Confronting forecast models, reanalyses and land surface models with global remote sensing estimates of land-atmosphere coupling

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Toward Confronting forecast models, reanalyses and land surface models with global remote sensing estimates of land-atmosphere coupling

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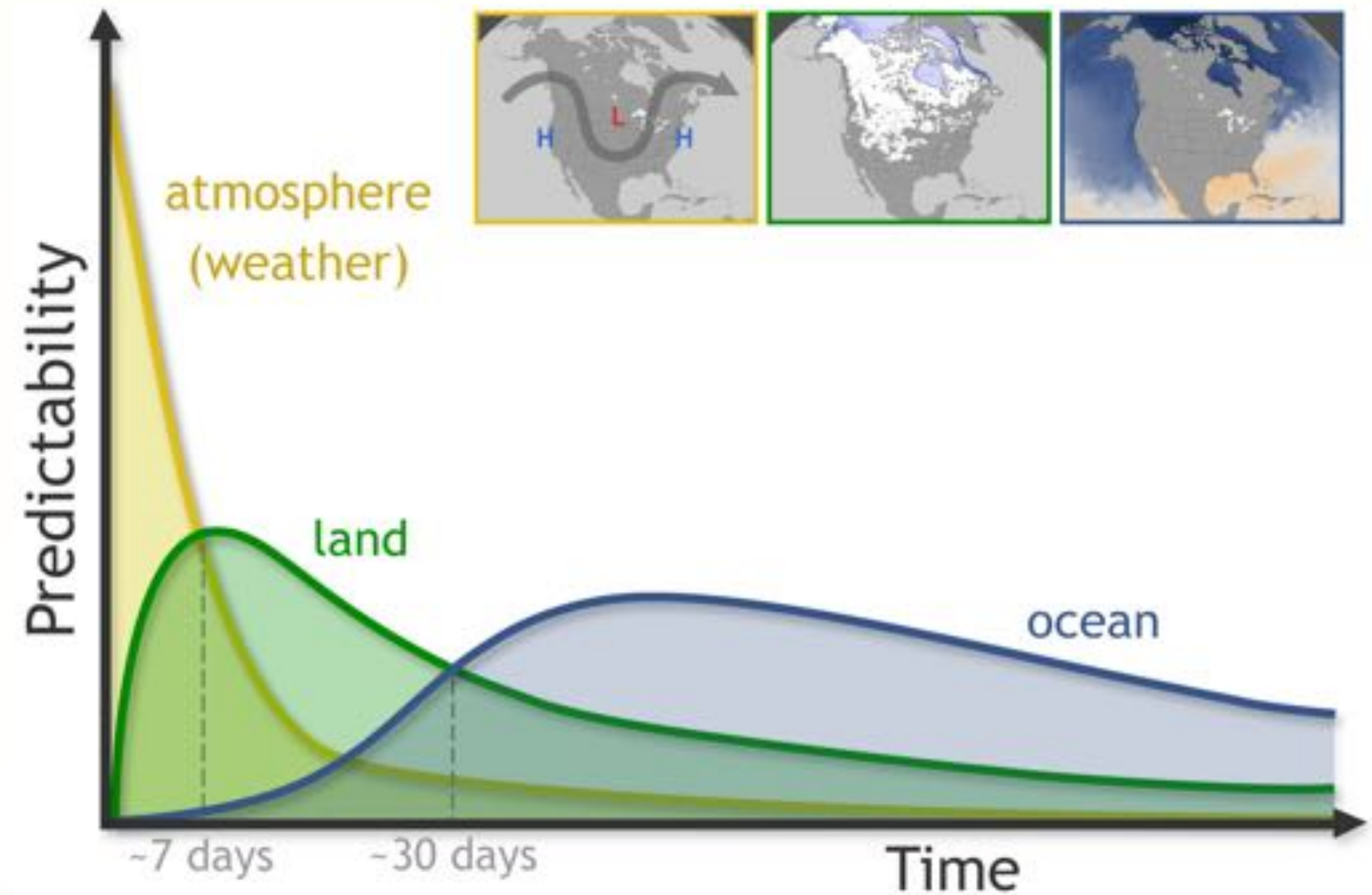
Predictability and Prediction

- Variations in land states (namely soil moisture but also snow) can provide predictability in the window (S2S) between deterministic (weather) and climate (O-A) time scales.



- Varying vegetation states (related to soil moisture anomalies) give predictability beyond S2S time scales.
- L-A coupling is active where there is sensitivity, variability and memory.

LoCo and Indices

- Local L-A coupling (LoCo) is a major thrust in GEWEX.
- A catalog of L-A coupling indices and metrics has been compiled at: http://tiny.cc/l-a-metrics
- A toolkit of code that can be implemented within coupled L-A models: http://www.coupling-metrics.com/
- All to aid diagnosis of L-A coupling within weather and climate models.

LAND–ATMOSPHERE INTERACTIONS

The LoCo Perspective

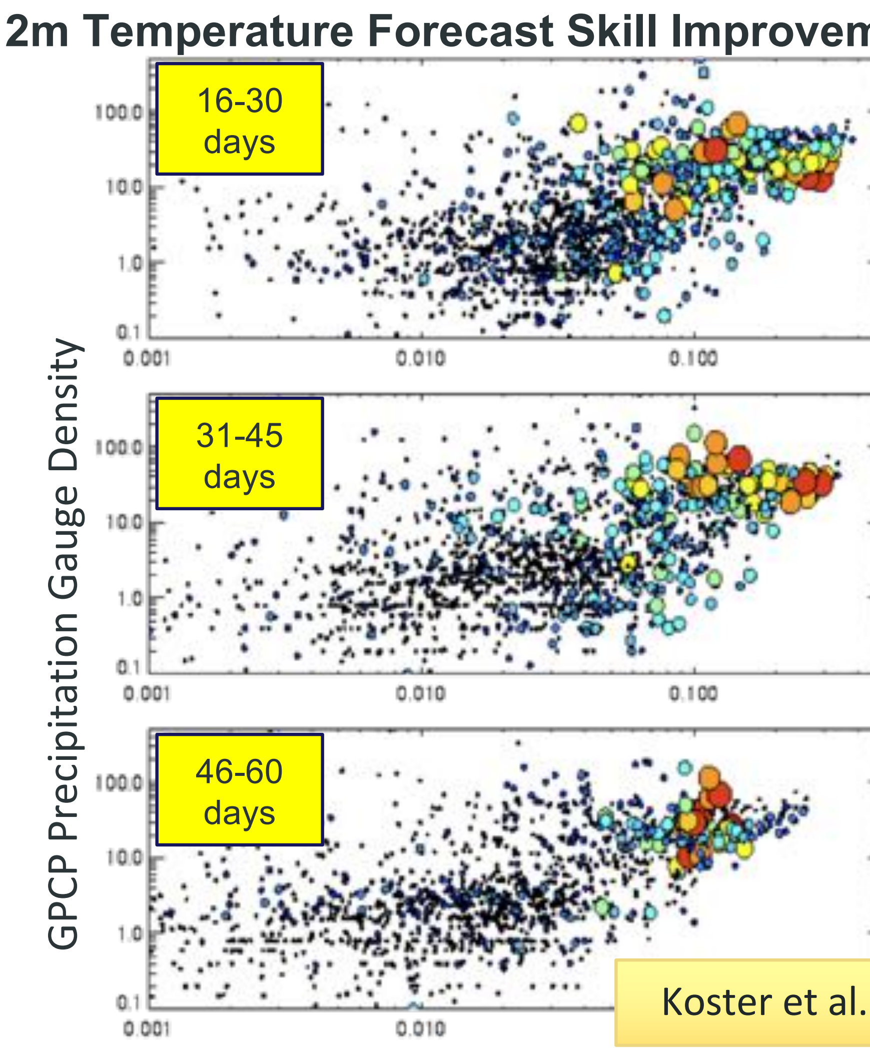
Joseph A. Santanello Jr., Paul A. Dirmeyer, Craig R. Ferguson, Kirsten L. Findell, Ahmed B. Tawfik, Alexis Berg, Michael Ek, Pierre Gentine, Benoit P. Guillod, Chiel van Heerwaarden, Joshua Roundy, and Volker Wulfmeyer

Metrics derived by the LoCo working group have matured and begun to enter the mainstream, signaling the success of the GEWEX approach to foster grassroots participation.

BAMS, June 2018 (EOR available)

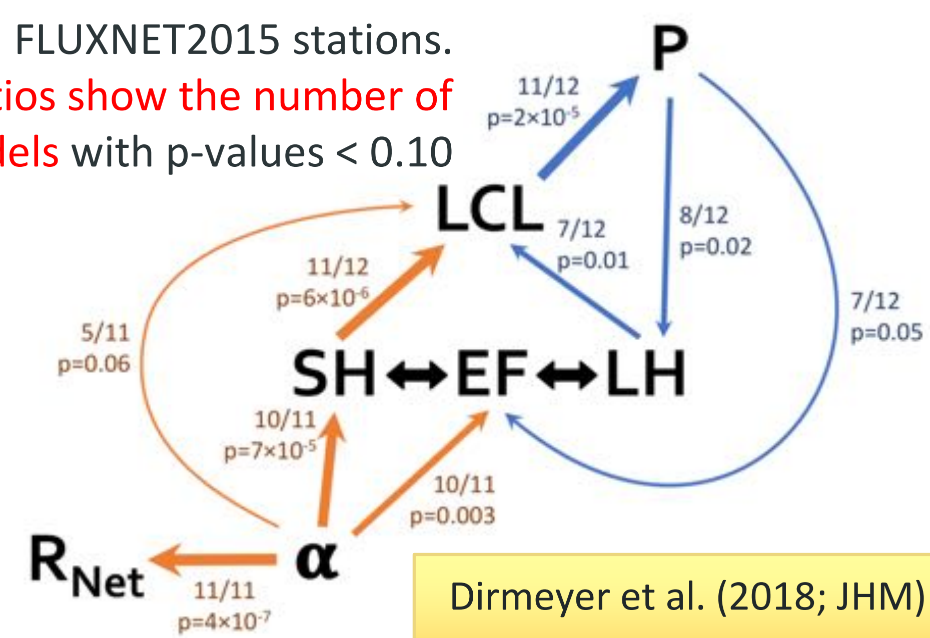
Multi-Model Studies

- GLACE demonstrated "hotspots" of L-A coupling
- GLACE-2 demonstrated L-A improves forecasts
- "Confront" models to identify L-A shortcomings
- Diurnal Cycle Expt. (DICE) taking first steps to investigate L-A coupling in models at the process level



Koster et al. (2011; JHM)

Error propagation from their rank correlations across FLUXNET2015 stations. Ratios show the number of models with p-values < 0.10



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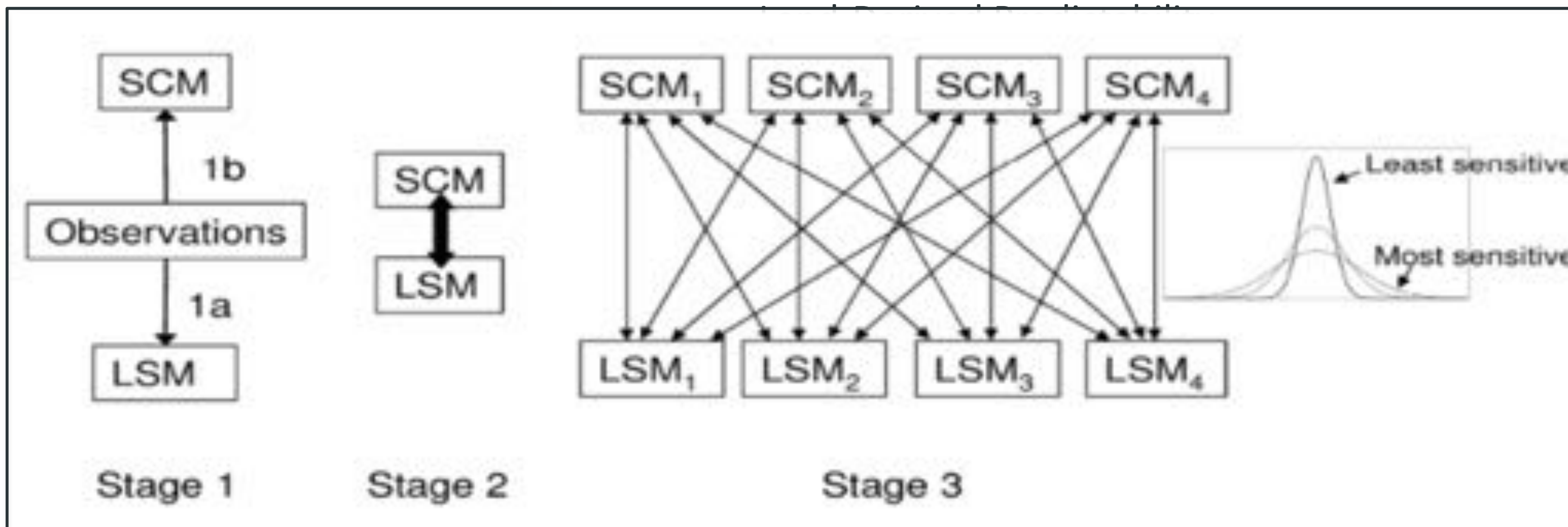
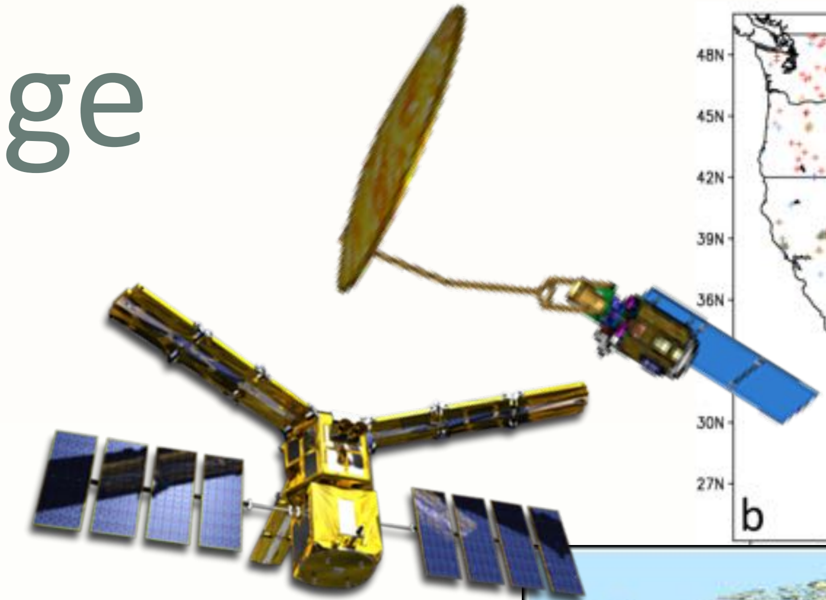
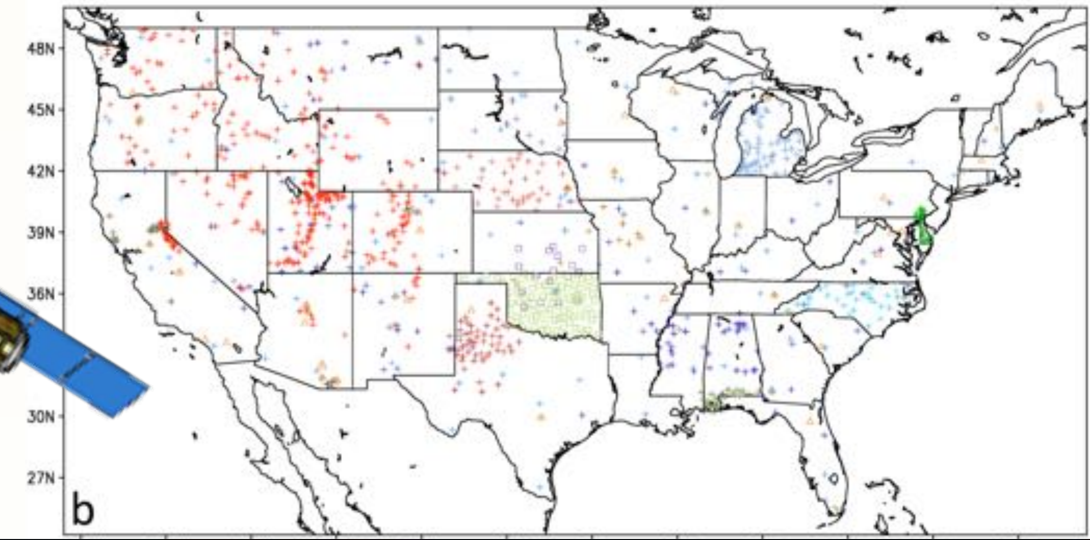
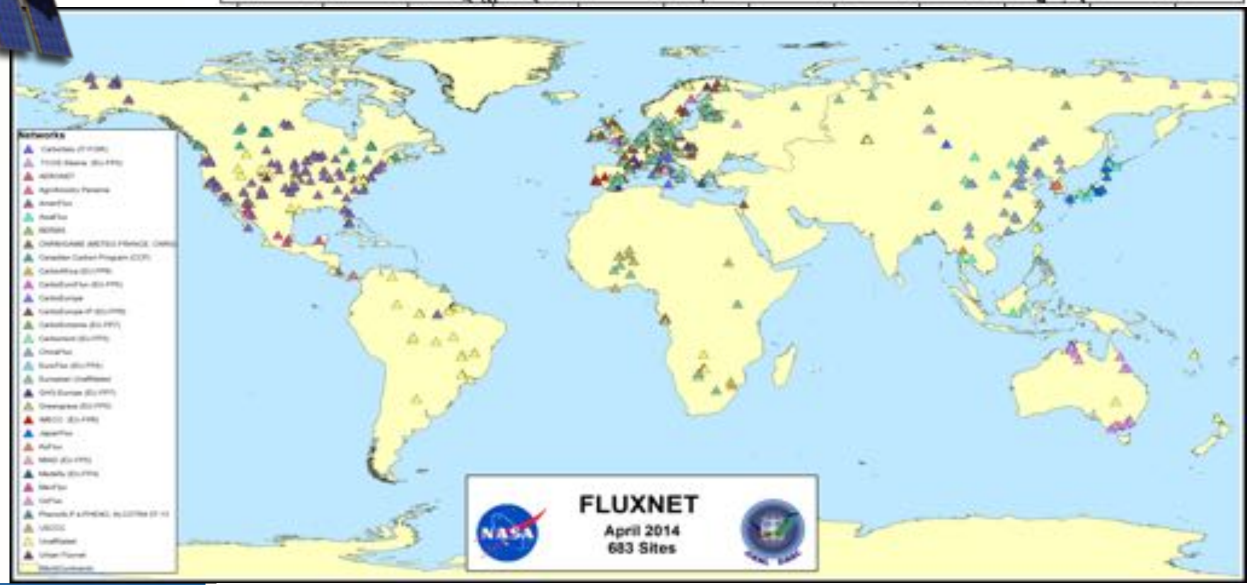


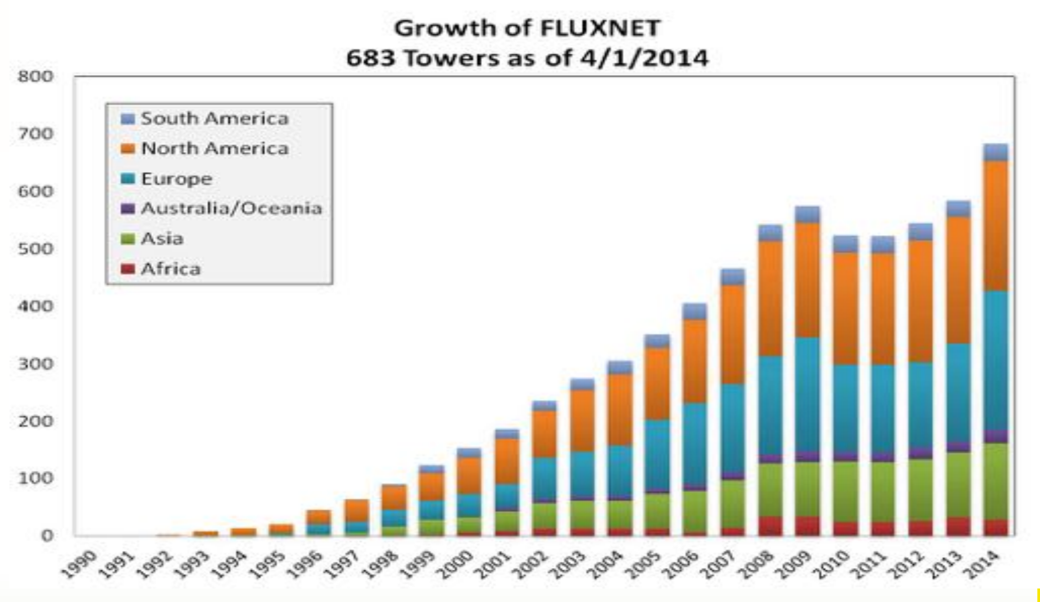
Entering Golden Age for L-A data





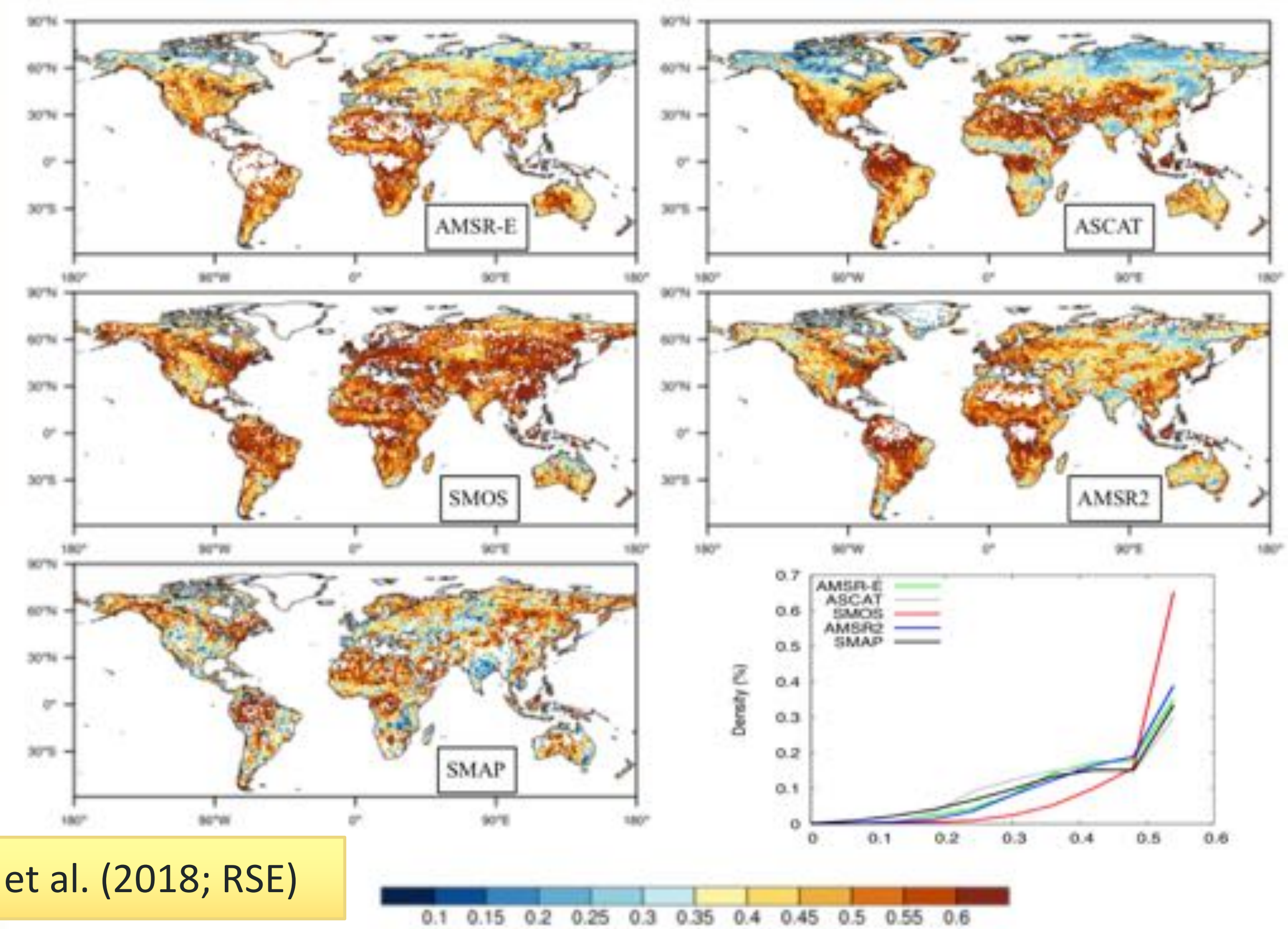
- *In situ* fluxes (FluxNET, ARM/CART, field campaigns, etc.), soil moisture networks of networks (NASMDB, ISMN)
- Remote sensing (orbital platforms, radar, lidar, cosmic ray, GPS, etc.)
- Long time series, co-location, QC are **essential** – we need land, meteo & PBL measurements together!!



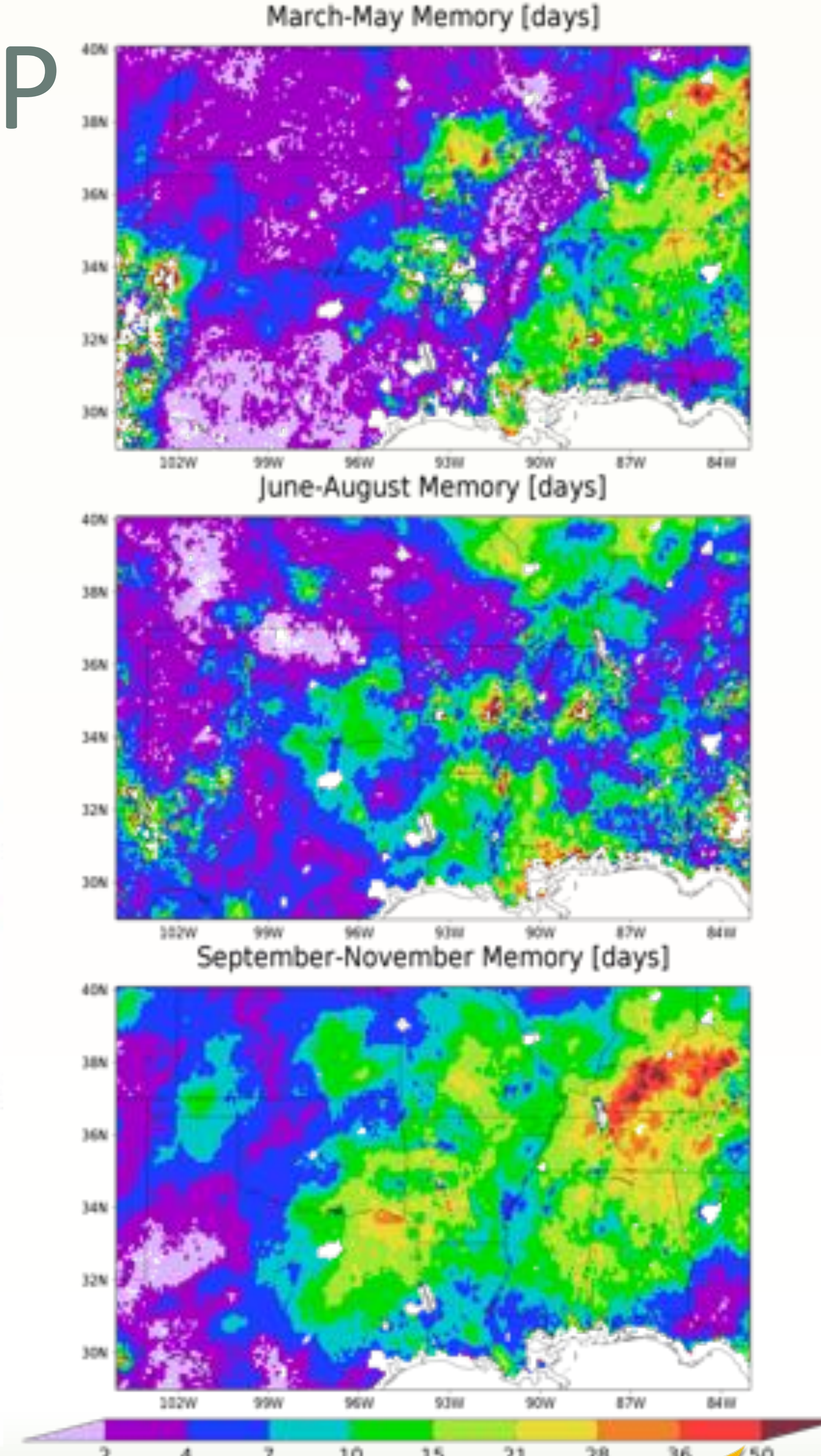


Soil Moisture Memory in SMAP

- Blending AM and PM passes, we estimate soil moisture memory (lagged autocorrelation drops below e^{-1}) taking advantage of the unequal overpass intervals (8-day repeat cycle).
- Can also estimate error variance ratios.



Kumar et al. (2018; RSE)



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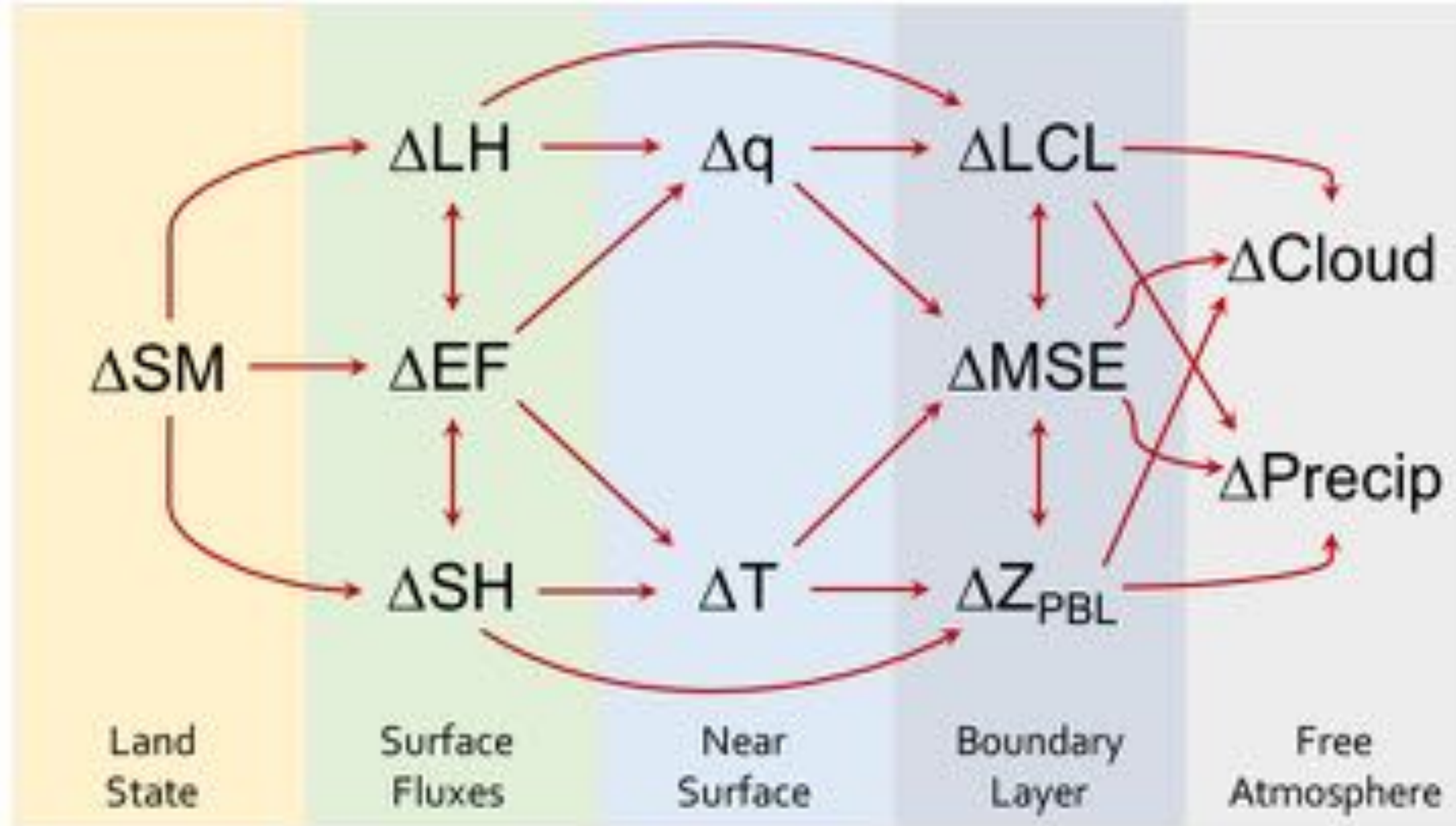
Observability

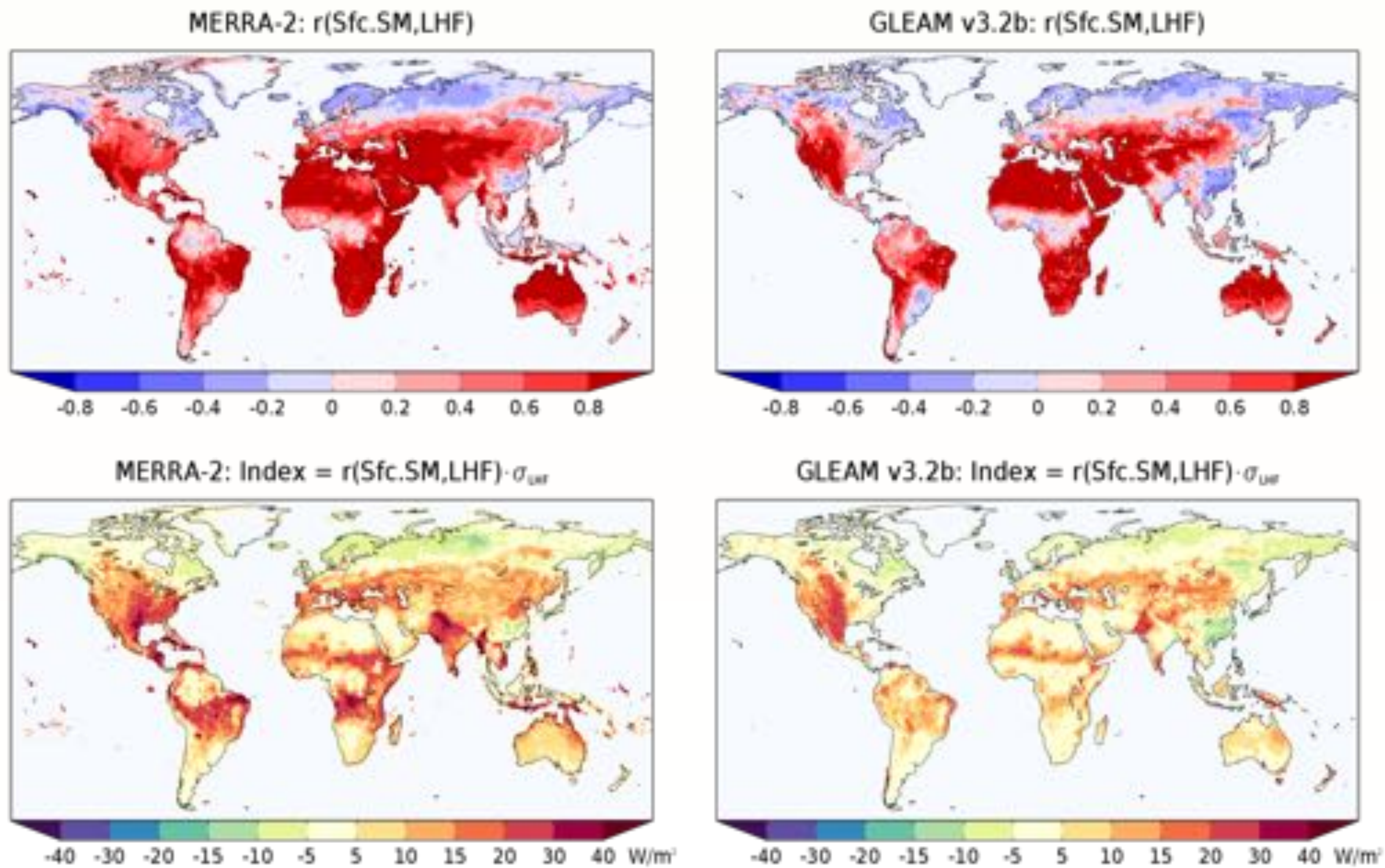


- How much of the process linkage in L-A feedbacks can we observe globally, using remote sensing?
- How can satellites complement flux towers, met stations, etc.?
- How do satellite estimates compare to today's yardstick: reanalyses?
- Can we get reliable enough estimates of the spatial distribution of the strengths and variability in these linkages to inform model development, and improve weather and climate forecasts?
- What are the current capabilities? What should be pursue next?

Soil Moisture : Latent Heat (ET) via GLEAM

- There is basic agreement between energy- versus moisture-limited regimes, terrestrial coupling index.
- Eastern US, S. Asia among regions with noticeable shift in regimes; overall GLEAM tends more towards energy-limited.
- GLEAM generally weaker on coupling index except central-western North America – noise effect?

JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



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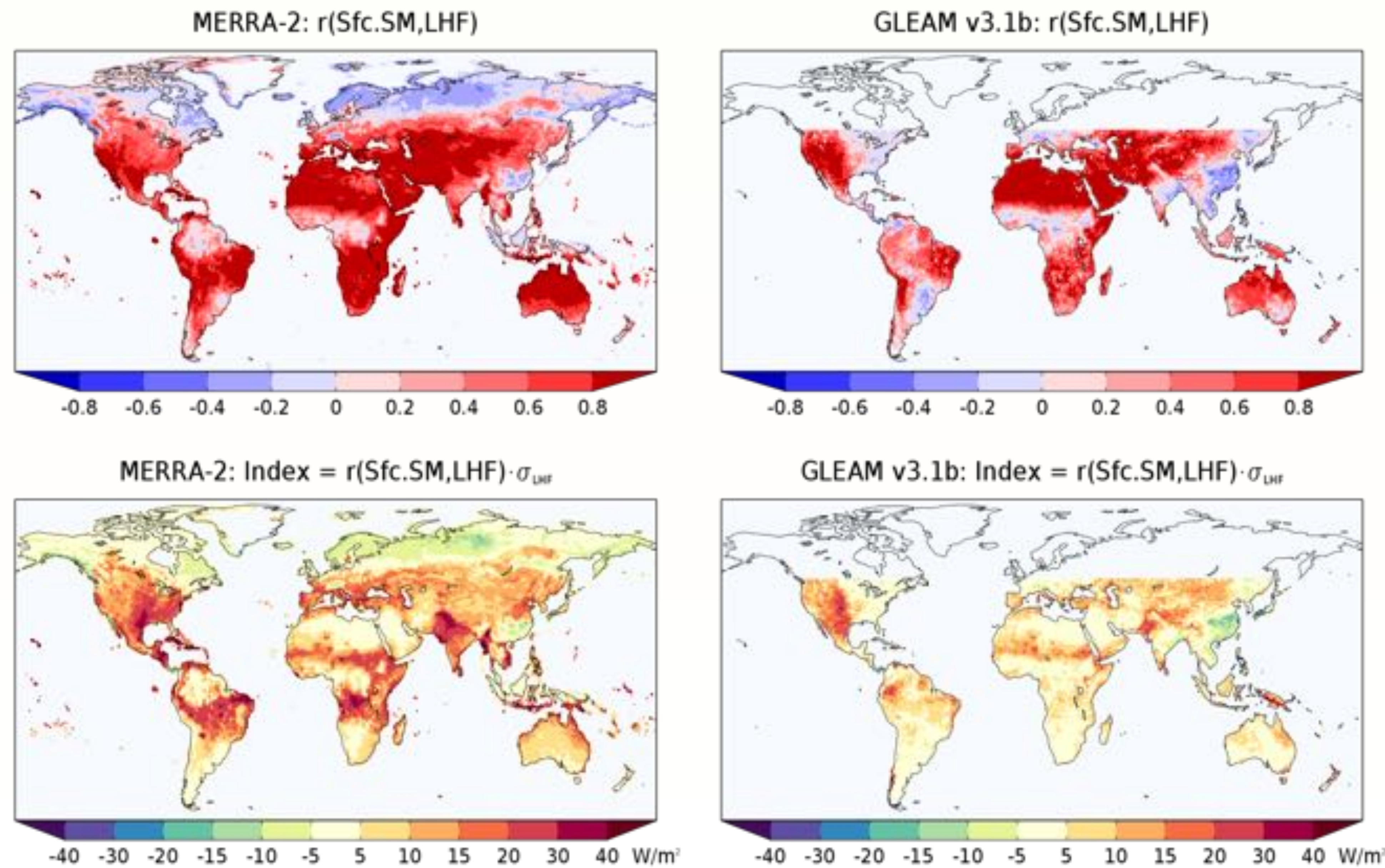

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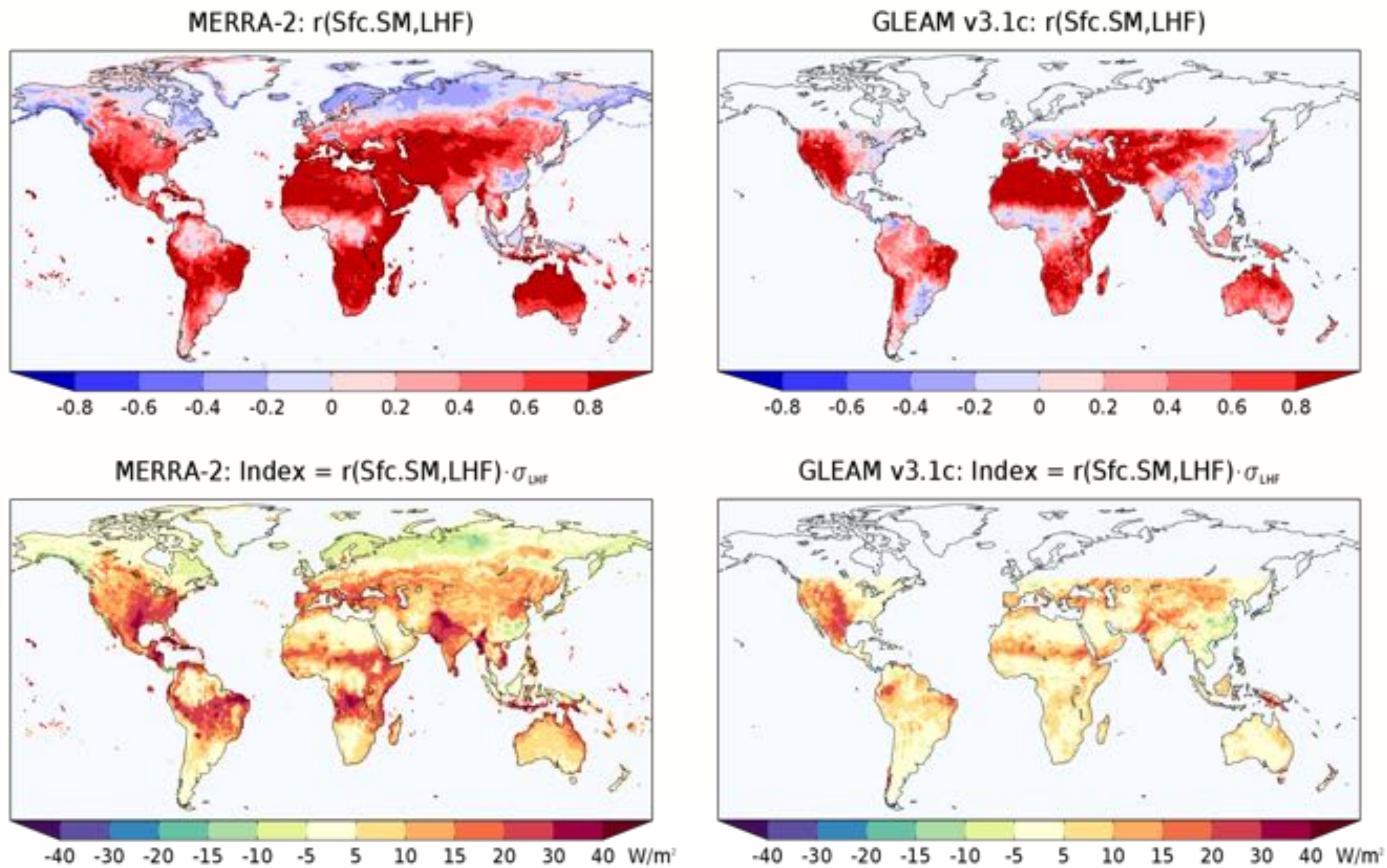
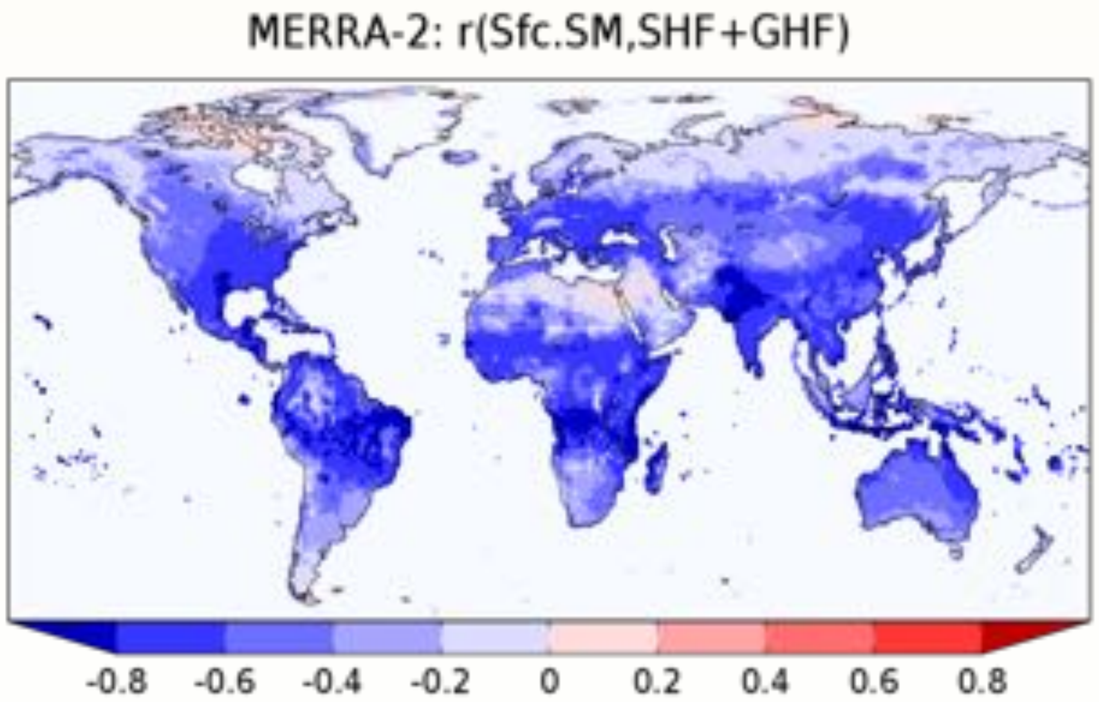
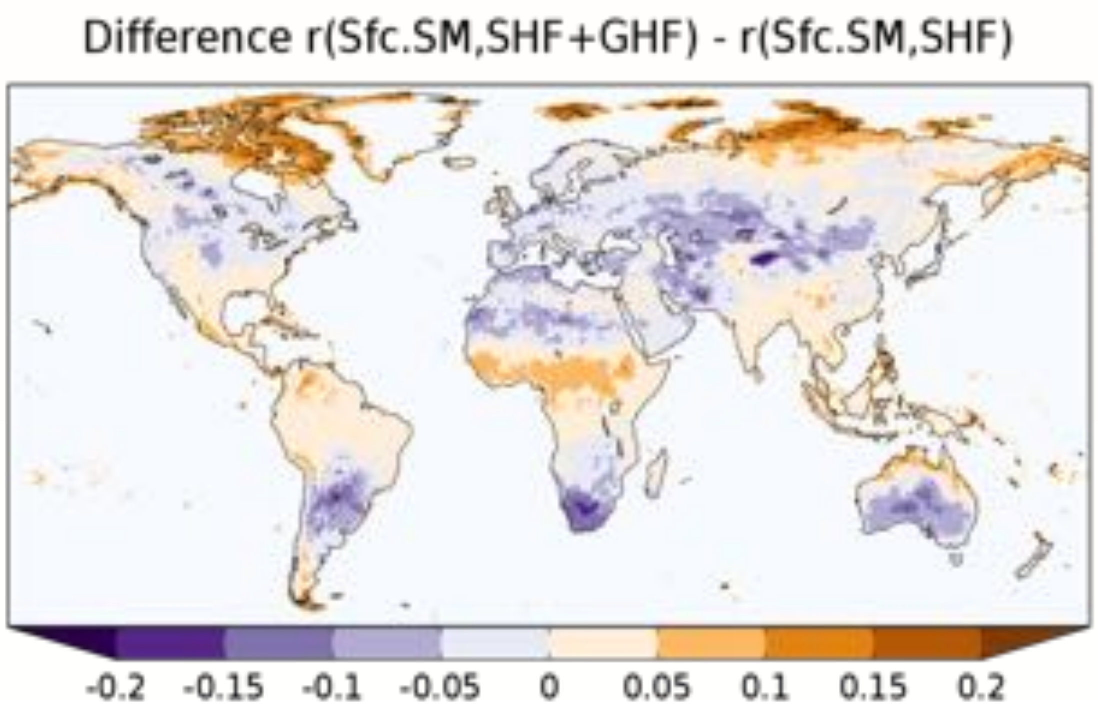


Sensible Heat?

- Soil moisture pathway to PBL development runs thru SHF.
- Don't have a very believable global gridded remote sensing based sensible heat analysis.
- We do have a nice gridded surface radiation product (CERES SYN1deg-Day TERRA+NPP Edition 1A).
- Can estimate via:

$$SHF + GHF = R_{NET}[\text{CERES}] - LHF[\text{GLEAM}]$$





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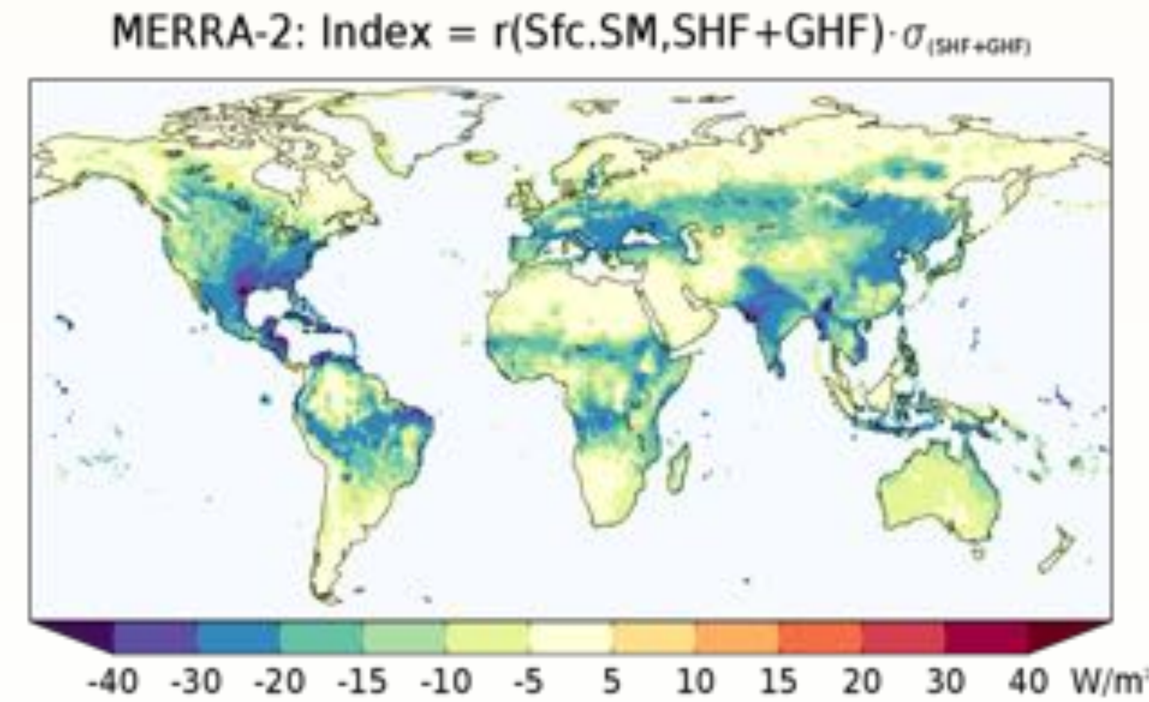
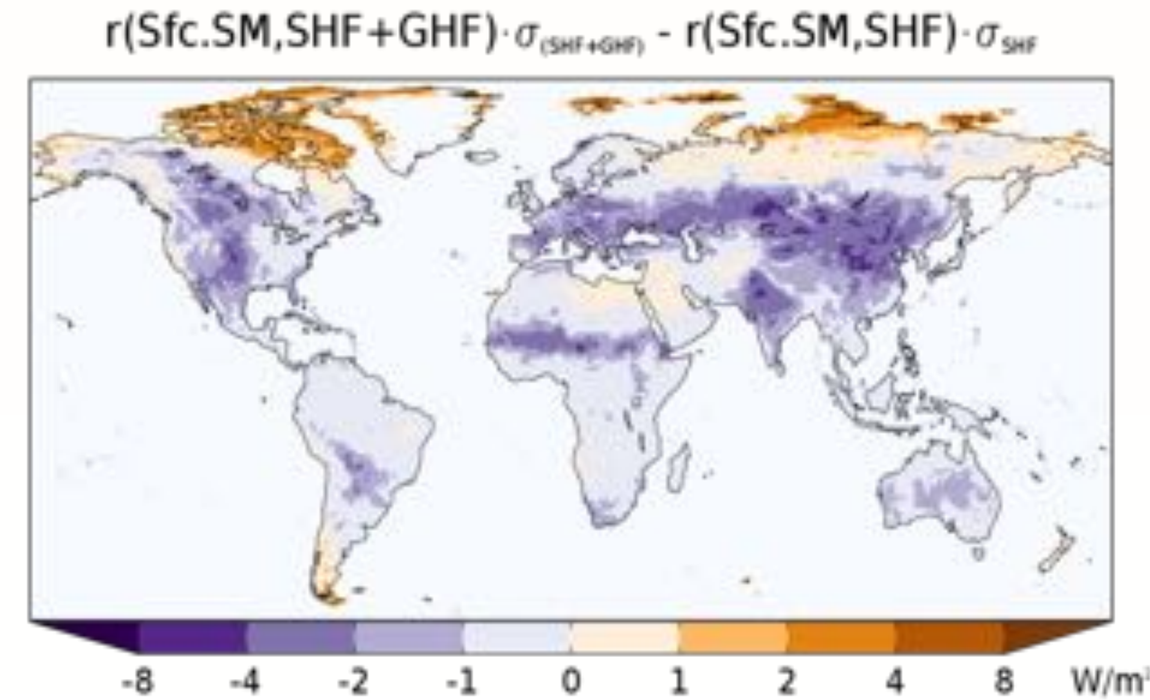
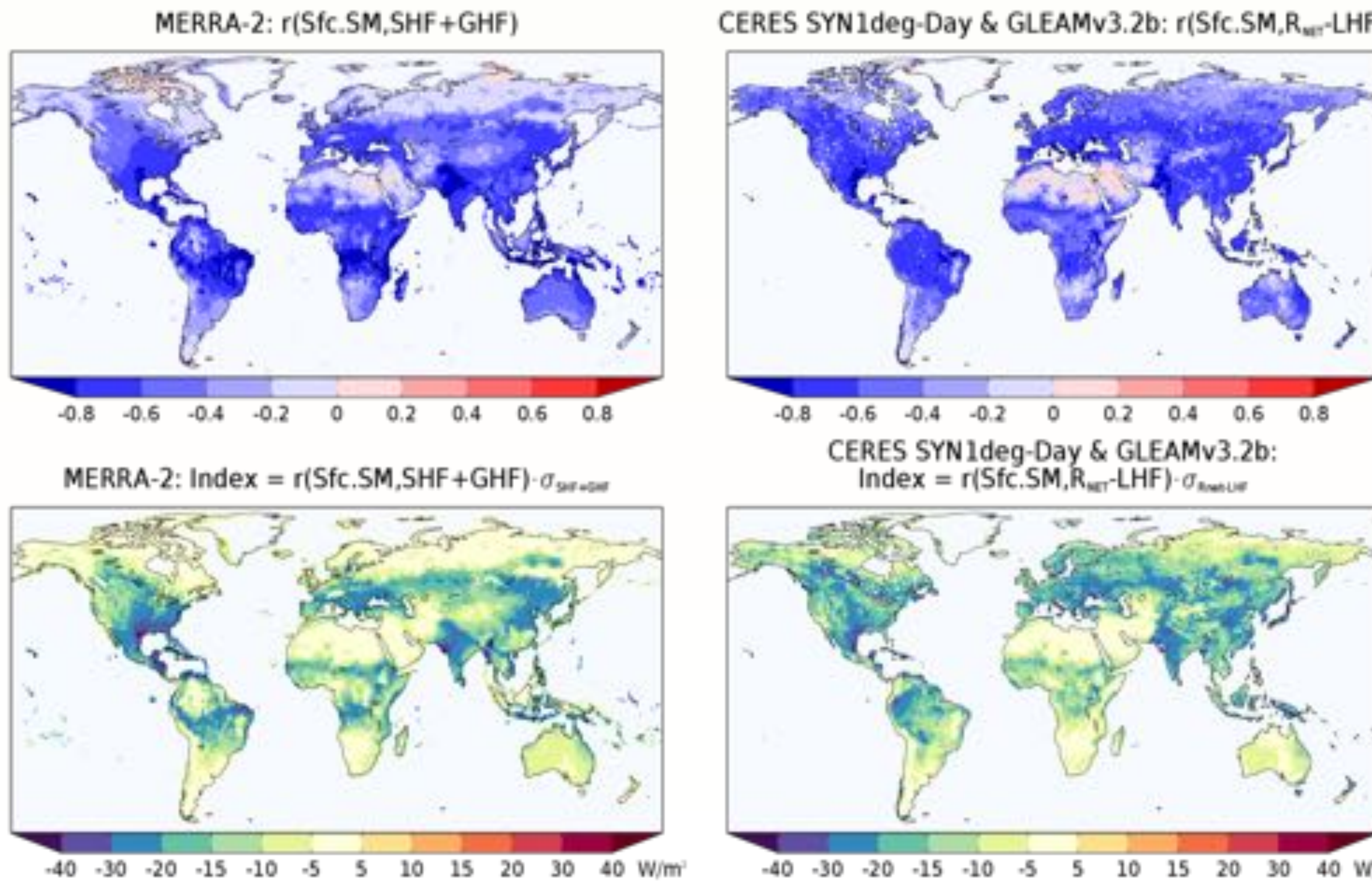




Soil Moisture : Sensible Heat

- CERES+GLEAM suggests overall stronger mid-latitude coupling than MERRA-2.
- Meanwhile, MERRA-2 hotspots (e.g., Texas, Yucatan, Gujarat) appear weaker.
- CERES+GLEAM suggests stronger linkage at high-latitudes, less over Sahara & Arabia, than MERRA-2.

JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



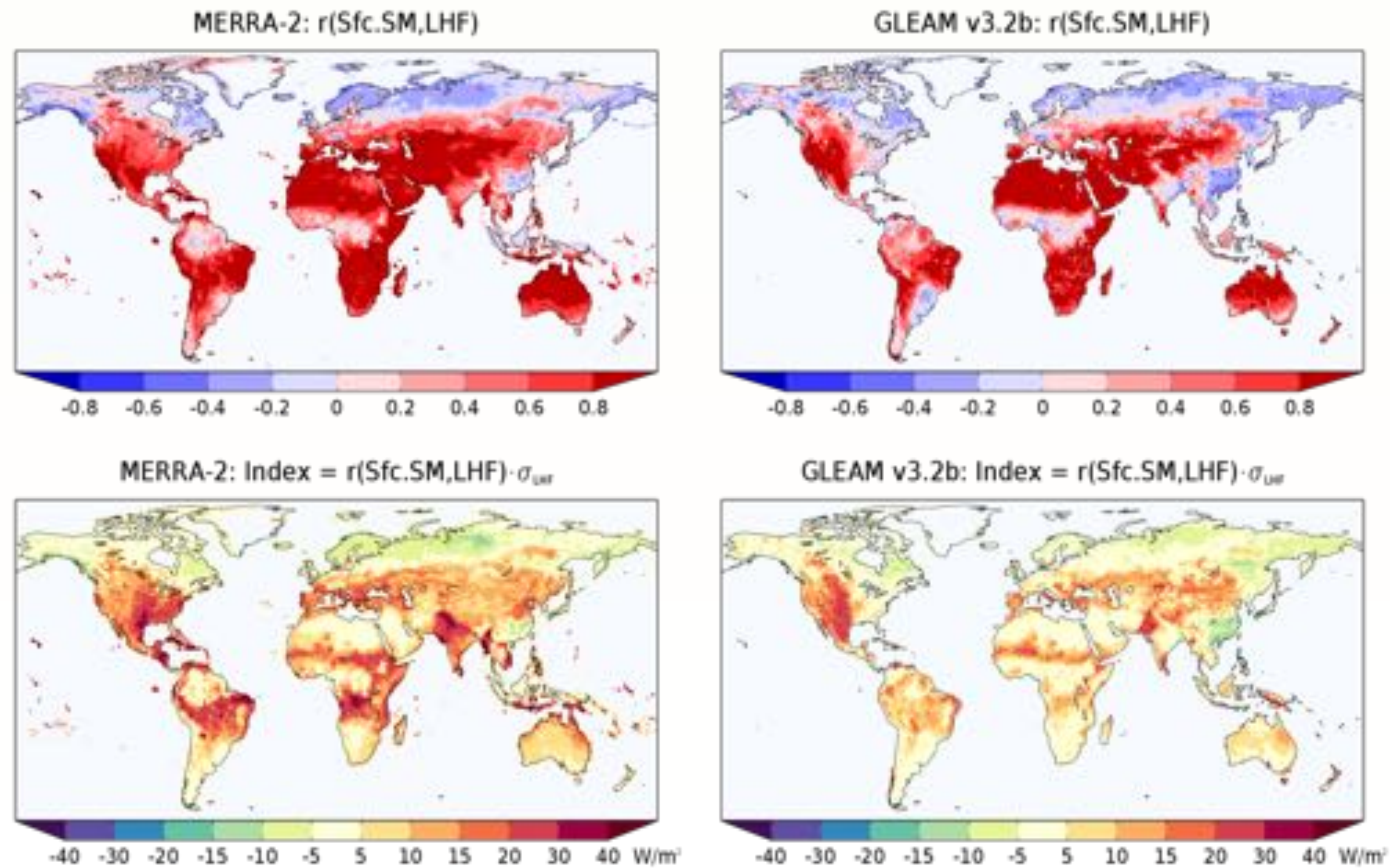
But we know there are errors…

- GCM output like MERRA-2 has no *measurement* (random) error, but plenty of other error sources due to data & model compromises (parameterizations, resolution, assimilation scheme, etc.)
- Satellite observations do have random measurement error, plus view angle, georegistration, attenuation, calibration drift, orbit drift, sensor degradation, retrieval algorithms, etc.
- Many of these errors have much longer time scales than 1-day. Perhaps day-to-day changes (deltas) are more reliable than daily means? What if we build our temporal correlations and coupling indices on the deltas?

Soil Moisture : Latent Heat

- What we had before: widespread positive correlations, classical hotspots (in NH: Sahel, central NA, Indus Valley, Eurasian Steppes).

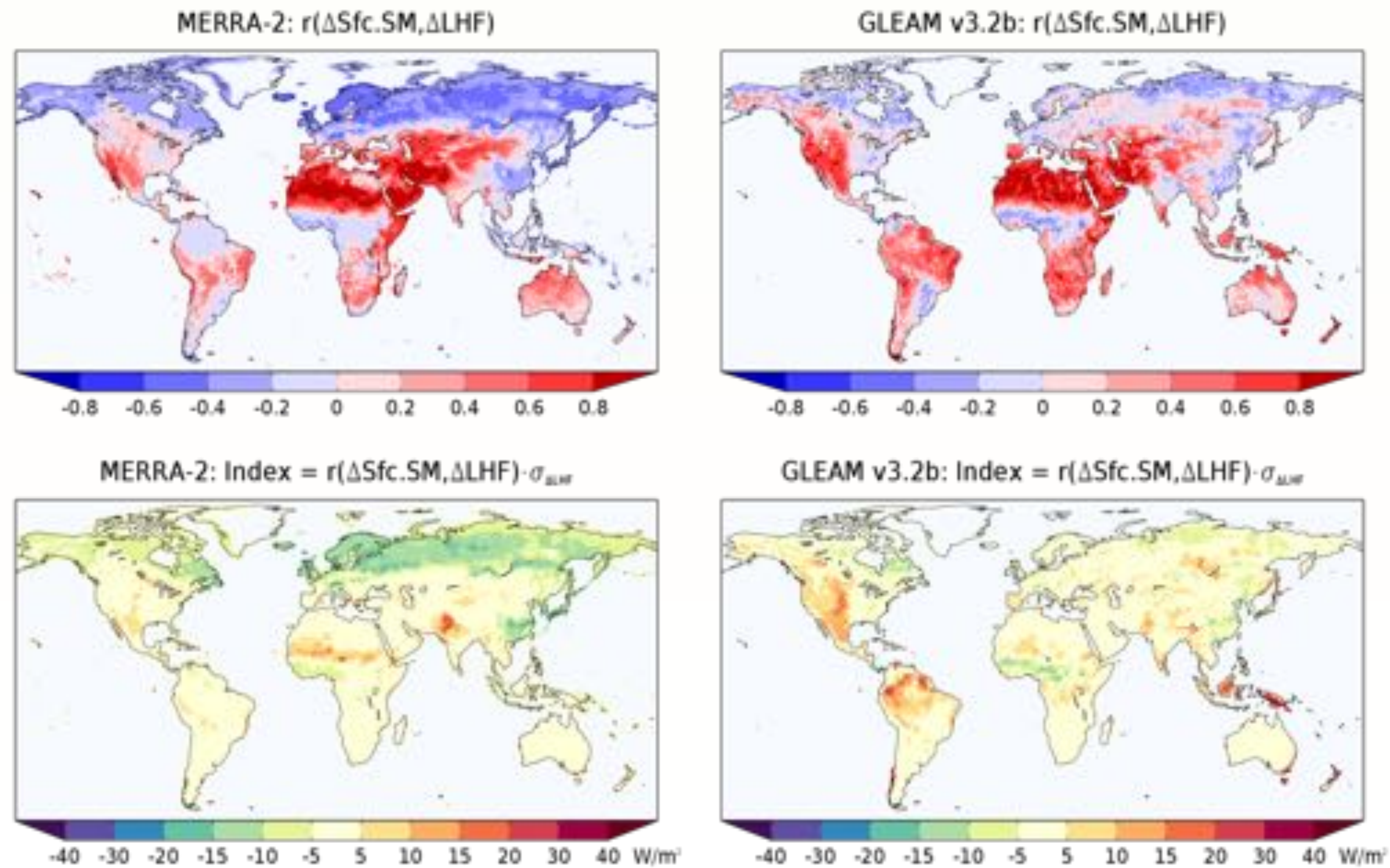
JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



ΔSoil Moisture : ΔLatent Heat

- What we had before: widespread positive correlations, classical hotspots (in NH: Sahel, central NA, Indus Valley, Eurasian Steppes).
- Using *deltas*, huge contraction of positive correlations; hotspots shrink or disappear, uncoupled (energy-limited) areas expand.
- GLEAM registers tropics. V3.1 looks similar.

JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



Soil Moisture : Sensible Heat

- Before, strong coupling in semiarid to semi-humid regions; not in very wet, very dry, winter (SH mid-latitudes); hottest spots in NH subtropics.

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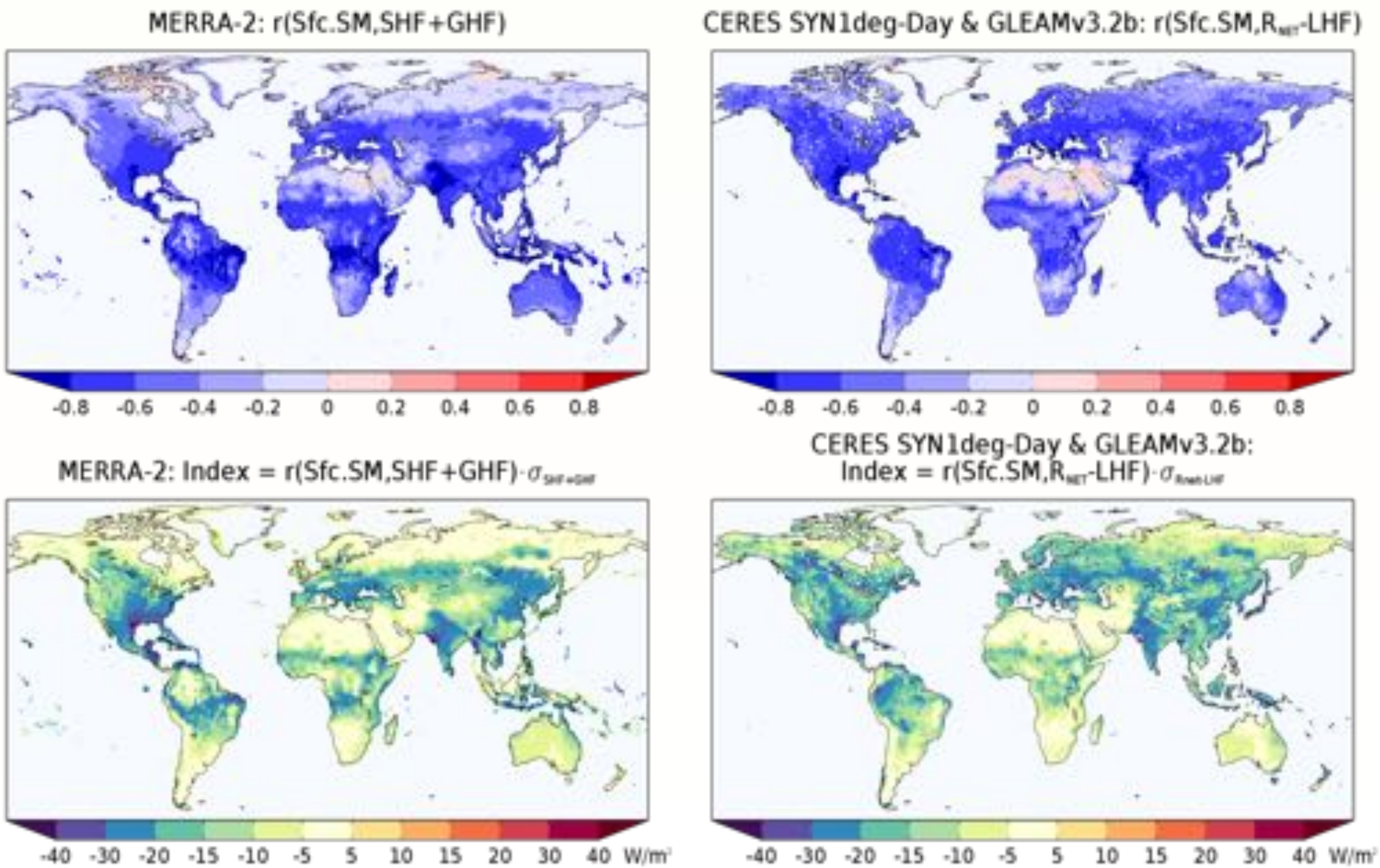
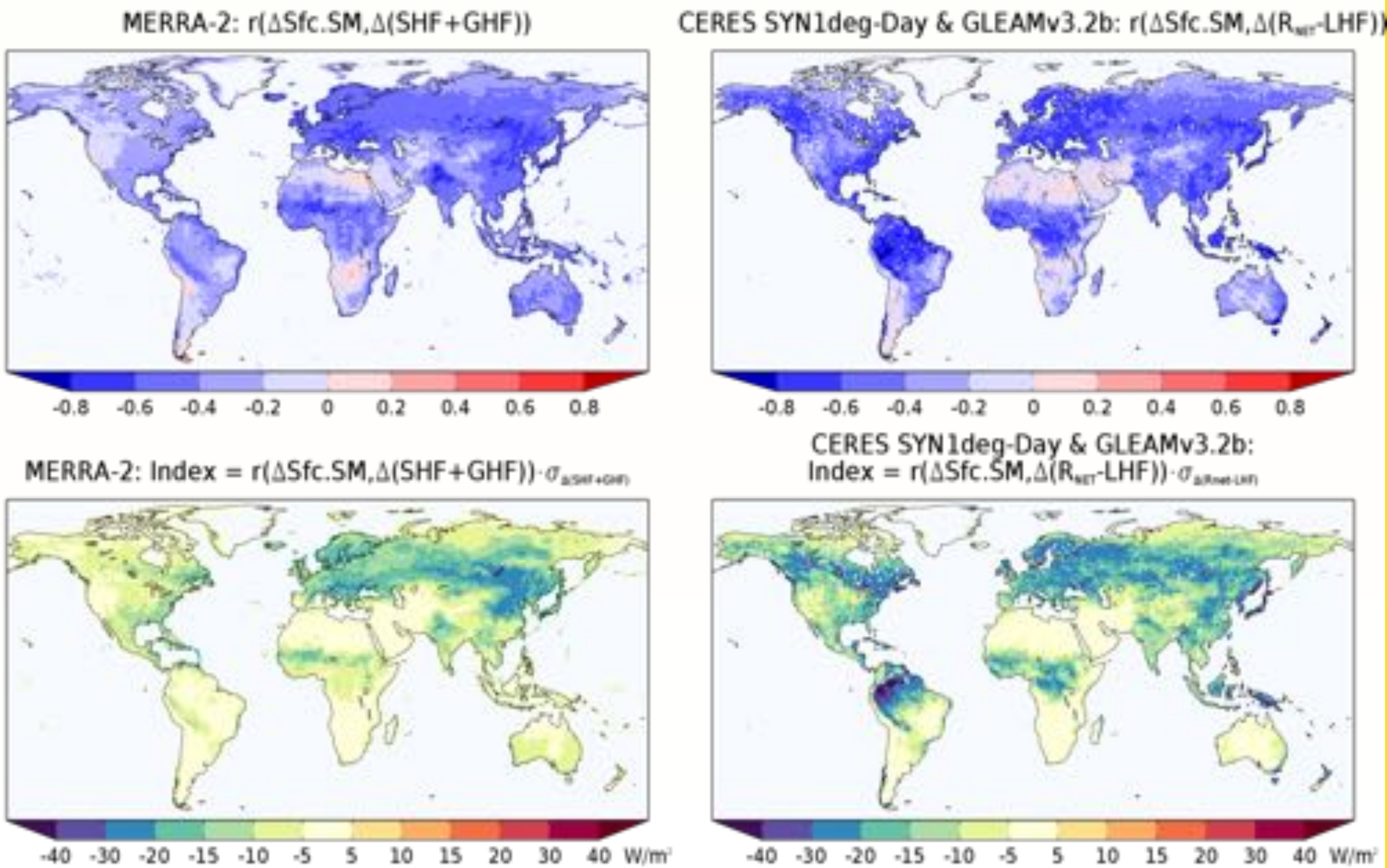


ΔSoil Moisture : ΔSensible Heat

- Before, strong coupling in semiarid to semi-humid regions; not in very wet, very dry, winter (SH mid-latitudes); hottest spots in NH subtropics.
- Using *deltas*, coupling zones move north, abandoning subtropics.
- Big disparity over deep tropics – satellite says highly coupled, MERRA-2 nothing. Why?

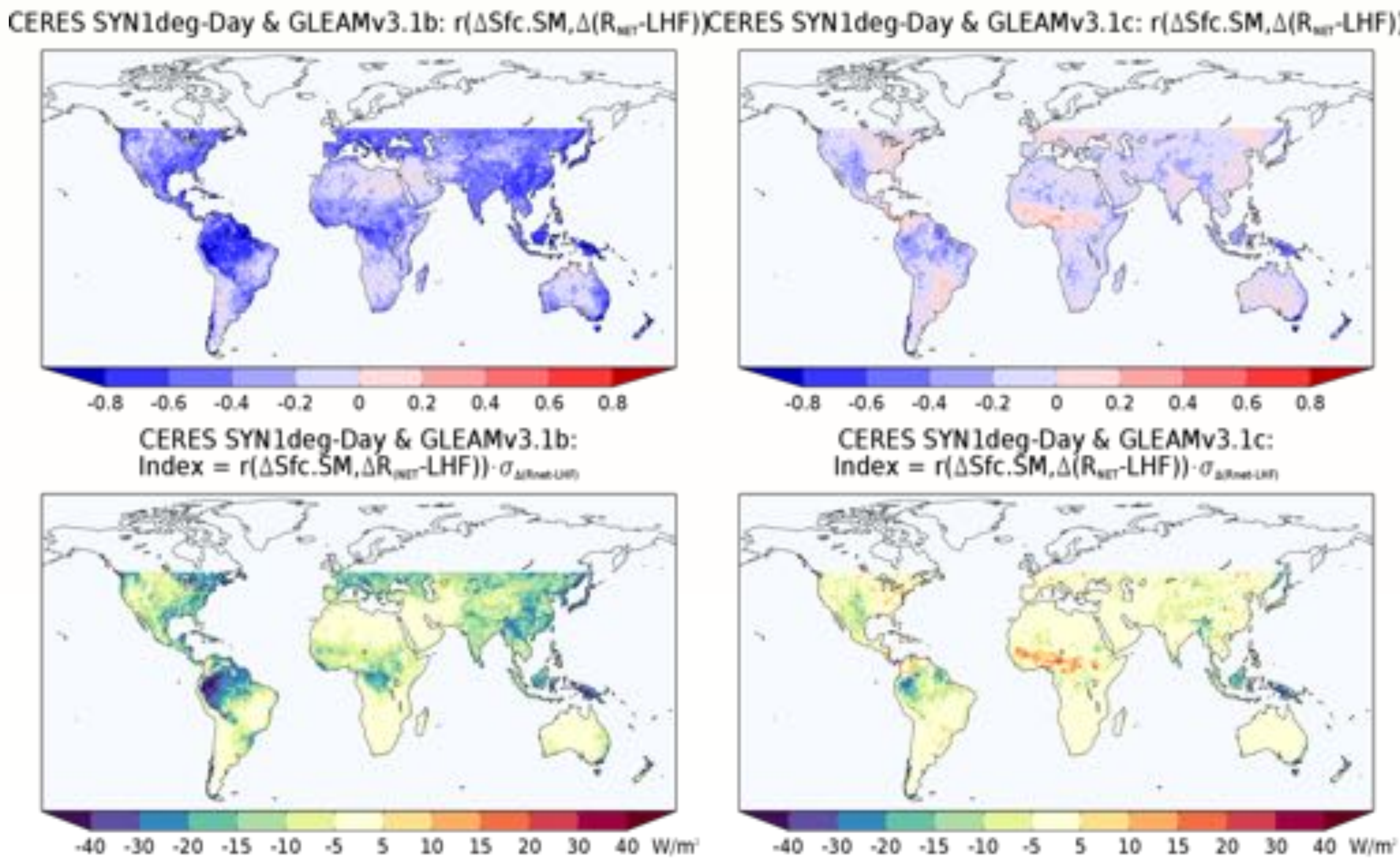
JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



ΔSoil Moisture : ΔSensible Heat

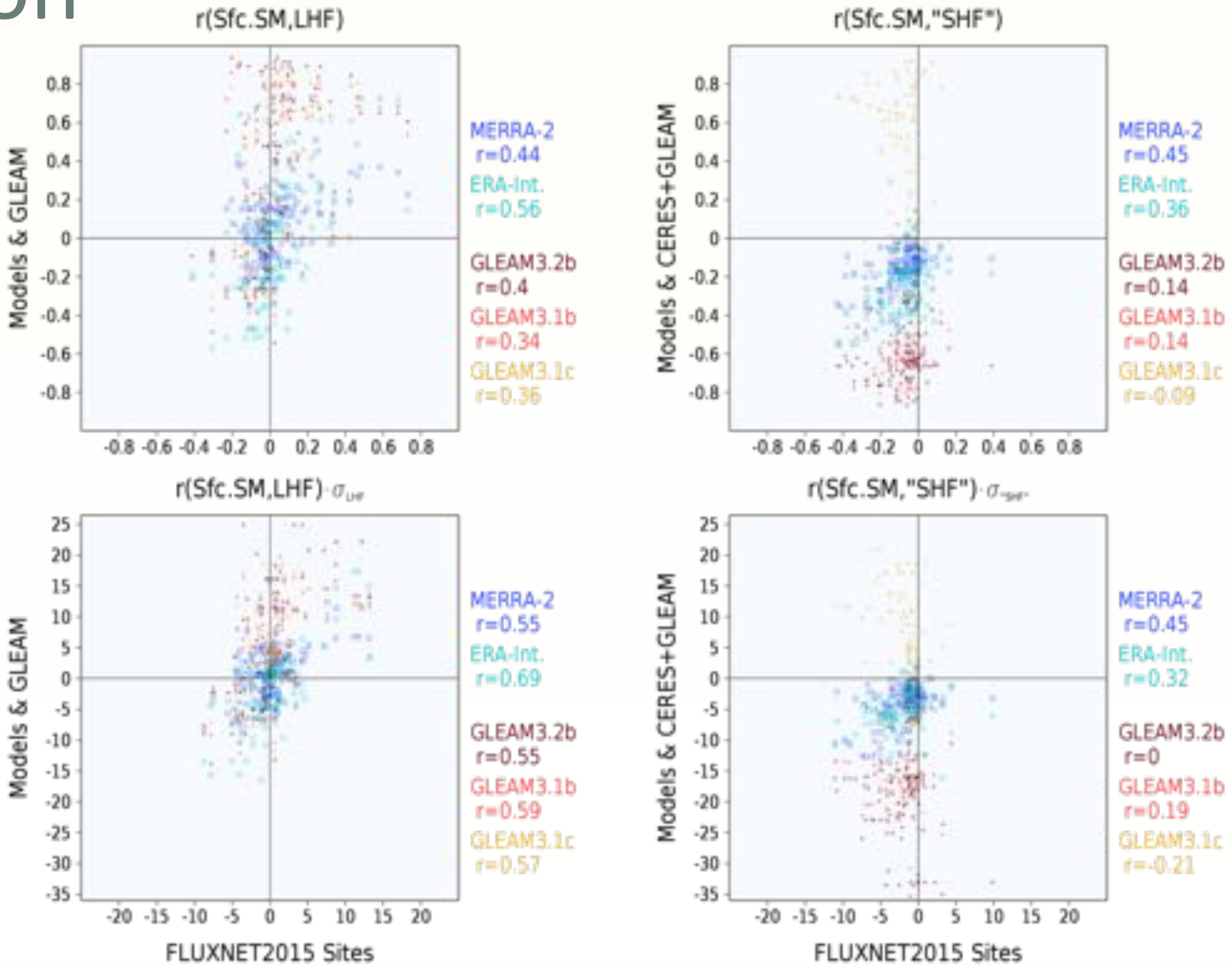
- Estimates from GLEAM v3.1b resemble v3.2b, but v3.1c (SMOS only) is very different – extremely weak with positive correlations in Sudan/Guinea belt.
- Disparities in ΔSM:ΔLHF were not nearly so stark.
- Generally, stats with ΔX will emphasize a much narrower time scale than X; implications….

JJA means (GLEAMv3.1b&c: 2012-2015)



In situ validation

- Comparing one questionable global estimate of L-A coupling against another is not very satisfying.
- Comparison with FLUXNET2015 stations (166) for JJA shows GLEAM SM:LHF approaches reanalyses; SM:SHF … meh, sampling problem? FLUXNET sparse in subtropics and tropics.



Atm. leg: PBL Incubator

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Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space

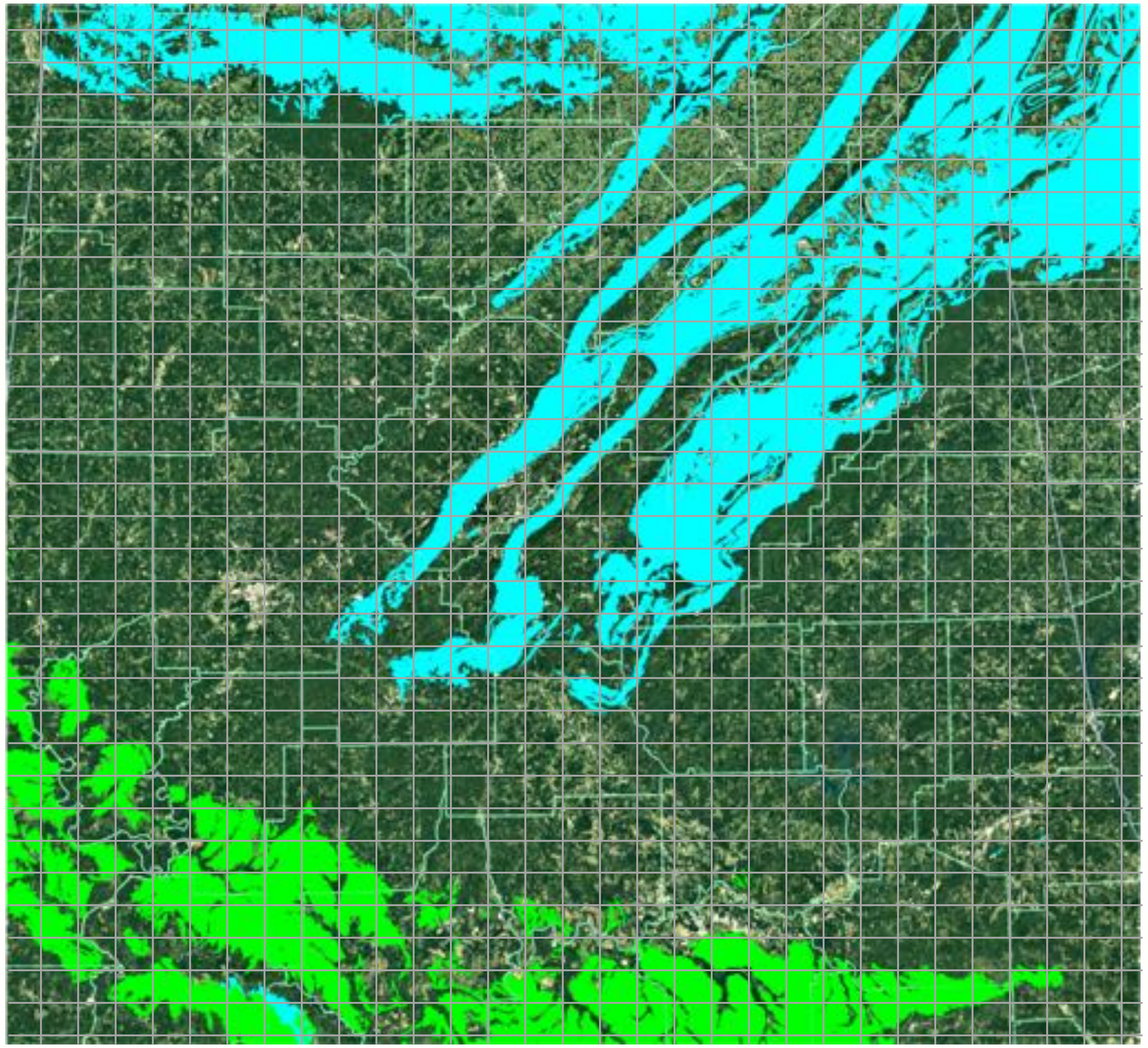
TABLE S.2 Observing System Priorities

Targeted Observable	Science/Applications Summary	Candidate Measurement Approach	Designated	Explorer	Incubation
Planetary Boundary Layer	**Diurnal 3D PBL thermodynamic properties and 2D PBL structure** to understand the impact of PBL processes on weather and AQ through high vertical and temporal profiling of PBL temperature, moisture and heights	Microwave, hyperspectral IR sounder(s) (e.g., in geo or small sat constellation), GPS radio occultation for diurnal PBL temperature and humidity and heights; water vapor profiling DIAL lidar; and lidar** for PBL height			X
Surface Topography and Vegetation	**High-resolution global topography** including bare surface land topography ice topography, vegetation structure, and shallow water bathymetry	Radar; or lidar**			X

- The decadal survey of NASA Earth observation plans now includes boundary layer measurements from space.
- The PBL is listed as an 'Incubator' measurement, and the PBL is mentioned >100 times throughout the report as a high priority and cross-cutting science measurement.
- Many GEWEX scientists involved in bringing this about!

Does Shallow Subsurface Karst Affect Soil Moisture Memory?

- High-resolution GIS data set of karst in the US (Dan Doctor, USGS)
- Generate gridded karst coverage percentage on SMAP 9km grid.



Dirmeyer & Norton (2018; Hydrol., in prep)

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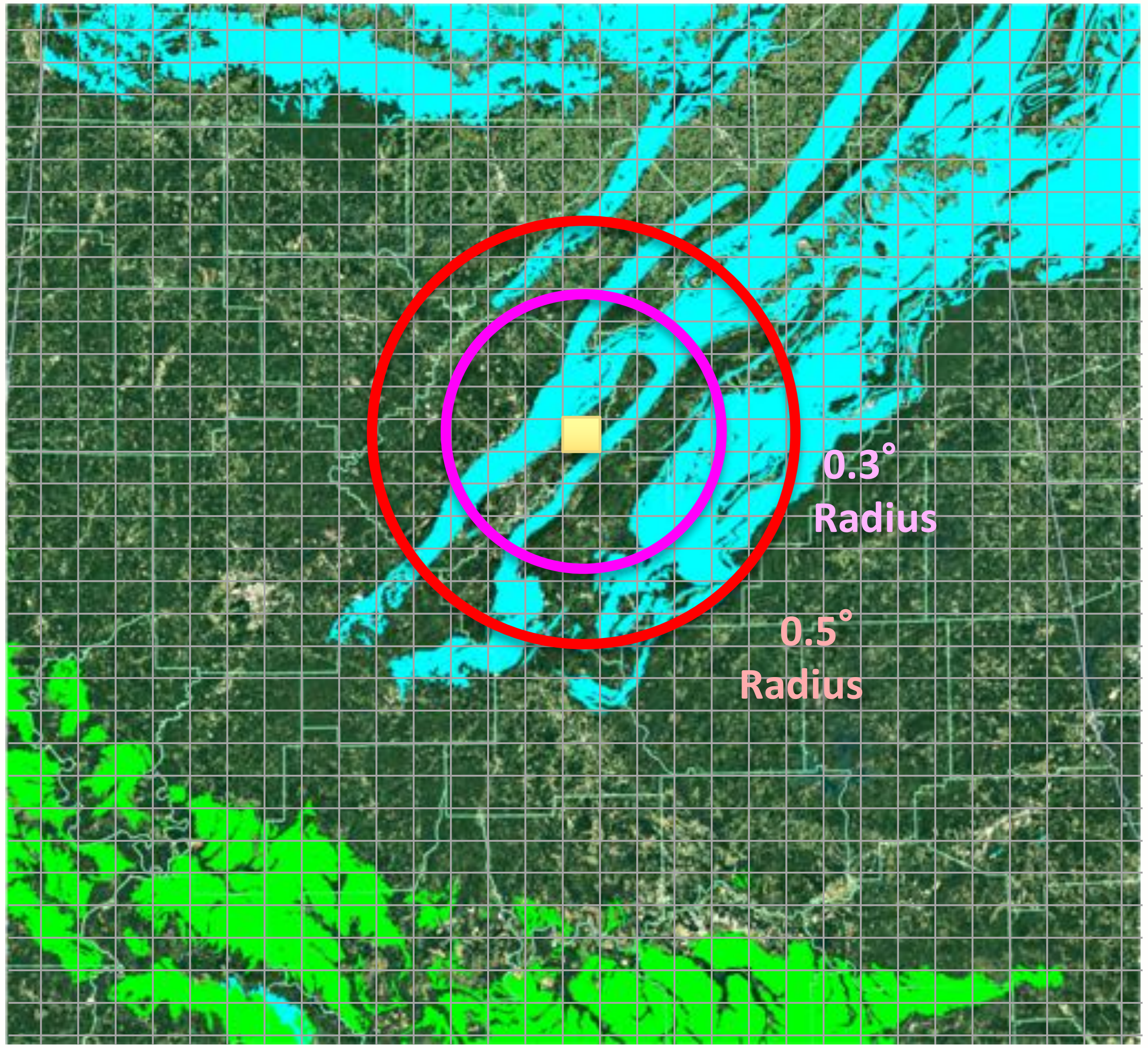
  - Std. dev. of karst coverage
  - r^2 between karst & soil moisture memory by season



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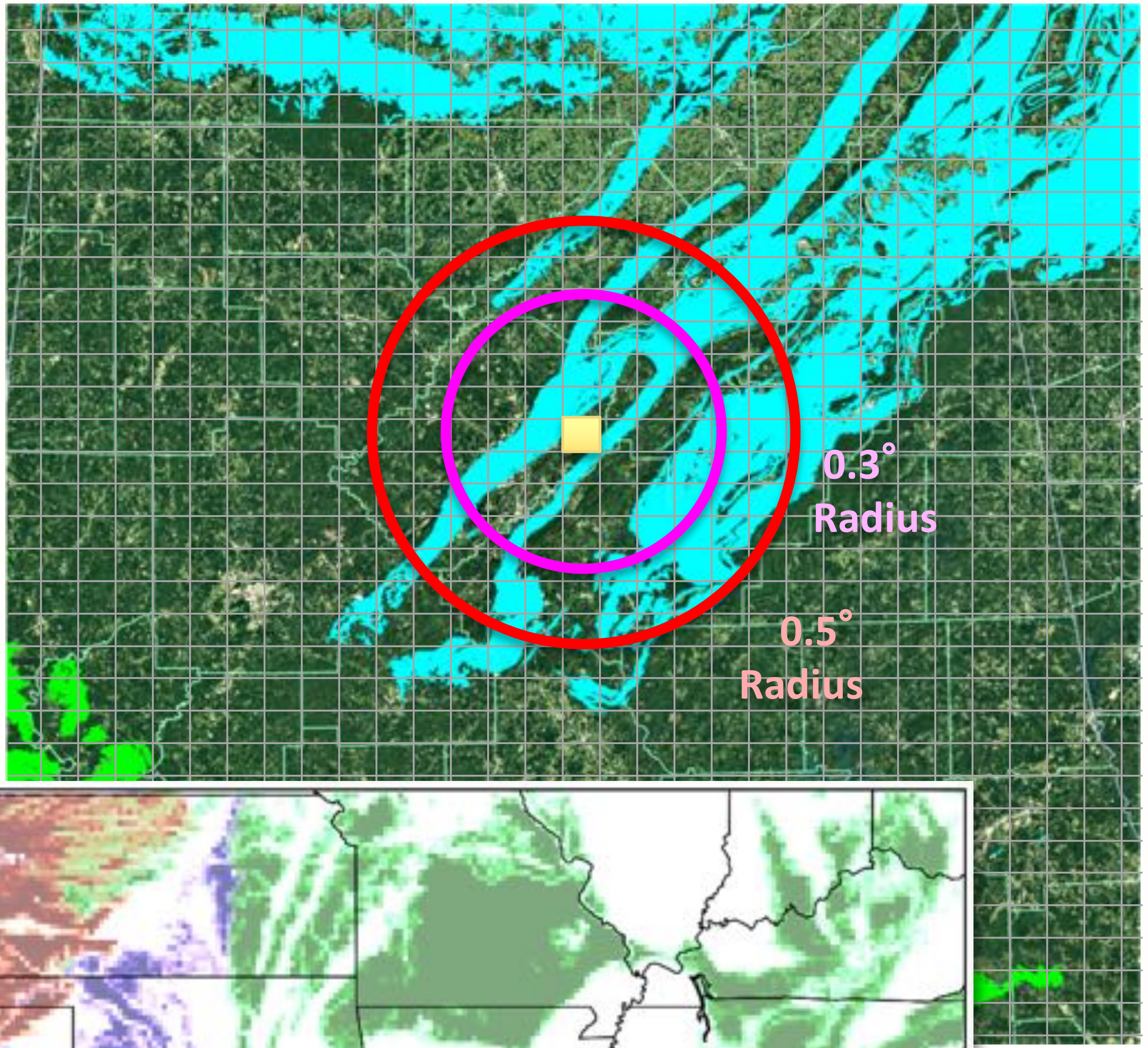
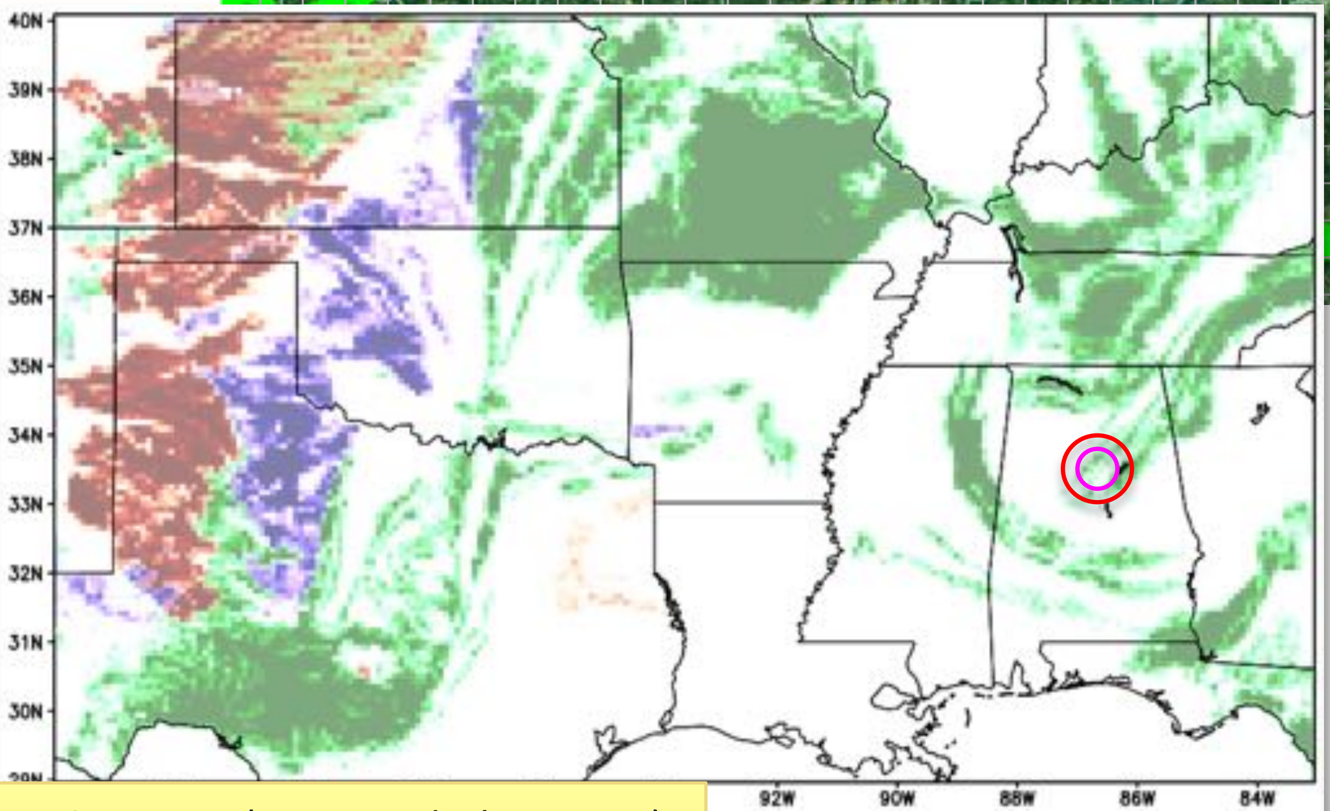
- In radius around each grid point, calculate:
  - Std. dev. of karst coverage
  - r^2 between karst & soil moisture memory by season
- Calculate spatial correlation between those two terms over southern US.

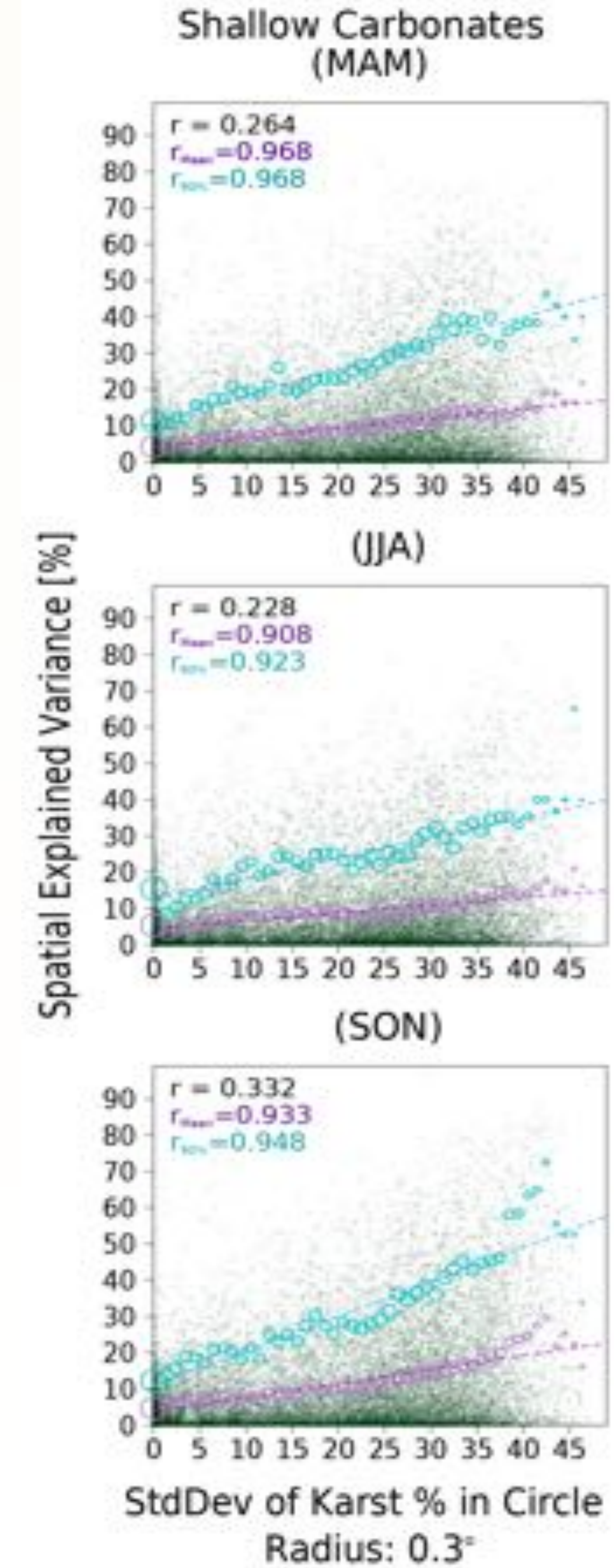




Dirmeyer & Norton (2018; Hydrol., in prep)

Satellite evidence

- Monte Carlo (non-parametric) sample testing shows significant relationships emerge for total karst during spring (p=0.03) and fall (p=0.10).
- Expectedly, we also see strong relationships with surface soil properties, especially porosity (highest in summer) and saturated hydraulic conductivity (highest in spring and fall); gSSURGO and STATSGO are consistent in these results.
- Implications:
  - *Critical zone* structure appears to be important to surface soil moisture, and thus potentially L-A interactions.
  - May be able to infer surface & subsurface properties from satellite soil moisture in remote regions.



Balsamo et al. (2018; RSES, in prep)

Summary

- L-A feedbacks proving to be especially important for S2S forecasting.
- Coupled L-A models could be more *up to the task*. The necessary data to confront models ranges from <u>sparse</u> to <u>nonexistent</u>.
- Satellites provide unlimited spatial coverage, but can we wring the necessary information from remote sensing.
- As a test, we calculate a couple of classical "terrestrial coupling" metrics using best available satellite data (GLEAM, CERES), compare to reanalysis estimates, confront with FLUXNET2015.
- Note that SMAP data carry signal of subsurface geologic properties that can contribute to L-A feedbacks through preferential drainage. Potential to deduce hidden land properties from satellite.


Thank You!

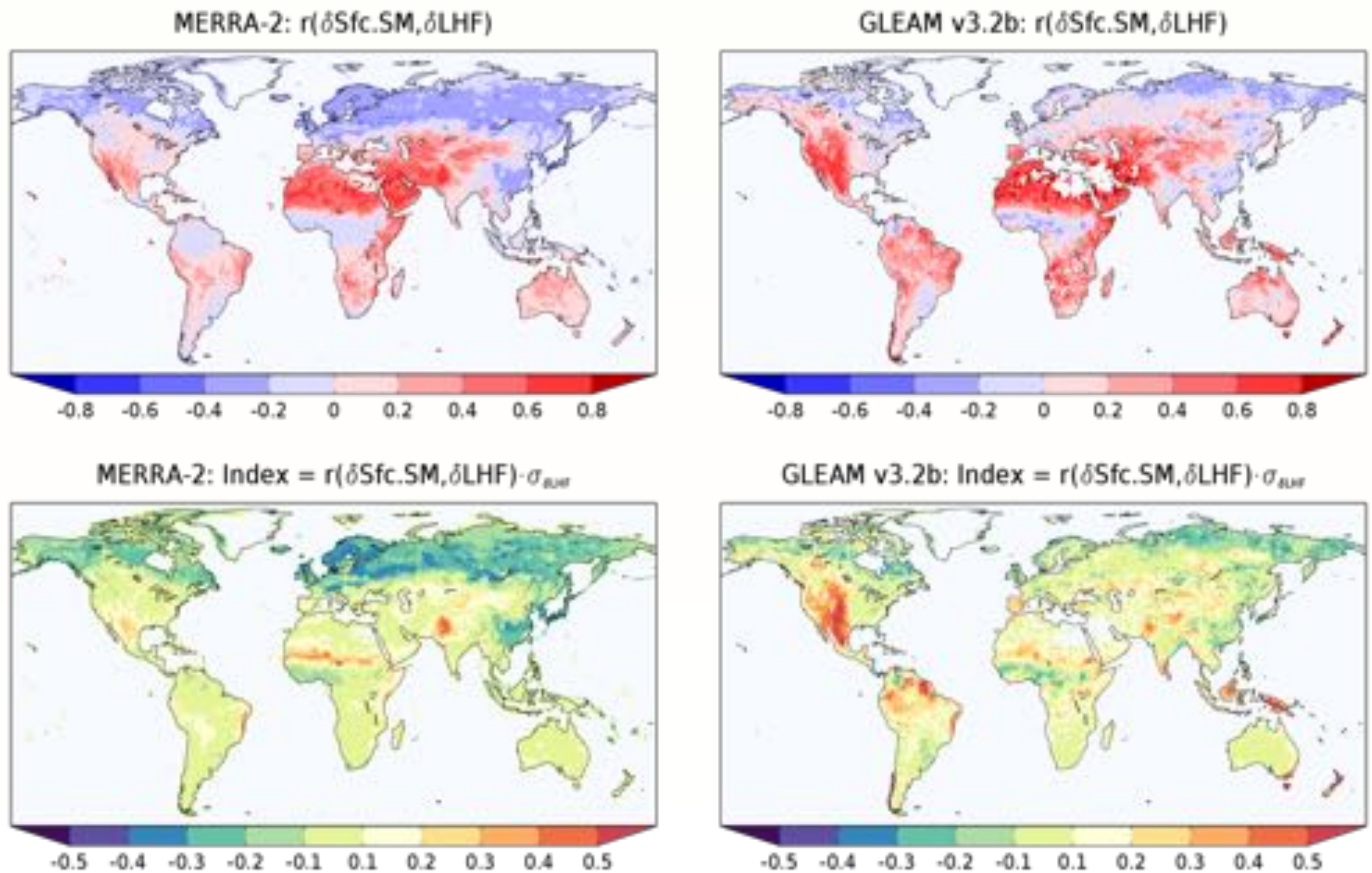
Further accounting for errors

- We also try basing correlations, variances on a ternary set:
  - Day-to-day increase: δ=+1
  - No change (within threshold): δ=0
  - Day-to-day decrease: δ=−1
- For soil moisture, the no-change range is $\pm$0.01
- For surface heat fluxes, the range is $\pm$5 W/m^2
- A test of concordance, a la Kendall rank correlation, but not going fully that route:
  - Still applying the Pearson's formulation, which has a physical meaning consistent with construction of the coupling index.

δSoil Moisture : δLatent Heat

- Positive correlation areas and intensities don't really change.
- Negative areas expand and intensify.
- Approaches need to be explored further – what can be done to capitalize on the strengths of remote-sensing observations to understand L-A interactions?

JJA means (MERRA: 1980-2017, GLEAMv3.2b:2012-2017)



δSoil Moisture : δSensible Heat

- Strong links become even more widespread.
- Note that in this ternary approach, the index loses its physical dimension, necessarily has a range of ±1.

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