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

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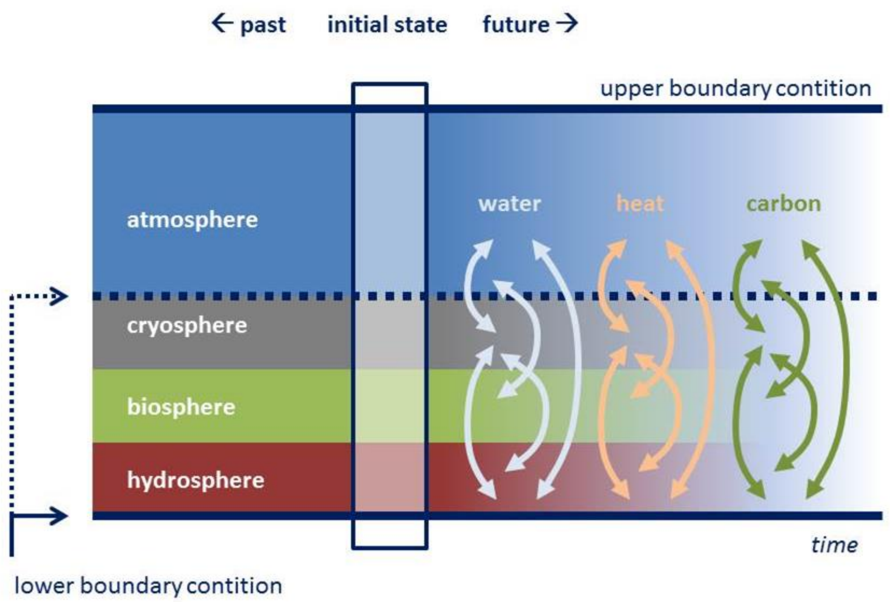


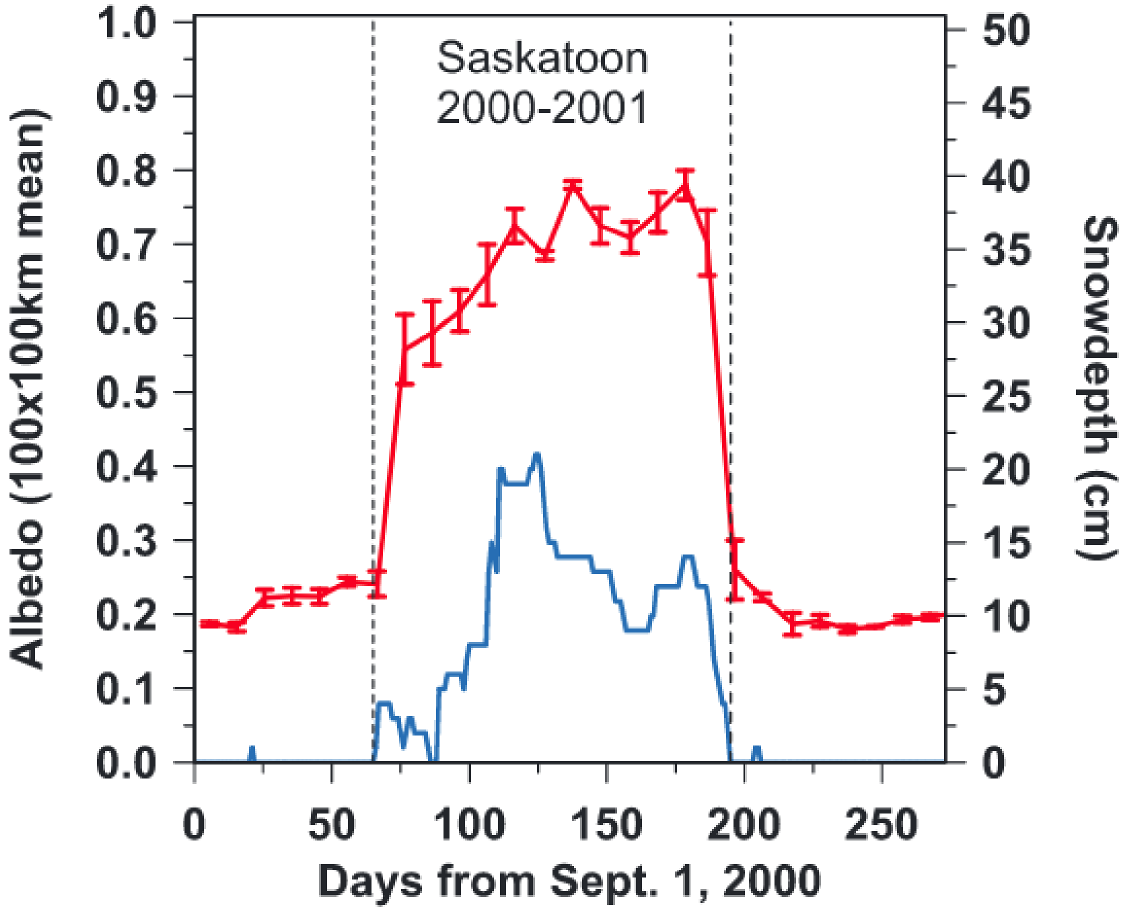
Why do we care about land processes?

- Energy-budget
  - Albedo

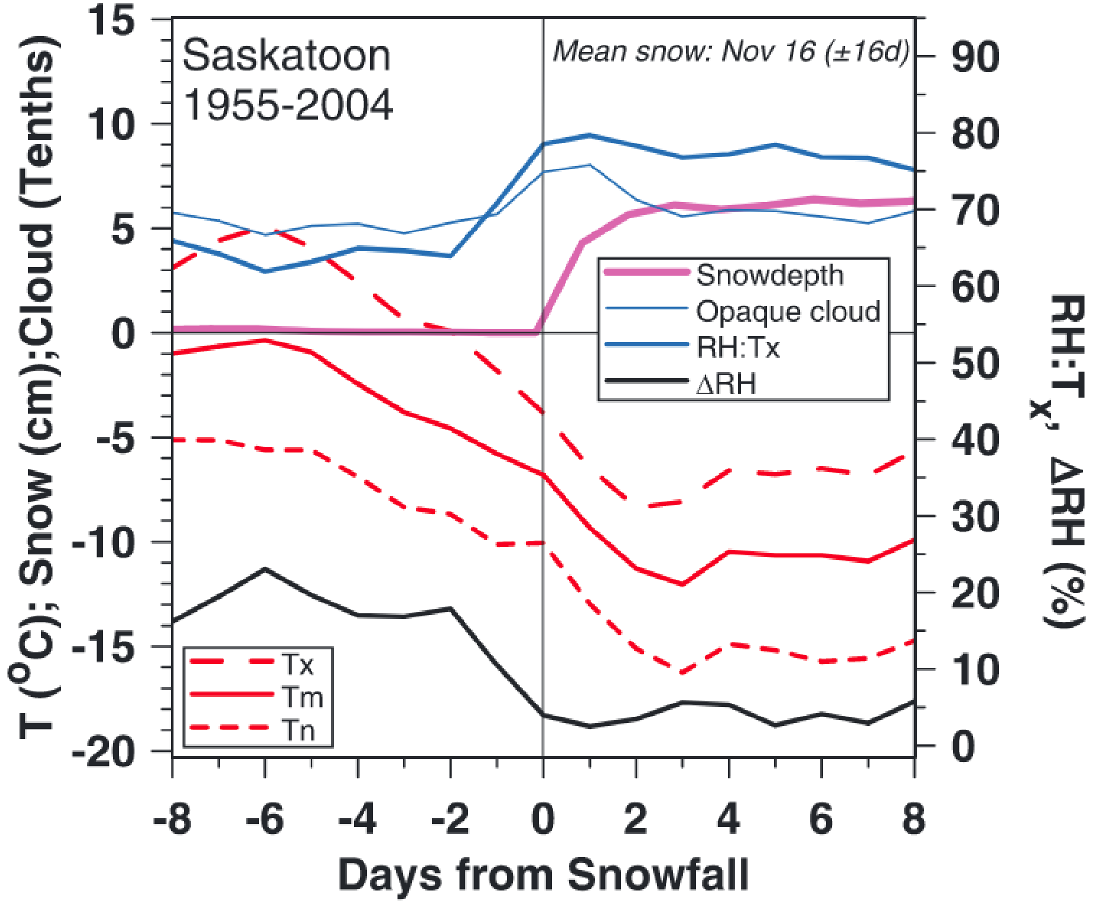
Surface	Albedo
Dark forest	9-12%
Grassland	15-20%
Bare soil	20-30%
Snow in forest	15-25%
Open snow	50-85%

Example of snow transitions

Snow and albedo



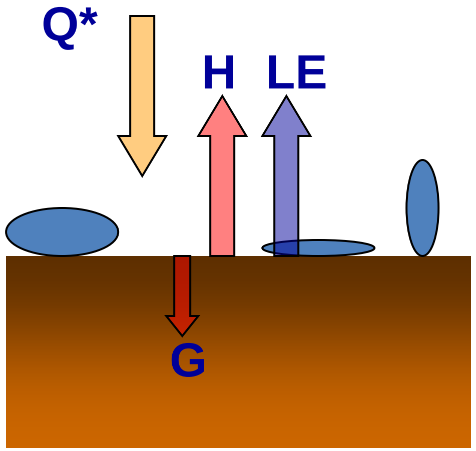
Snow and surface meteorology



Betts et al., (2014)

Why do we care about land processes?

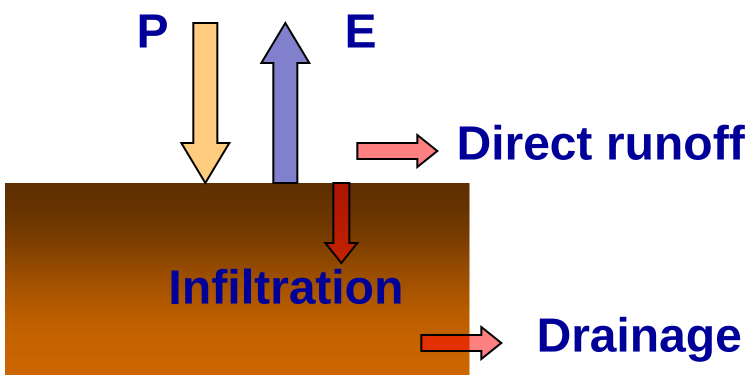
- Energy-budget
  - Albedo
  - Evaporative fraction



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

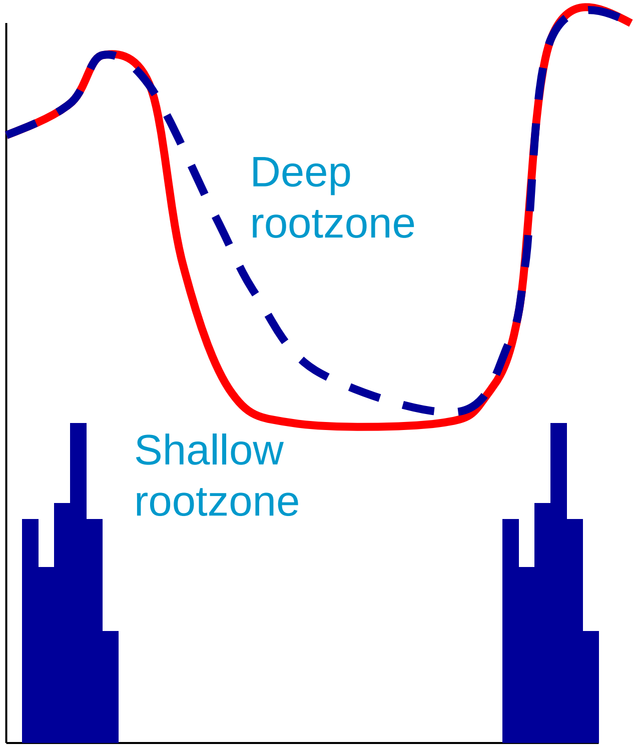
Why do we care about land processes?

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



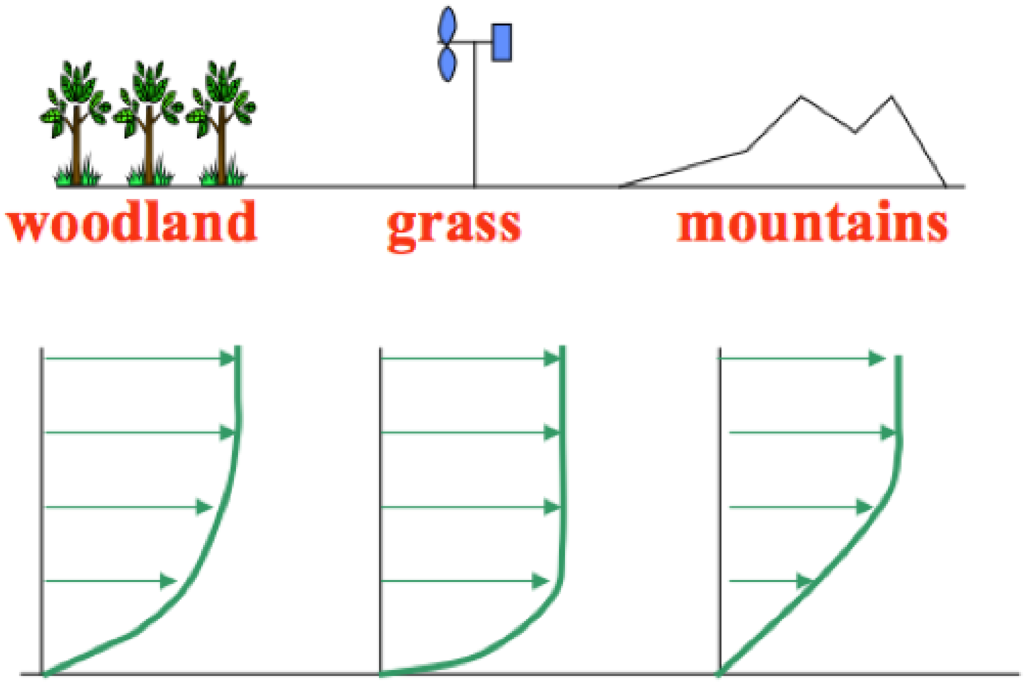
Land processes in atmospheric models

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



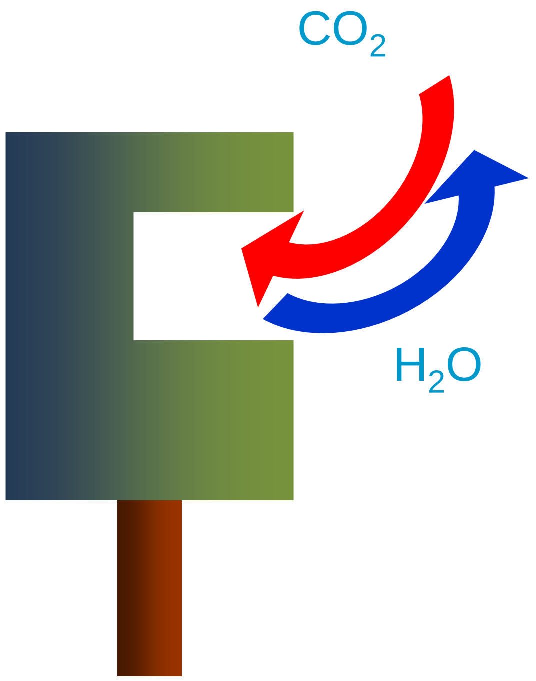
Land processes in atmospheric models

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



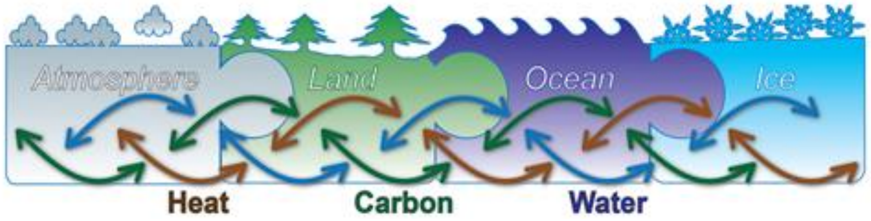
Land processes in atmospheric models

- 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

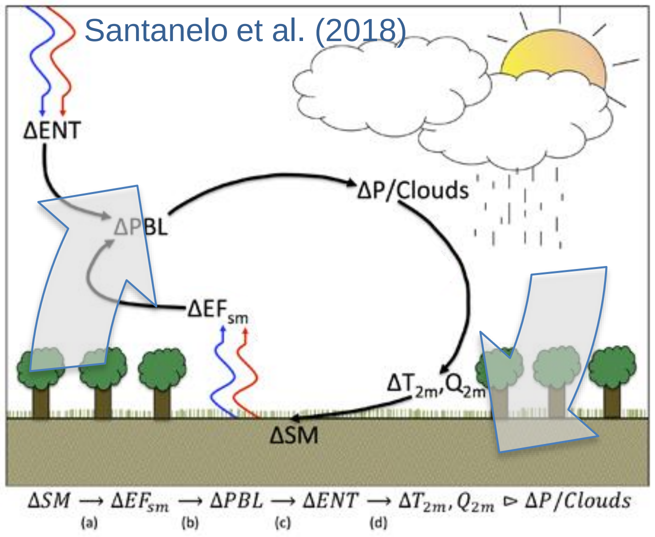


What is needed to contribute to predictability?

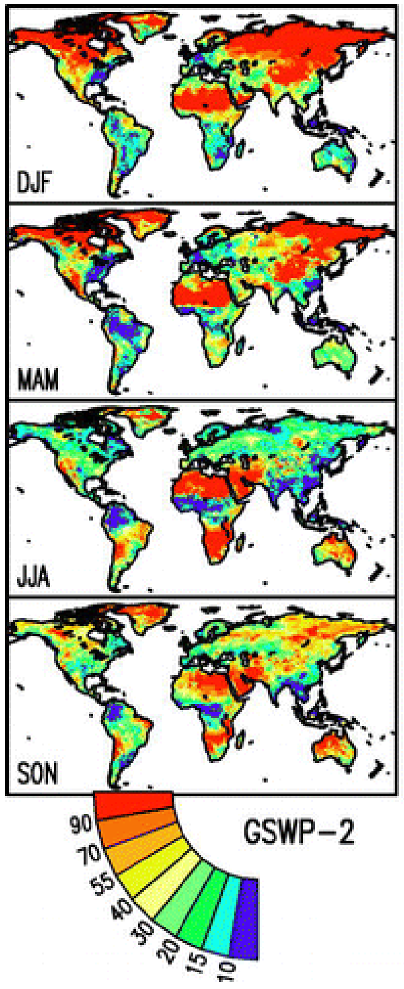
- In the climate system all processes are connected



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



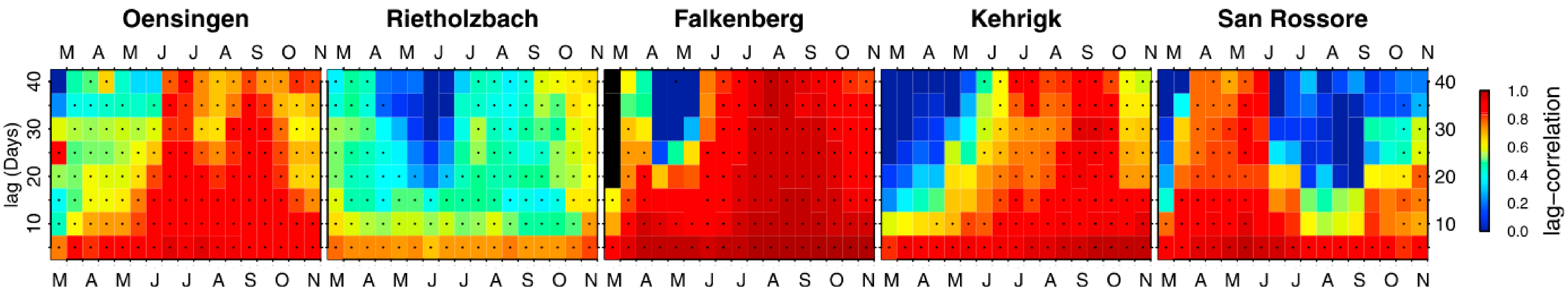
Dirmeyer et al, 2009



Soil moisture memory (days)

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

Soil moisture predictability (observation-based estimates)



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

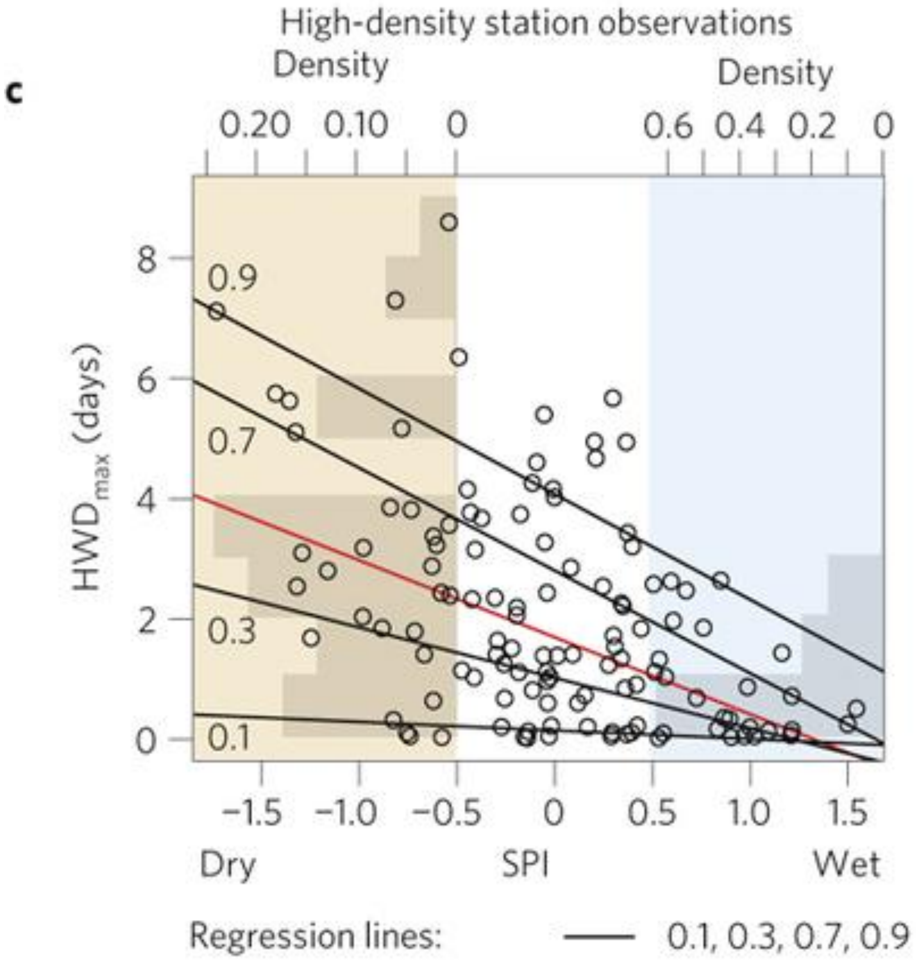
$$c_s w_{n+lag,y} = c_s w_{n,y} + P_{n,y} - E_{n,y} - Q_{n,y}$$

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)

Measures to quantify land-atmosphere coupling

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



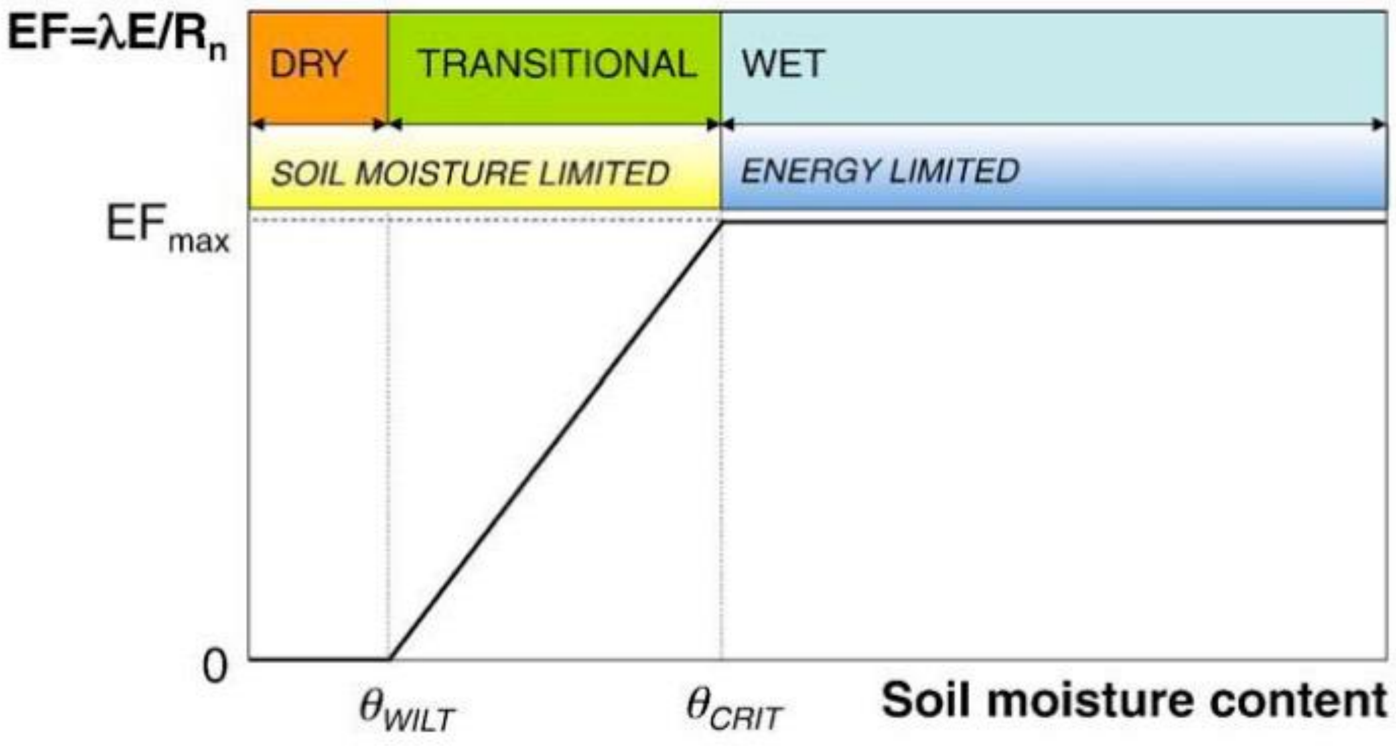
SPI=Standardized Precipitation Index (measure of soil moisture deficit over preceeding 6 months)
HWD$_{max}$=maximum heatwave duration

Predictability over wet conditions better than over dry conditions

Hirschi et al, 2011, Nat Geo

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

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

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

Seneviratne et al., 2010

Measures to quantify land-atmosphere coupling

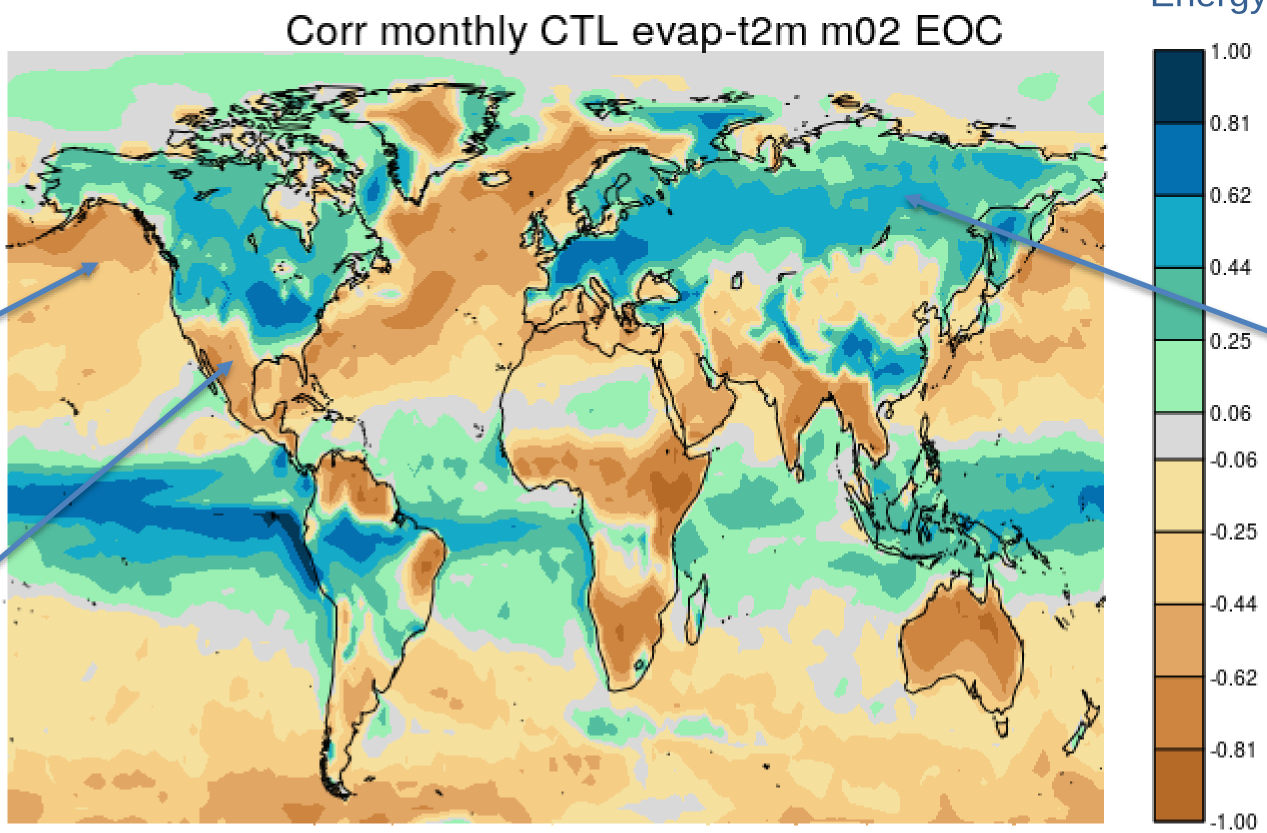
- From (pseudo)observations:
  – Correlation between evaporation and temperature

Feb-Apr

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

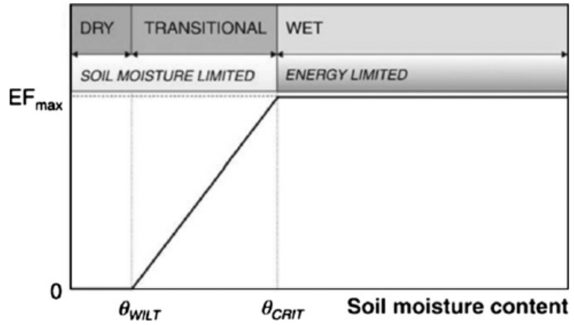
Energy limited



Soil water limited

If soils are wet, higher temperatures drive higher evaporation

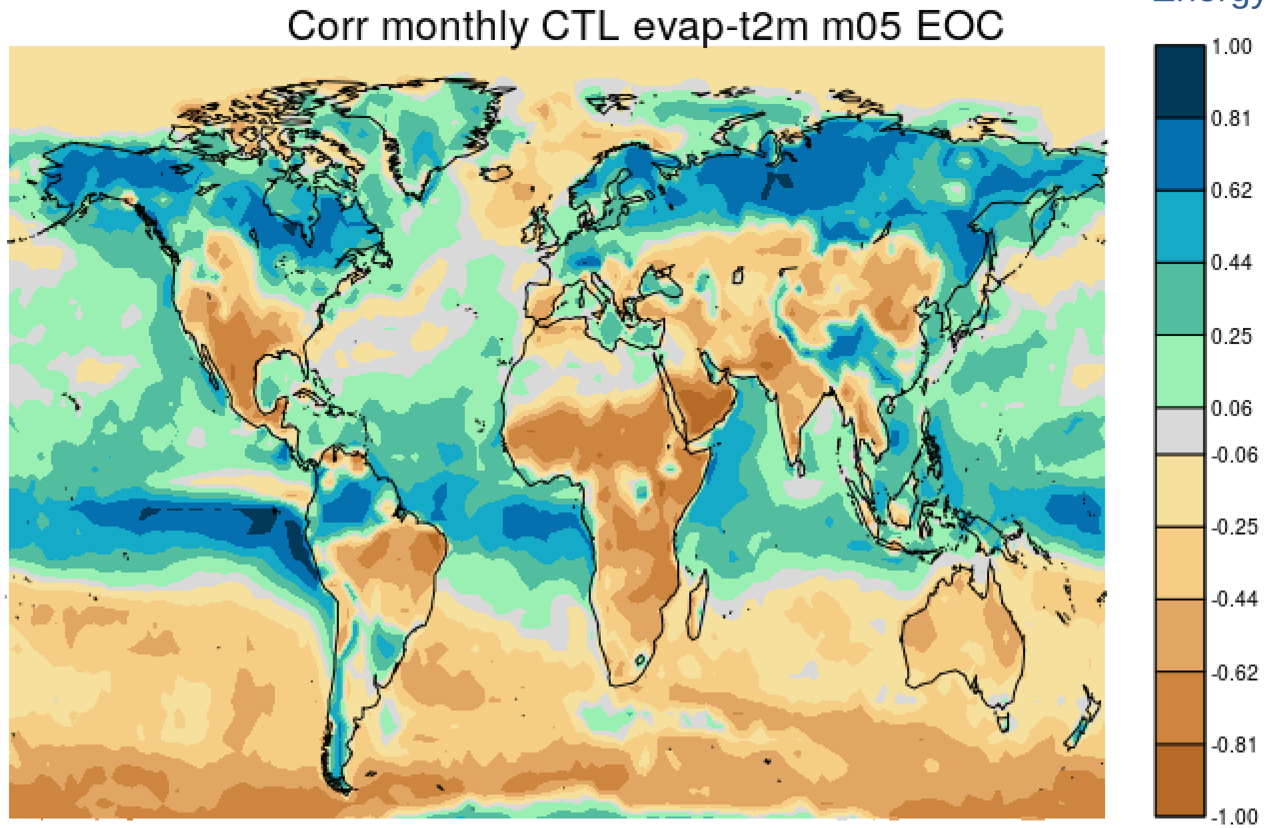
Seneviratne et al, 2010



Measures to quantify land-atmosphere coupling

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

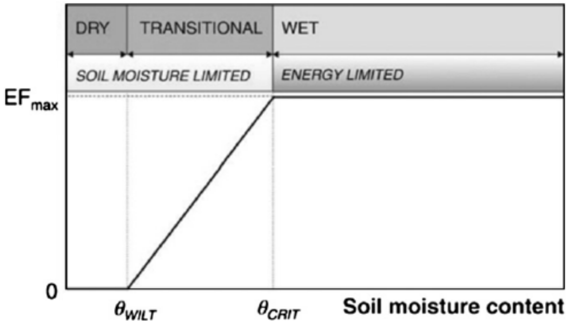
May-Jul



Energy limited

Soil water limited

Seneviratne et al, 2010



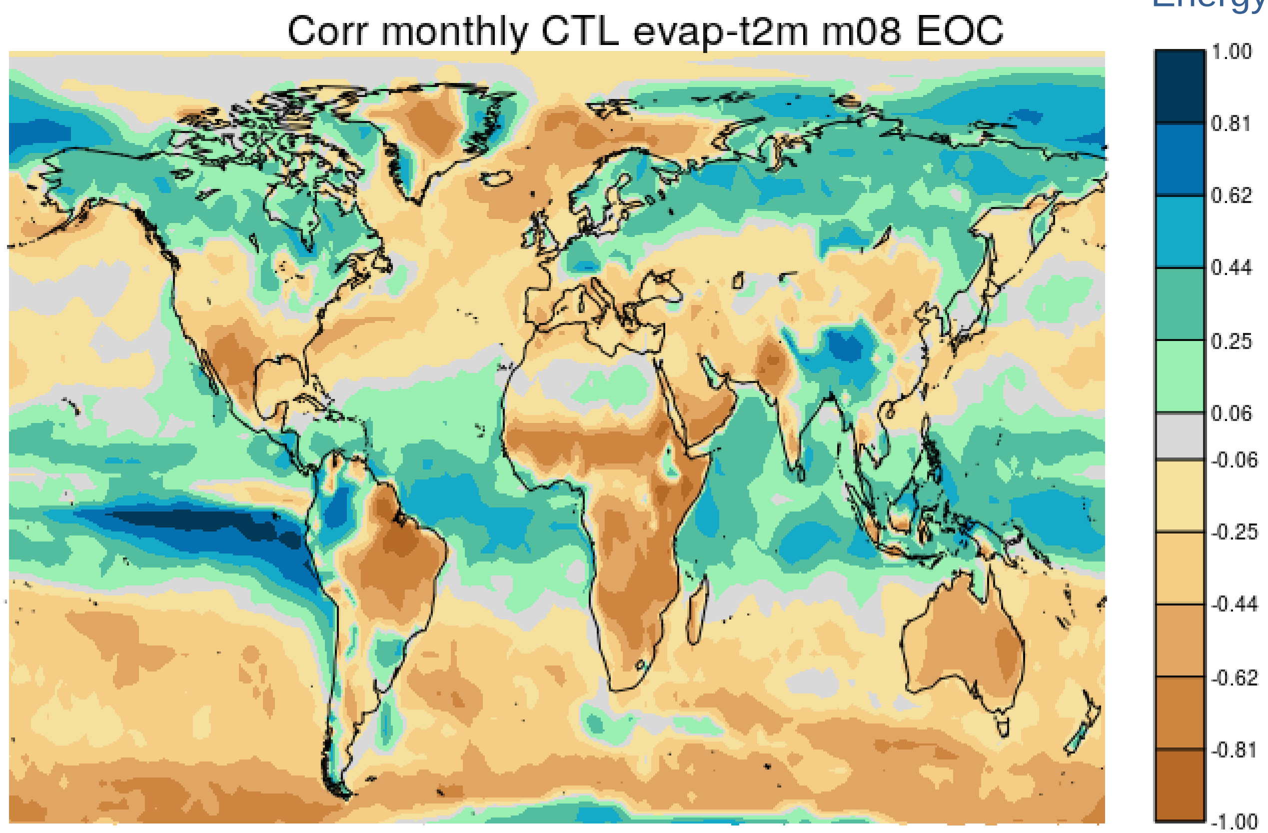
Measures to quantify land-atmosphere coupling

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

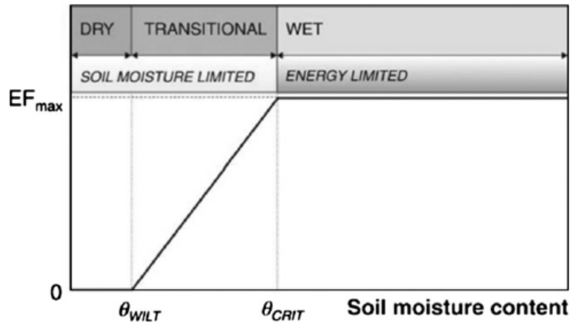
Aug-Oct

Seneviratne et al, 2010

Energy limited



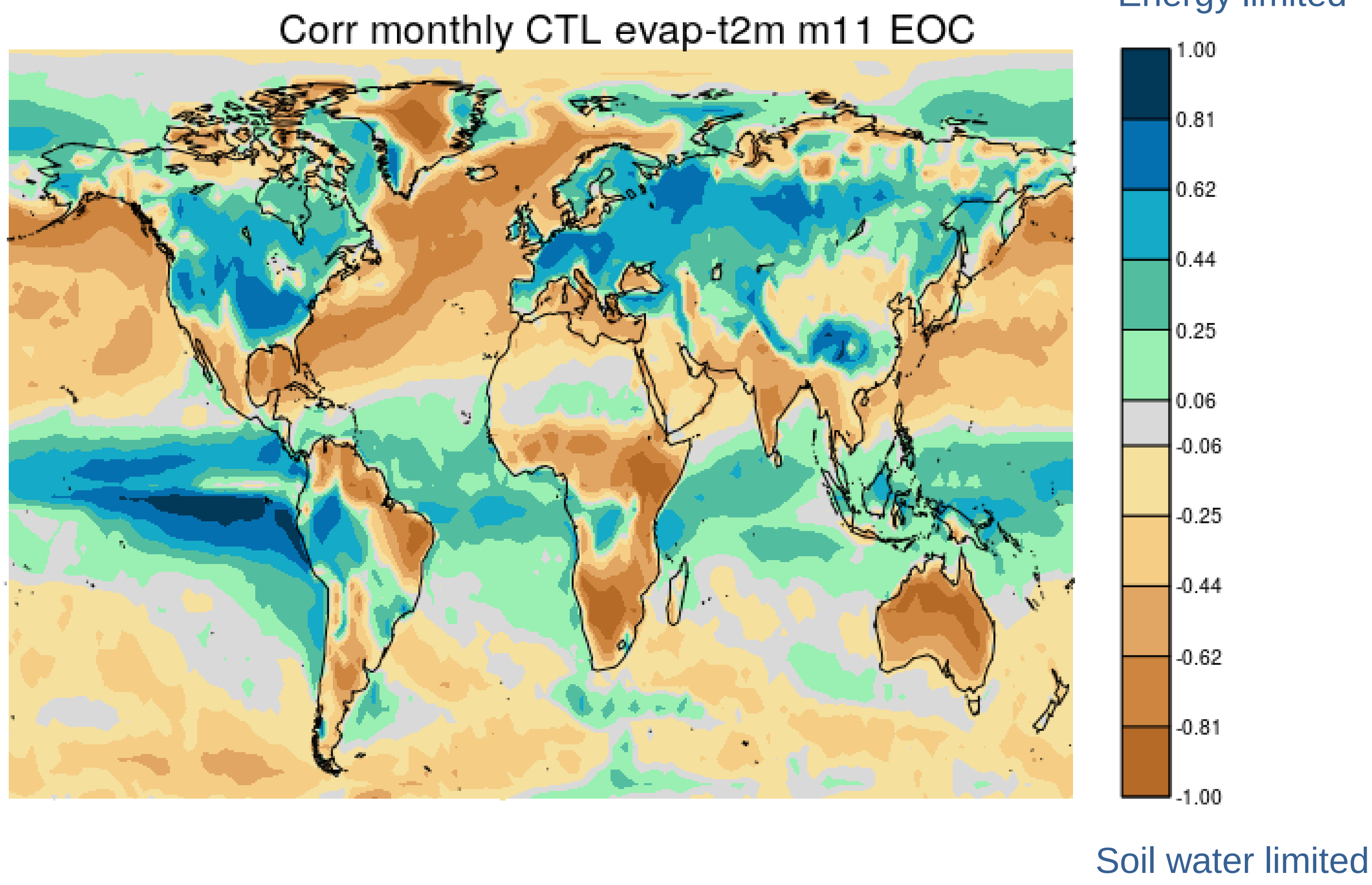
Soil water limited



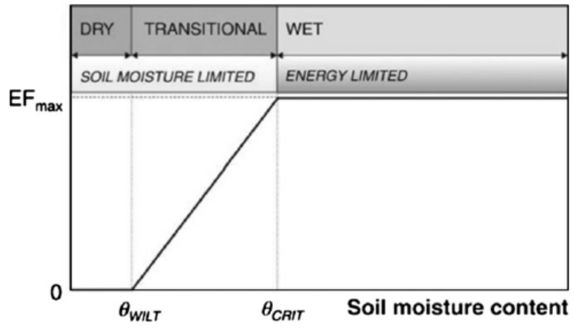
Measures to quantify land-atmosphere coupling

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

Nov-Jan

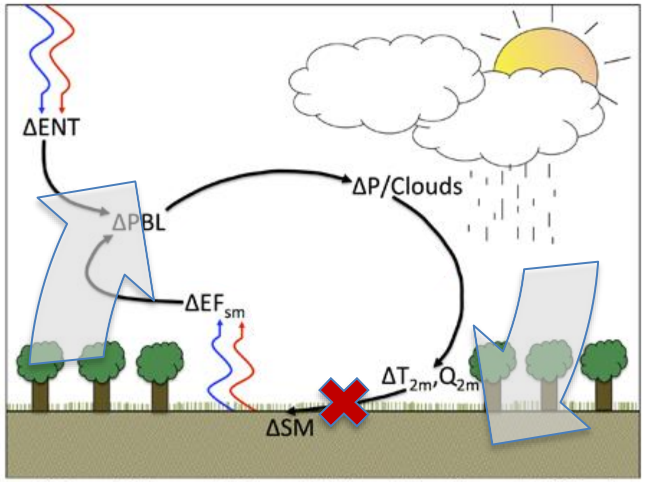


Seneviratne et al, 2010



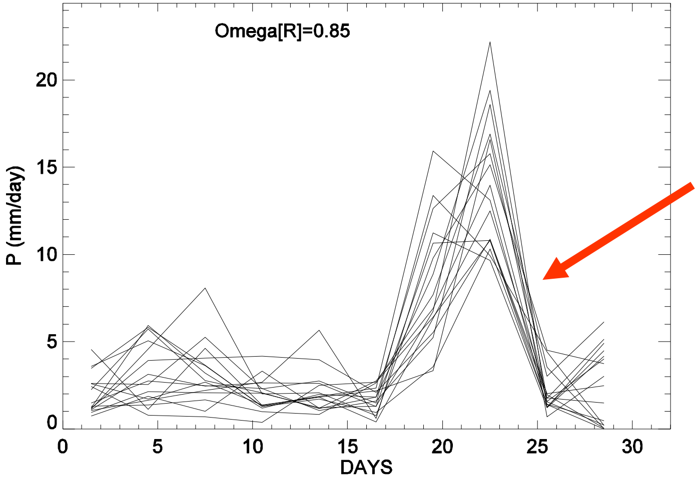
Measures to quantify land-atmosphere coupling

- 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

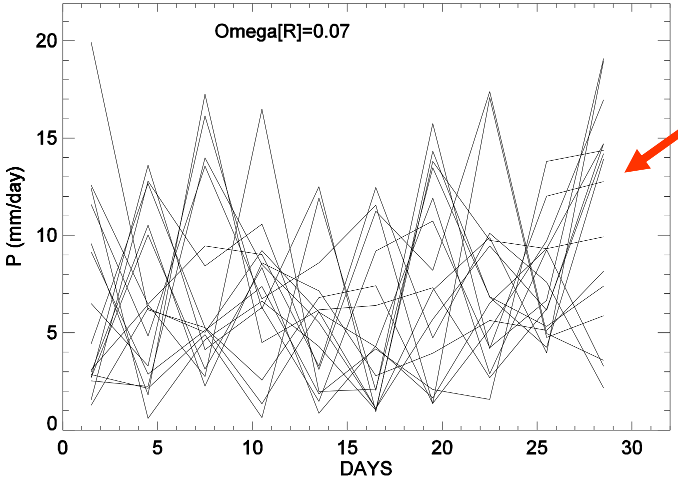


$\Delta SM \underset{(a)}{\longrightarrow} \Delta EF_{sm} \underset{(b)}{\longrightarrow} \Delta PBL \underset{(c)}{\longrightarrow} \Delta ENT \underset{(d)}{\longrightarrow} \Delta T_{2m}, Q_{2m} \triangleright \Delta P/Clouds$

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:

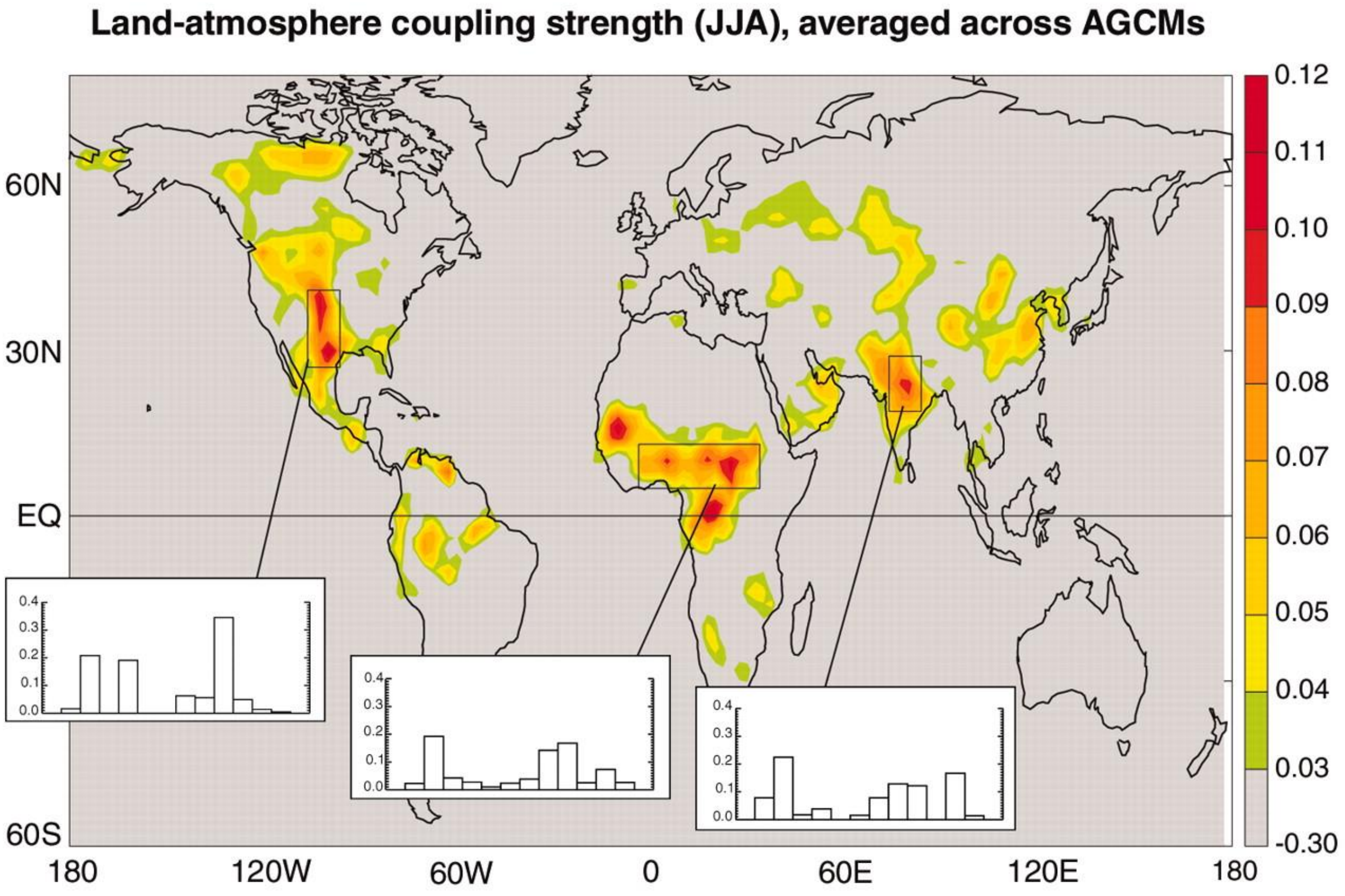
$$\Omega = (16\sigma^2_{<X>} - \sigma^2_X)/15\sigma^2_X$$

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

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

GLACE

Areas with strong feedback on precipitation



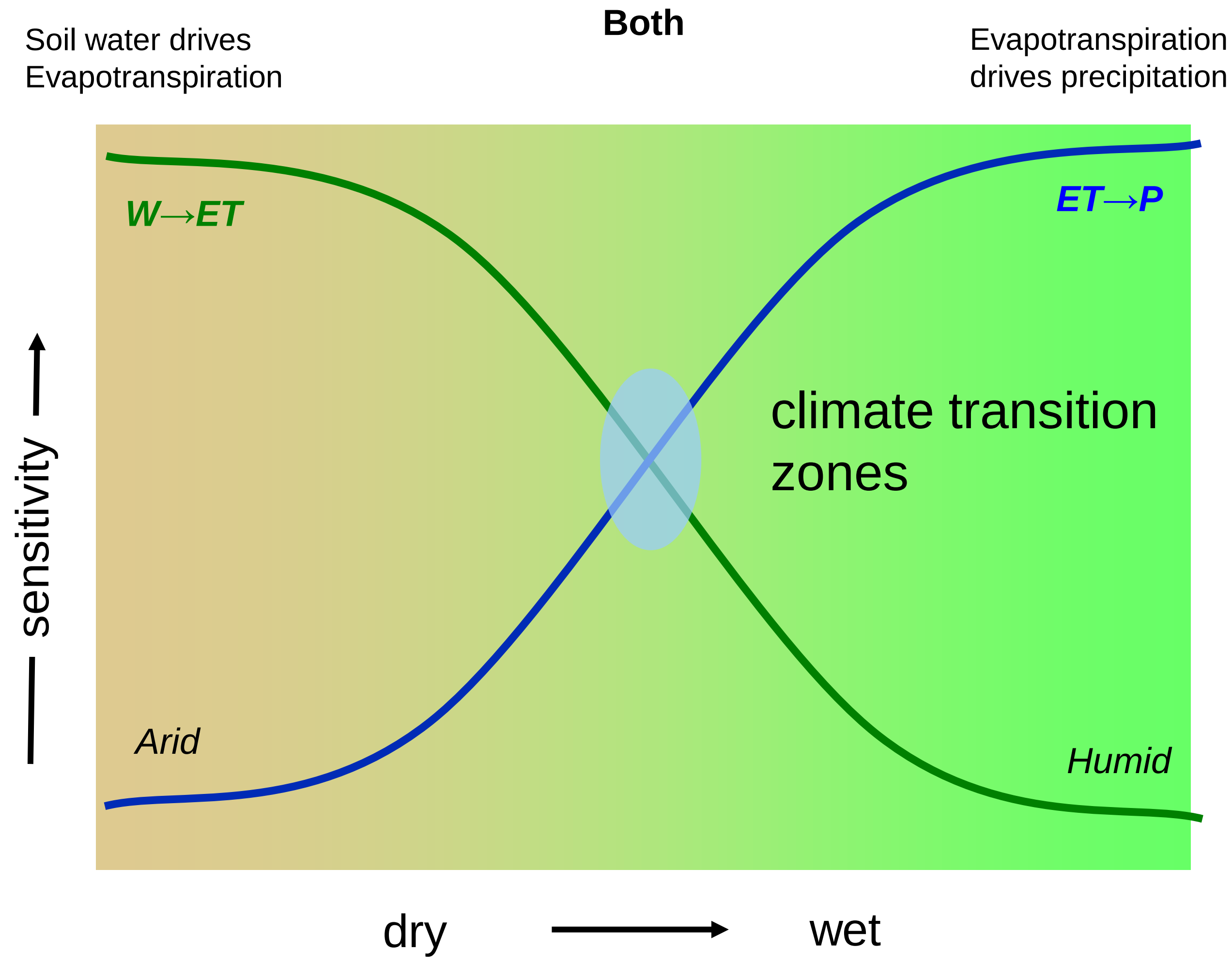
Ω(S)-Ω(W)

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.

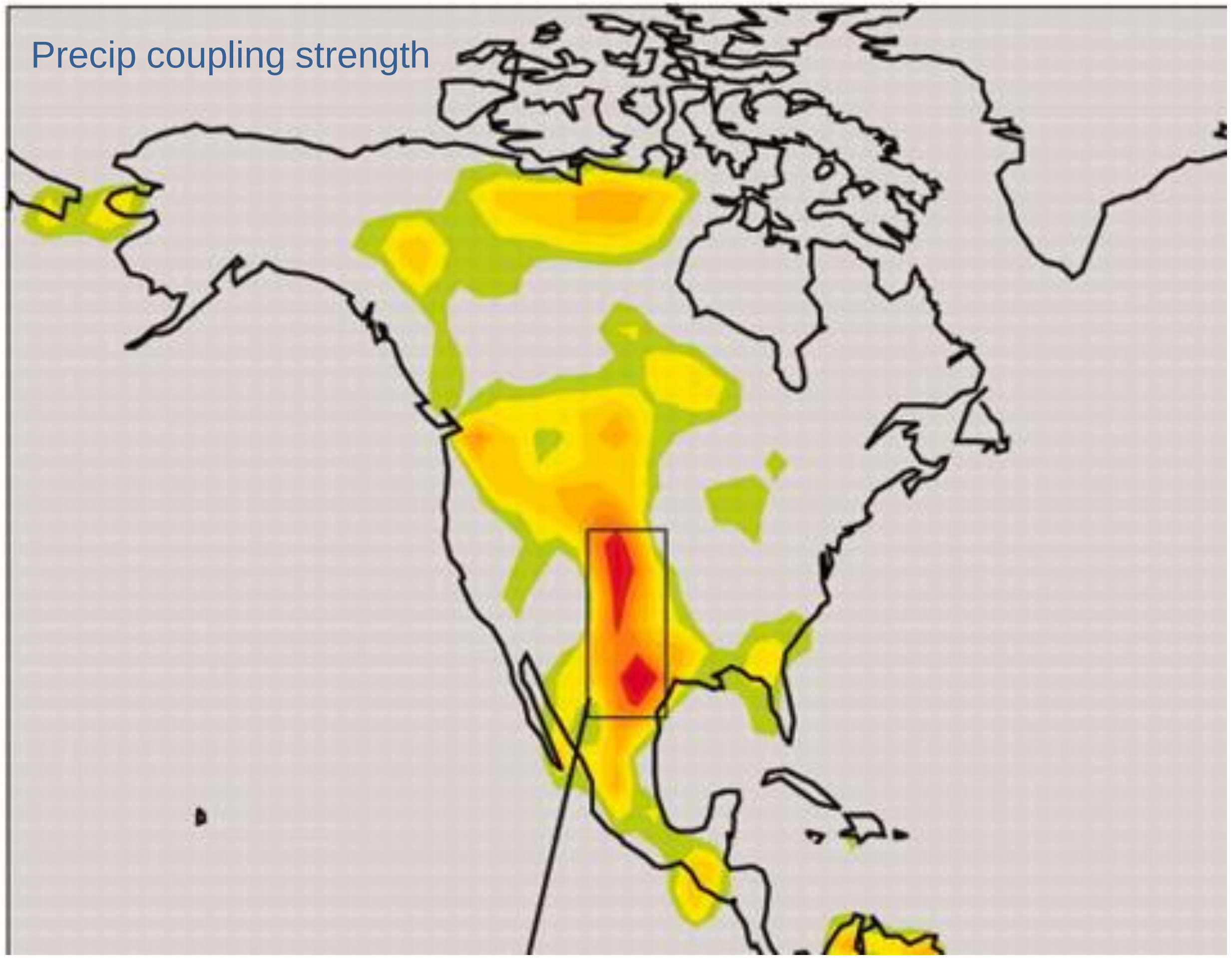
Koster et al, 2004, Science

GLACE

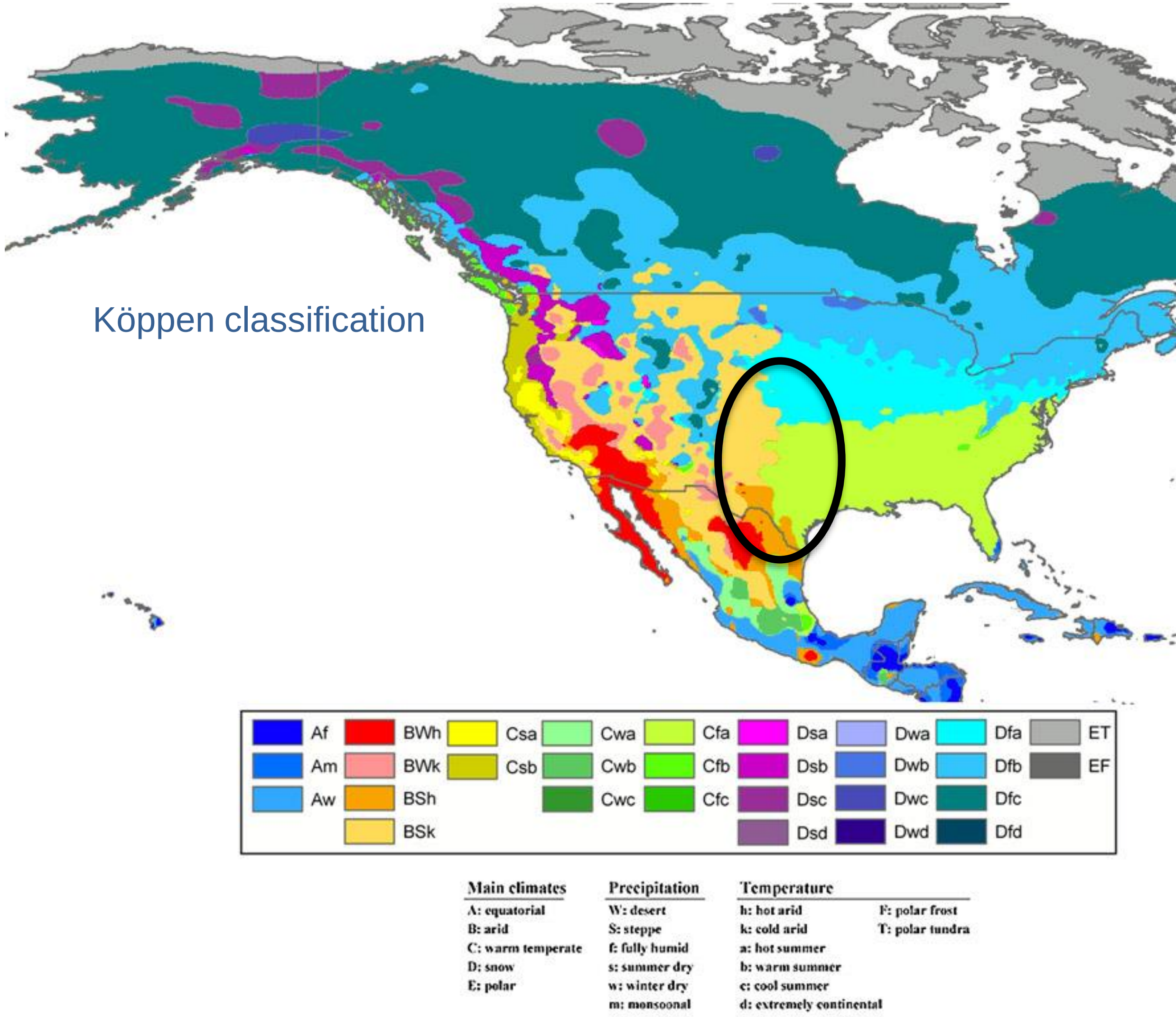
Strong precipitation coupling needs combination of sensitivities



Strong feedback on precipitation at transition between arid and temperate zones



Köppen classification

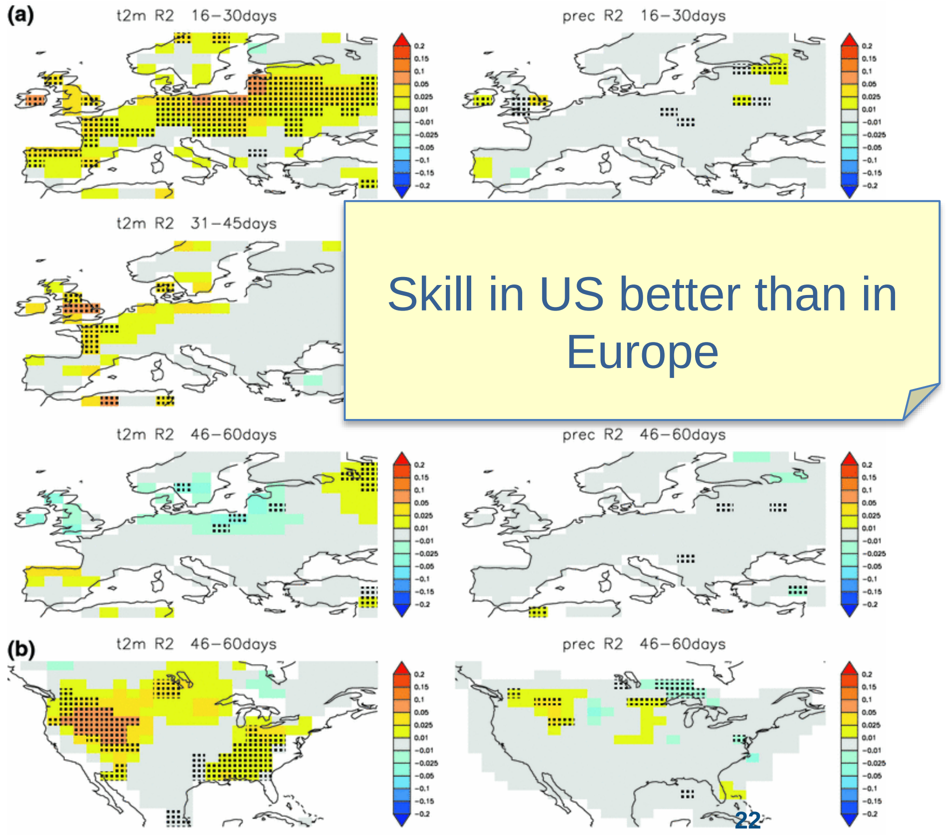


Koster et al, 2004, Science

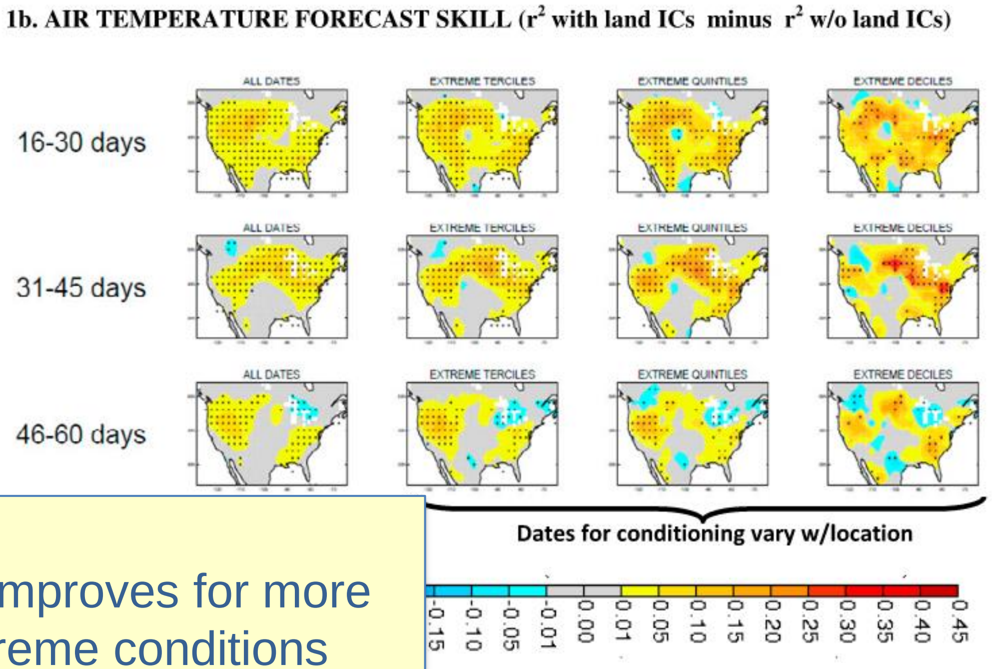
Some “real” land-surface predictability experiments

- Global Land Atmosphere Coupling Experiment – 2
  - Compare 2 ensembles of 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



Skill in US better than in Europe



Skill improves for more extreme conditions

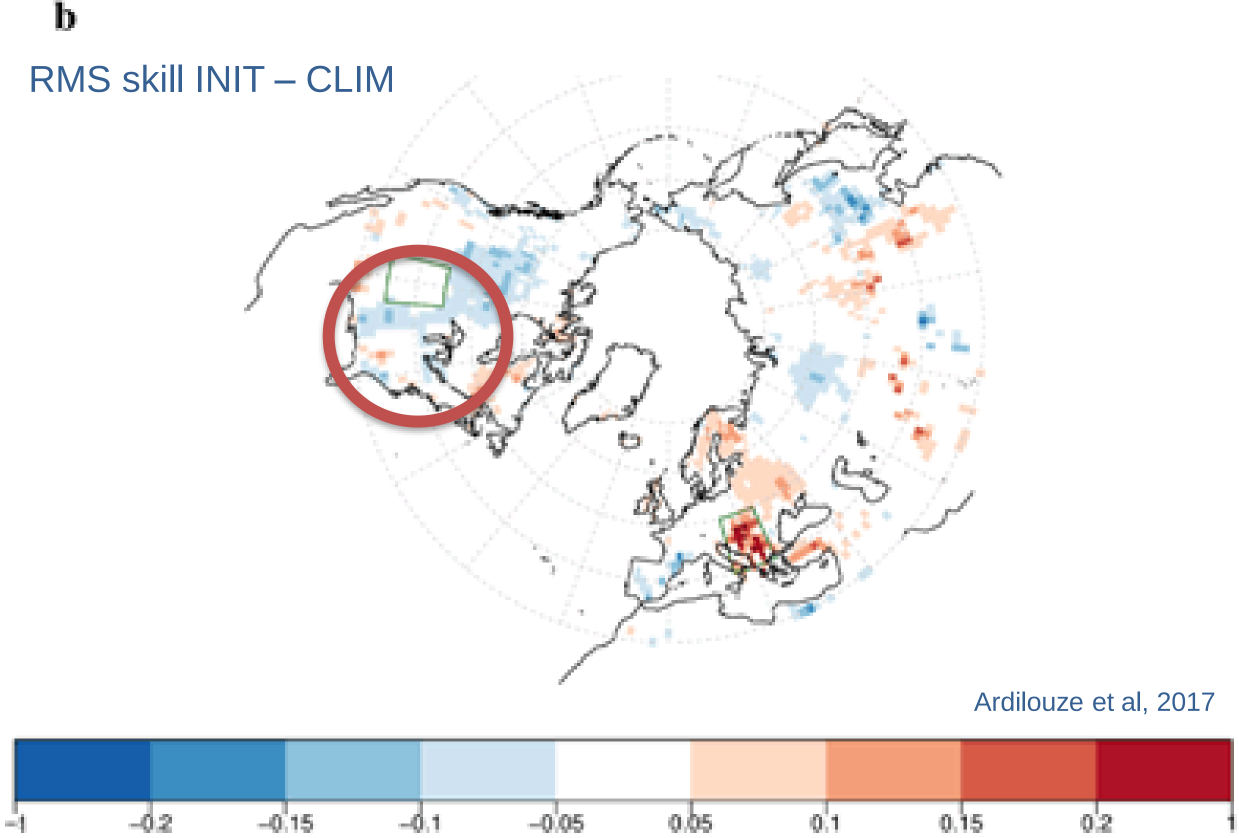
Koster et al, 2010

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)

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).

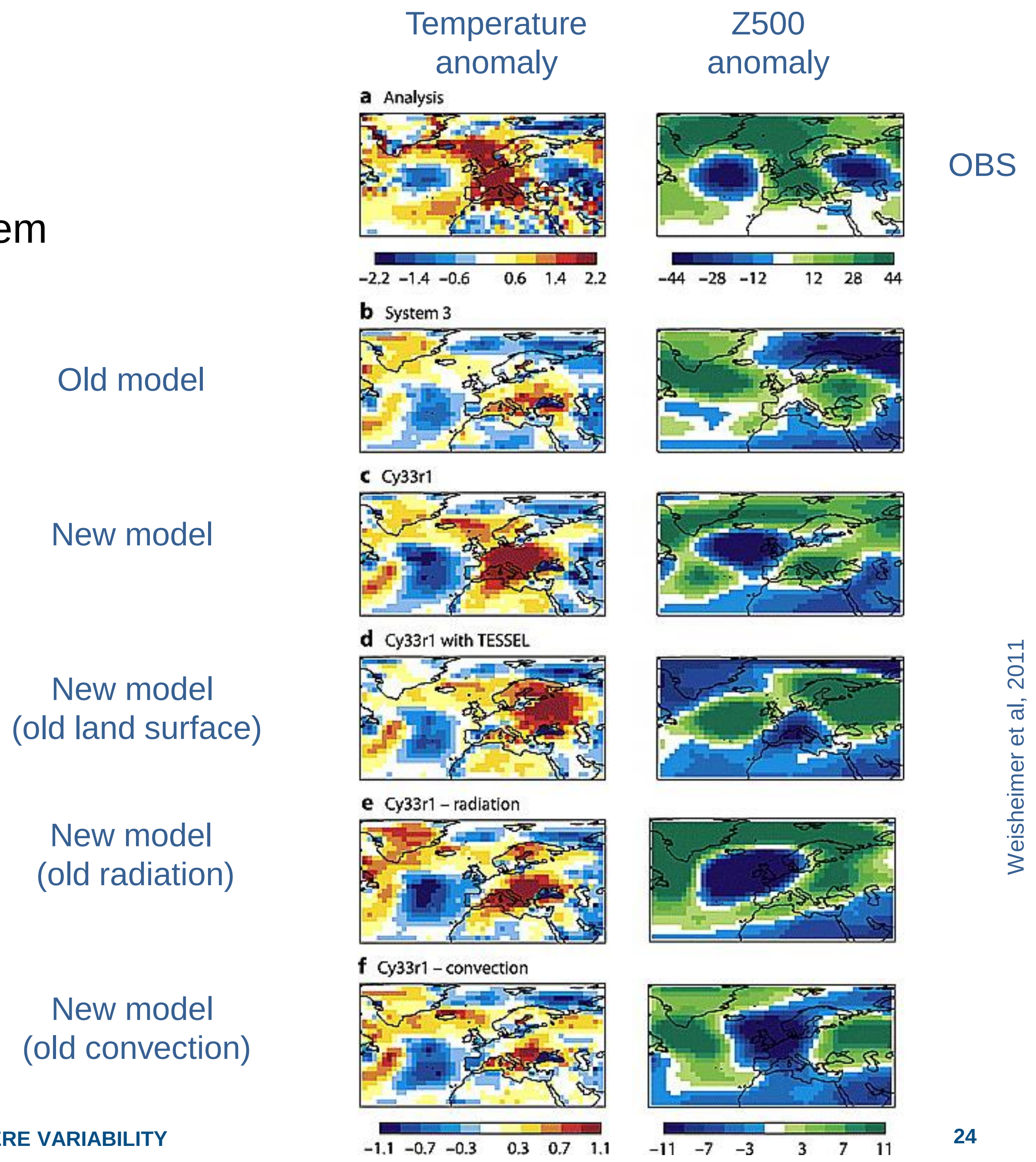


Ardilouze et al, 2017

Prediction of an individual event

- European heat wave 2003
- Different set-ups of ECMWF forecasting system

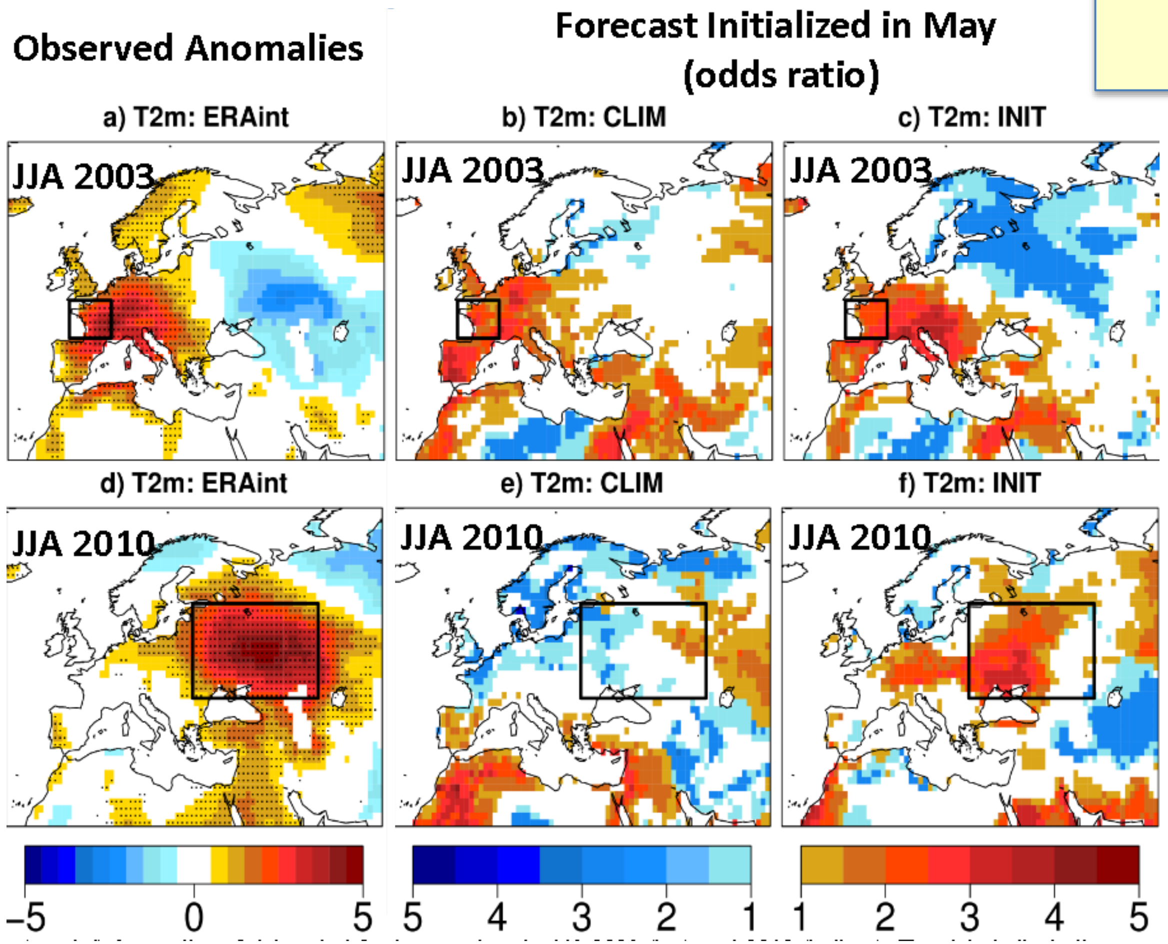
Combination of land surface and atmosphere is needed to improve forecasts



New study, somewhat different results again

- 5 models, comparing INIT with CLIM initialization
- Start date 1 May, evaluation JJA

European heatwave 2003 is less affected by soil than Russian heatwave 2010

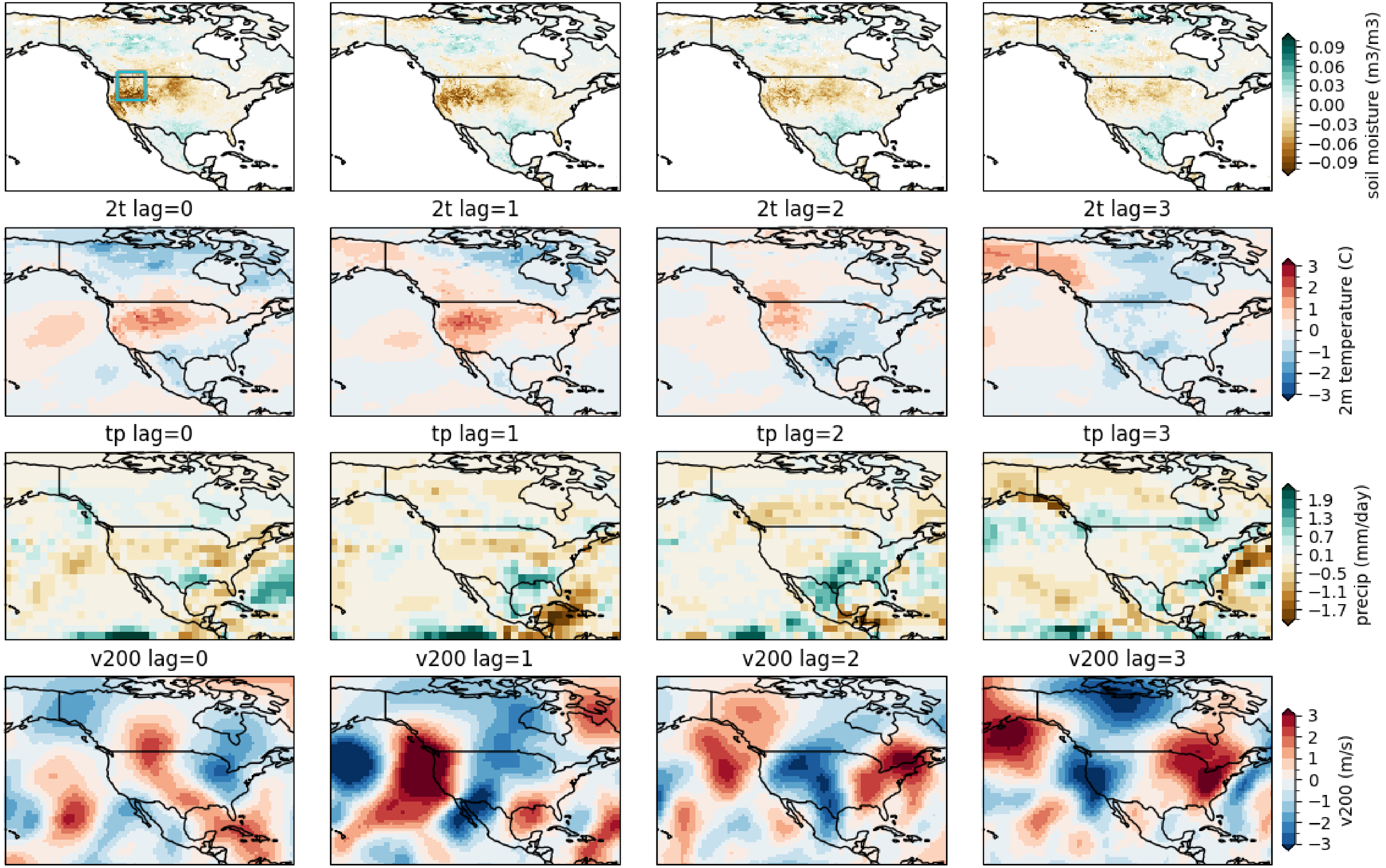


Prodhomme et al, 2015

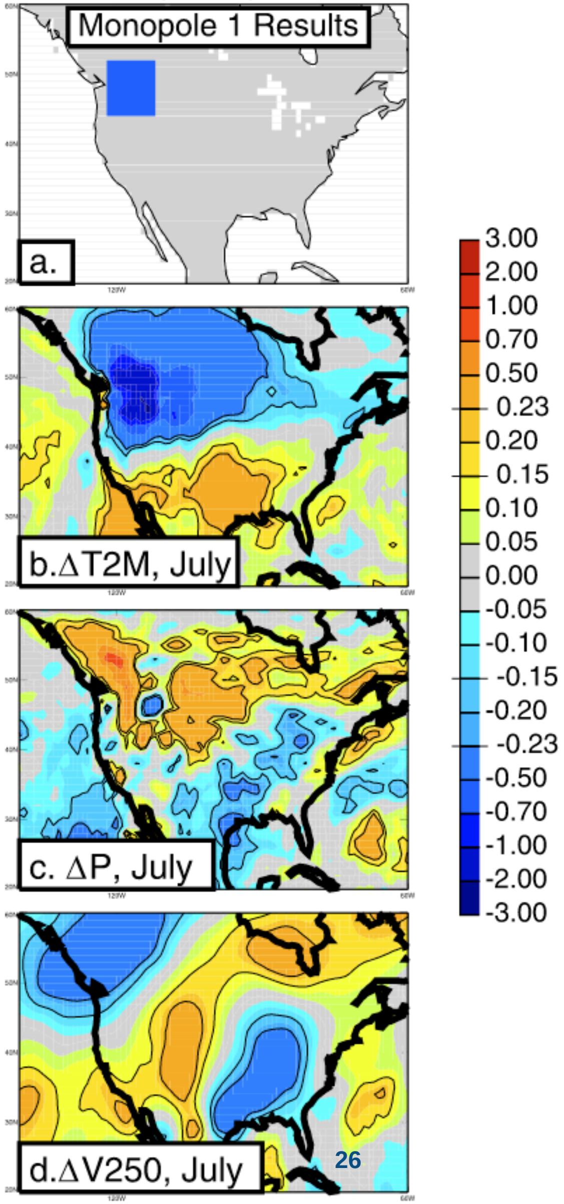
Odds ratio: relative enhancement of probability of being in either the upper (red) or lower (blue) quintile. So a value of 3 means a 60% chance of being in the uppermost/lowermost quintile category.

Remote responses to May soil-moisture anomalies

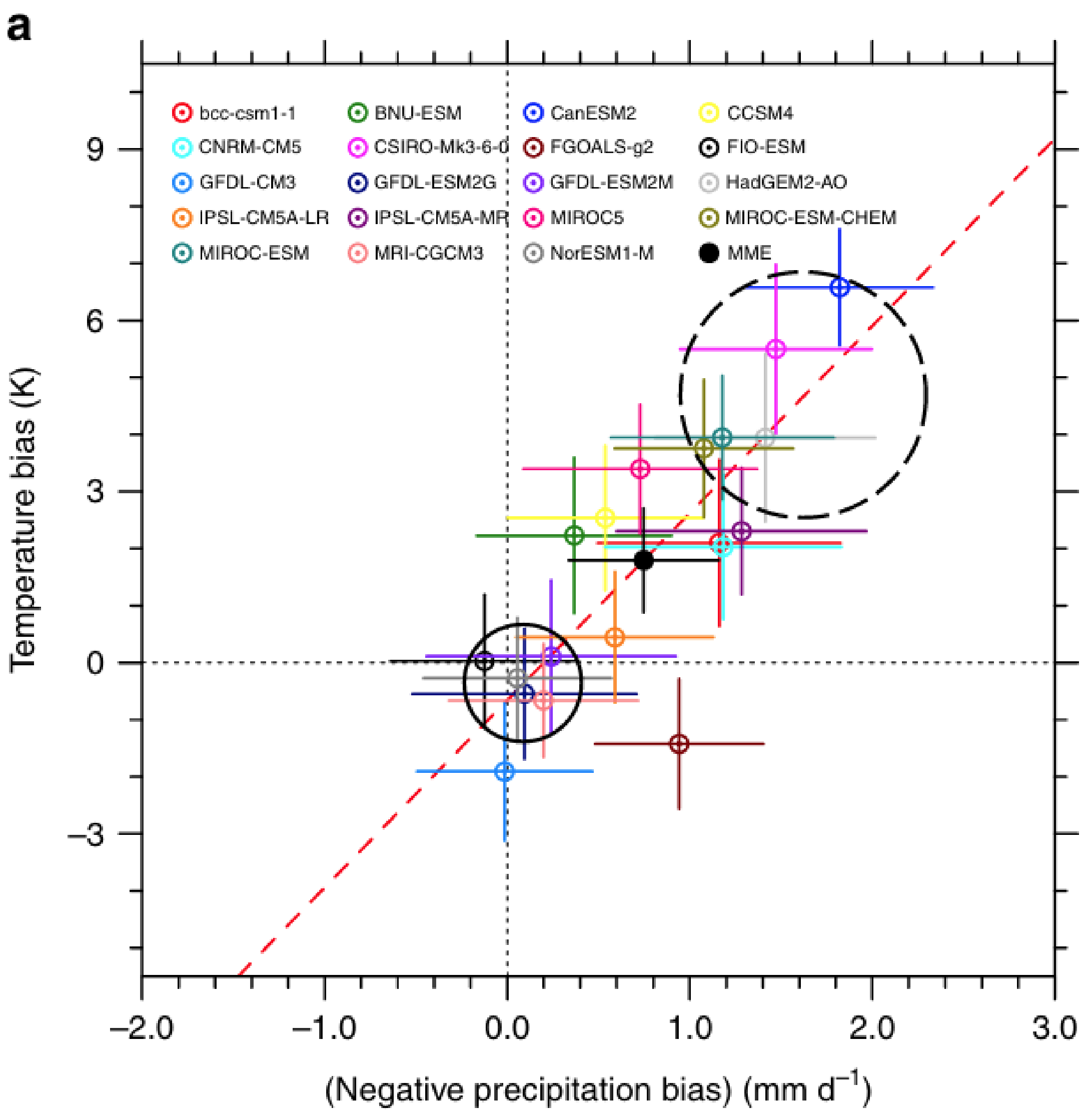
May June Jul Aug

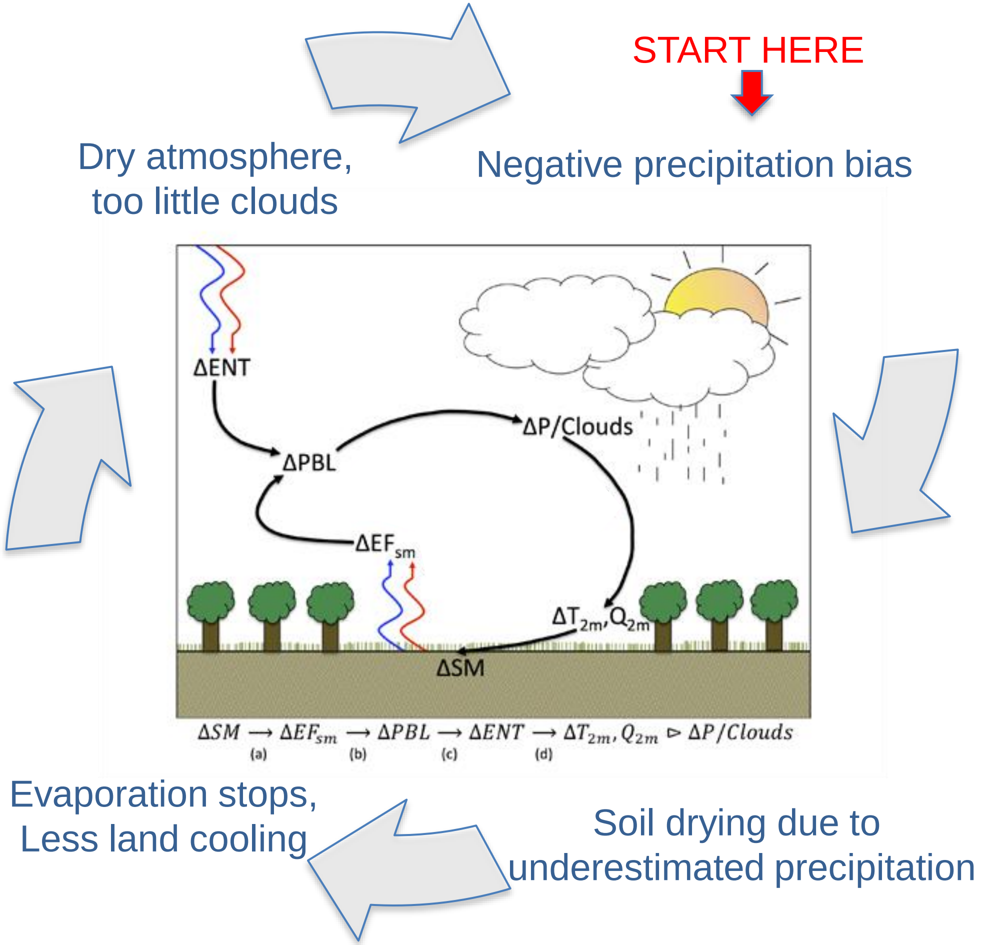


Model results: Koster et al., (2014)



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





Lin et al., 2017
Nat Comm

New developments

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.

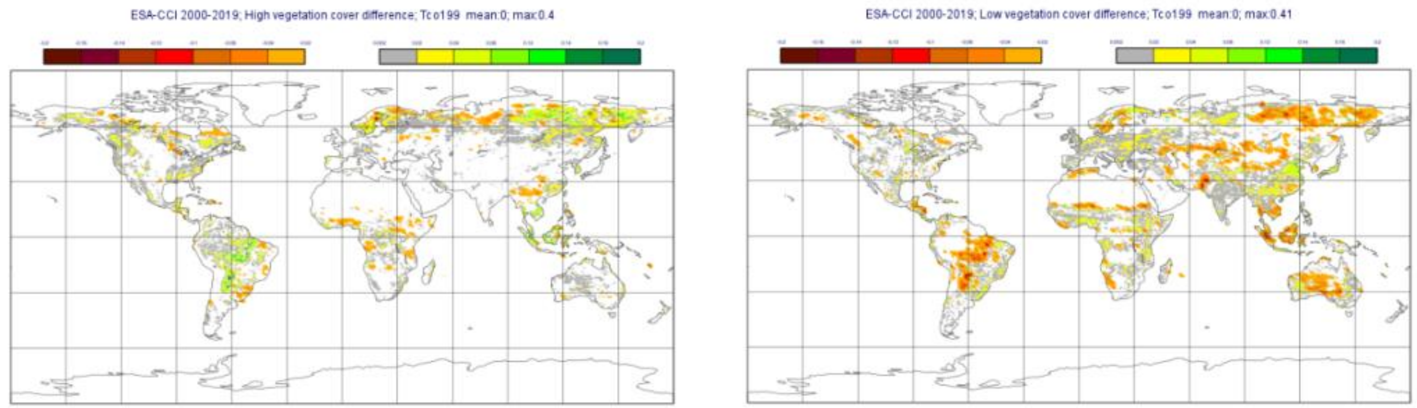


Figure 3: Vegetation cover differences between 2000 minus 2019 (right) for low vegetation and (left) for high vegetation covers.

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

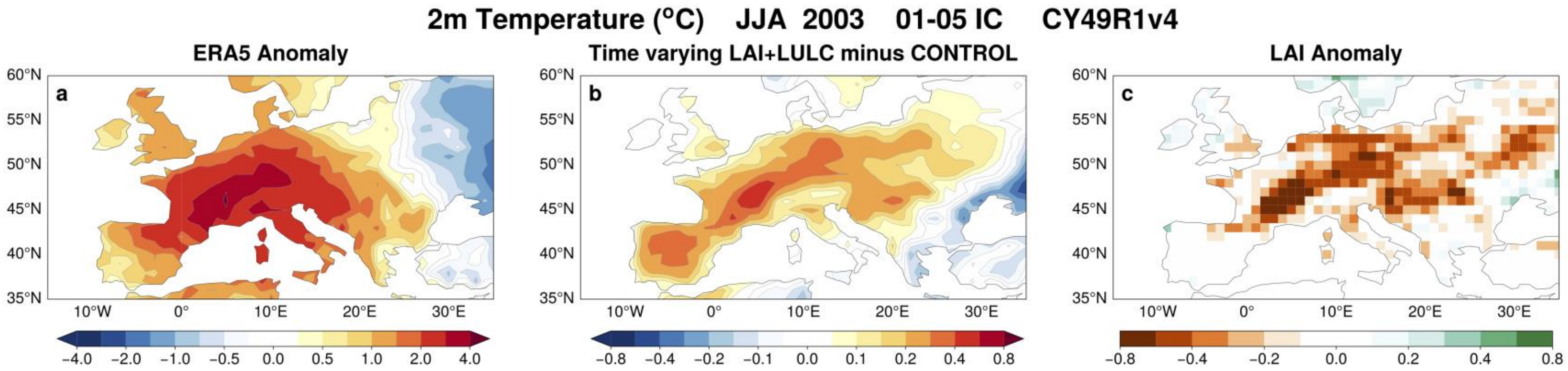


Figure: June-to-August 2003 seasonal mean 2m temperature over Europe: (a) ERA5 anomaly and (b) difference between LAI+LULC and CONTROL experiments. Also plotted in (c) is the Leaf Area Index anomaly.

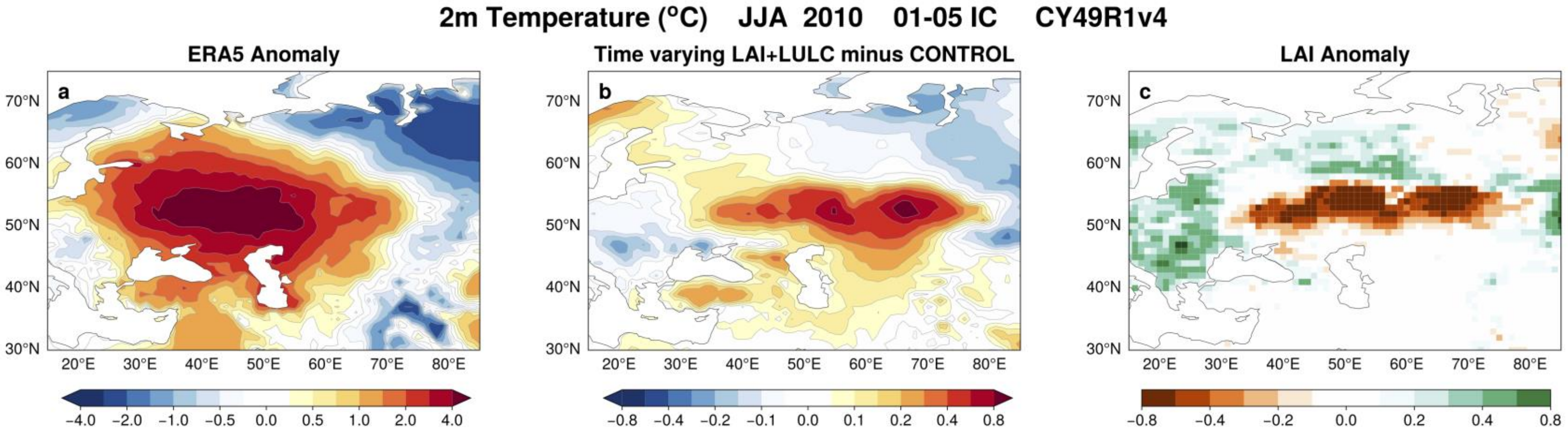
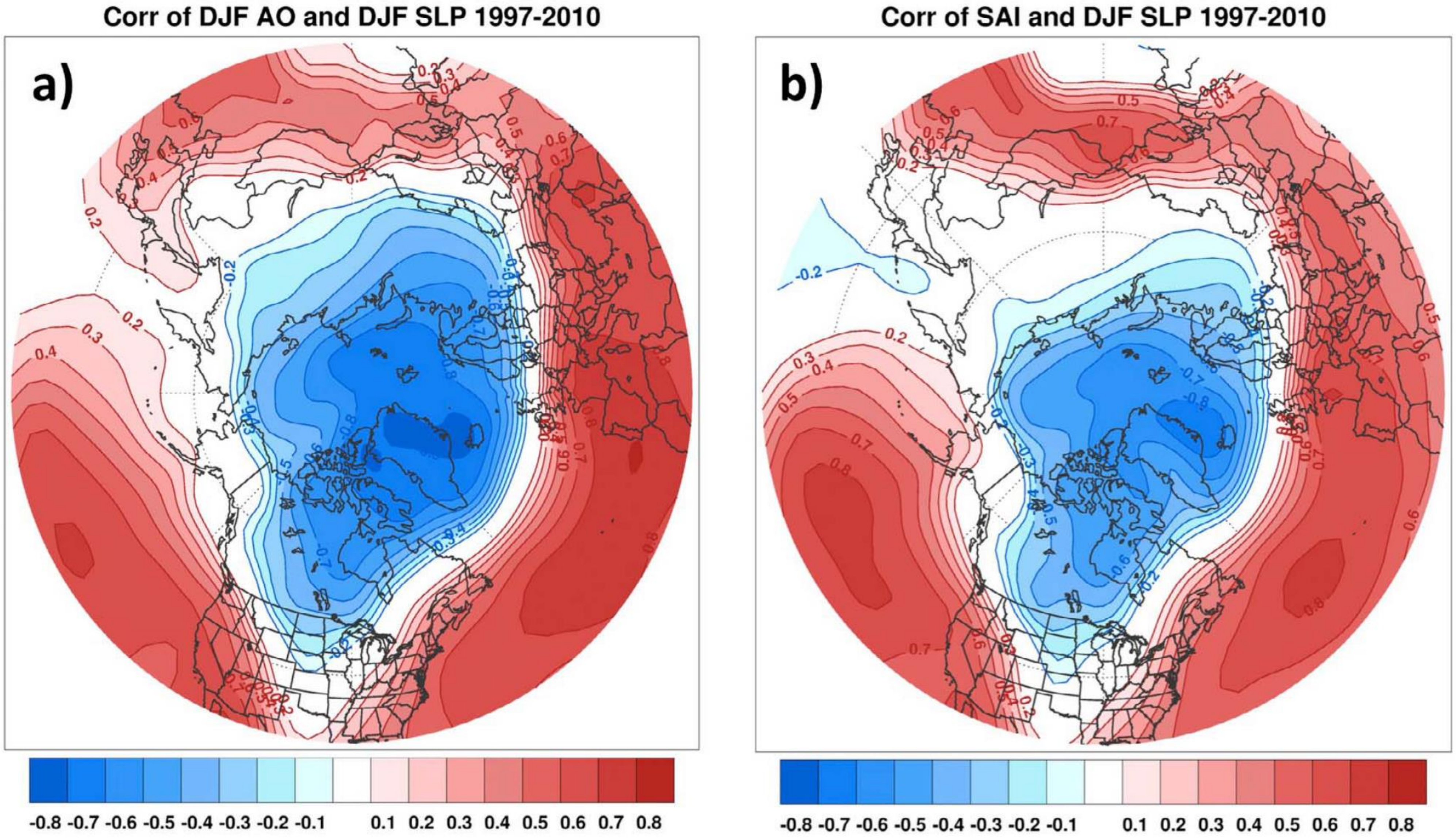


Figure: Same as above, but for 2010.

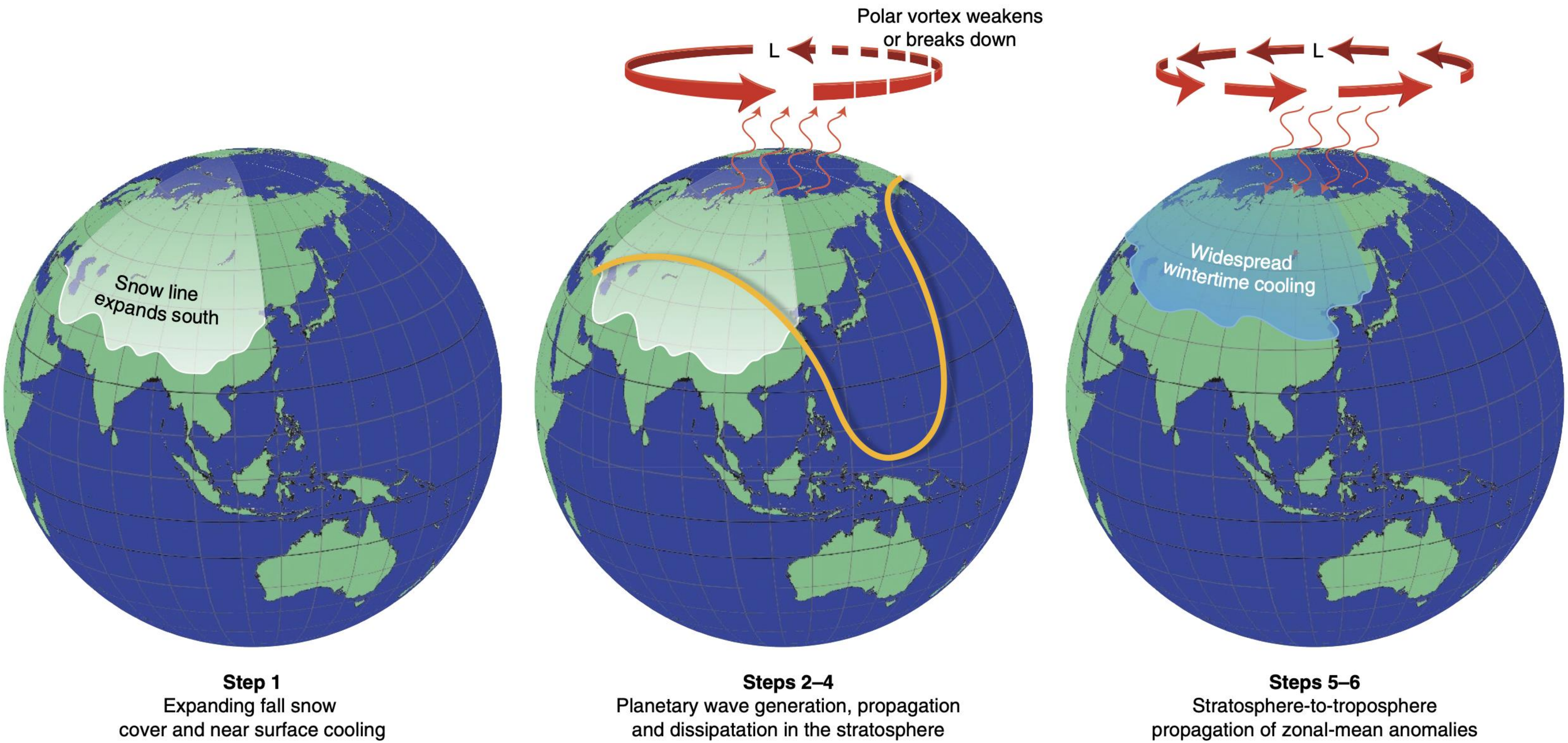
Slide from Retish Senan

Snow cover as a predictor of the Arctic Oscillation



Cohen and Jones (2011)

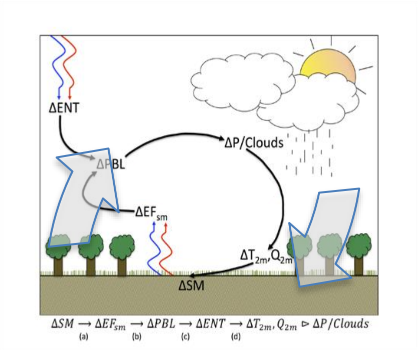
A mechanistic view of remote response to snowcover

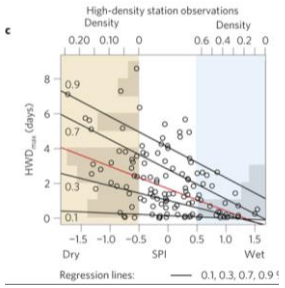


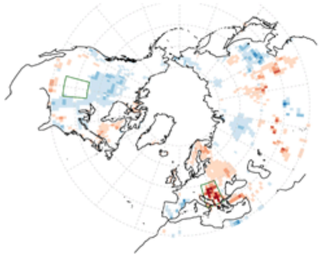
Henderson et al., (2018), Nat Clim

Summary

- For land-related predictability we need
  - Variability
  - Memory (soil moisture, snow mass, vegetation, …)
  - Coupling
- Predictability affects multiple time scales which can interact
  - Predictions of heatwaves → short time scales
  - Predictions of long warm/cool spells → seasonal time scales
- 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.







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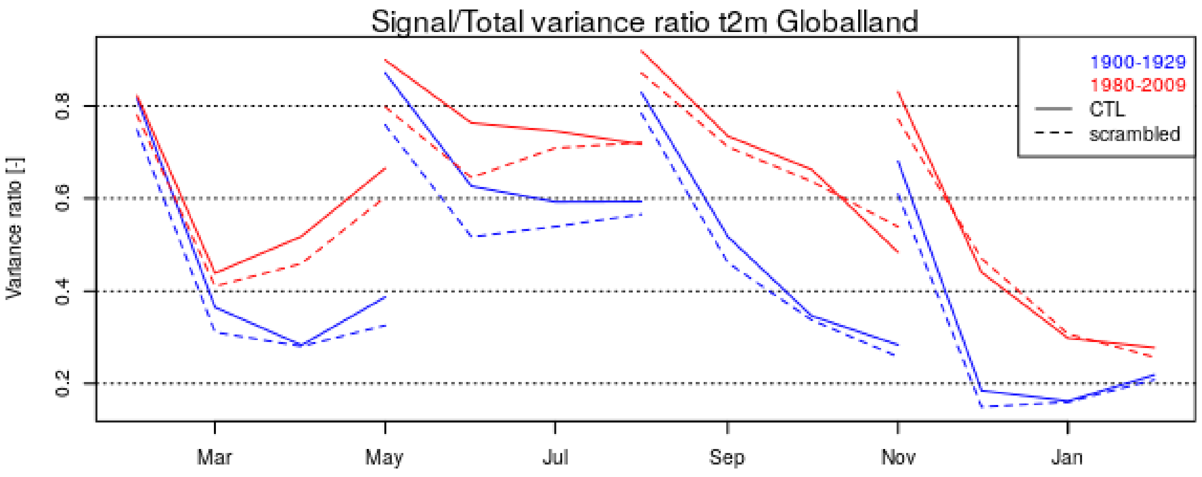
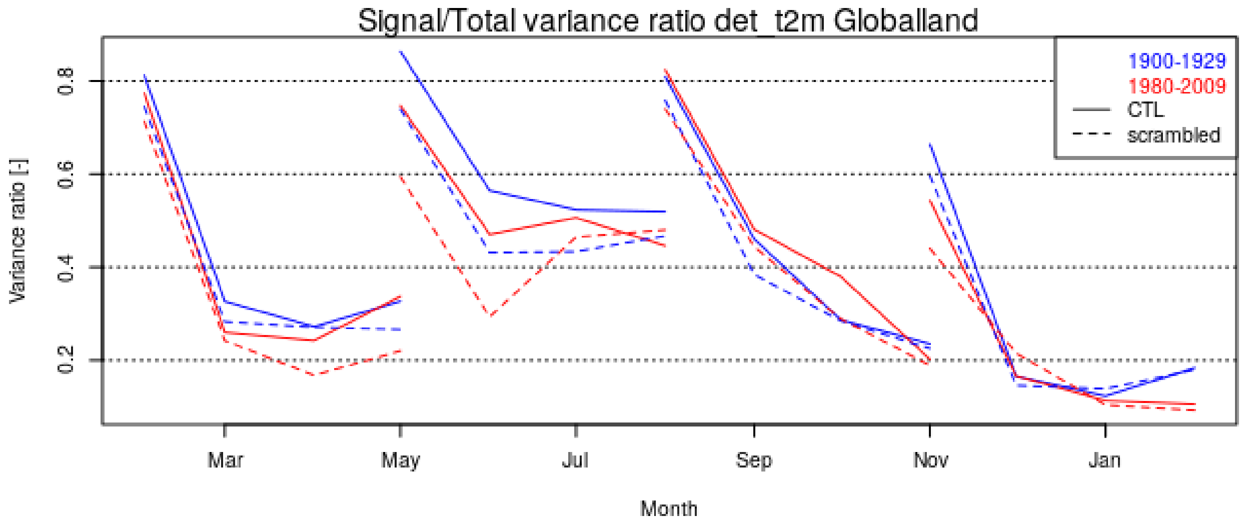
Additional slides

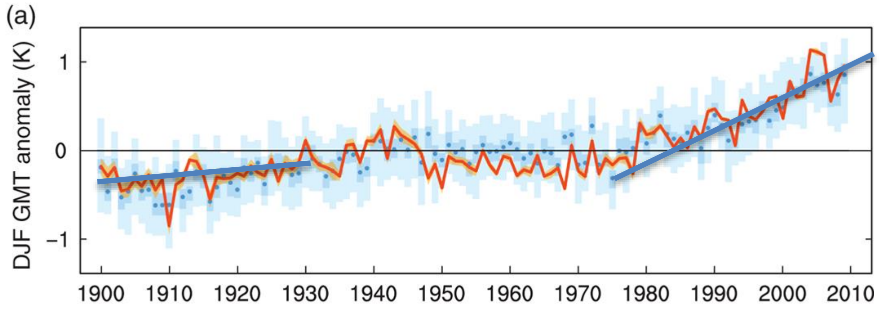
Trend contributes to T2m predictability





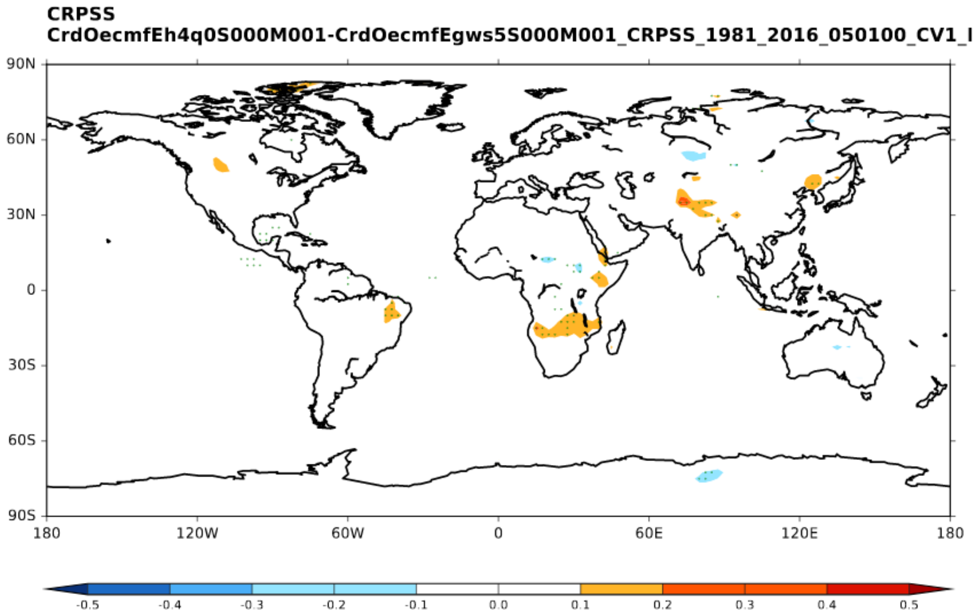
Note: initialized land surface (solid line) gives additional signal in T2m, especially in early summer. Note these plots show predictability not skill – extra skill would require the additional land surface signal to be correct.

Before detrending

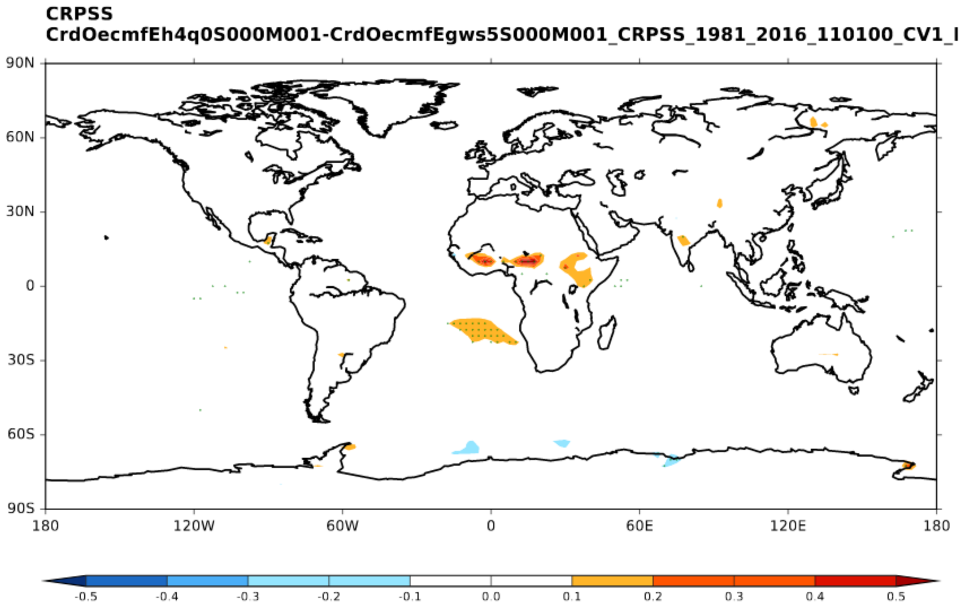


After detrending

Impact on T2m forecast skill of improved land surface initial conditions



JJA



DJF

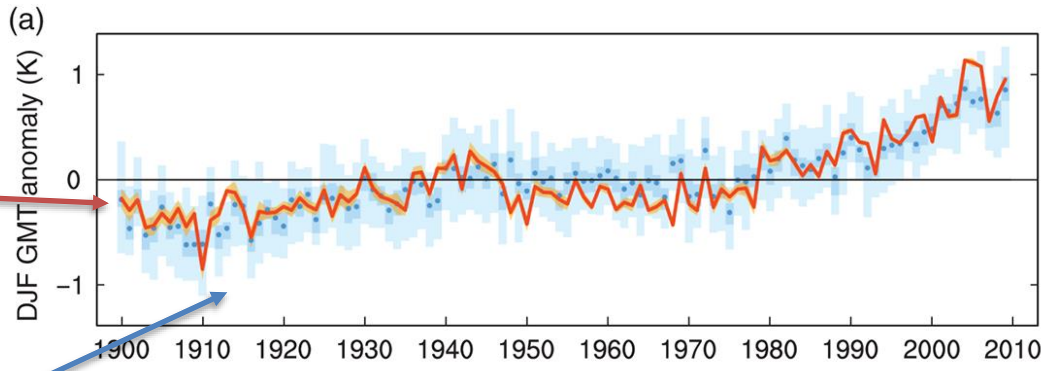
Difference in CRPSS skill from 36 years of re-forecasts with 51 member ensembles, comparing Cy46r1 (ERA5 ICs) and Cy45r1 (SEAS5 ICs). Sensitivity experiments (lower resolution, smaller ensemble size) confirm that the main driver of improvement is change in ICs, not the model.

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

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

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



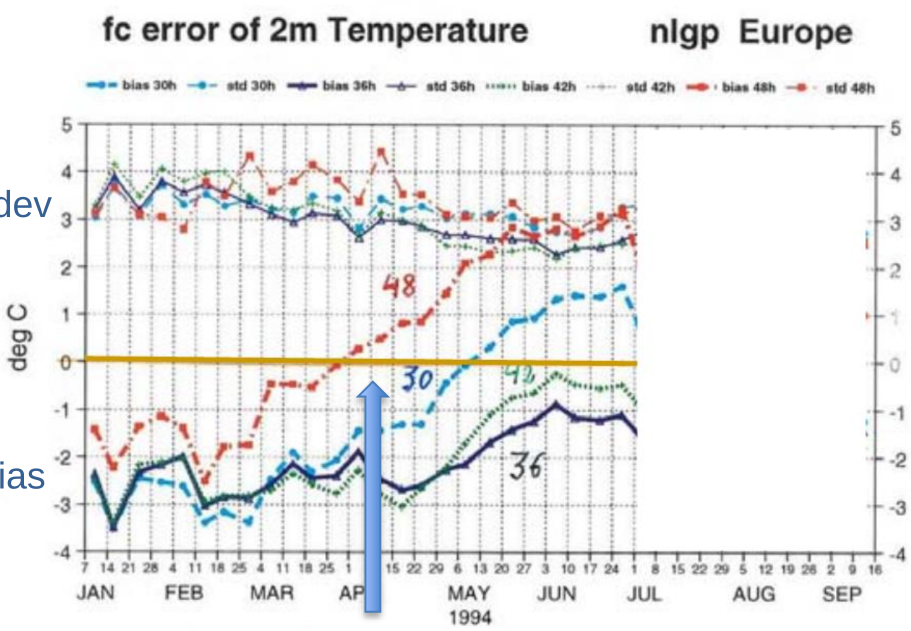
An anecdote demonstrating impact of soil moisture

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

stddev

Model normally too cold

bias

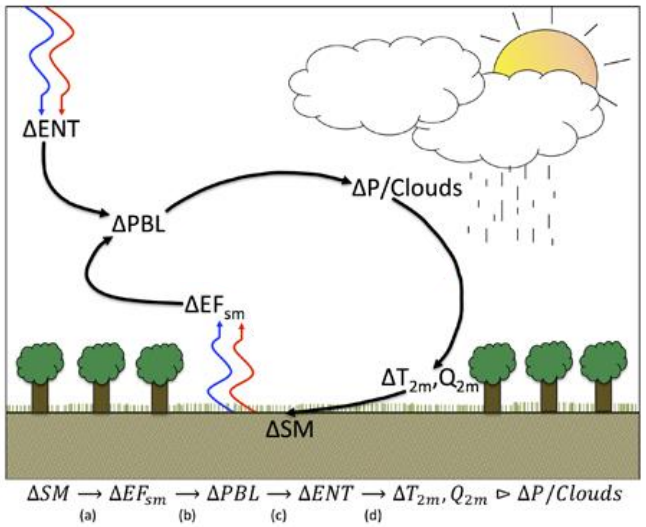


Suddenly extreme warm dry drift

START HERE

Dry atmosphere, too little clouds

Positive radiation bias



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)