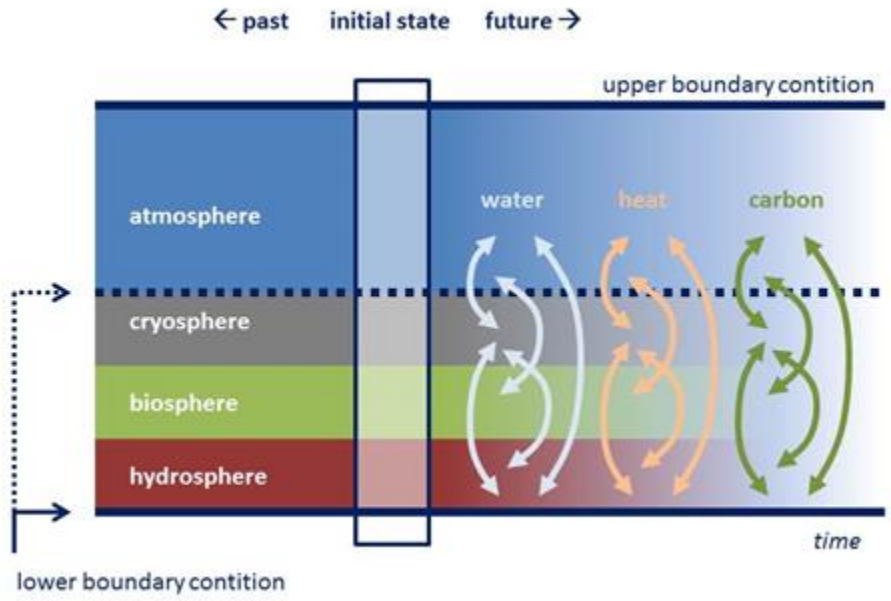
Coupled land-atmosphere variability and predictability

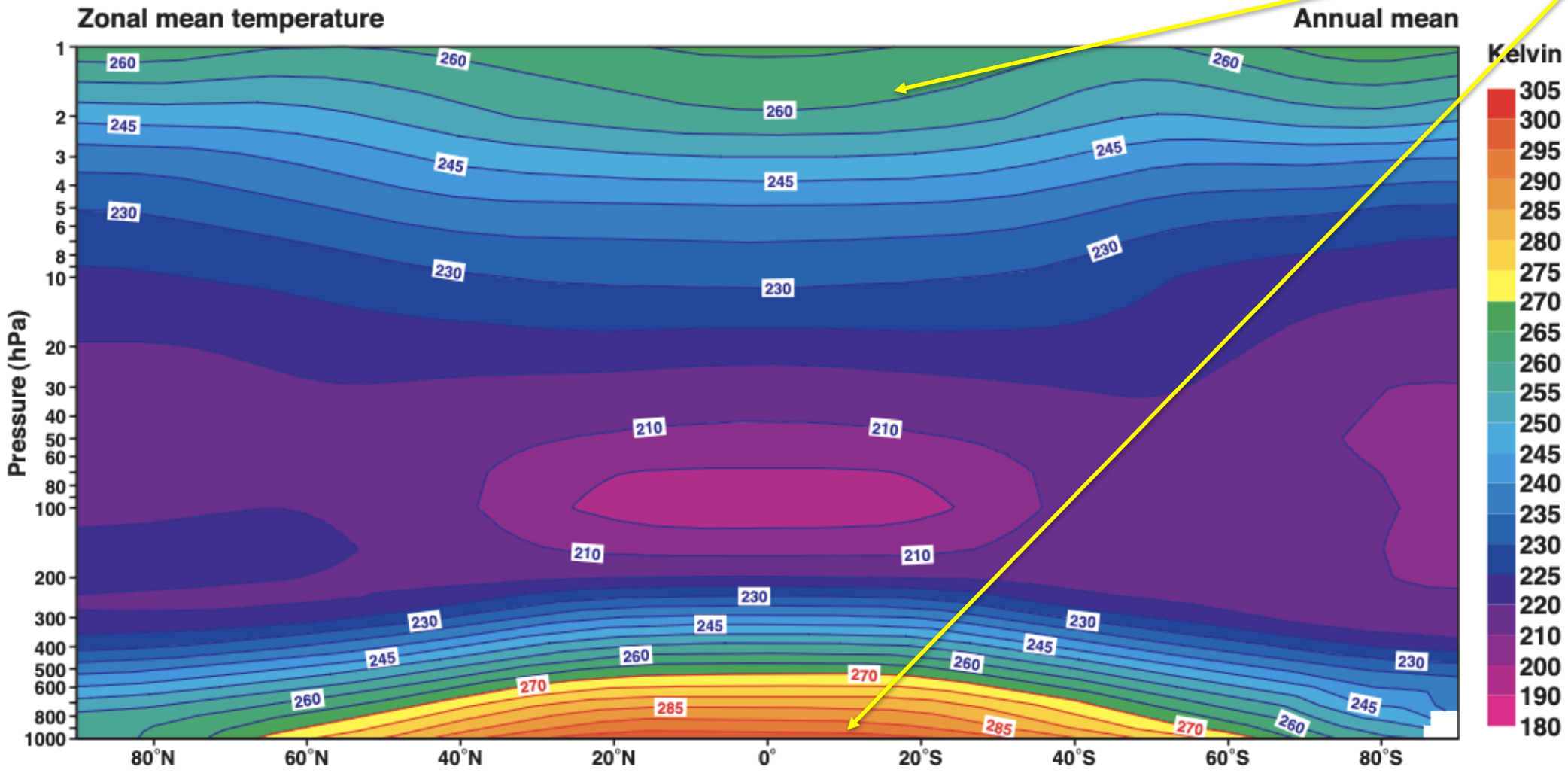
Jonny Day / Bart van den Hurk / Tim Stockdale

jonathan.day@ecmwf.int



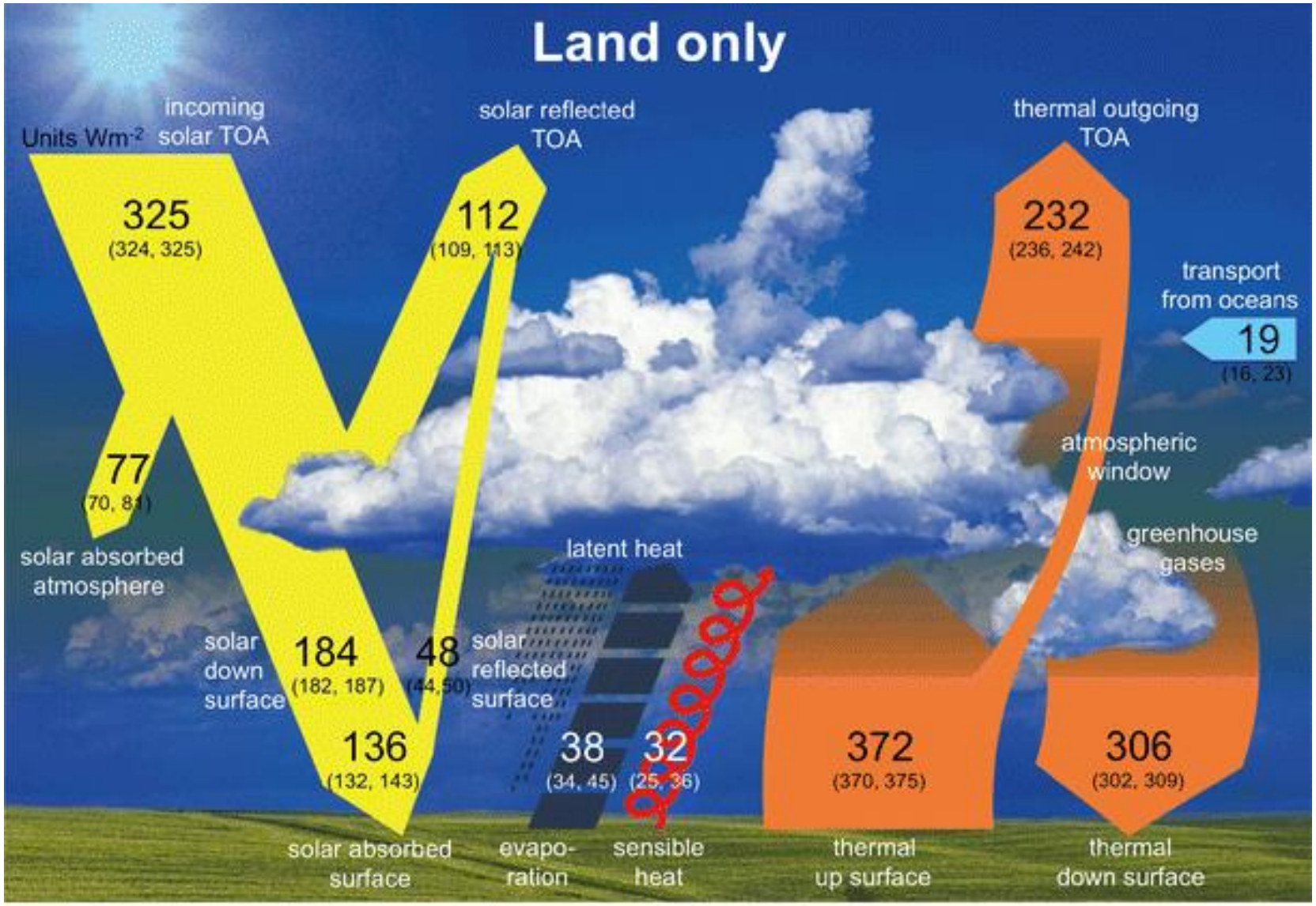
ECMWF

Is the atmosphere heated from above or below?



ECMWF

Earths energy budget



Wild et al. (2014)

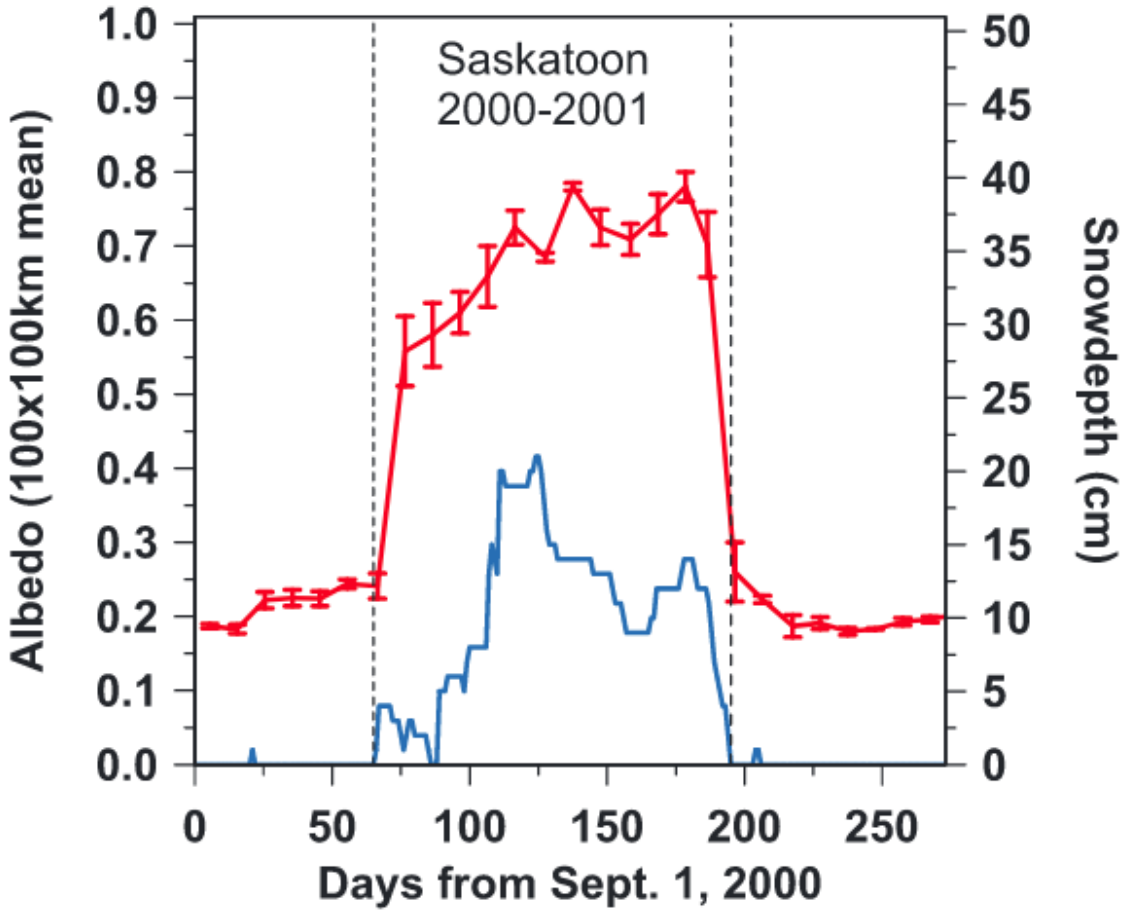
Why do we care about land processes?

- Energy-budget
  - Albedo

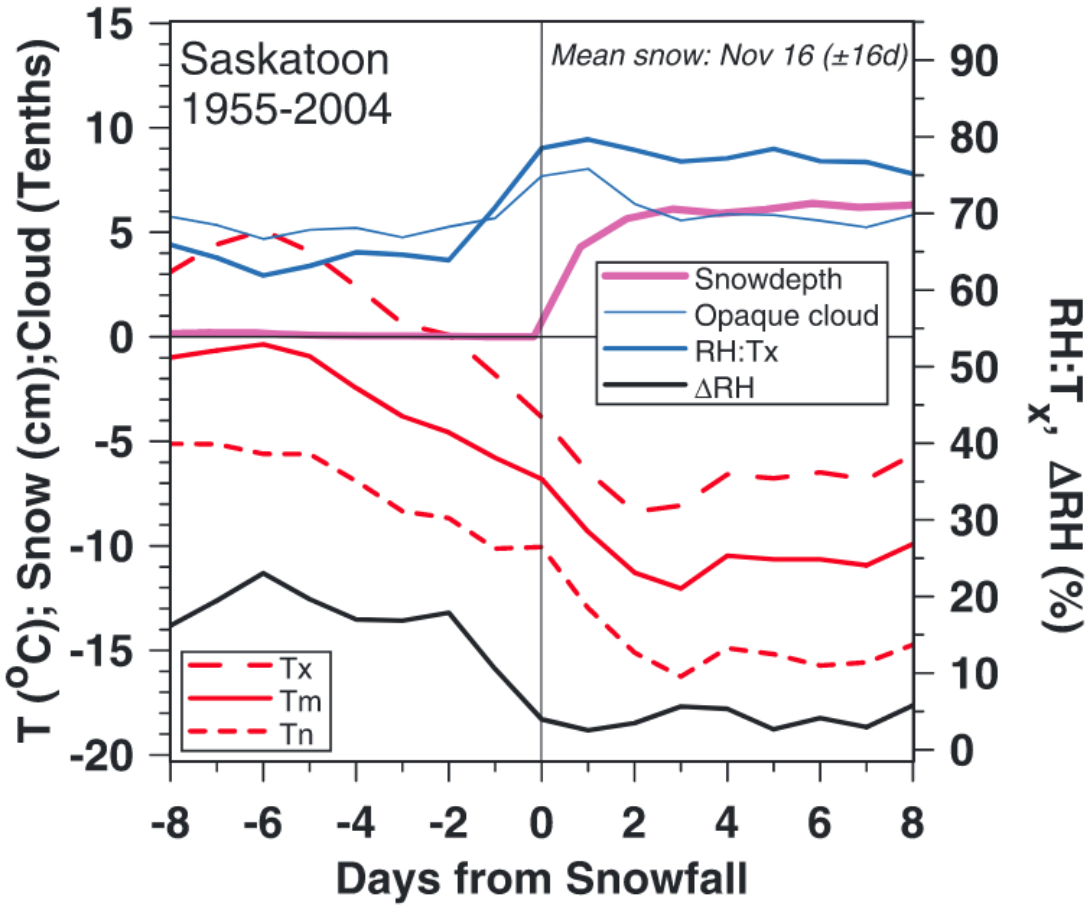
Surface	Albedo
Dark forest	9-12%
Grassland	15-20%
Bare soil	20-30%
Snow in forest	15-25%
Open snow	50-85%

Example of snow transitions

Snow and albedo



Snow and surface meteorology

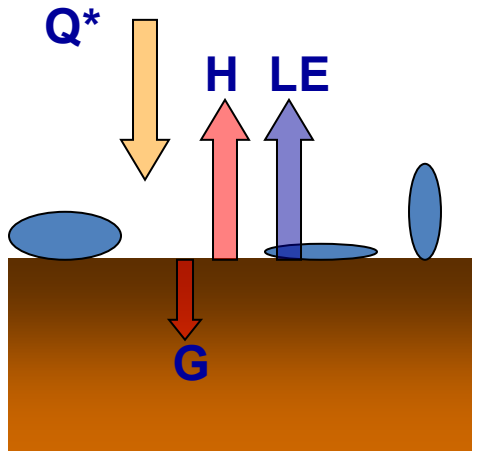


Betts et al., (2014)

ECMWF

Why do we care about land processes?

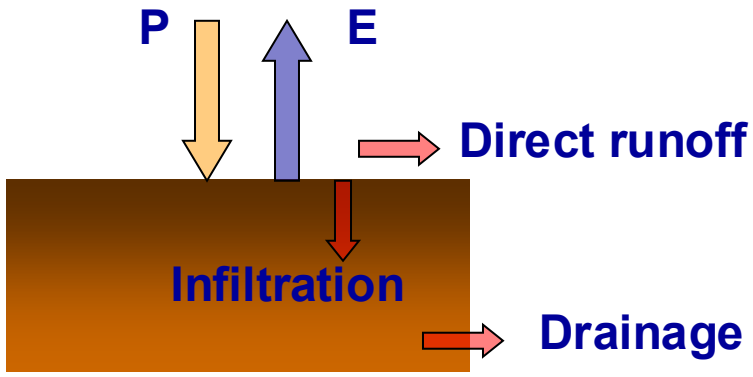
- Energy-budget
  - Albedo
  - Evaporative fraction



Surface	LE/Q*
Boreal forest	25%
Forest in temperate climate	65%
Dry vineyard	20%
Irrigated field in dry area	100%

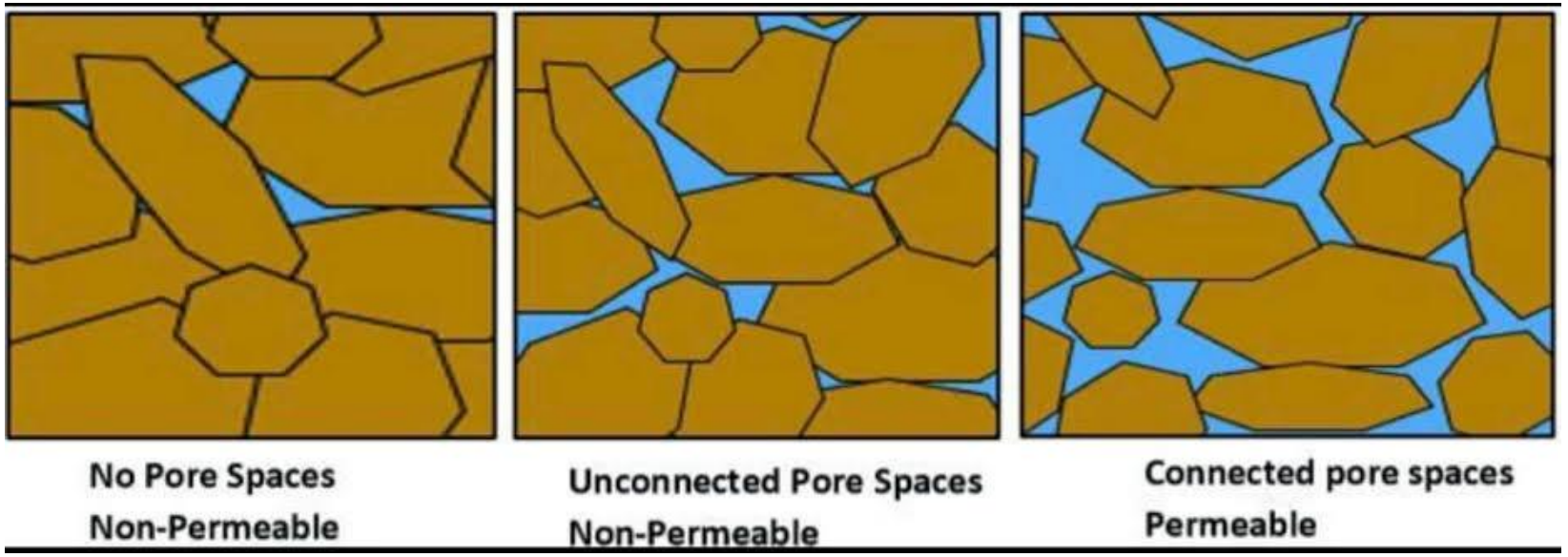
Why do we care about land processes?

- Energy-budget
  - Albedo
  - Evaporative fraction
- Water budget
  - Runoff-fraction



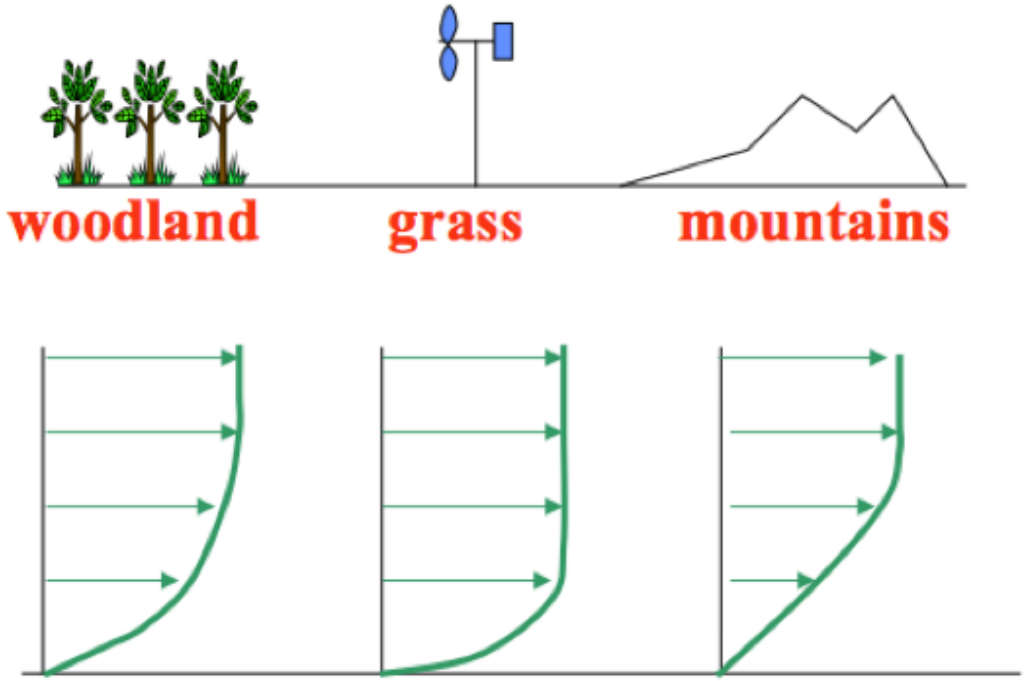
Land processes in atmospheric models

- Energy-budget
  - Albedo
  - Evaporative fraction
- Water budget
  - Runoff-fraction
  - Soil water reservoir



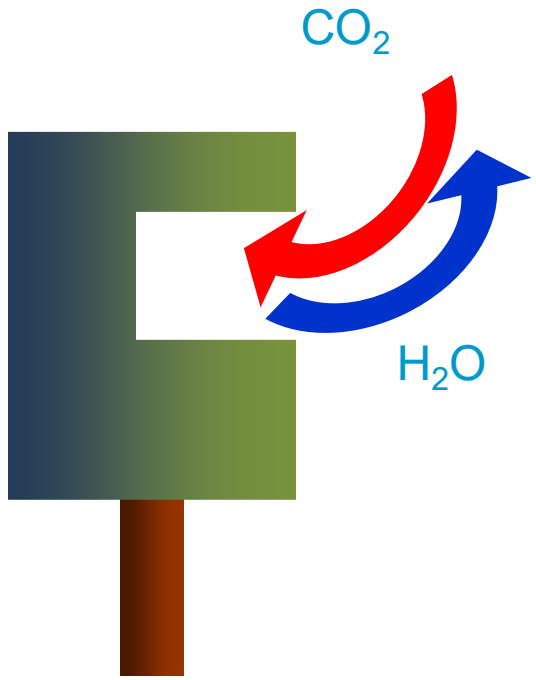
Land processes in atmospheric models

- Energy-budget
  - Albedo
  - Evaporative fraction
- Water budget
  - Runoff-fraction
  - Soil water reservoir
- Momentum budget
  - Roughness elements



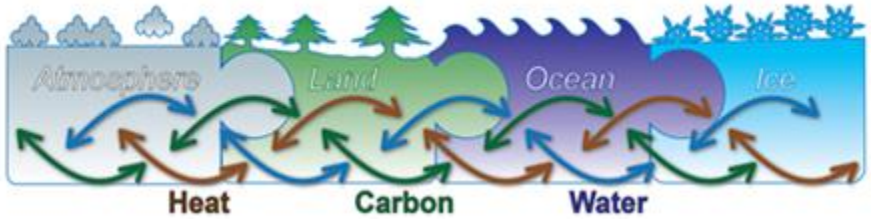
Land processes in atmospheric models

- Energy-budget
  - Albedo
  - Evaporative fraction
- Water budget
  - Runoff-fraction
  - Soil water reservoir
- Momentum budget
  - Roughness elements
- Carbon budget
  - Not directly relevant for seasonal forecasting, but vegetation changes have feedbacks on other processes and are important for climate modelling

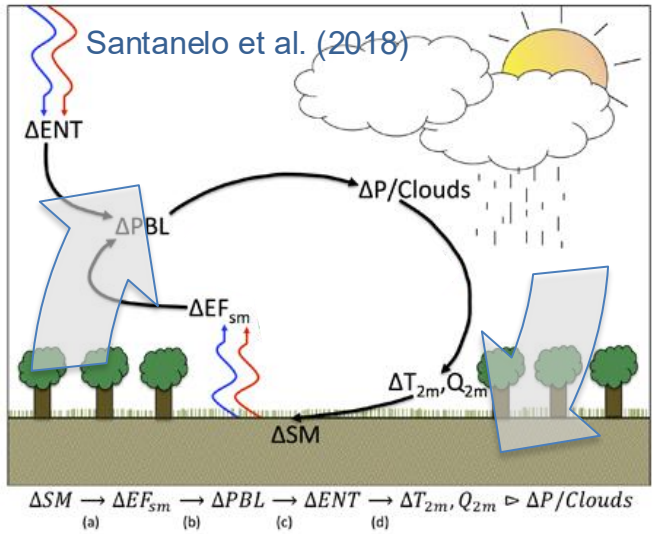


What is needed to contribute to predictability?

- In the climate system all processes are connected



- A systematic influence of land surface on atmosphere requires:
  - **Variability**
  - **Memory**
  - **Coupling to the atmosphere**



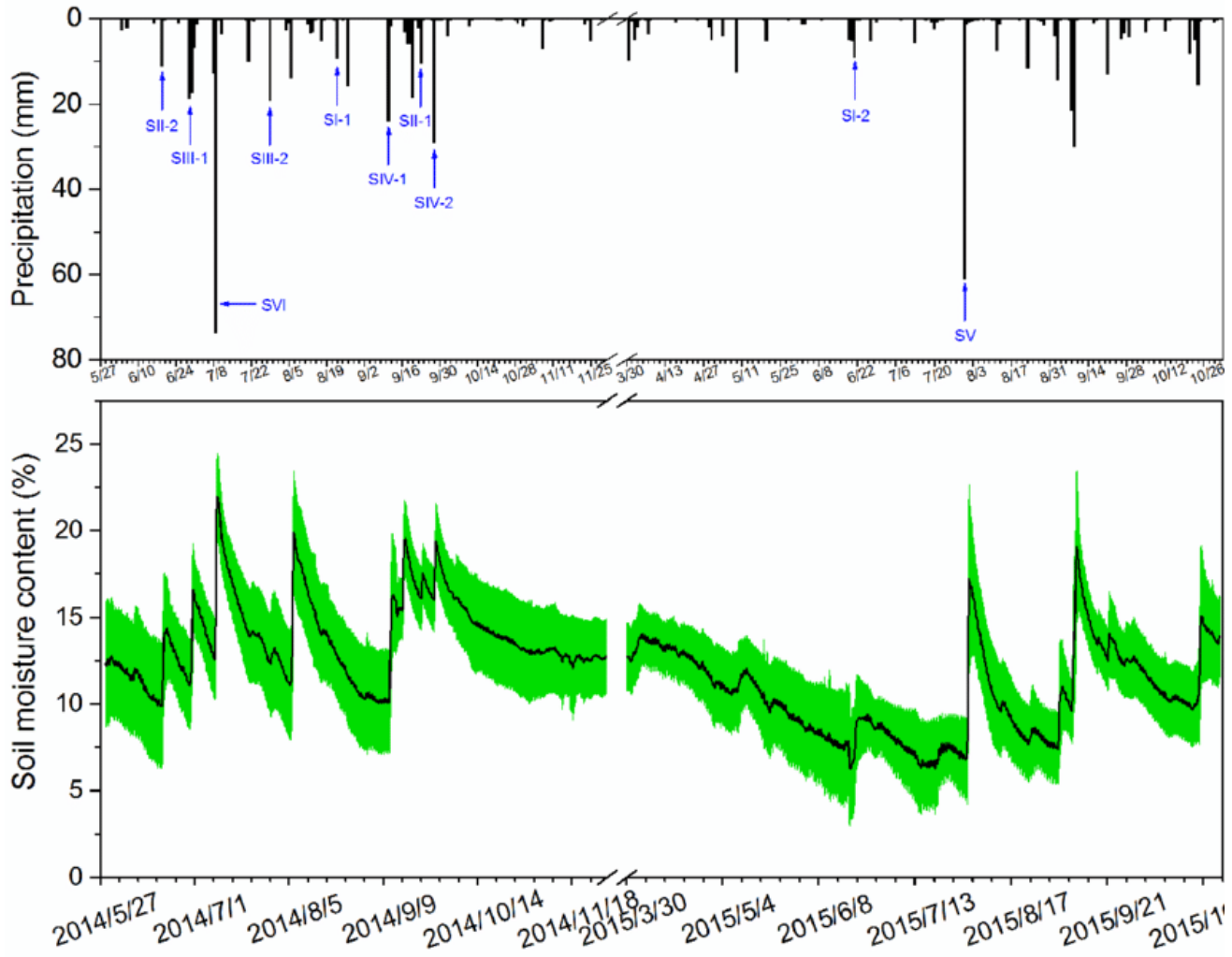
Otherwise: Can just use downstream/application models,
e.g. crop modelling, hydrology flood forecasting, fire risk models etc

Soil moisture predictability

$$c_s w_{n+lag,y} = c_s w_{n,y} + P_{n,y} - E_{n,y} - Q_{n,y}$$

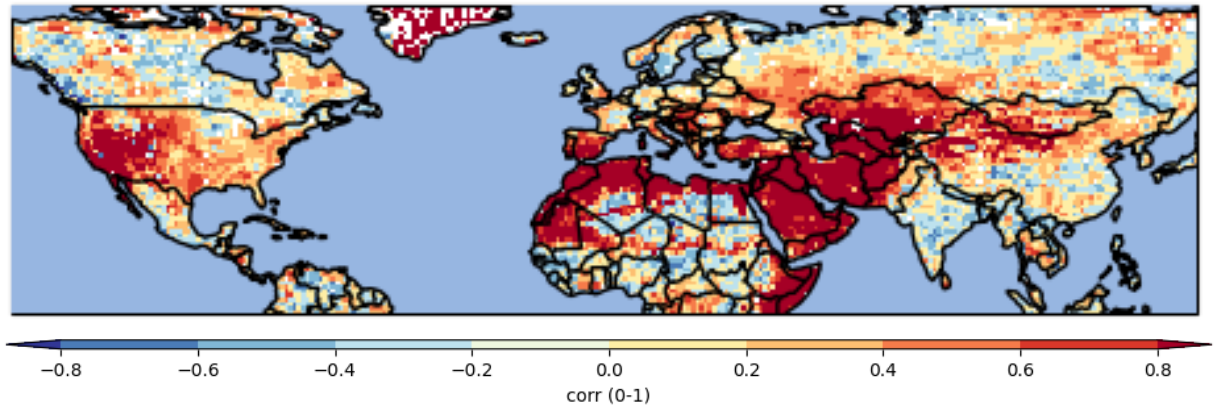
$$\rho(w_n, w_{n+lag}) = \frac{cov(w_n, w_{n+lag})}{\sigma_{w_n} \sigma_{w_{n+lag}}}$$

Wn=soil moisture at time n
Pn=total precipitation between time n and n+lag
En=total evaporation between time n and n+lag
Qn=total runoff between time n and n+lag
Cs=water holding capacity

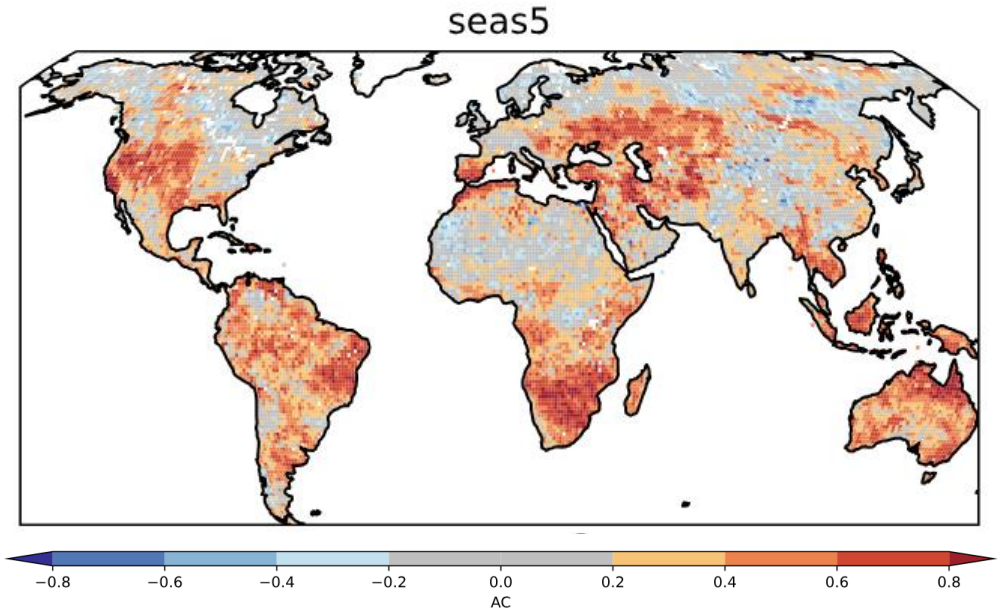


Spatial variation in persistence and skill of root-zone soil-moisture

r(May,Sep)



Seasonal forecast anomaly correlation JJA

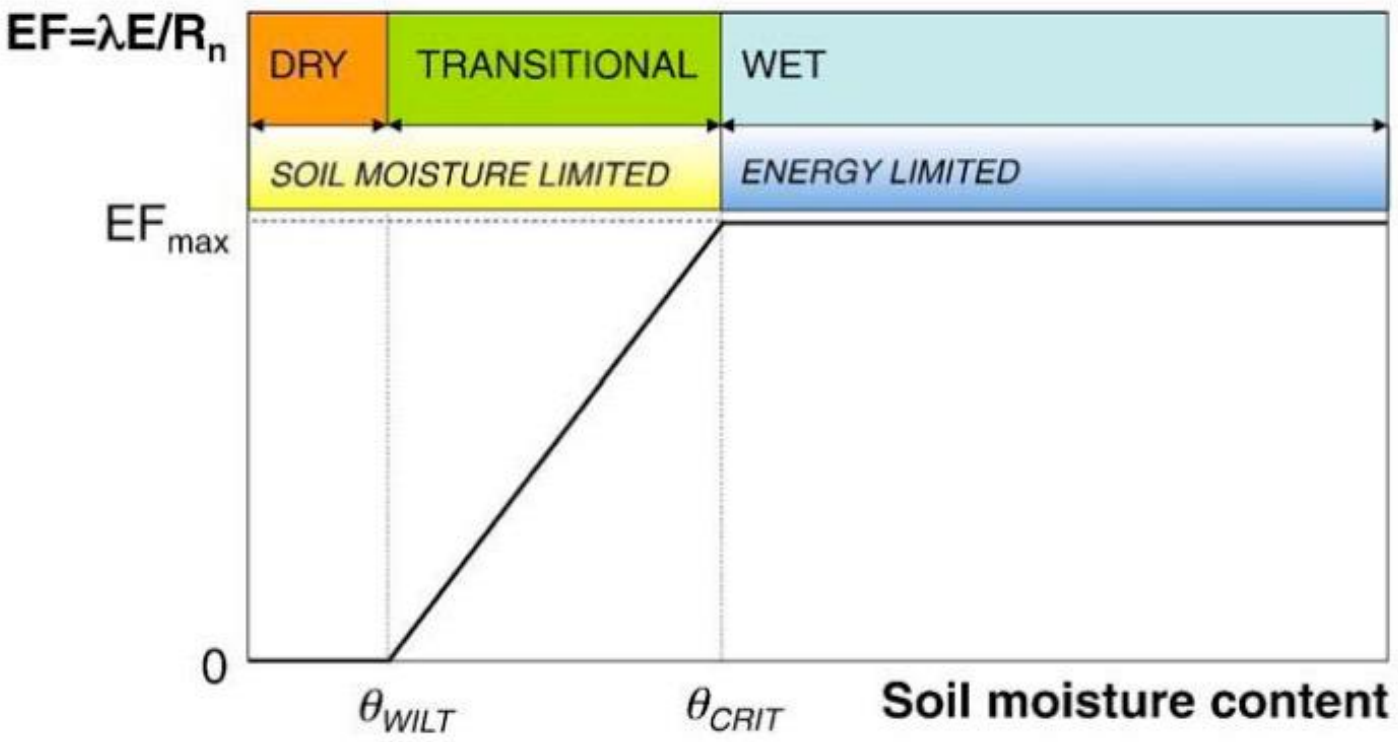


Day et al., 2025

ECMWF

Funded by the European Union

Soil-moisture atmosphere coupling



$$E = \beta E_{POT} = \beta \rho_a \left[\frac{q_{sat}(T_s) - q_r}{r_a} \right]$$

with

$$\beta = \frac{\theta - \theta_{WILT}}{\theta_{CRIT} - \theta_{WILT}} \quad \text{for} \; \theta_{WILT} \leq \theta \leq \theta_{CRIT}$$

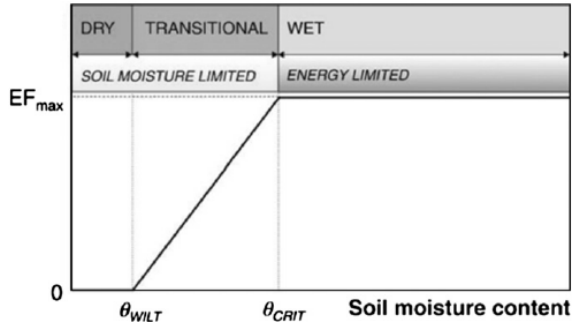
$$\beta = 1 \; \text{for} \; \theta > \theta_{CRIT}$$
$$\beta = 0 \; \text{for} \; \theta < \theta_{WILT}$$

Seneviratne et al., 2010

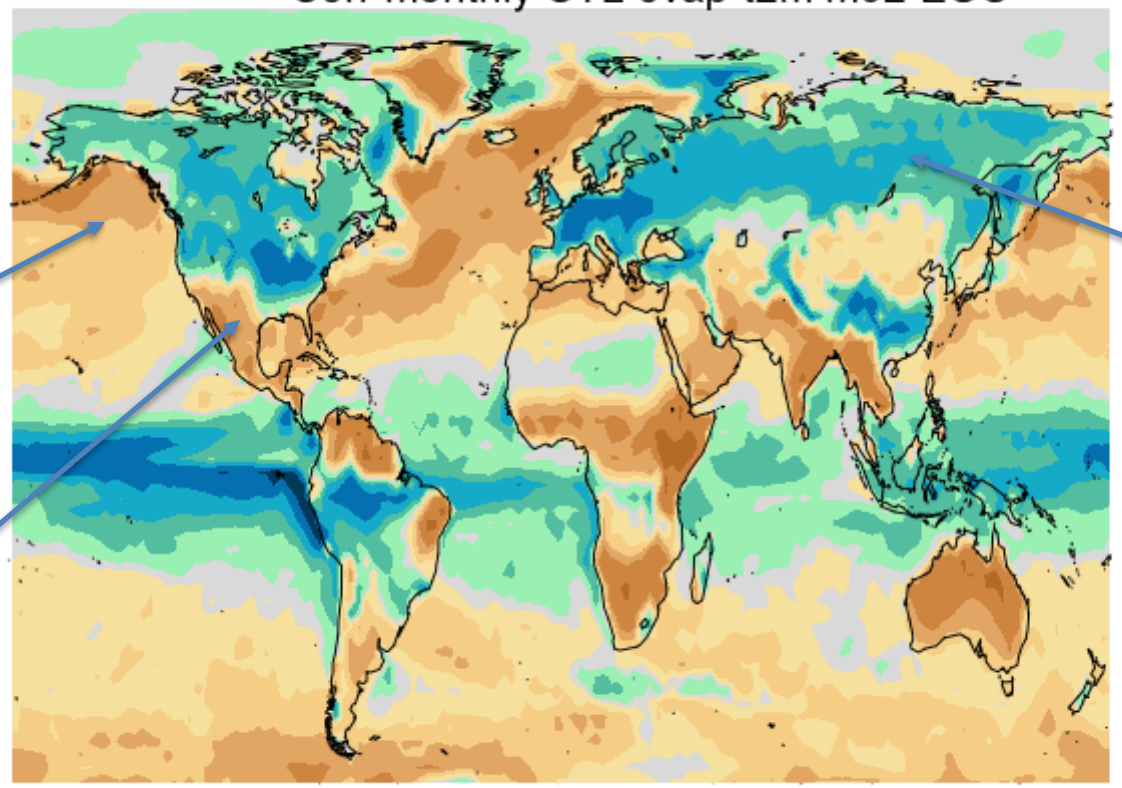
Measures to quantify land-atmosphere coupling

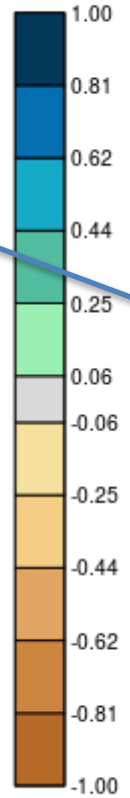
- From (pseudo)observations:
  - Correlation between evaporation and temperature

Seneviratne et al, 2010



Feb-Apr





Energy limited

Soil water limited

Over mid-latitude oceans, evaporation depends on humidity: colder air is generally drier

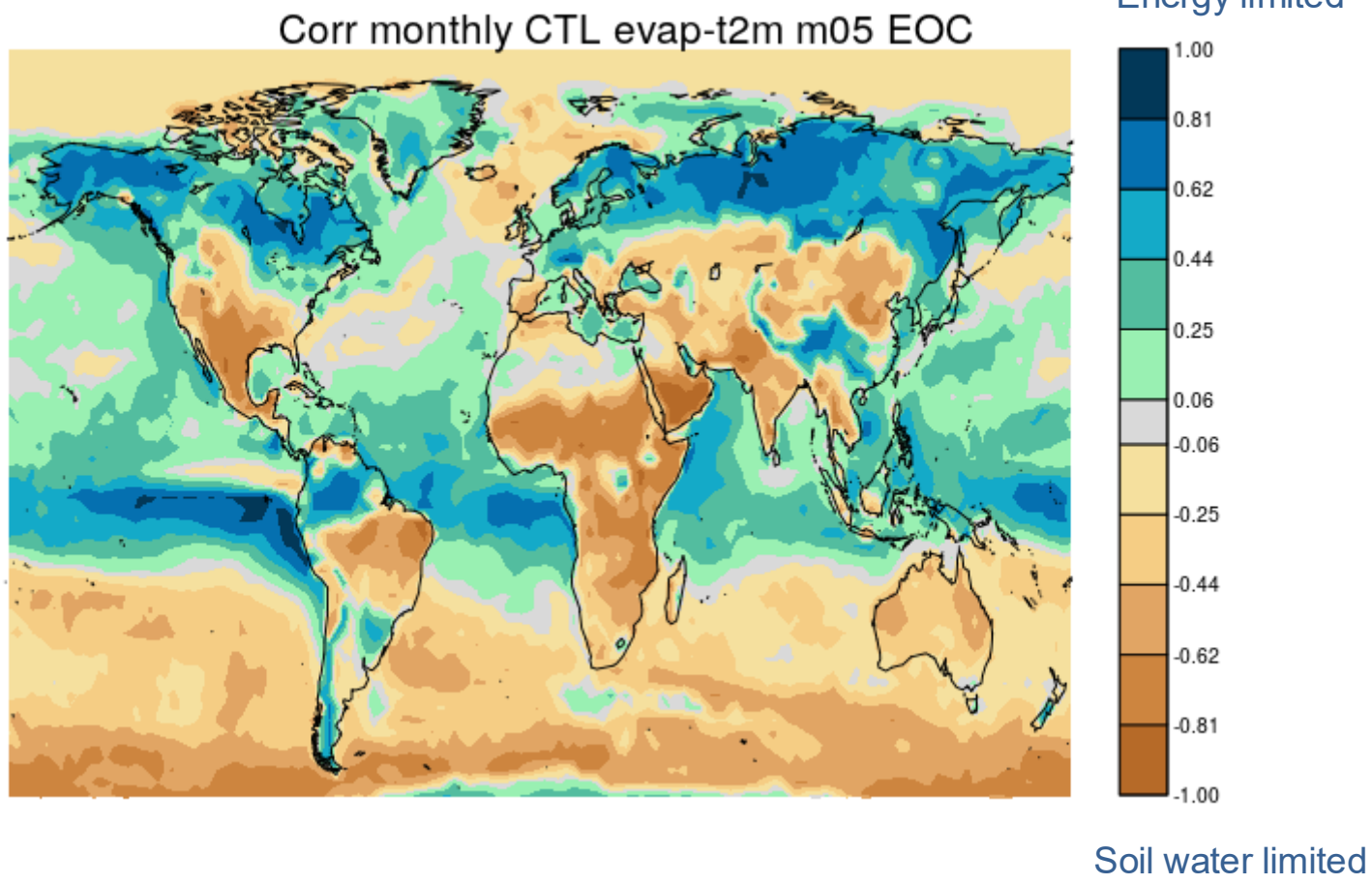
Over moisture-limited land, drier conditions reduce evaporation and cause higher temperatures

If soils are wet, higher temperatures drive higher evaporation

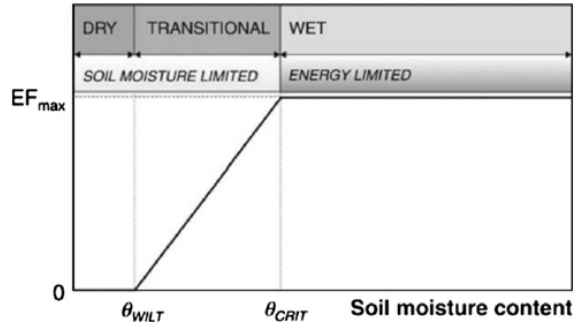
Measures to quantify land-atmosphere coupling

- From (pseudo)observations:
  - Correlation between evaporation and temperature

May-Jul



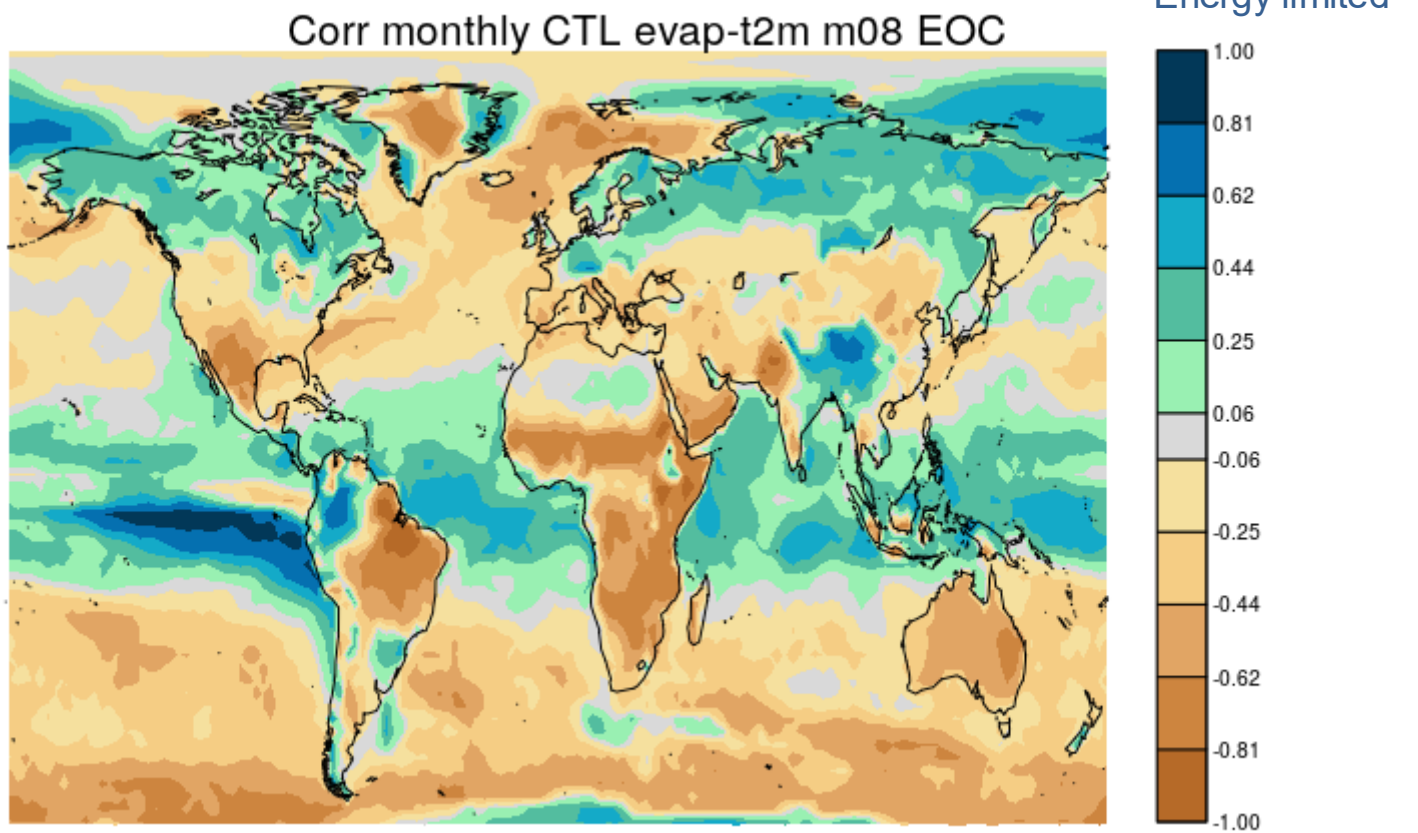
Seneviratne et al, 2010



Measures to quantify land-atmosphere coupling

- From (pseudo)observations:
  - Correlation between evaporation and temperature

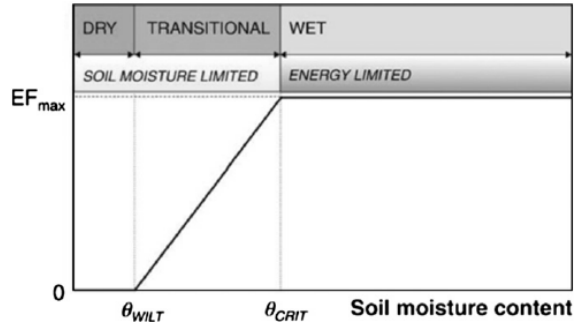
Aug-Oct



Energy limited

Soil water limited

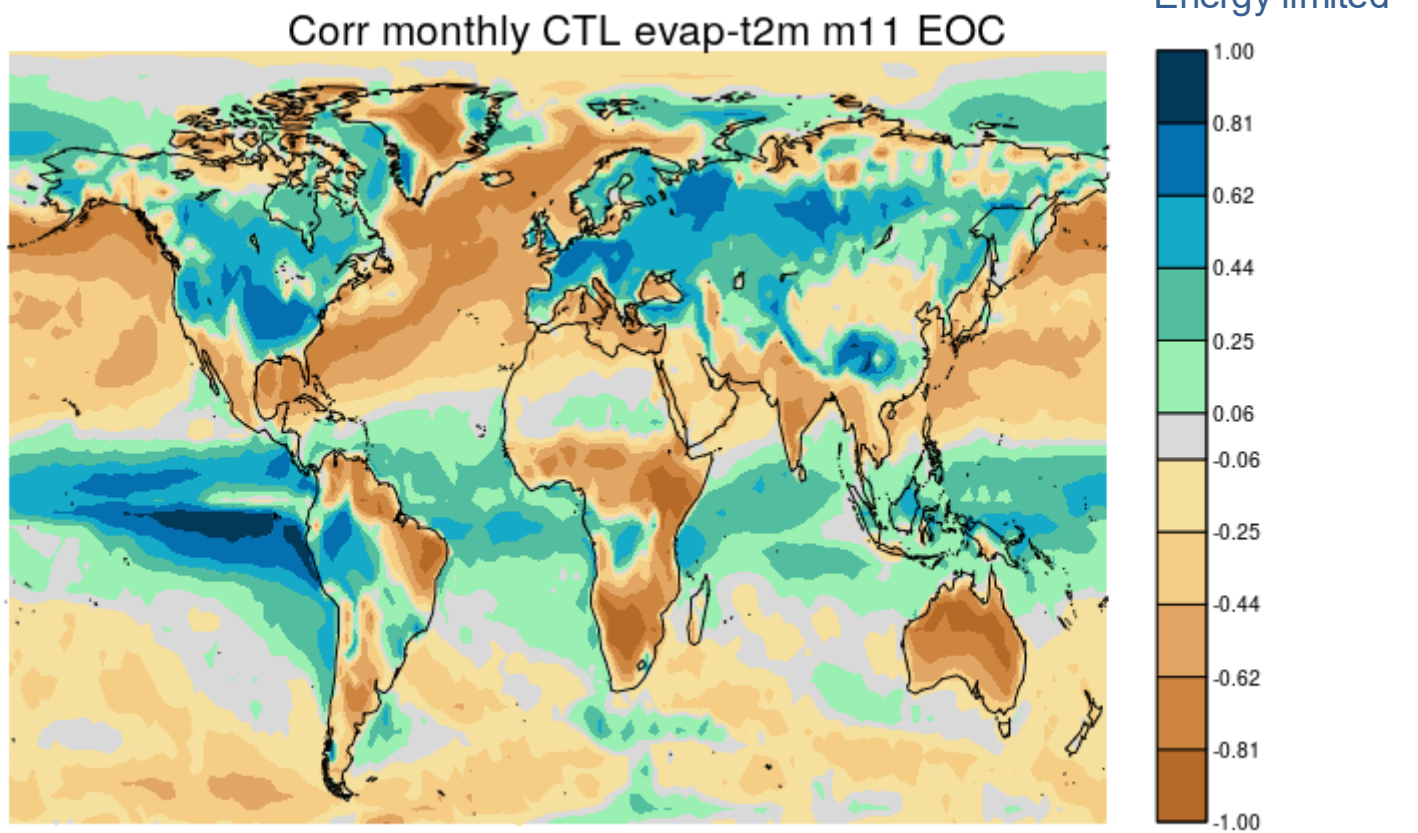
Seneviratne et al, 2010



Measures to quantify land-atmosphere coupling

- From (pseudo)observations:
  - Correlation between evaporation and temperature

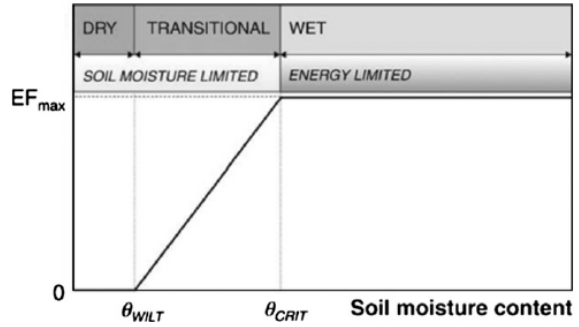
Nov-Jan



Energy limited

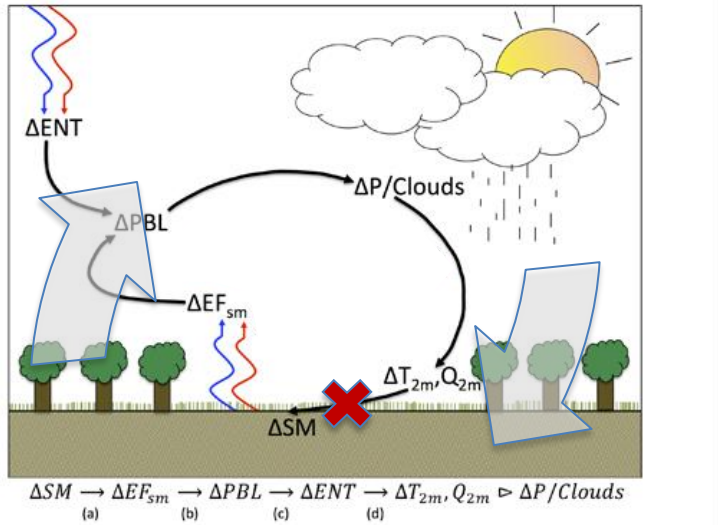
Soil water limited

Seneviratne et al, 2010

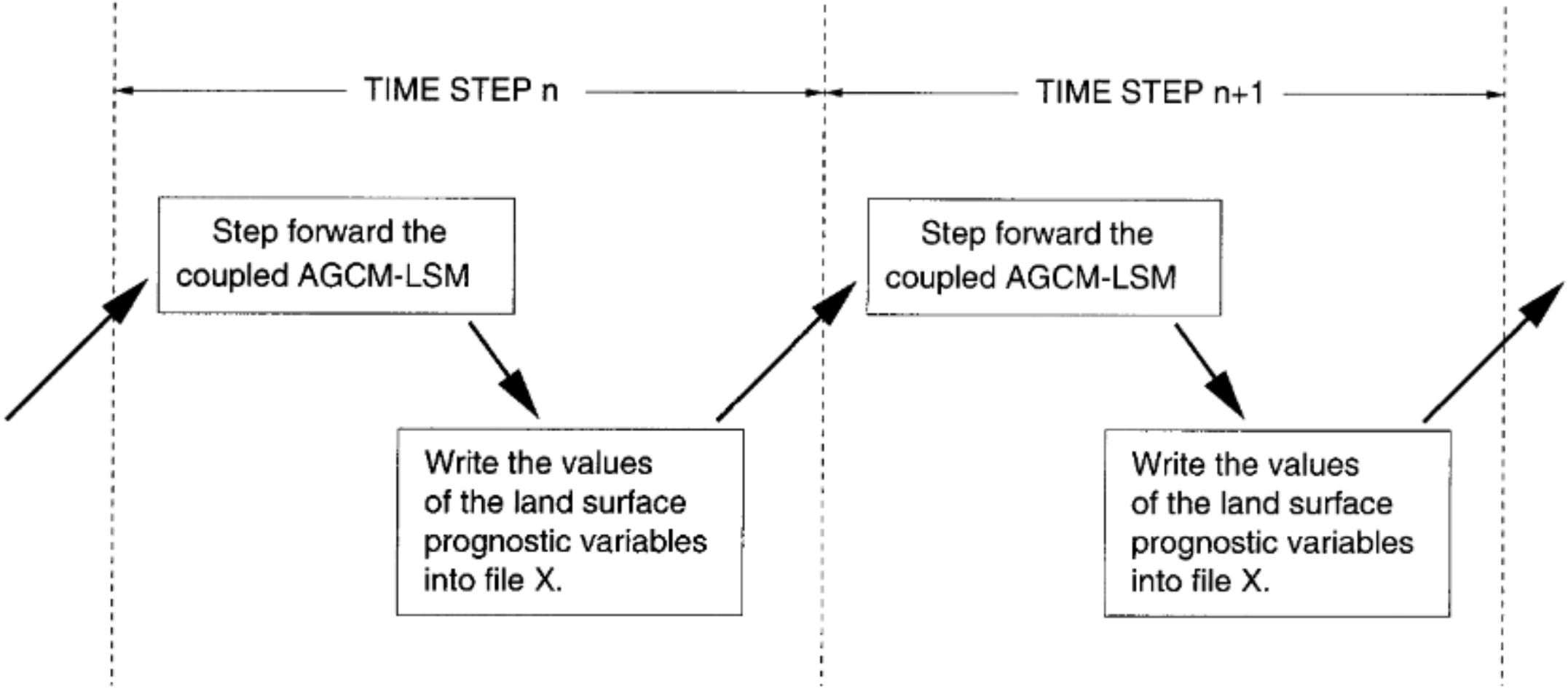


Measures to quantify land-atmosphere coupling

- From a model experiment (GLACE = Global Land Atmosphere Coupling Experiment)
- How?
  - Simulate the hydrological cycle **with** (*W*) and **without** (*R*) interactive land-atmosphere coupling and compare.
- How to remove coupling?
  - In second ensemble (*R*), replace soil moisture in all ensemble members by values from one of the integrations in the first (interactive) ensemble.
- How to measure the effect?
  - Ensemble simulations
  - Compare within-ensemble spread



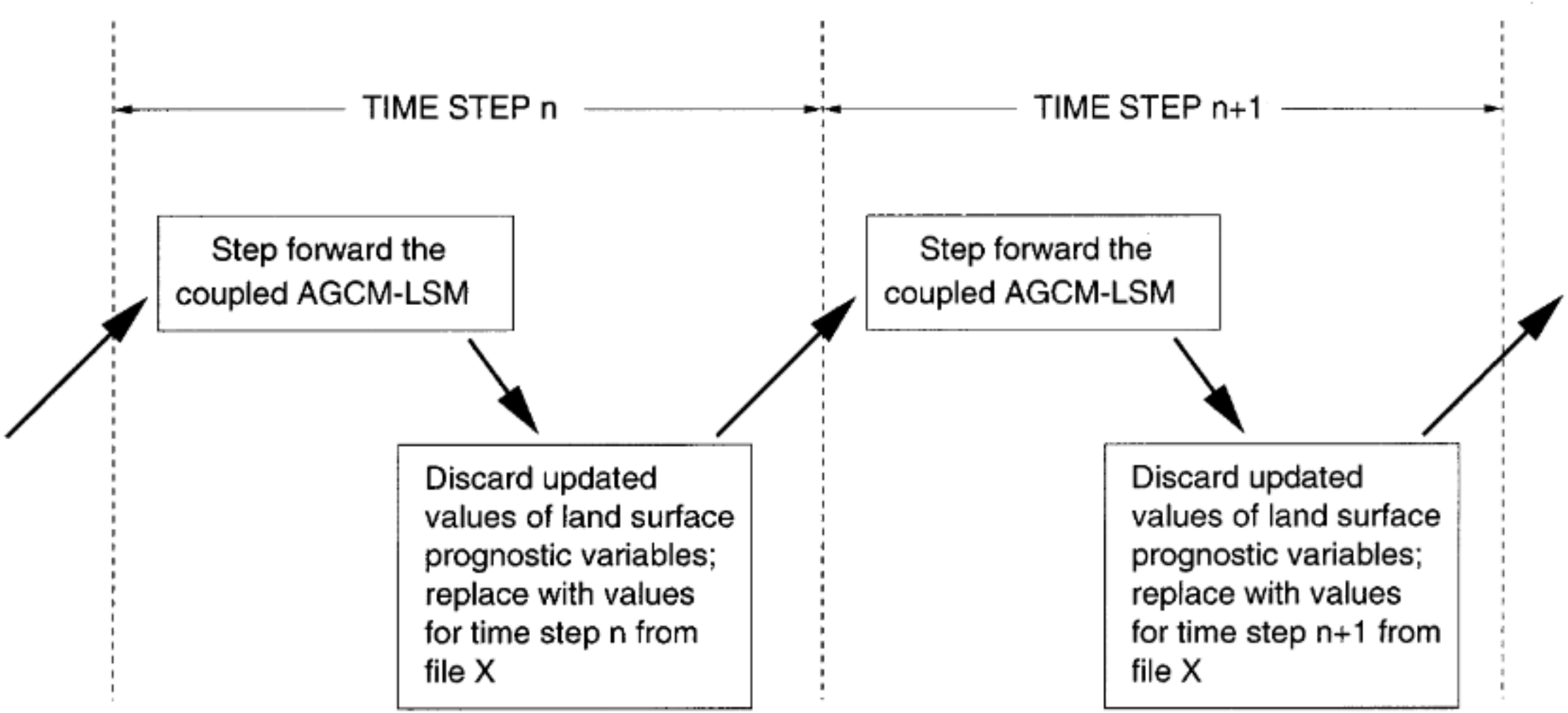
PART 1: ESTABLISH A TIME SERIES OF SURFACE CONDITIONS (Simulation W1).



(Repeat without writing to obtain simulations W2-W16.)

Koster et al, 2002

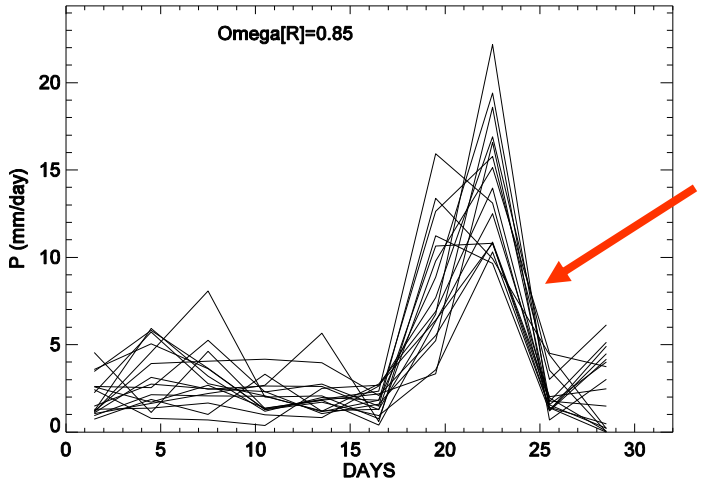
PART 2: RUN 16-MEMBER ENSEMBLE, WITH EACH MEMBER FORCED TO MAINTAIN THE SAME TIME SERIES OF SURFACE PROGNOSTIC VARIABLES (Simulations R1-R16).



ECMWF

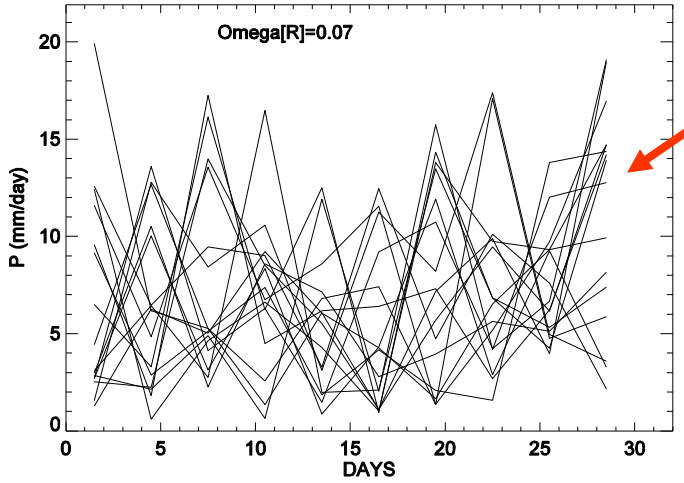
Koster et al, 2002

Comparison of precipitation between ensembles



All simulations in ensemble respond to the specified land surface boundary condition in the same way

→ strong coupling



Simulations in ensemble have no coherent response to the specified land surface boundary condition

→ weak coupling

Koster et al, 2002

Diagnostics:

$$\Omega = (16\sigma^2_{<X>} - \sigma^2_X)/15\sigma^2_X$$

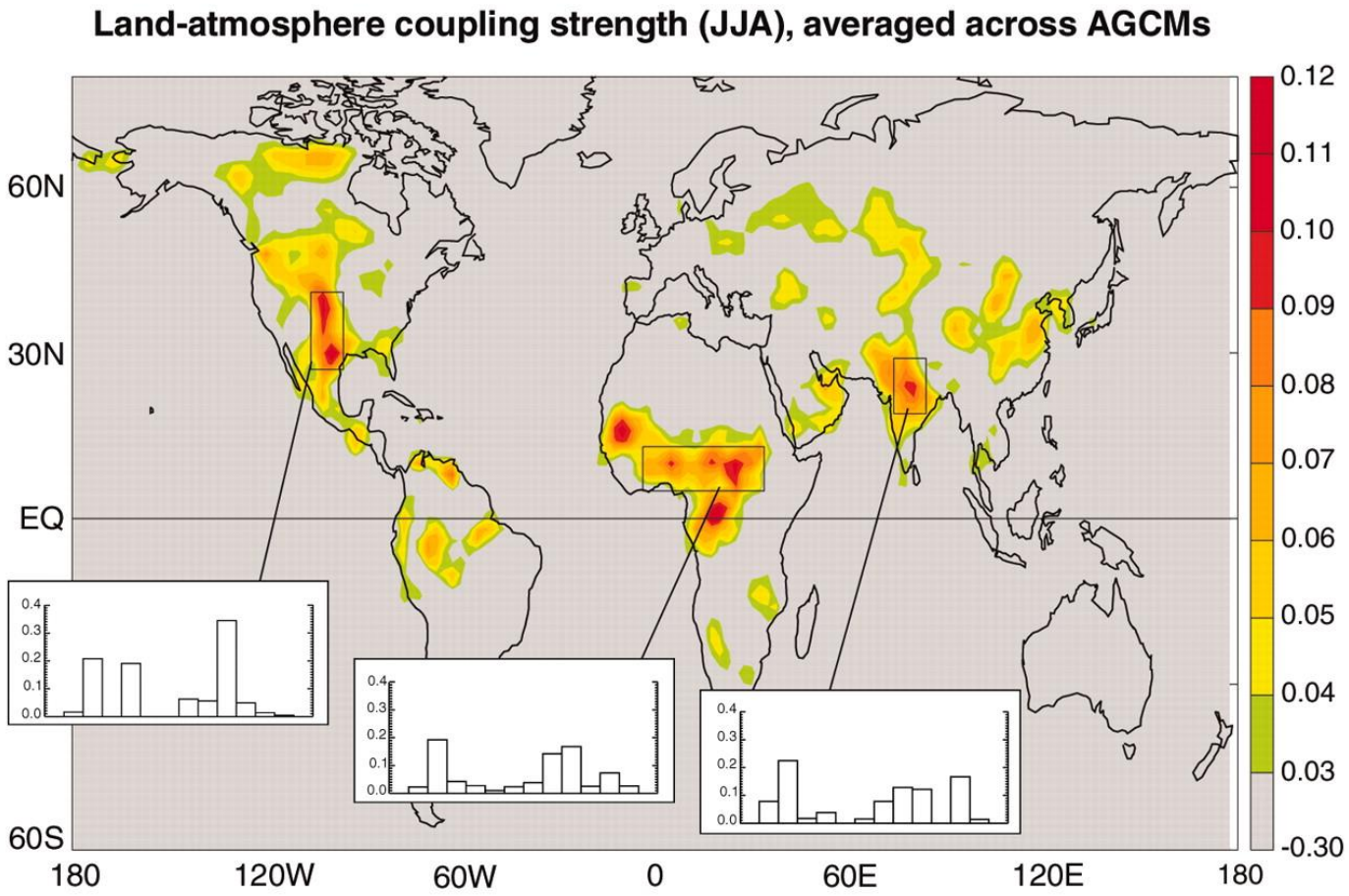
Ω(W)= fraction of variance "explained" (forced) by all boundary and initial conditions

Ω(R)-Ω(W)= fraction of variance "explained" by prescription of subsurface soil moisture variables

ECMWF

GLACE

Areas with strong positive soil-moisture feedback on precipitation



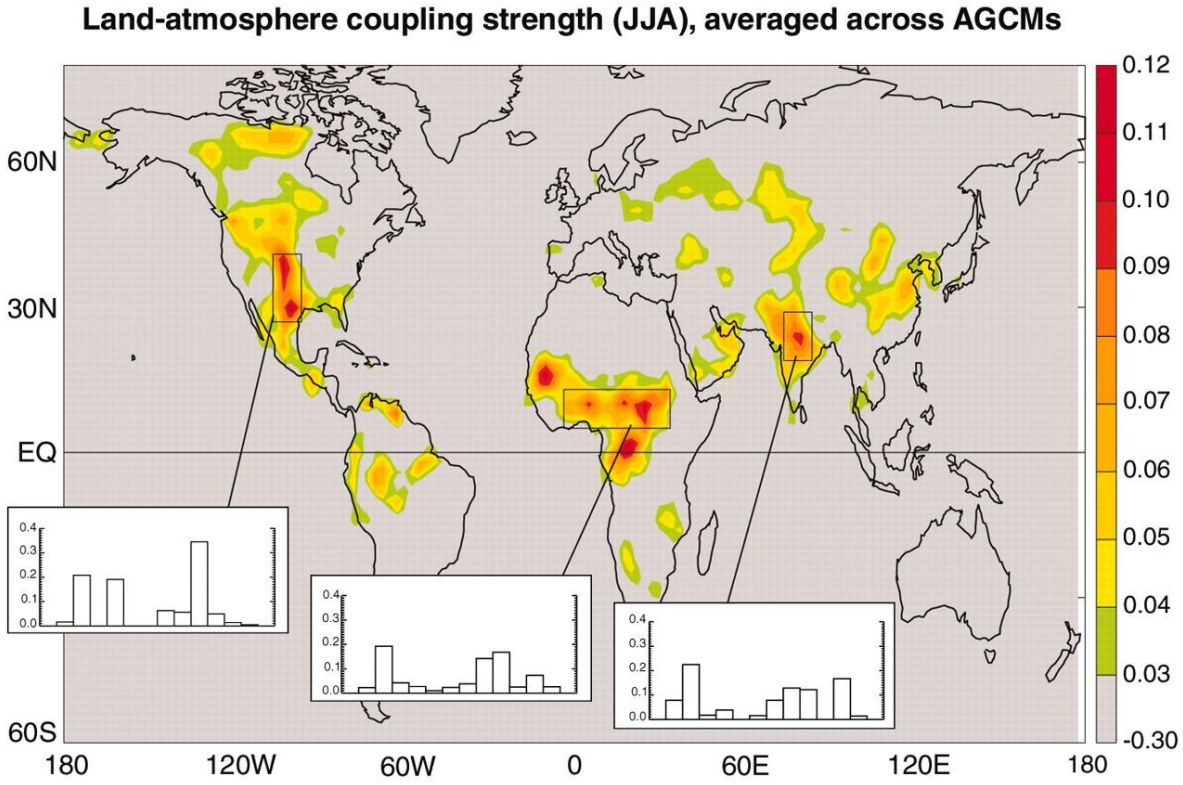
This is a famous figure, and looks very nice. But note that different models gave substantially different results. Model representation of land surface processes is improving, but still has some way to go.

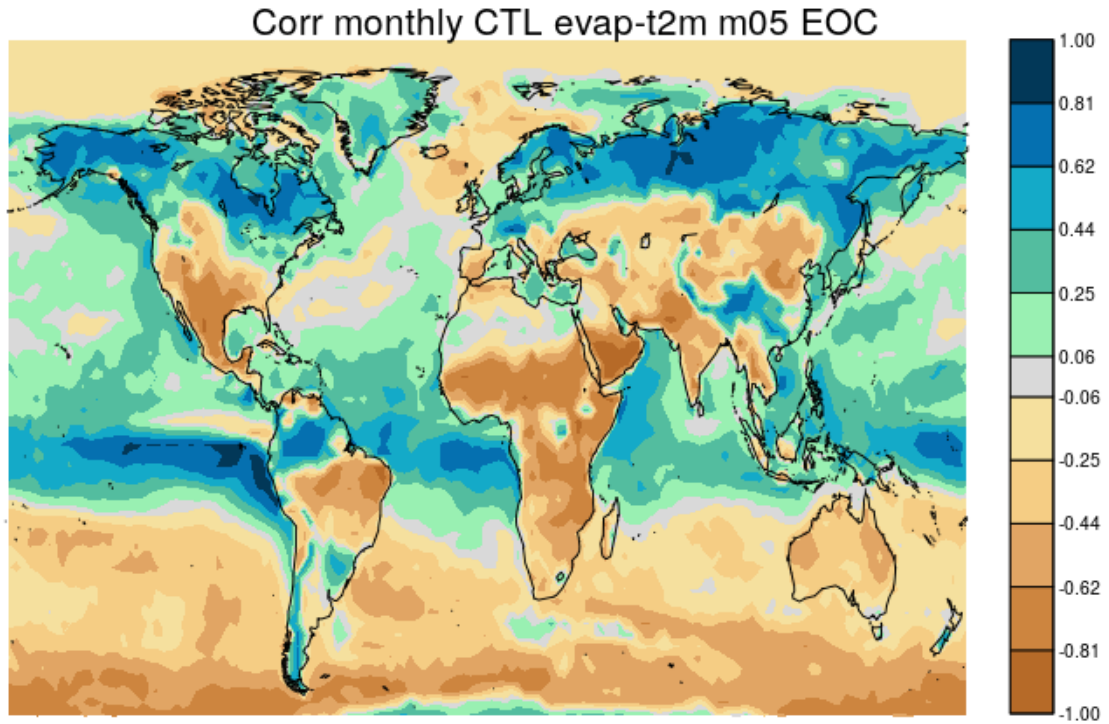
Koster et al, 2004, Science

ECMWF

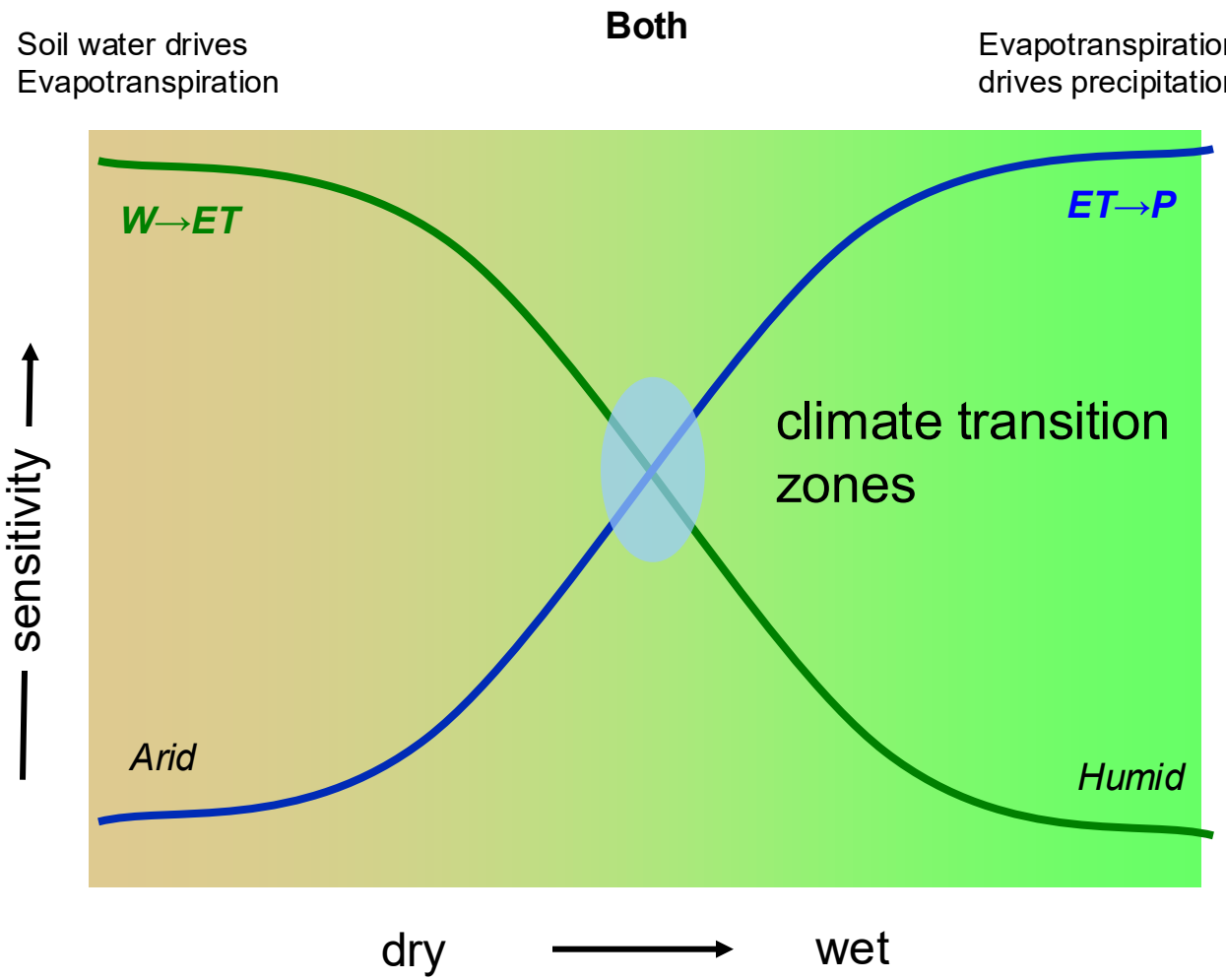
GLACE

Compare diagnostic and prognostic measure

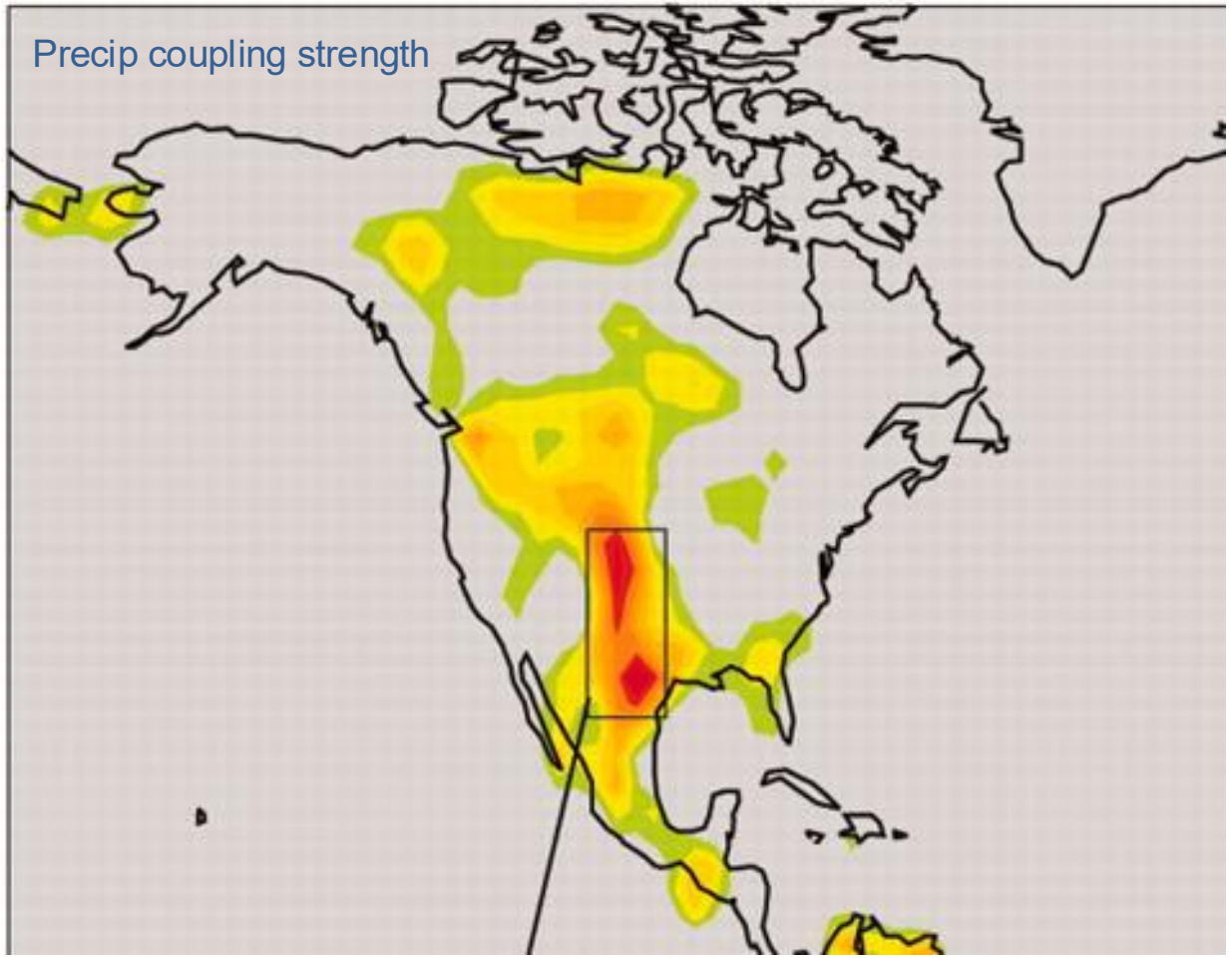


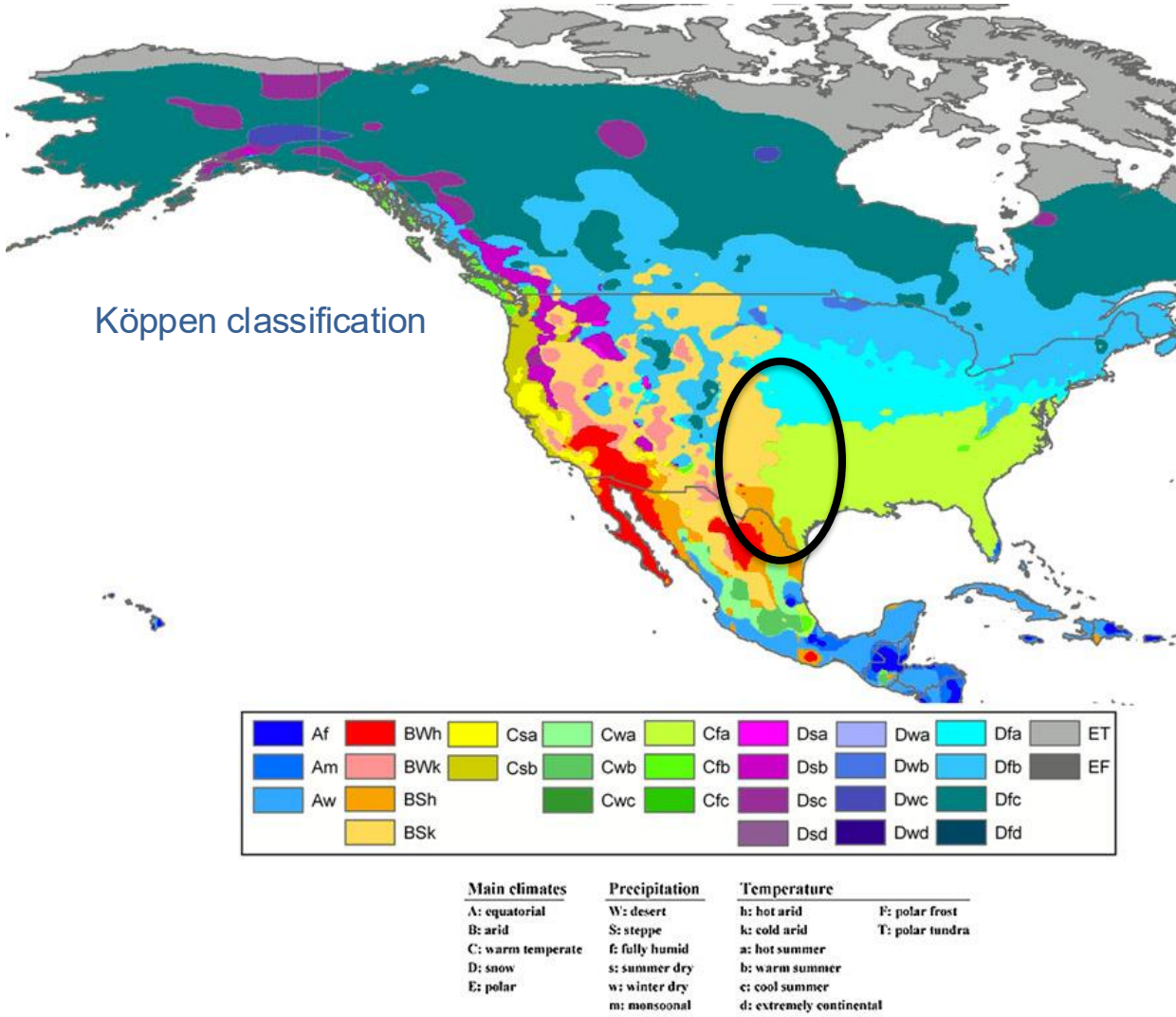


Strong precipitation coupling needs a combination of sensitivities



Strong feedback on precipitation at transition between arid and temperate zones

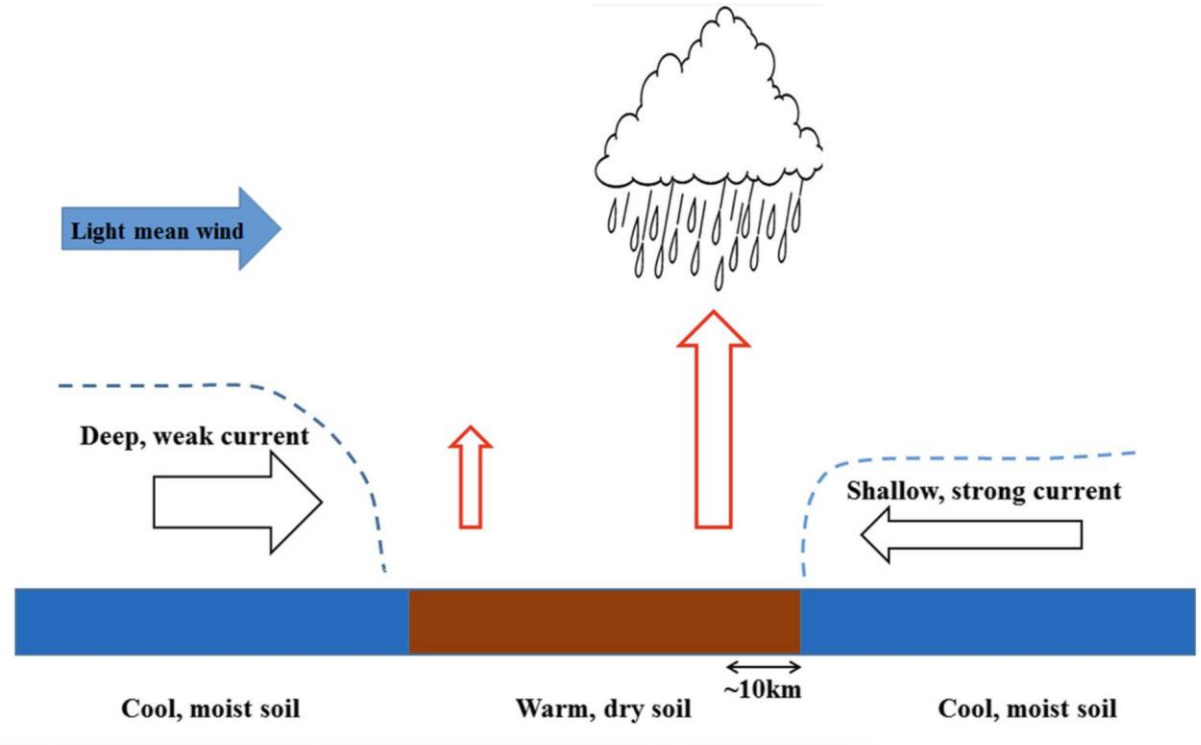




Koster et al, 2004, Science

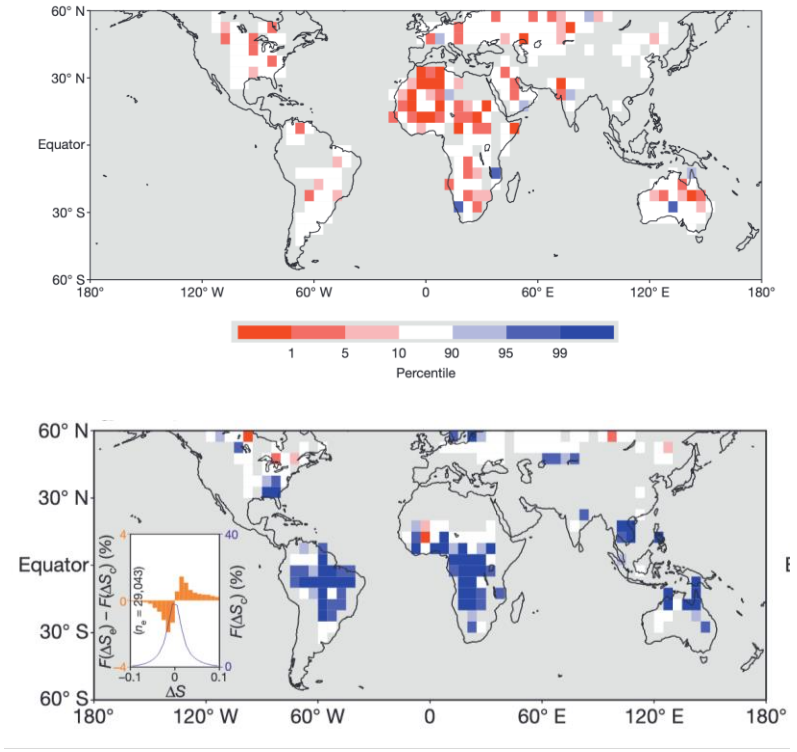
A spatial view on soil-moisture atmosphere coupling

- Chris Taylor et al.:
  - Afternoon rain more likely over drier soils (Nature 2012), apparently at odds with Koster et al. citing errors in convective scale processes in GCMs used by Koster.



Taylor et al. (2011)

Preference for afternoon precipitation over dry soil in obs and a GCM

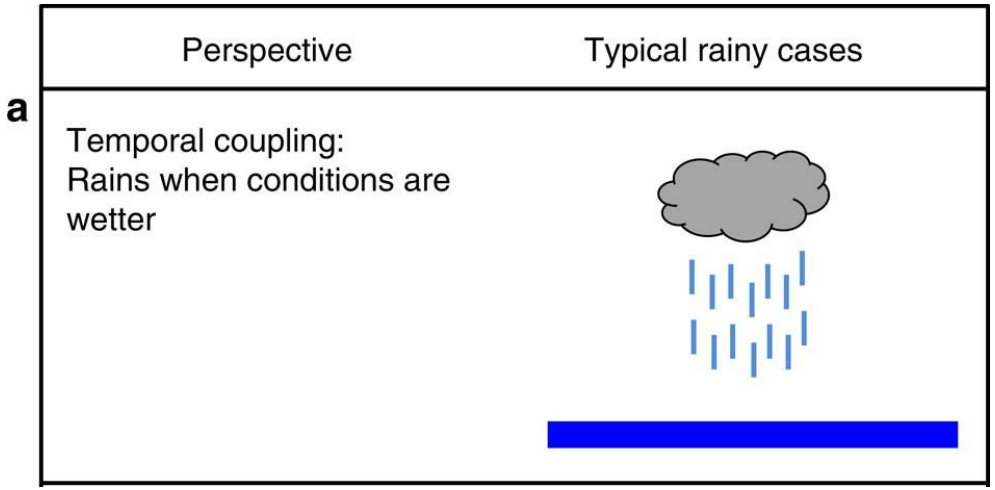


Taylor et al. (2012)

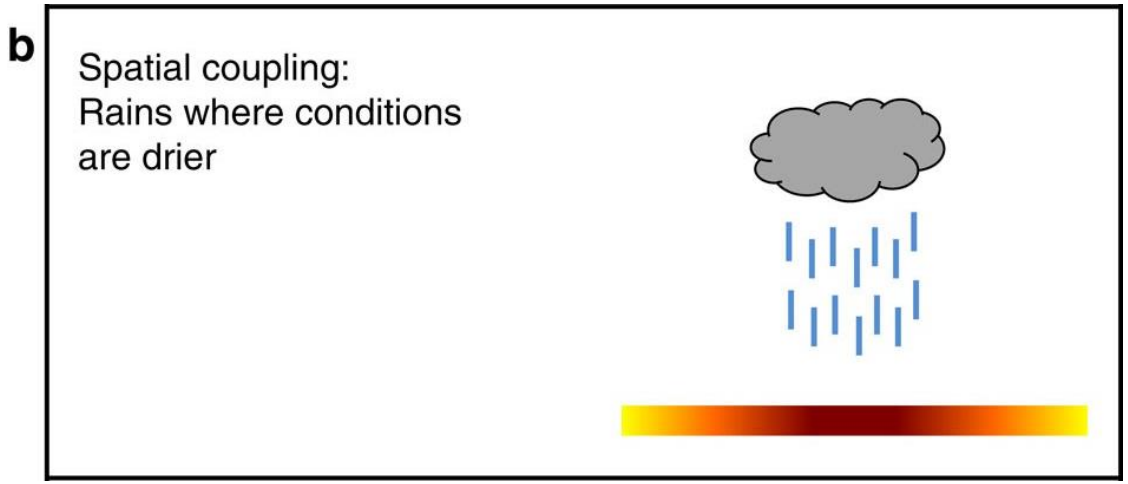
The Resolution!

- Guillod et al. (2015), Nat. Comms

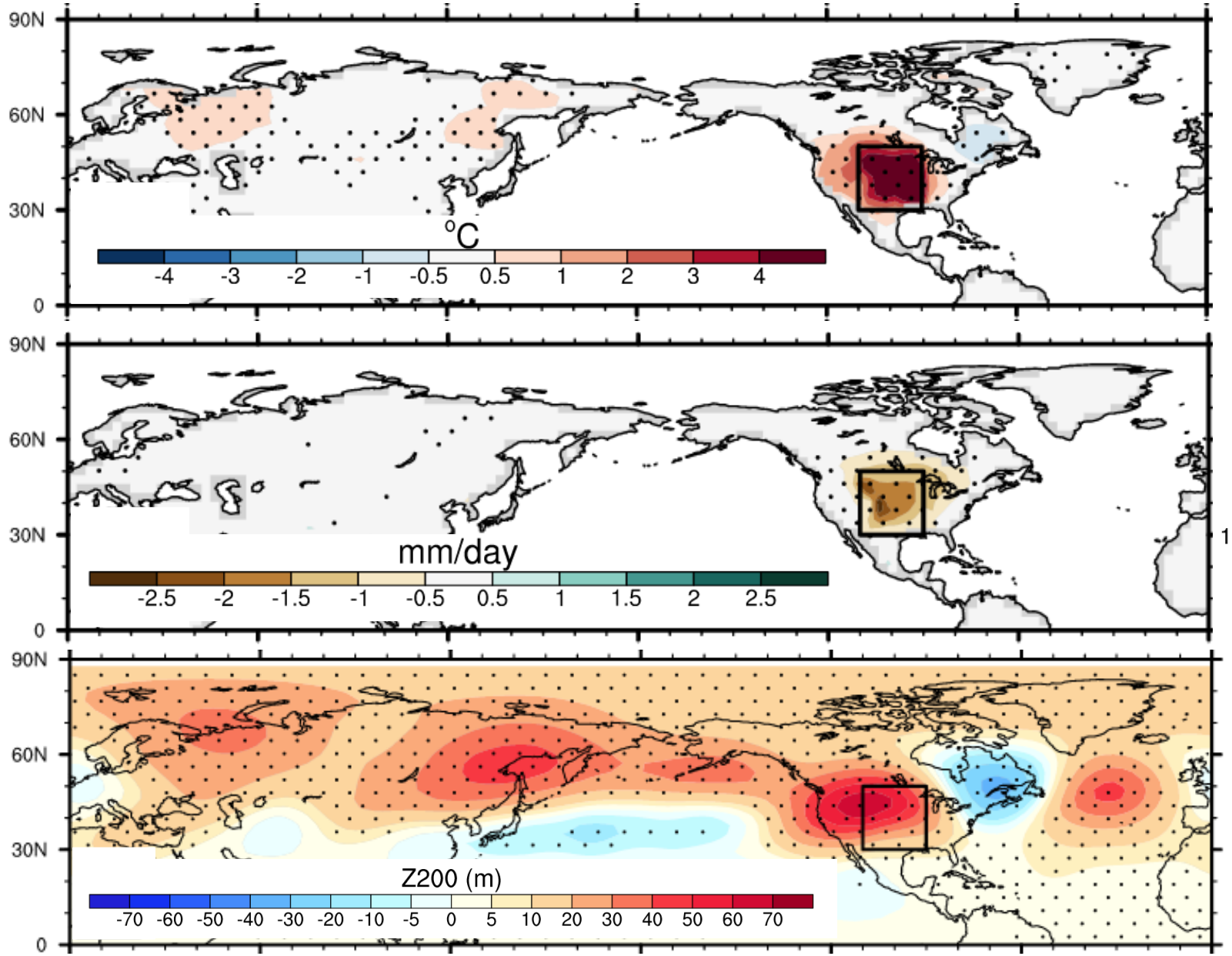
Koster emphasizes the temporal coupling

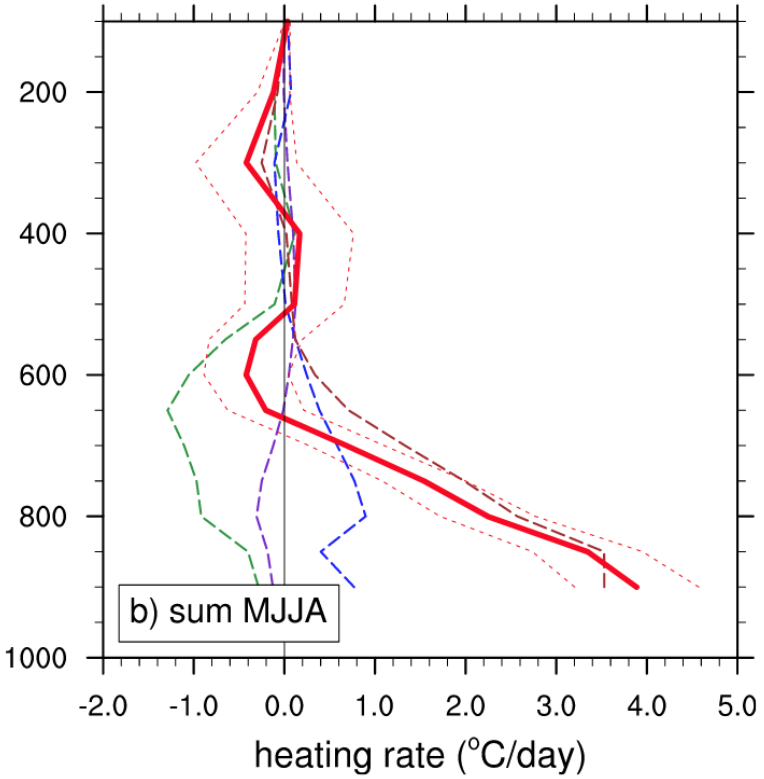


Taylor emphasizes the spatial



Remote response to soil-moisture depletion on upper atmosphere

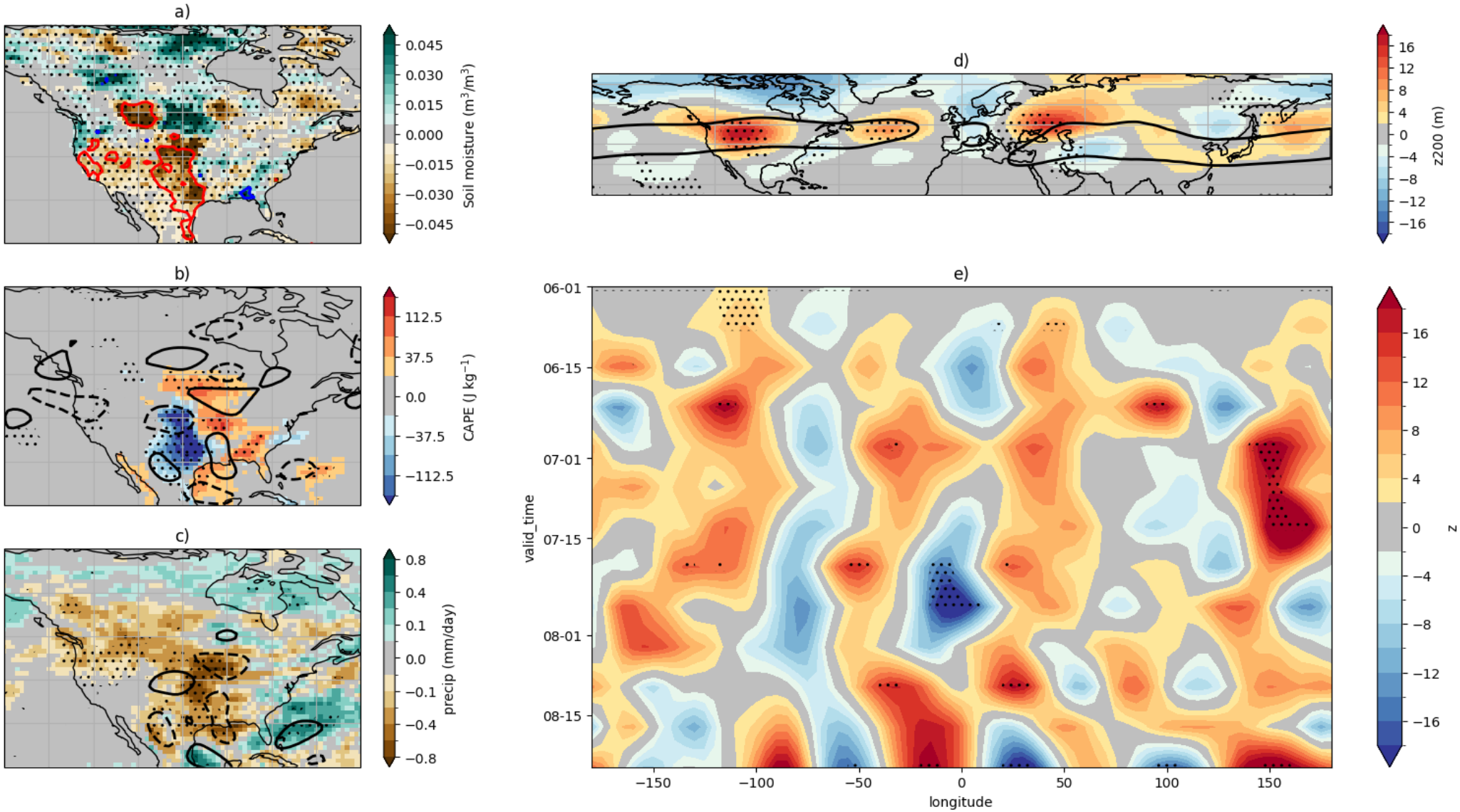




Total ens avg
Total ens avg+1stddev
Total ens avg-1stddev
Vertical diffusion
Longwave
Sortwave
Latent heat

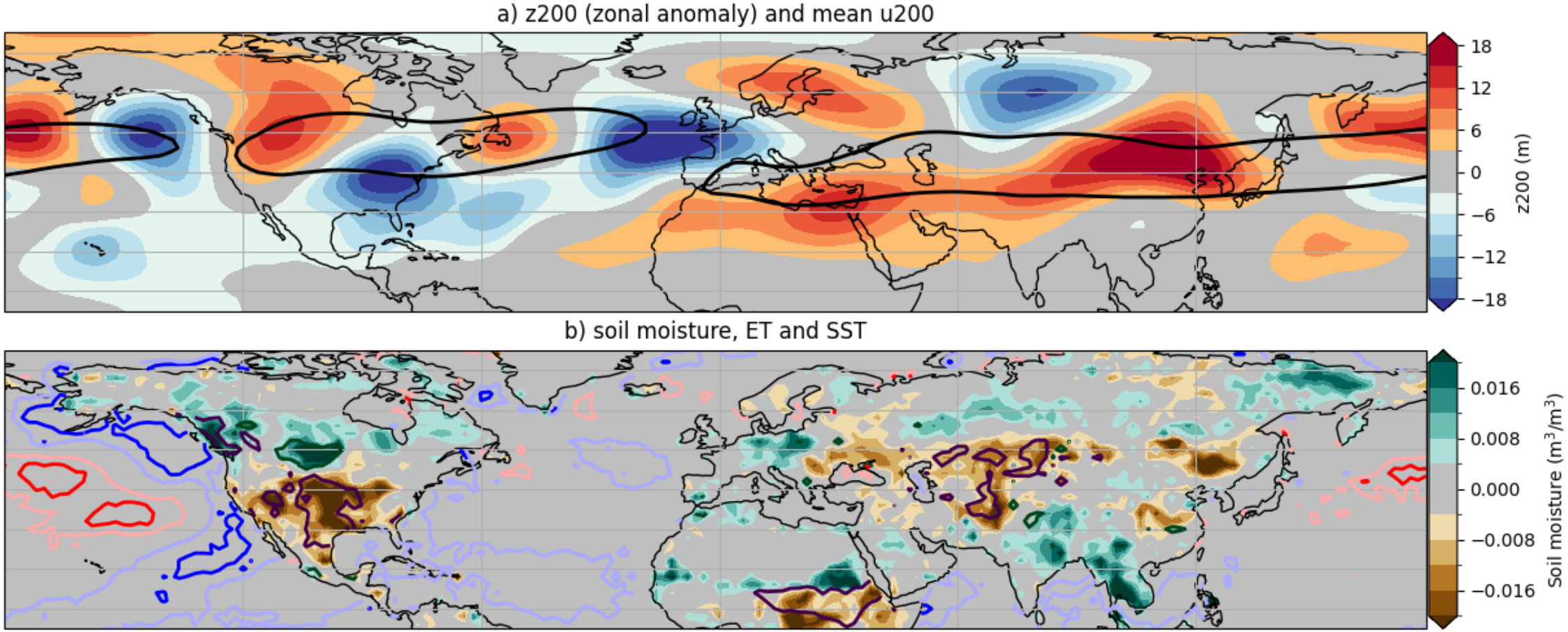
Teng et al. (2019)

Sensitivity experiment: Impact of North American soil-moisture in JJA 2022 (following a La-Nina)



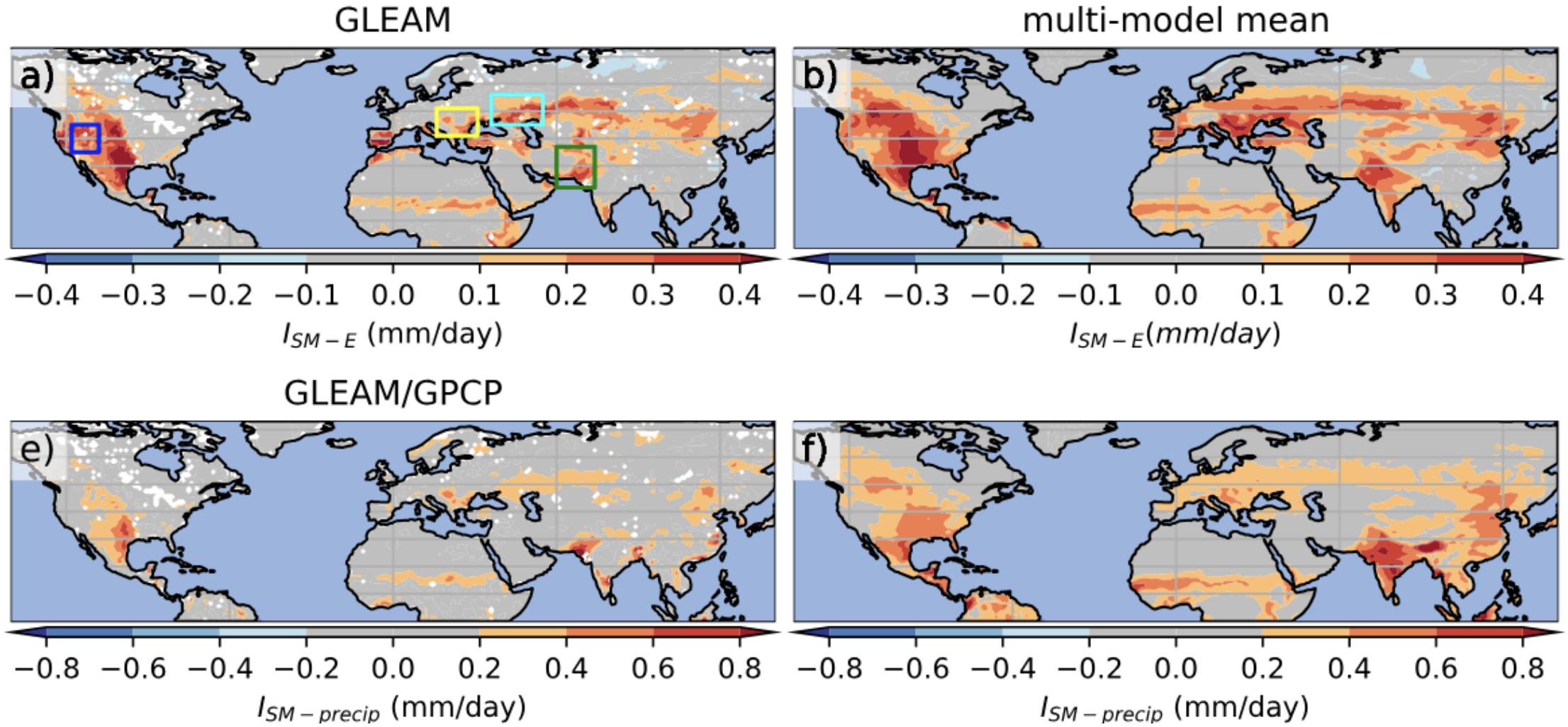
Day et al. (in review)

Difference between phases JJAs following La-Nina vs El-Nino



Day et al. (in review)

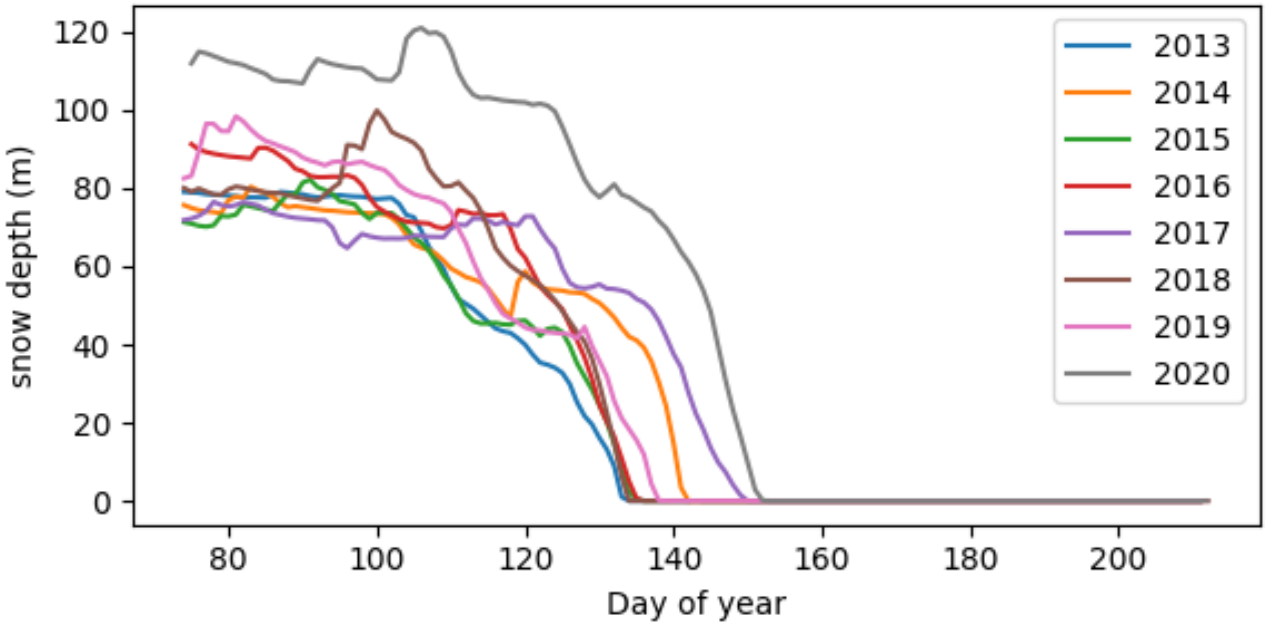
How well do GCMs capture soil-moisture-atmosphere coupling?

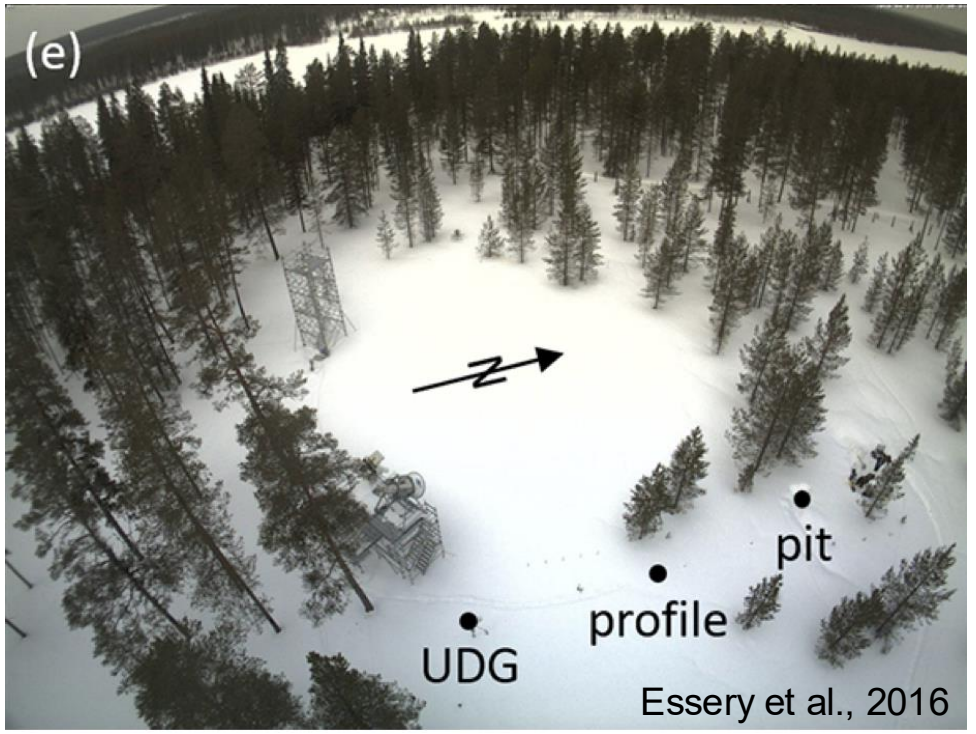


Day et al. (2025)

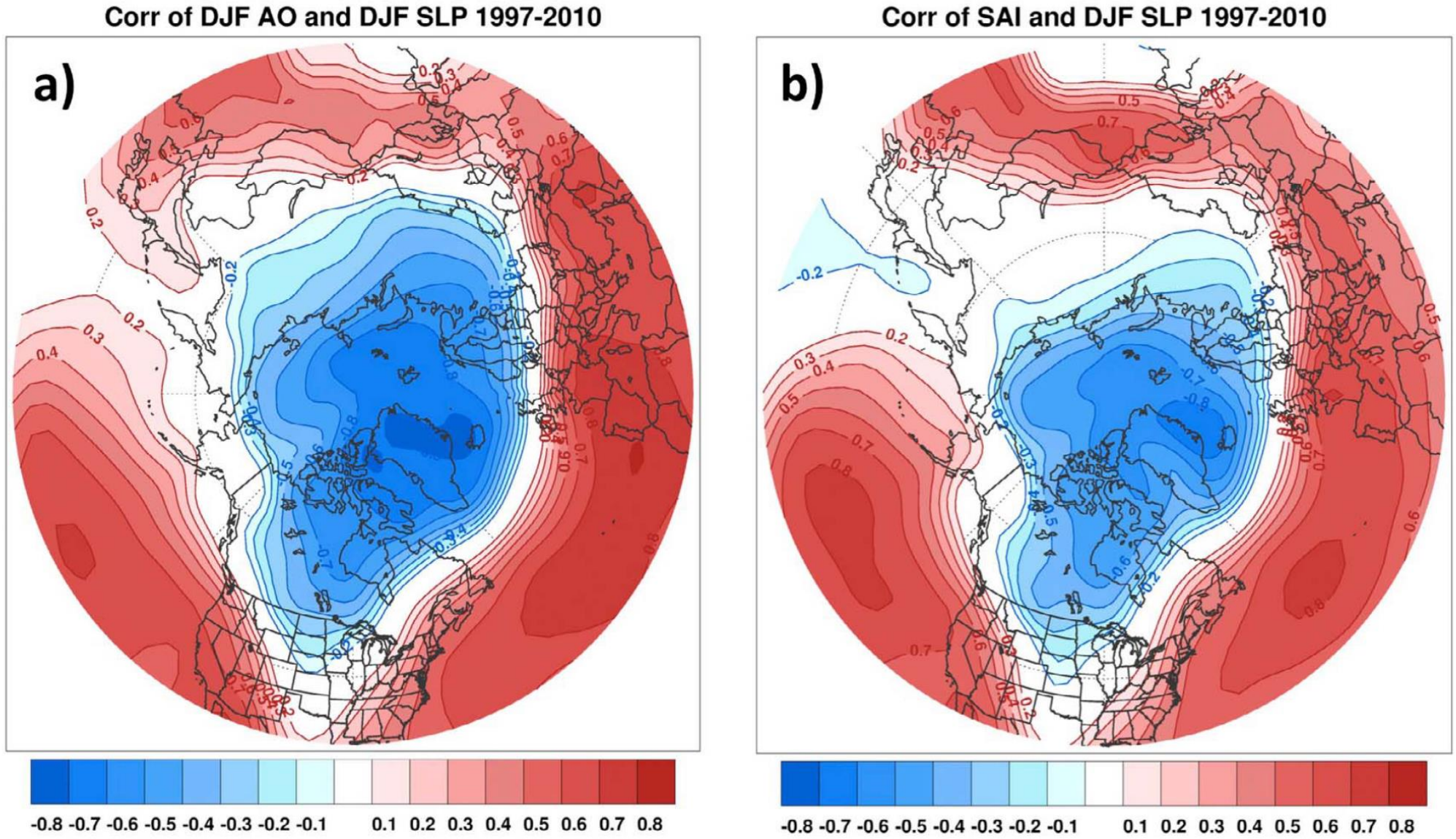
Snow depth memory

Sodankyla, Northern Finland



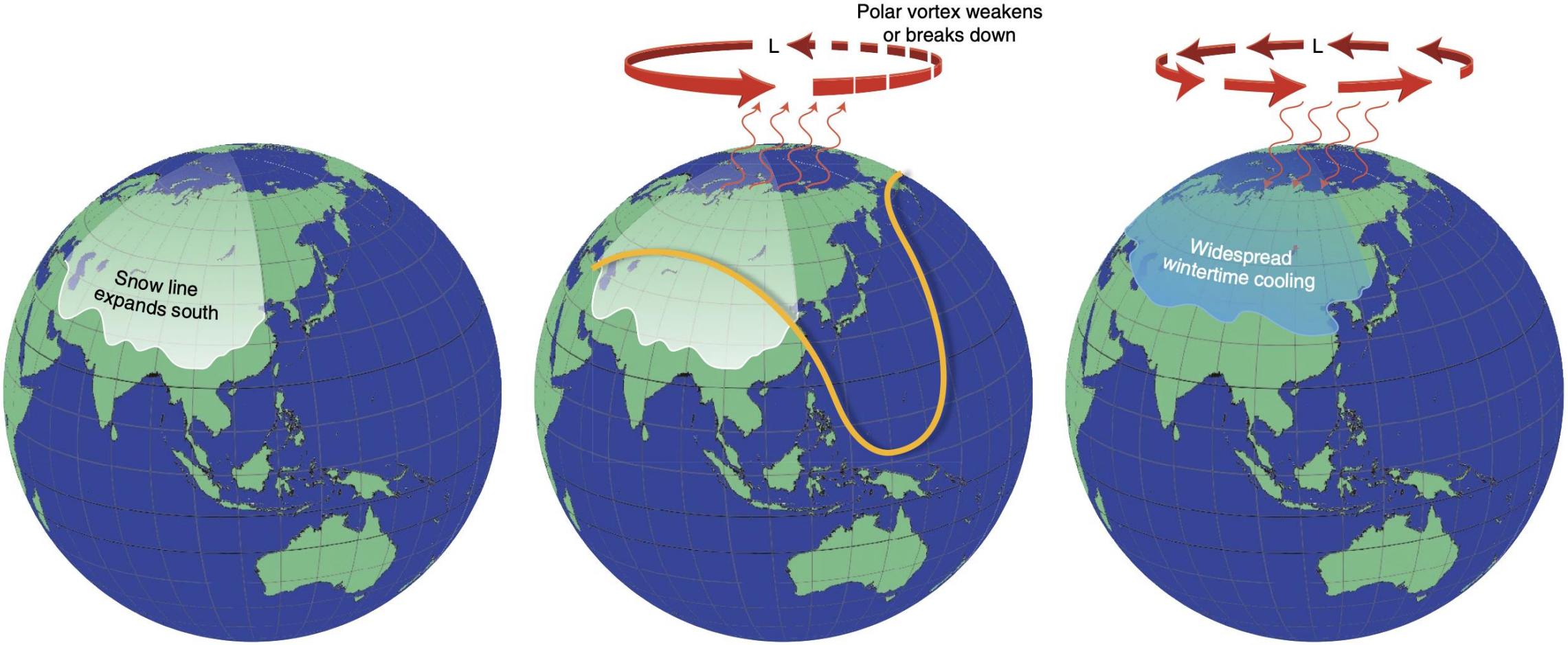


Snow cover as a predictor of the Arctic Oscillation



Cohen and Jones (2011)

A mechanistic view of remote response to snowcover



Step 1
Expanding fall snow cover and near surface cooling

Steps 2–4
Planetary wave generation, propagation and dissipatation in the stratosphere

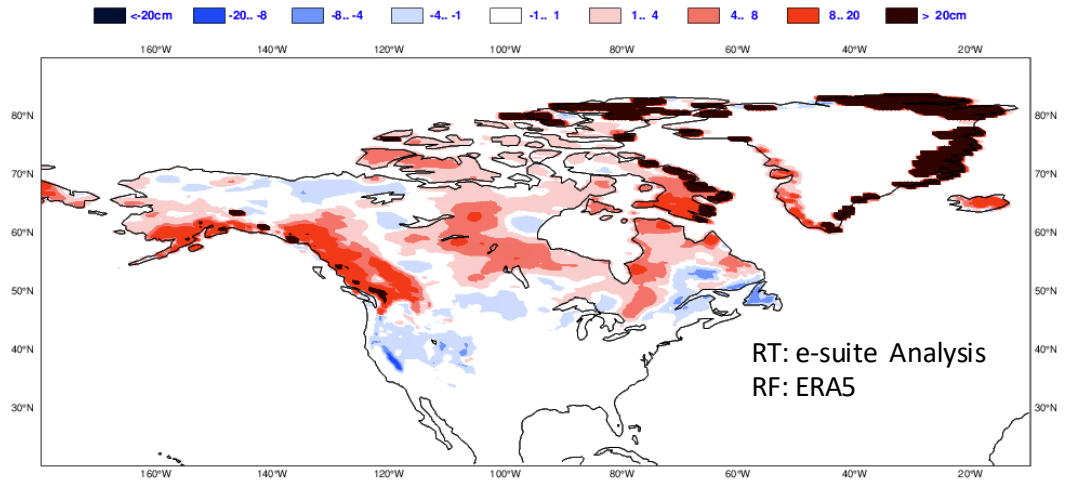
Steps 5–6
Stratosphere-to-troposphere propagation of zonal-mean anomalies

ECMWF

Henderson et al., (2018), Nat Clim

Funded by the European Union

From the next model cycle each ECMWF system will have its own land-surface analysis (initial conditions)



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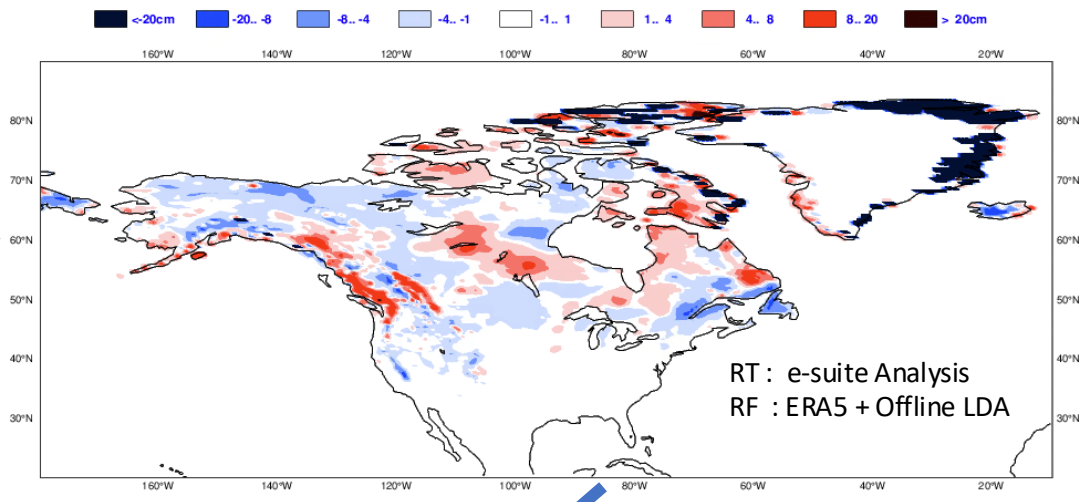

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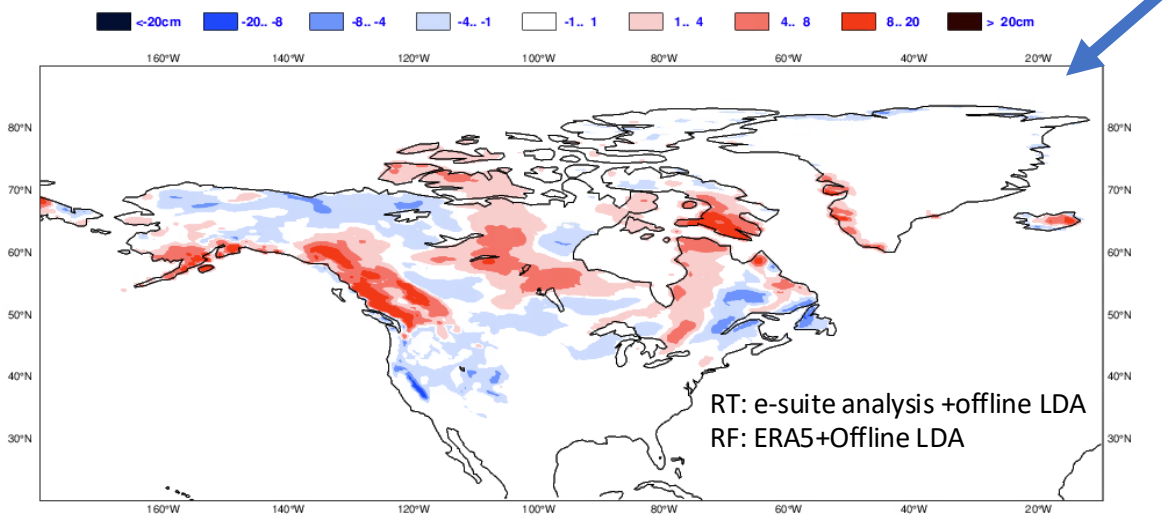
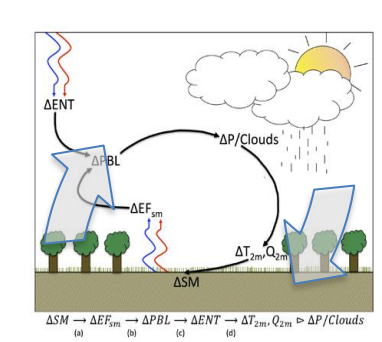
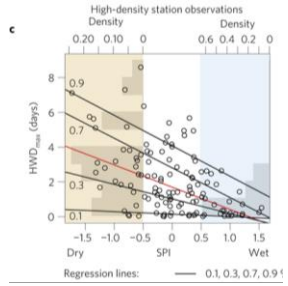


Summary

- For land-related predictability we need
  - Variability
  - Memory (soil moisture, snow mass, vegetation, …)
  - Coupling



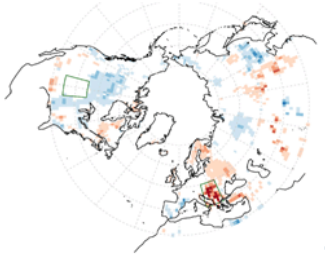
- How to measure land-atmosphere coupling/predictability
  - Diagnostic measures: correlation, regression, composite analysis, etc.
  - Prognostic measures: intervening in GCM experiments (GLACE, Teng et al., etc.).



- Land surface signal is small in some regions but large in certain “hotspots”
  - Evaporation limited vs Energy Limited soils
  - Transition zones between semi-arid and humid climates.

- Errors in land-atmosphere feedbacks can lead to large biases that degrade prediction skill on subseasonal-to-centennial timescales.

- Land-surface properties need special treatment (e.g. new LDAS at ECMWF)



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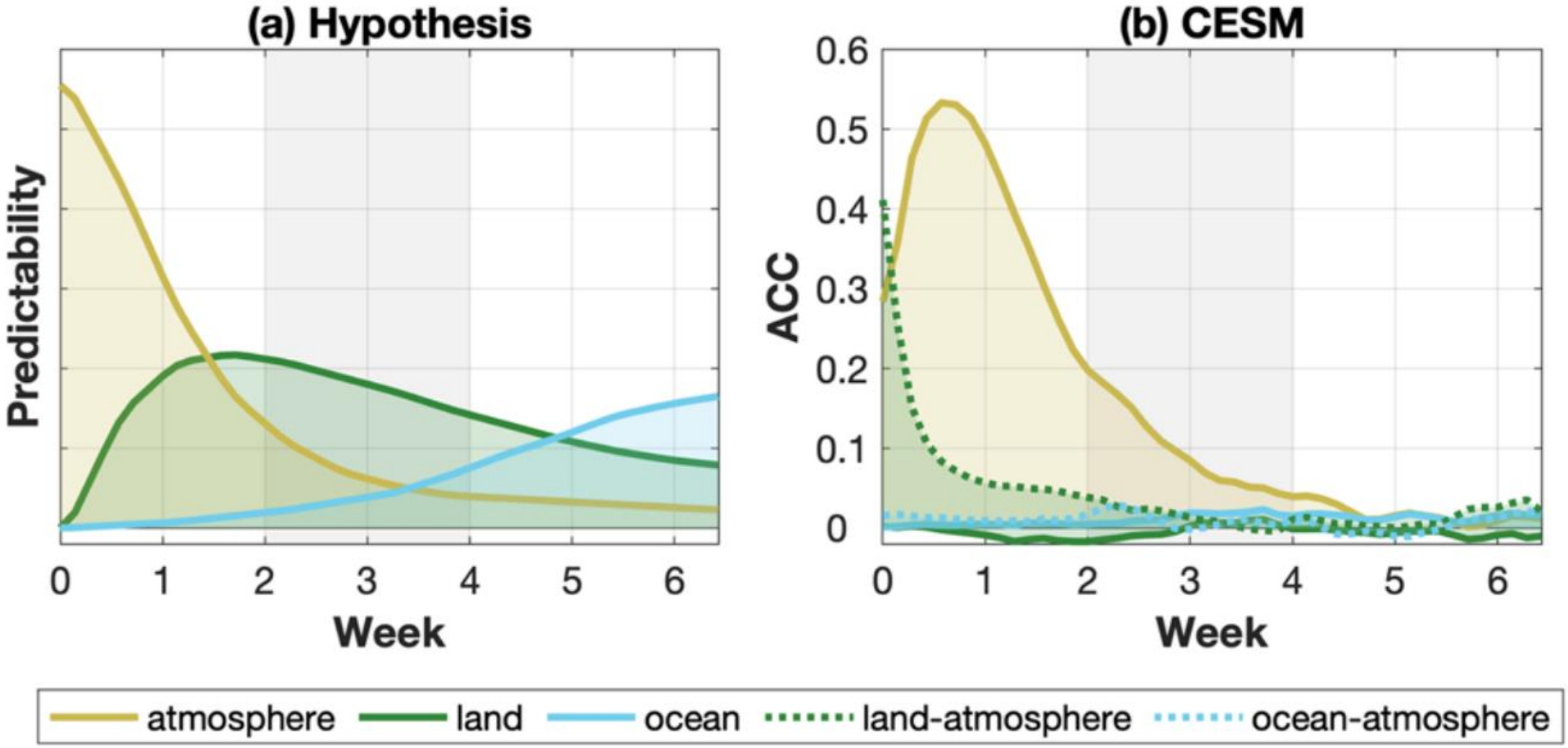
Additional slides

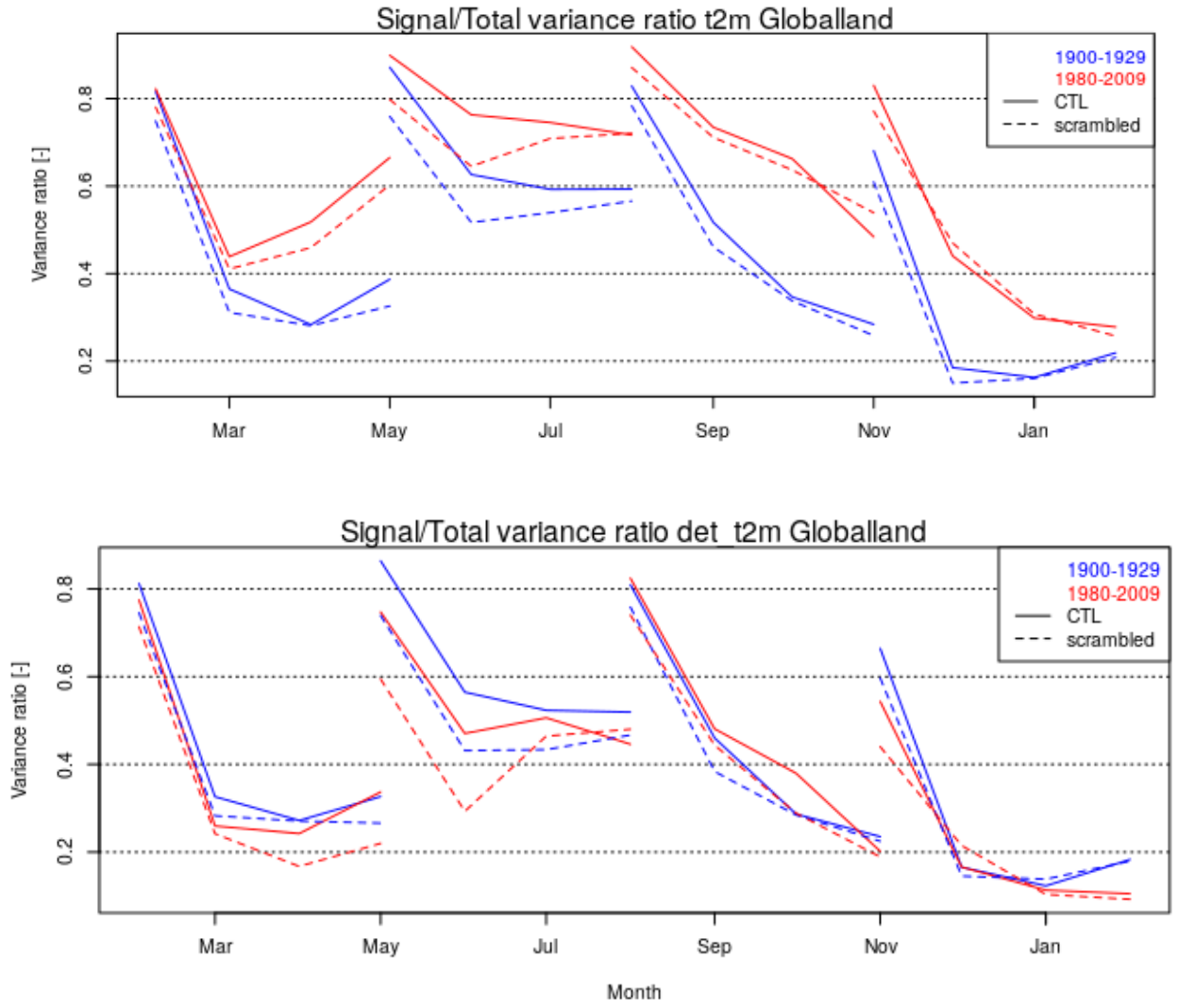
How important is the land-surface?



ECMWF

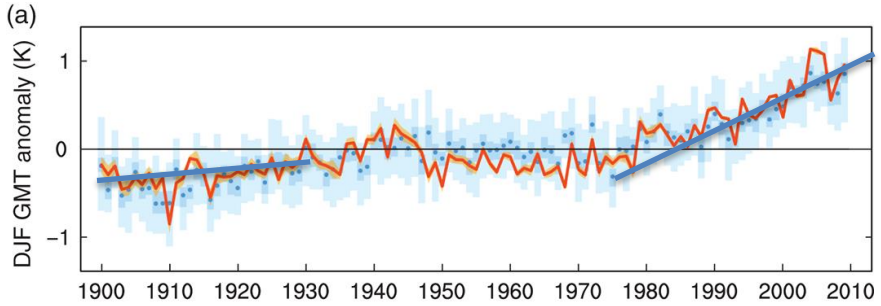
Richter et al. (2024)

Trend contributes to T2m predictability



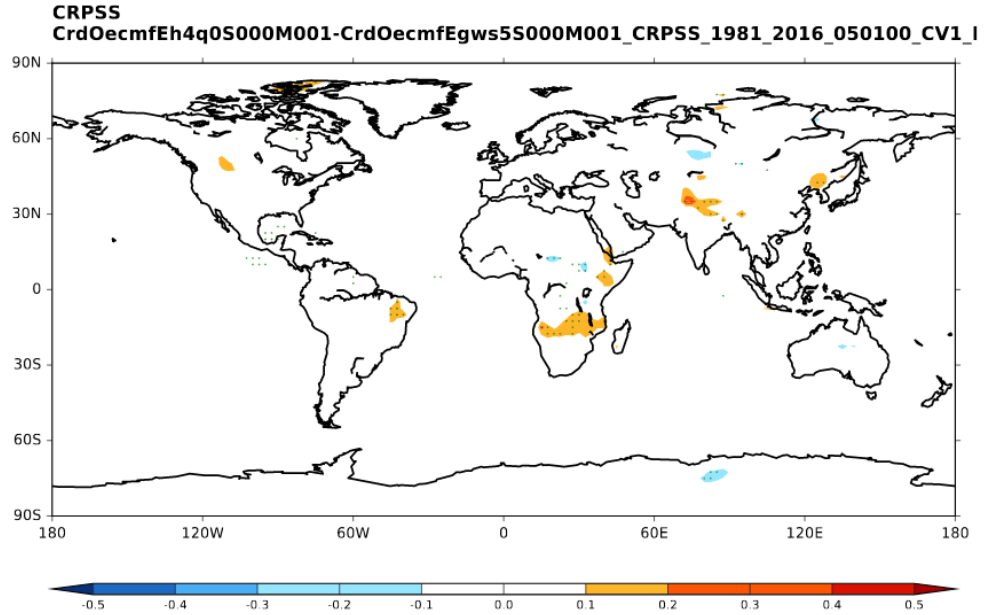
Note: initialized land surface (solid line) gives additional signal in T2m, especially in early summer. Note these plots show predictability not skill – extra skill would require the additional land surface signal to be correct.

Before detrending

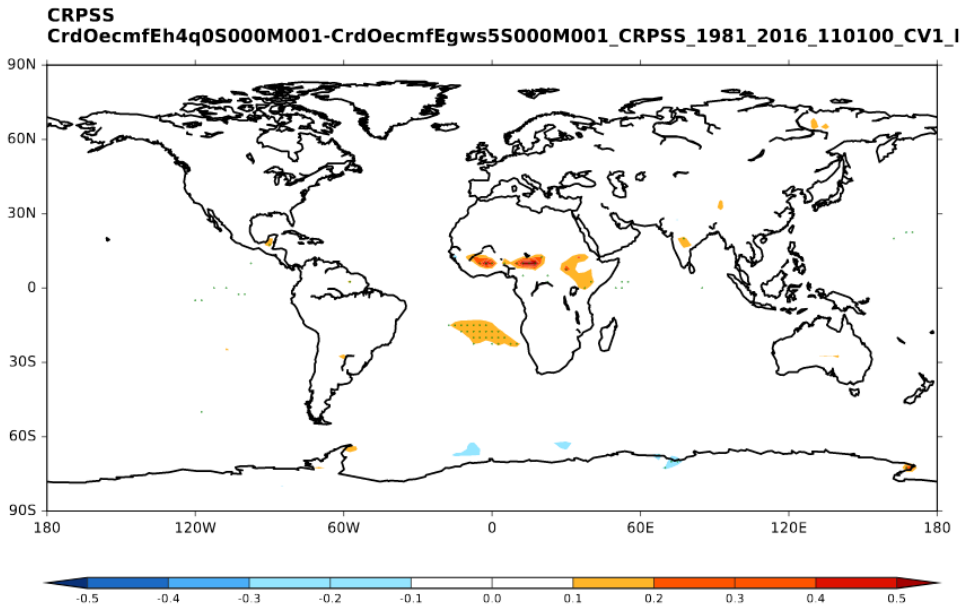


After detrending

Impact on T2m forecast skill of improved land surface initial conditions



JJA



DJF

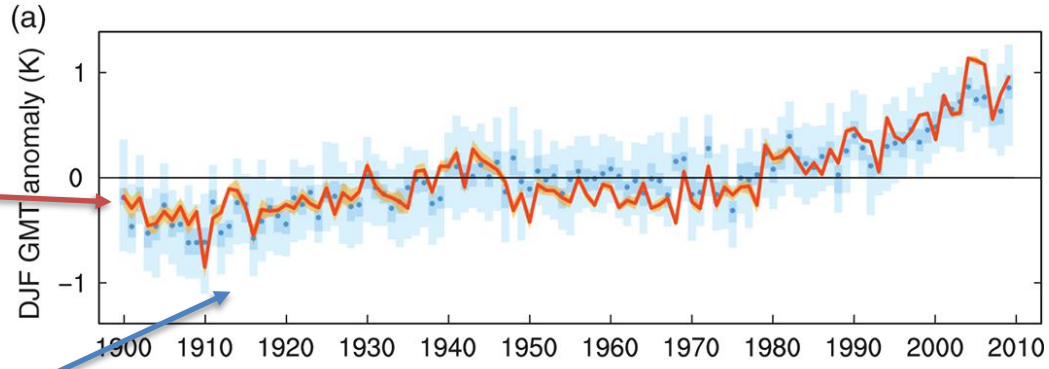
Difference in CRPSS skill from 36 years of re-forecasts with 51 member ensembles, comparing Cy46r1 (ERA5 ICs) and Cy45r1 (SEAS5 ICs). Sensitivity experiments (lower resolution, smaller ensemble size) confirm that the main driver of improvement is change in ICs, not the model.

How about trends in predictability?

- Can we see climate trends in predictability?
  - Model experiment: compare ensemble seasonal forecasts 1900-1929 to 1980-2009
- Can we see trend in land surface contribution to this predictability?
  - Model experiment: same forecasts but with random initial land conditions
- Metric: ratio between **signal** and **total** variance

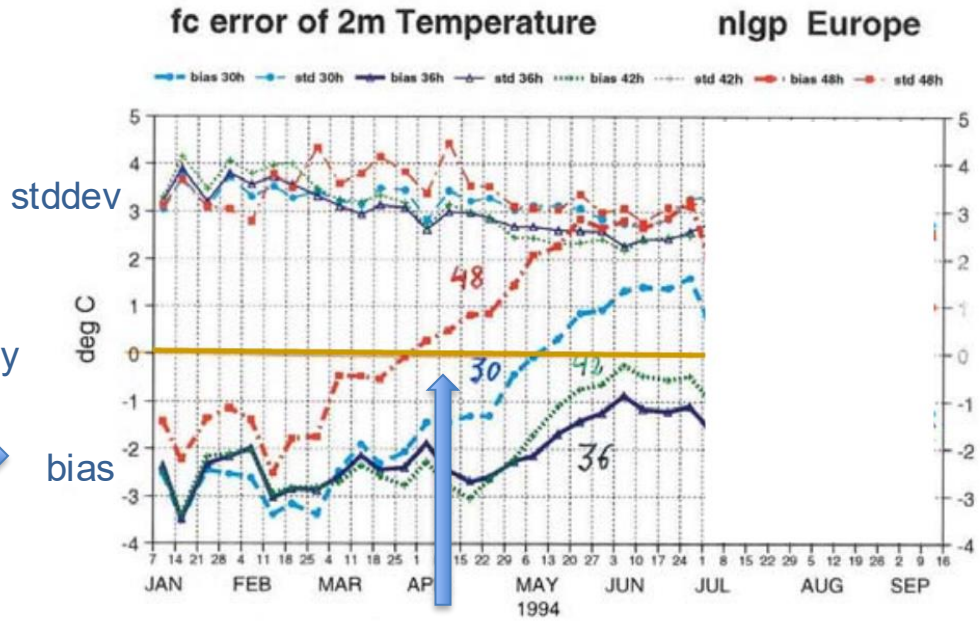
$$V_S = \frac{1}{N}\sum_{n=1}^{N}(\overline{x}_n - \overline{\overline{x}})^2$$

$$V_T = \frac{1}{NE}\sum_{n=1}^{N}\sum_{e=1}^{E}(x_{en} - \overline{\overline{x}})^2.$$



An anecdote demonstrating impact of soil moisture

- Mid ’90’s: introduction of **prognostic soil moisture** scheme



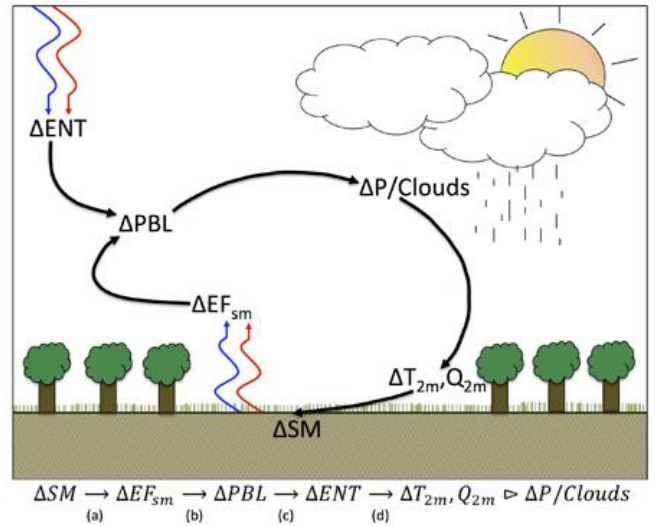
Model normally too cold

Suddenly extreme warm dry drift

START HERE

Positive radiation bias

Dry atmosphere, too little clouds



Evaporation stops, Less land cooling

Soil drying due to overestimated evaporation

- Soil moisture **data assimilation** needed to control drift

(Root cause of drift was model bias, but once unphysical constraint was removed, model bias led to errors that grew over time)