
21z on 20 Nov 2018

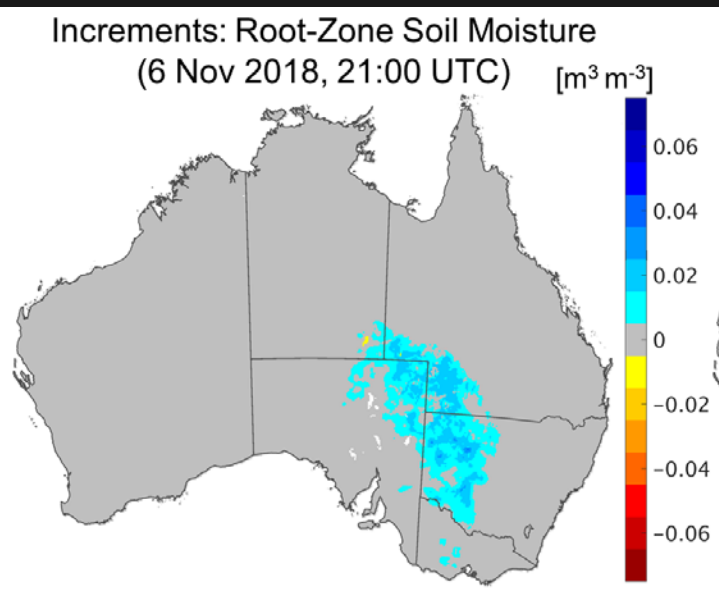
System prevents operators from exporting L4_SM data until approved by scientist.

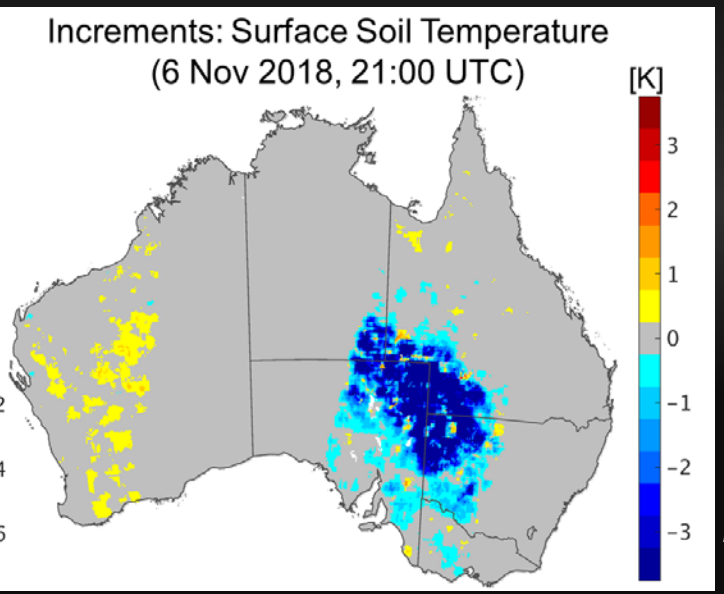
Tb Analysis in Australia (6 Nov 2018, 21z)





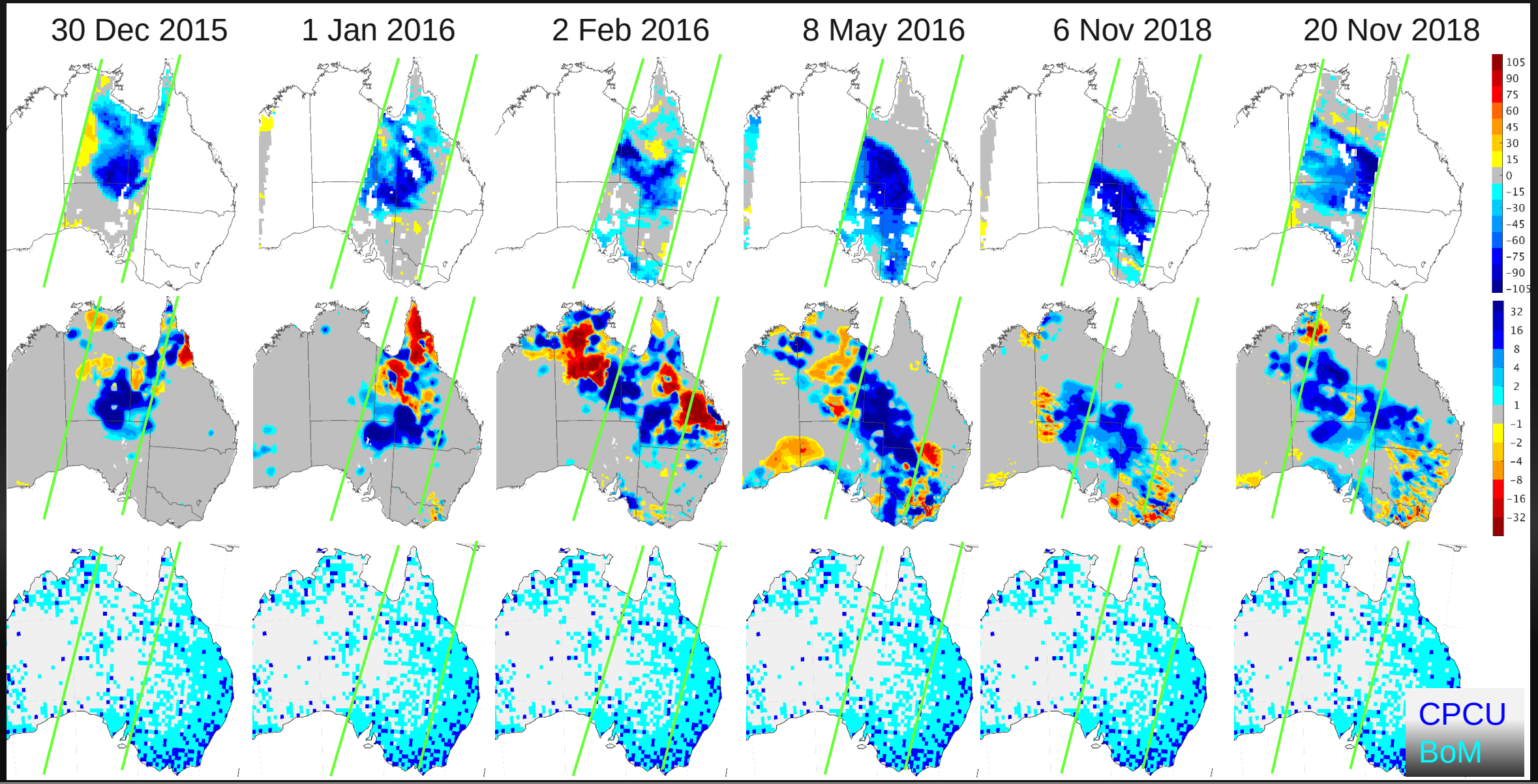




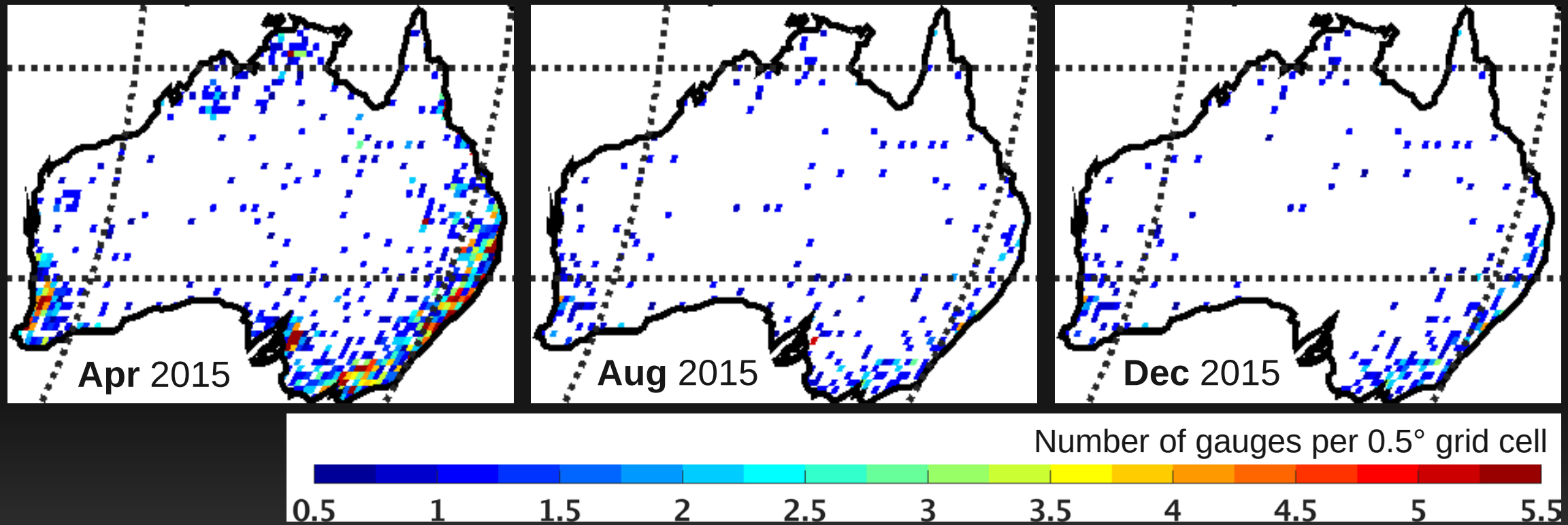


A similar case for May 8, 2016 is discussed in *Reichle et al.* 2017
doi:10.1175/JHM-D-17-0130.1

Events with std-dev(O-F)>20 K (through Dec 2018)



Disappearing CPCU Gauges



During the first few months of SMAP, there was a considerable drop in the number of gauges that contribute to the CPCU product.

Subsequent analysis is for Aug 2015 to Jul 2018.

From Case Study to Systematic Investigation

Objective:

Quantitatively relate soil moisture analysis increments to precip errors.

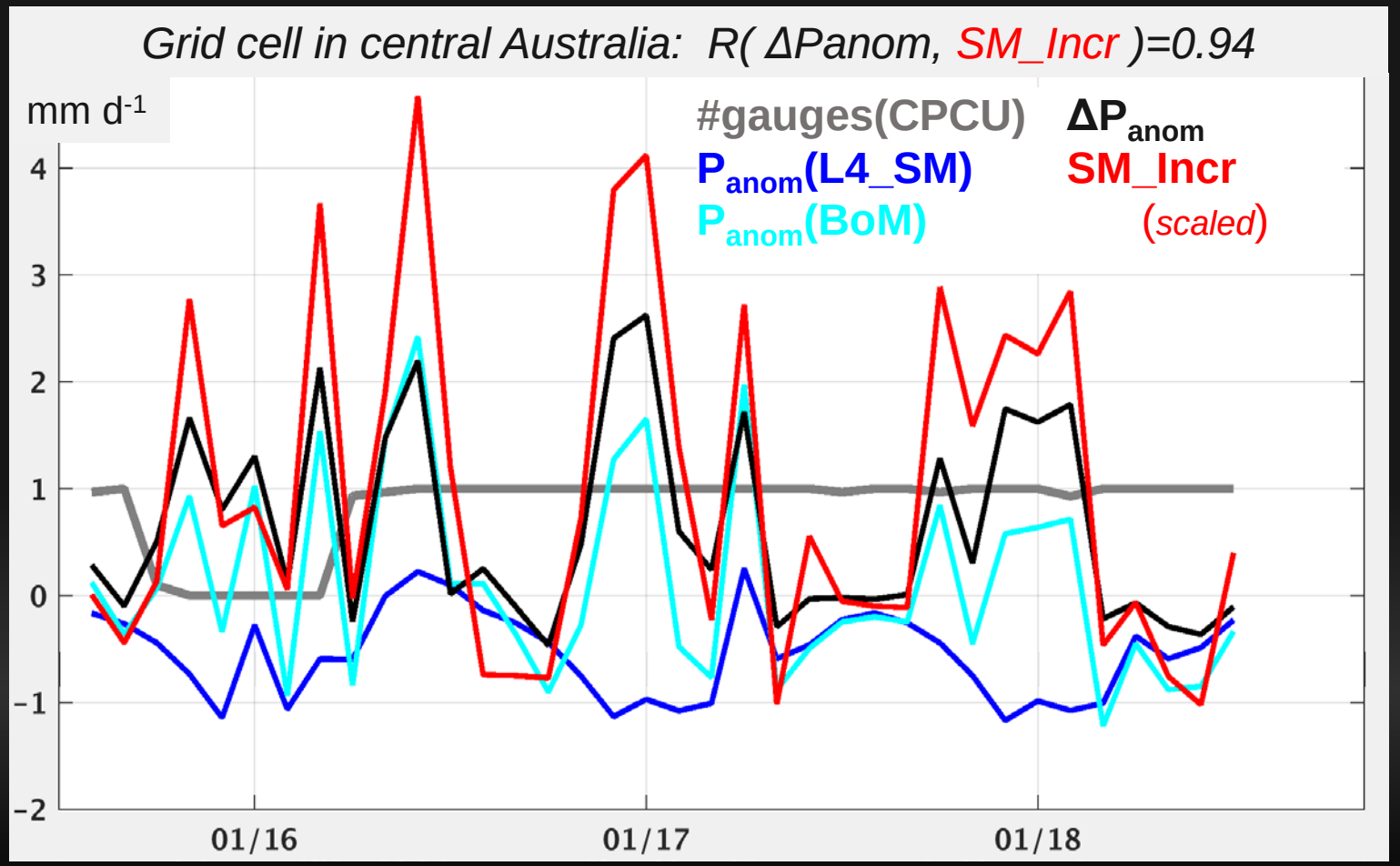
Assuming that

1) BoM precip is correct and L4_SM precip is wrong,

2) soil moisture errors result *only* from precip errors, and

3) seasonally varying *climatological* bias in L4_SM precip does *not* result in soil moisture increments (b/c of L4_SM calibration):

→ **L4_SM soil moisture increments should be correlated with errors in L4_SM precip *anomalies*** (w.r.t. BoM).



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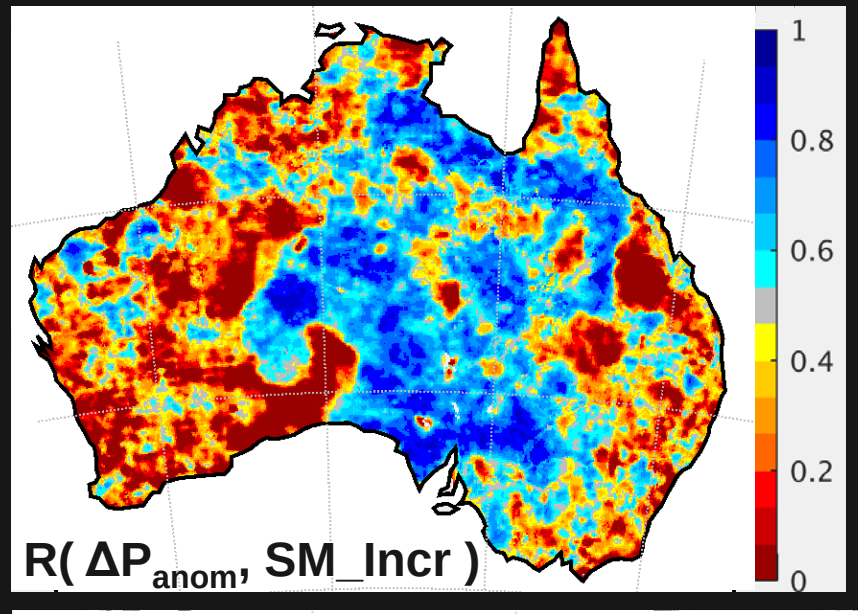
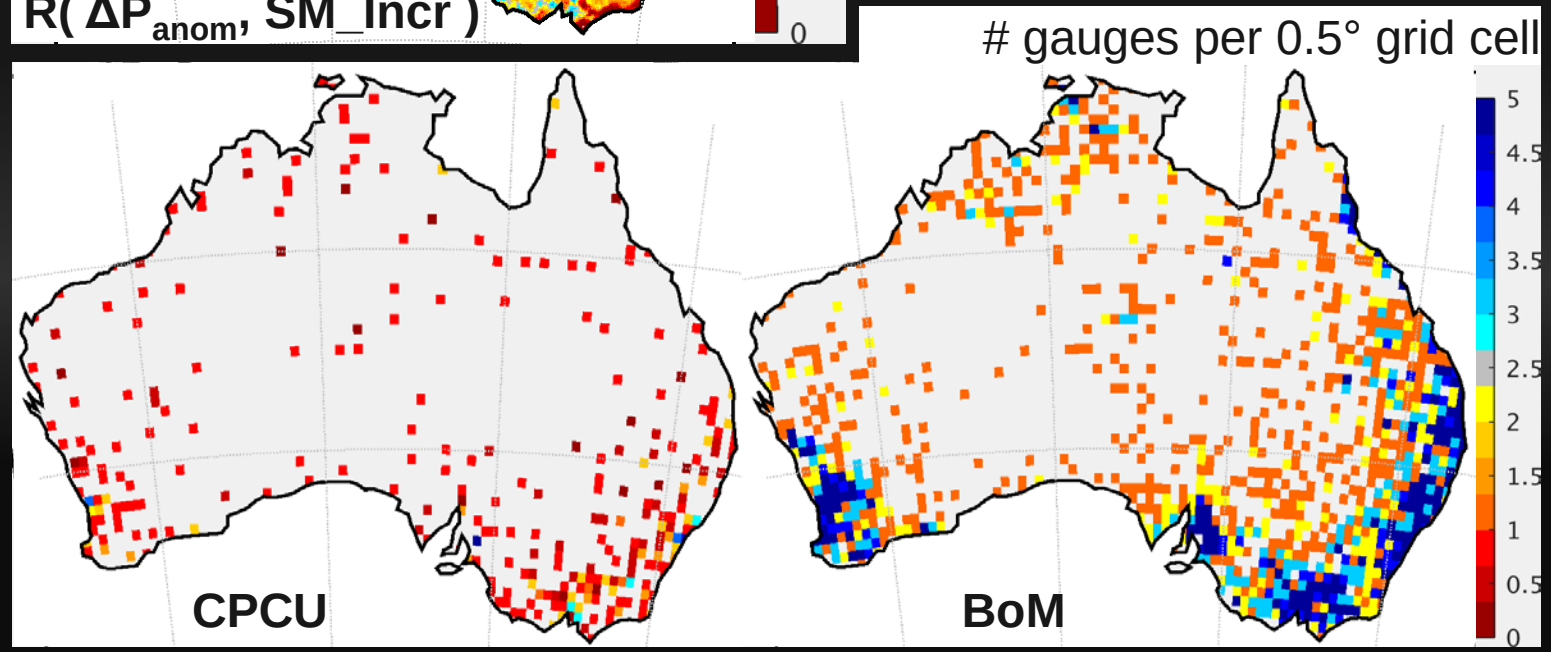


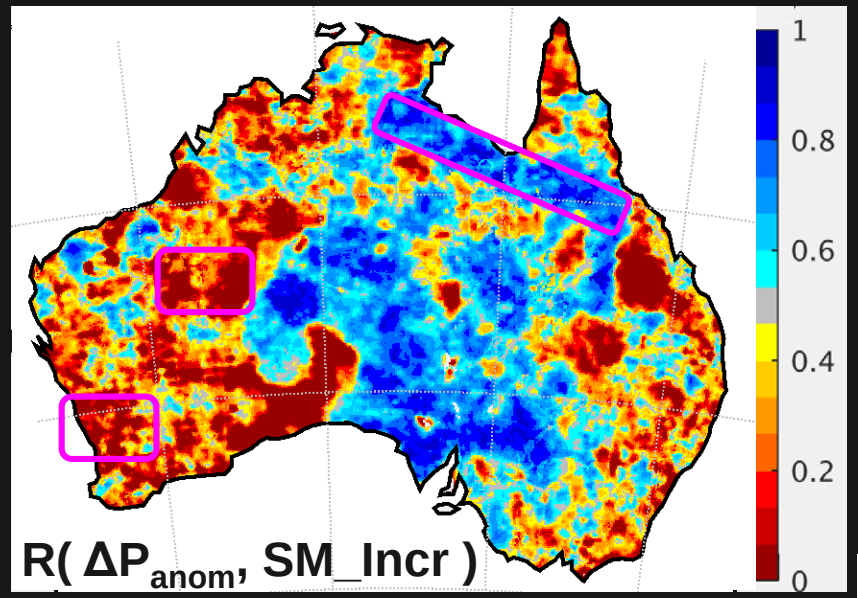


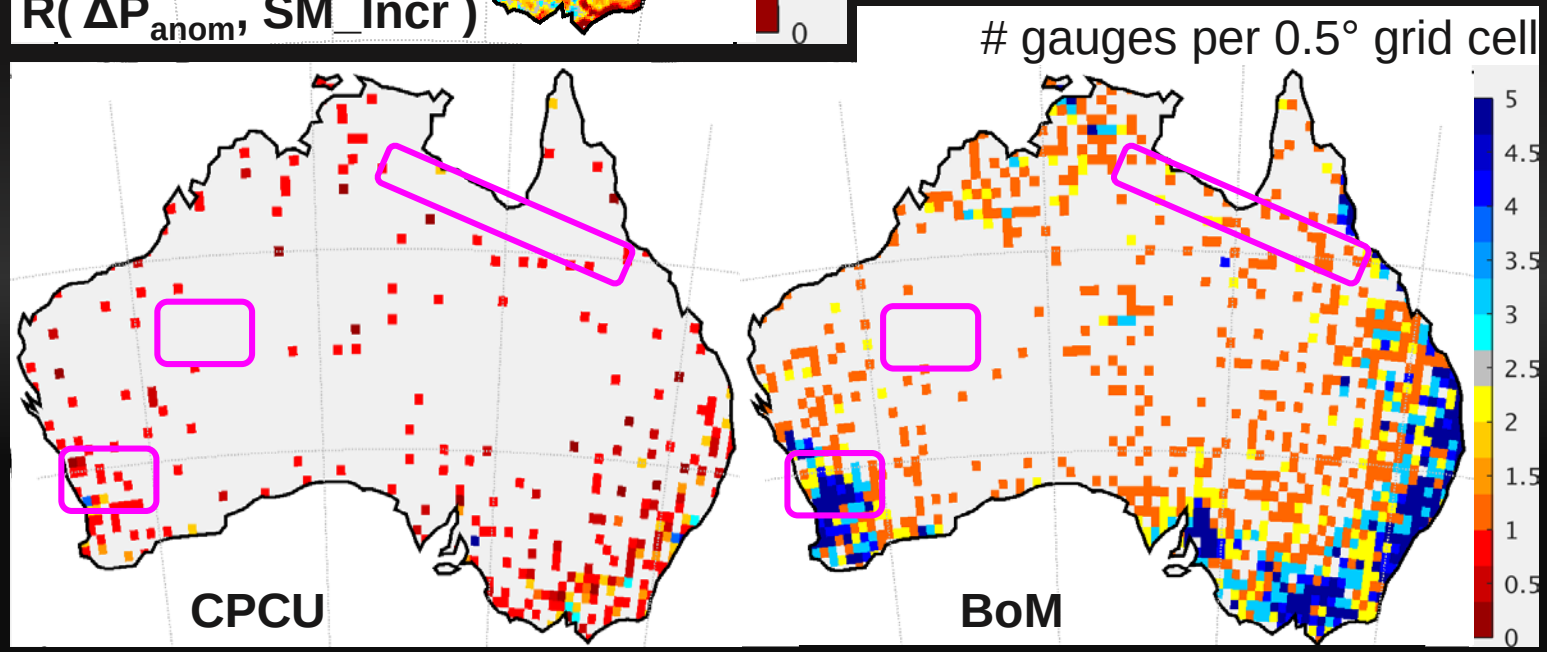
From Case Study to Systematic Investigation

Expect **high** correlation where BoM has good gauge coverage and CPCU has little or none.

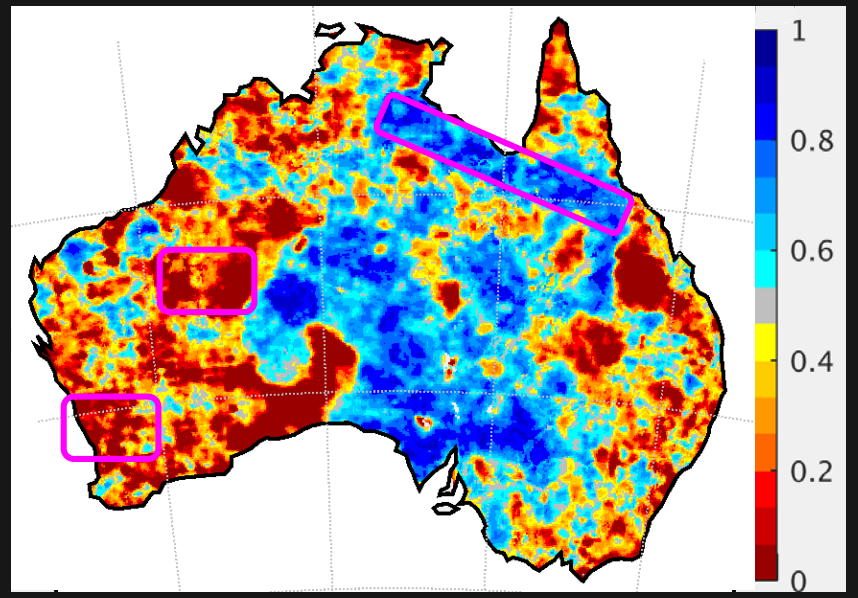
Expect **low** correlation where <u>both</u> CPCU and BoM have sufficient gauges or

<u>both</u> do <u>not</u> have gauges.

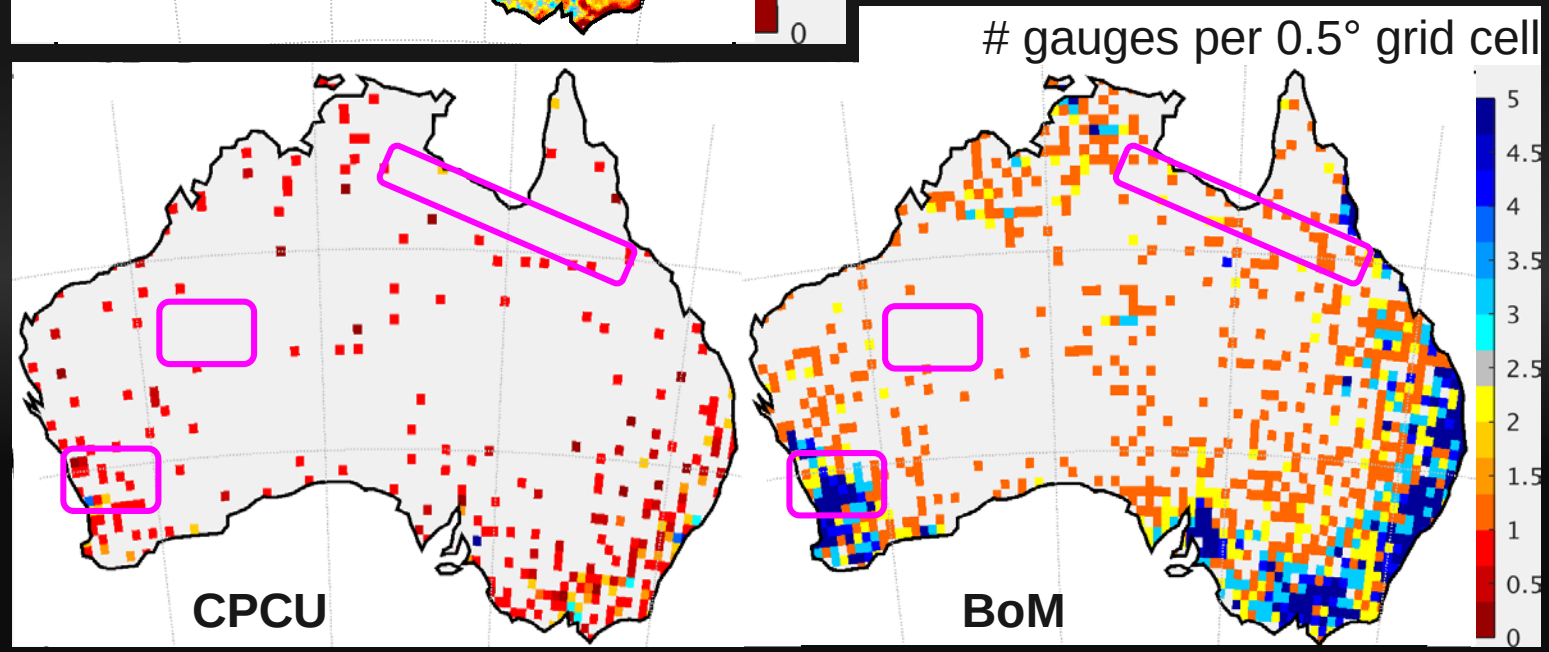




How Can We Explain the Correlation Pattern?



Gauge density does not work, after all (not shown).

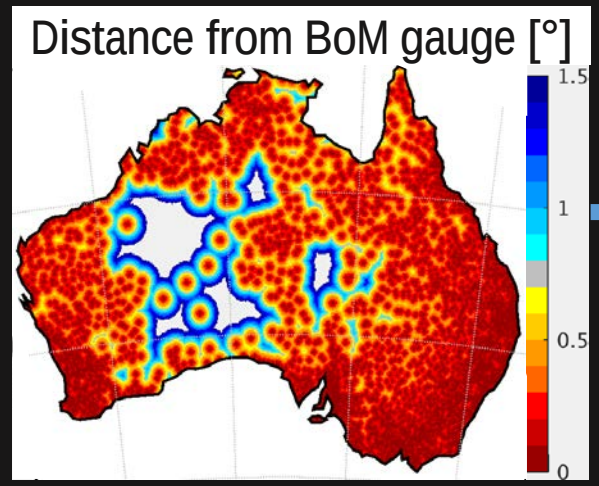


How Can We Explain the Correlation Pattern?

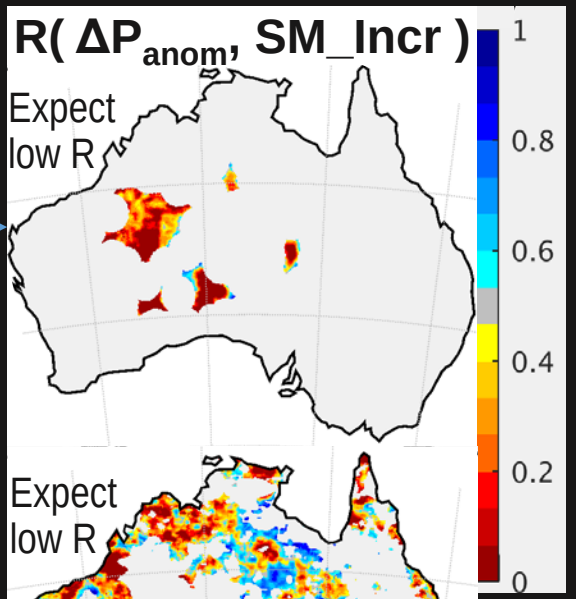
New approach:

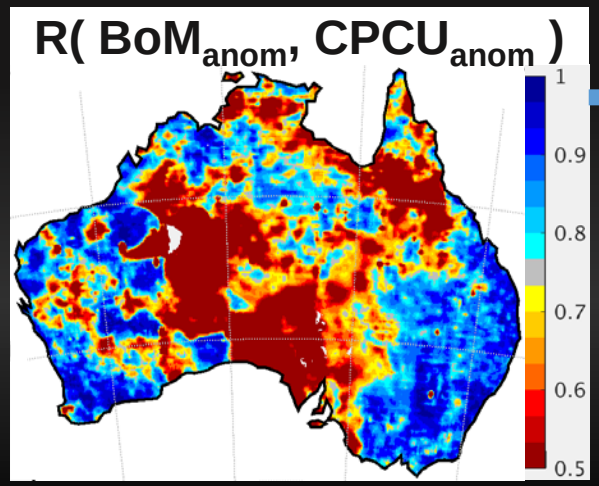
- BoM precipitation is bad if distance from nearest gauge > 1.5°
- L4_SM precipitation is ok where there is agreement with BoM:

  R (BoM_{anom},$CPCU_{anom}$)>0.7

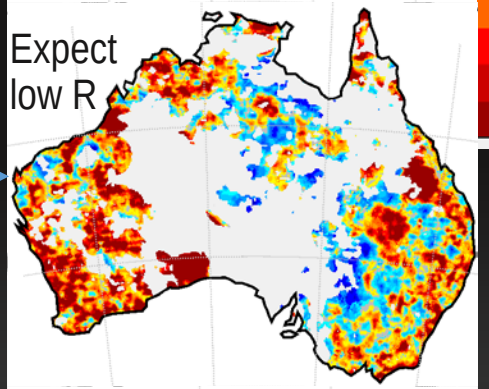


dist>1.5°

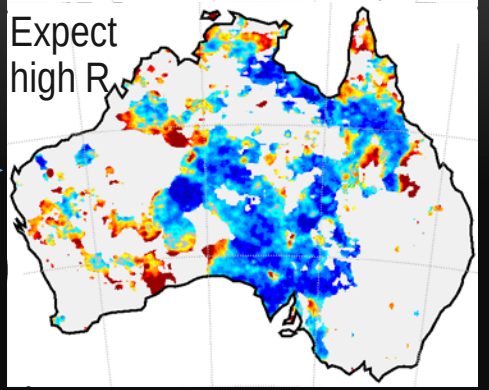




R>0.7



R<0.7



➔ SMAP soil moisture analysis increments are consistent with known errors in L4_SM precipitation forcing.

Evaluating L4_SM Using ASCAT Soil Moisture

- Triple collocation (TC) can estimate the (anomaly) skill of a soil moisture product (w.r.t. unkown truth), provided two independent products are available.

  Typical triplet: Model / Passive / Active

- However, L4_SM merges modeling and passive microwave observations.

- Dong et al. (2019), GRL, introduced a method to compute skill improvement using only one independent product (e.g., ASCAT):

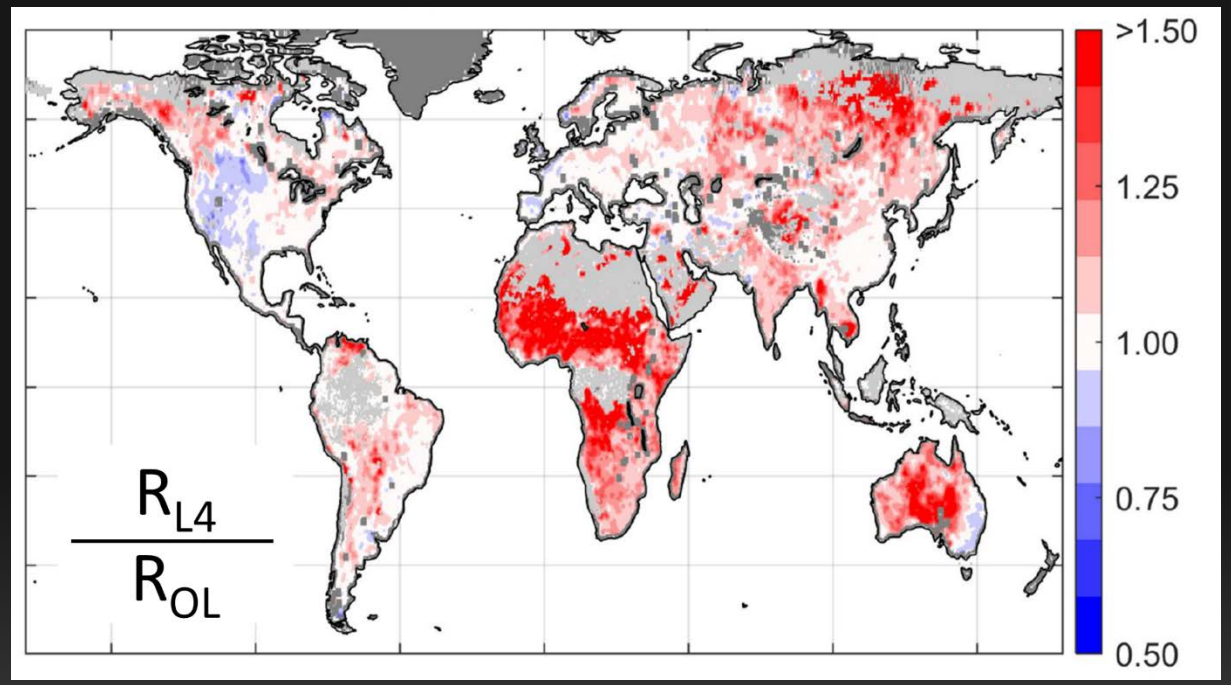
  $R\_ratio \equiv R_{L4,\theta} / R_{OL,\theta}$ (ratio of L4 and OL skill vs. truth θ)

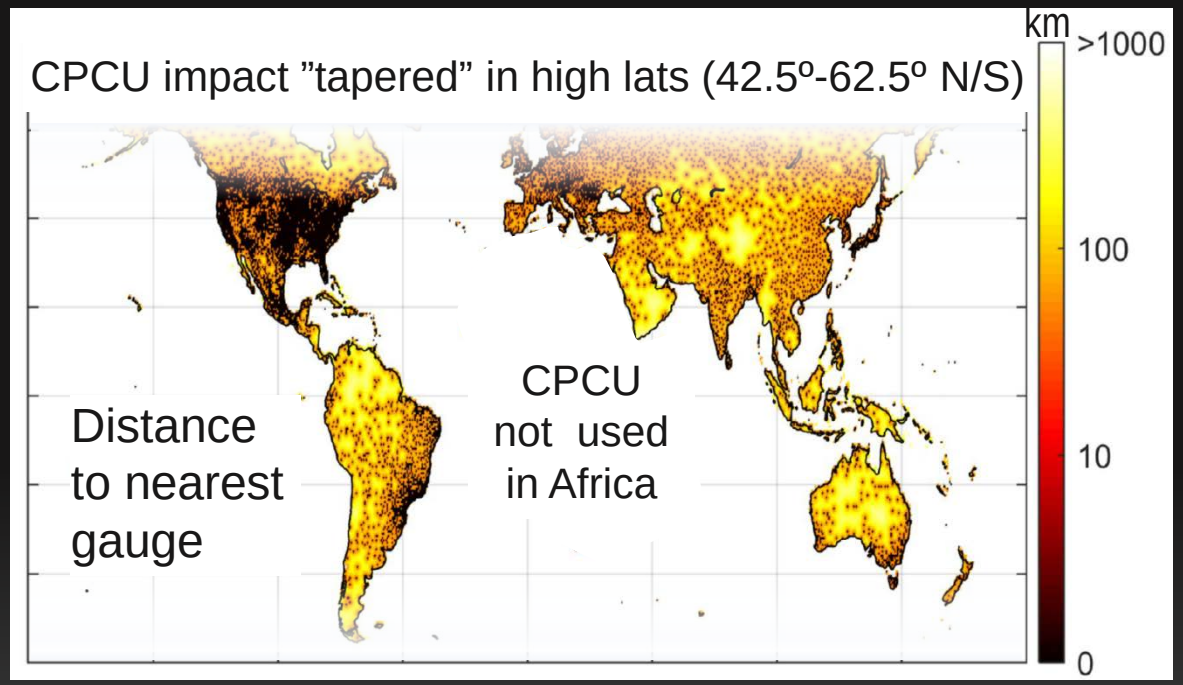
  (after some math) $= R_{L4,ASC} / R_{OL,ASC}$ (ratio of L4 and OL skill vs. ASCAT)

  where R is the anomaly correlation coefficient and OL is a model-only simulation.

Dong et al. 2019, GRL, doi:10.1029/2019GL083398

Skill Improvement from SMAP Data Assimilation





Greatest skill improvement from SMAP assimilation in otherwise data-sparse regions.

Verification with in situ measurements suggests that ASCAT-based metric underestimates true skill improvement (not shown).

Dong et al. 2019, GRL, doi:10.1029/2019GL083398

Summary and Conclusion

Using independent BoM precipitation data, we find that SMAP assimilation corrects known errors in L4_SM precipitation forcing in Australia.

Using independent ASCAT soil moisture retrievals, we find that soil moisture skill improvement from SMAP assimilation is greatest in otherwise data-sparse regions.

The patterns of corrections/improvements are highly consistent, which further confirms the value of SMAP in data-sparse regions.