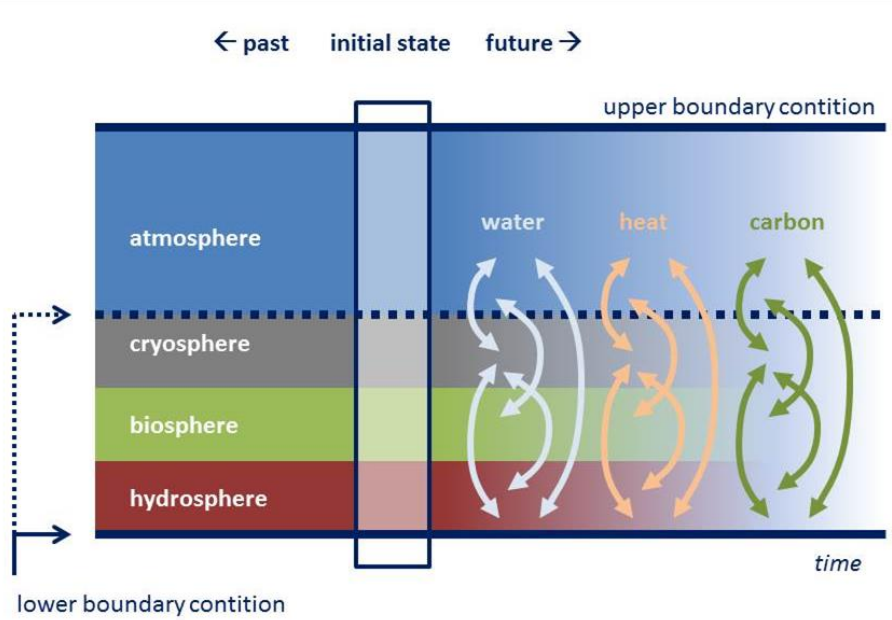
Coupled land-atmosphere variability: does land contribute to predictability?

Bart van den Hurk

Visiting scientist @ECMWF Mar-May 2017

Bart.vandenhurk@ecmwf.int



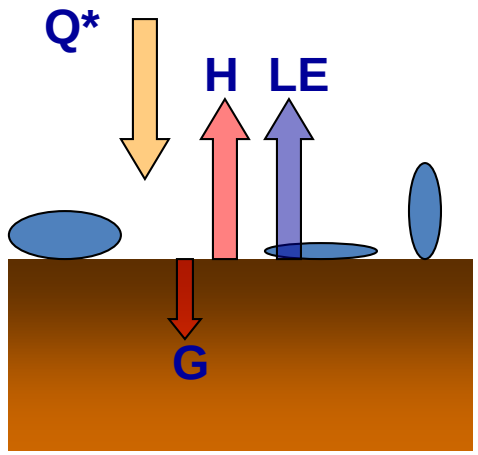
Why do we care about land processes?

- 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%

Why do we care about land processes?

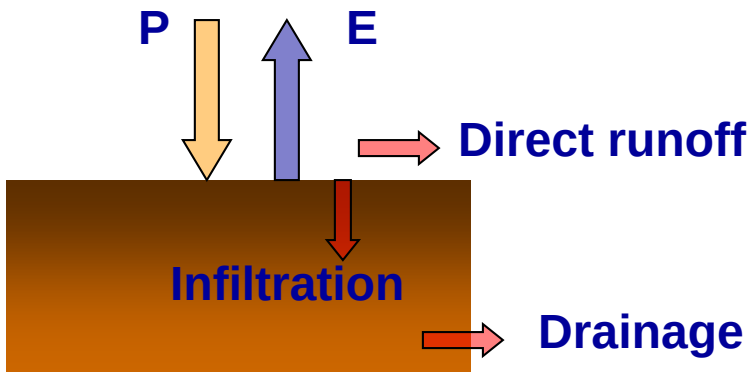
- Energy-budget
  - Albedo
  - Evaporative fraction



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

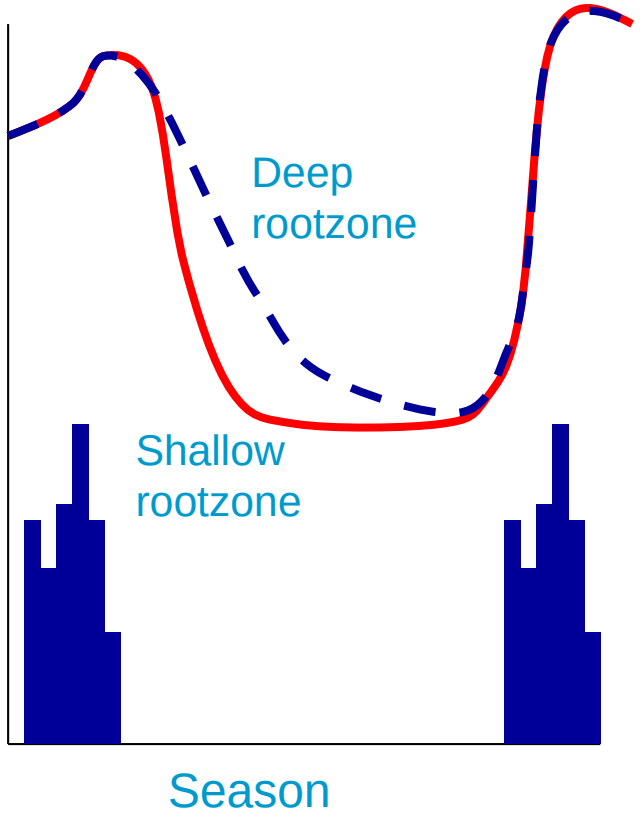
Why do we care about land processes?

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



Landprocesses in atmospheric models

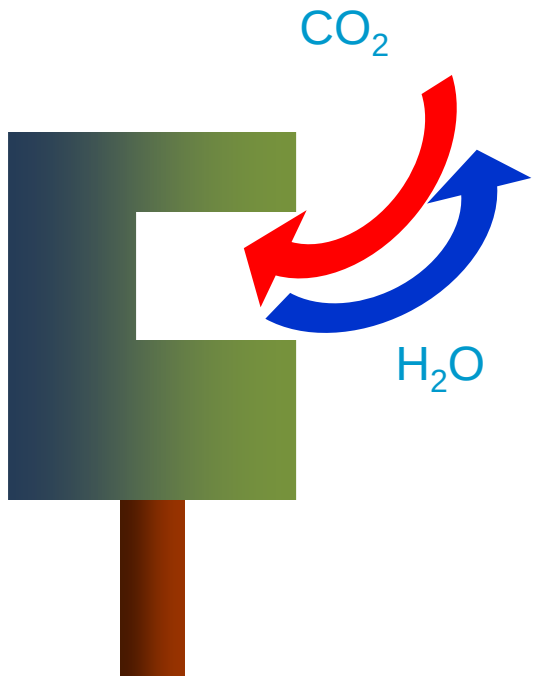
- Energy-budget
  - Albedo
  - Evaporative fraction
- Water budget
  - Runoff-fraction
  - Soil water reservoir



ECMWF

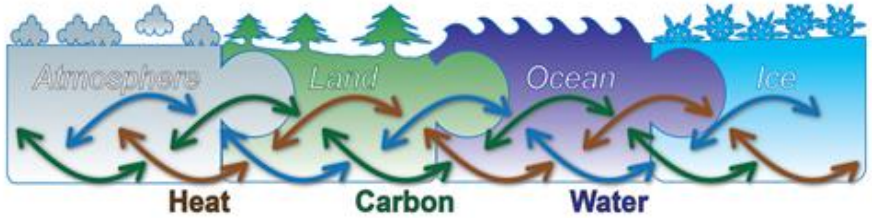
Landprocesses in atmospheric models

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

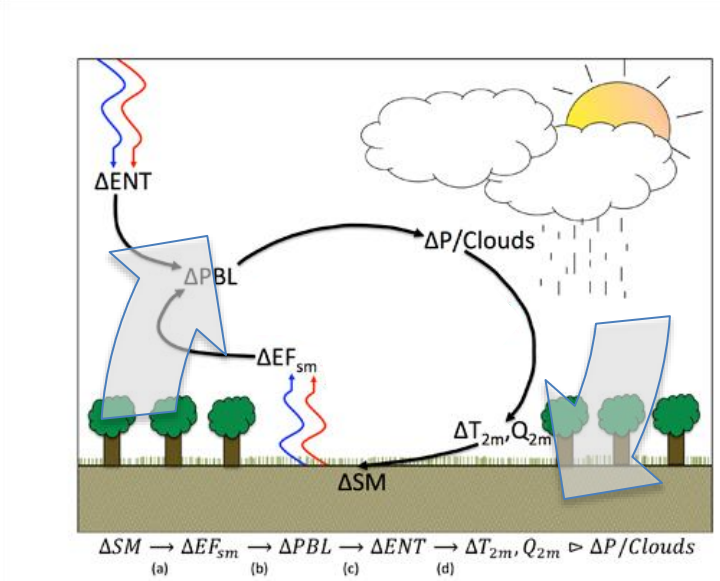


What is needed to contribute to predictability?

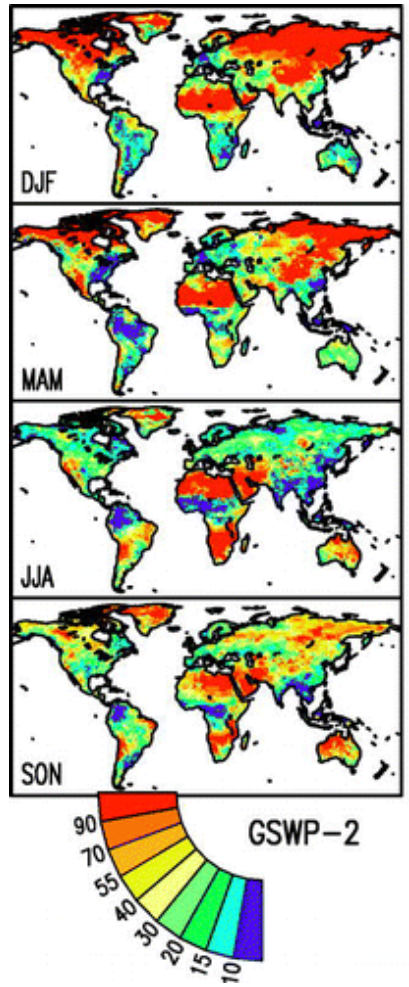
- In the climate system all processes are connected



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



Dirmeyer et al, 2009

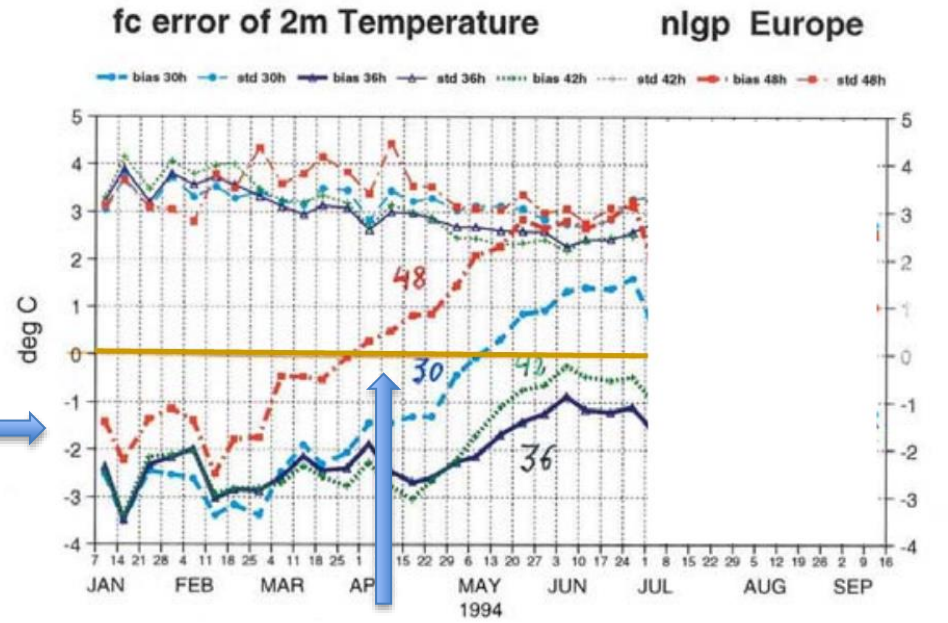


ECMWF

An anecdote demonstrating impact of soil moisture

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

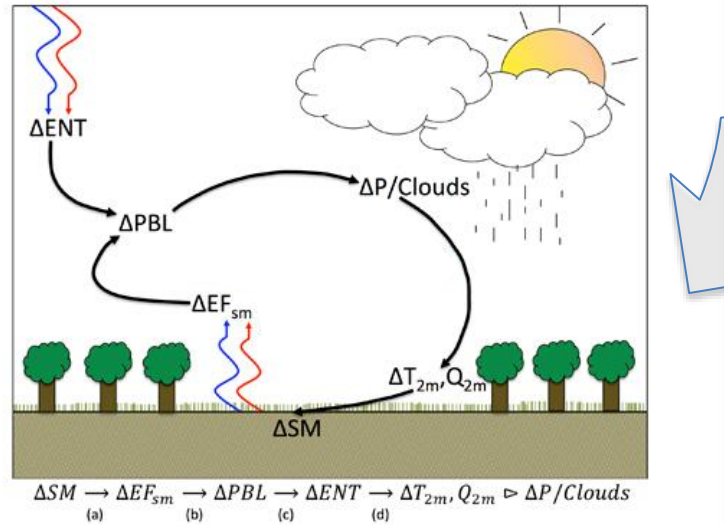
Model normally too cold



Suddenly extreme warm dry drift

Dry atmosphere, too little clouds

Positive radiation bias



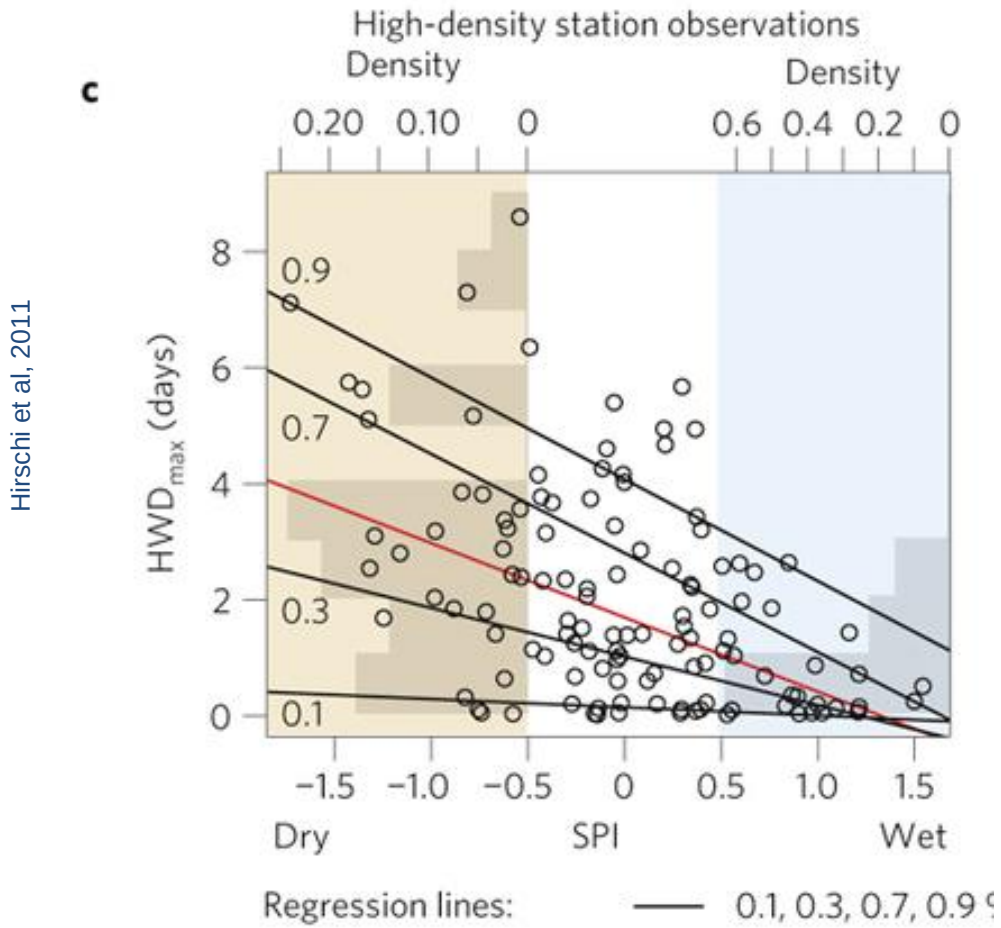
Evaporation stops, Less land cooling

Soil drying due to overestimated evaporation

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

Measures to quantify land-atmosphere coupling

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



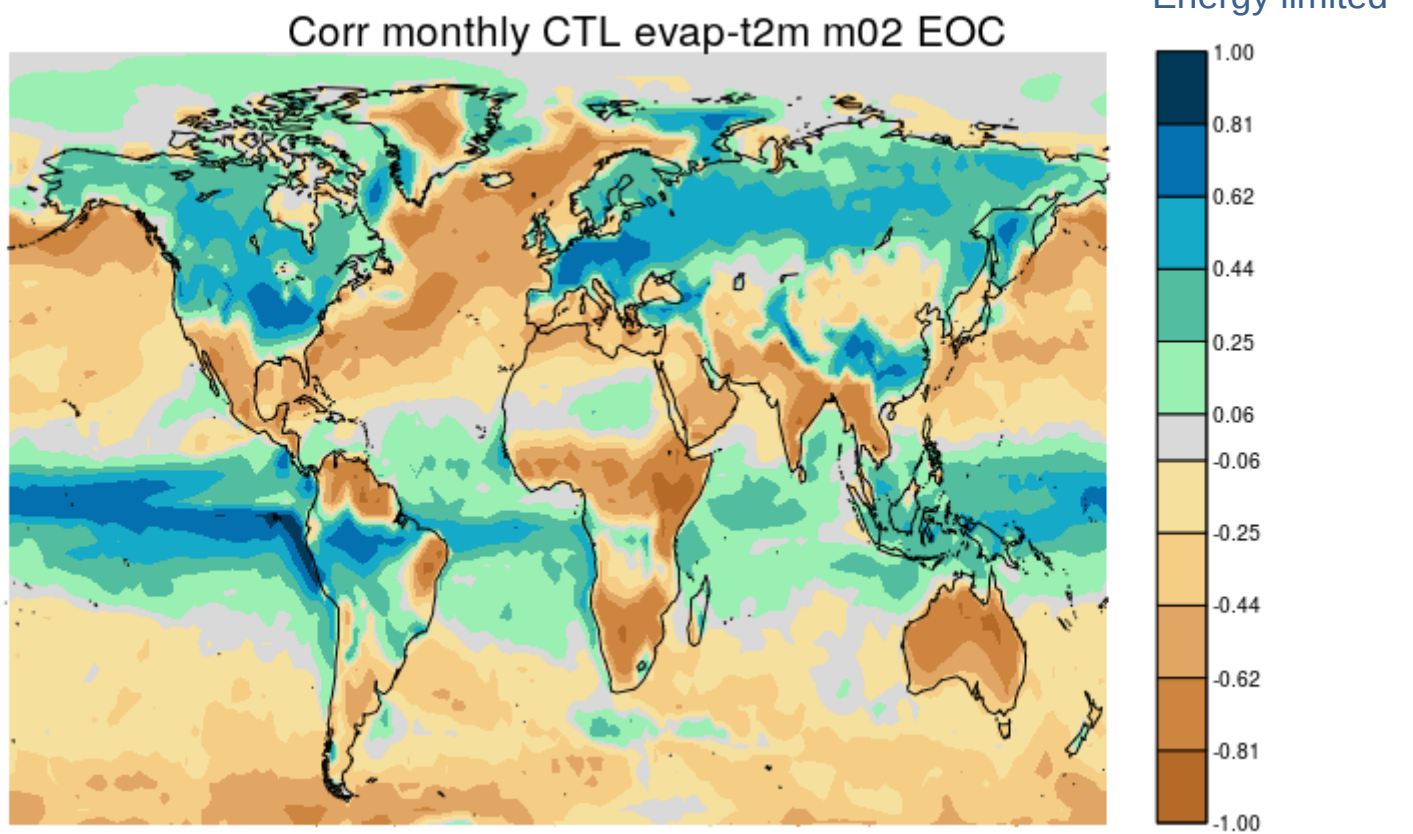
Hirschi et al, 2011

Predictability over wet conditions better than over dry conditions

Measures to quantify land-atmosphere coupling

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

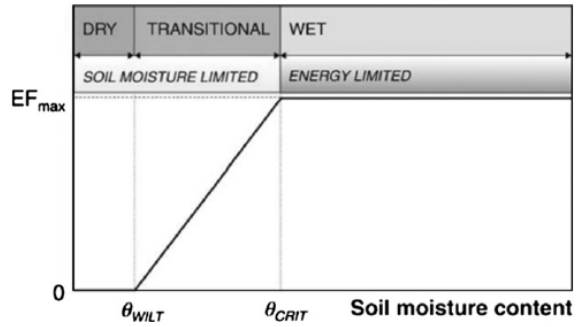
Feb-Apr



Energy limited

Soil water limited

Seneviratne et al, 2010

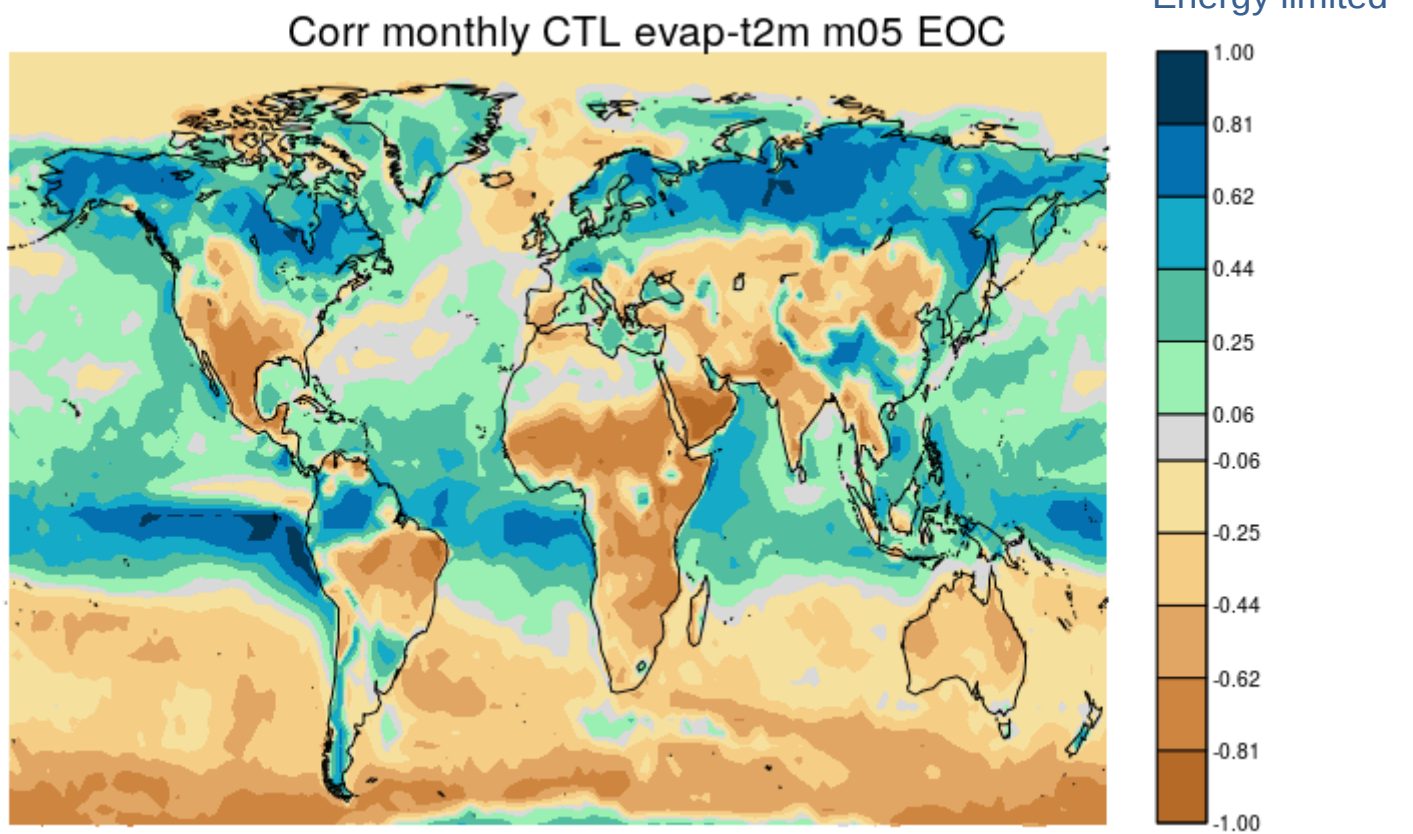


ECMWF

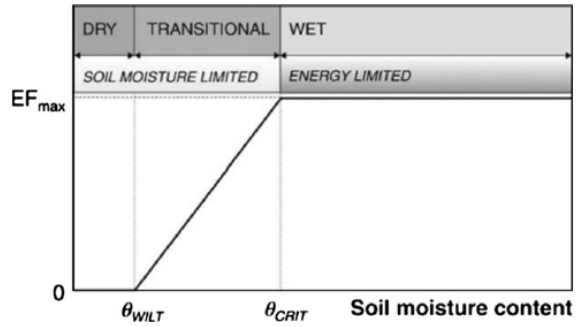
Measures to quantify land-atmosphere coupling

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

May-Jul



Seneviratne et al, 2010

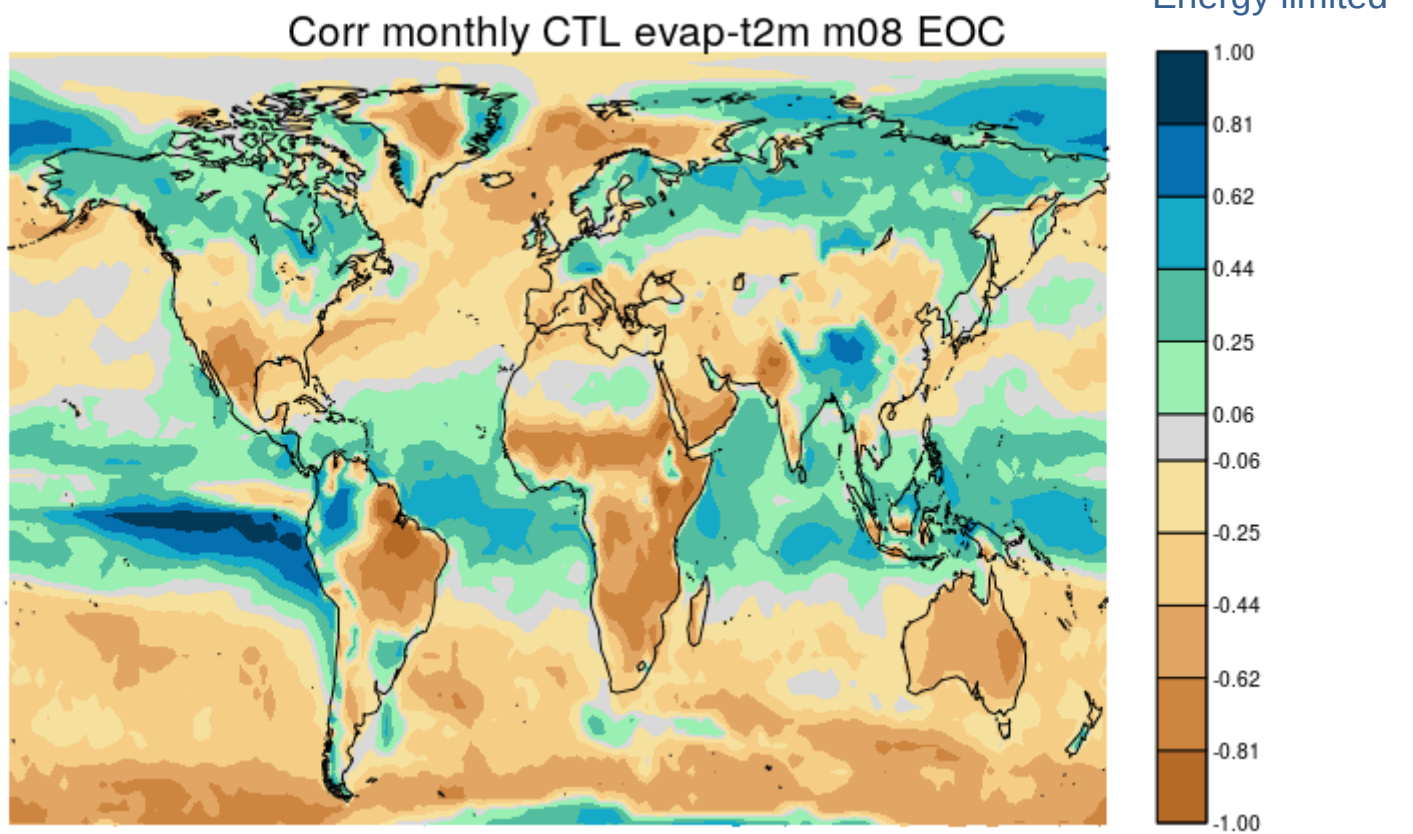


ECMWF

Measures to quantify land-atmosphere coupling

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

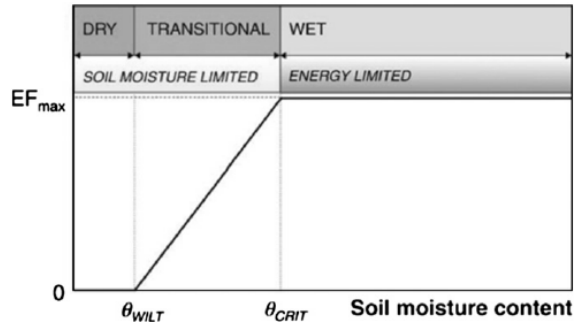
Aug-Oct



Energy limited

Soil water limited

Seneviratne et al, 2010

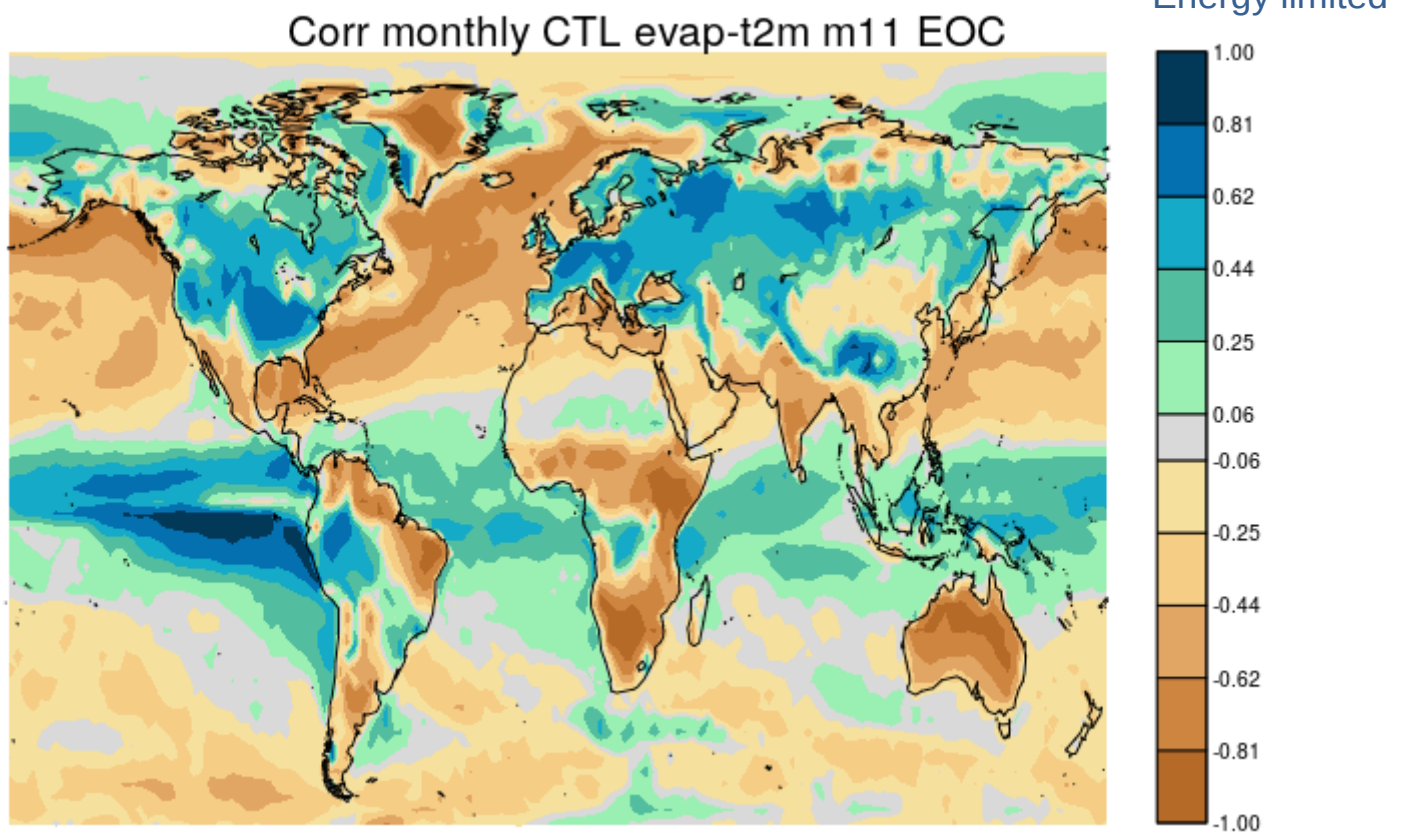


ECMWF

Measures to quantify land-atmosphere coupling

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

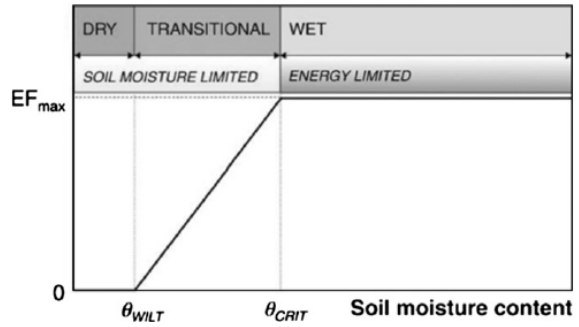
Nov-Jan



Energy limited

Soil water limited

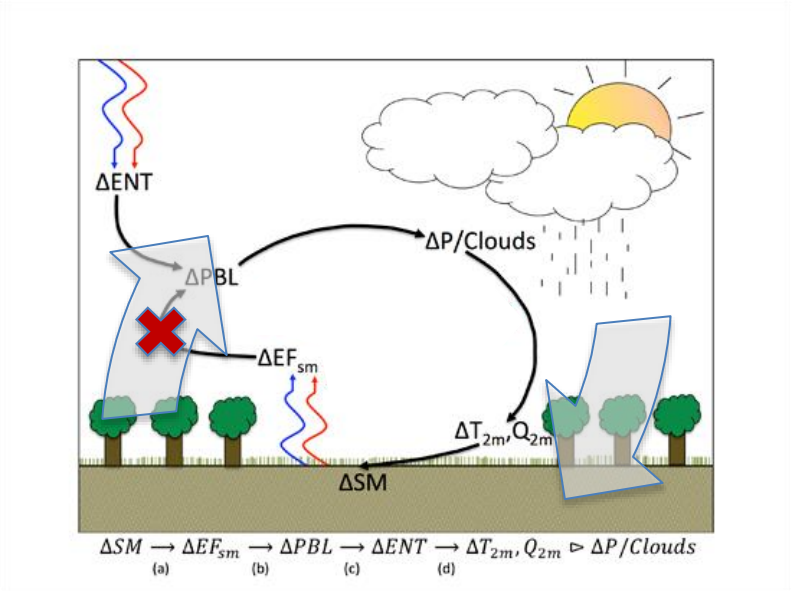
Seneviratne et al, 2010



ECMWF

Measures to quantify land-atmosphere coupling

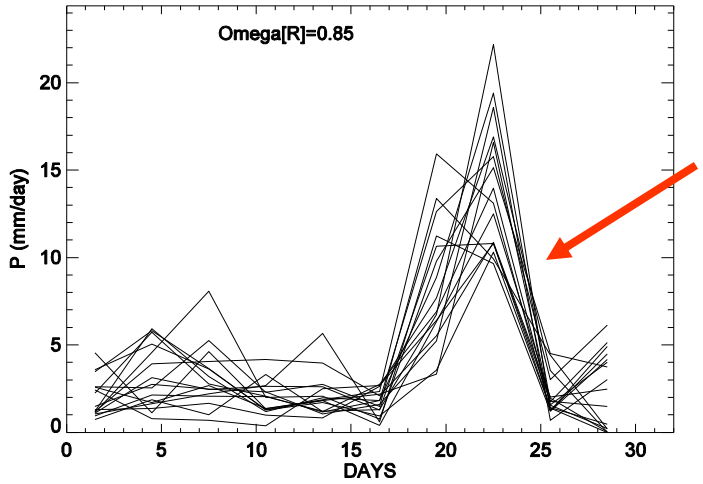
- From a model experiment (GLACE = Global Land Atmosphere Coupling Experiment)
- How?
  - Simulate the hydrological cycle **without** interactive land-atmosphere coupling and compare.
- How?
  - Replace interactive land surface by something that is prescribed and not interactive.
- How to measure the effect?
  - Ensemble simulations
  - Compare within-ensemble spread



ECMWF

GLACE

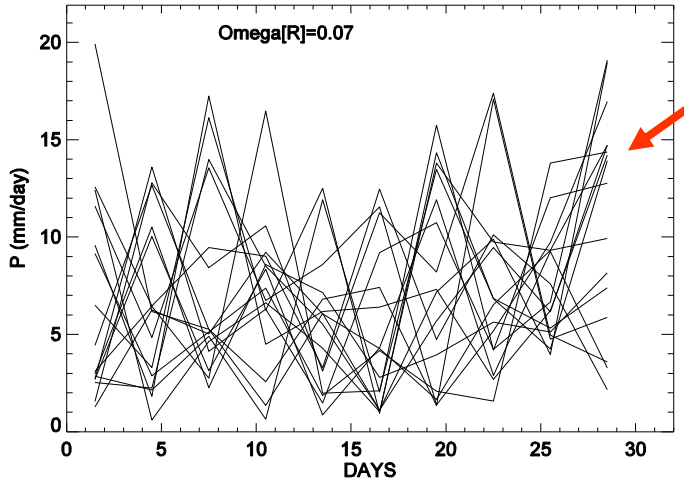
Comparison between ensembles



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

→ strong coupling

$$\Omega = \frac{\sigma_P^2(W) - \sigma_P^2(S)}{\sigma_P^2(W)}$$



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

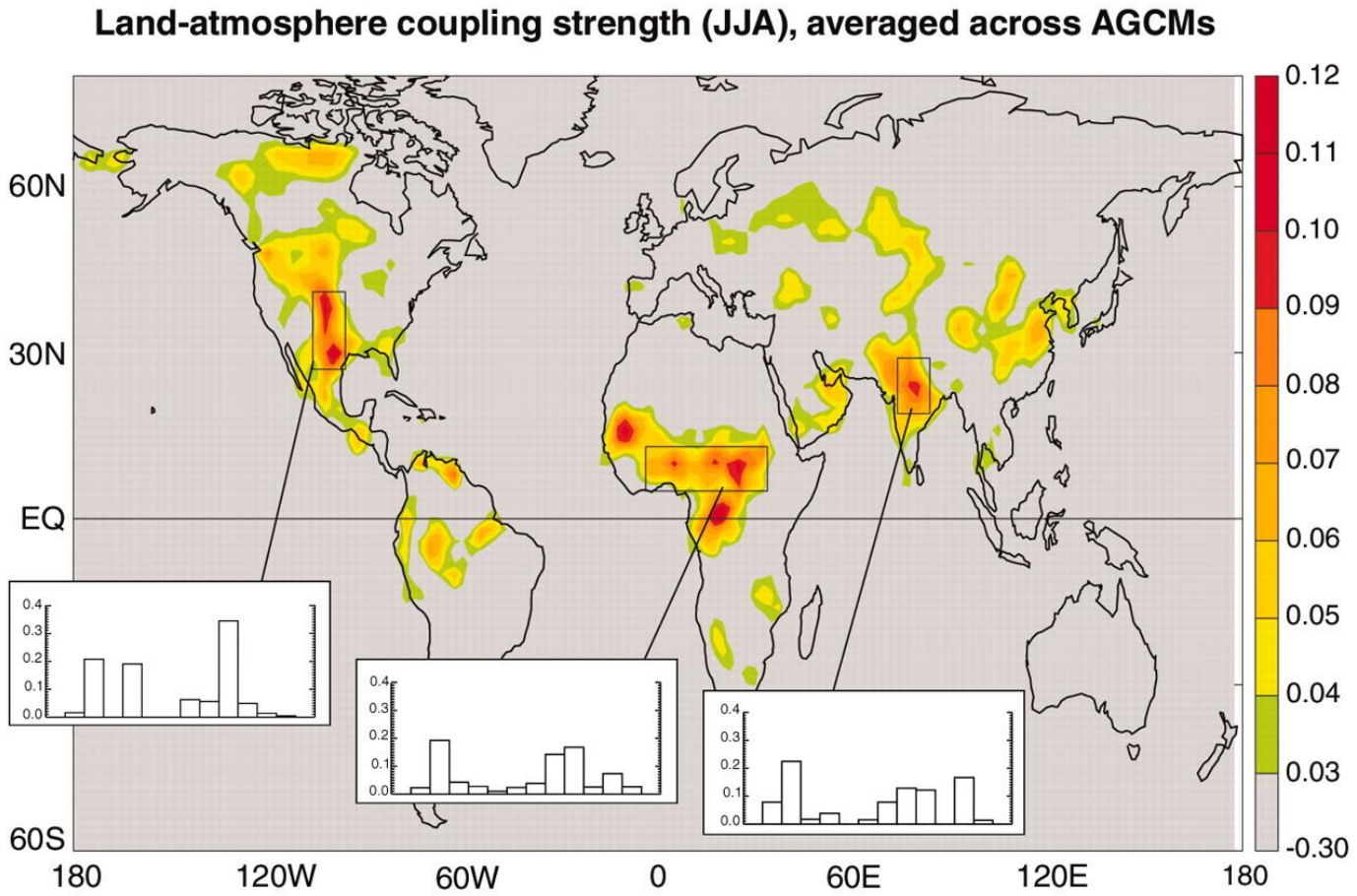
→ weak coupling

ECMWF

Koster et al, 2004, Science

GLACE

Areas with strong feedback



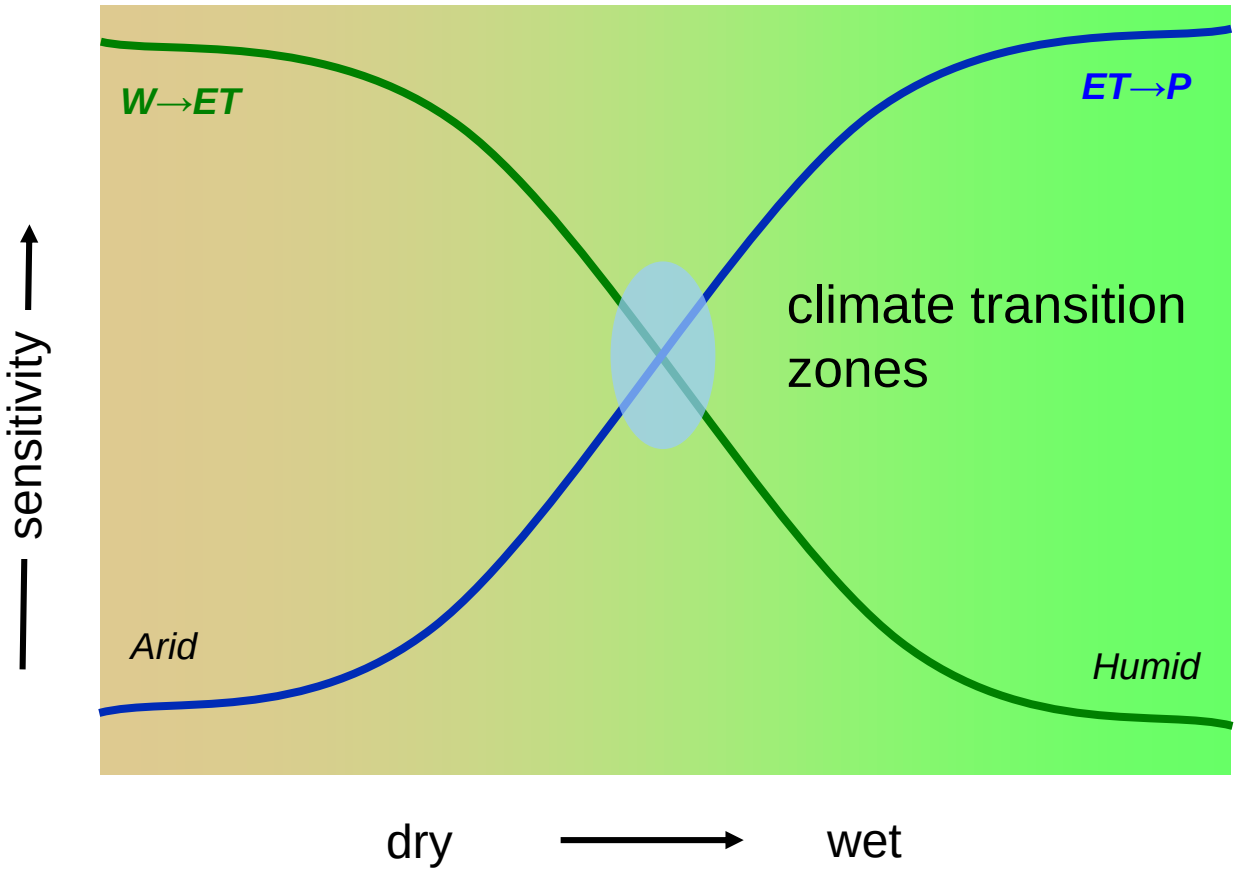
$$\Omega = \frac{\sigma_P^2(W) - \sigma_P^2(S)}{\sigma_P^2(W)}$$

Koster et al, 2004, Science

ECMWF

GLACE

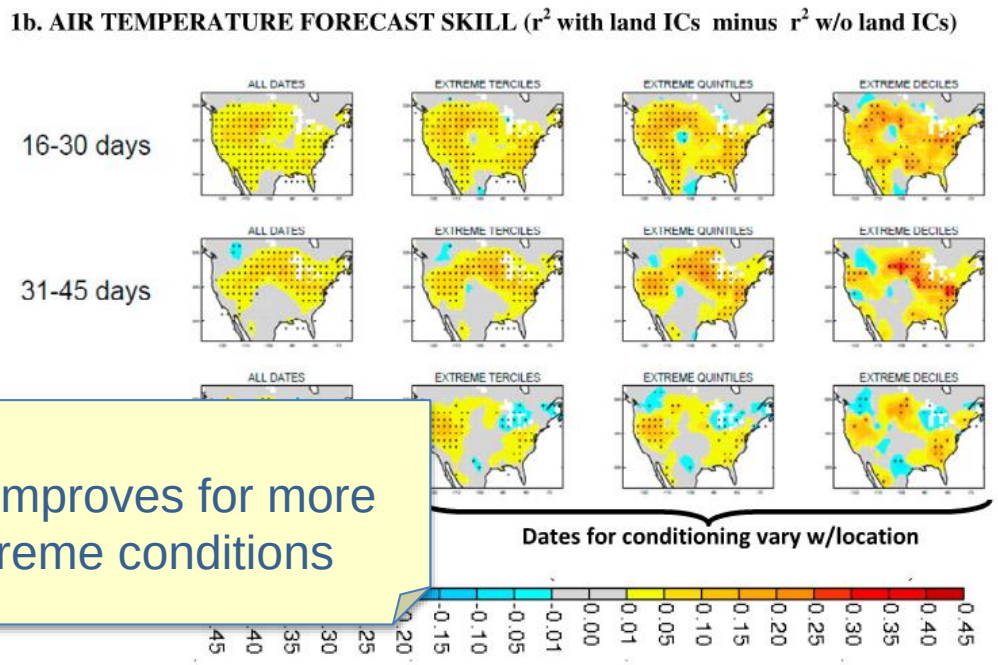
Strong coupling needs combination of sensitivities



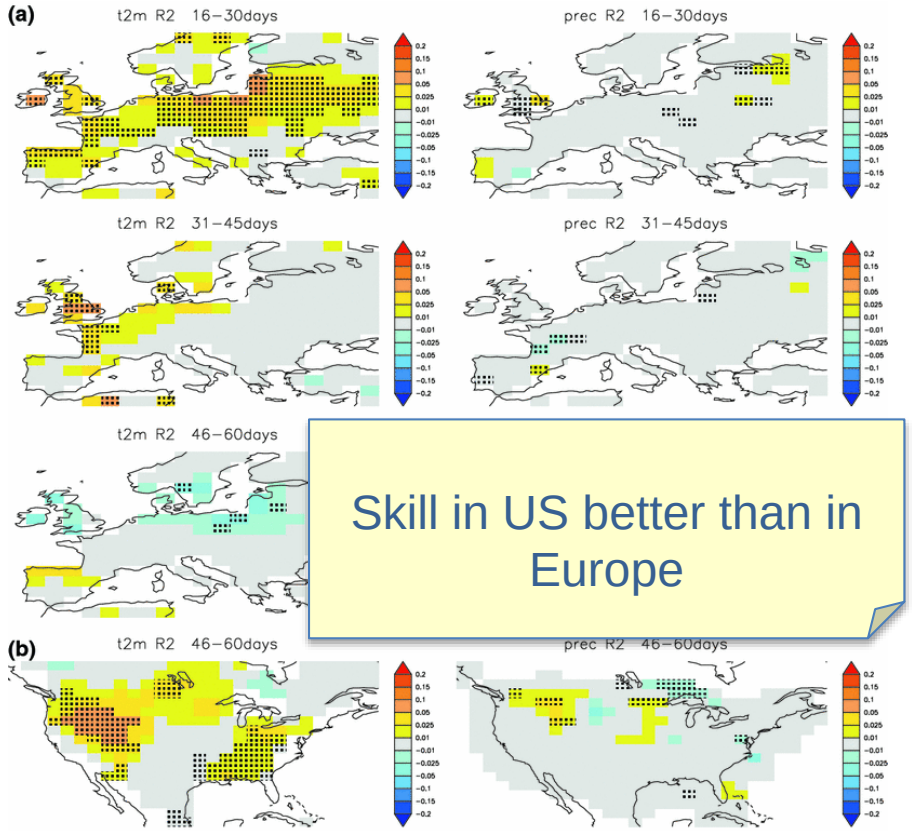
Some “real” land-surface predictability experiments

- 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 improves for more extreme conditions



Skill in US better than in Europe

ECMWF

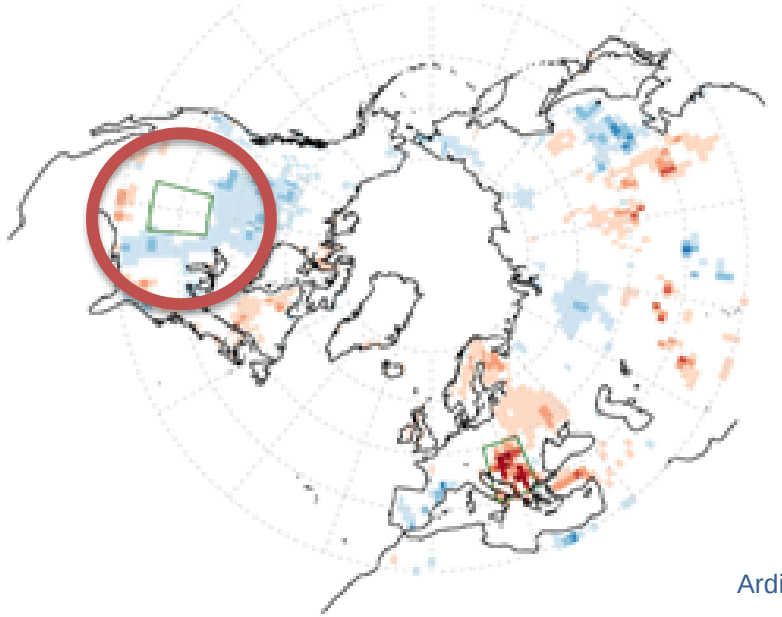
Koster et al, 2010

Similar set-up, different results!

- Similar to GLACE-2, 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

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

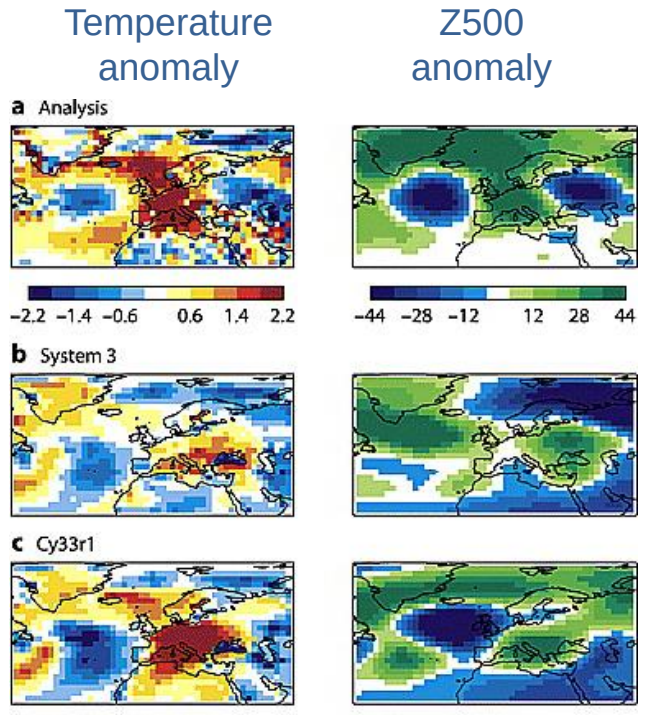


Ardilouze et al, 2017

ECMWF

Prediction an individual event

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



OBS

Old model

New model

Combination of land surface and atmosphere is needed to improve forecasts

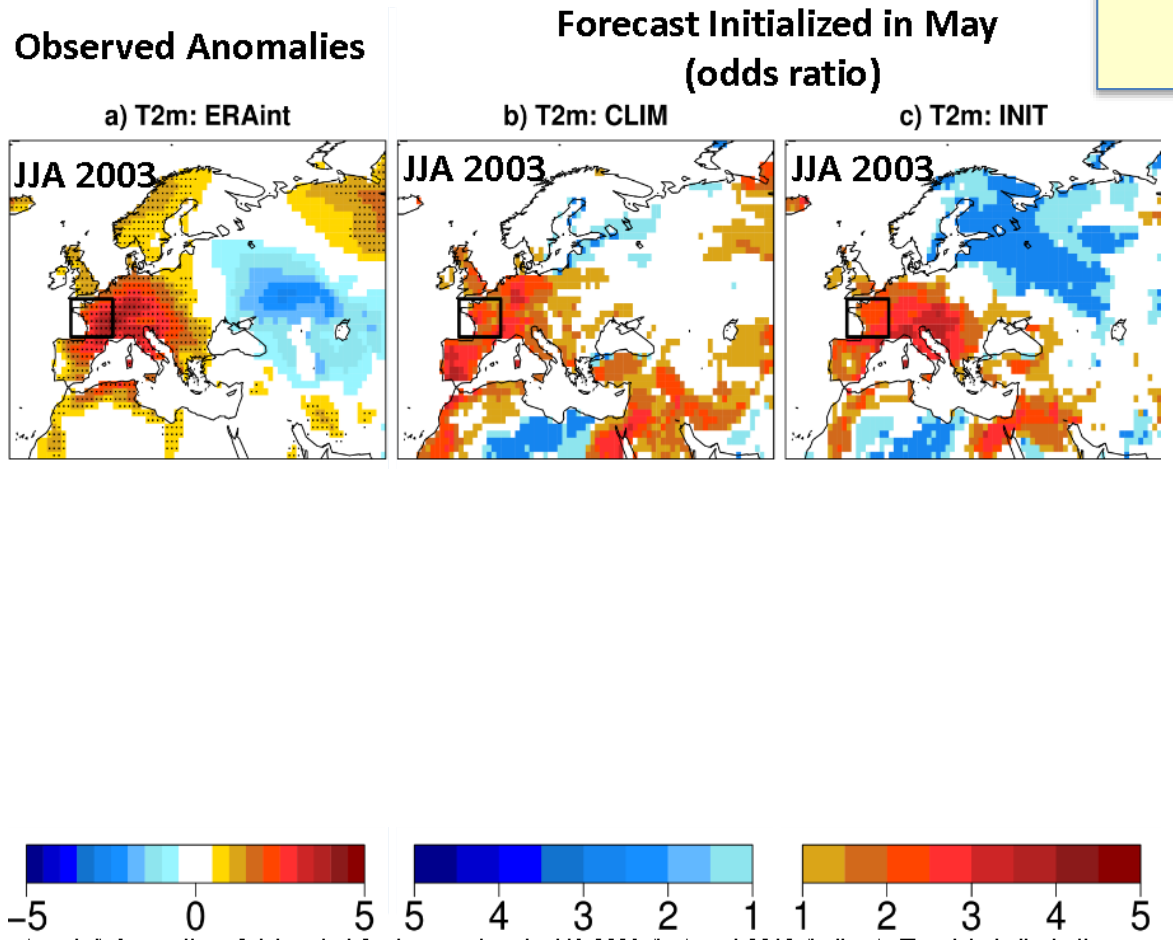
Weisheimer et al,

ECMWF

New study, different results!

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

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



Prodhomme et al, 2015

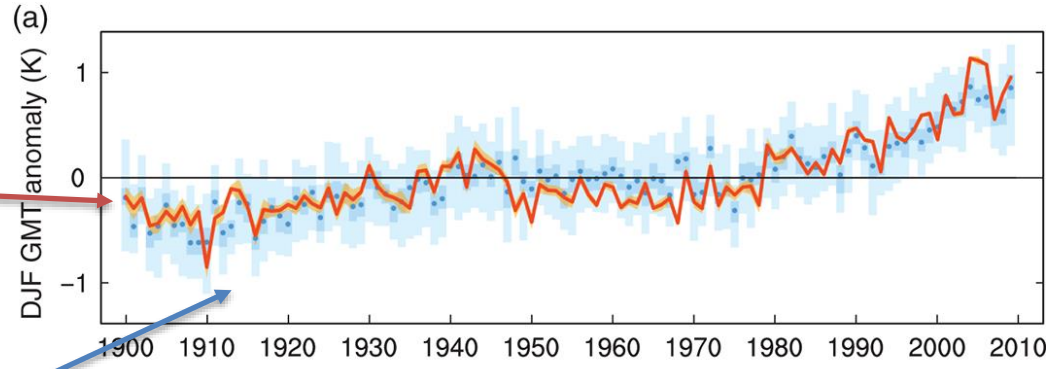
ECMWF

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

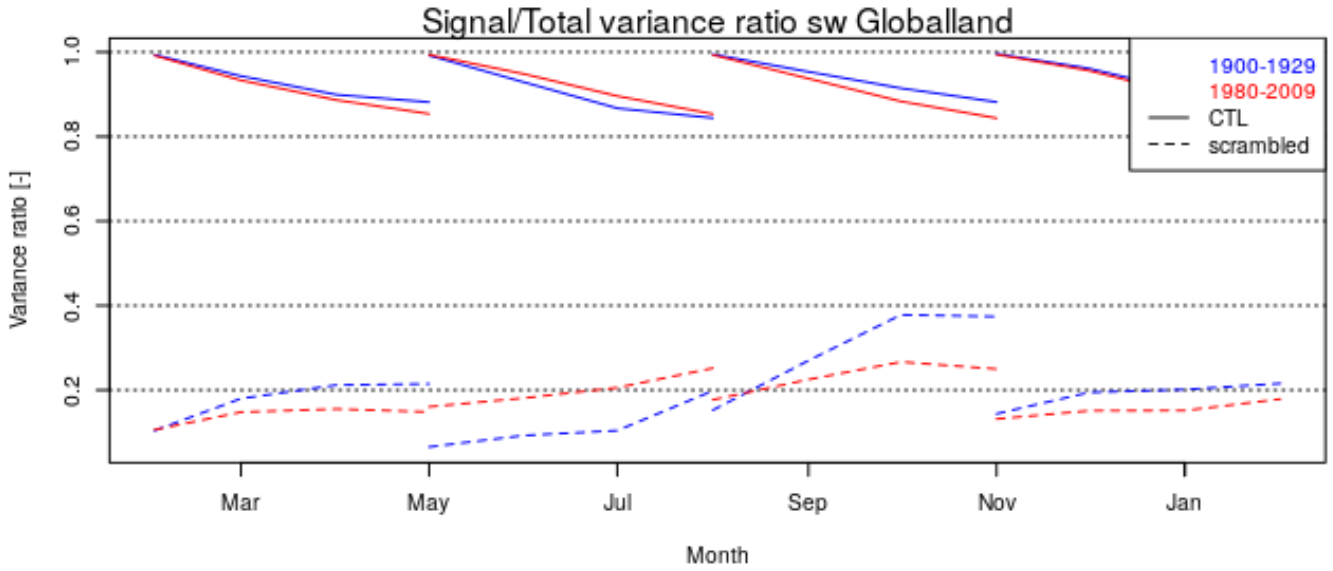
$$V_S = \frac{1}{N}\sum_{n=1}^{N}(\overline{x}_n - \overline{\overline{x}})^2$$

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

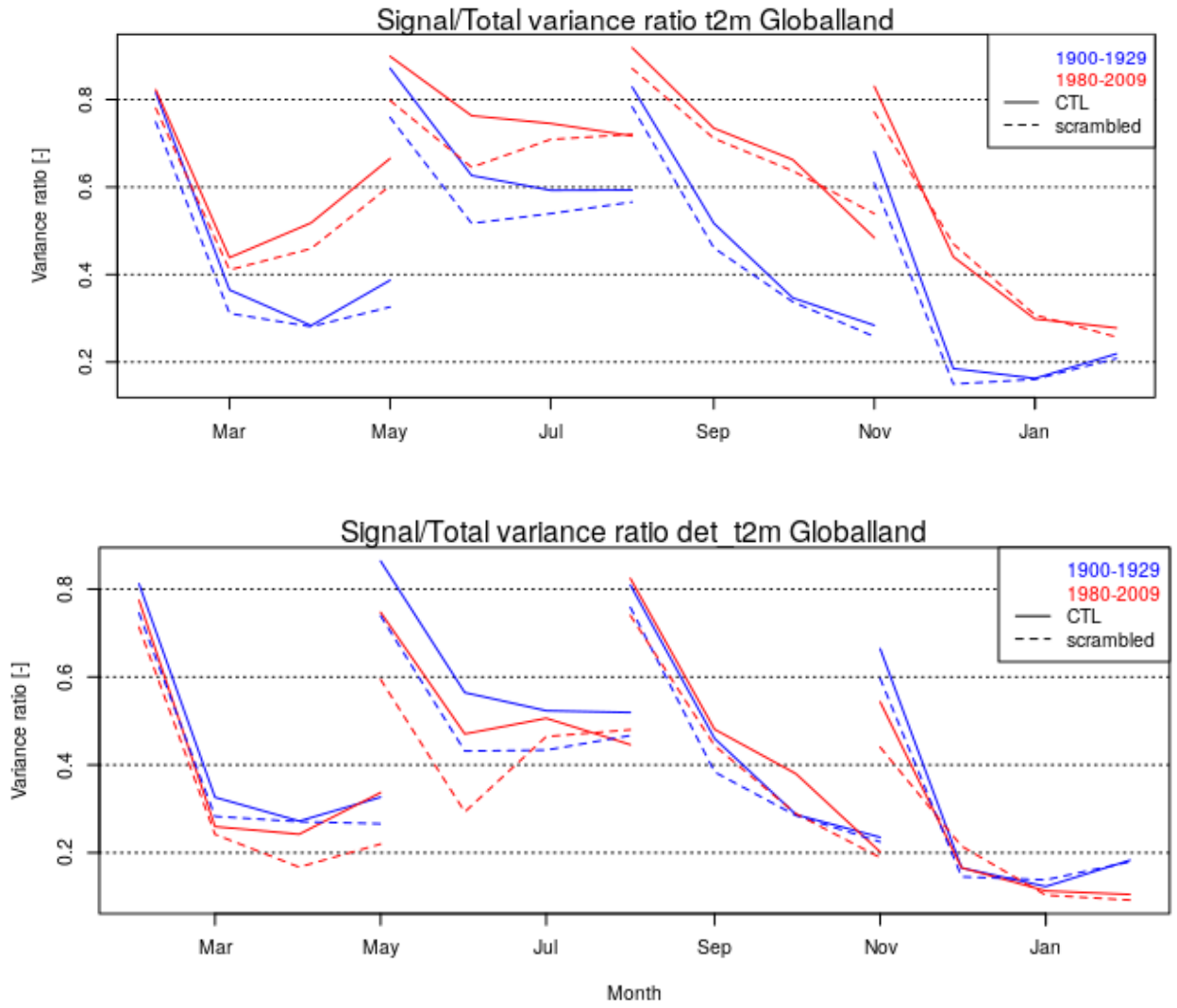


Results for global land area

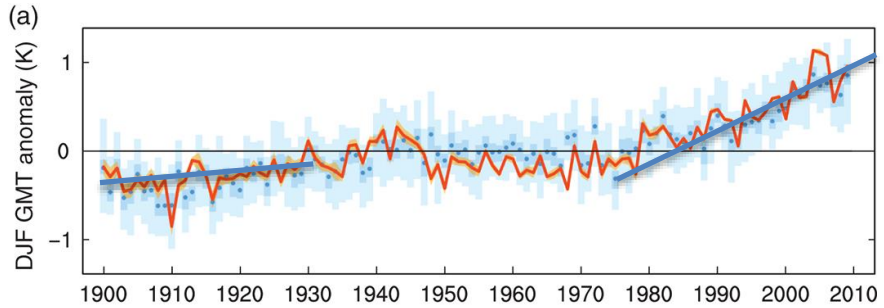
Total soil water



Trend contributes to predictability!

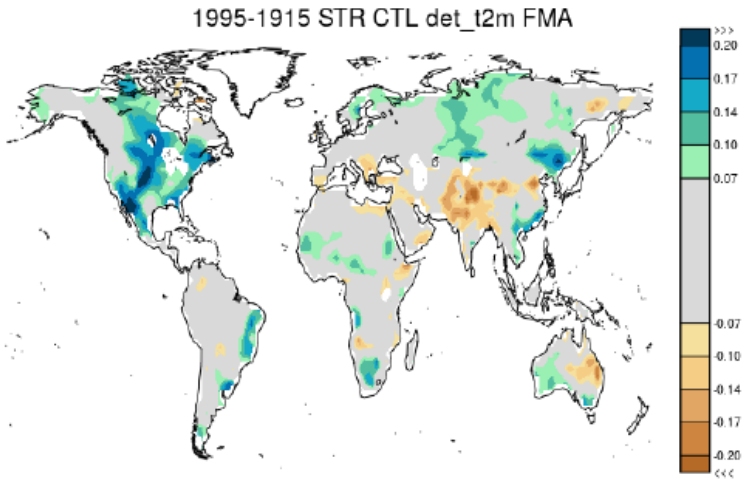


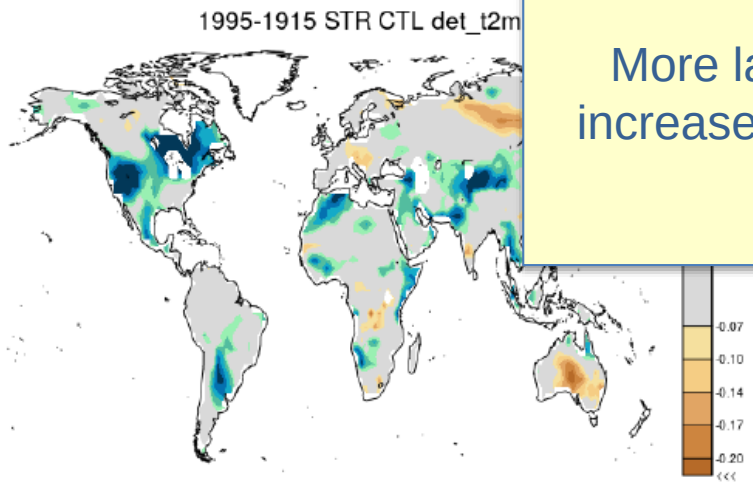
Before detrending

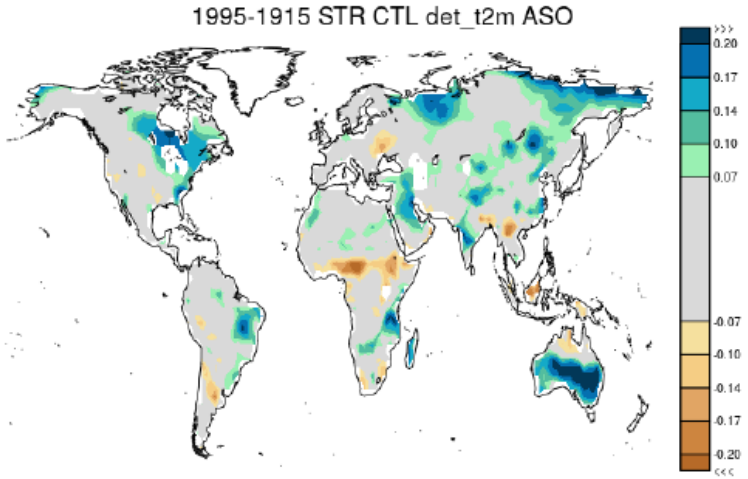


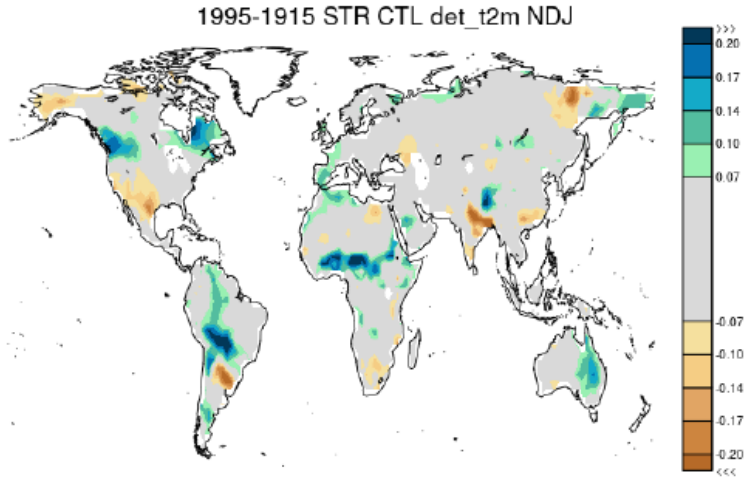
After detrending

Trend in predictability of t2m (after detrending)



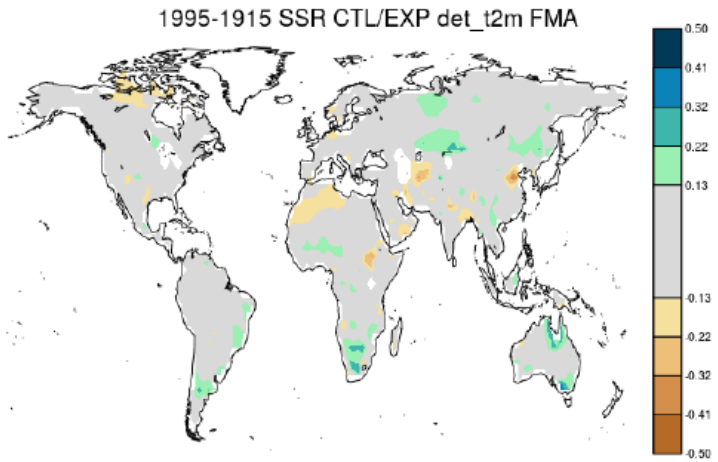


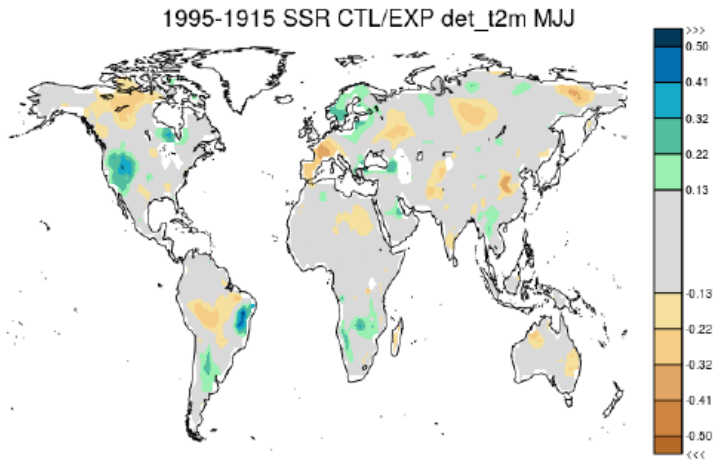


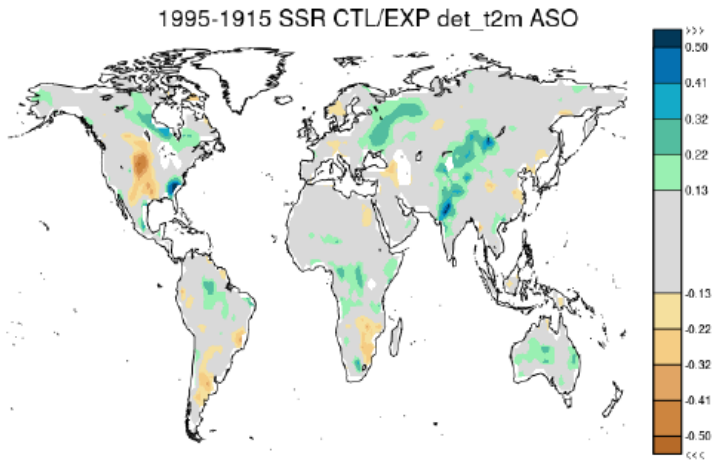


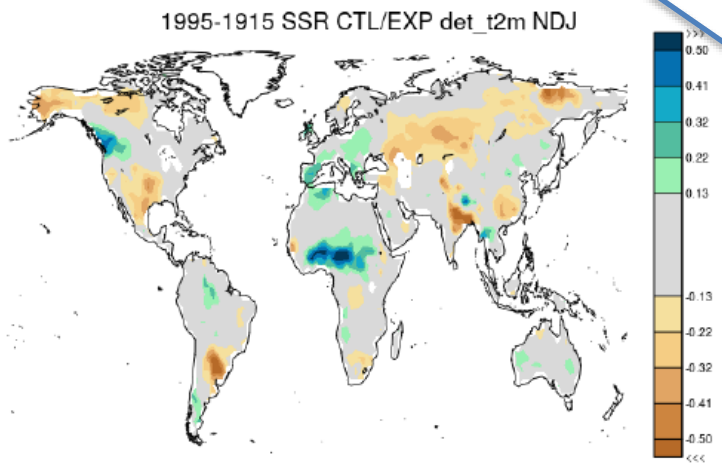
More land area with increased predictability

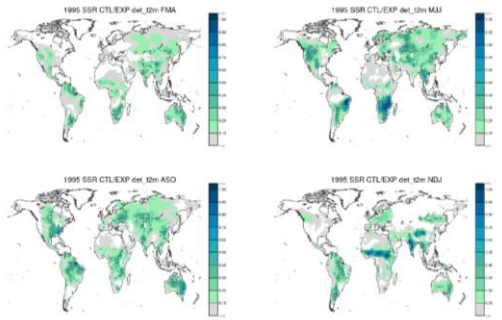
Trend in contribution of land initialization









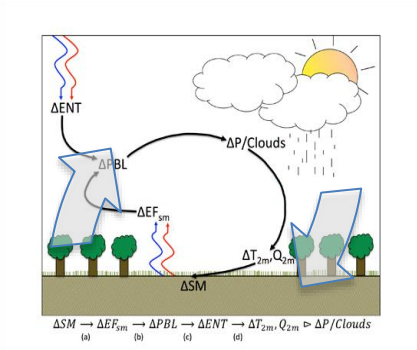


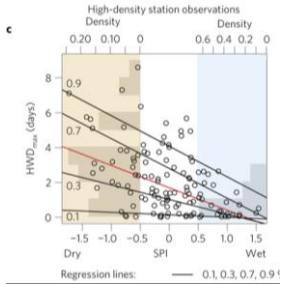
Although land surface does contribute to **predictability**, the contribution to the **trend** is limited

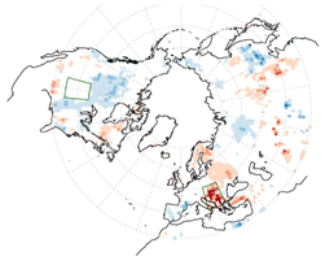
ECMWF

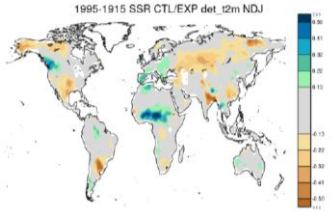
Conclusions

- For land-related predictability we need
  - Variability
  - Memory
  - 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 noisy climate system
  - We need unbiased model systems…
  - … and pretty large ensembles and long periods
- Predictability of t2m tends to increase
  - But land surface does not play a dominant role









BART VAN DEN HURK – HURKVD@KNMI.NL

References

C. Ardilouze et al., ‘Multi-model assessment of the impact of soil moisture initialization on mid-latitude summer predictability’, Climate Dynamics, pp. 1–16, 2017.

B. van den Hurk, F. Doblas-Reyes, G. Balsamo, R. D. Koster, S. I. Seneviratne, and H. Camargo, ‘Soil moisture effects on seasonal temperature and precipitation forecast scores in Europe’, Climate Dynamics, vol. 38, no. 1, pp. 349–362, 2012.

C. Prodhomme, F. Doblas-Reyes, O. Bellprat, and E. Dutra, ‘Impact of land-surface initialization on sub-seasonal to seasonal forecasts over Europe’, Climate Dynamics, vol. 47, no. 3, pp. 919–935, 2016.

R. D. Koster et al., ‘Regions of Strong Coupling Between Soil Moisture and Precipitation’, Science, vol. 305, no. 5687, pp. 1138–1140, Aug. 2004.

R. D. Koster et al., ‘Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment’, Geophys. Res. Lett., vol. 37, no. 2, p. L02402, Jan. 2010.

P. A. Dirmeyer, C. A. Schlosser, and K. L. Brubaker, ‘Precipitation, Recycling, and Land Memory: An Integrated Analysis’, J. Hydrometeor., vol. 10, no. 1, pp. 278–288, Feb. 2009.

M. Hirschi et al., ‘Observational evidence for soil-moisture impact on hot extremes in southeastern Europe’, Nature Geosci, vol. 4, no. 1, pp. 17–21, Jan. 2011.

S. I. Seneviratne et al., ‘Investigating soil moisture–climate interactions in a changing climate: A review’, Earth-Science Reviews, vol. 99, no. 3–4, pp. 125–161, mei 2010.

A. Weisheimer, F. J. Doblas-Reyes, T. Jung, and T. N. Palmer, ‘On the predictability of the extreme summer 2003 over Europe’, Geophys. Res. Lett., vol. 38, no. 5, p. n/a-n/a, Mar. 2011.