Coupled land-atmosphere variability: does land contribute to predictability?

Jonny Day / Bart van den Hurk / Tim Stockdale

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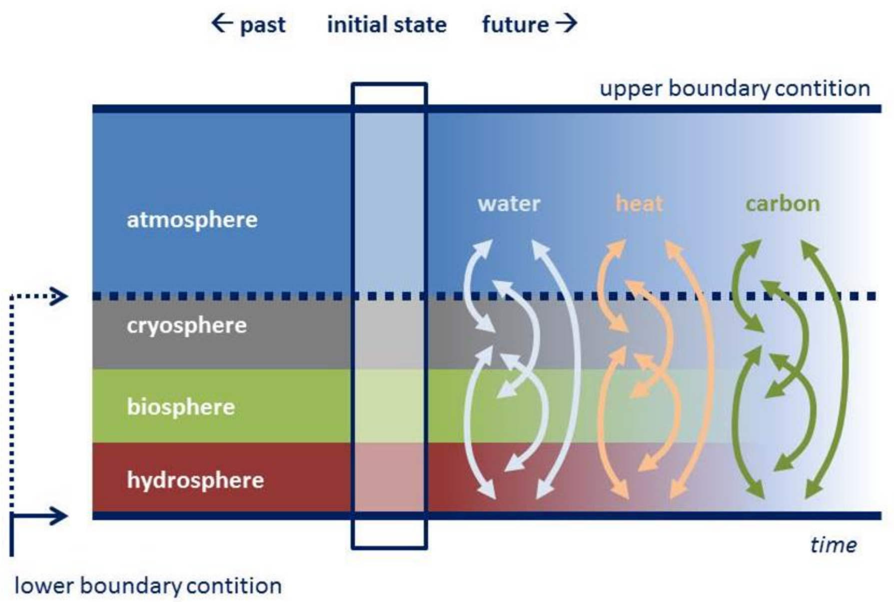


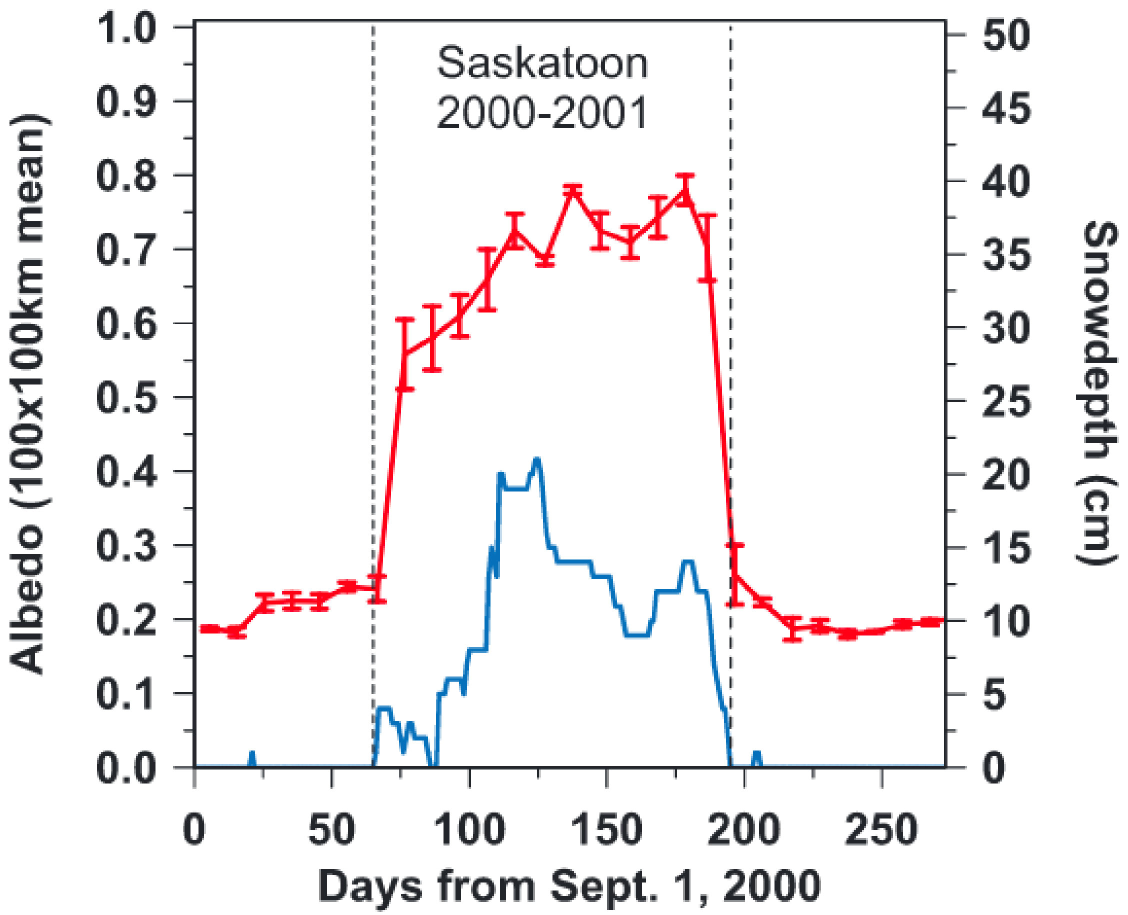
Why do we care about land processes?

- Energy-budget
  - Albedo

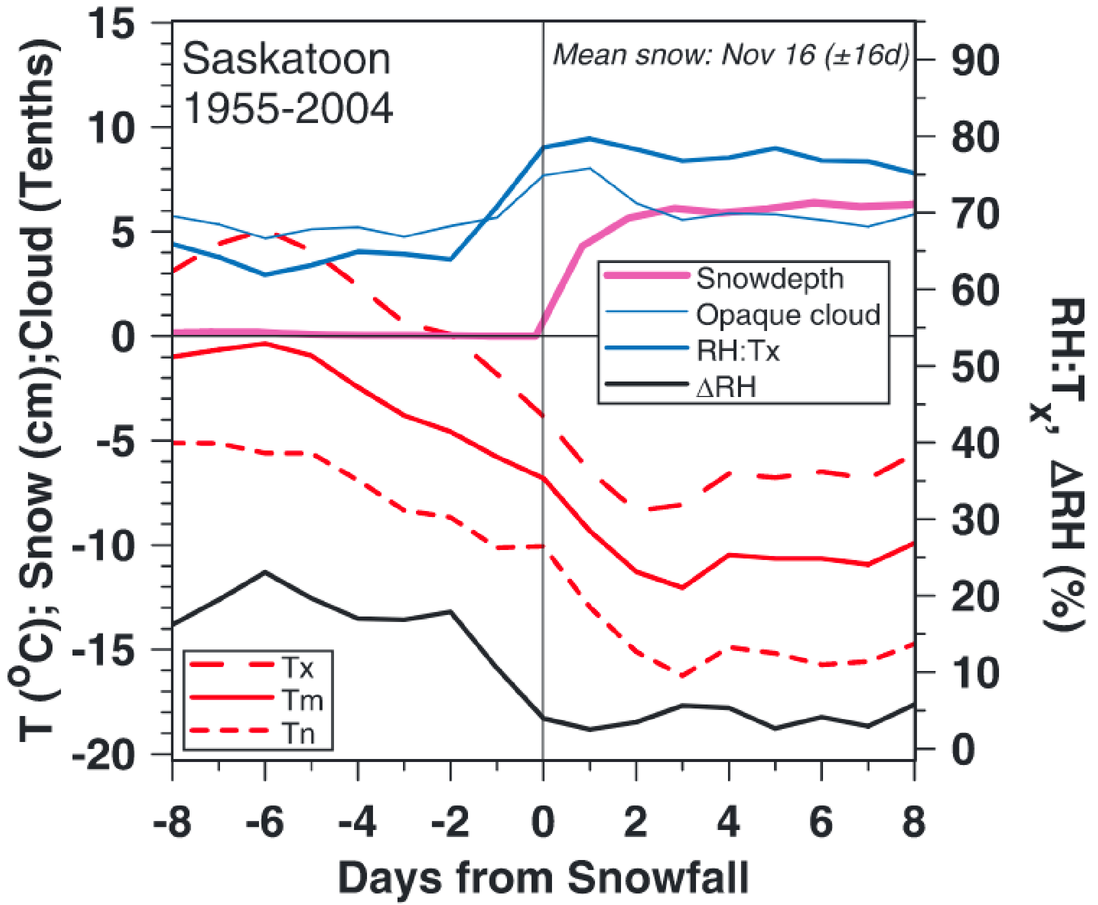
Surface	Albedo
Dark forest	9-12%
Grassland	15-20%
Bare soil	20-30%
Snow in forest	15-25%
Open snow	50-85%

Example of snow transitions

Snow and albedo



Snow and surface meteorology

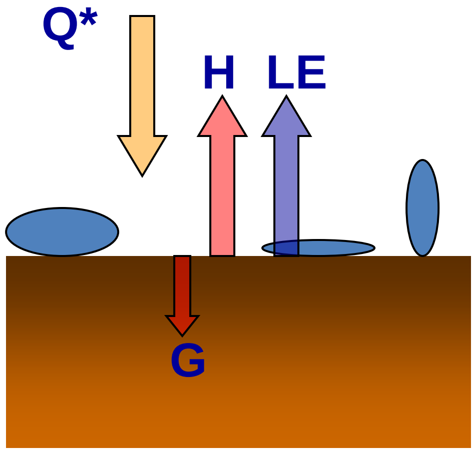


Betts et al., (2014)

ECMWF

Why do we care about land processes?

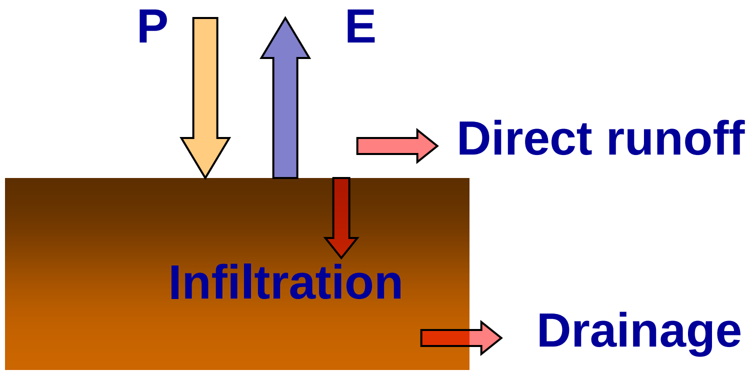
- Energy-budget
  - Albedo
  - Evaporative fraction



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

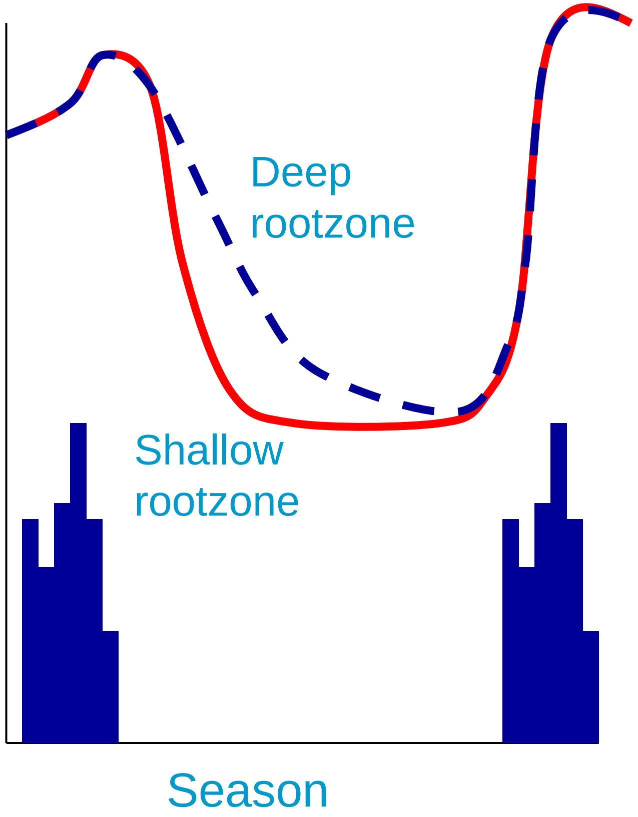
Why do we care about land processes?

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



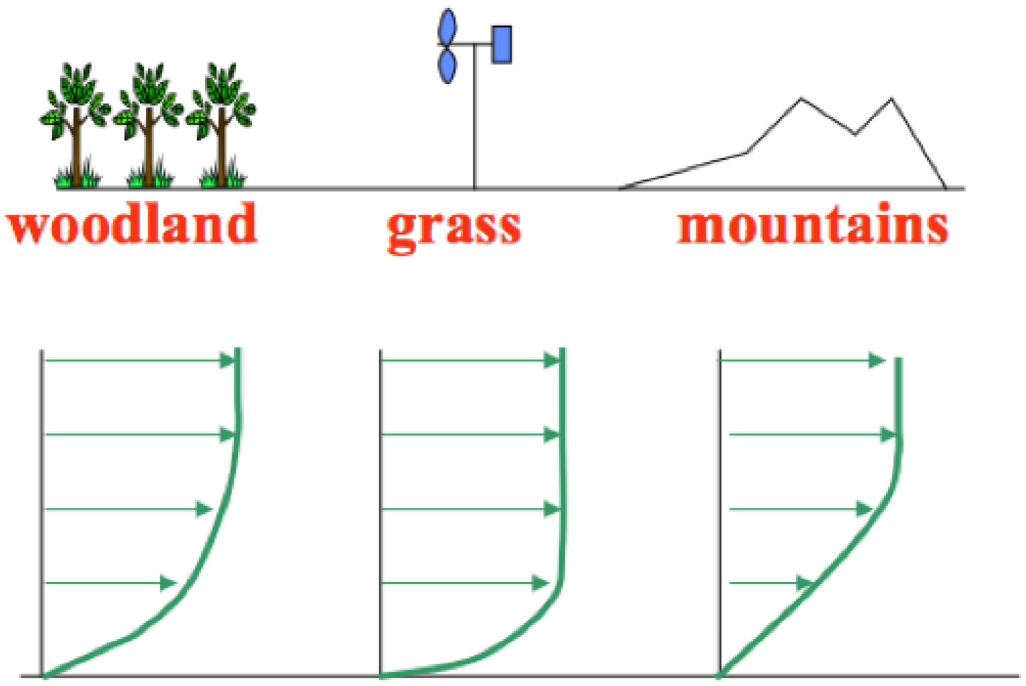
Land processes in atmospheric models

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



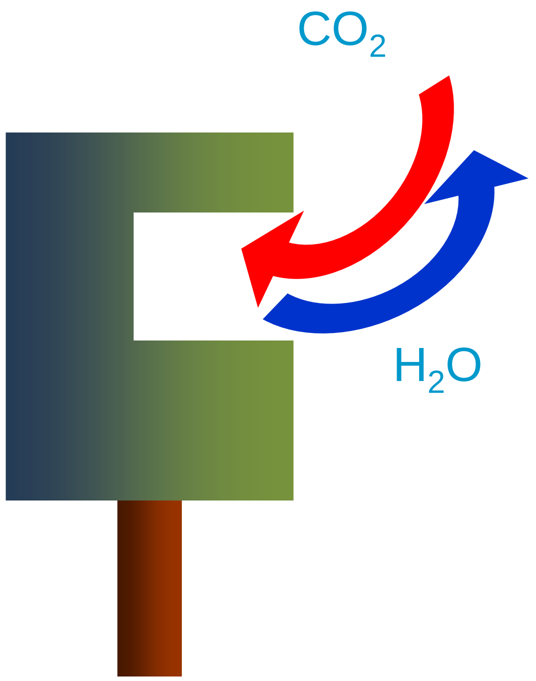
Land processes in atmospheric models

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



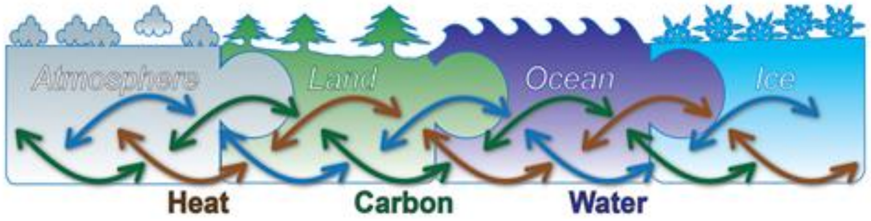
Land processes in atmospheric models

- 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

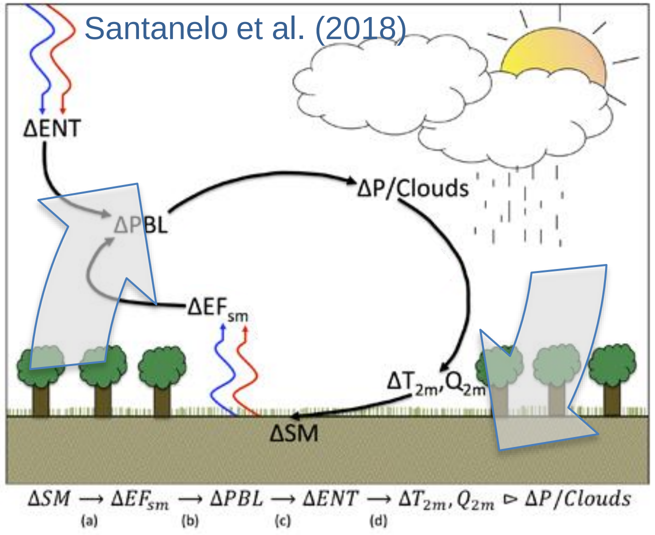


What is needed to contribute to predictability?

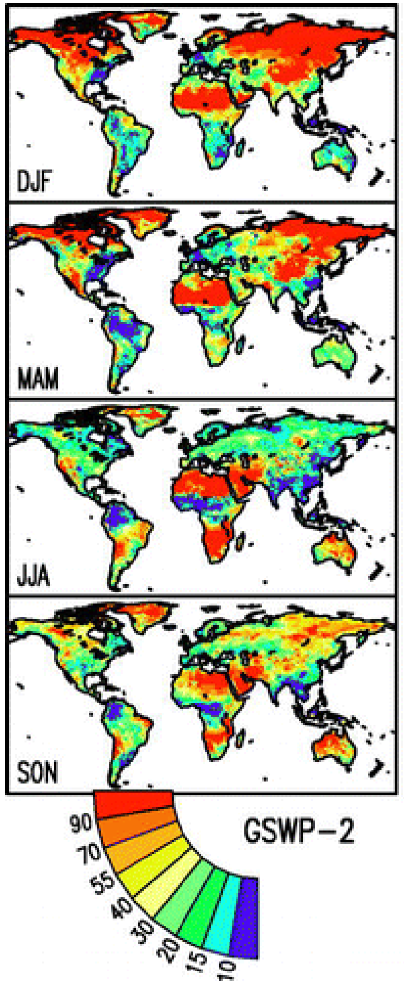
- In the climate system all processes are connected



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



Dirmeyer et al, 2009



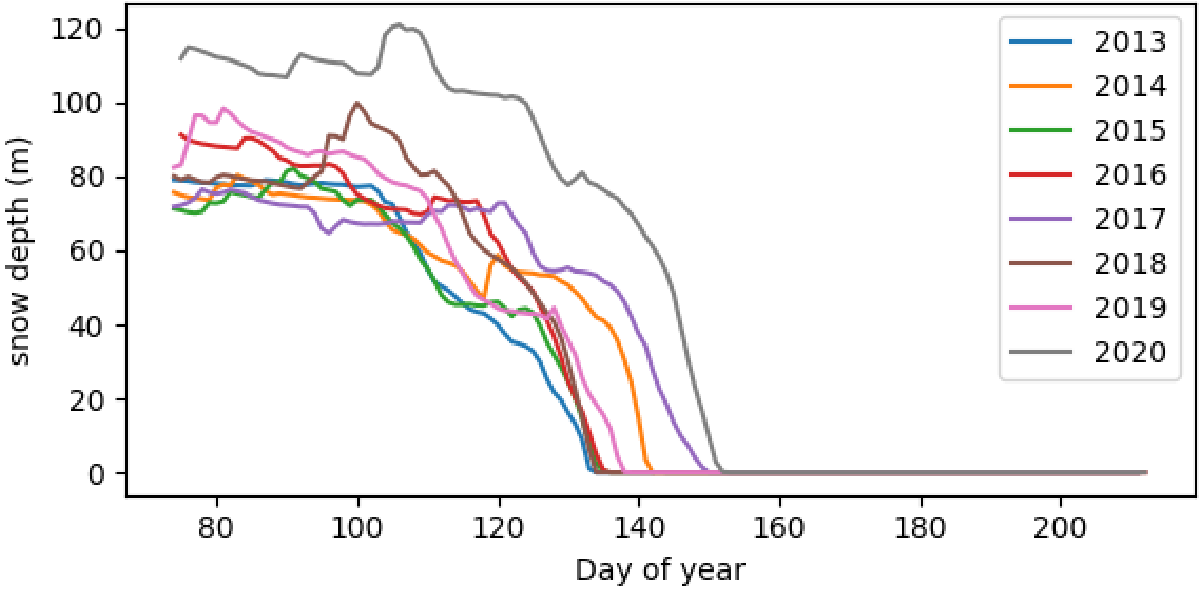
Soil moisture memory (days)

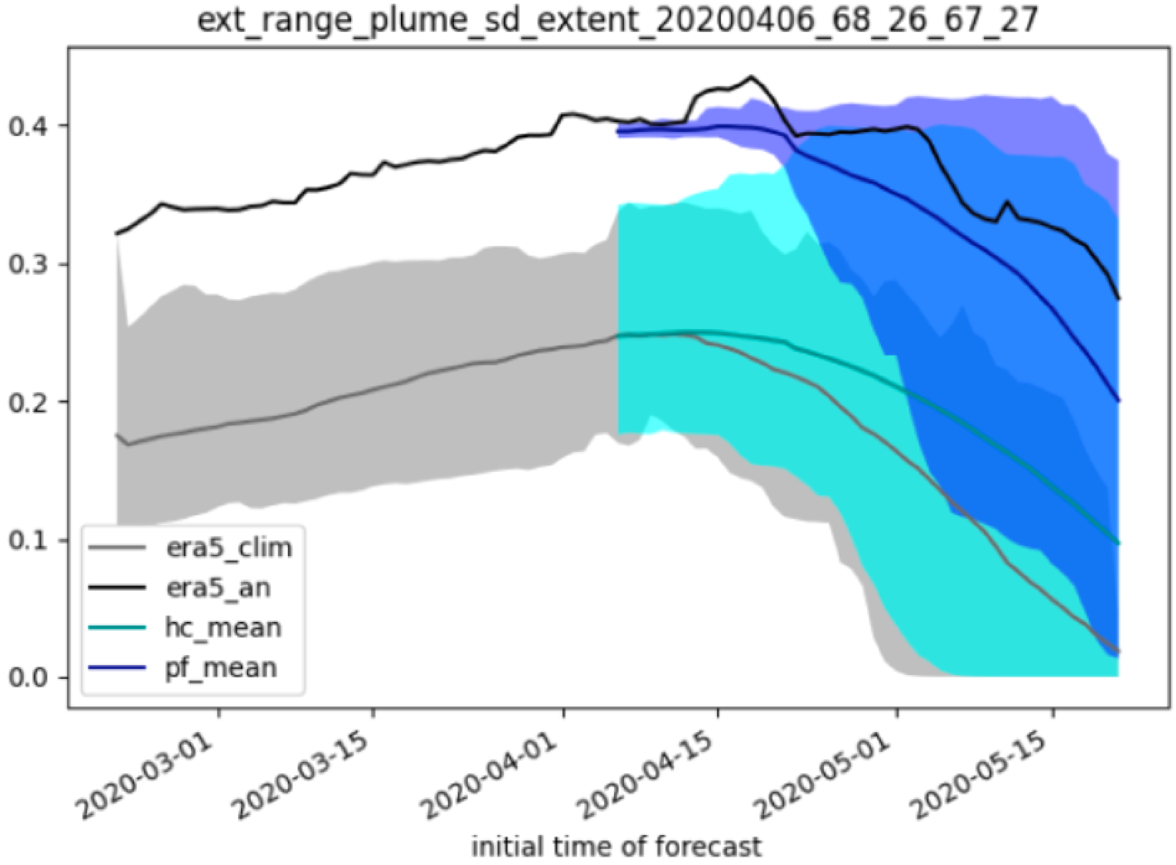
Otherwise: Can just use downstream/application models,
e.g. crop modelling, hydrology flood forecasting, fire risk models etc

ECMWF

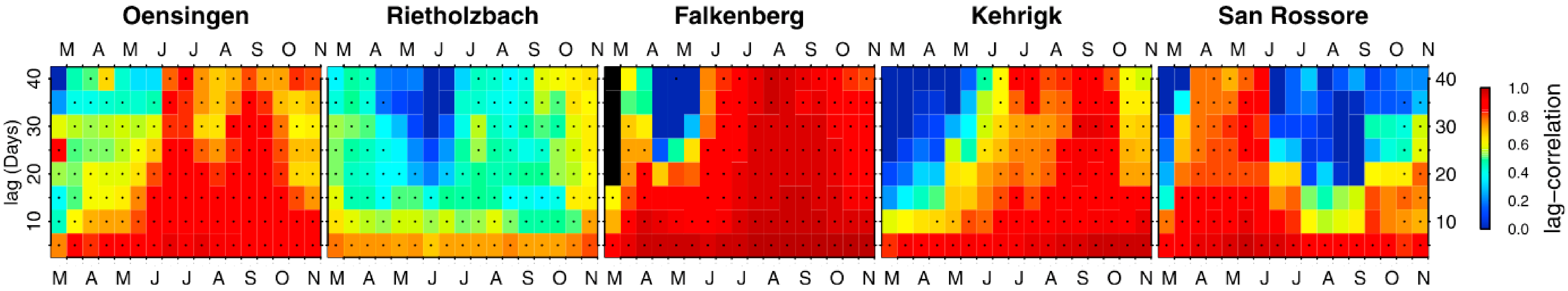
Snow depth memory

Sodankyla, Northern Finland





Soil moisture predictability (observation-based estimates)



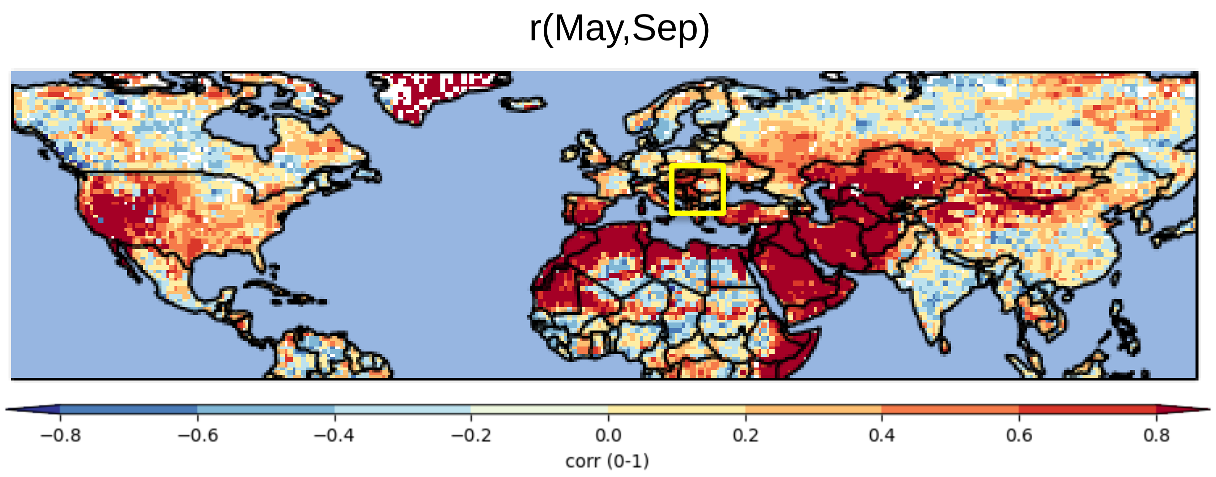
$$c_s w_{n+lag,y} = c_s w_{n,y} + P_{n,y} - E_{n,y} - Q_{n,y}$$

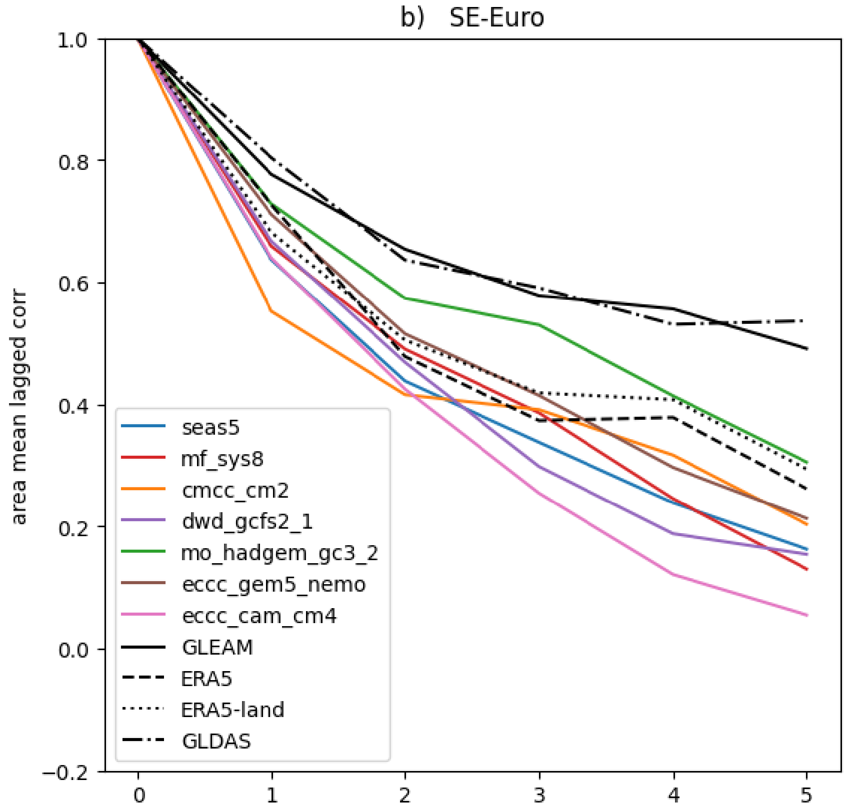
$$\rho\left(w_n, w_{n+lag}\right) = \frac{cov\left(w_n, w_{n+lag}\right)}{\sigma_{w_n}\sigma_{w_{n+lag}}}$$

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

Orth and Seneviratne (2012)

Spatial variation in persistence but high uncertainty

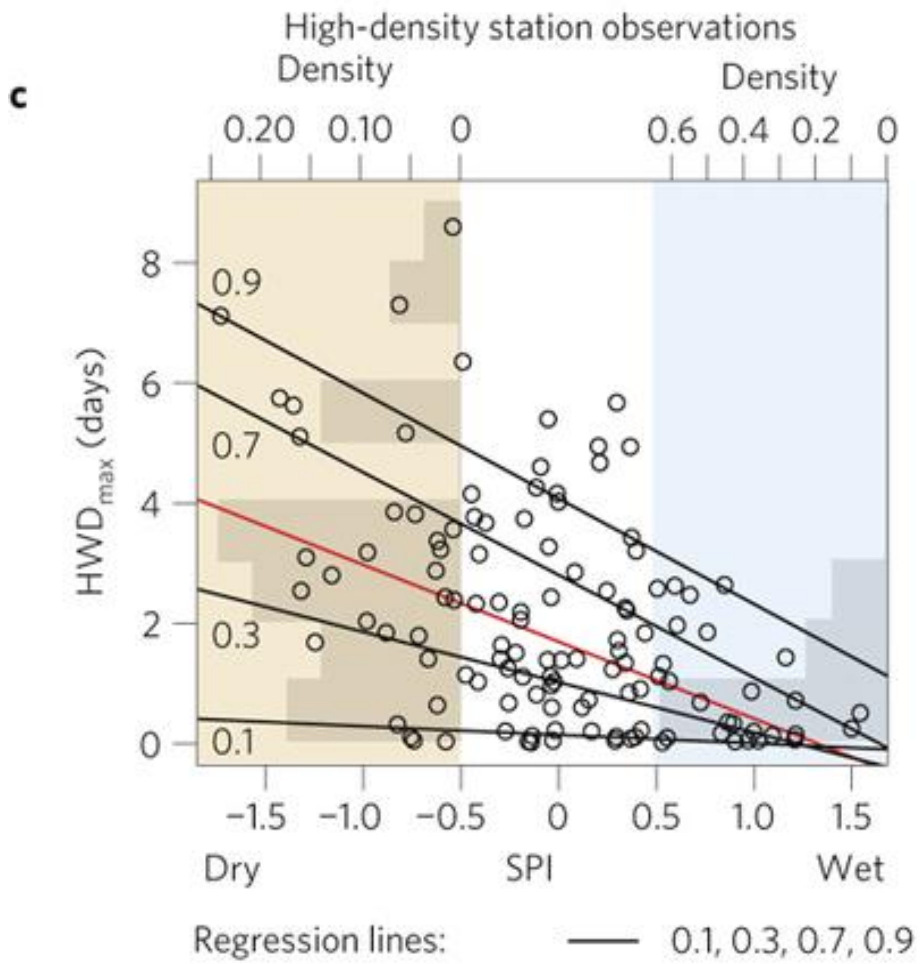




ECMWF

Measures to quantify land-atmosphere coupling

- From observations:
  - relation between (soil) wetness and extreme temperatures



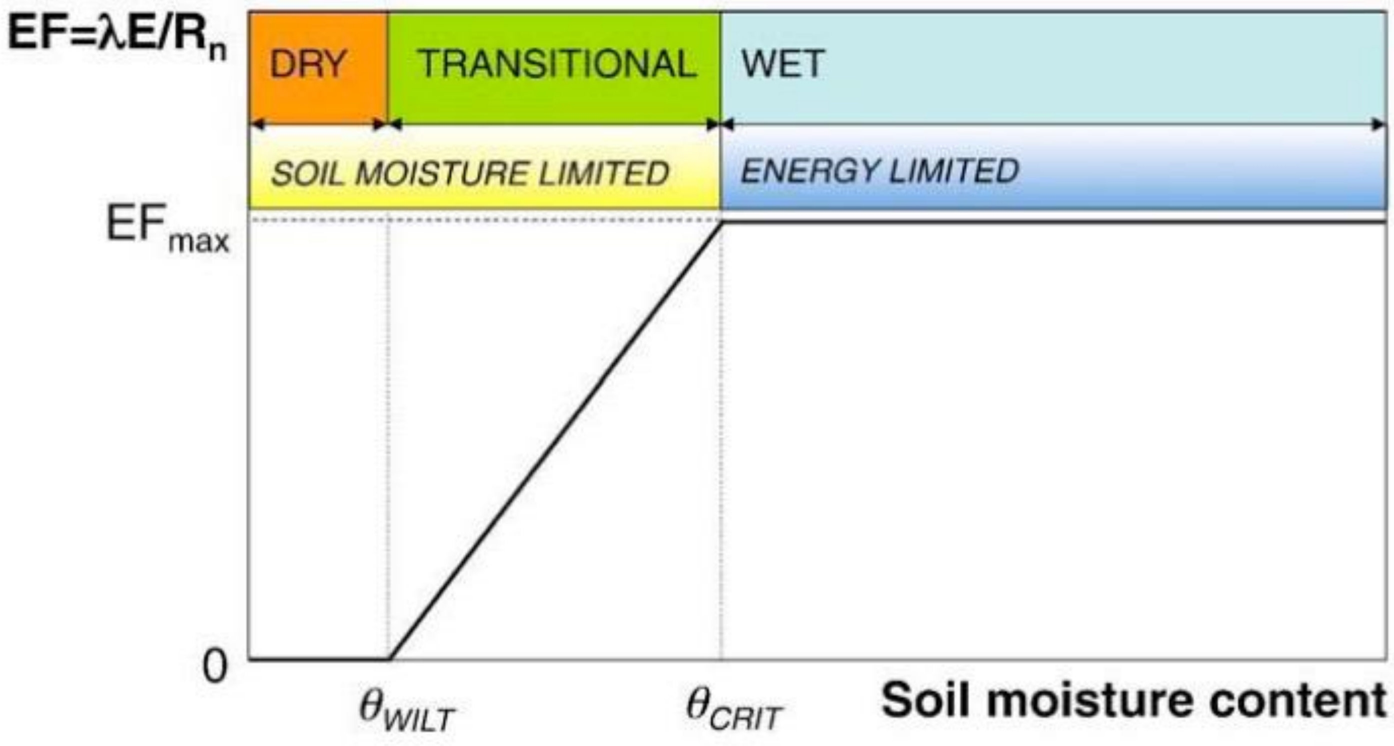
SPI=Standardized Precipitation Index (measure of soil moisture deficit over preceeding 6 months)

HWD_{max}=maximum heatwave duration

Predictability over wet conditions better than over dry conditions

Hirschi et al, 2011, Nat Geo

Soil-moisture atmosphere coupling



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

with

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

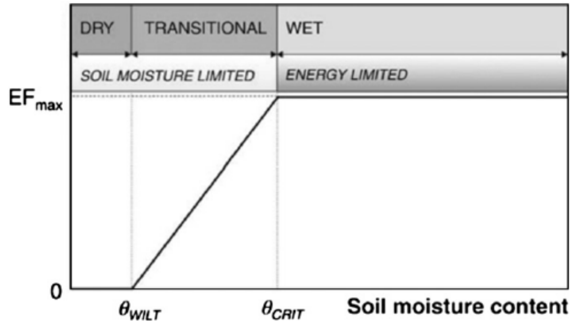
$$\beta = 1 \text{ for } \theta > \theta_{CRIT}$$
$$\beta = 0 \text{ for } \theta < \theta_{WILT}$$

Seneviratne et al., 2010

Measures to quantify land-atmosphere coupling

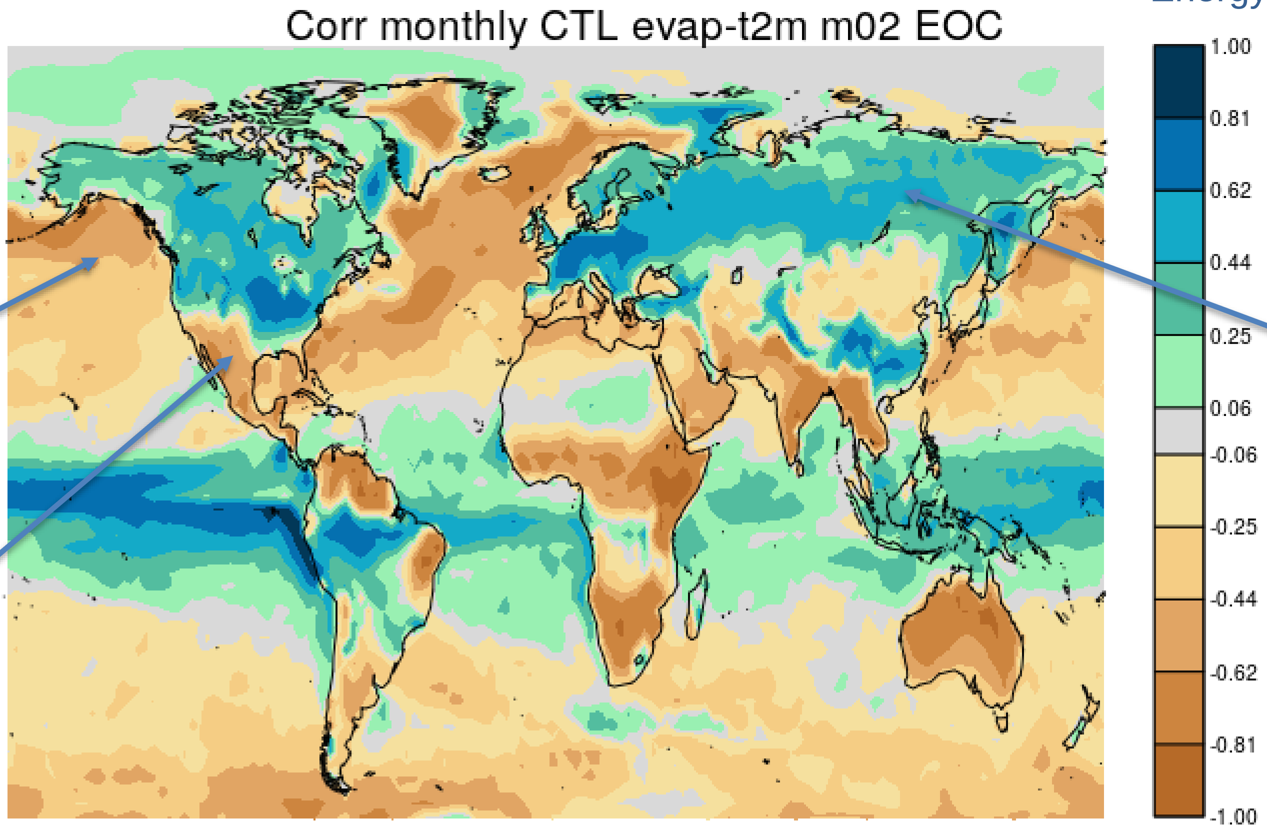
- From (pseudo)observations:
  - Correlation between evaporation and temperature

Seneviratne et al, 2010



Feb-Apr

Energy limited



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

Soil water limited

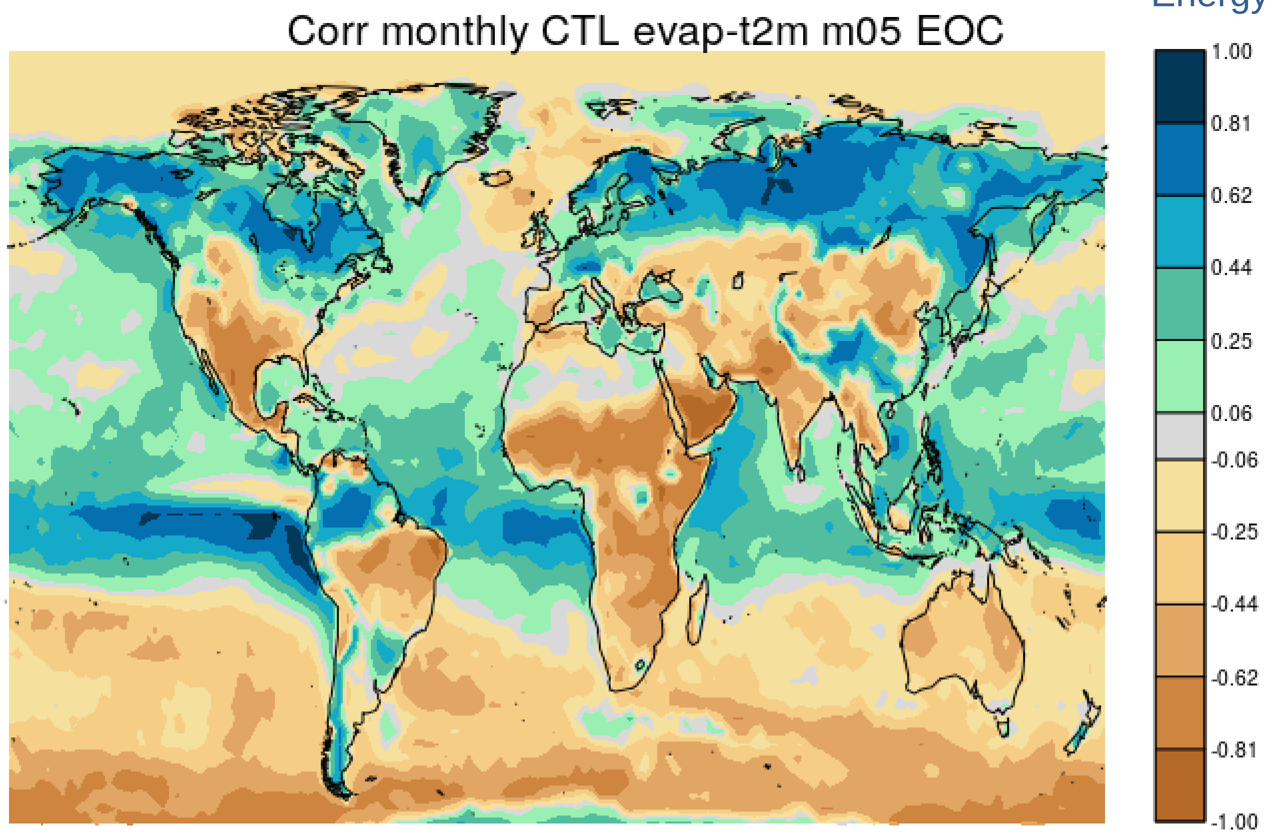
ECMWF

Measures to quantify land-atmosphere coupling

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

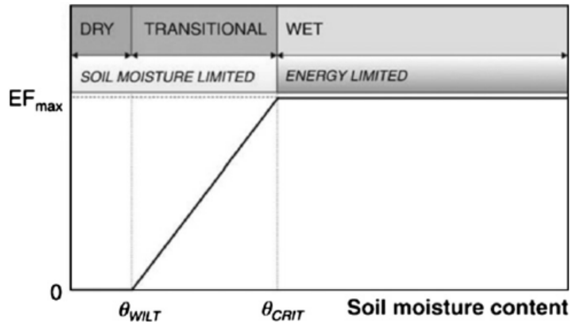
May-Jul

Energy limited



Soil water limited

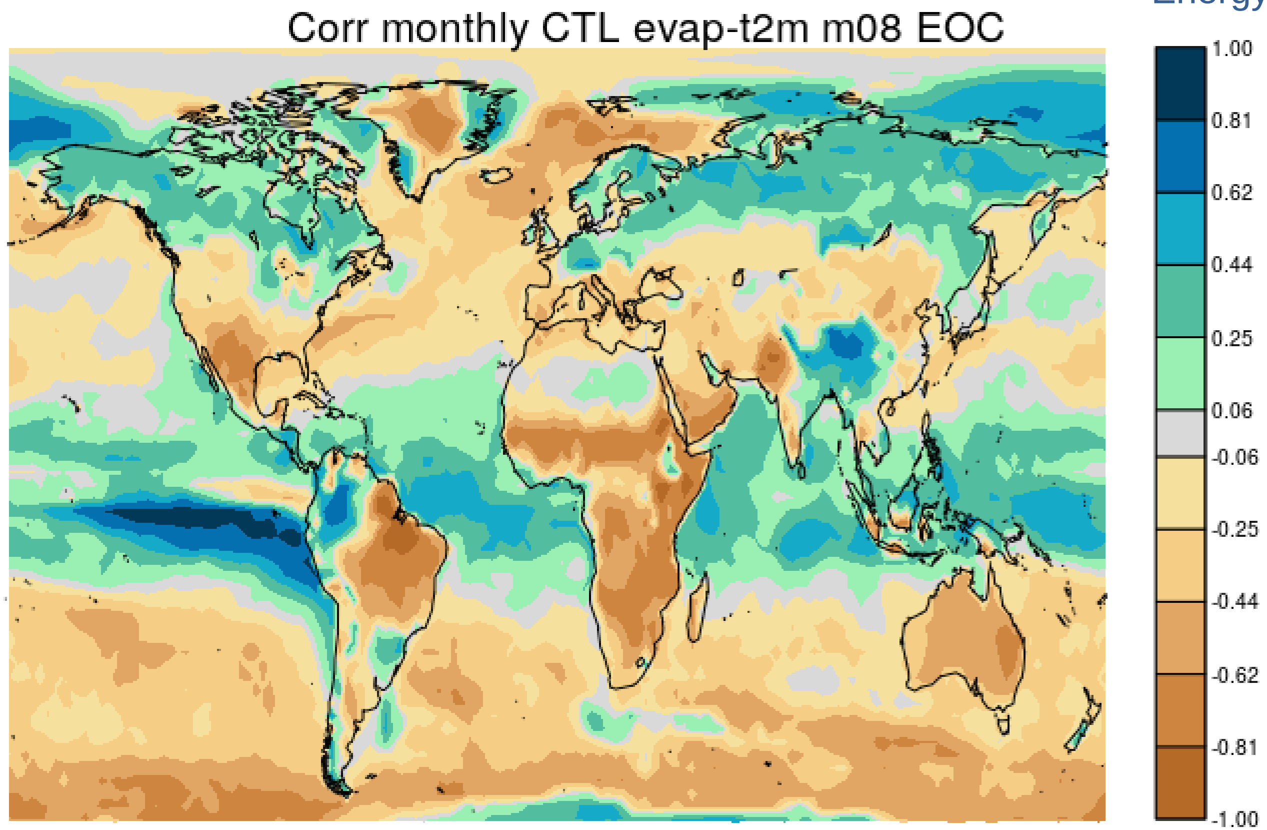
Seneviratne et al, 2010



Measures to quantify land-atmosphere coupling

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

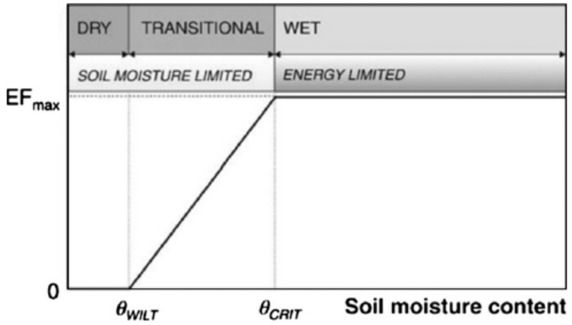
Aug-Oct



Energy limited

Soil water limited

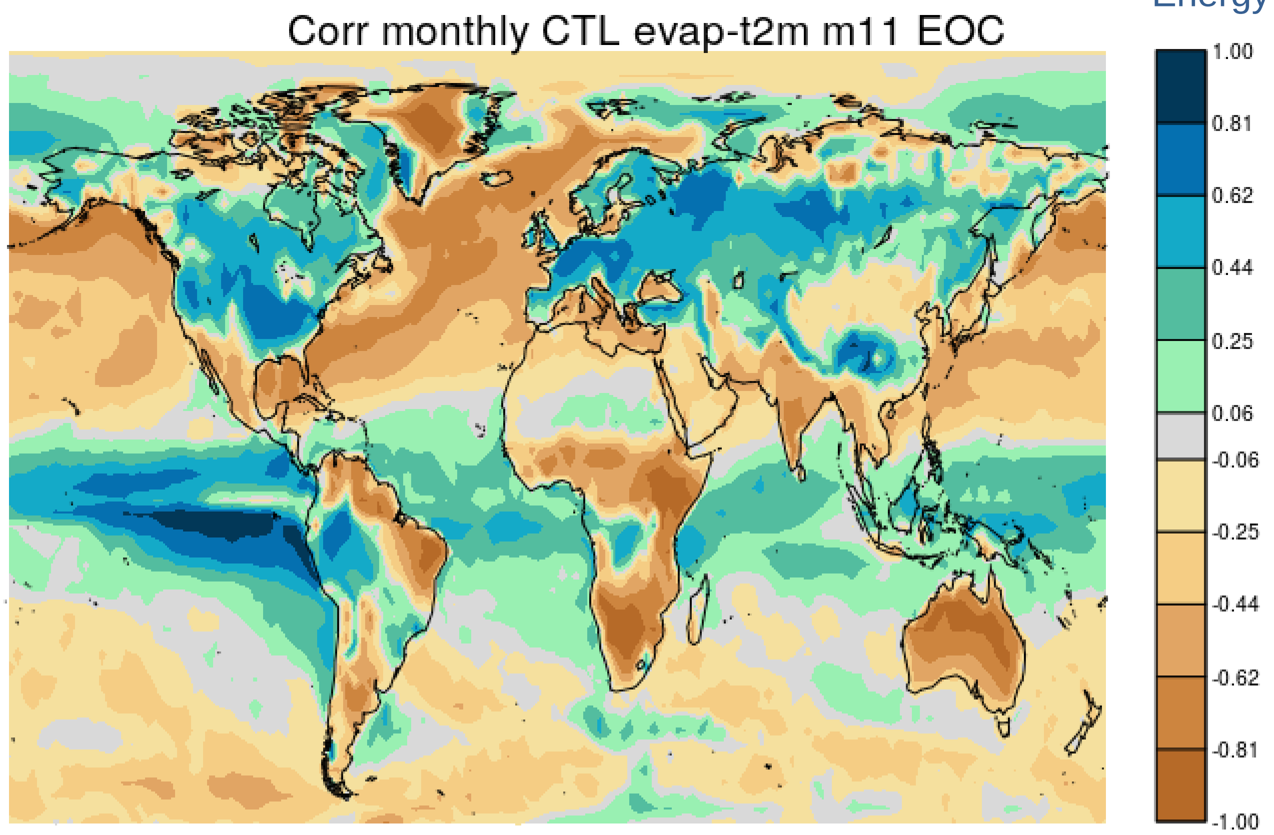
Seneviratne et al, 2010



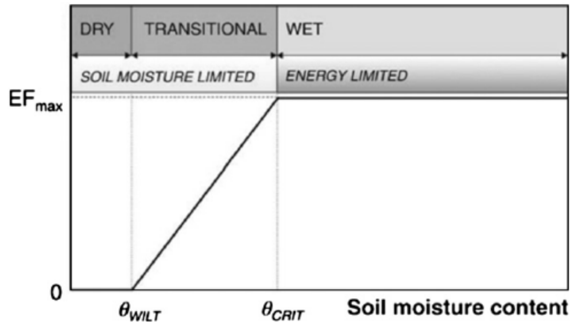
Measures to quantify land-atmosphere coupling

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

Nov-Jan

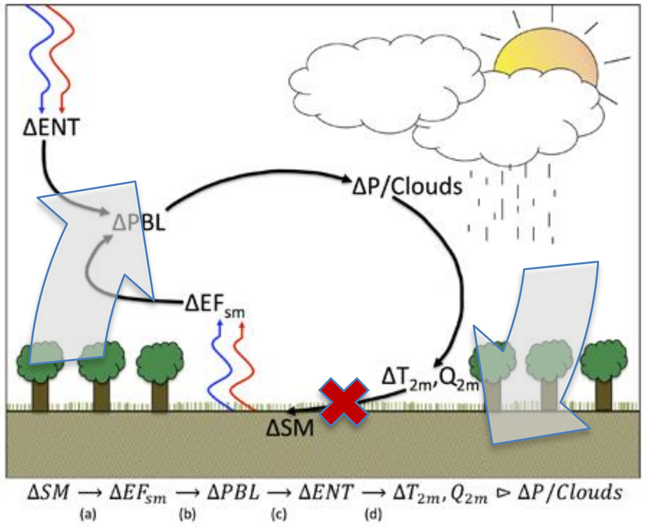


Seneviratne et al, 2010



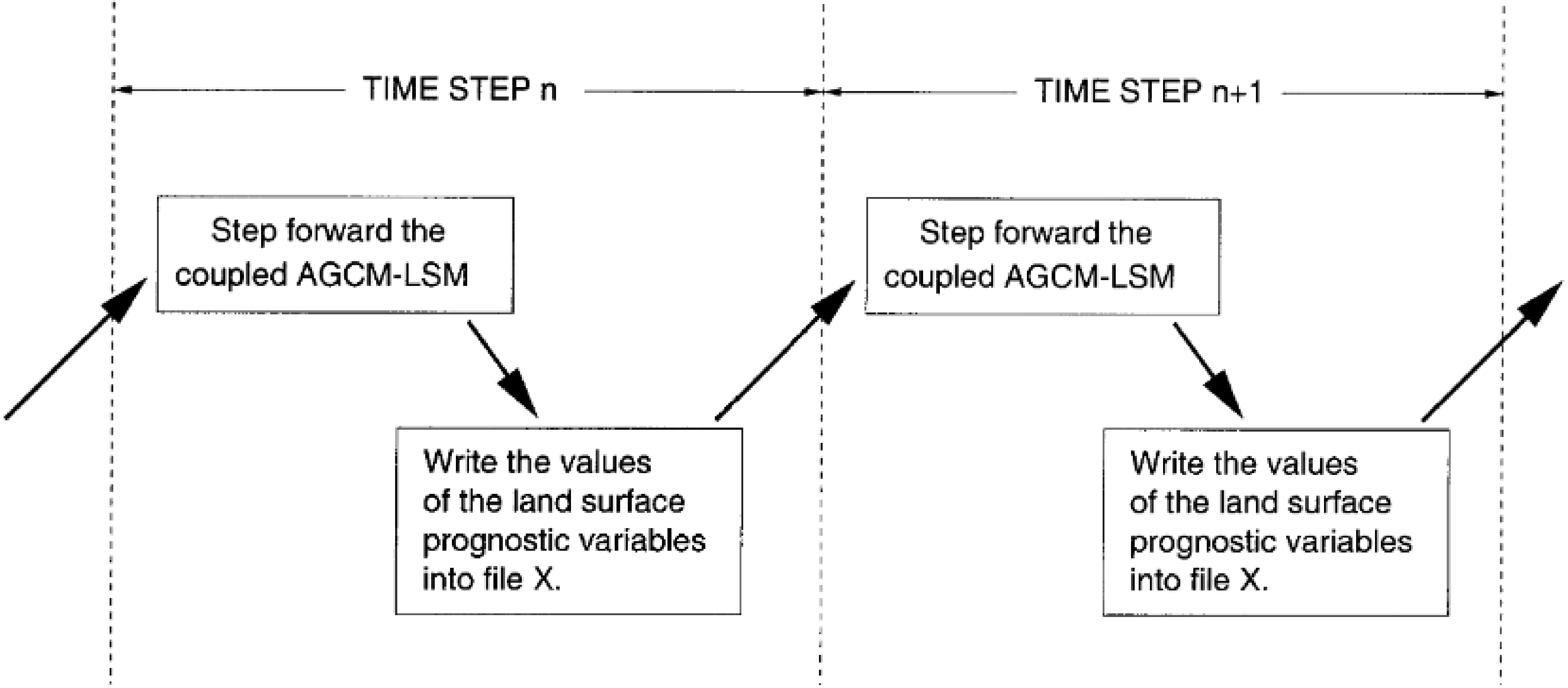
Measures to quantify land-atmosphere coupling

- From a model experiment (GLACE = Global Land Atmosphere Coupling Experiment)
- How?
  - Simulate the hydrological cycle **with** (*W*) and **without** (*S*) interactive land-atmosphere coupling and compare.
- How to remove coupling?
  - In second ensemble (*S*), 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



GLACE

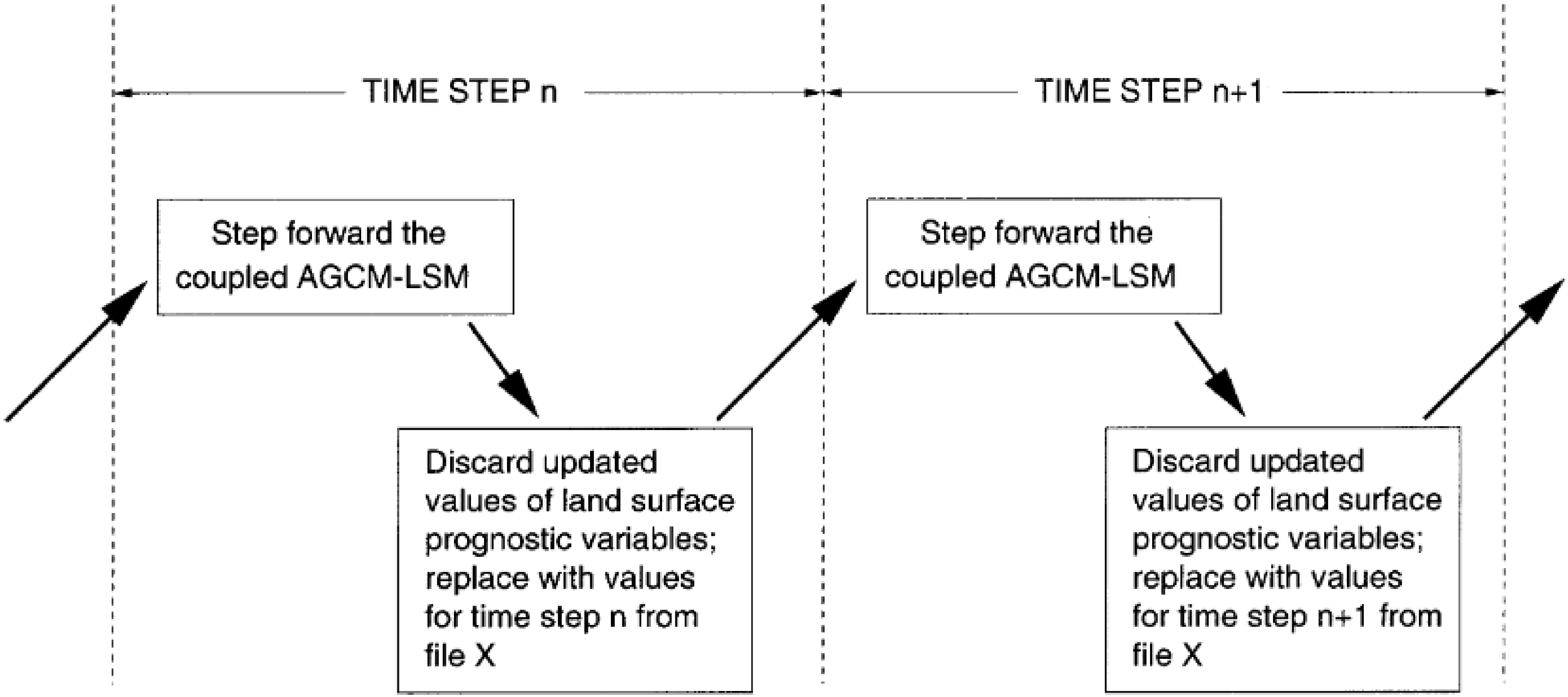
PART 1: ESTABLISH A TIME SERIES OF SURFACE CONDITIONS (Simulation W1).



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

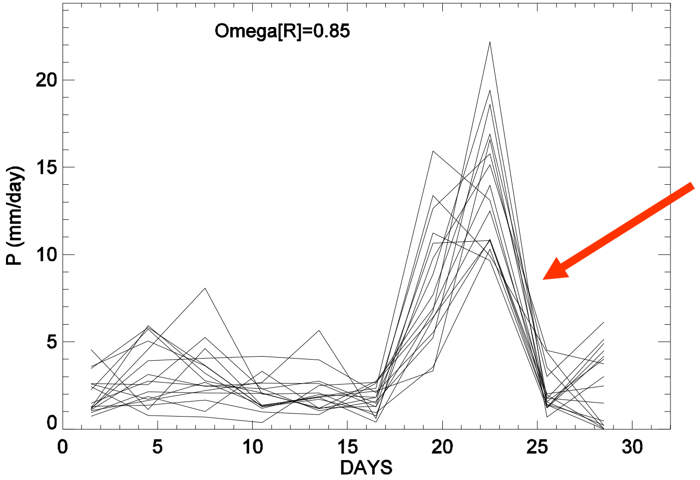
Koster et al, 2002

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



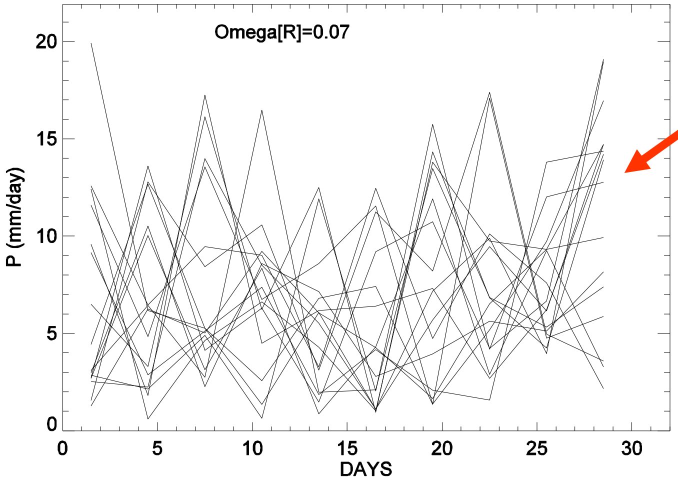
Koster et al, 2002

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

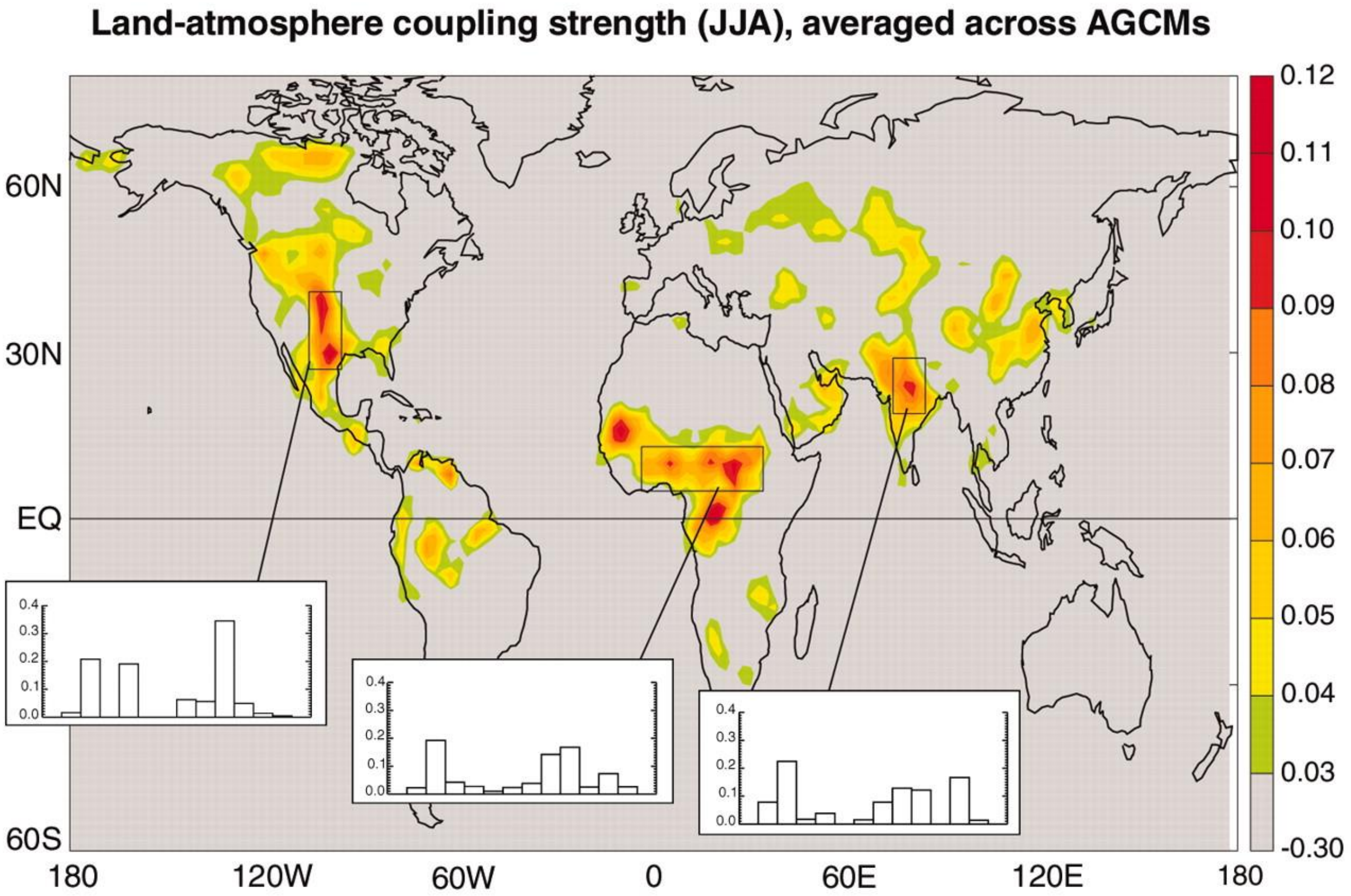
Diagnostics:

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

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

Areas with strong feedback on precipitation



Ω(R)-Ω(W)

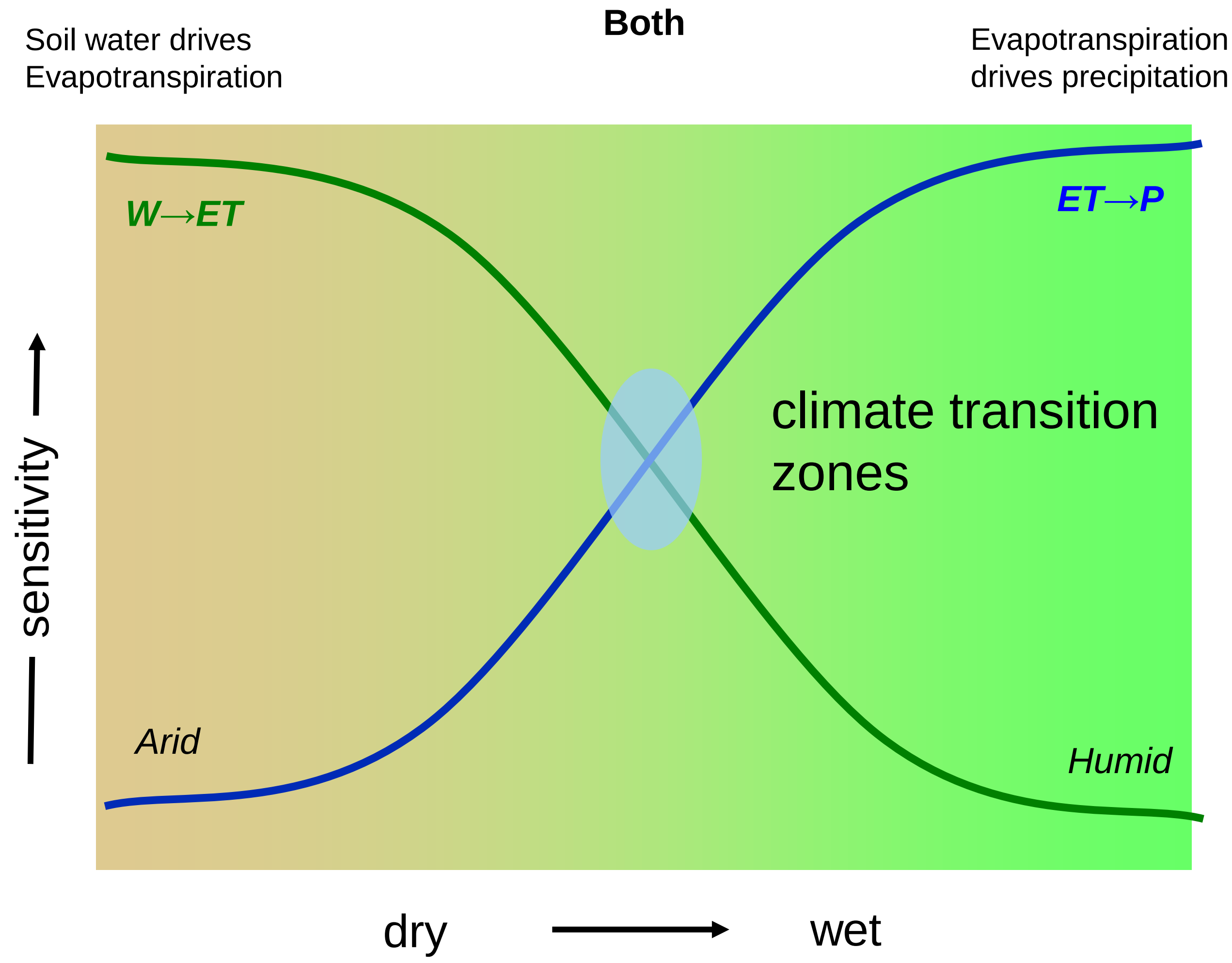
This is a famous figure, and looks very nice. But note that different models gave substantially different results. Model representation of land surface processes is improving, but still has some way to go.

Koster et al, 2004, Science

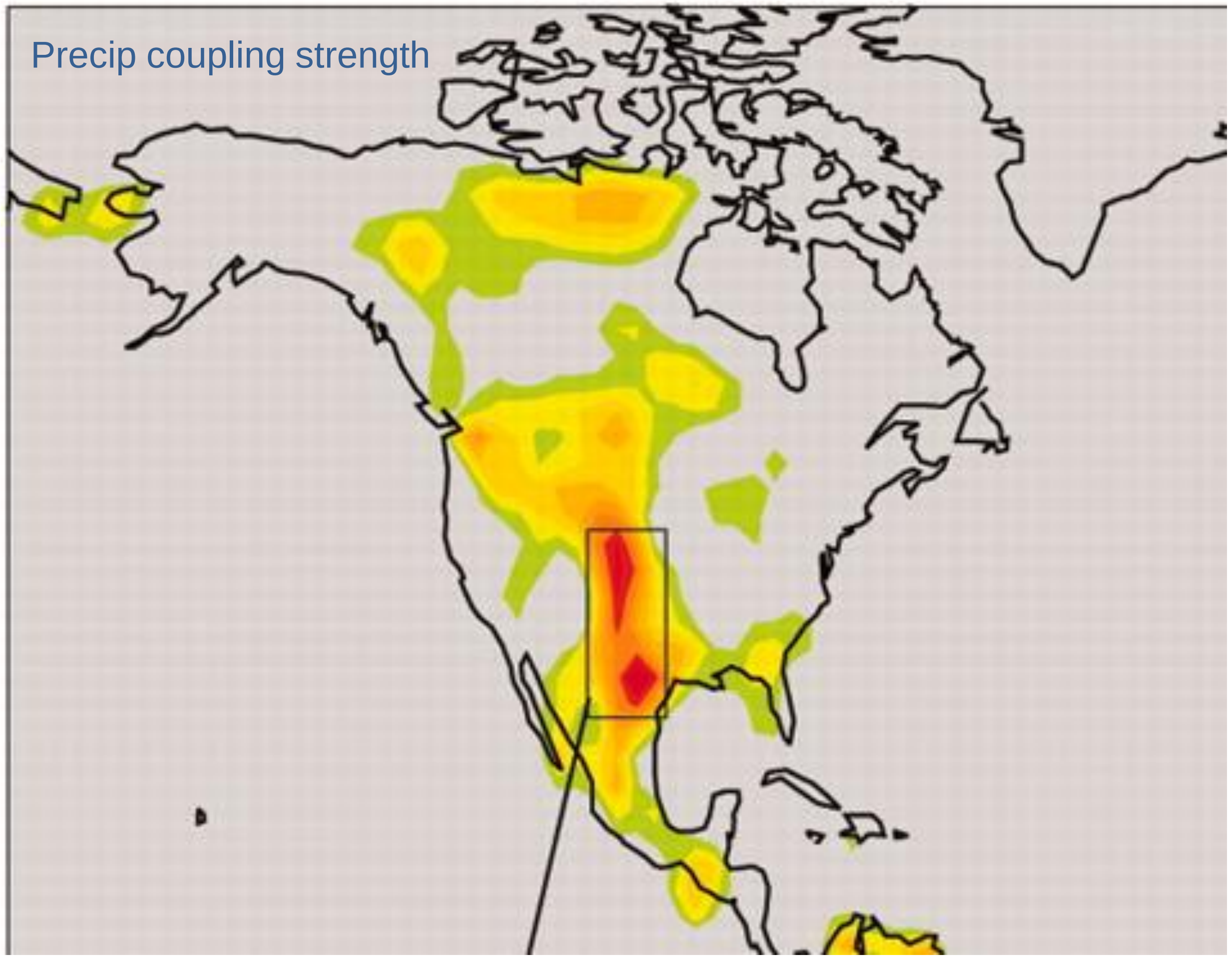
ECMWF

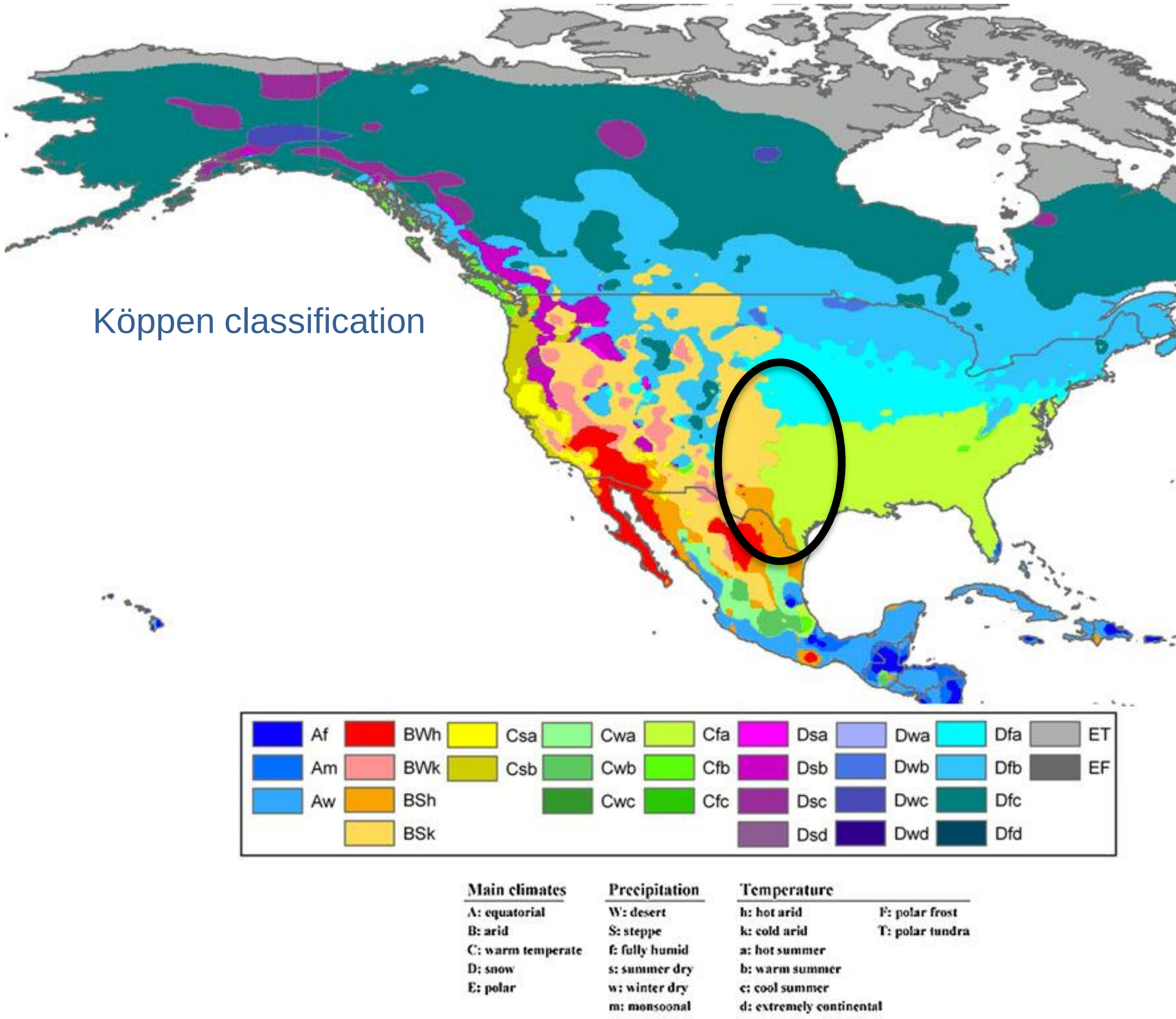
GLACE

Strong precipitation coupling needs combination of sensitivities



Strong feedback on precipitation at transition between arid and temperate zones



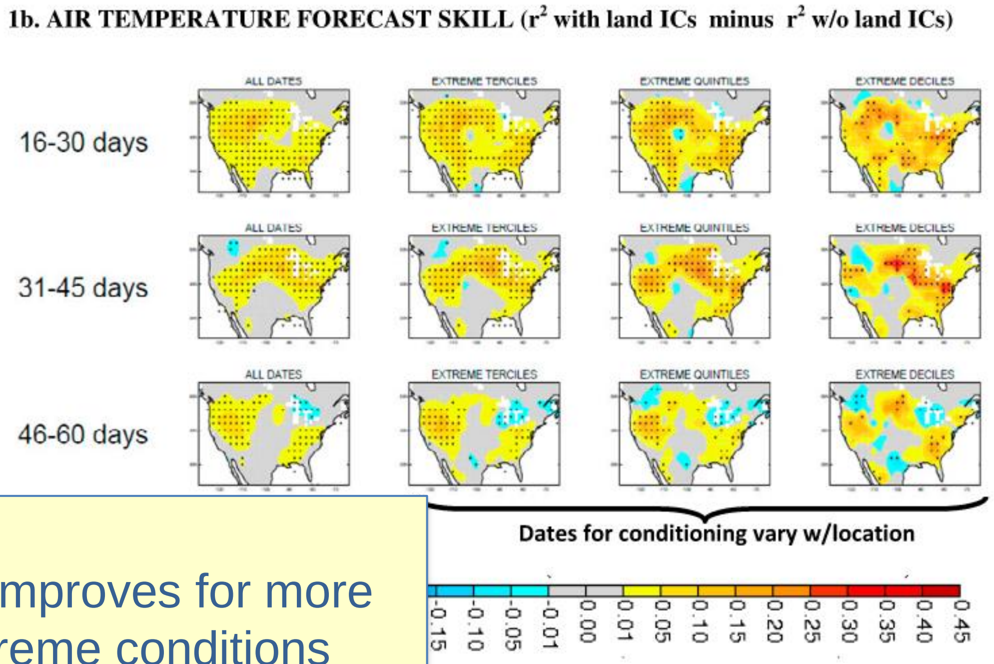


Koster et al, 2004, Science

Some “real” land-surface predictability experiments

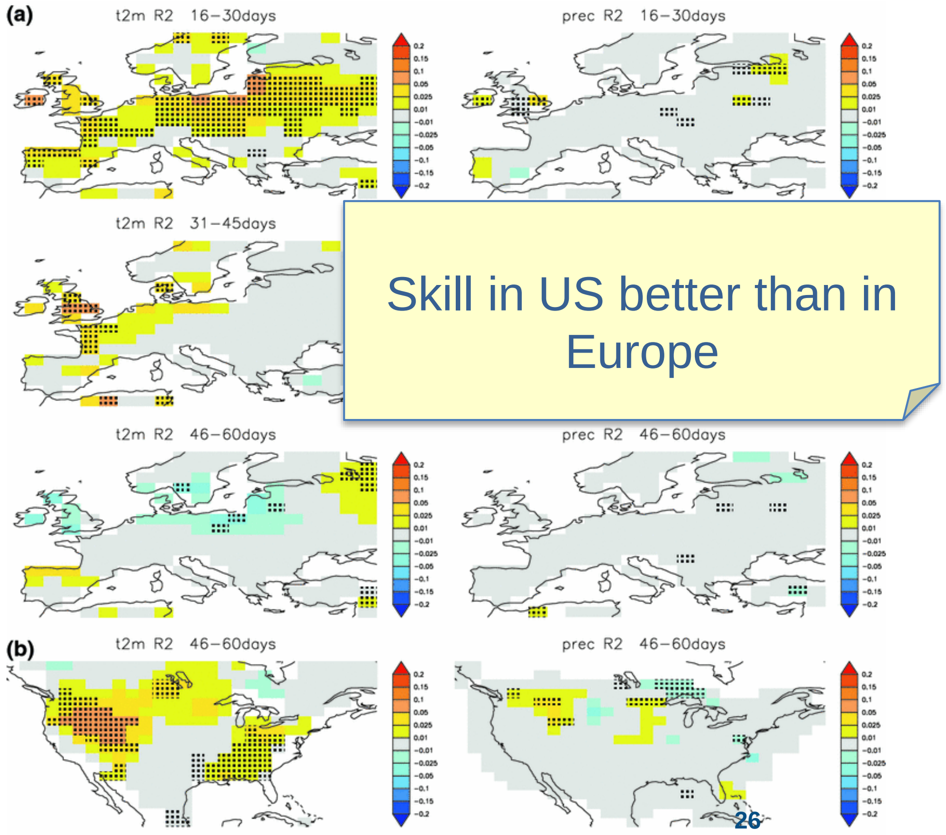
- Global Land Atmosphere Coupling Experiment – 2
  - Compare 2 ensembles of sub-seasonal forecasts (8 weeks ahead)
    - Ensemble 1: all members use the same realistic initial conditions
    - Ensemble 2: every member gets a randomly selected initial condition
  - Measure R^2 difference using real observations

Van den Hurk et al, 2012



Koster et al, 2010

Skill improves for more extreme conditions

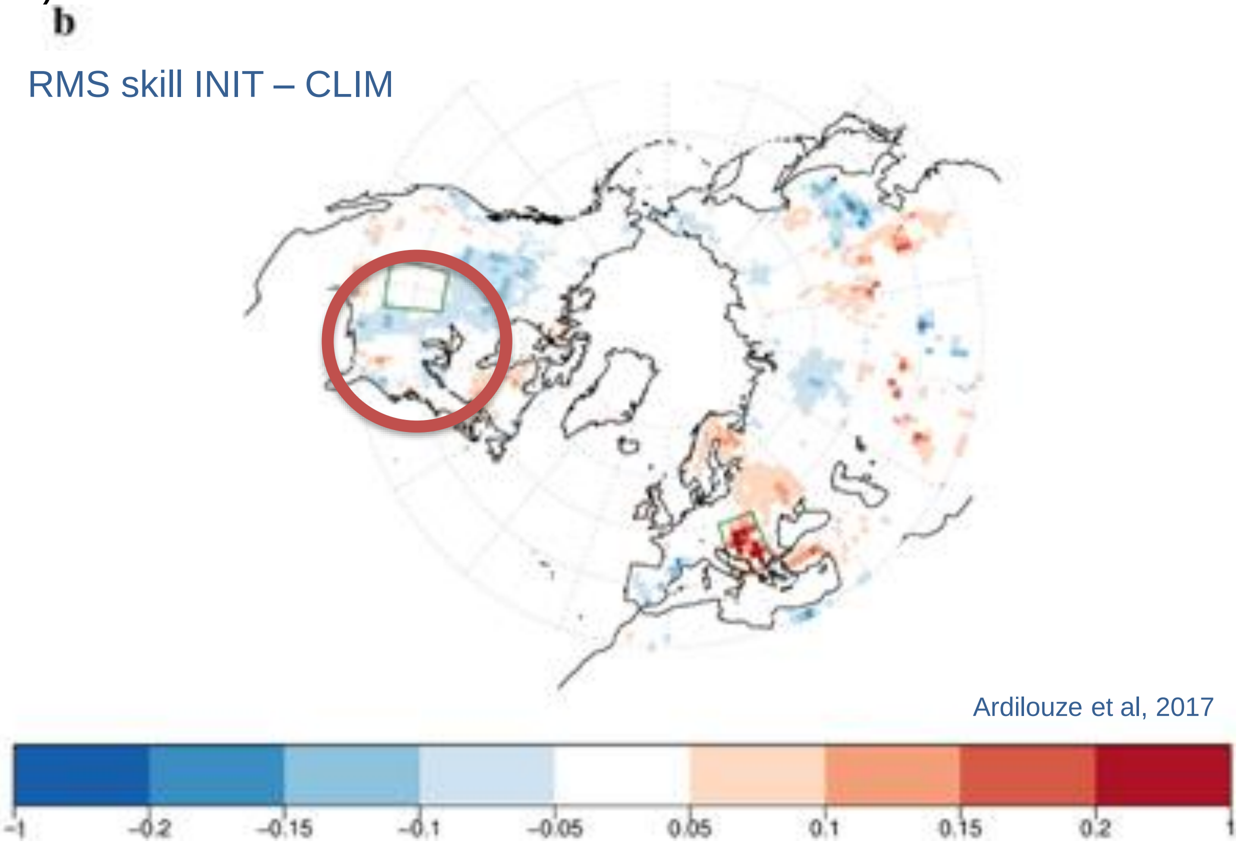


Skill in US better than in Europe

Another experiment, similar set-up, different results!

- Similar to GLACE-2, multi-model study (5 models), but
  - comparing realistic versus climatological initial conditions
  - coupled ocean model instead of prescribed SSTs
  - Longer period (19 yrs instead of 10 yrs)

RMS skill INIT – CLIM

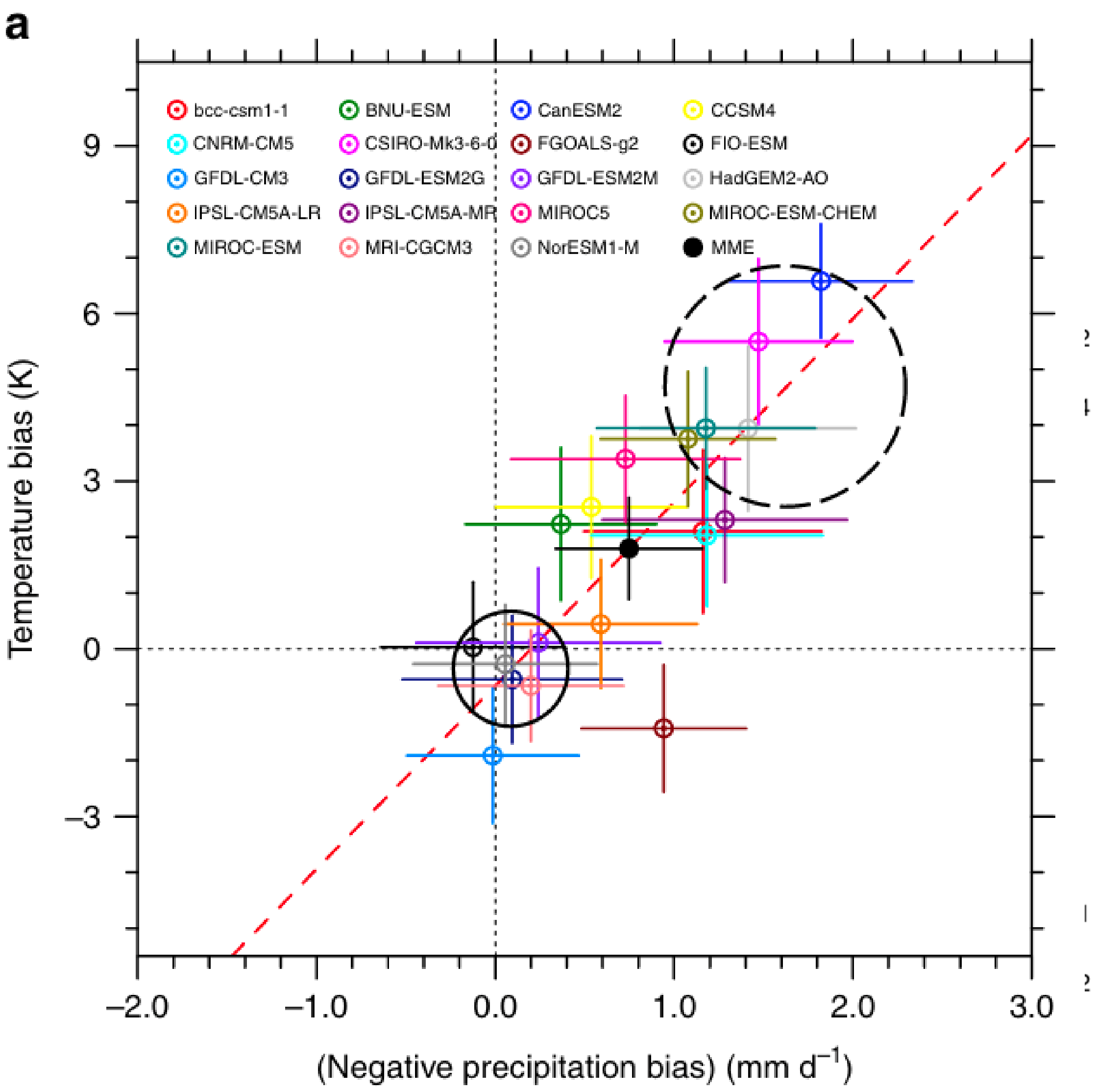


Ardilouze et al, 2017

Model bias in correlation between soil moisture and temperature gives poor results in US

(Models have dry bias, which results in a too-strong sensitivity of T2m to initial soil moisture).

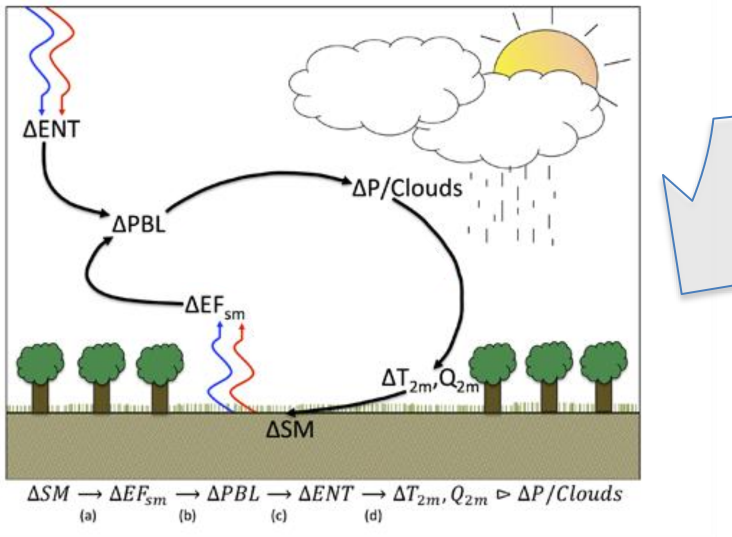
Role of soil-moisture-precipitation feedbacks in climate model biases



START HERE

Negative precipitation bias

Dry atmosphere, too little clouds

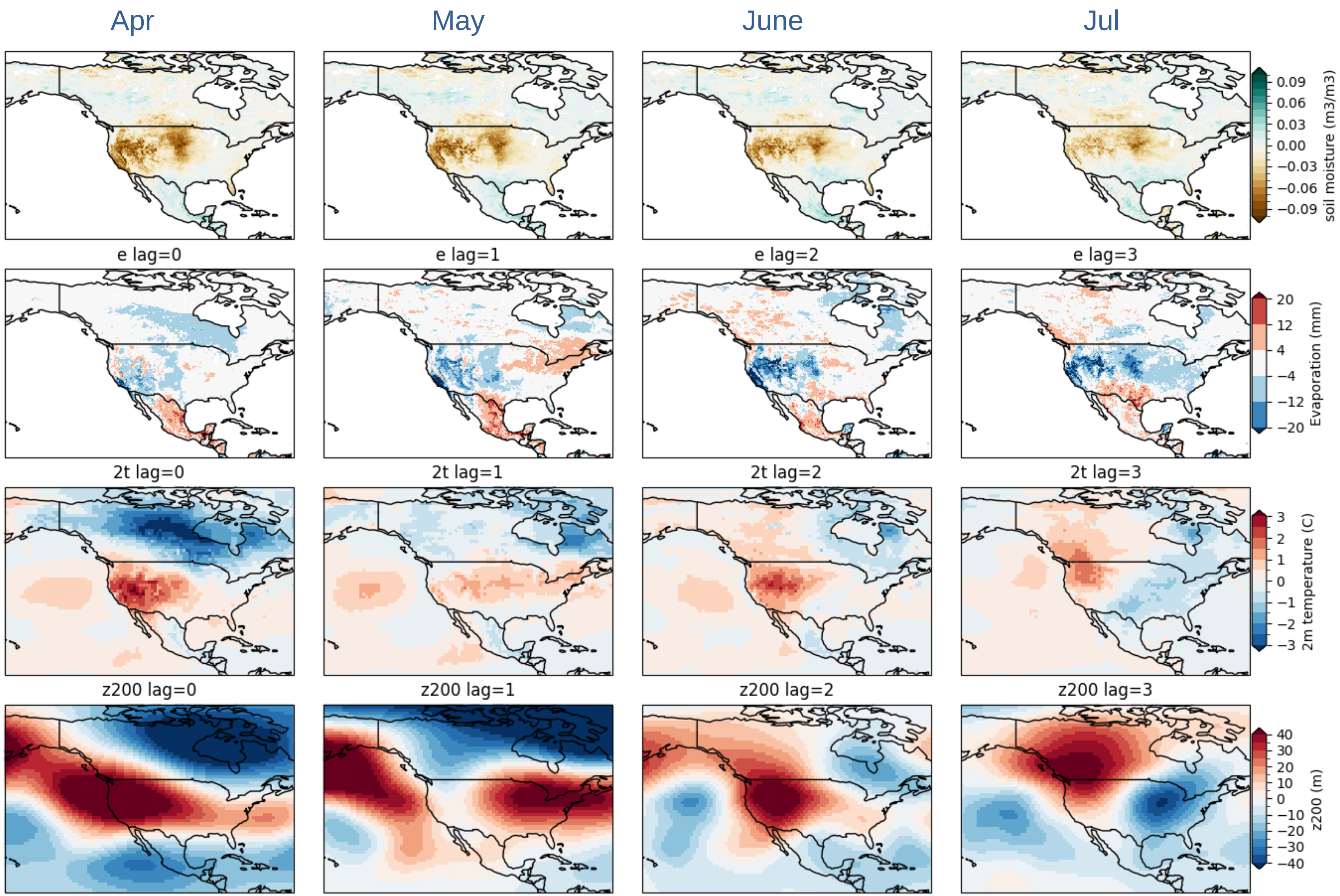


Soil drying due to underestimated precipitation

Evaporation stops, Less land cooling

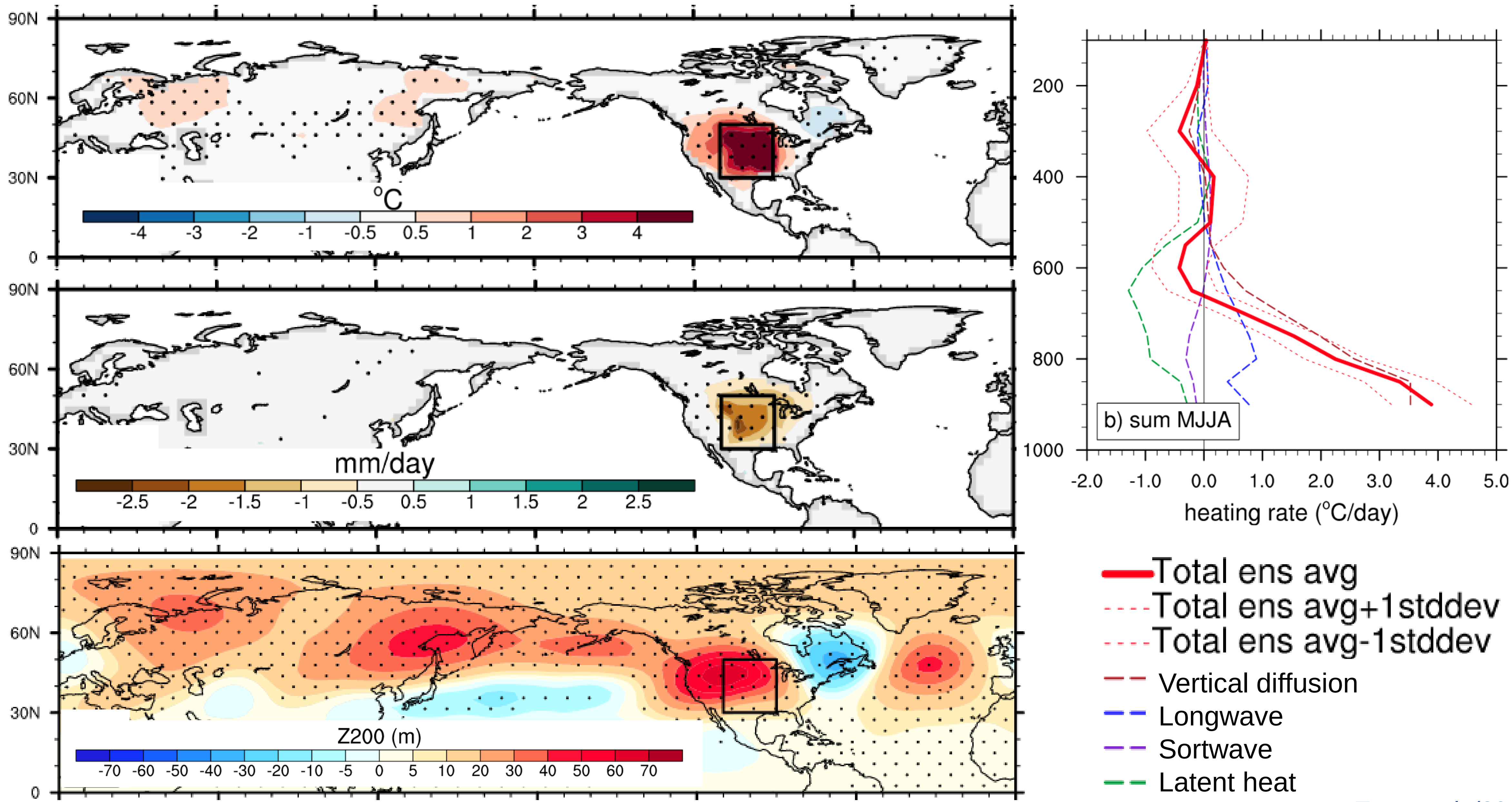
Lin et al., 2017
Nat Comm

Remote responses to April soil-moisture anomalies (EOF1)



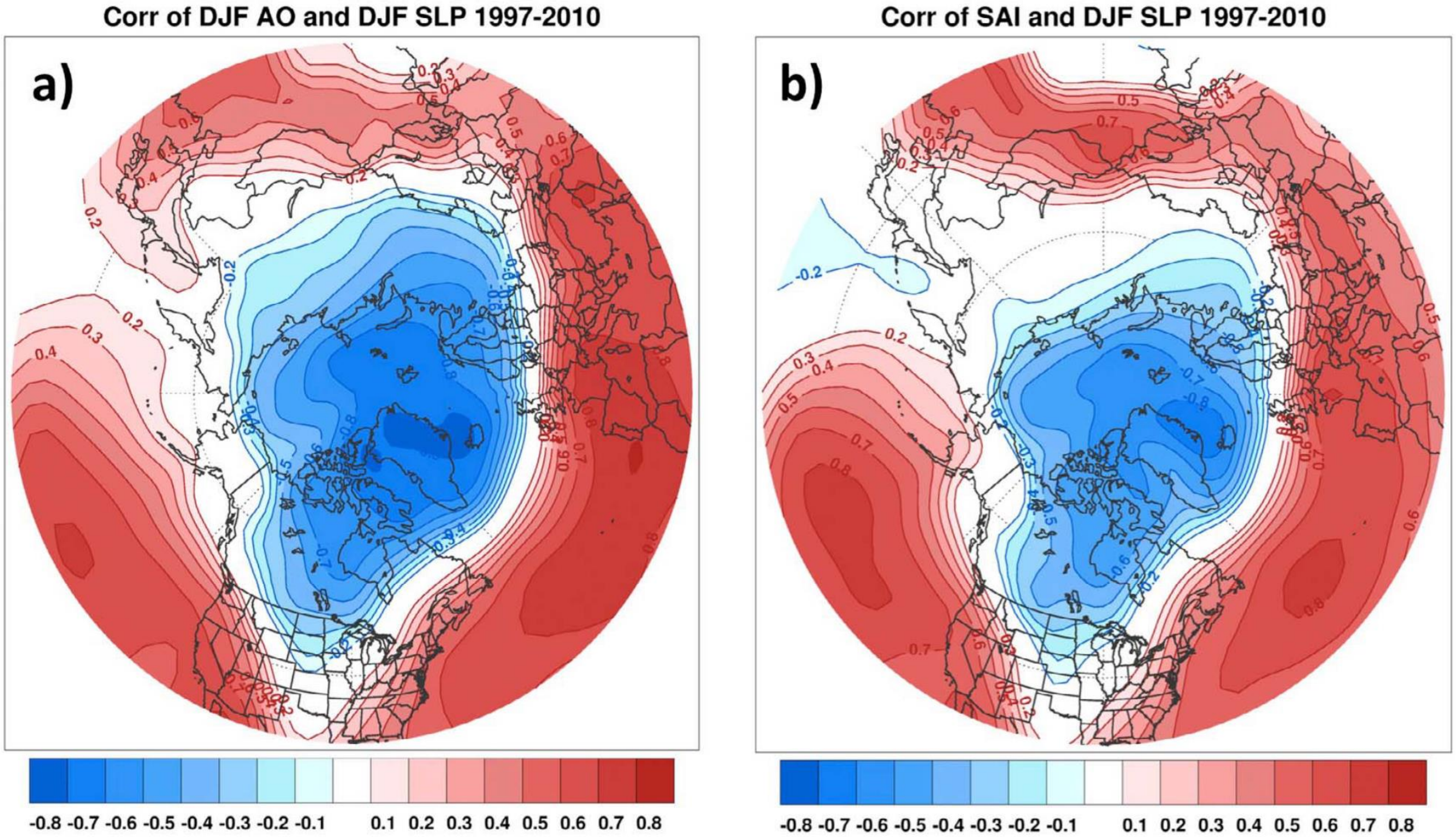
See also Koster et al., (2014)

Remote response to soil-moisture depletion on upper atmosphere



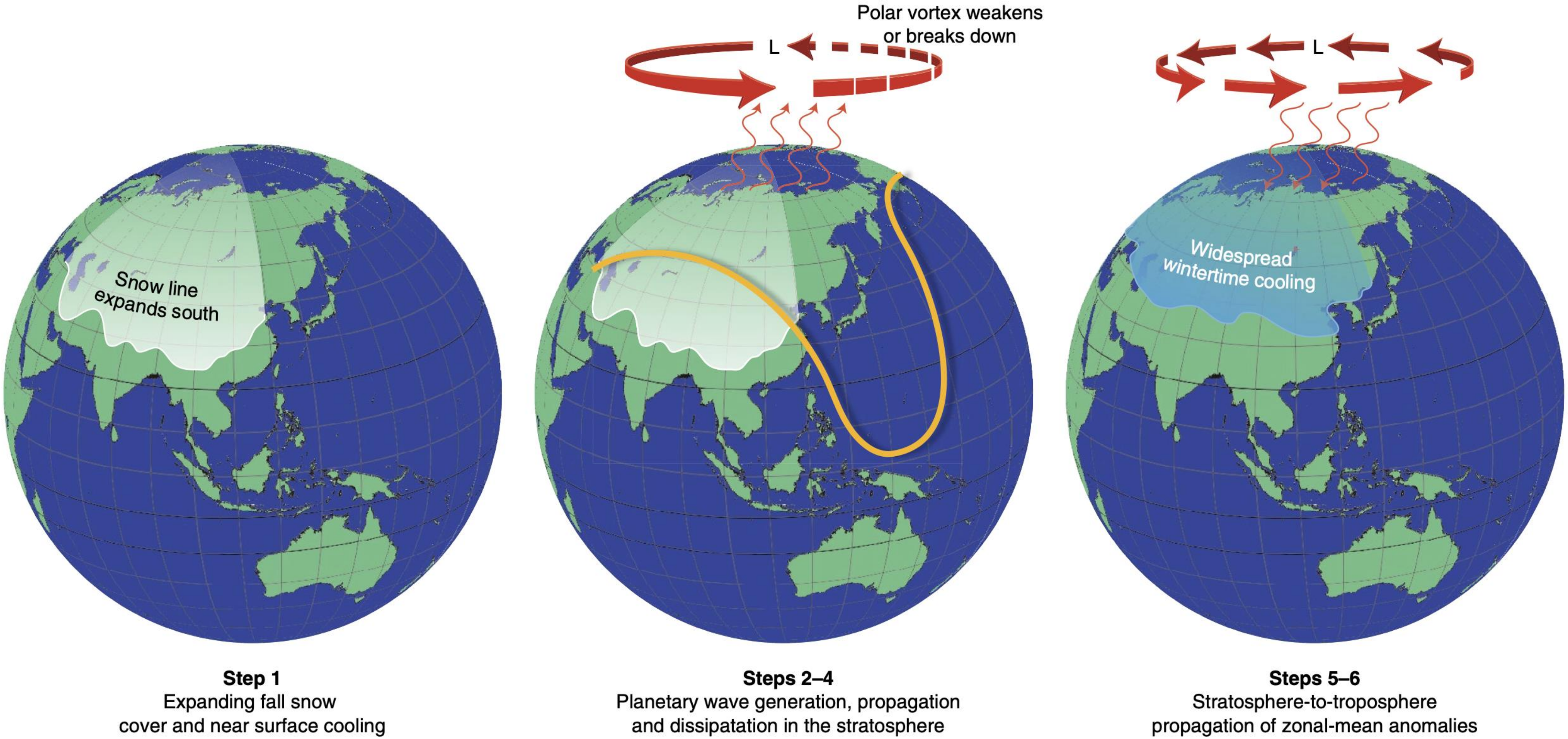
Teng et al. (2011)

Snow cover as a predictor of the Arctic Oscillation



Cohen and Jones (2011)

A mechanistic view of remote response to snowcover



Henderson et al., (2018), Nat Clim

Towards time-varying land use and vegetation cover

CONFESS project

- Multiple aspects, land is one part: see https://confess-h2020.eu/
- Vegetation dataset of land use/land cover (Land use/Land cover) and Leaf Area index (LAI), 1993-2020
- Experiments to explore impact of specified and interactive vegetation on seasonal prediction systems.

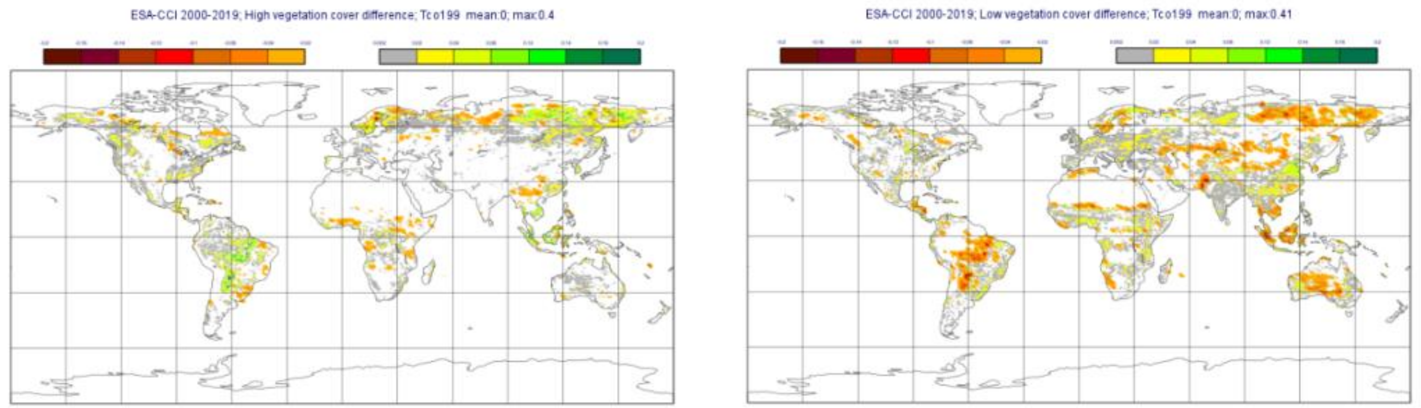


Figure 3: Vegetation cover differences between 2000 minus 2019 (right) for low vegetation and (left) for high vegetation covers.

From Boussetta and Balsamo, 2021 (CONFESS Deliverable D1.1)

- Work on interactive vegetation and predictability is continuing in the CERISE project.

Impact of time varying land properties on seasonal reforecasts

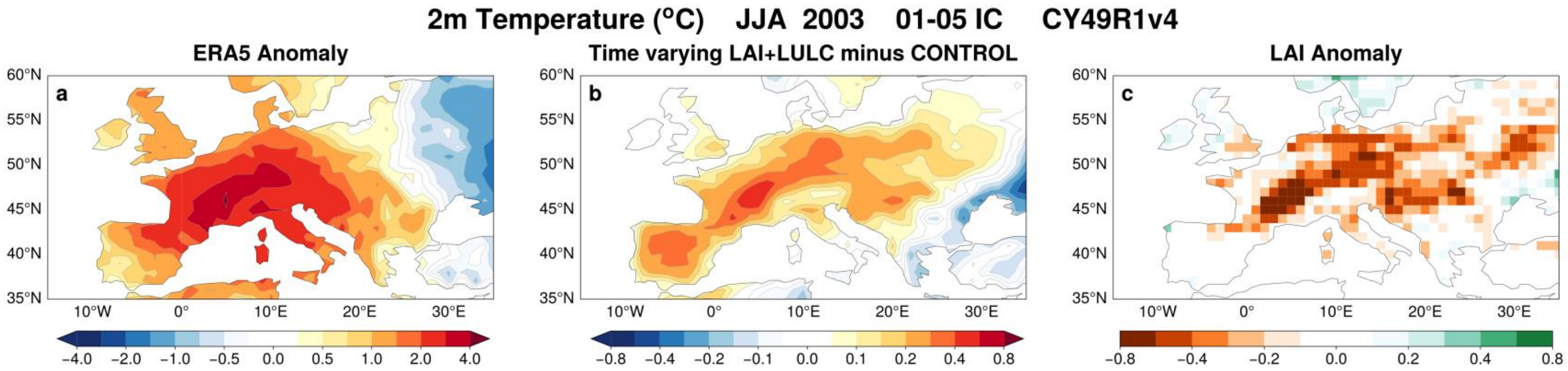


Figure: June-to-August 2003 seasonal mean 2m temperature over Europe: (a) ERA5 anomaly and (b) difference between LAI+LULC and CONTROL experiments. Also plotted in (c) is the Leaf Area Index anomaly.

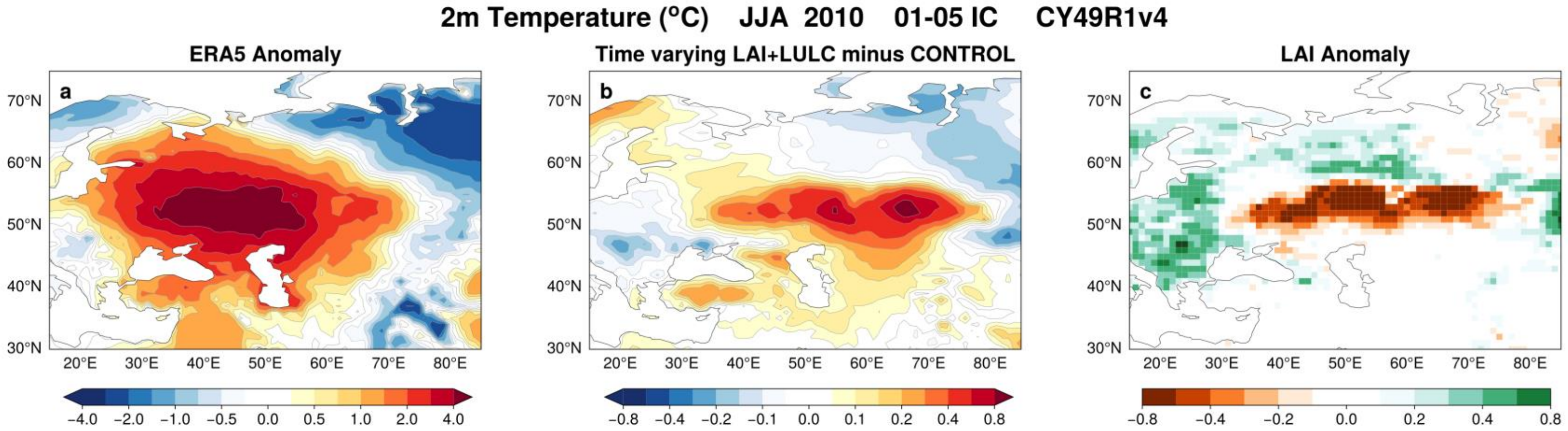
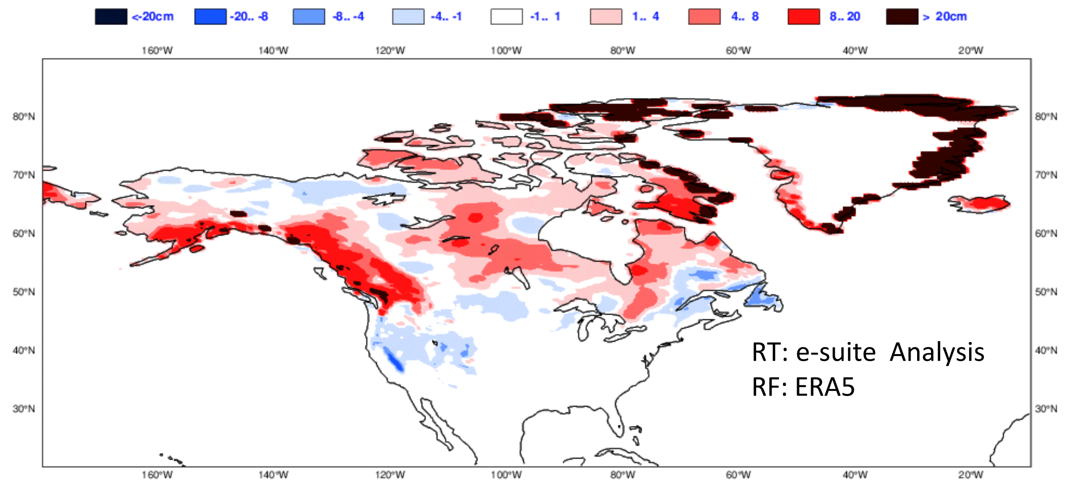


Figure: Same as above, but for 2010.

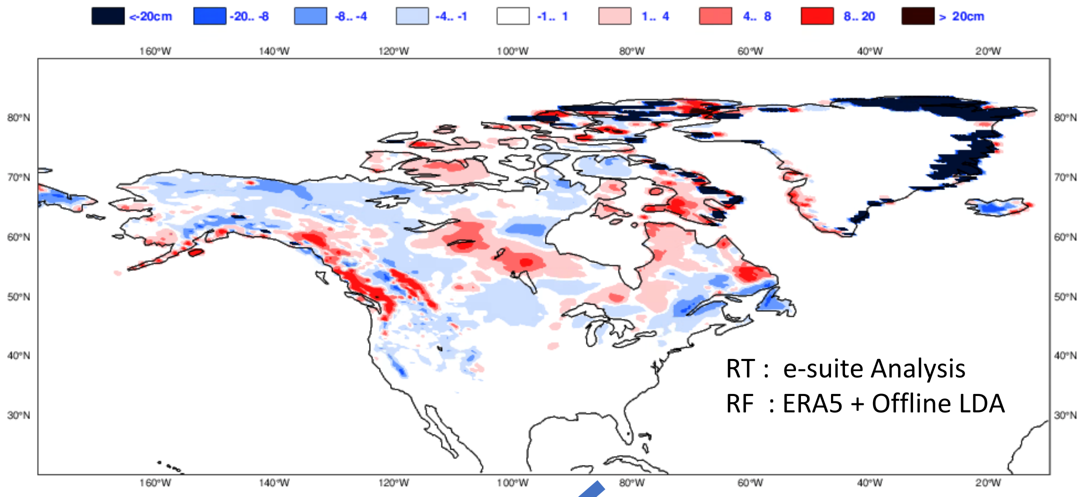
Slide from Retish Senan

Funded by the
European Union

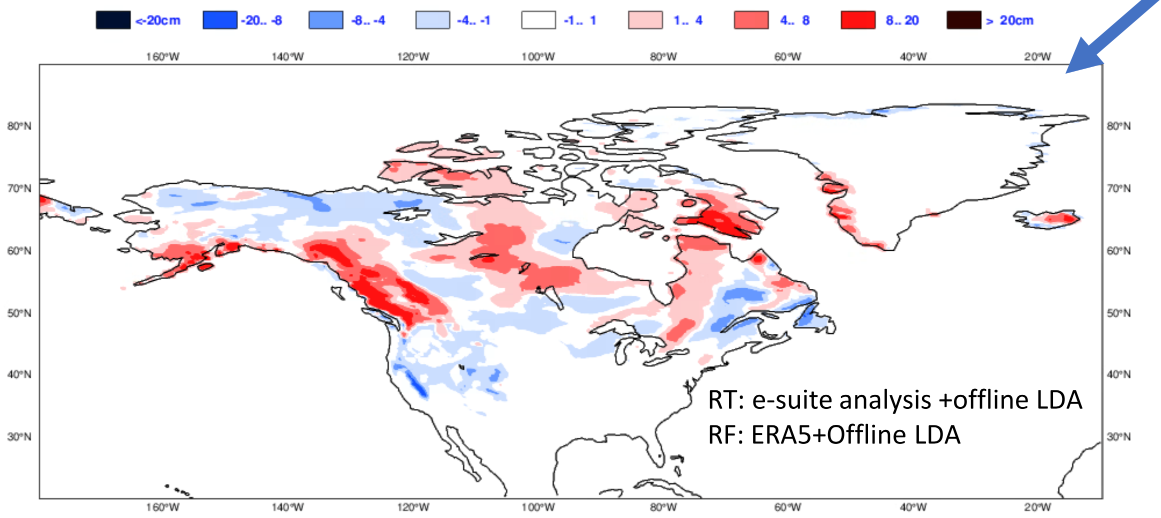
From the next model cycle each ECMWF system will have its own land-surface analysis (initial conditions)



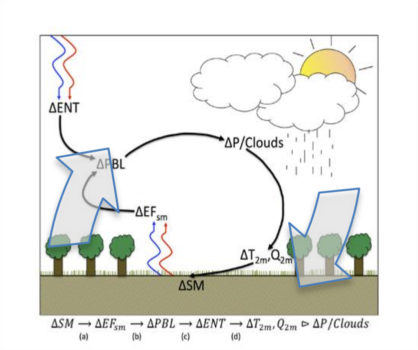
49R1



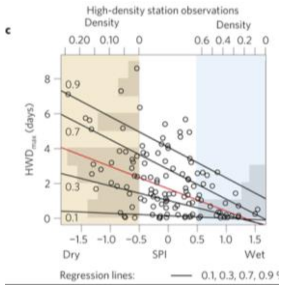
50R1



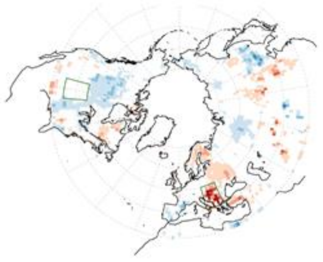
Summary



- 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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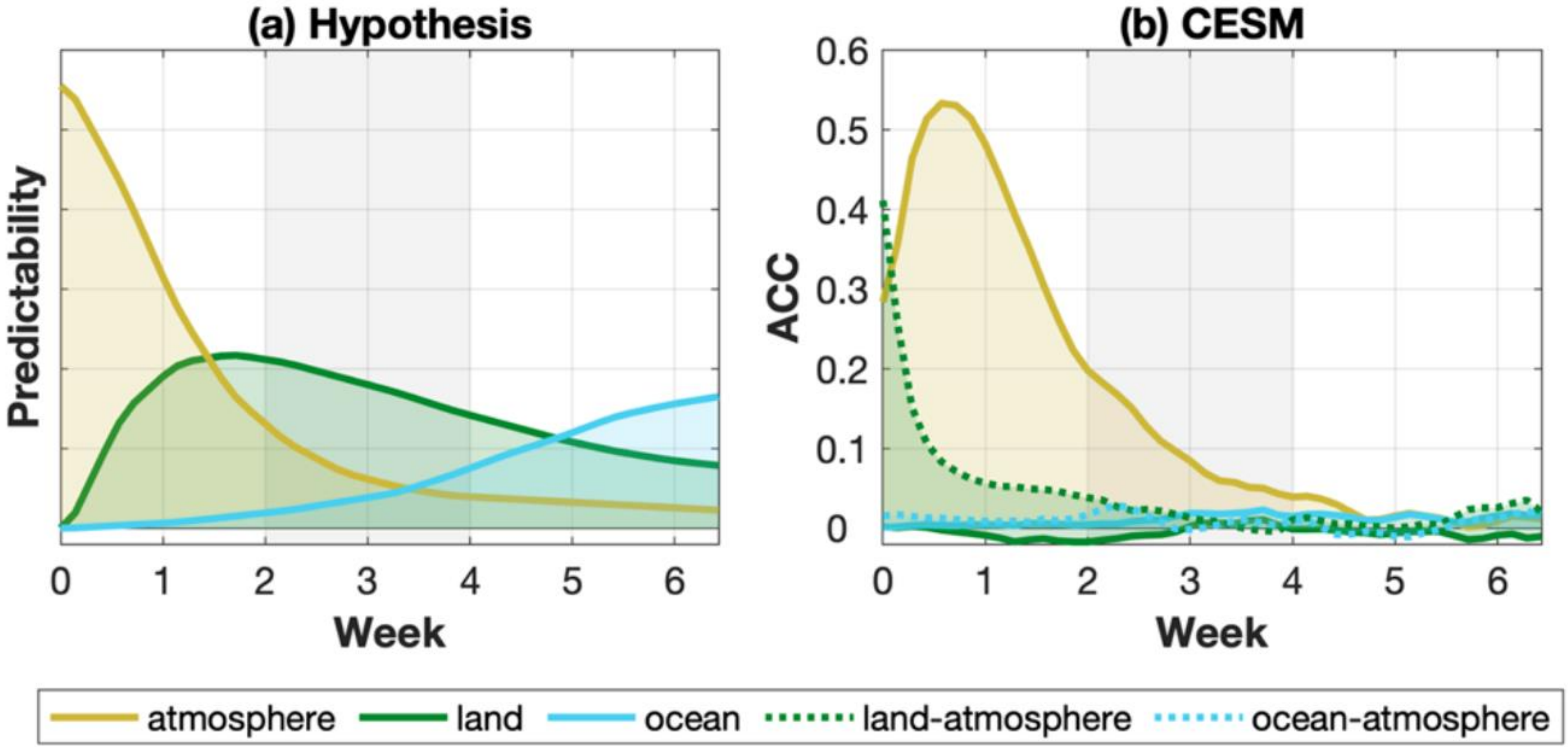
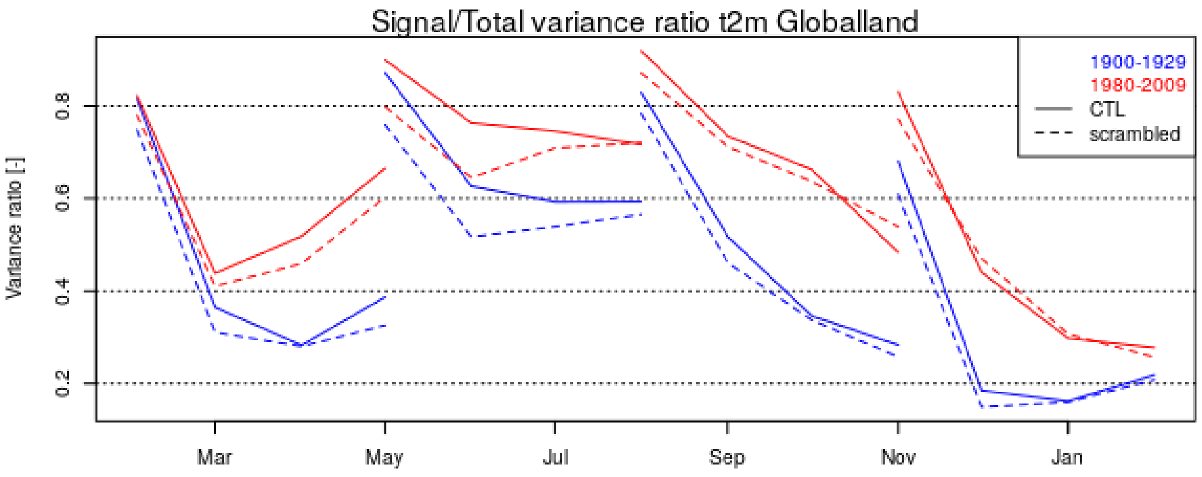
Additional slides

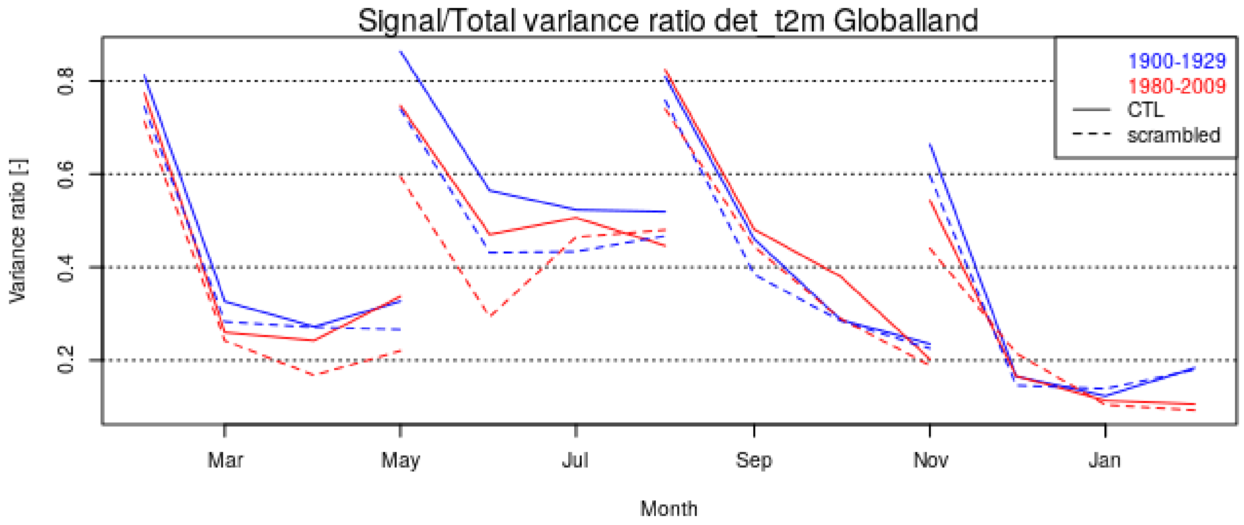
How important is the land-surface?



Richter et al. (2024)

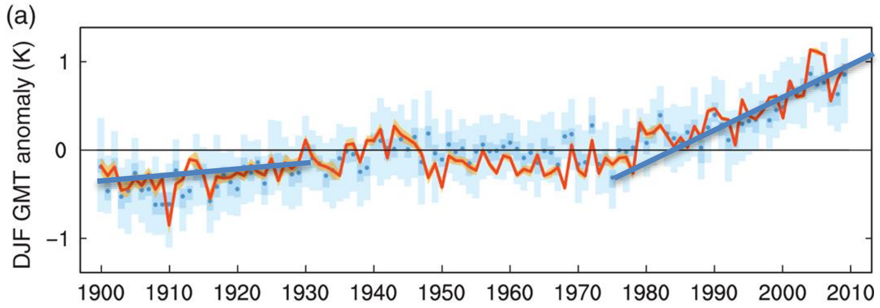
Trend contributes to T2m predictability





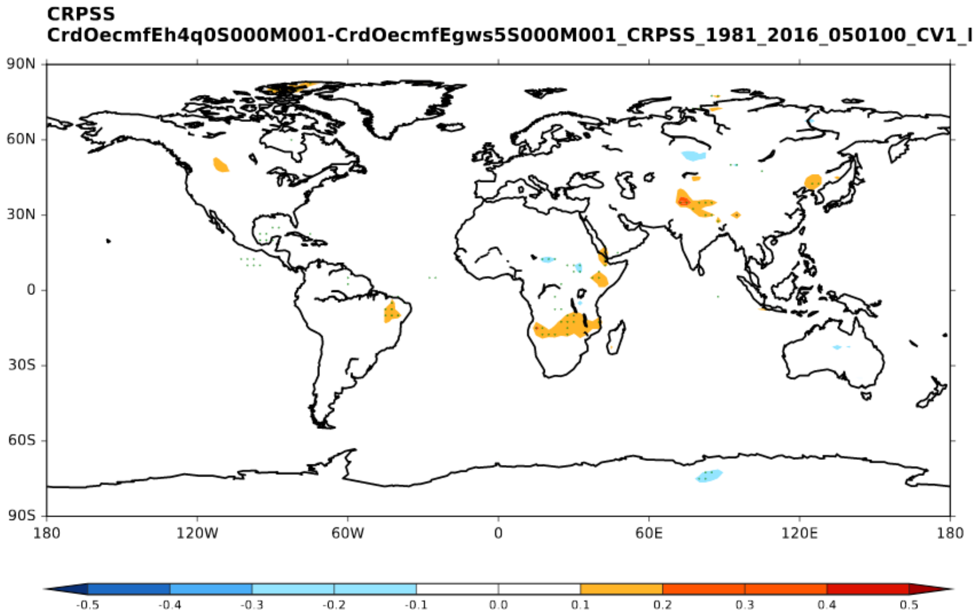
Note: initialized land surface (solid line) gives additional signal in T2m, especially in early summer. Note these plots show predictability not skill – extra skill would require the additional land surface signal to be correct.

Before detrending

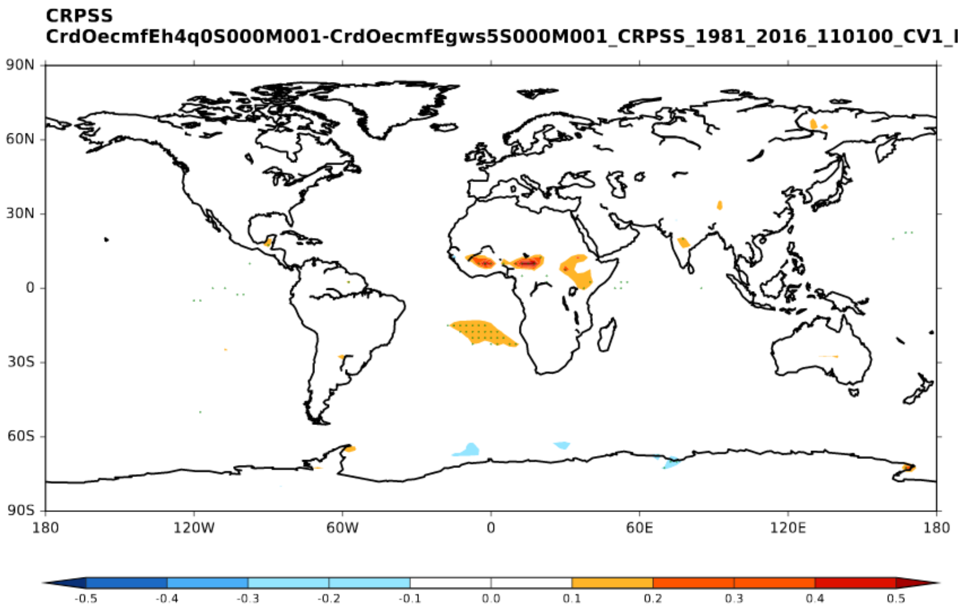


After detrending

Impact on T2m forecast skill of improved land surface initial conditions



JJA



DJF

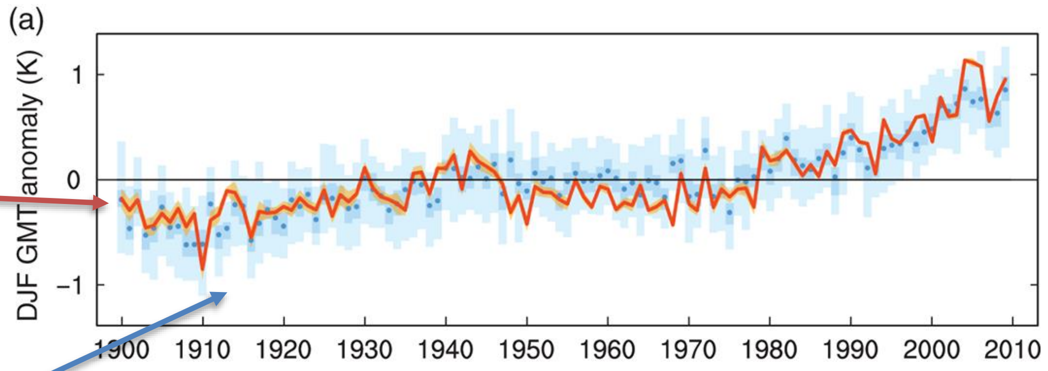
Difference in CRPSS skill from 36 years of re-forecasts with 51 member ensembles, comparing Cy46r1 (ERA5 ICs) and Cy45r1 (SEAS5 ICs). Sensitivity experiments (lower resolution, smaller ensemble size) confirm that the main driver of improvement is change in ICs, not the model.

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

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

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



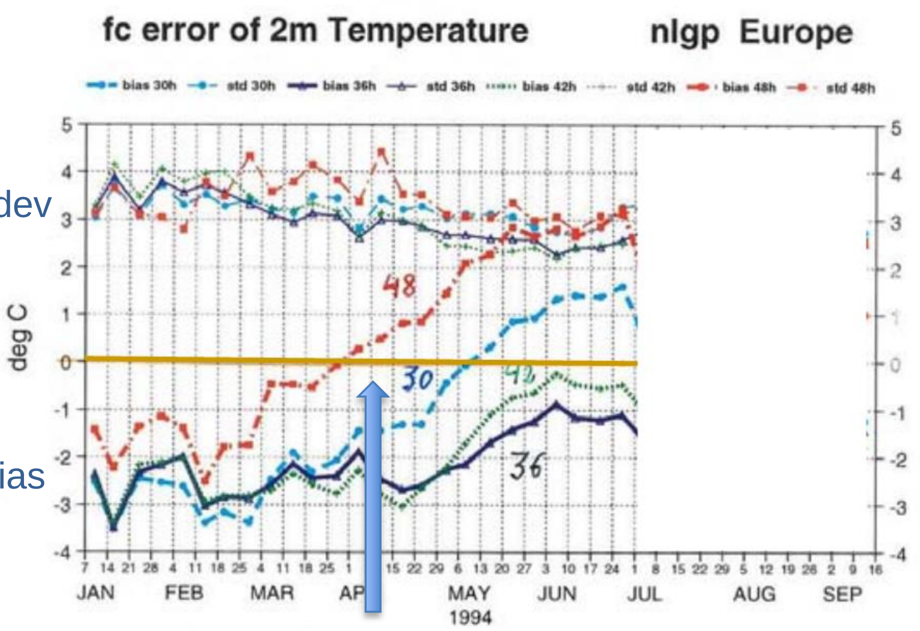
An anecdote demonstrating impact of soil moisture

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

stddev

Model normally too cold

bias

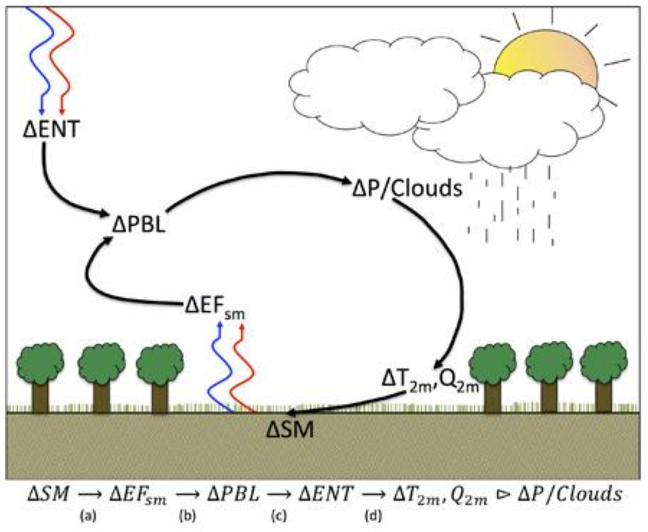


Suddenly extreme warm dry drift

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)