Validation of CESM Land–Atmosphere Coupling Using Observationally Derived Metrics

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Global Land-Atmosphere Coupling: **A Challenge for Model Validation**

Models **disagree** on the strength of the coupling metric in hotspot regions *(Koster et al. 2004).*

Which model is correct?

Results can be validated locally at **Flux tower sites.**

Limited global distribution

Short duration

The need for **global observationally-based datasets** for assessing the results of weather and climate models.

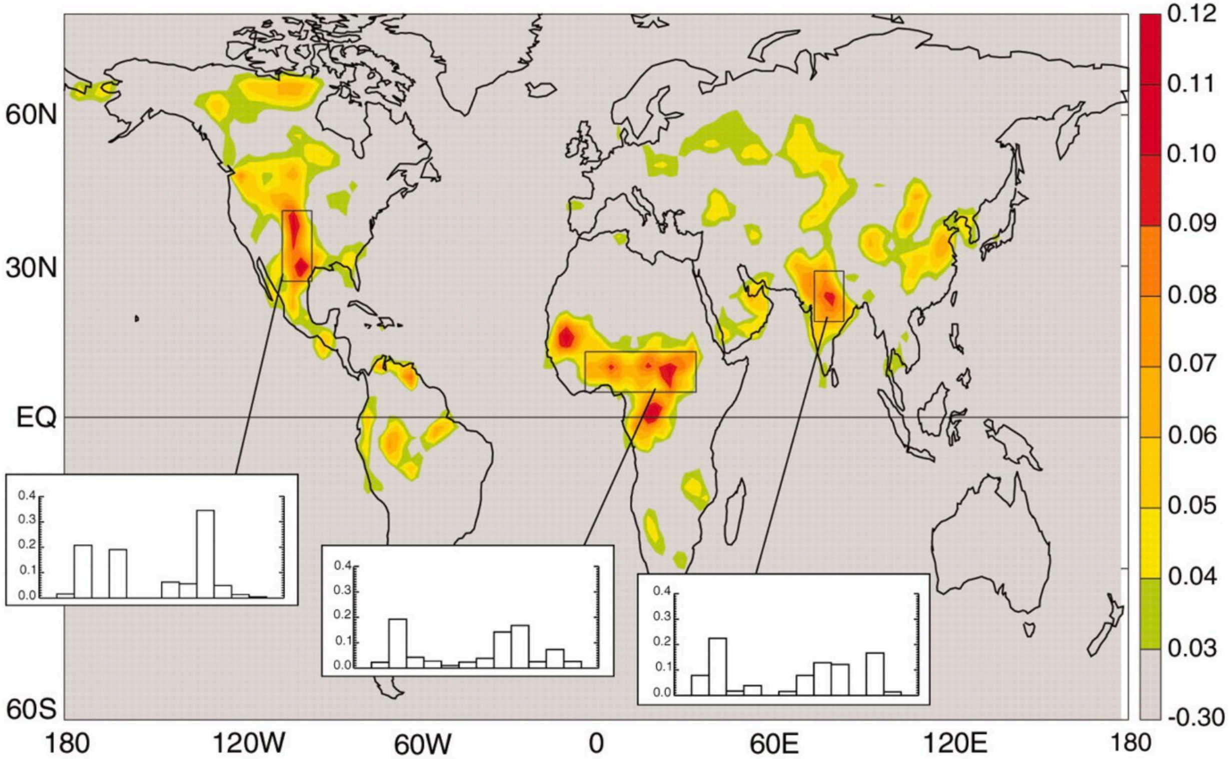


Fig1. Global distribution of L-A coupling metric (SM and P) averaged across AGCMs during boreal summer *(Koster et al. 2004).*

Advancing Global L-A Coupling Metrics: **From Observational Corrections to Model Validation**

We have an incomplete picture of the **reality** of **global L-A coupling** for **model validation**.

We produced a **global corrected L-A coupling metric** using **observational gridded data**, while accounting for the **observational random errors in soil moisture satellite measurements.**

(Tavakoli & Dirmeyer, 2025, in preparation)

What do I mean by corrected observational metrics?

We can quantify the magnitude of stochastic random errors in the SM time series.

(Delworth and Manabe. 1988) *(Robock et al., 1995)* *(Vinnikov et al.1996)*

Advancing Global L-A Coupling Metrics: **From Observational Corrections to Model Validation**

Now that we have globally corrected observational gridded LA coupling metrics, what's next?

Conduct a comprehensive **comparison** between **Corrected Observational** LA coupling metrics and **Model-Based Estimates.**

Why this is important?

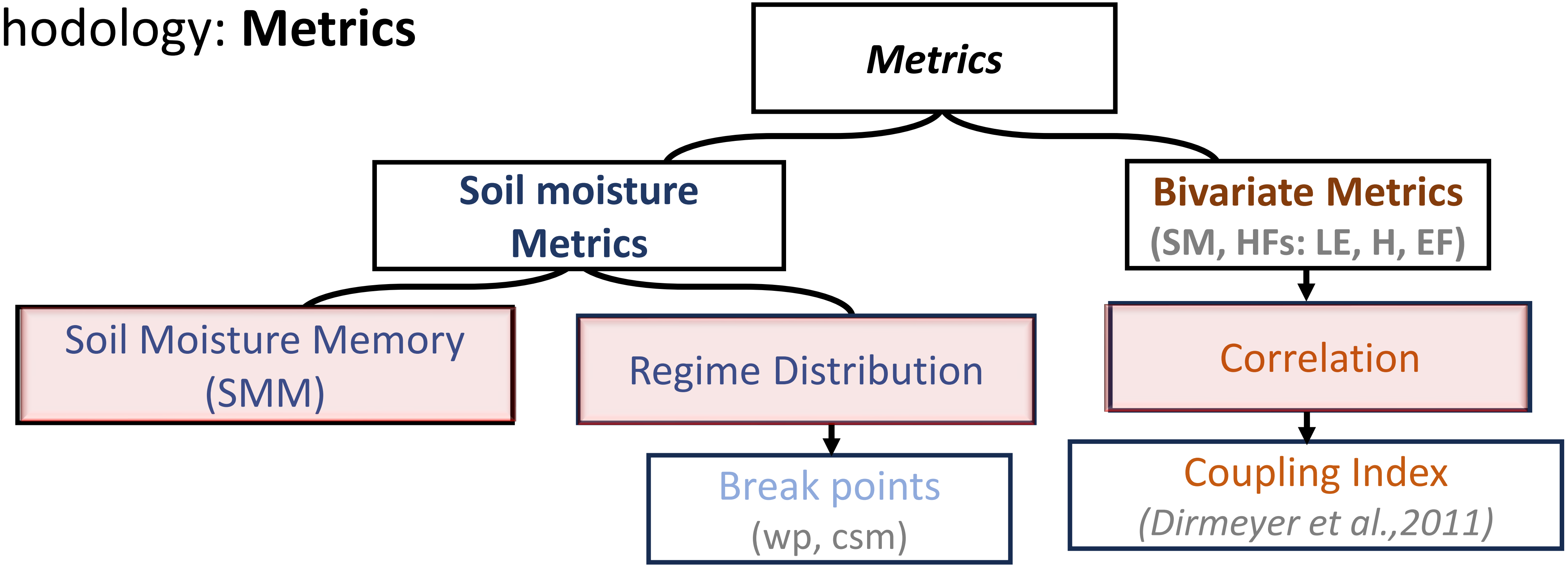
Identify global regimes and hotspots for LA interactions in models

Highlight regions where model biases are most pronounced

Interpret spatial patterns and seasonal variations in coupling metrics

Provide guidance for model development

Methodology: **Metrics**



Metrics

Soil moisture Metrics

Soil Moisture Memory (SMM)

Regime Distribution

Break points (wp, csm)

Bivariate Metrics
(SM, HFs: LE, H, EF)

Correlation

Coupling Index
(Dirmeyer et al.,2011)

(b)

(a)

Fig2. (a) Conceptual SM – EF model *(Seneviratne et al.2010),* (b) Six potential segmented regression models.

Methodology: **Data Description**

	Variable Name	Source	Spatial Resolution	Surface Soil Layer
Observation	Soil Moisture	Soil Moisture Active Passive Satellite **(SMAP L3)**	9 Km*9 Km	0 - 5 cm
		Climate Change Initiative **(ESA CCI v08.1)**	0.25°*0.25°	0 - 5 cm
		SoMo.ml	0.25°*0.25°	0 –10 cm 10 – 30 cm 30 – 50 cm
	Surface Heat Fluxes	Global Land Evaporation Amsterdam Model **(GLEAM) v4.1a**	0.1°*0.1°	------
Model	Soil Moisture Surface Heat Fluxes	CESM2 **- AMIP** **- CLM**	0.94° lat*1.25° lon	0 – 10 cm 10 – 30 cm 30 – 50 cm

Results: **Global JJA SMM Differences (Models vs CCI)**

JJA

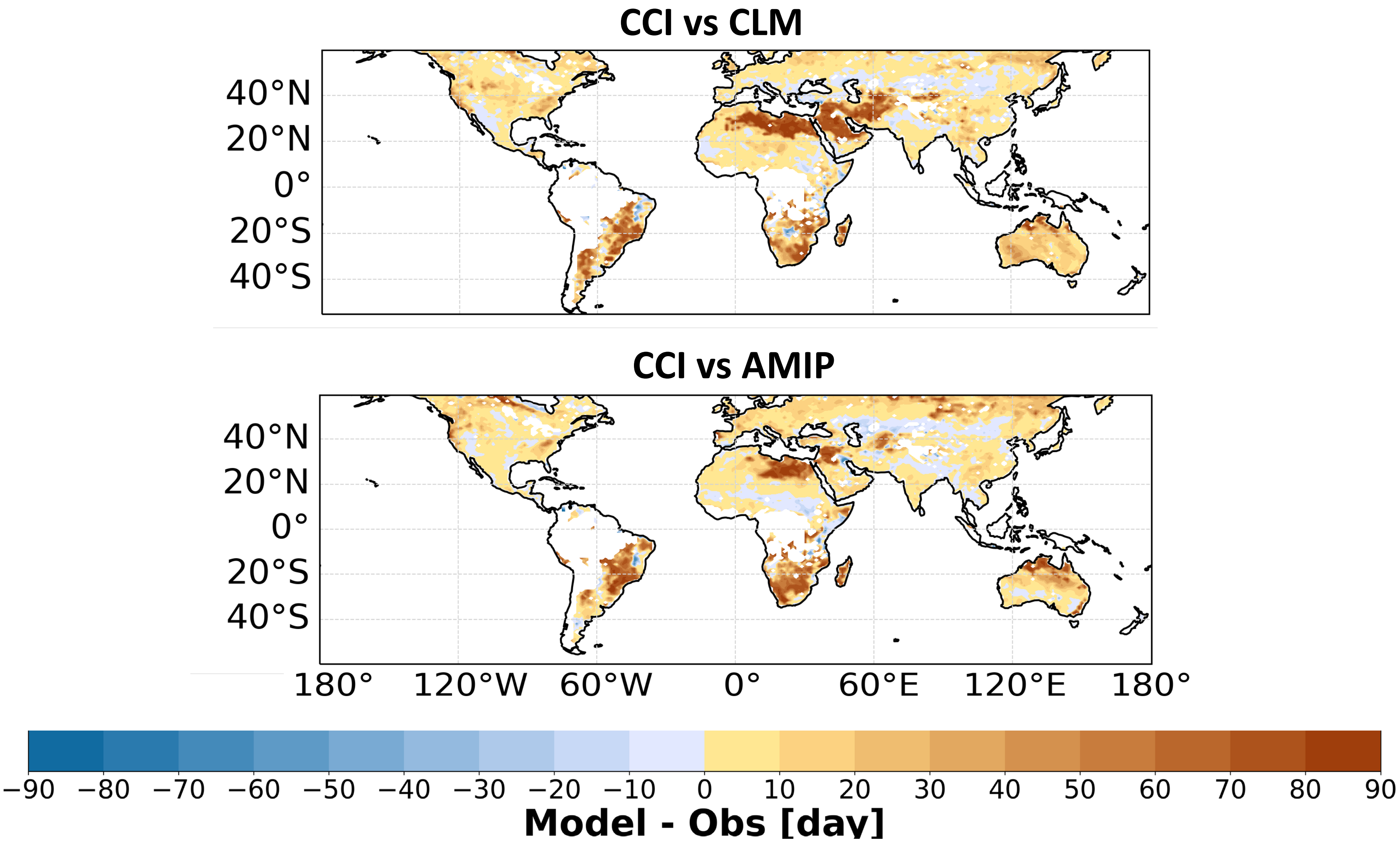


Fig3. SMM differences in model vs CCI during JJA.

Results: **Global JJA SMM Differences (Models vs Observations)**

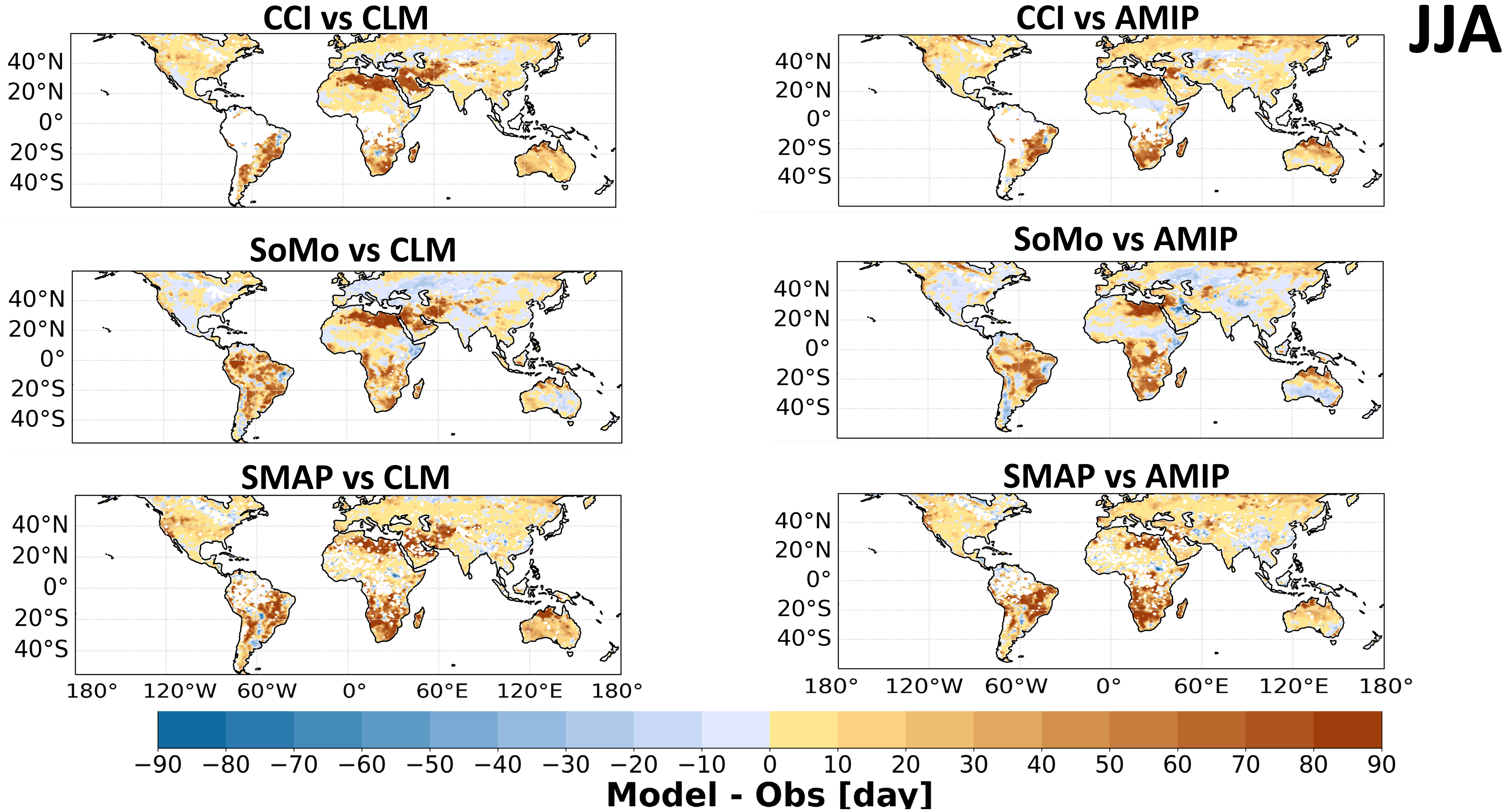


Fig4. SMM differences in model vs observational products during JJA.

Results: **Global JJA Correlation Comparison (Models vs Observations)**

JJA

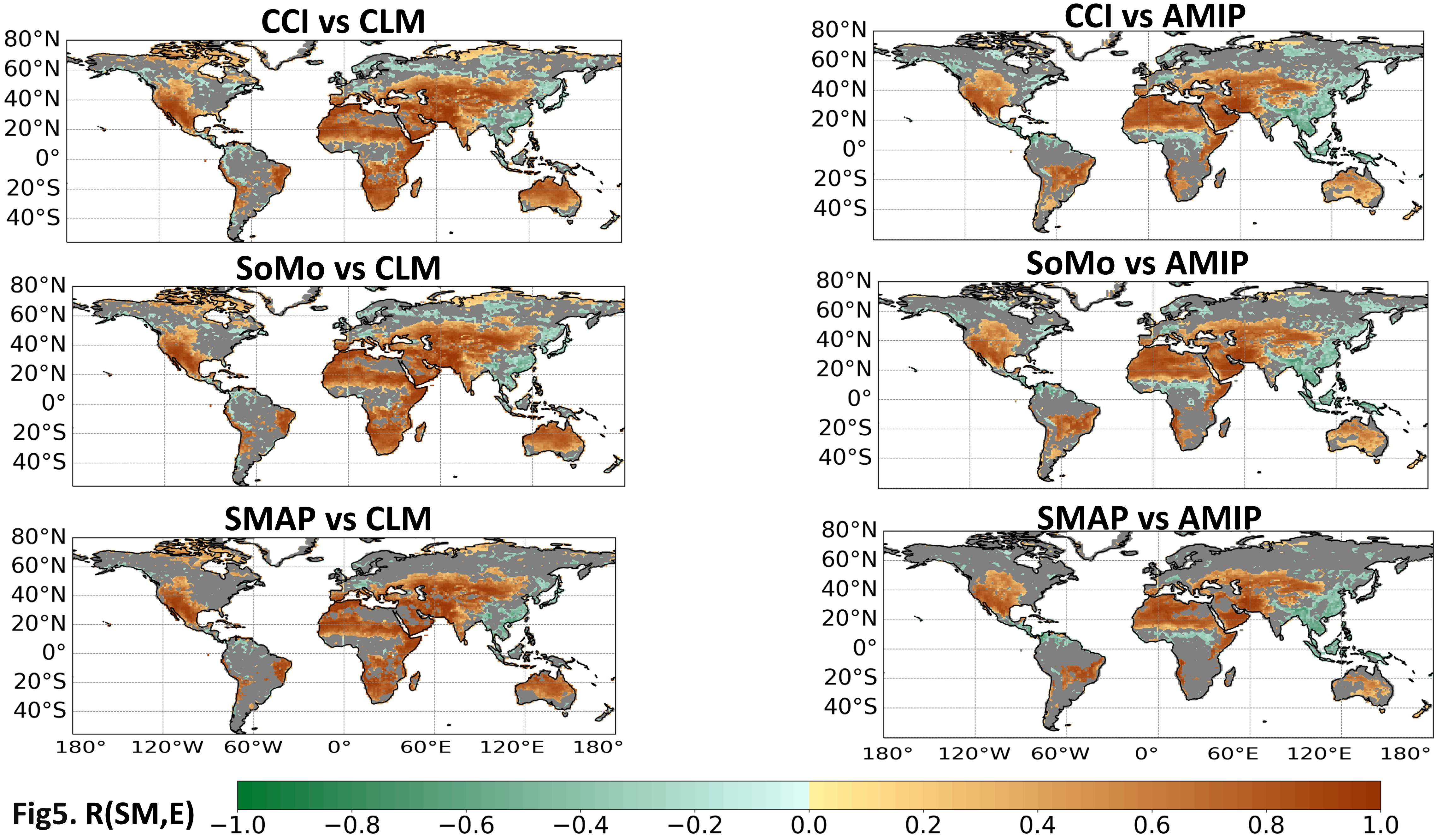


Fig5. R(SM,E)

Preliminary Results : **Global SM-EF Regime Distribution**

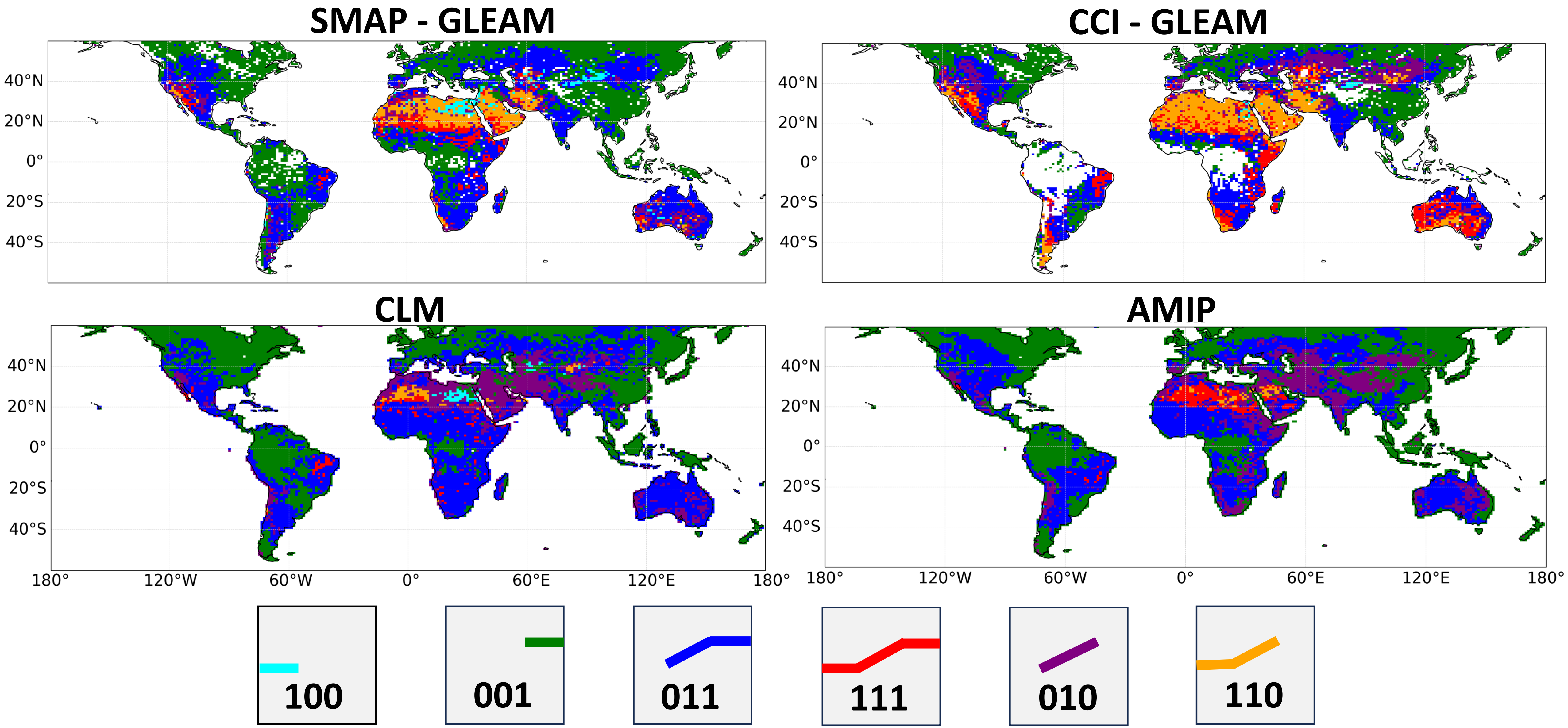


Fig6. Global distribution of SM-EF regimes.

Results: **Evaporation or Transpiration?**

$$\Delta R = \left(\frac{RMSE_{L3} - RMSE_{L1}}{RMSE_{L3}}\right) * 100$$

$\Delta R < 0$:

Deeply rooted vegetation

>> Transpiration

$\Delta R > 0$:

Bare soil

>> Evaporation

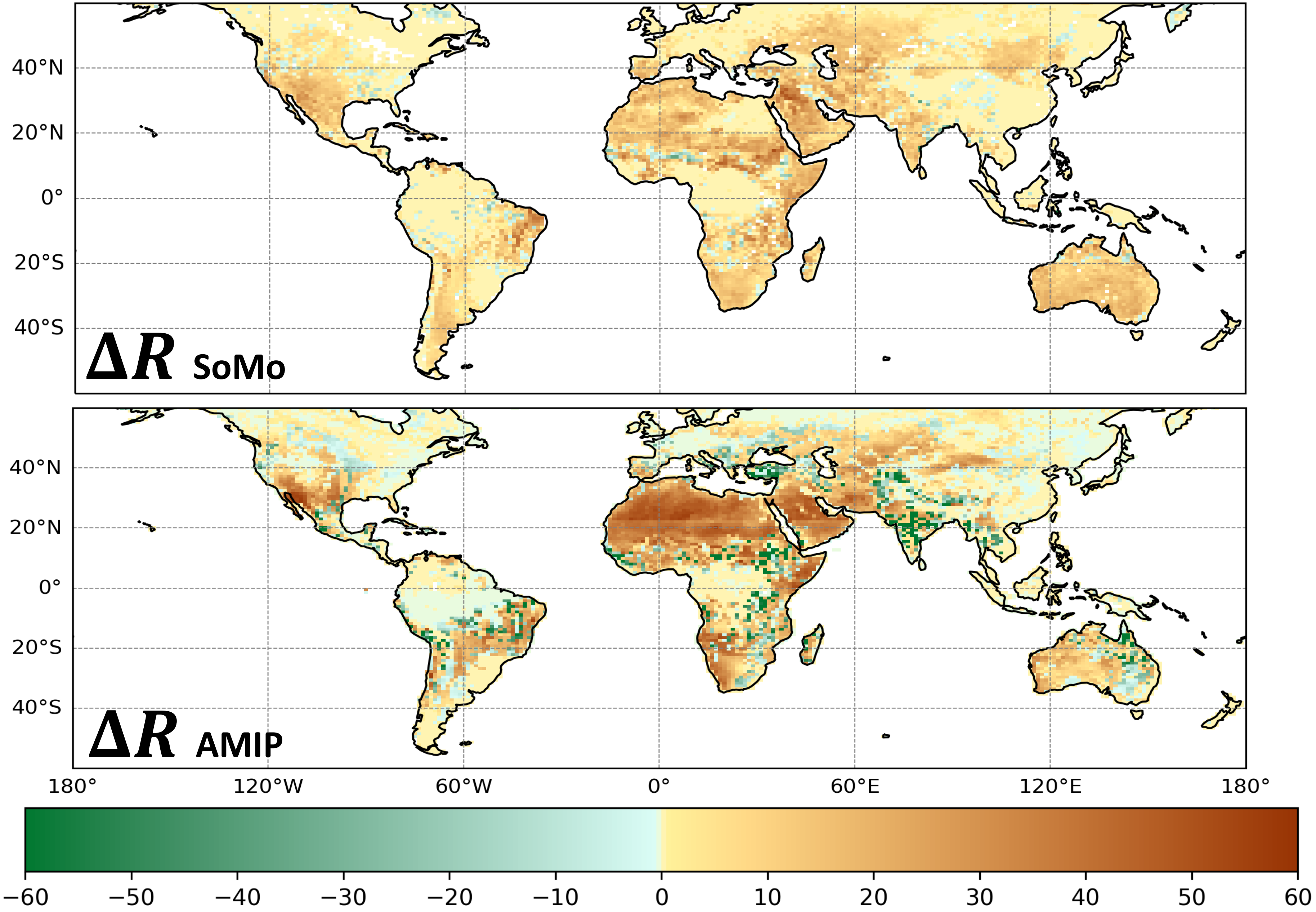


Fig7. Relative RMSE Differences Across Layer 1 and 3 (AMIP vs SoMo)

Conclusion:

This work represents an important step toward **validating** the global **model-derived LA coupling metrics** against **<u>corrected</u> observational estimates**.

1. The largest disparities in SMM typically occur in monsoon and semi-arid zones, where seasonal rainfall is strongly influenced by large-scale circulation patterns that are challenging for models to capture accurately.
2. Soil moisture in both CLM and AMIP exerts more control on surface fluxes than in observations.
3. These biases in model soil moisture may be due to precipitation biases within the models.
4. The minimum model conductance is the highest among all vegetation types, indicating the least response to soil moisture variations, suggesting that factors other than soil moisture are influencing the system.
5. Although AMIP and CLM appear very similar and their deviations are subtle, the CLM model seems to govern most of these metrics.
6. Models tend to be wetter compared to observations in regime distributions due to their strong capillary action in models.
7. Although AMIP simulations can better capture the influence of subsurface soil moisture on transpiration in agricultural, grassland, and savanna areas, this controlling effect is not evident in deep tropical forests, China, or the eastern United States.

To be continued...

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