Impact of SMAP-based precipitation estimates in a system that already assimilates SMAP data: How complementary is the added information?

Randal Koster, Qing Liu, and Rolf Reichle

ST Meeting, 17 November 2021

L4_SM Algorithm

Precipitation observations

NWP surface meteorology

SMAP observations
36-km brightness temperatures

Ensemble Kalman Filter (EnKF):
Optimal update of land model's soil moisture states using error covariance statistics sampled from a 24-member ensemble.

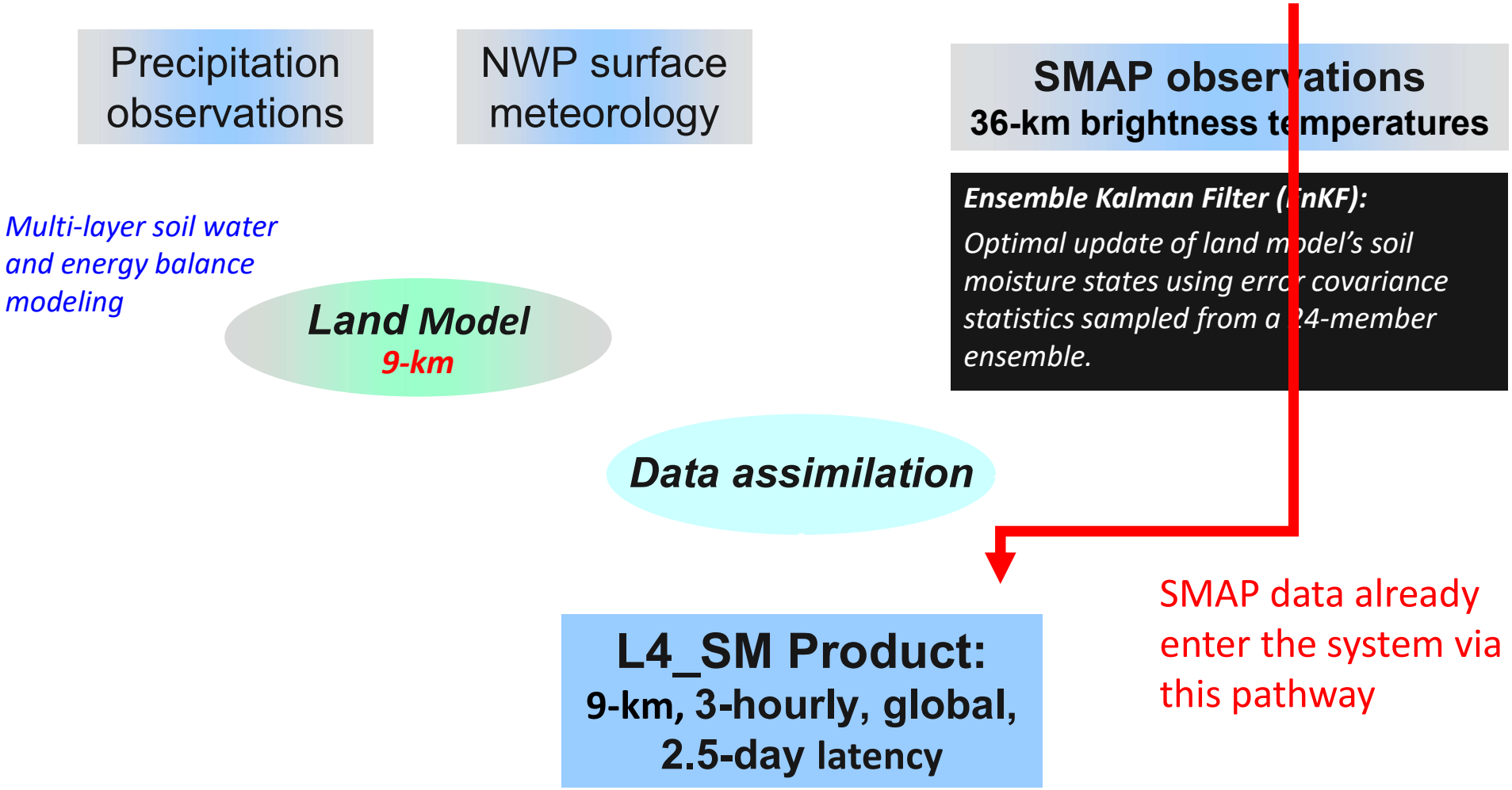
Multi-layer soil water and energy balance modeling

Land Model
9-km

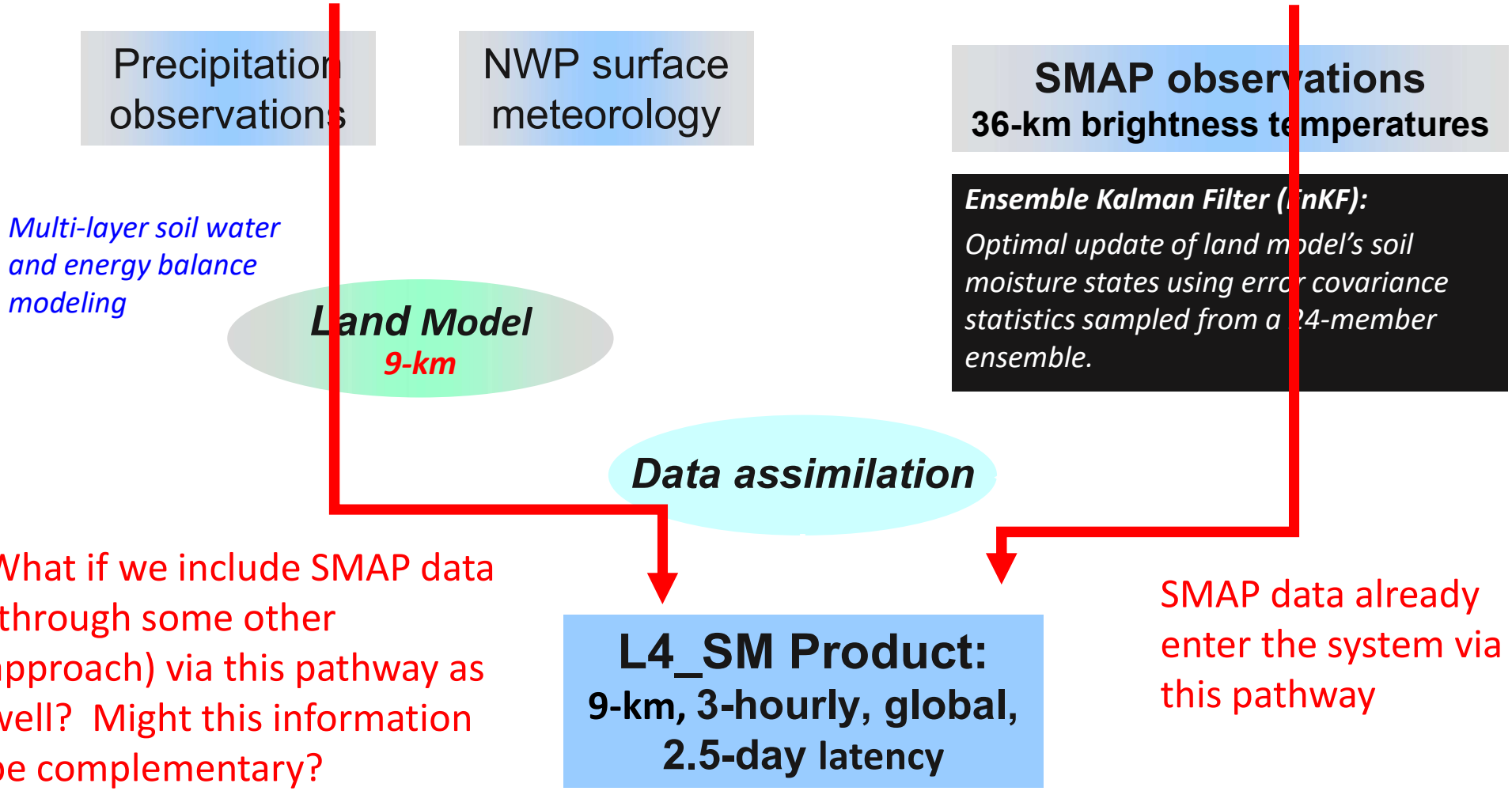
Data assimilation

L4_SM Product:
9-km, 3-hourly, global, 2.5-day latency

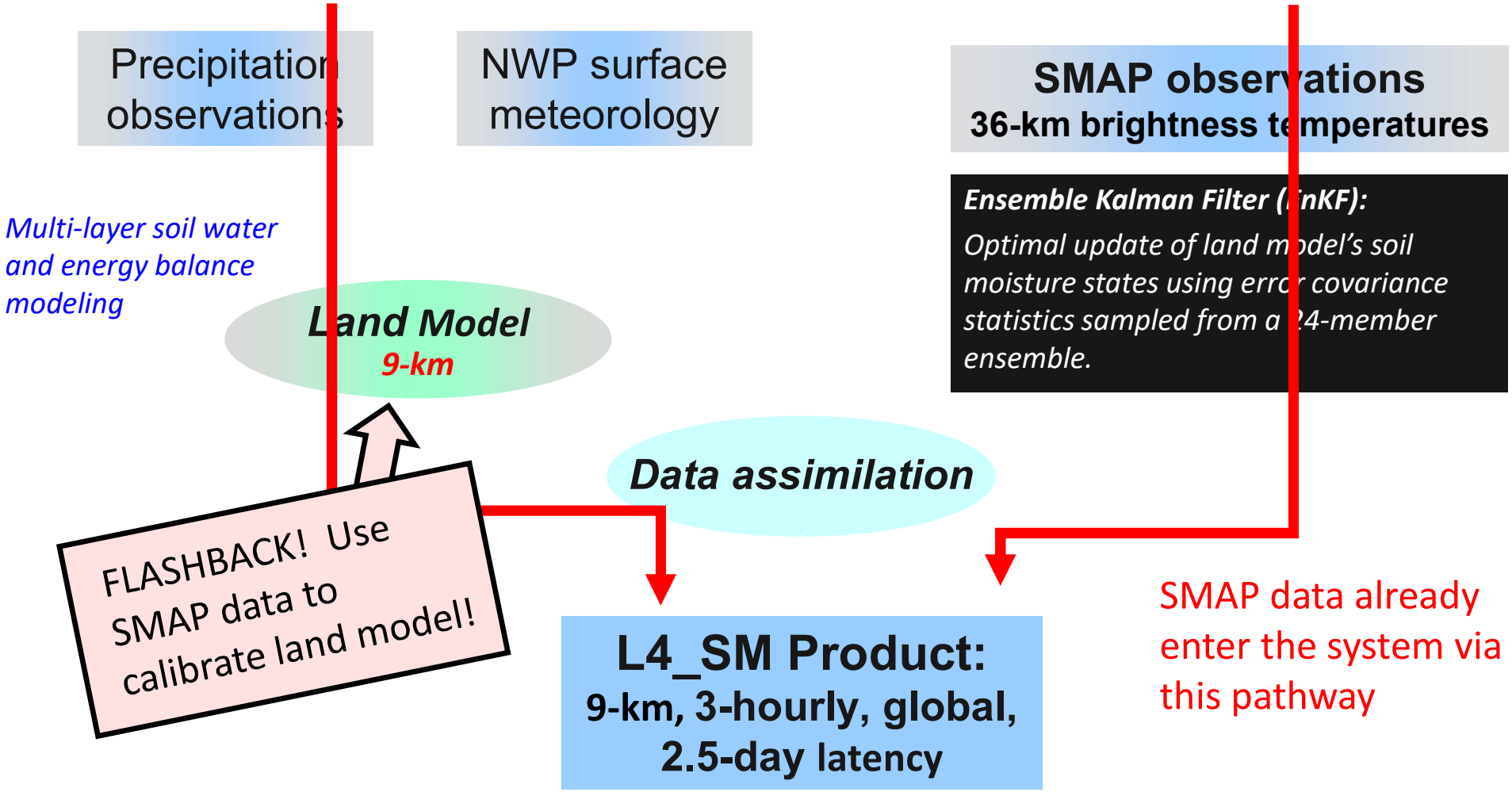
L4_SM Algorithm



L4_SM Algorithm



L4_SM Algorithm



Improved Hydrological Simulation Using SMAP Data:
Relative Impacts of Model Calibration and Data Assimilation

Koster, Liu, Mahanama, and Reichle, 2018. *J. Hydromet.,* DOI: 10.1175/JHM-D-17-0228.1.

(Don't read this whole thing!)

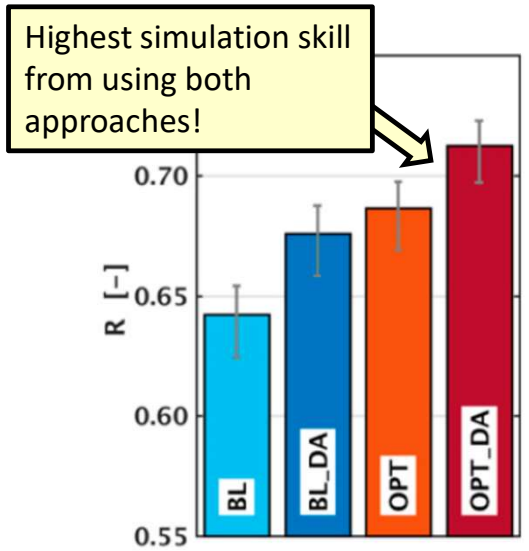
SMAP highlight from a few years ago. Basically, complementary contributions to skill were found.

Problem: Data assimilation is one approach for utilizing satellite-based data in hydrological simulation, and model calibration is another. To what extent do these two approaches extract complementary information?

Finding: We calibrate a land surface model parameter using SMAP data. We then perform 4 hydrological simulations across the continental US in which the calibrated parameter and SMAP data assimilation are used in different combinations:

- No calibration, no data assimilation (BL)
- Data assimilation, but no calibration (BL_DA)
- Calibration, but no data assimilation (OPT)
- Calibration and data assimilation (OPT_DA)

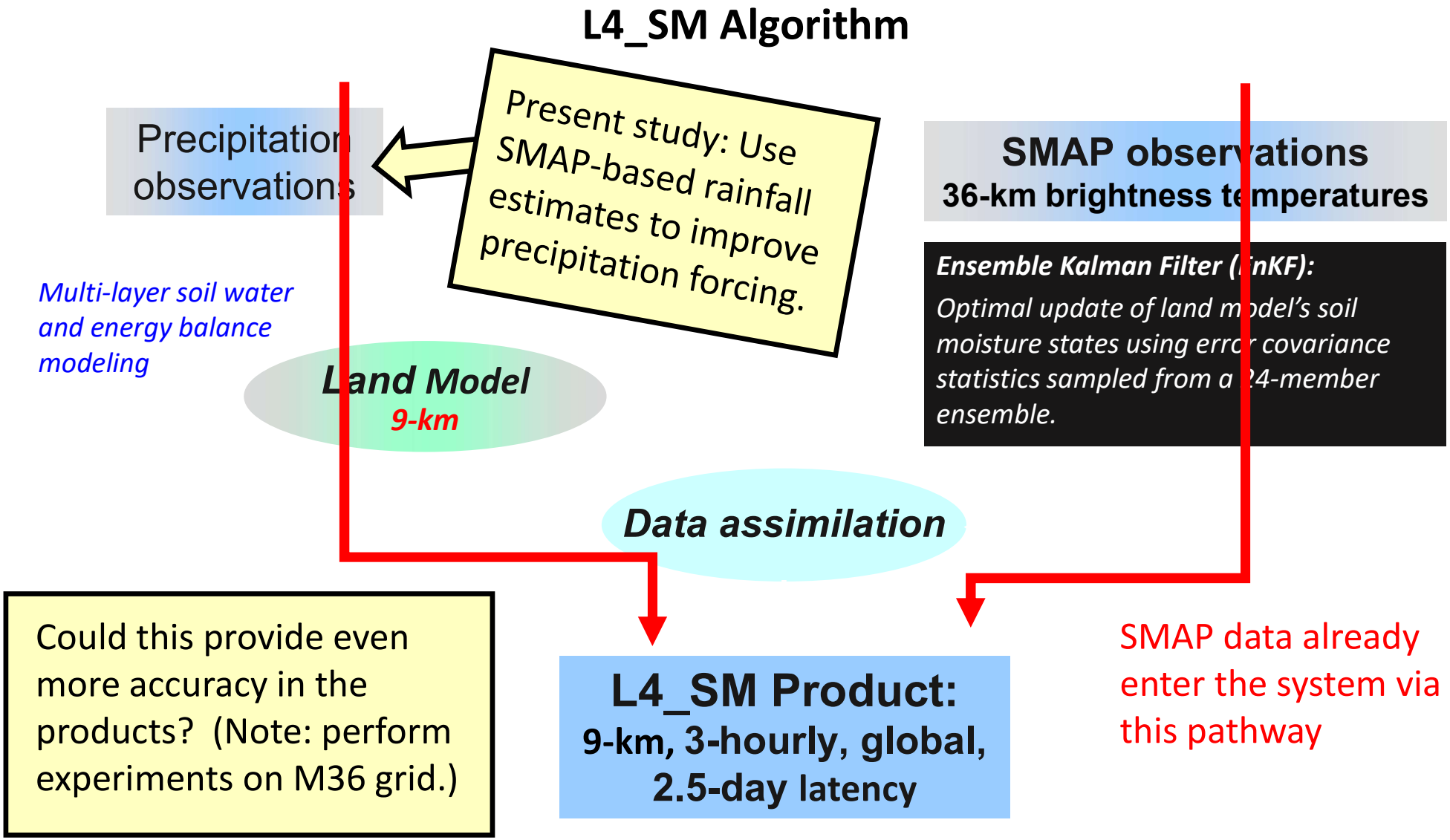
⇨ Using both data assimilation and model calibration provides the highest simulation skill.



Accuracy of simulated soil moisture (vs. in situ obs)

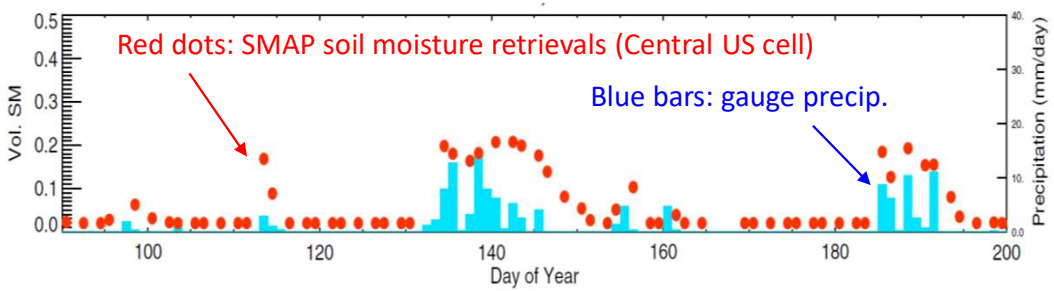
FLASHBACK!

Significance: Data assimilation and model calibration effectively access independent information contained within the SMAP dataset. Those applying SMAP data to hydrological simulation might do well to use both approaches.

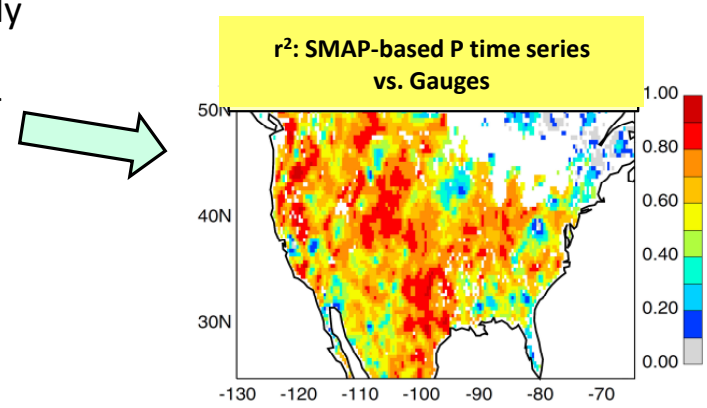

L4_SM Algorithm
Precipitation observations
Present study: Use SMAP-based rainfall estimates to improve precipitation forcing.
SMAP observations
36-km brightness temperatures
Multi-layer soil water and energy balance modeling
Land Model
9-km
Ensemble Kalman Filter (EnKF):
Optimal update of land model's soil moisture states using error covariance statistics sampled from a 24-member ensemble.
Data assimilation
Could this provide even more accuracy in the products? (Note: perform experiments on M36 grid.)
L4_SM Product:
9-km, 3-hourly, global, 2.5-day latency
SMAP data already enter the system via this pathway

A refresher: precipitation estimates from SMAP

As you would expect, SMAP soil moisture retrievals and independent precipitation measurements show significant consistency.

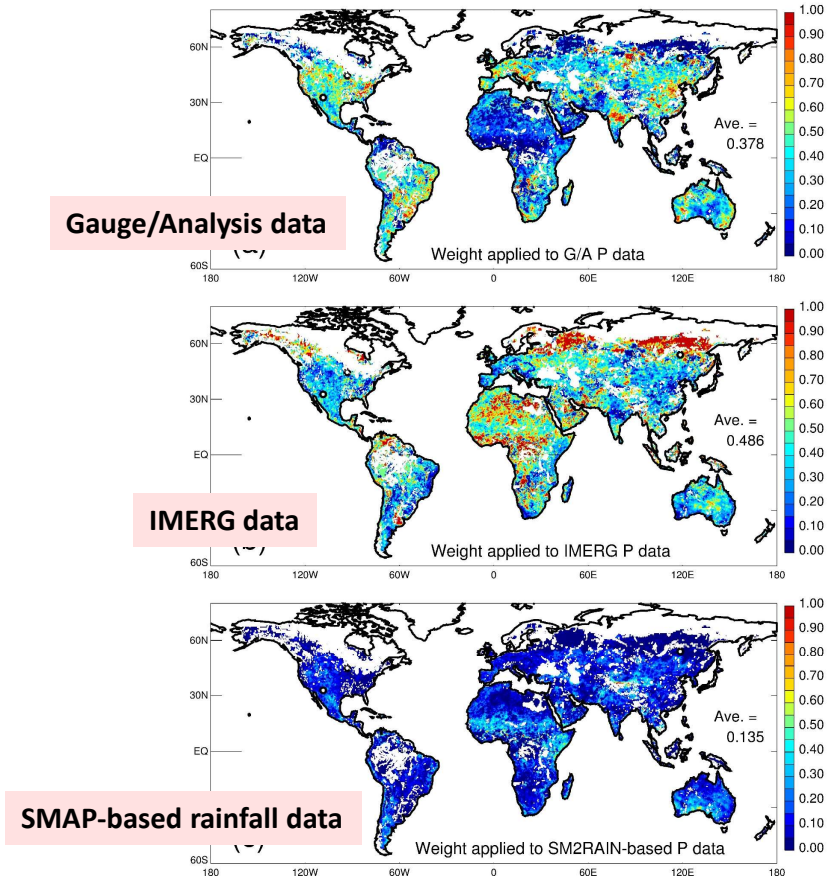


Approaches have been developed (e.g., Brocca et al. 2013) to translate soil moisture variations into estimates of precipitation time series. Over the last few years, we have applied these approaches extensively to SMAP Level-2 retrievals. The resulting SMAP-based precipitation time series appear realistic.

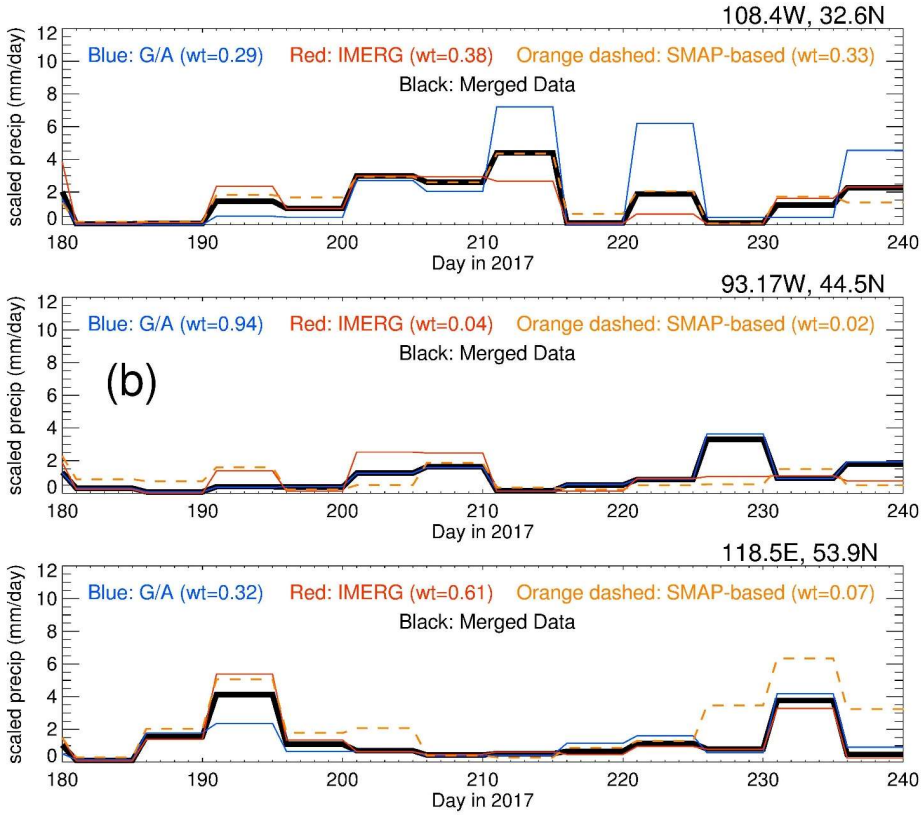


A refresher: merging different precipitation datasets using a triple-collocation approach

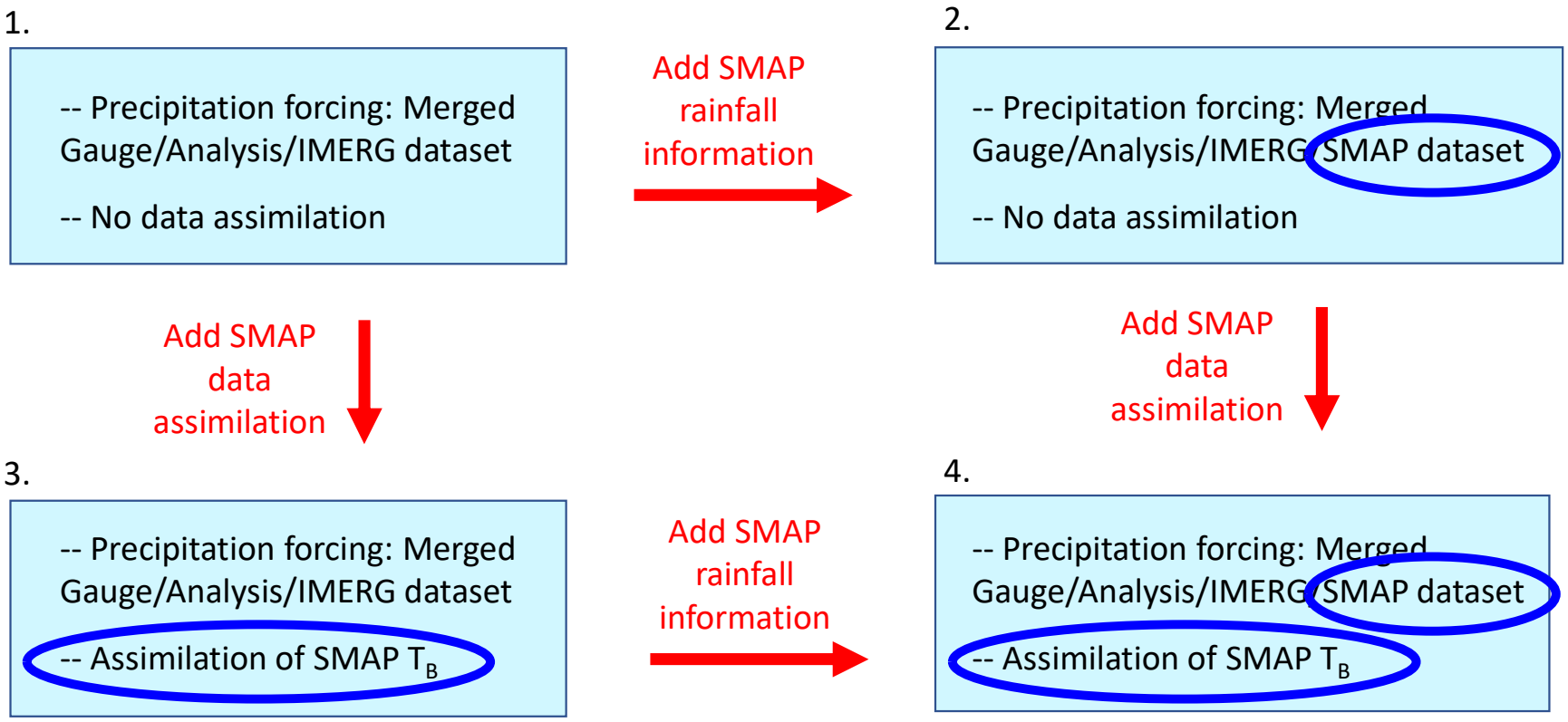
Weights applied in merging



Sample Time Series



Okay, with all that preamble, here are our 4 experiments. All are performed with the L4_SM system, but on the M36 EASE grid, and using a merged Gauge/Analysis/IMERG rainfall products as the control.

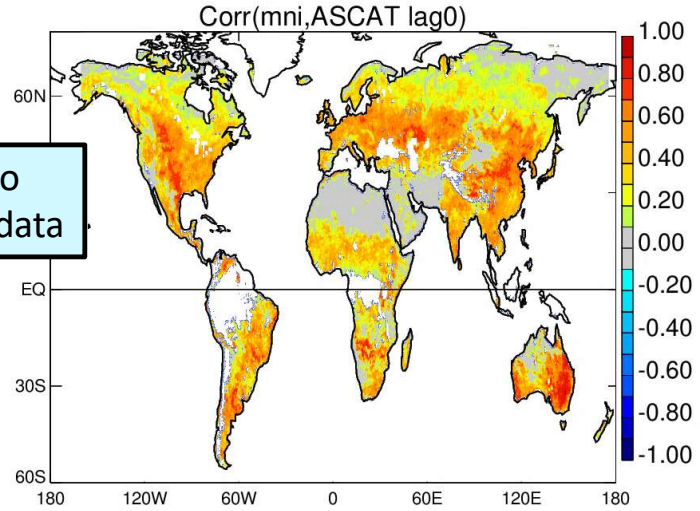


Compute near-surface soil moisture using L4_SM hydrological modeling system (M36 grid) with each configuration for May-September of 2015-2018. Compare to independent ASCAT data.

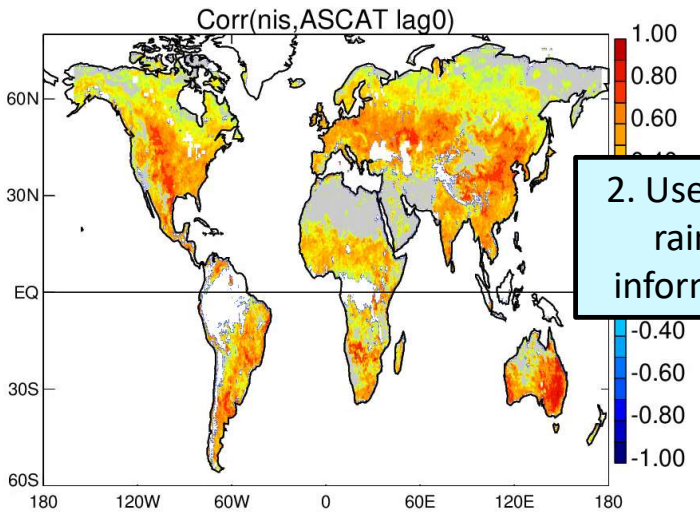
Skill metric: anomaly correlation coefficient.

When comparing experiments, first square the anomaly correlation coefficient before taking differences.

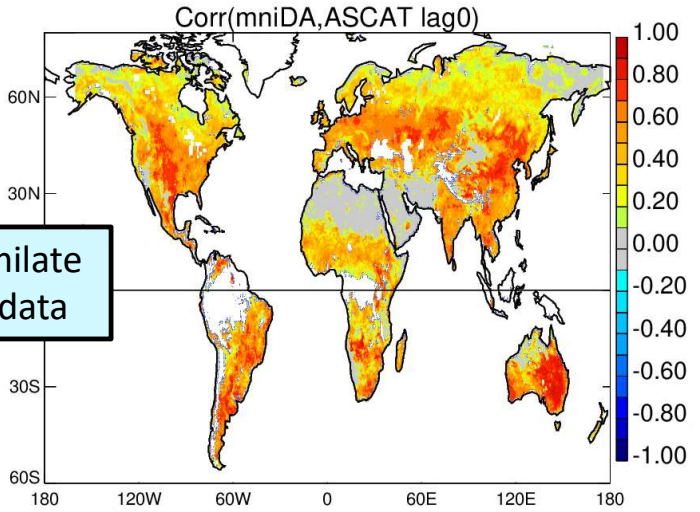
1. No SMAP data



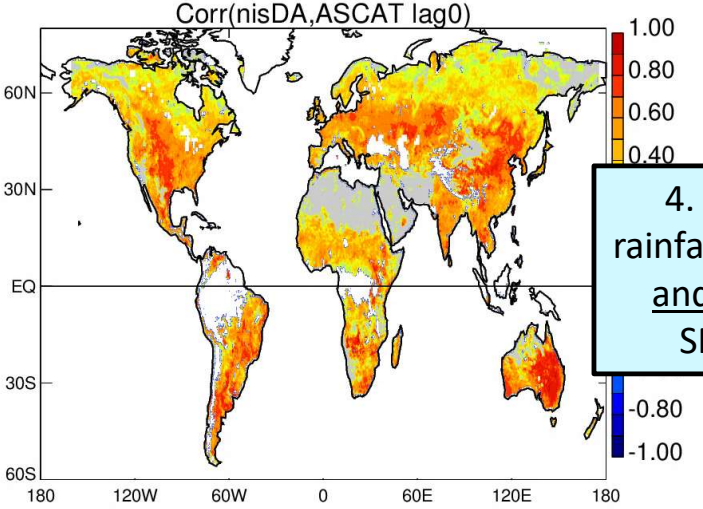
2. Use SMAP rainfall information



3. Assimilate SMAP data

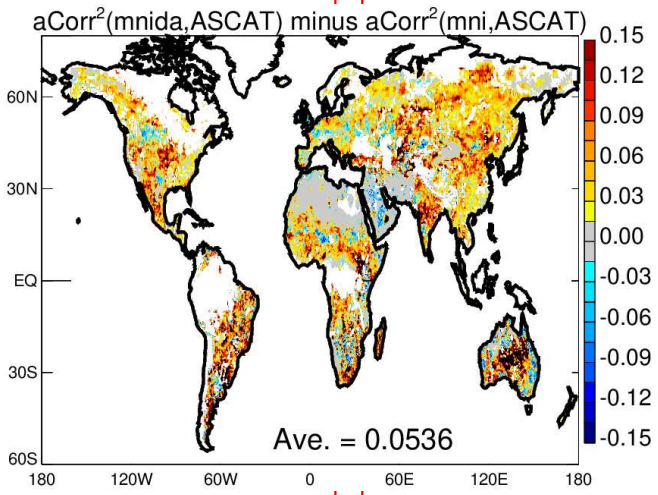


4. Use SMAP rainfall information and assimilate SMAP data



r^2 differences

1. No SMAP data

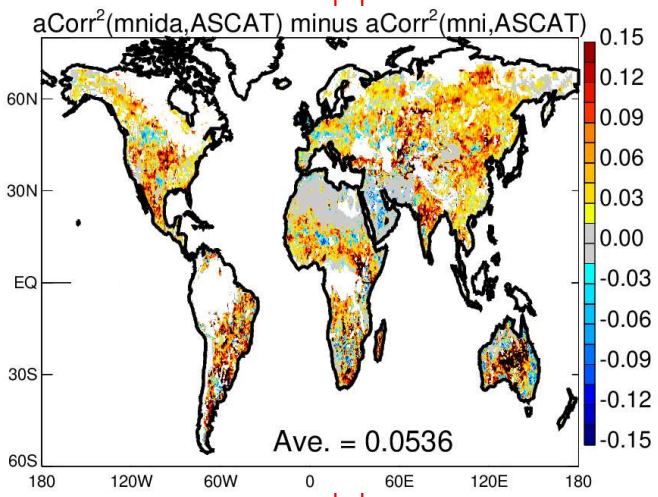


(Increase in r^2 skill due to assimilating SMAP T_B)

3. Assimilate SMAP data

r^2 differences

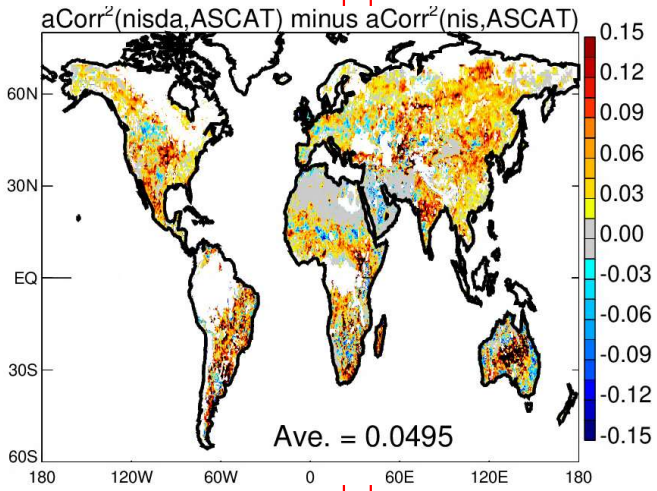
1. No SMAP data



3. Assimilate SMAP data

(Increase in r^2 skill due to assimilating SMAP T_B)

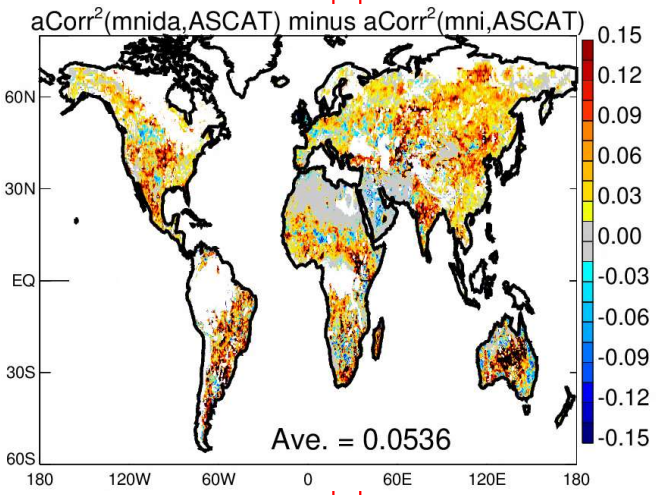
2. Use SMAP rainfall information



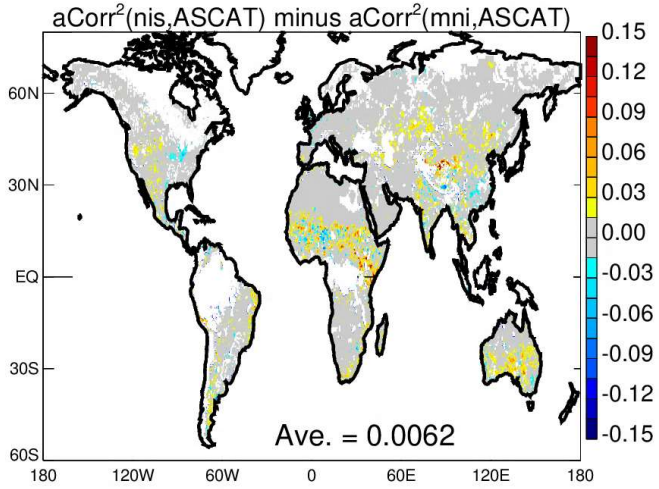
4. Use SMAP rainfall information and assimilate SMAP data

r^2 differences

1. No SMAP data

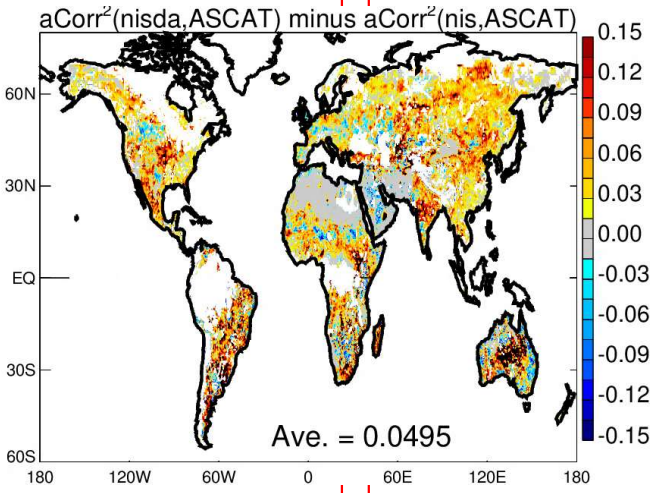


3. Assimilate SMAP data



(Increase in r^2 skill due to including SMAP-based rainfall)

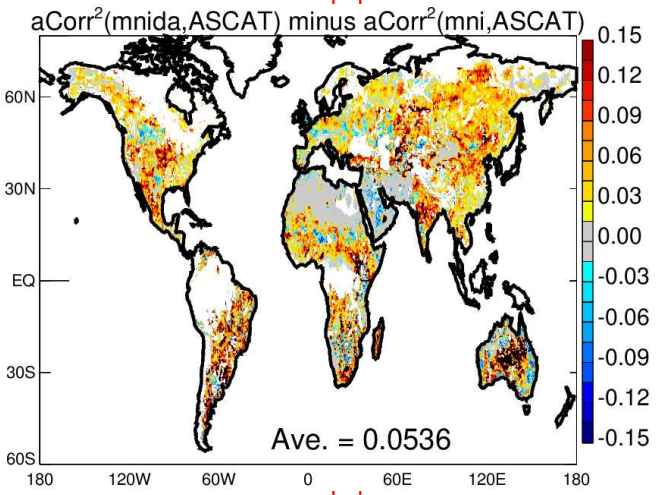
2. Use SMAP rainfall information



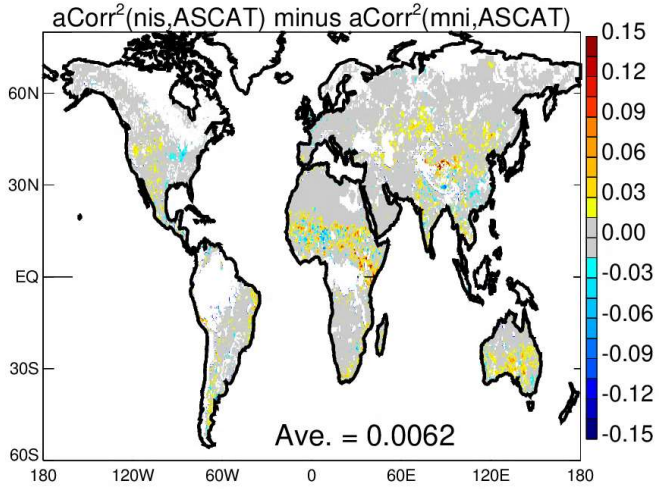
4. Use SMAP rainfall information and assimilate SMAP data

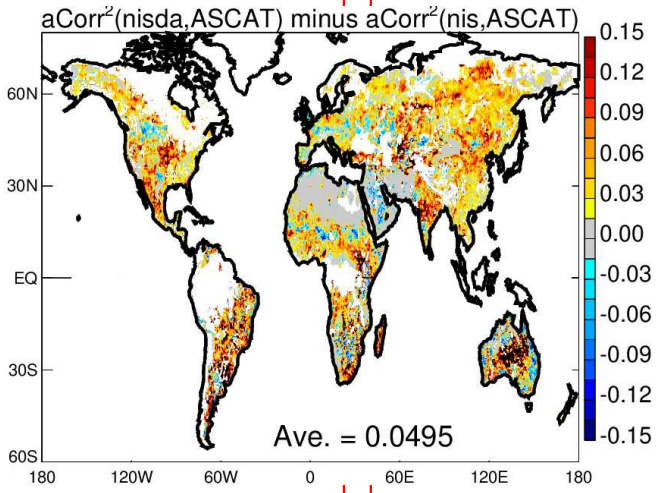
r^2 differences

1. No SMAP data

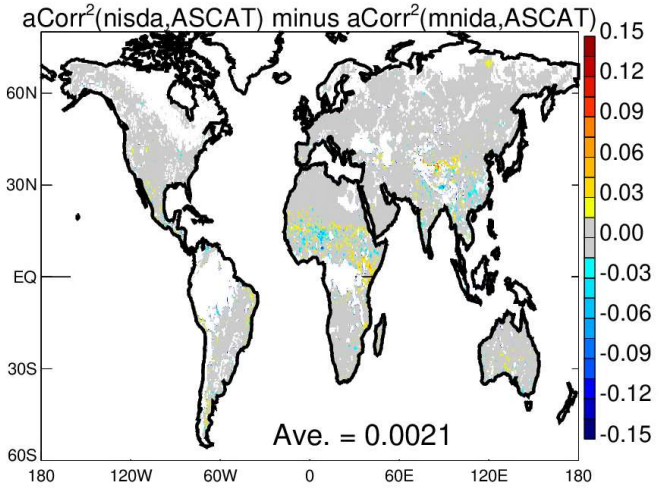


2. Use SMAP rainfall information





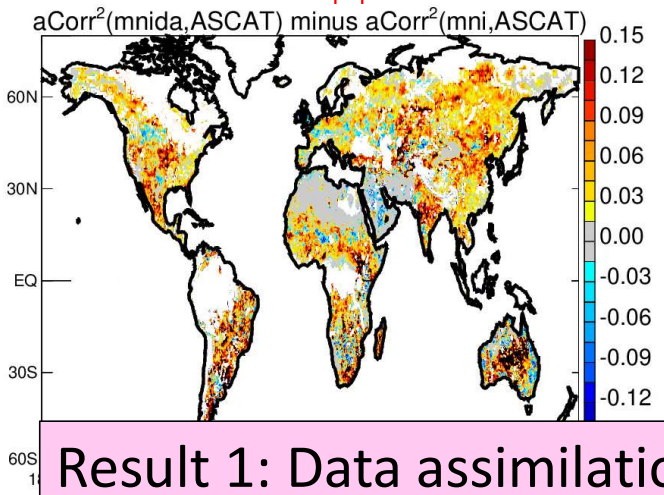
3. Assimilate SMAP data

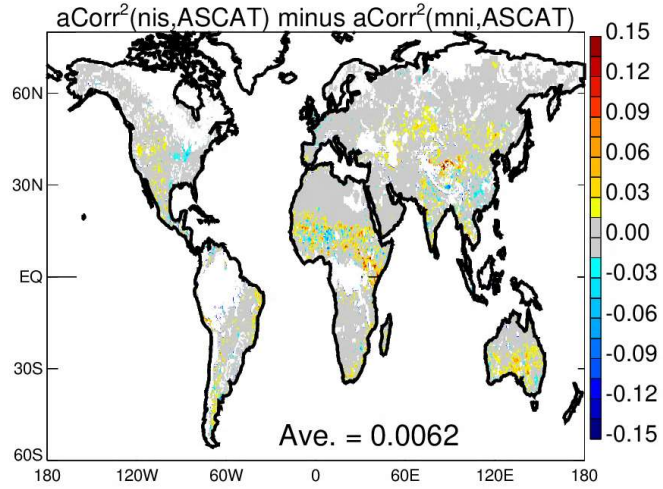


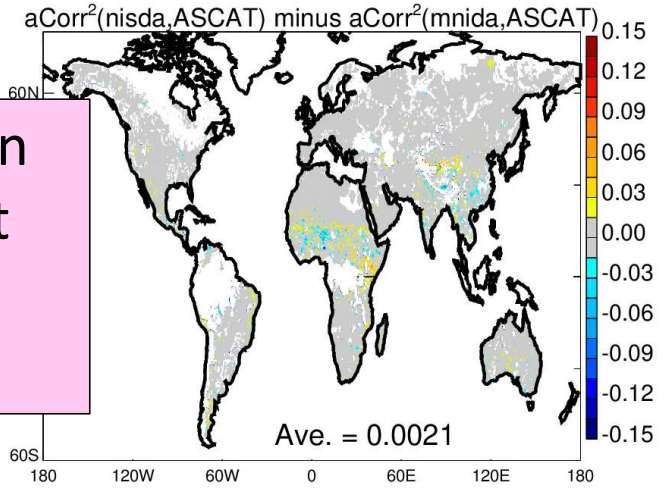
4. Use SMAP rainfall information and assimilate SMAP data

r^2 differences

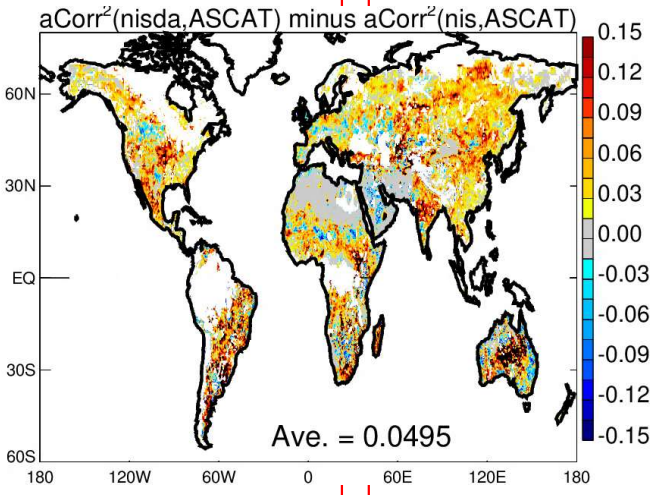
1. No SMAP data







2. Use SMAP rainfall information

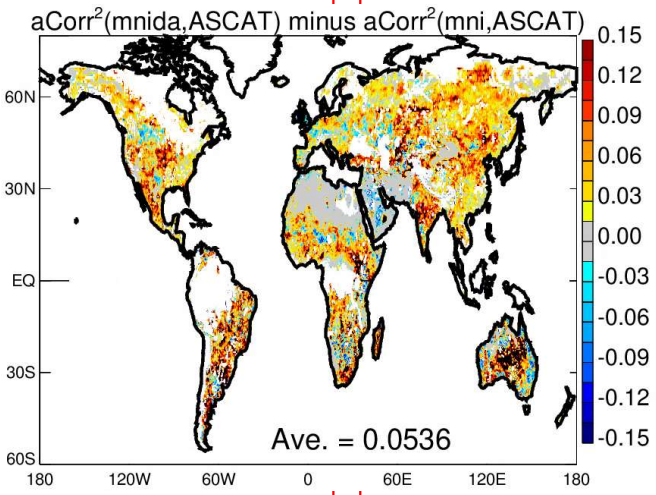


4. Use SMAP rainfall information <u>and</u> assimilate SMAP data

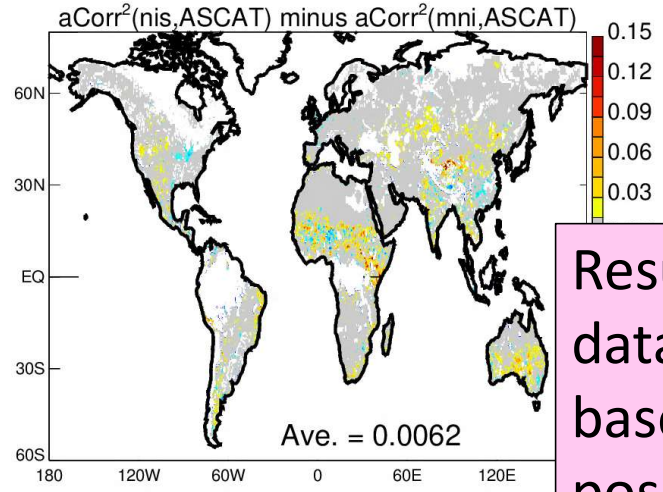
Result 1: Data assimilation impacts dwarf the impact on skill of using SMAP-based rainfall

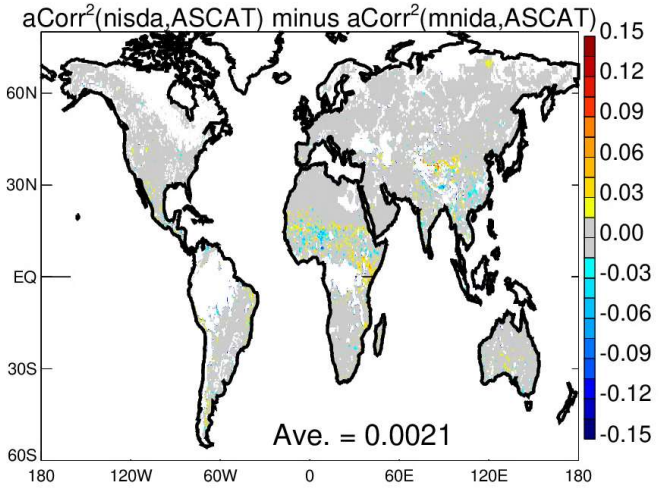
r^2 differences

1. No SMAP data

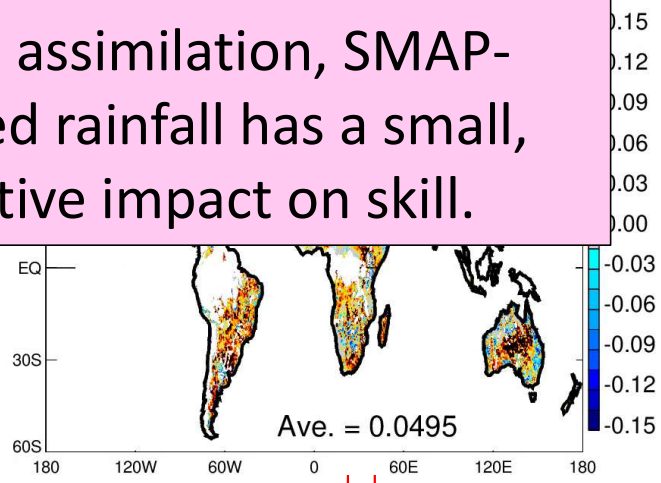


3. Assimilate SMAP data





2. Use SMAP rainfall information

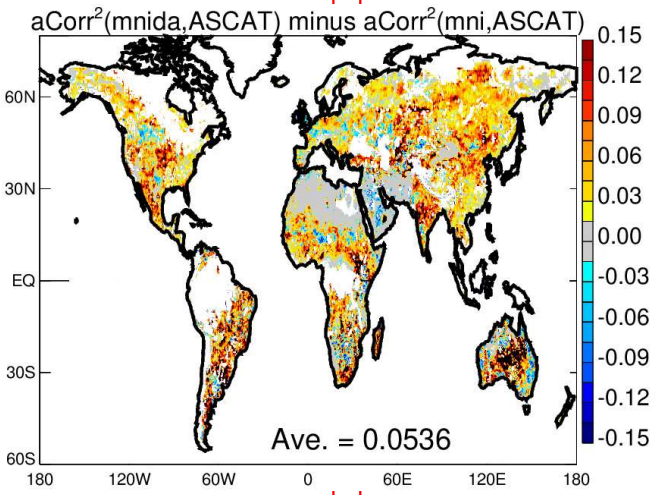


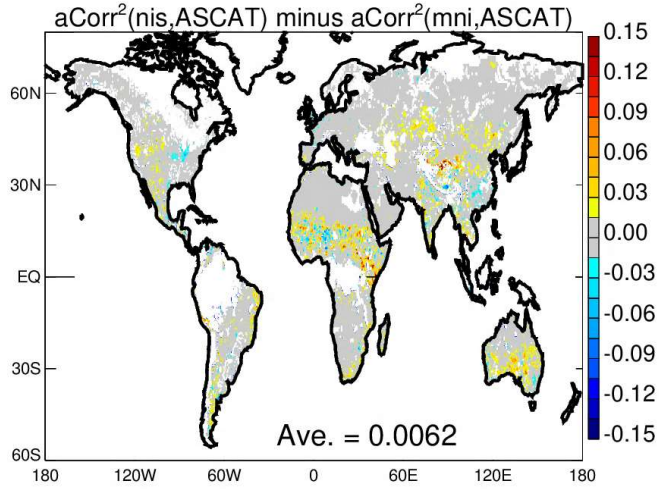
4. Use SMAP rainfall information and assimilate SMAP data

Result 2: In the absence of data assimilation, SMAP-based rainfall has a small, positive impact on skill.

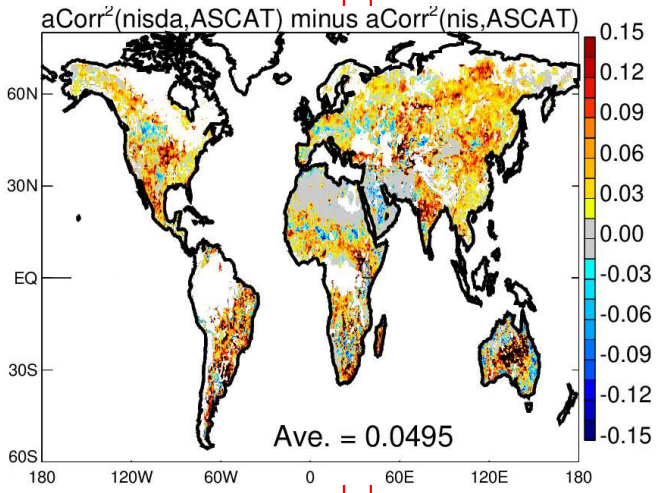
r^2 differences

1. No SMAP data

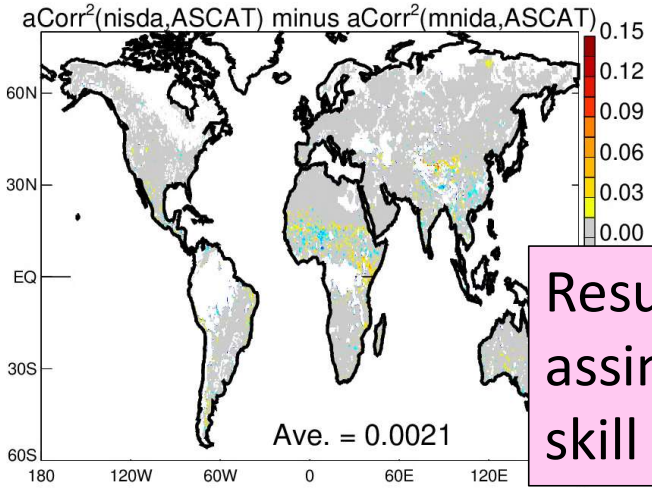




2. Use SMAP rainfall information



3. Assimilate SMAP data



Result 3: However, with data assimilation, that impact on skill diminishes markedly.

Overall, a “negative” result: utilizing SMAP-based rainfall in the L4_SM data assimilation system does not add much in the way of complementary information.

Still, we wouldn’t have known if we hadn’t tried!