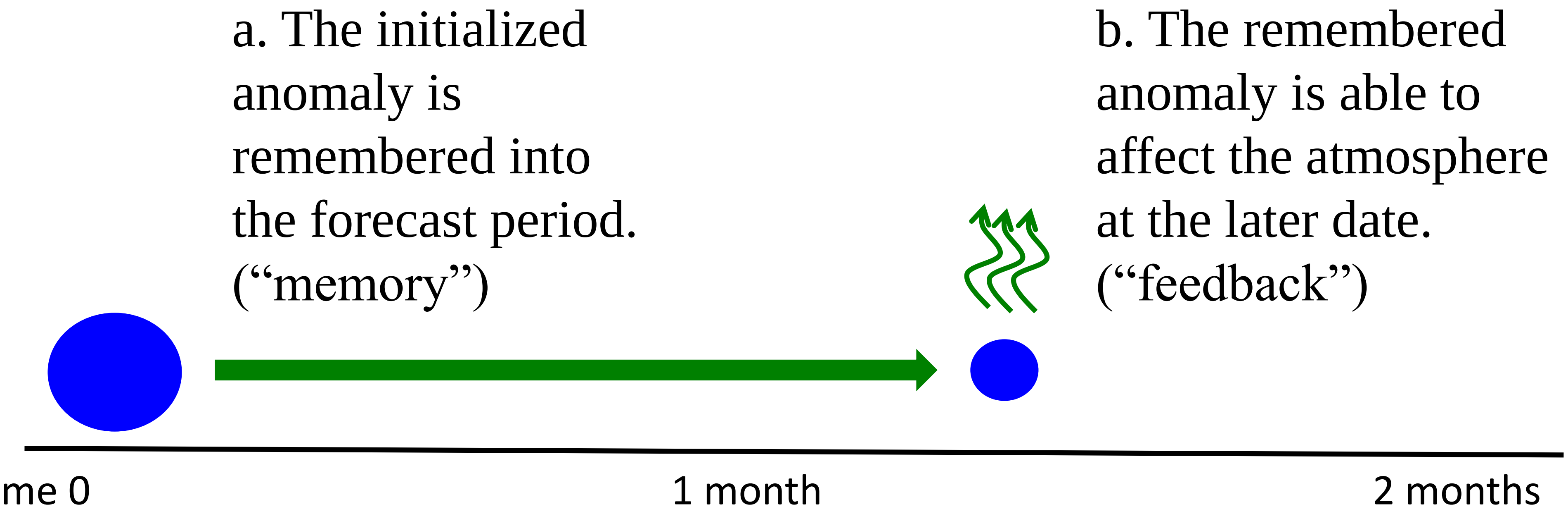
Contribution of Land Surface States to Sub-seasonal Predictability

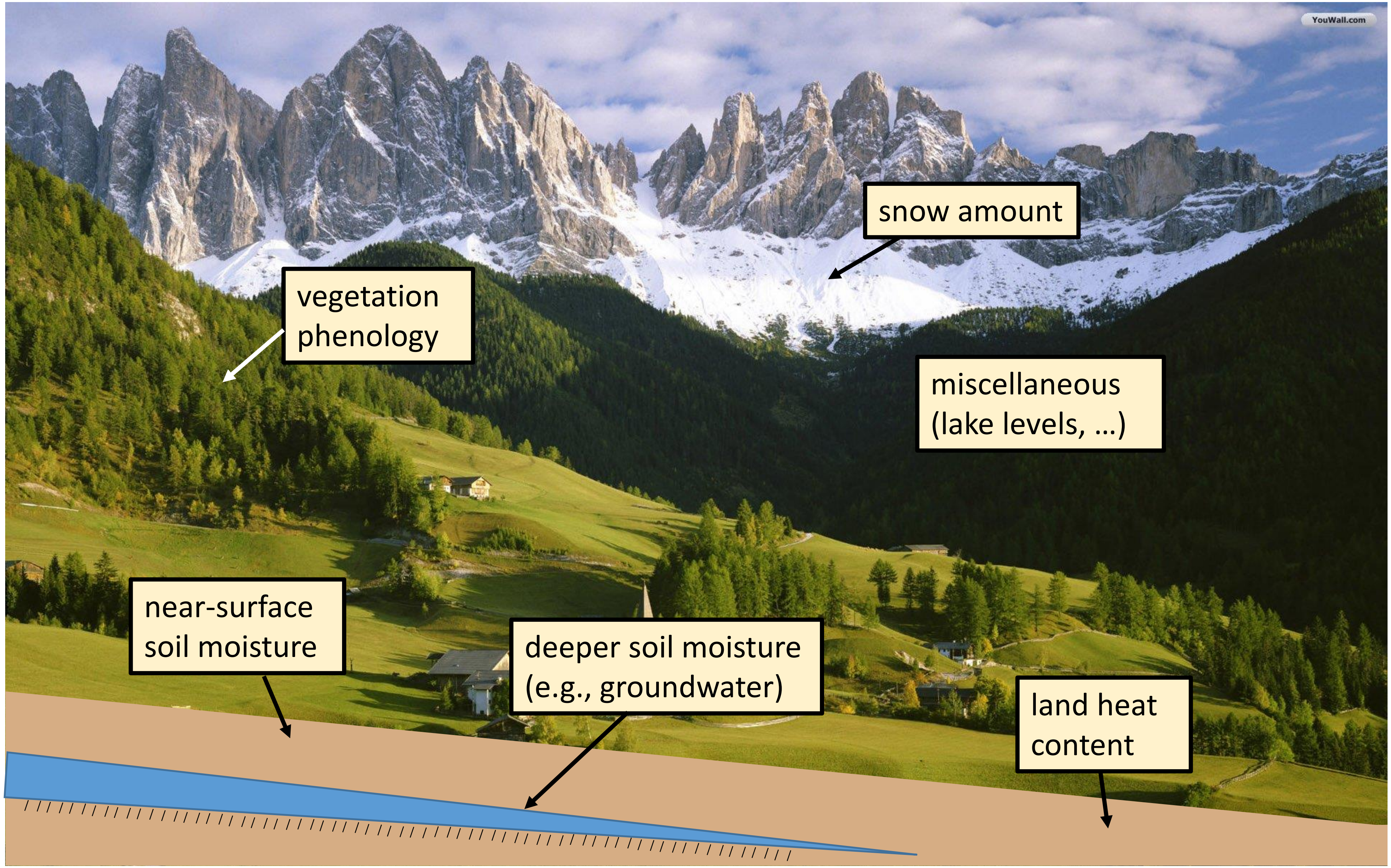
Randal Koster
Global Modeling and Assimilation Office
NASA/GSFC
Greenbelt, MD USA

Theoretical Underpinning

An initialized land state can affect a forecast if the following two things happen:

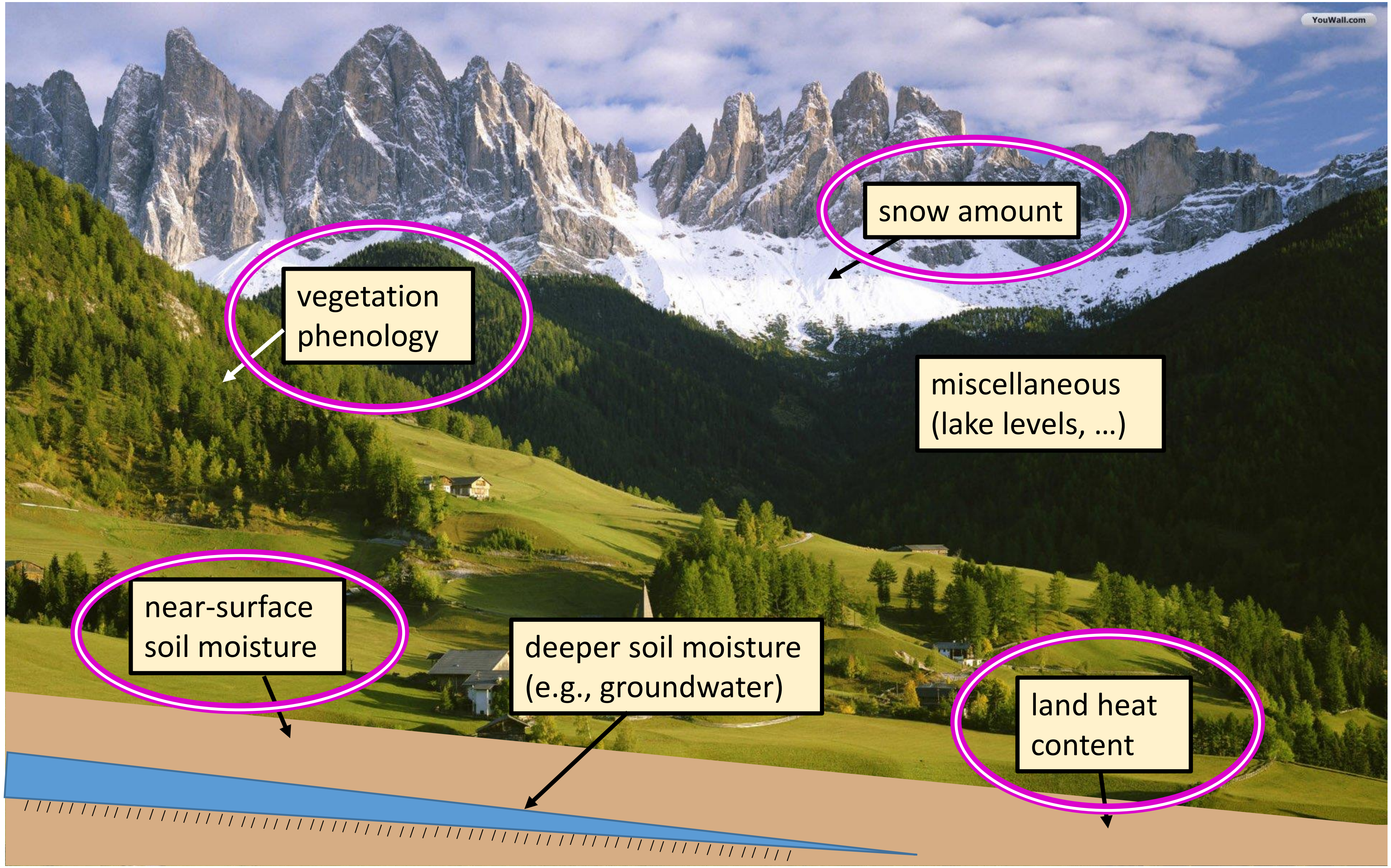


Which land states might have usable memory?



(Image stolen from internet!)

For which land states has an impact of initialization on forecasts been demonstrated?



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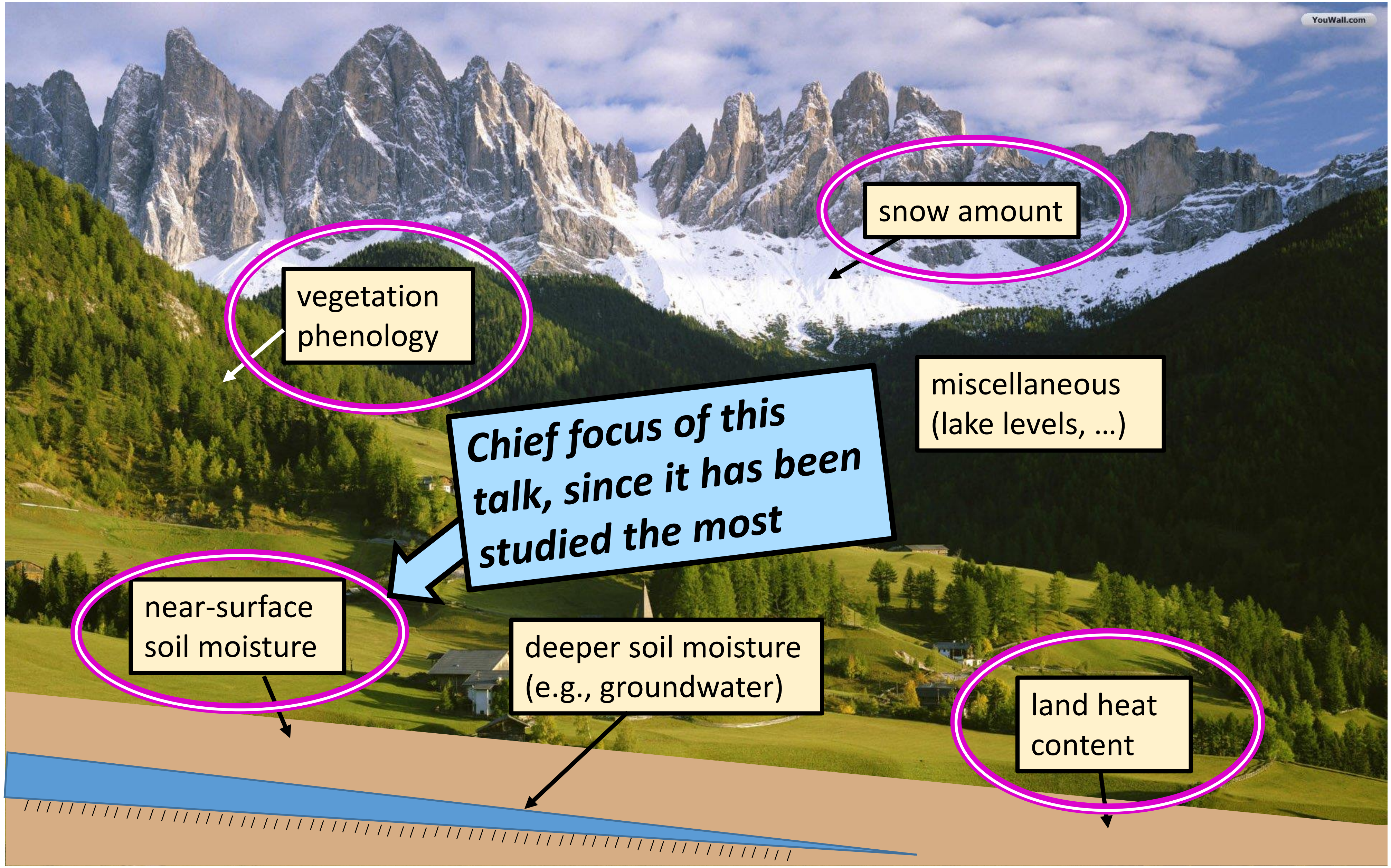
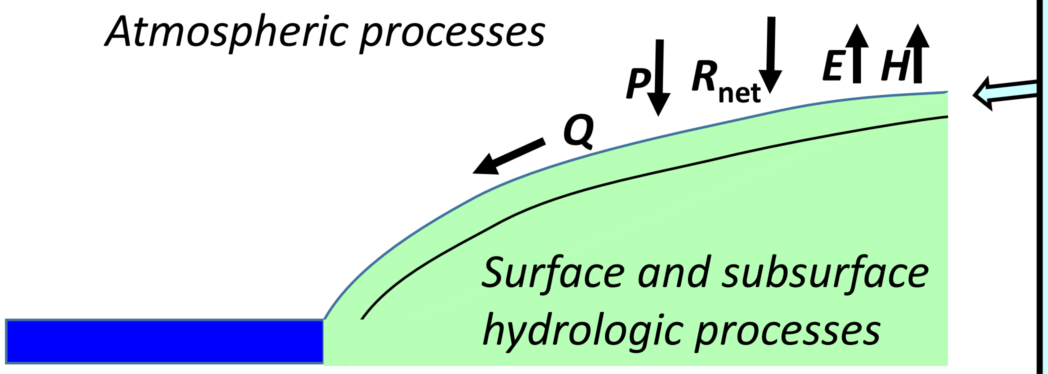


(Image stolen from internet!)

Soil moisture in the climate system

The moisture in the top two meters or so of soil is a tiny fraction (<0.05%) of the Earth's water. However, because it lies at the *interface* between the land and atmosphere, it has an *inordinate impact* on climate and its variability.



Surface soil moisture controls:

(i) Precipitation (P) partitioning:

$$\boldsymbol{P = E + Q + \Delta} \textbf{ water storage}$$

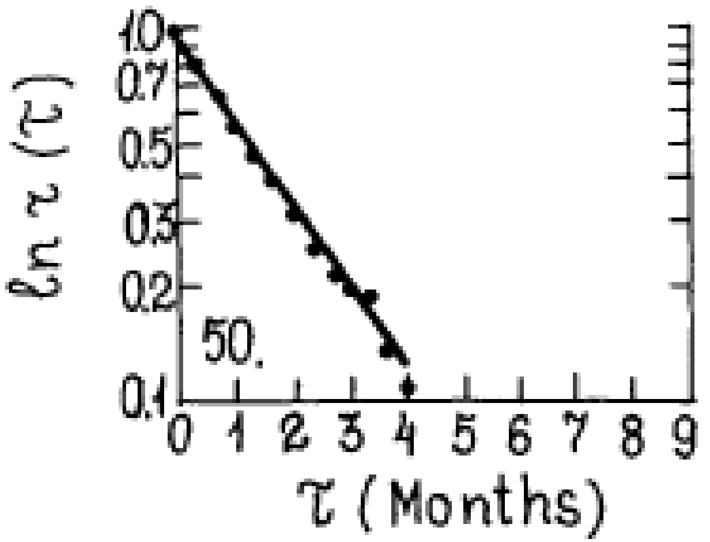
E= evapotranspiration
Q=runoff

(ii) Net radiation (R_{net}) partitioning:

$$\boldsymbol{R_{net} = \lambda E + H + \Delta} \textbf{ energy storage}$$

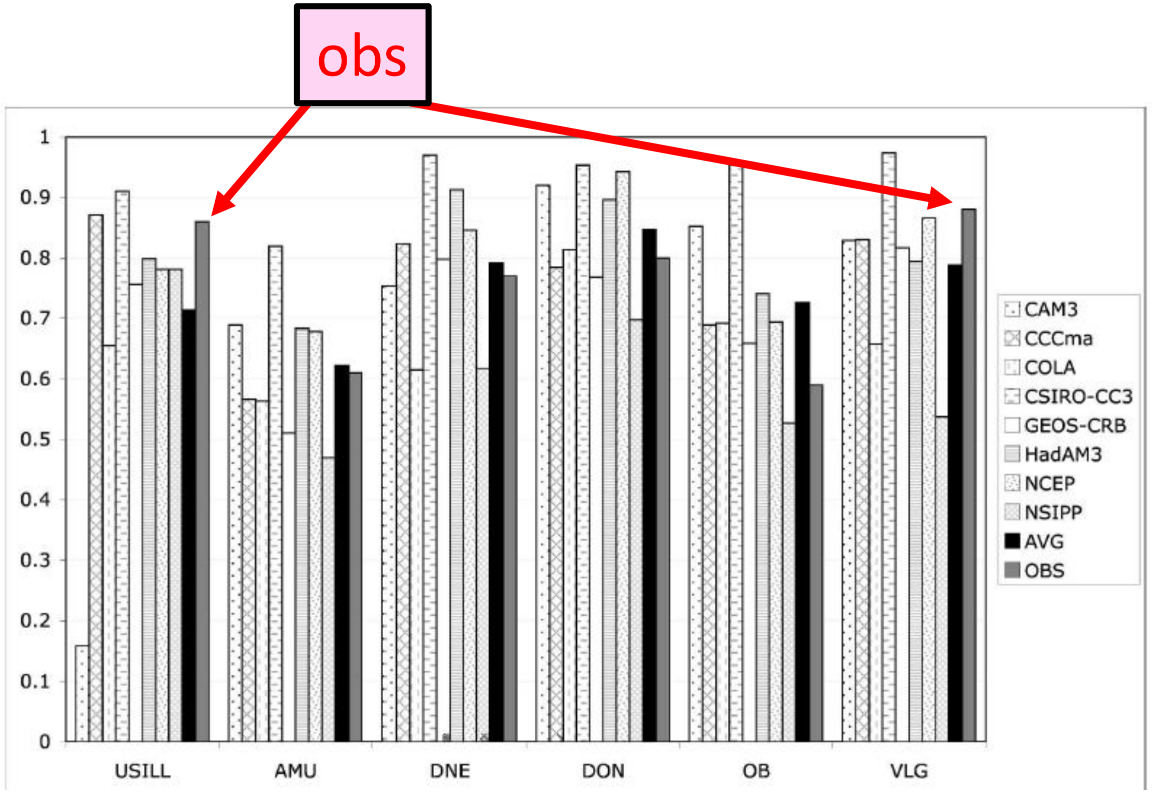
H = sensible heat flux
λ = latent heat of vaporization

Soil moisture memory is well-established; estimated time-scales range from weeks to months.



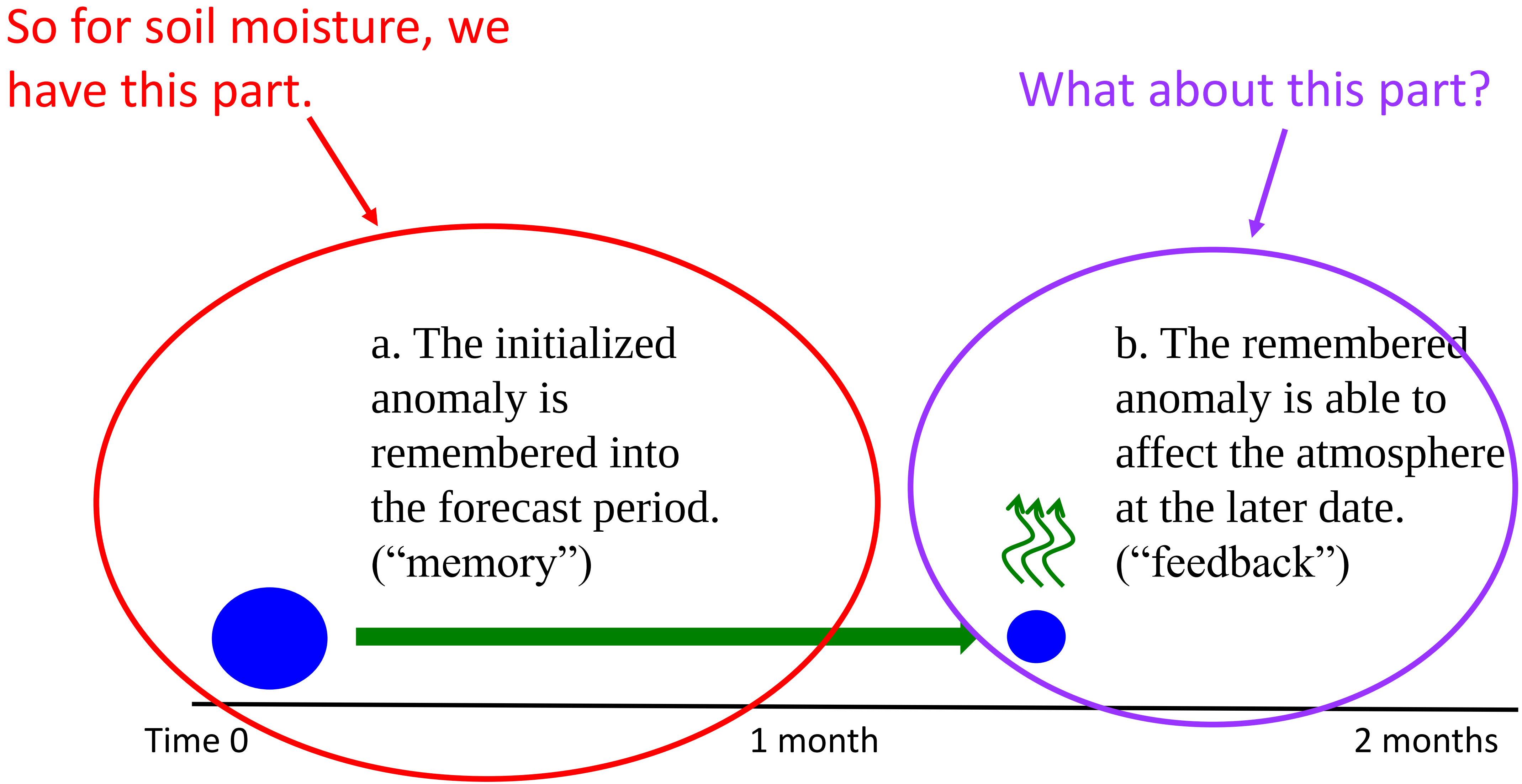
"empirical autocorrelation function"

Vinnekov and Yeserkepova, J. Climate, 4, 66-79, 1991



~1-month-lagged autocorrelations of soil moisture (boreal summer)

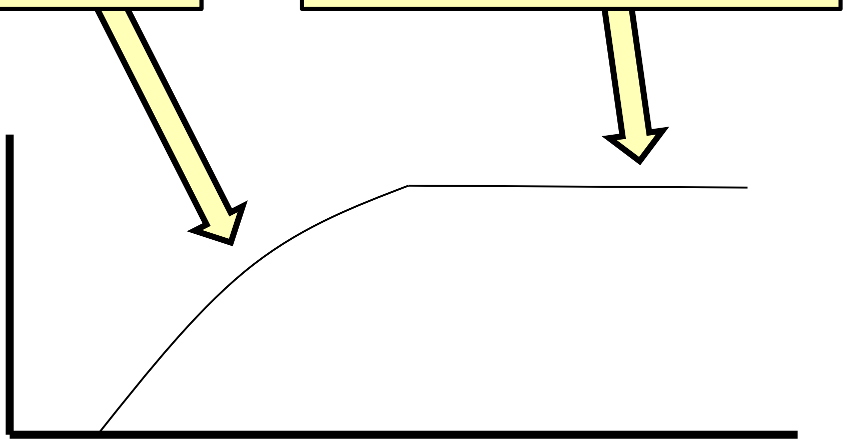
Seneviratne et al., J. Hydromet., 7, 1090-1112, 2006


So for soil moisture, we have this part.
What about this part?
a. The initialized anomaly is remembered into the forecast period. (“memory”)
b. The remembered anomaly is able to affect the atmosphere at the later date. (“feedback”)
Time 0
1 month
2 months

Conventional wisdom regarding control of soil moisture on evapotranspiration (and thereby on climate, forecasts)

For drier conditions, evapotranspiration varies with soil moisture

For wetter conditions, evapotranspiration largely independent of soil moisture



Evapotranspiration, normalized by incoming energy

Relevant observations are rare, but where they exist, they support this idea….

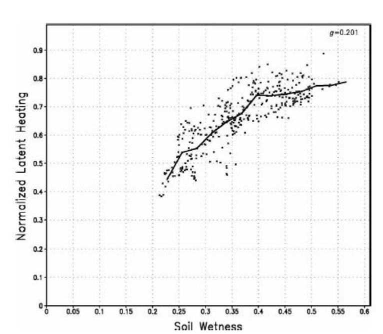


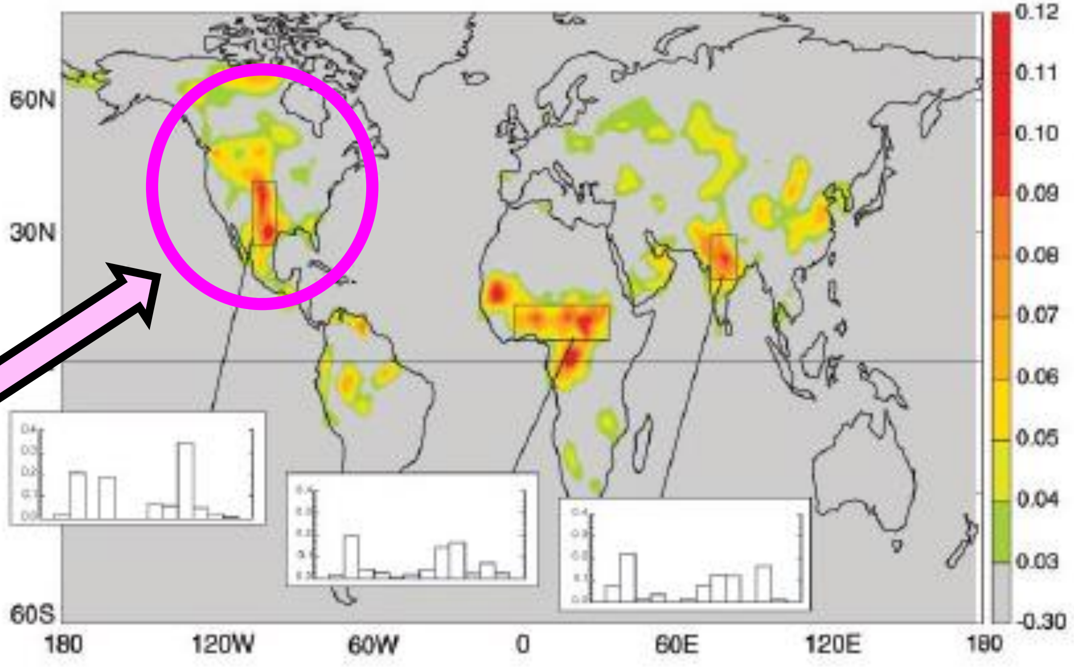
FIG. 8. As in Fig. 3 but for observed average over ARM Extended Facility sites.

Dirmeyer *et al.*, *J. Hydromet.*, 7, 1177–1198, 2006

Because of this relationship, the connection between soil moisture and the atmosphere (through the former's effect on evapotranspiration) is strongest in the transition zones between dry and wet areas.

Shown here: results from the multi-model GLACE experiment. Indicated is where soil moisture variability helps guide short-term boreal summer rainfall variability.

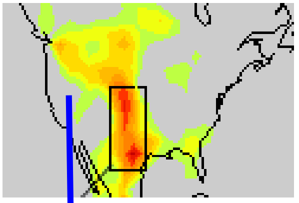
Why are the transition areas important? See next slide, which focuses on North America…

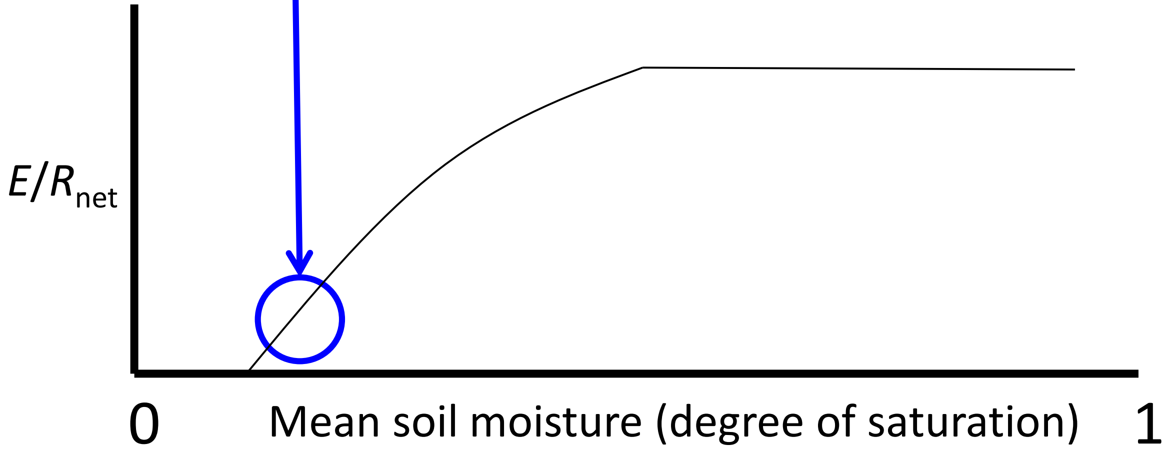


Koster *et al.*, *Science*, 305, 1138–1140, 2004

Explanation for why soil moisture feedback on the atmosphere is strongest in transition zones

When it is really dry, *E* is too small (and varies too little) to have an effect.





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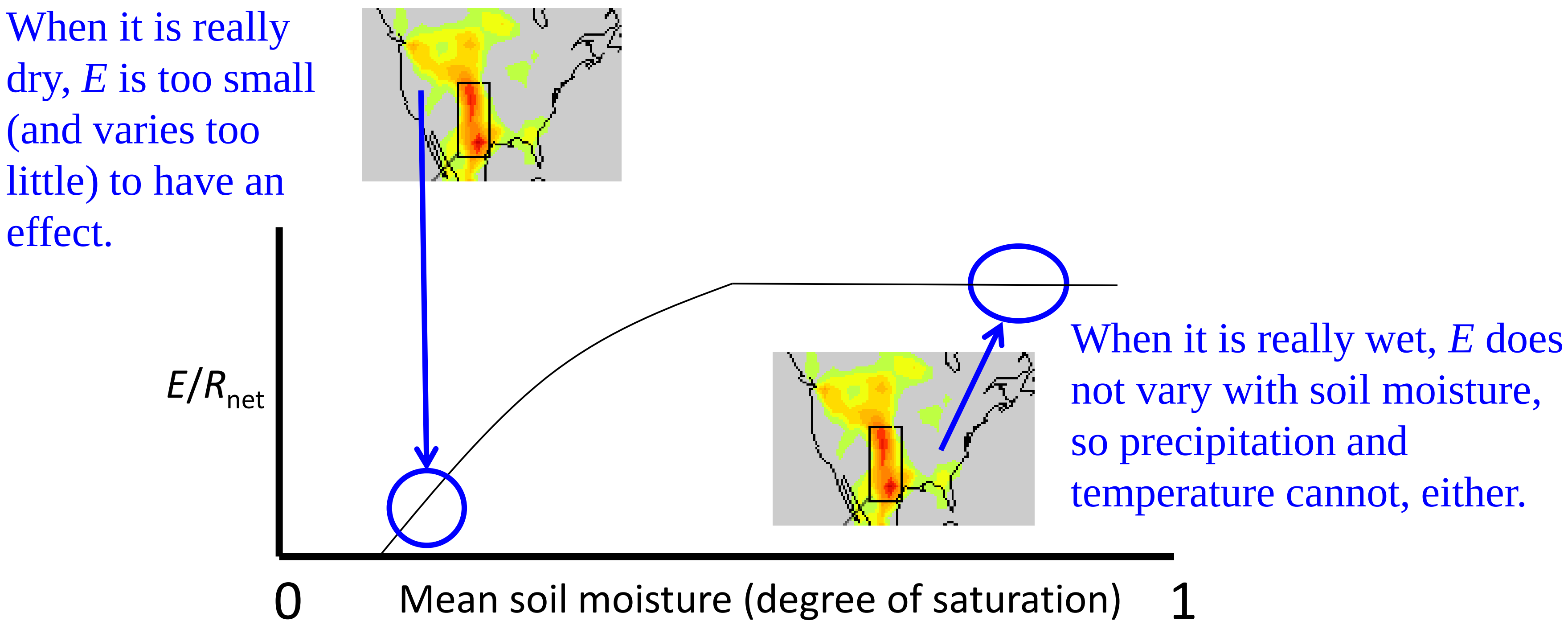

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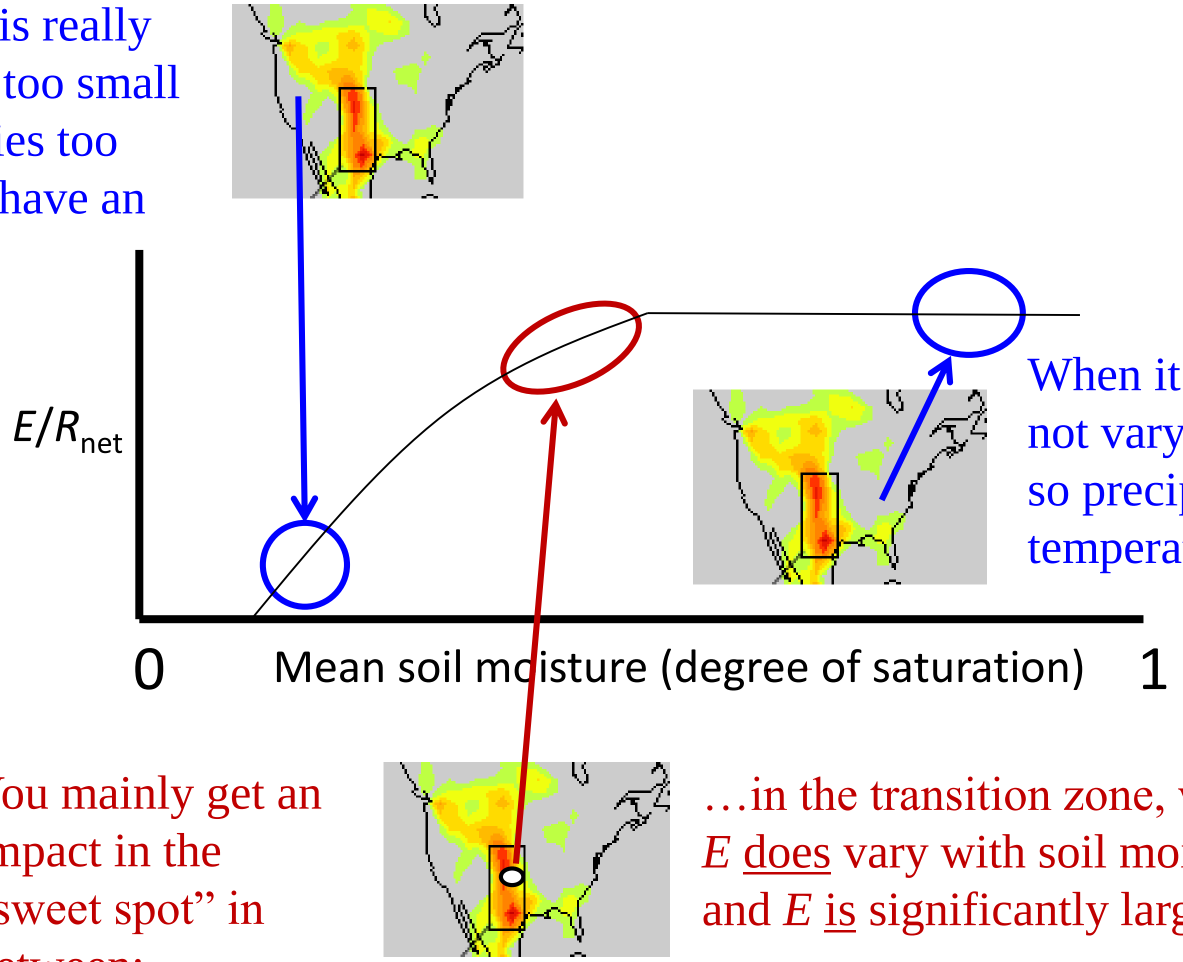
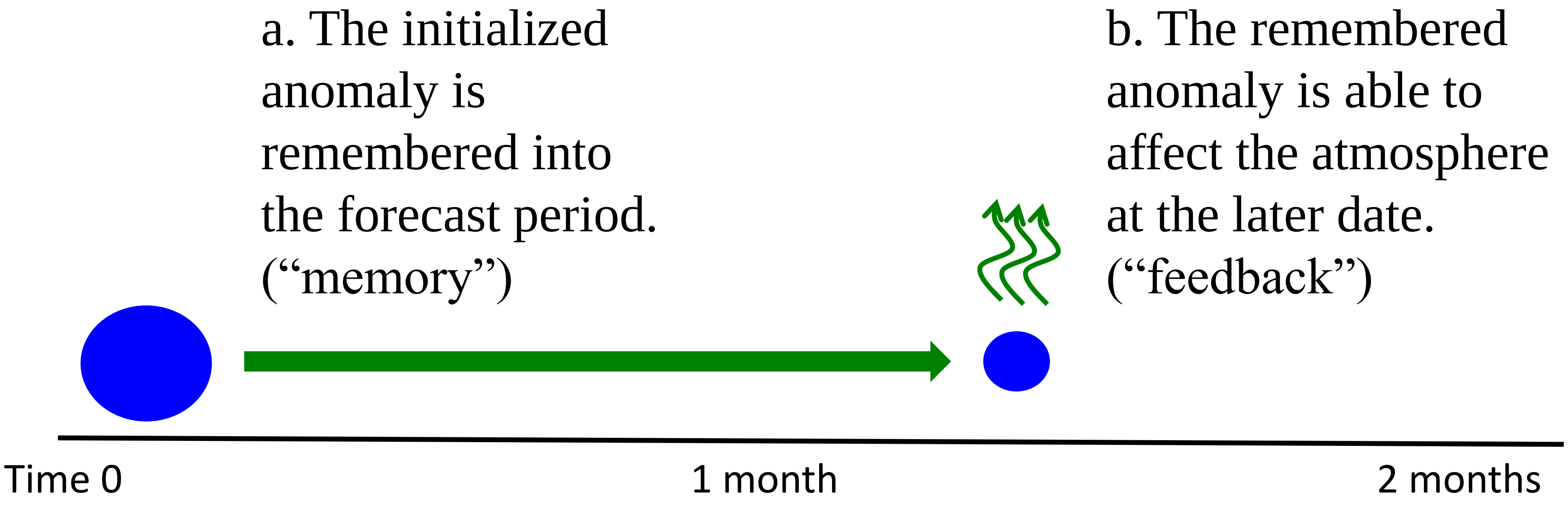


When it is really wet, *E* does not vary with soil moisture, so precipitation and temperature cannot, either.

You mainly get an impact in the “sweet spot” in between:

…in the transition zone, where *E* does vary with soil moisture and *E* is significantly large.

So, for soil moisture, we seem to have both of these parts, at least in some areas.

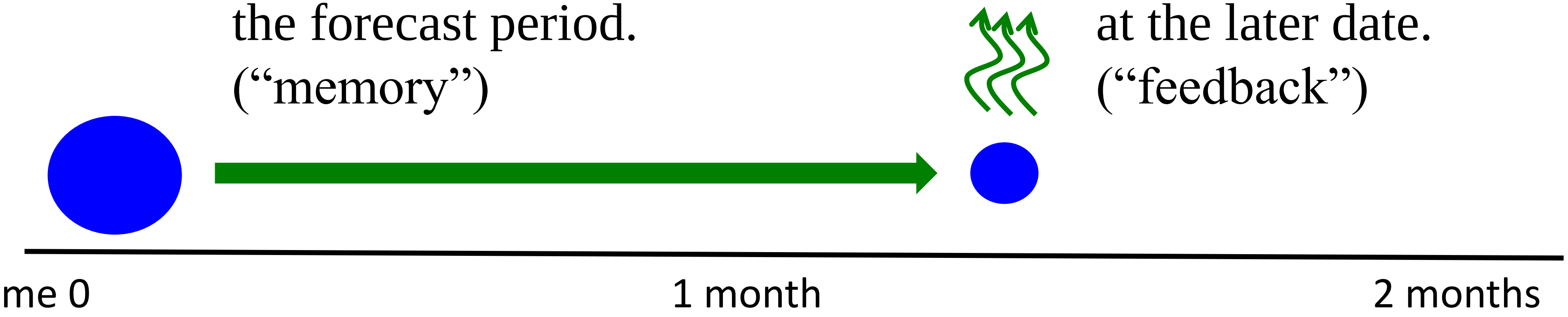


So, for soil moisture, we seem to have both of these parts, at least in some areas.

Does accurate soil moisture initialization actually lead to increased forecast skill?

...mbered into the forecast period. ("memory")

...bered anomaly is able to affect the atmosphere at the later date. ("feedback")



Estimations of forecast skill associated with soil moisture initialization

GLACE-2: **The second phase of the Global Land-Atmosphere Coupling Experiment**
(an international, multi-institution project)

Koster *et al.*, *J. Hydromet*., 12, 804-822, 2011

Gist of experiment:

1. Perform two sets of forecast simulations:
   (i) with accurate soil moisture initial conditions (ICs)
   (ii) without accurate soil moisture ICs
2. Compare forecasted *P*, *T* to obs.
3. Compute soil moisture contribution to forecast skill:

Skill from simulations w/ accurate land ICs − Skill from simulations w/o accurate land ICs = Skill due to land ICs

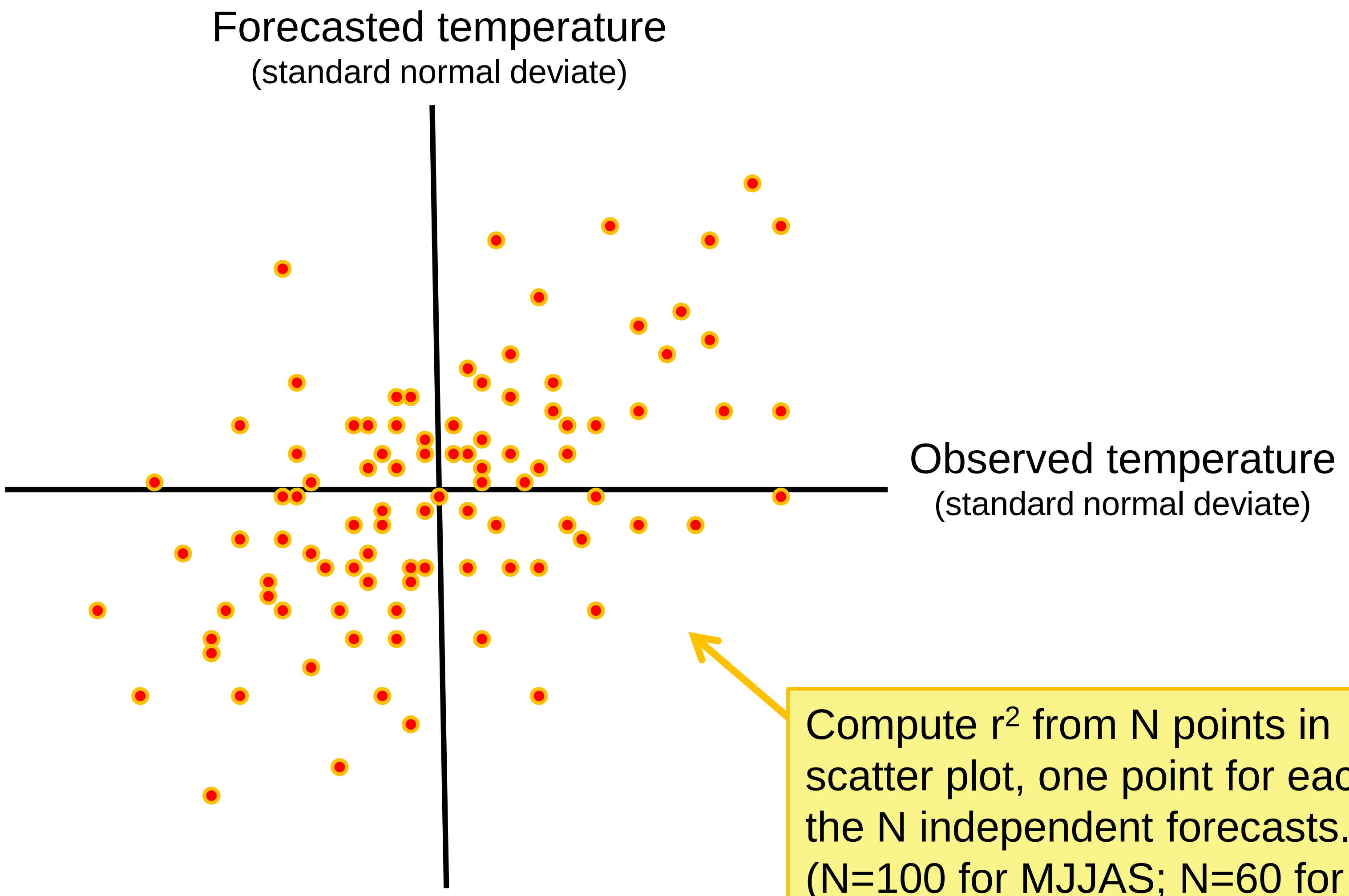
Baseline: 100 Forecast Start Dates

	Apr 1	Apr 15	May 1	May 15	Jun 1	Jun 15	Jul 1	Jul 15	Aug 1	Aug 15
1986	●	●	●	●	●	●	●	●	●	●
1987	●	●	●	●	●	●	●	●	●	●
1988	●	●	●	●	●	●	●	●	●	●
1989	●	●	●	●	●	●	●	●	●	●
1990	●	●	●	●	●	●	●	●	●	●
1991	●	●	●	●	●	●	●	●	●	●
1992	●	●	●	●	●	●	●	●	●	●
1993	●	●	●	●	●	●	●	●	●	●
1994	●	●	●	●	●	●	●	●	●	●
1995	●	●	●	●	●	●	●	●	●	●

Each ensemble consists of 10 simulations, each running for 2 months.

1000 2-month simulations.

Skill measure: r^2 when regressed against observations



Compute r^2 from N points in scatter plot, one point for each of the N independent forecasts. (N=100 for MJJAS; N=60 for JJA)

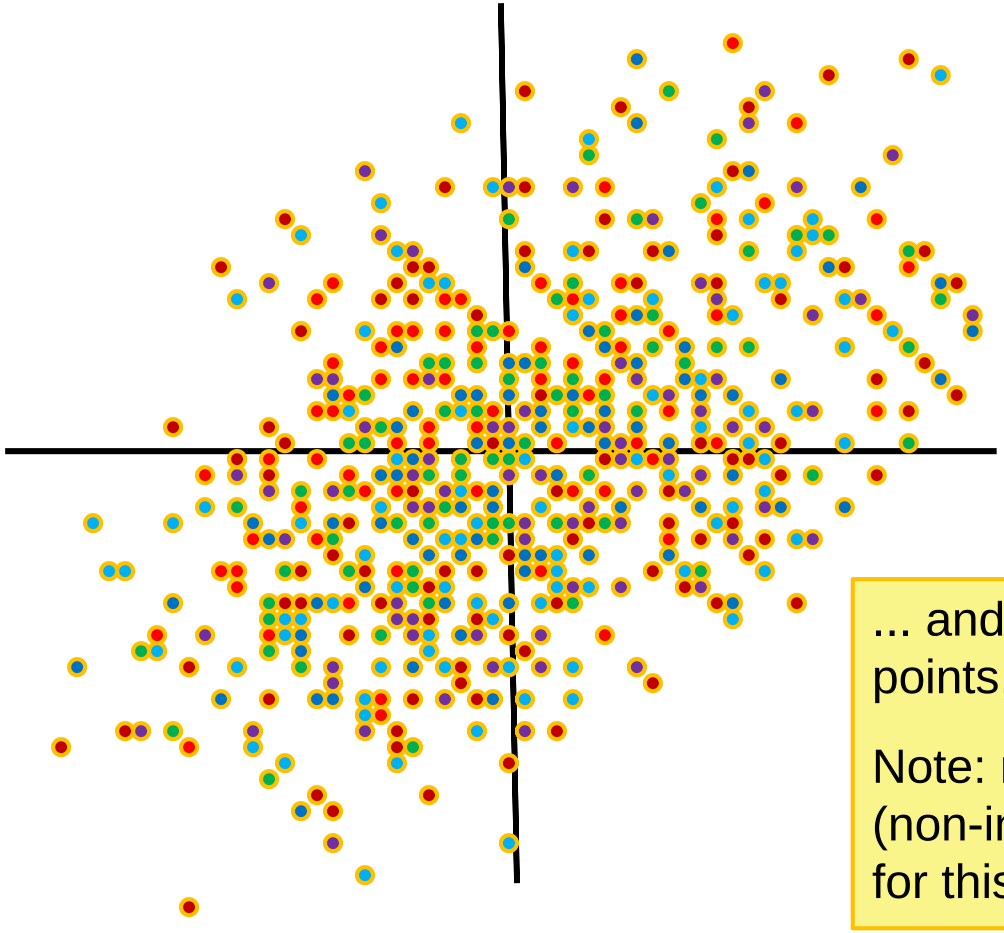
Participant List

Group/Model	# models	Points of Contact
1. NASA/GSFC (USA): GMAO seasonal forecast system (old and new)	2	R. Koster, S. Mahanama
2. COLA (USA): COLA GCM, NCAR/CAM GCM	2	P. Dirmeyer, Z. Guo
3. Princeton (USA): NCEP GCM	1	E. Wood, L. Luo
4. IACS (Switzerland): ECHAM GCM	1	S. Seneviratne, E. Davin
5. KNMI (Netherlands): ECMWF	1	B. van den Hurk
6. ECMWF	1	G. Balsamo, F. Doblas-Reyes
7. GFDL (USA): GFDL system	1	T. Gordon
8. U. Gothenburg (Sweden): NCAR	1	J.-H. Jeong
9. CCSR/NIES/FRCGC (Japan): CCSR GCM	1	T. Yamada
10. FSU/COAPS	1	M. Boisserie
11. CCCma (?)	1	B. Merryfield
	13 models	

Multi-model “consensus” measure of skill

Forecasted temperature
(standard normal deviate)

Plot results for all M models on the same scatterplot...



Observed temperature
(standard normal deviate)

... and then compute r^2 from 6MN points, N from each model.

Note: models may behave similarly (non-independently); must account for this in significance testing.

- We focus here on multi-model “consensus” view of skill.
- We focus here on JJA, the period when N.H. evaporation is strongest.
- We focus here on the U.S., for which:
  - -- models show strong inherent predictability associated with land initialization (GLACE-1!)
  - -- observations are reliable over the forecast period

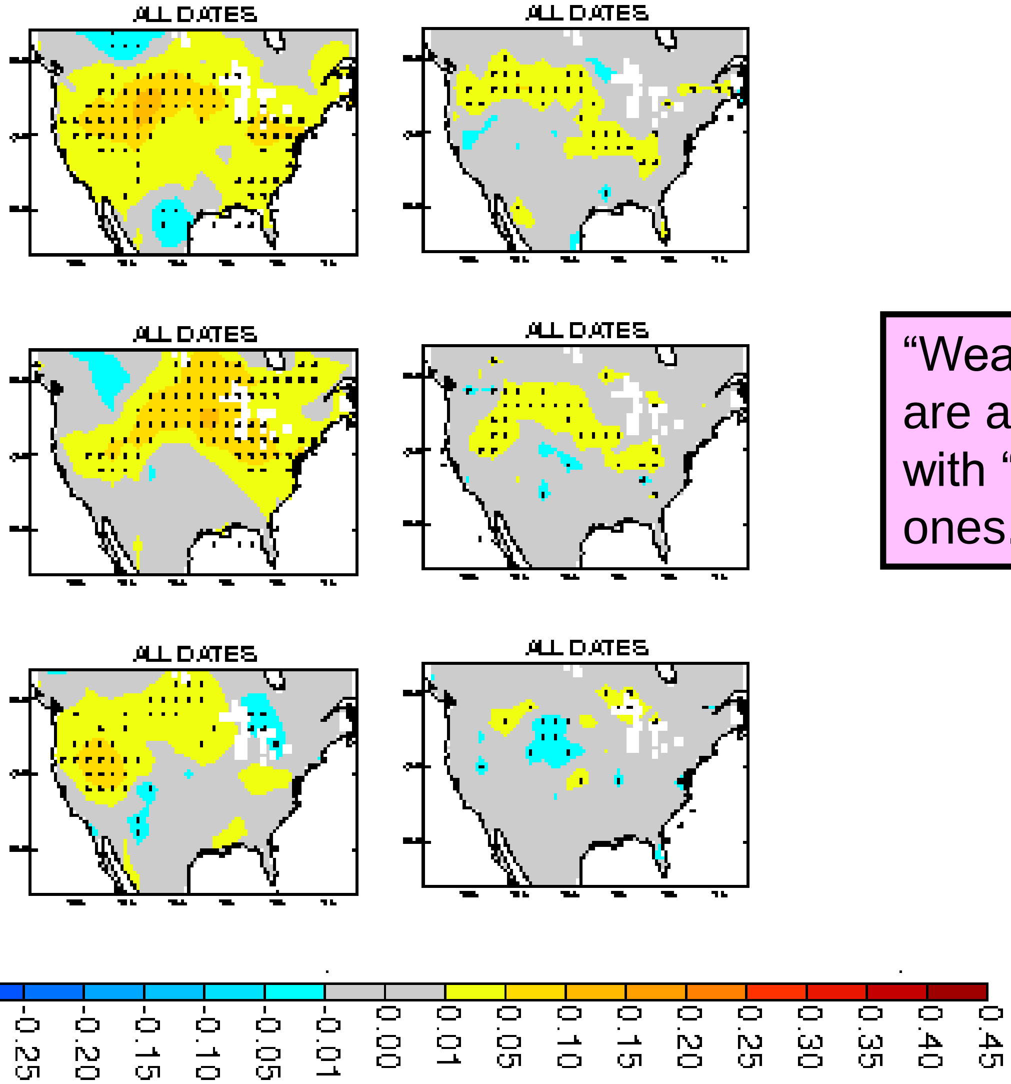
Forecasts: "Consensus" skill due to land initialization (JJA)

temperature precipitation

16-30 days

31-45 days

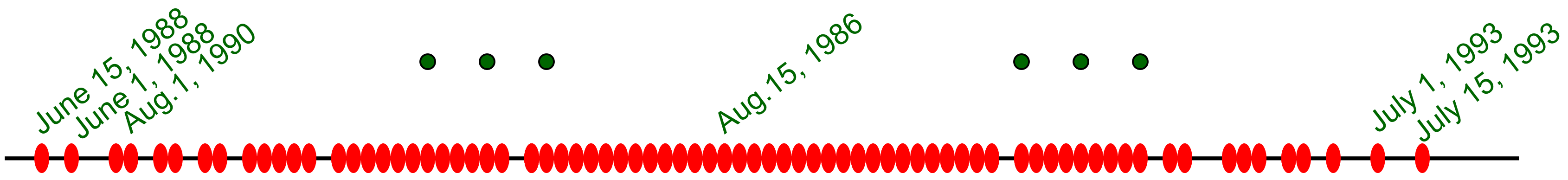
46-60 days



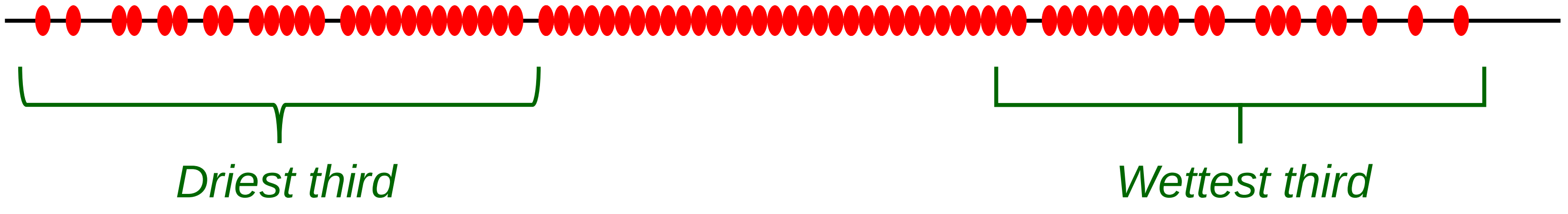
"Weaker" models are averaged in with "stronger" ones.

Conditional skill: Suppose we know at the start of a forecast that the initial soil moisture anomaly, W_i, is relatively large...

Step 1: At each grid cell, rank the forecast periods from lowest initial soil moisture to highest initial soil moisture:

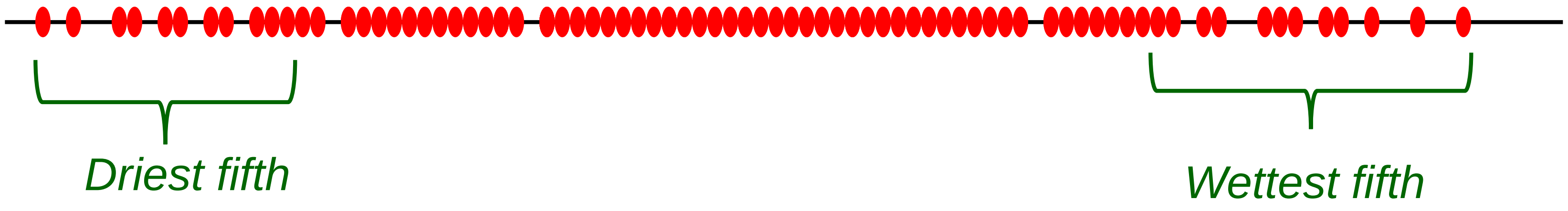


Step 2: Separate into terciles:

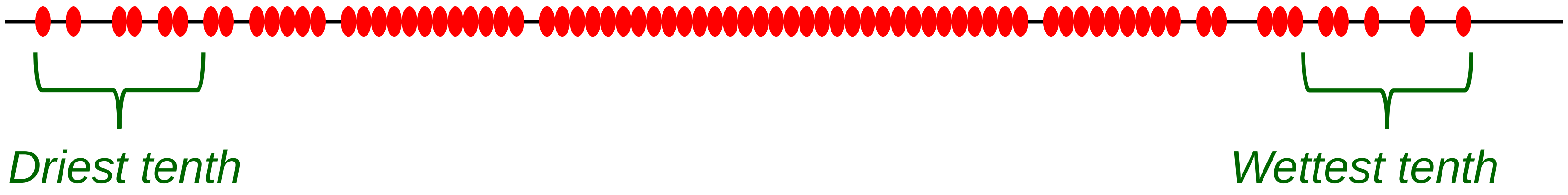


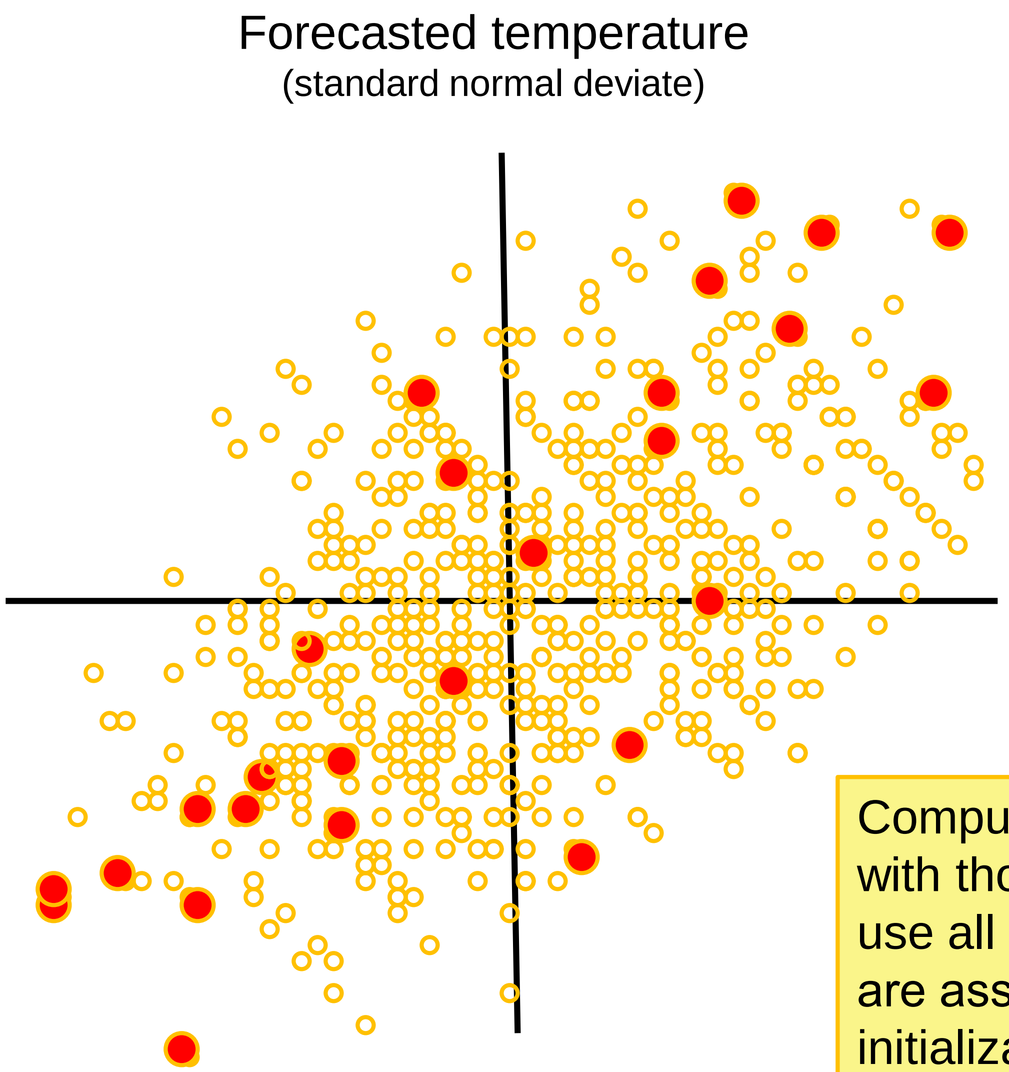
<u>Conditional skill:</u> Suppose we know at the start of a forecast that the initial soil moisture anomaly, W_i, is relatively large...

Step 2: Separate into quintiles:



Step 3: Separate into deciles:





Identify start dates for which W_i is in top or bottom tercile (or quintile, or decile)

Compute r^2 from only those points with those start dates. (As before, use all models together.) Here, we are assuming that “local impacts” of initialization are most important.

Temperature forecasts: Increase in skill due to land initialization (JJA)

(conditioned on strength of local initial soil moisture anomaly)

all points

Extreme terciles

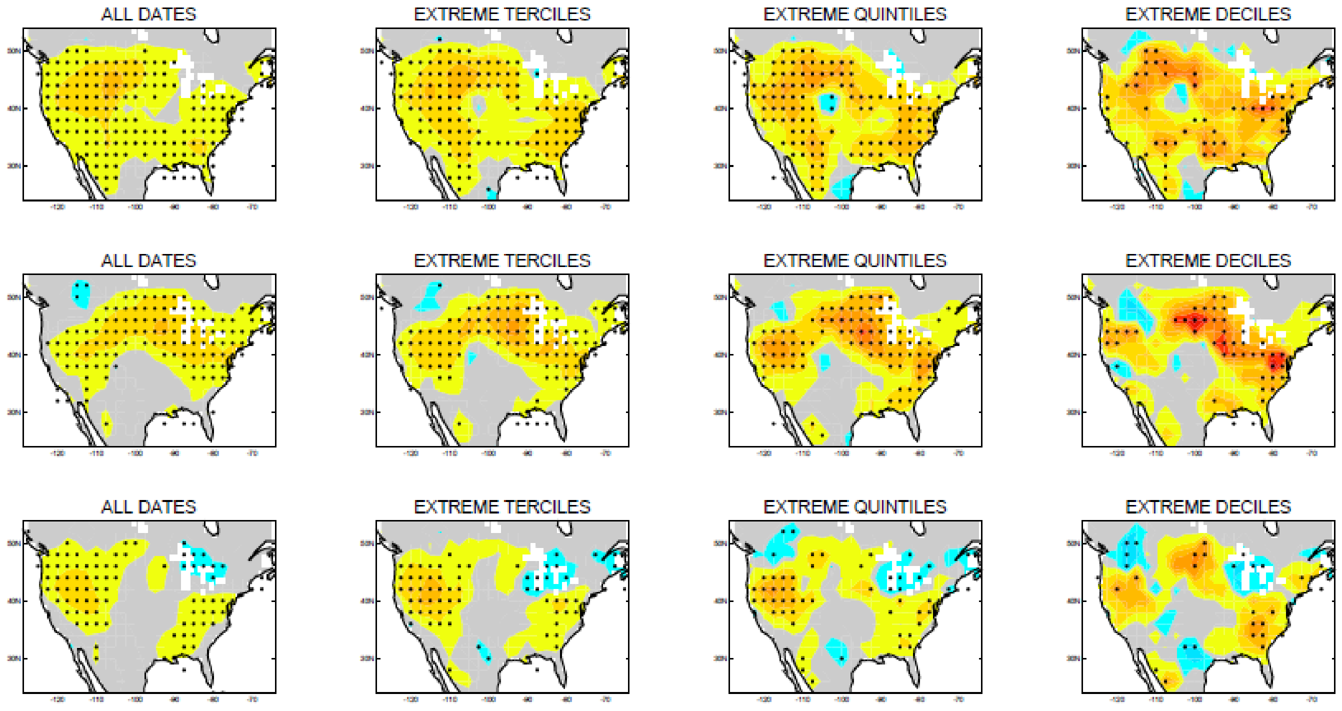
Extreme quintiles

Extreme deciles

16-30 days

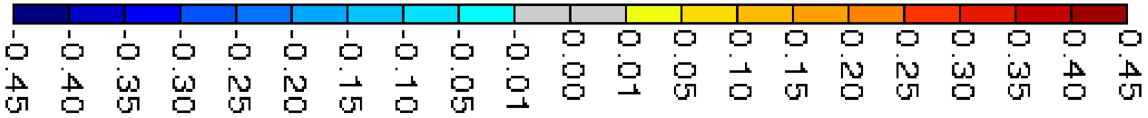
31-45 days

46-60 days



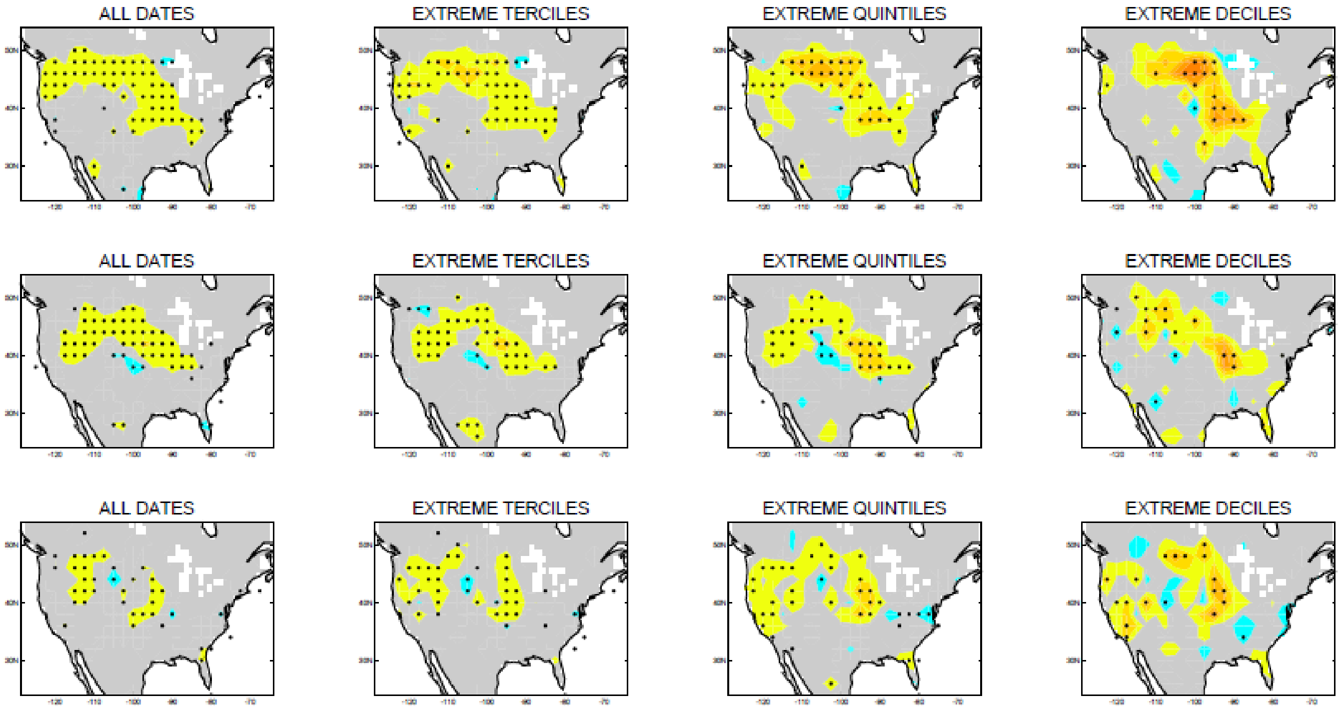
Dates for conditioning vary w/location

Forecast skill: r^2 with land ICs vs r^2 w/o land ICs



Precipitation forecasts: Increase in skill due to land initialization (JJA)
(conditioned on strength of local initial soil moisture anomaly)

	all points	Extreme terciles	Extreme quintiles	Extreme deciles
16-30 days				
31-45 days				
46-60 days				



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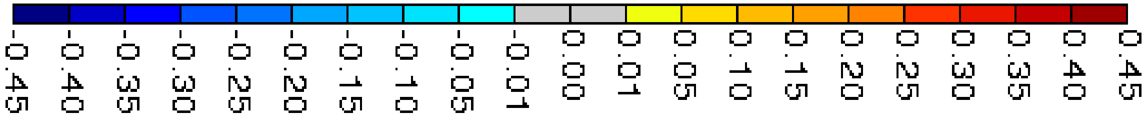
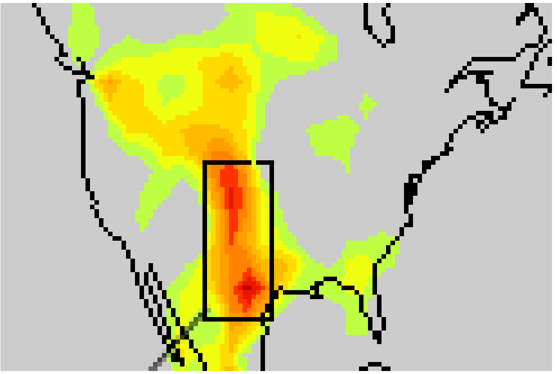


Note the contradiction between diagnosed coupling strength locations (from earlier) and locations where skill appears:

Coupling strength



Reasons for the discrepancy are somewhat unclear but may be related to:

-- different set of models, with different biases (different transition zones)

-- spatial differences in memory

-- ability to produce a feedback loop ("coupled mode") in the forecast system

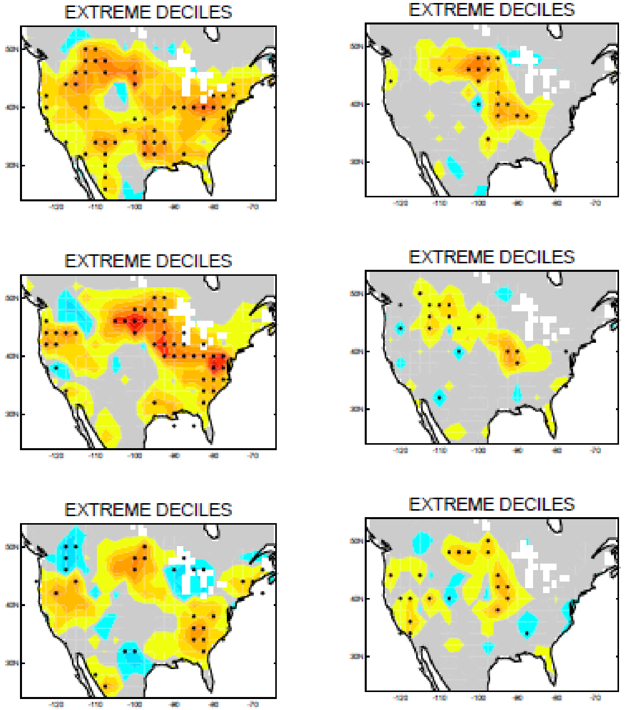
Skill levels (extreme deciles)

temperature | precipitation

16-30 days

31-45 days

46-60 days



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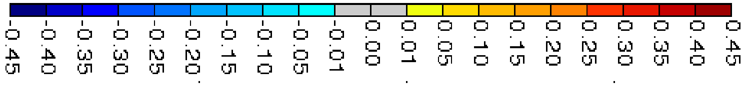

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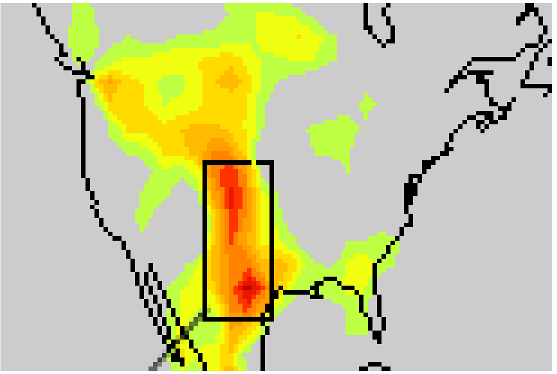

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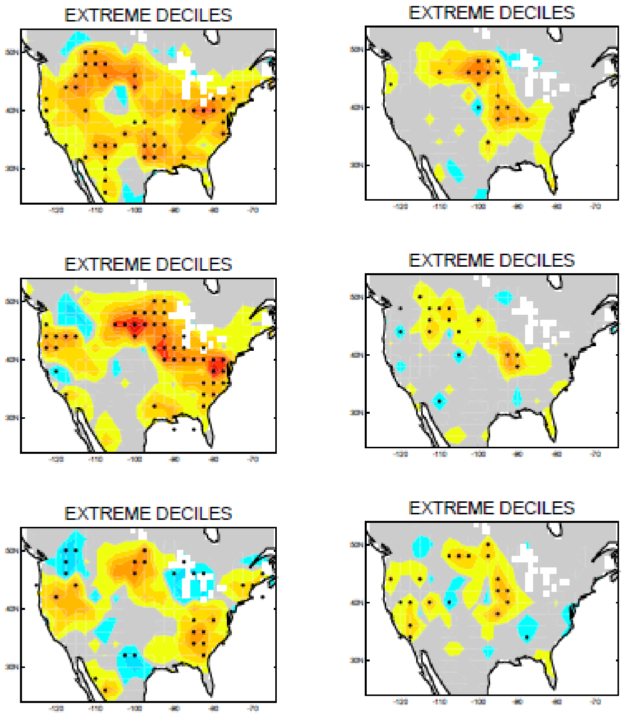

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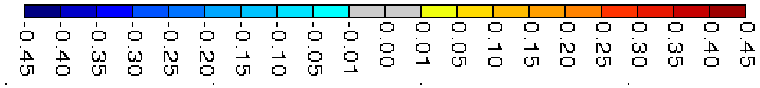

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-- different set of models, with different biases (different transition zones)

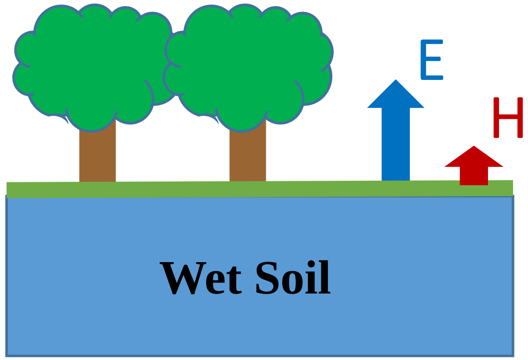
-- spatial differences in memory

-- ability to produce a feedback loop ("coupled mode") in the forecast system

perhaps not the primary reason, but scientifically exciting – worth a quick look!

Local vs. Remote Soil Moisture Impacts on the Atmosphere

1. Consider local effects.



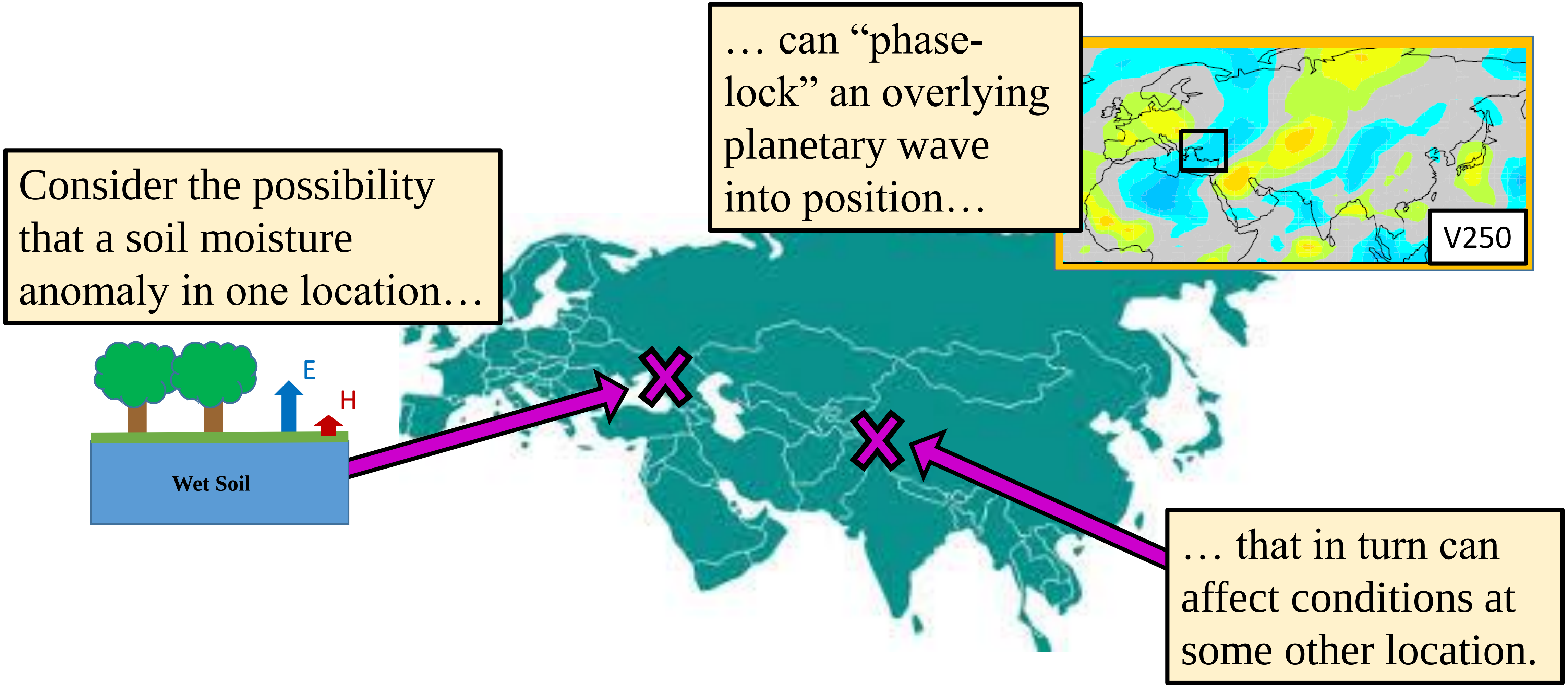
For example:

Wet soil ➪ higher evap., lower sensible heat flux

This can affect *<u>local</u>* *air temperature:*
➪ more evaporative cooling
➪ lower air temperature

It can also affect local *precipitation:*
➪ boundary layer modification
➪ conditions more conducive
(or perhaps less conducive)
to onset of moist convection

2. Now consider potential remote effects:



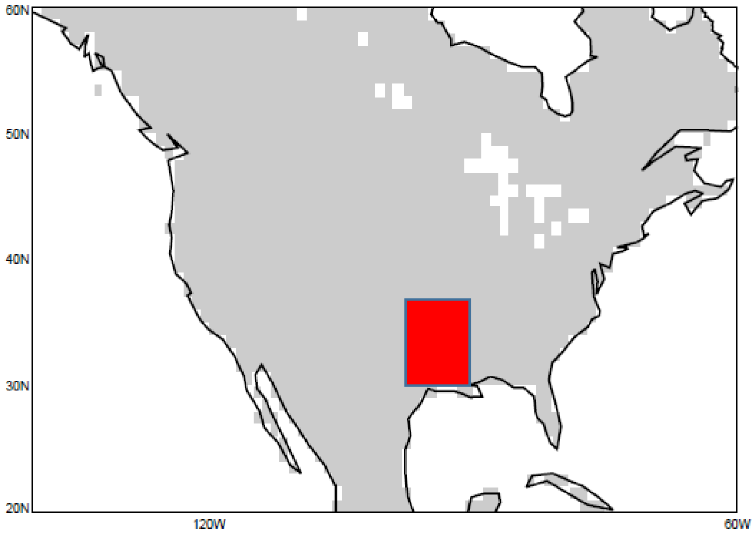
Experimental Design

Control: Ensemble (768 members) of April-July simulations using atmosphere-land components of the GEOS-5 system, at 1°×1° resolution.

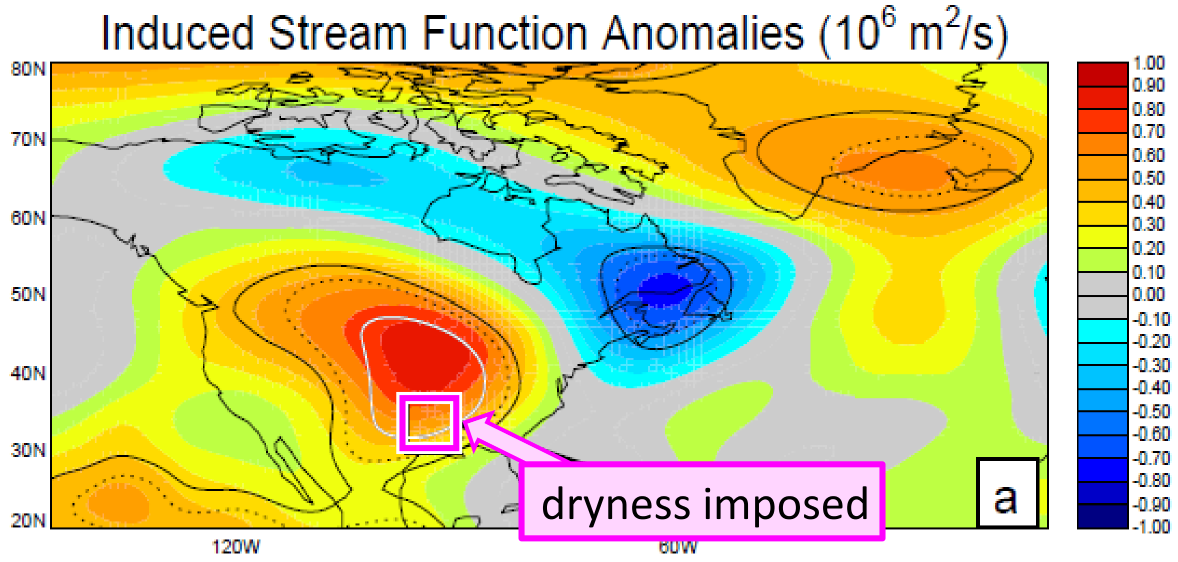
Experiment: Same as control, except:

(a) Smaller ensemble size (192 or 96 members)

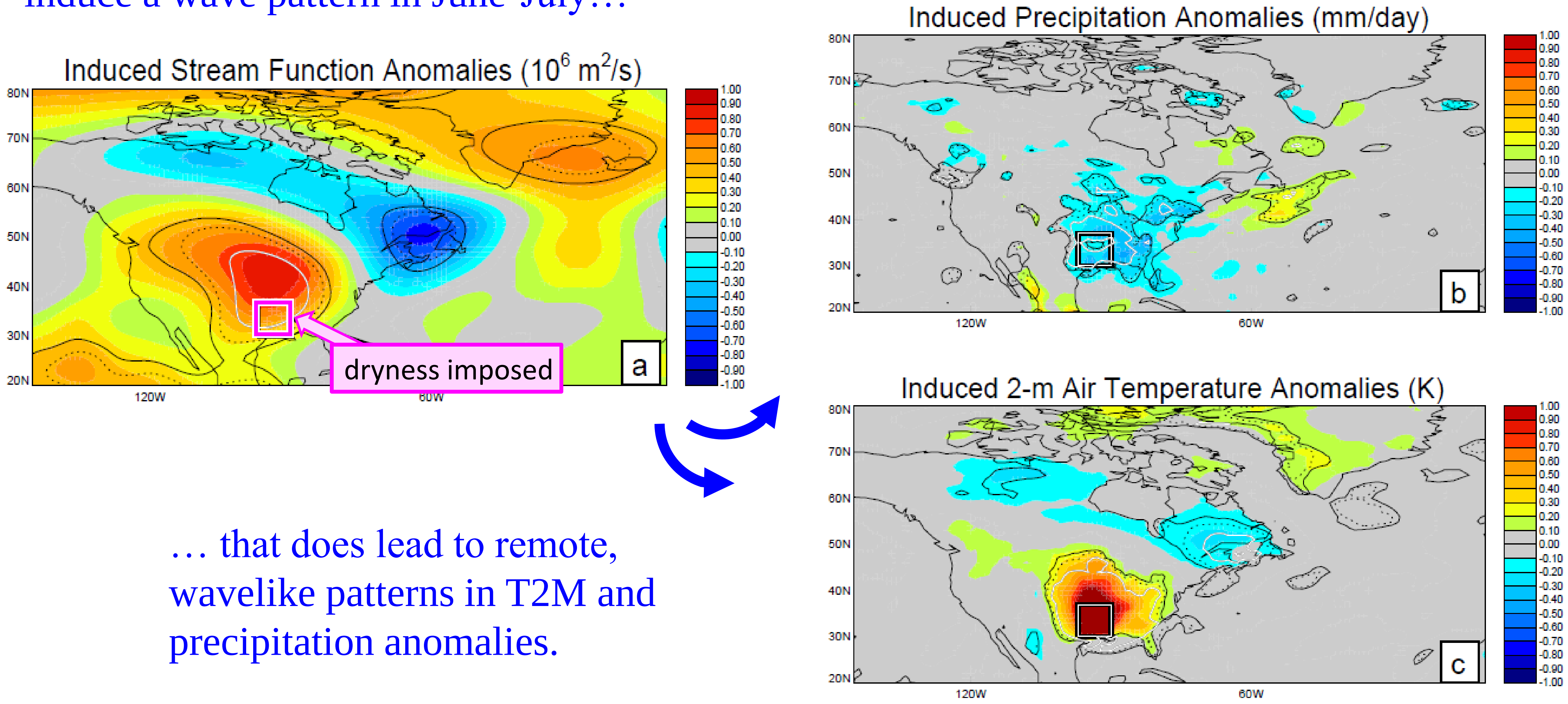
(b) Precipitation in a selected region is not allowed to hit the surface during April-June, *forcing the surface to become dry there*.



The dry surface anomaly does (on average) induce a wave pattern in June-July…

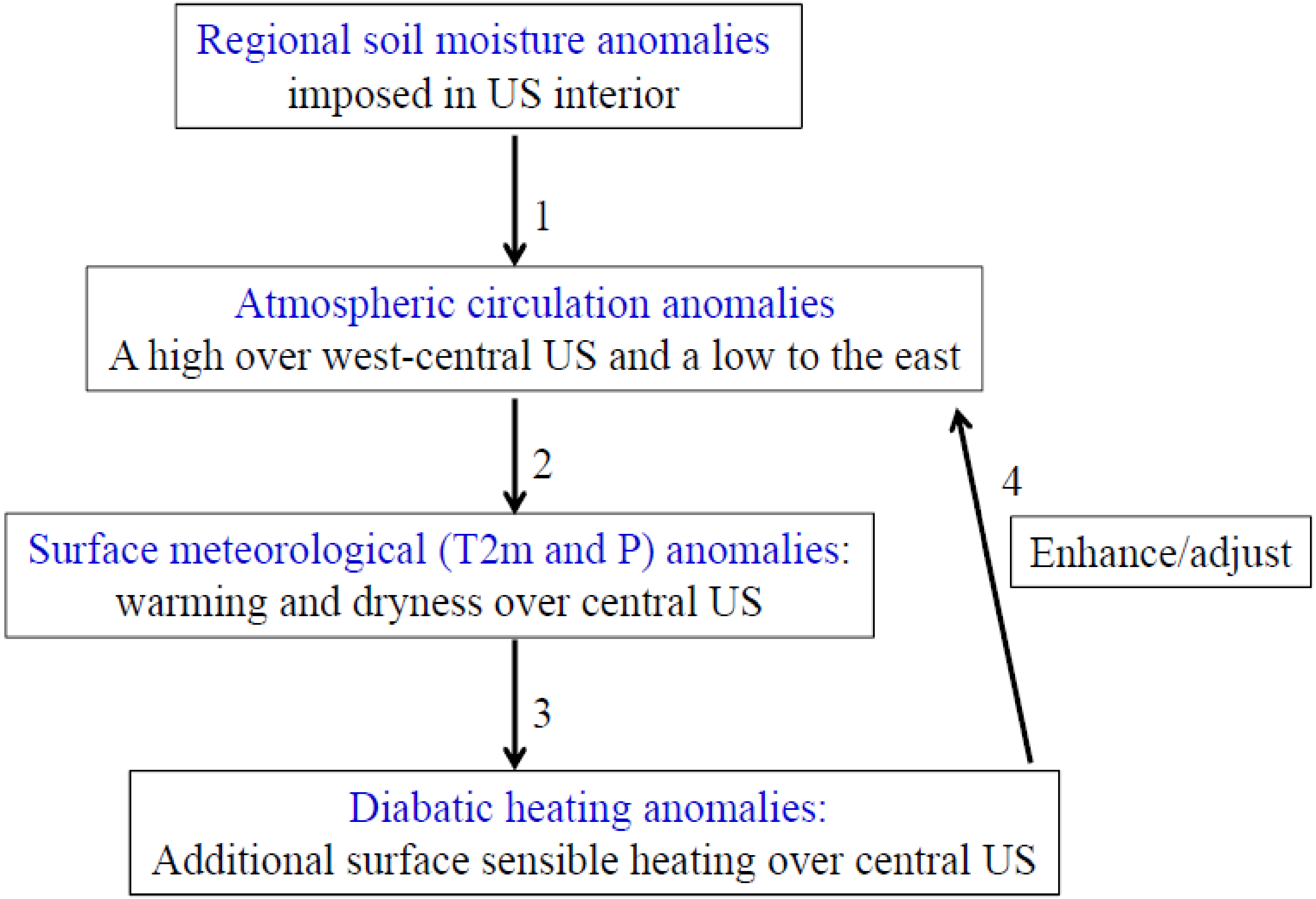


The dry surface anomaly does (on average) induce a wave pattern in June-July…



… that does lead to remote, wavelike patterns in T2M and precipitation anomalies.

This, along with a suite of additional "dry surface" experiments, suggests a feedback loop:



Regional soil moisture anomalies
imposed in US interior

1

Atmospheric circulation anomalies
A high over west-central US and a low to the east

2

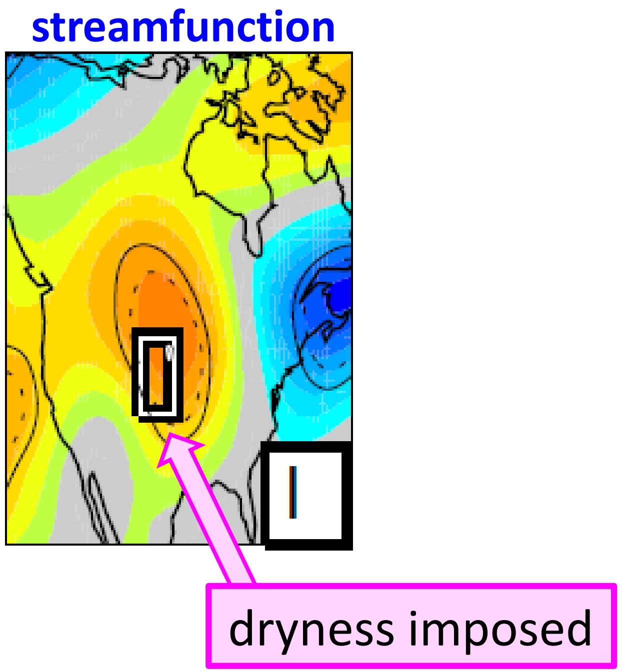
Surface meteorological (T2m and P) anomalies:
warming and dryness over central US

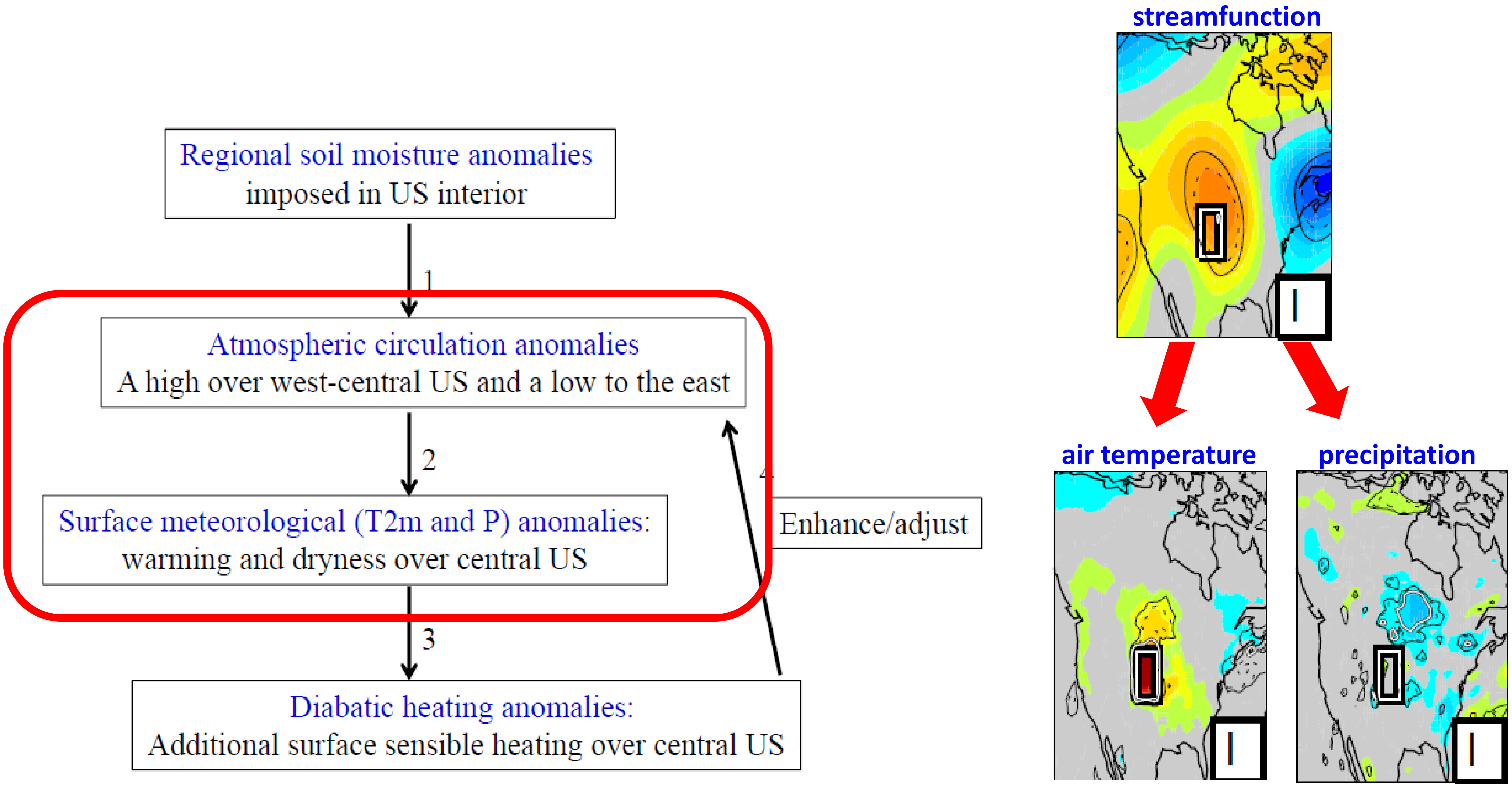
3

Diabatic heating anomalies:
Additional surface sensible heating over central US

4

Enhance/adjust

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Enhance/adjust
streamfunction
air temperature
precipitation

Regional soil moisture anomalies
imposed in US interior

↓ 1

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↓ 2

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Diabatic heating anomalies:
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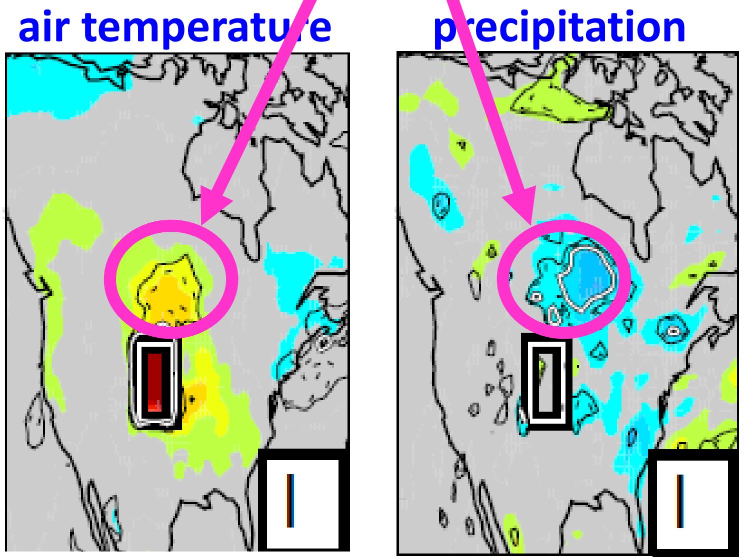
4 Enhance/adjust

Notice drying and warming even outside of original selected region



Regional soil moisture anomalies
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Surface meteorological (T2m and P) anomalies:
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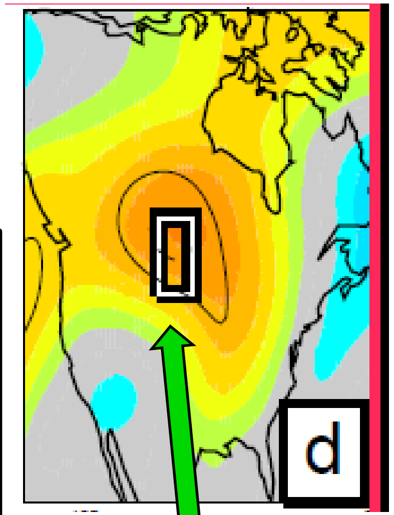
↓ 3

Diabatic heating anomalies:
Additional surface sensible heating over central US

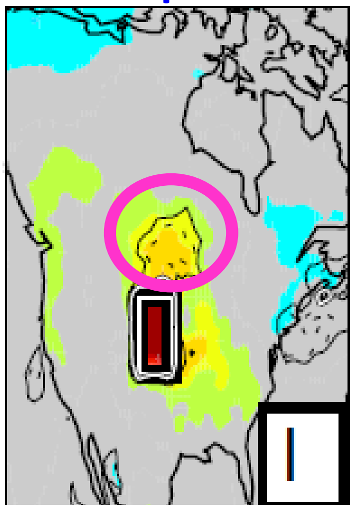
↑ 4

Enhance/adjust

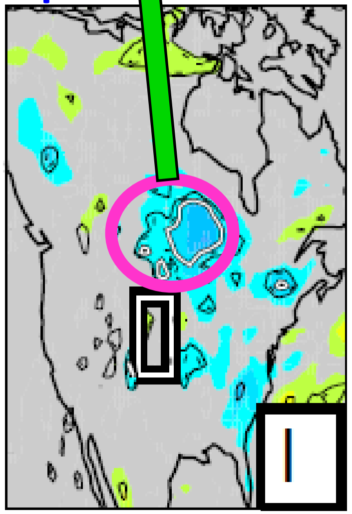
Dryness in these outside regions can in turn induce additional streamfunction changes



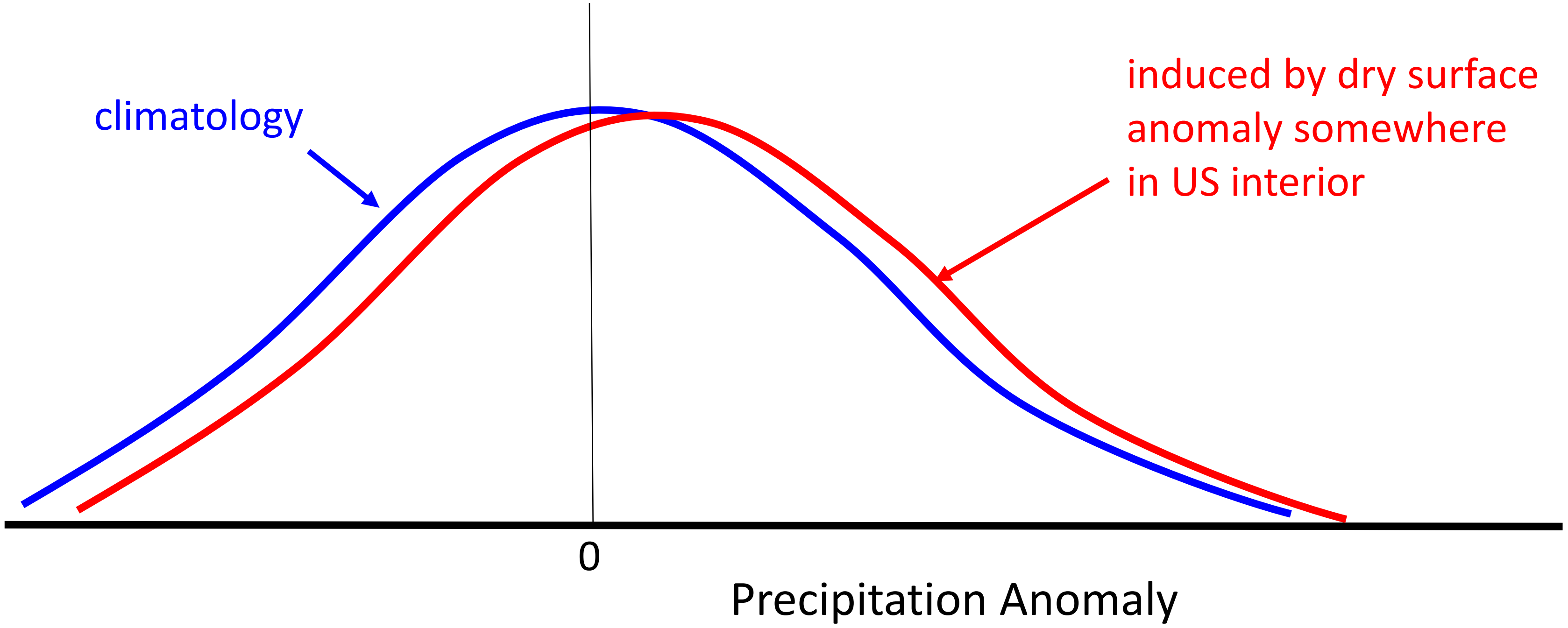
air temperature

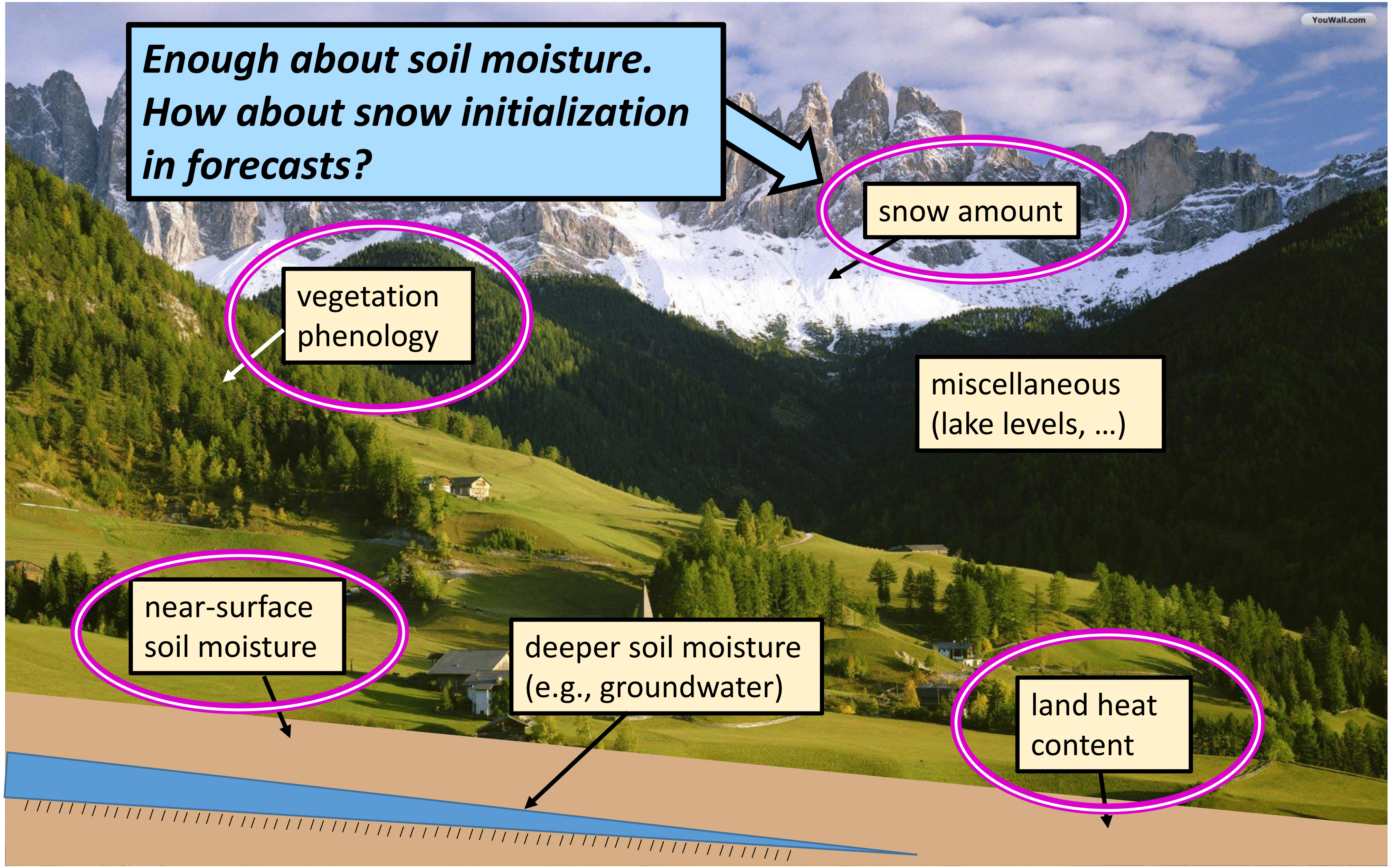


precipitation



Important consideration: Given the large number of ensemble members needed to extract the signals of interest from the AGCM, we are talking here about shifts in PDFs. These shifts are subtle, and their relevance (e.g.) to forecasting large-scale dryness are yet to be demonstrated.





(Image stolen from internet!)

Jaison Thomas and Aaron Berg performed two sets of forecasts initialized on April 1 for each year in 1986-2005:

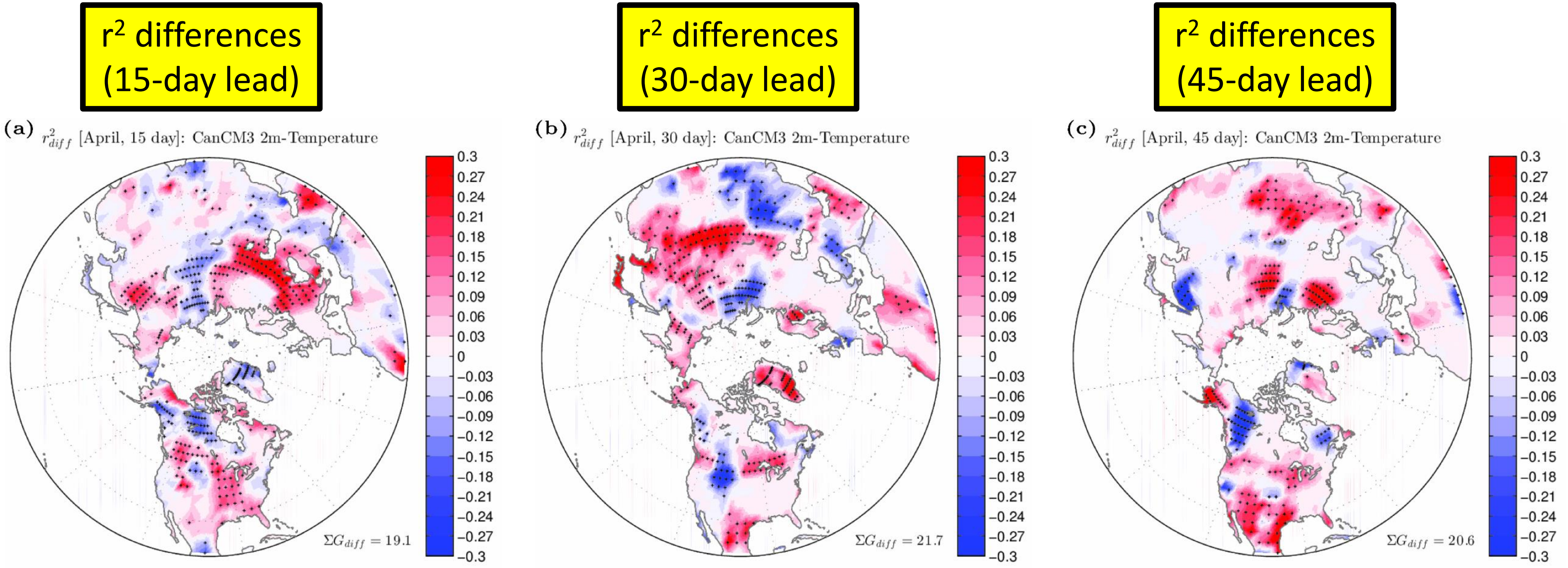
1) With realistic April 1 initializations of snow water equivalent, frozen soil moisture, and liquid soil moisture.
2) Without these realistic initializations.

Forecasted 15-day-average 2m temperatures were compared to observations (reanalysis).

As before,

Skill (r^2) from simulations w/ accurate land ICs − Skill (r^2) from simulations w/o accurate land ICs = Skill due to land ICs

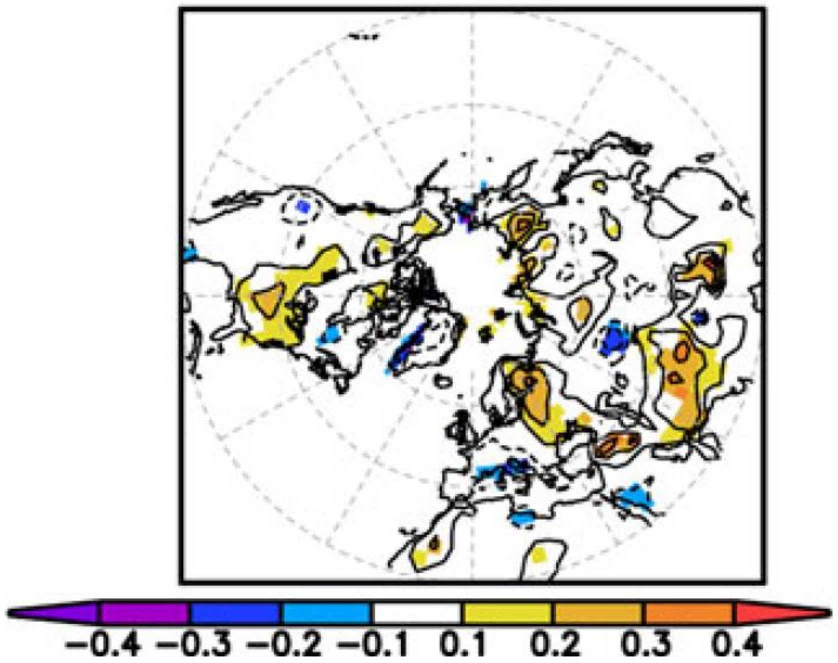
Snow and soil water contributions to skill:



Ambadan et al., Climate Dynamics, 47, 49-65, 2016

Another study: Peings et al. (Clim. Dyn., 37, 985-1004, 2011) performed an analysis evaluating the contribution of snow initialization to temperature and pressure forecast skill.

Increase in anomaly correlation coefficient due to snow initialization:
2-m air temperature



Snow initialization led to improvements in the 2-m temperature skill, mostly in the first 2 months following the March 1 initialization. The initialization had little impact on the large scale circulation, however, as indicated by predicted sea level pressure patterns.

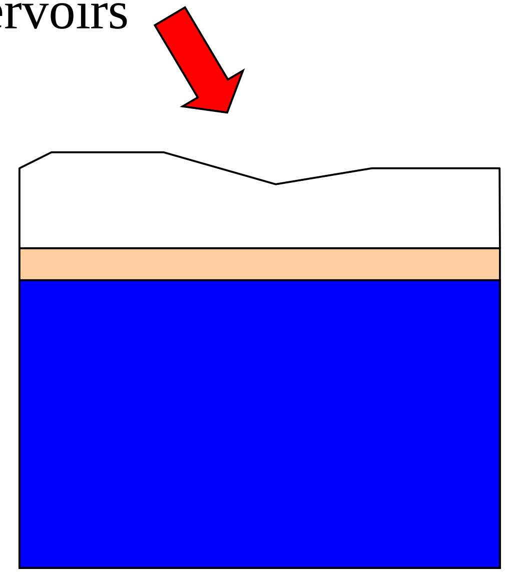
(With thanks to Herve Douville, Meteo-France)

Streamflow forecasting via snow and/or soil moisture initialization is also a subseasonal-to-seasonal forecast topic.

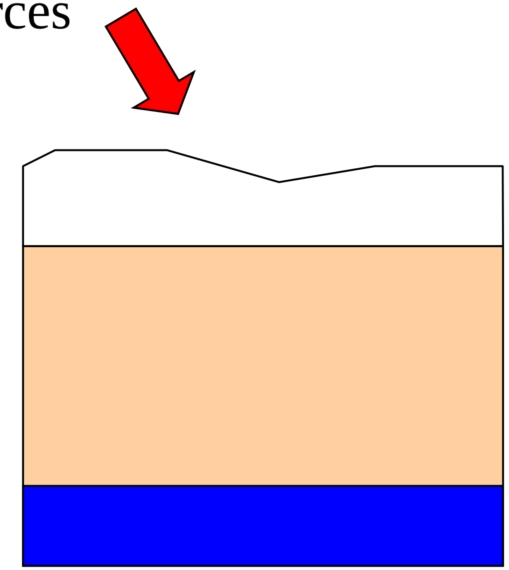
Obvious: Larger snowpack ⇨ Increased streamflow during snowmelt season.

Less obvious: Impact of soil moisture…

Snow (or rainfall) over wet soil: most of the meltwater runs off into streams, reservoirs



Snow (or rainfall) over dry soil: most of the meltwater infiltrates the soil and is lost to water resources



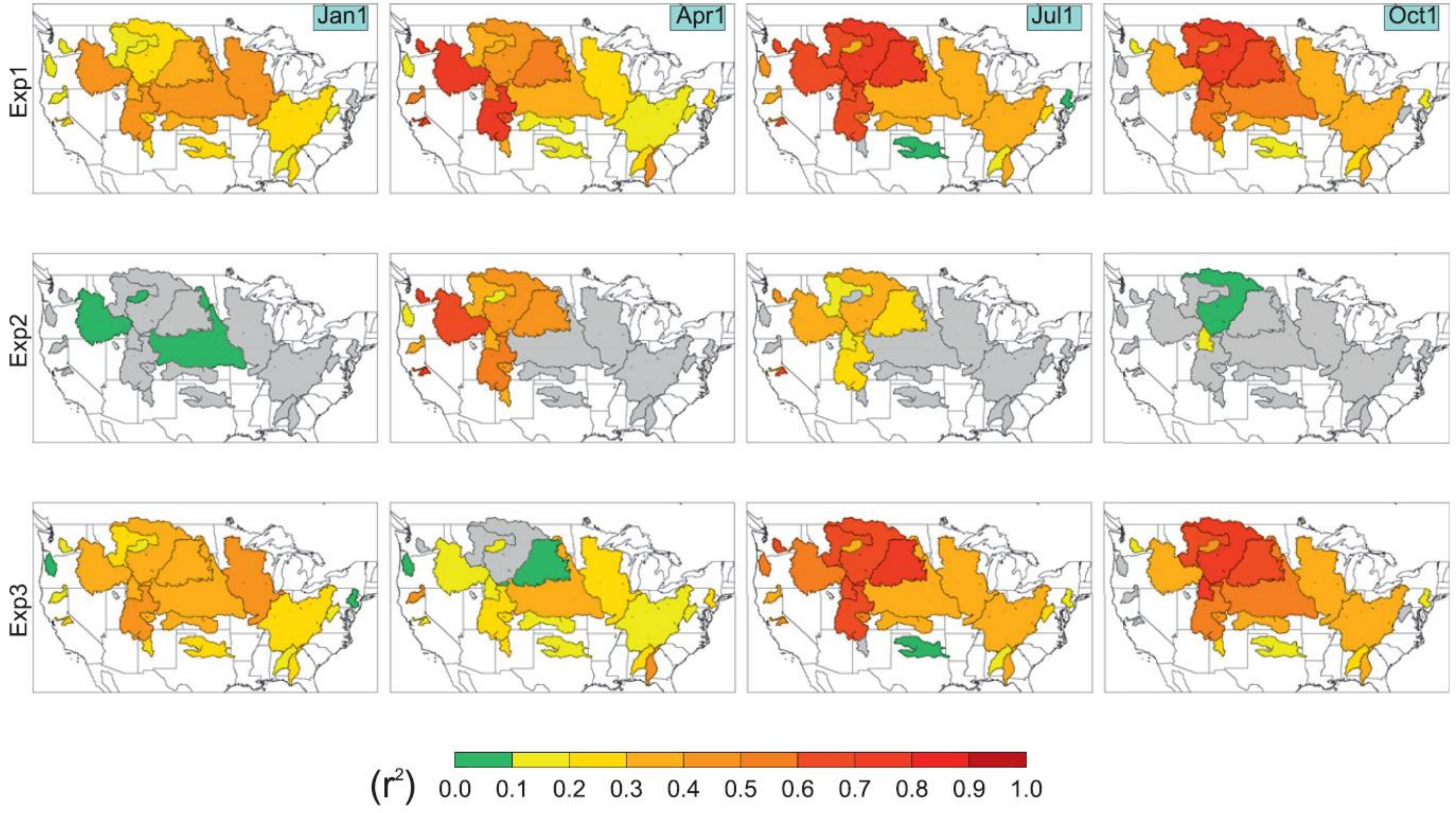
Knowledge of winter snow, soil moisture ⇨ streamflow forecast skill

Performed experiments; estimated contribution to 3-month streamflow forecast skill from snow and soil moisture ICs:

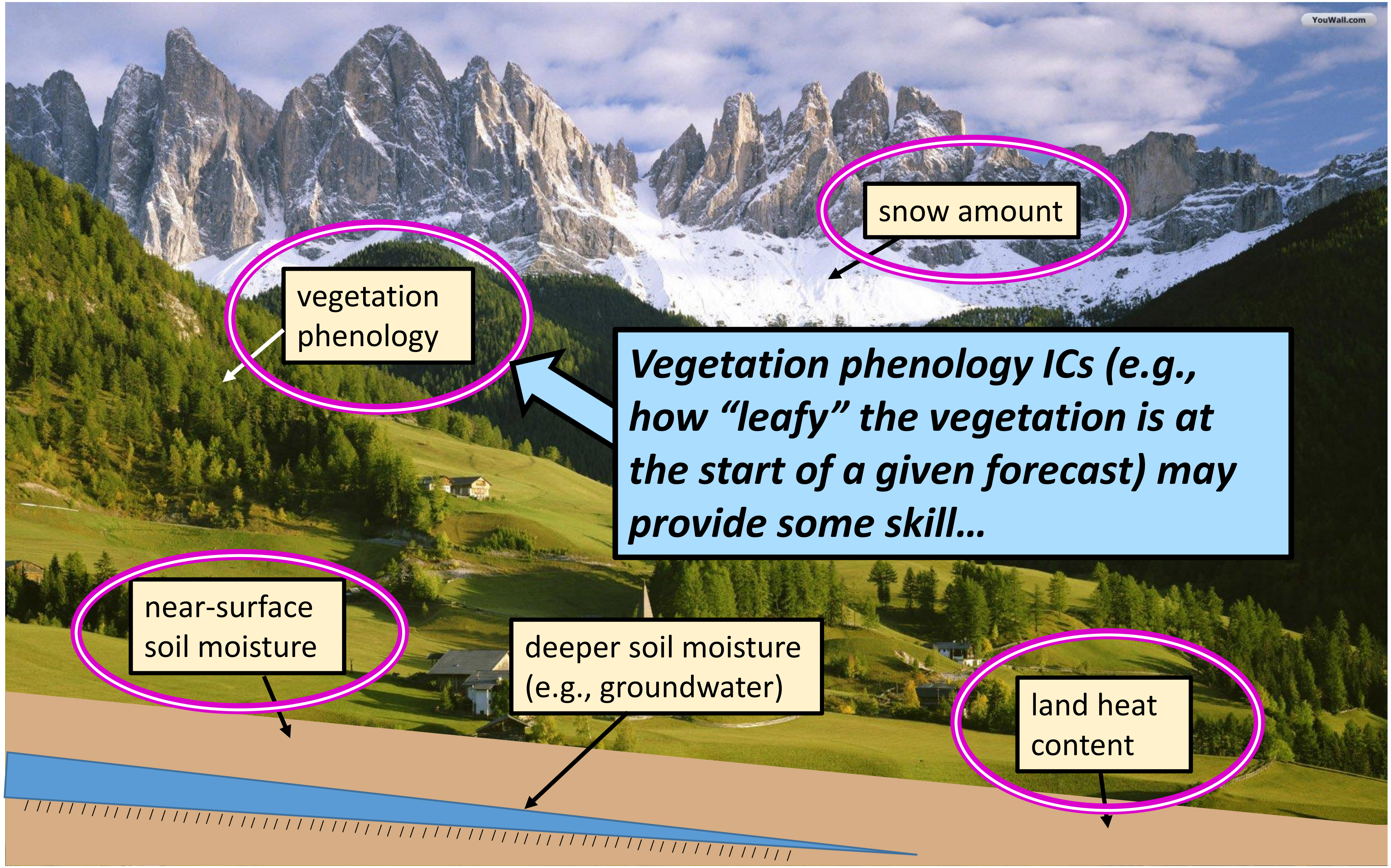
From both snow and soil moisture ICs

From snow ICs

From soil moisture ICs



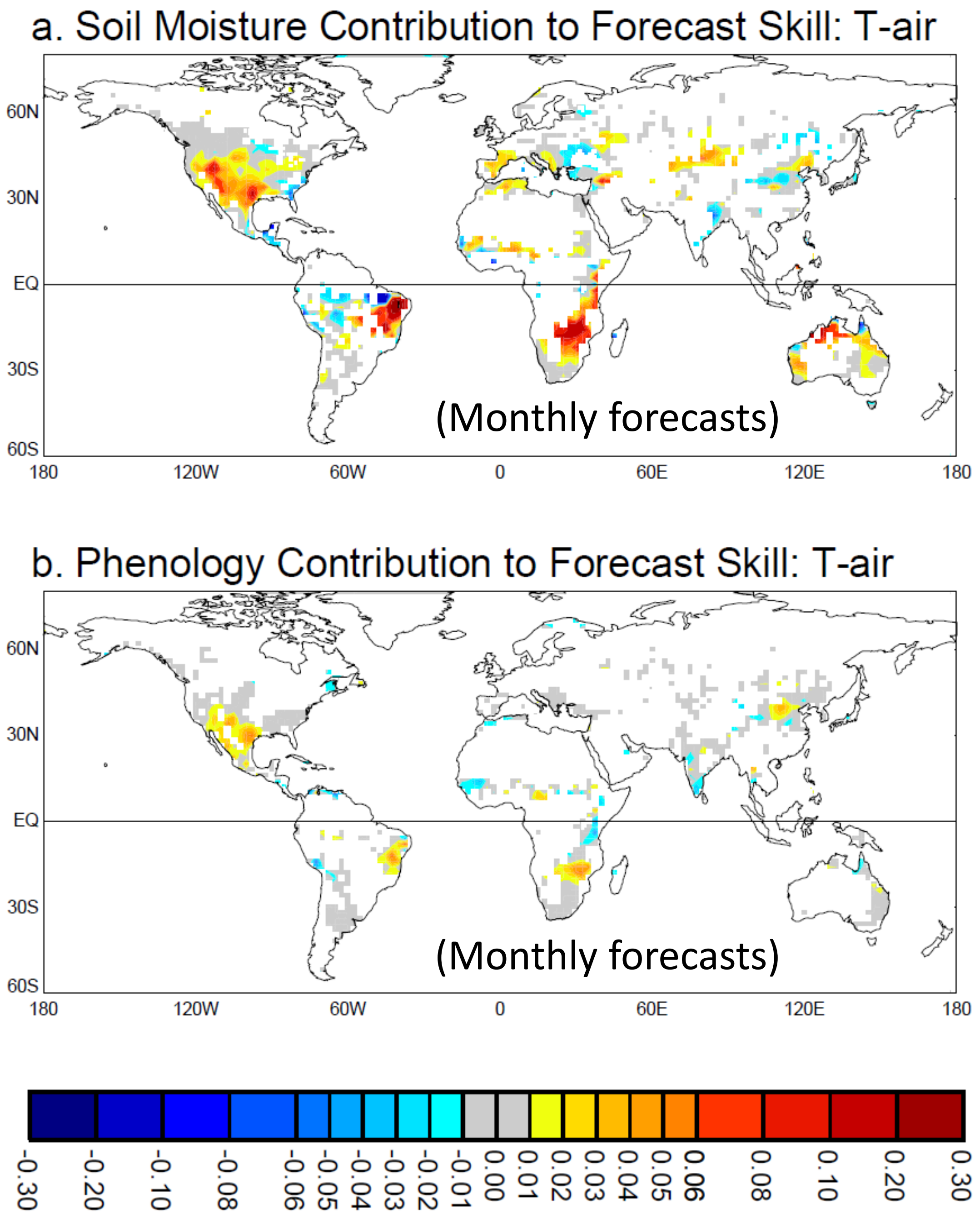
Mahanama et al., J. Hydromet., 13,189-203, 2012



(Image stolen from internet!)

Vegetation state. An experiment similar to GLACE-2, but focusing on the impacts of initialized vegetation state on monthly forecast skill (using a land model with dynamic phenology) was recently performed. In fact, the effects of both soil moisture and vegetation initialization were quantified with the same framework and compared side-by-side.

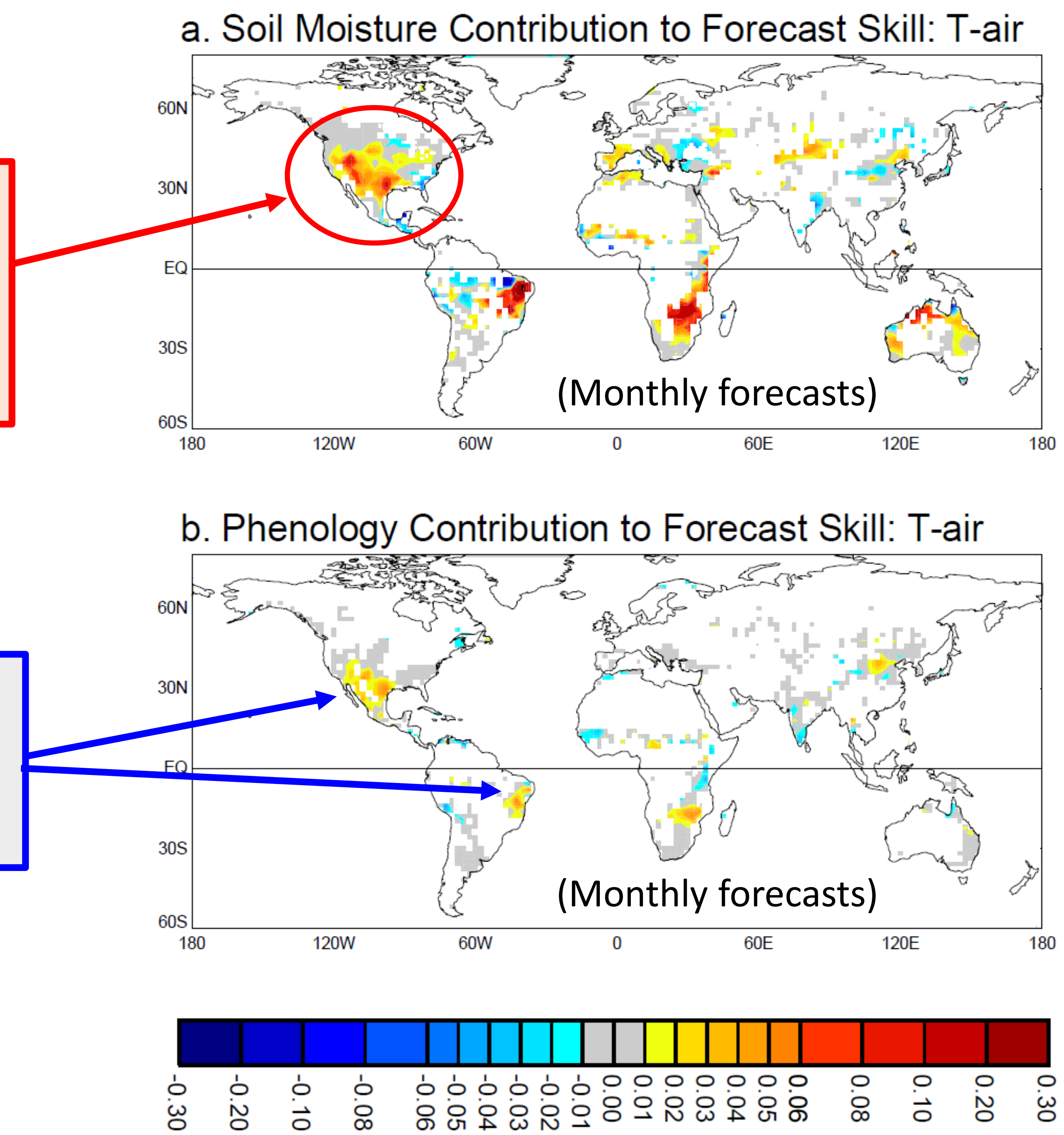
Skill (r^2) from simulations w/ accurate land ICs − Skill (r^2) from simulations w/o accurate land ICs = Skill due to land ICs



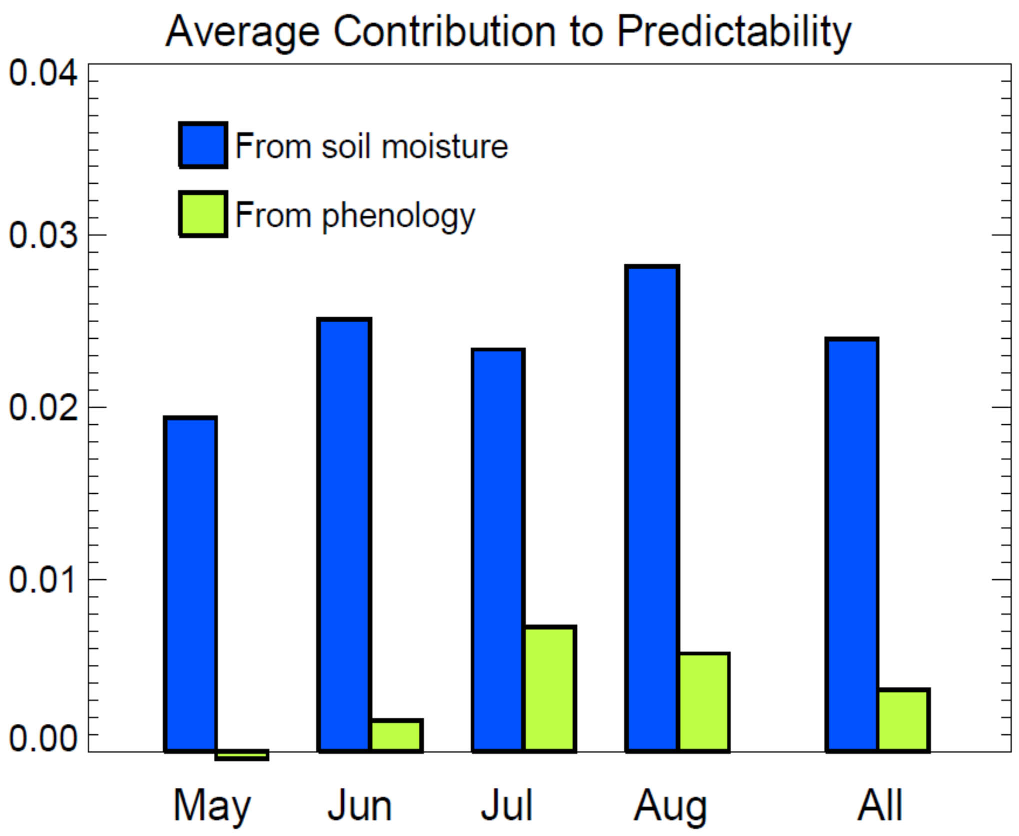
Koster and Walker, J. Hydromet., 16, 1456-1465, 2015

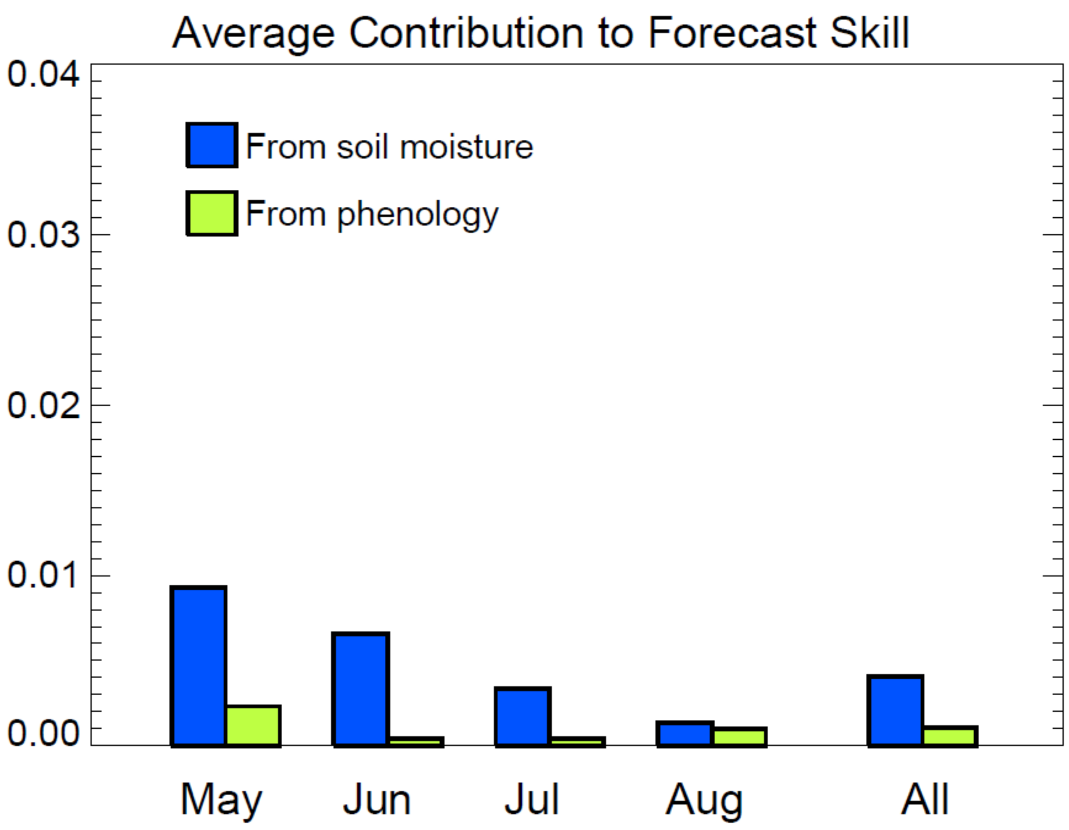
Note: some differences between this pattern (for single model) and that for multi-model GLACE-2 results

Many indications of positive impact, but with magnitudes smaller than that for soil moisture

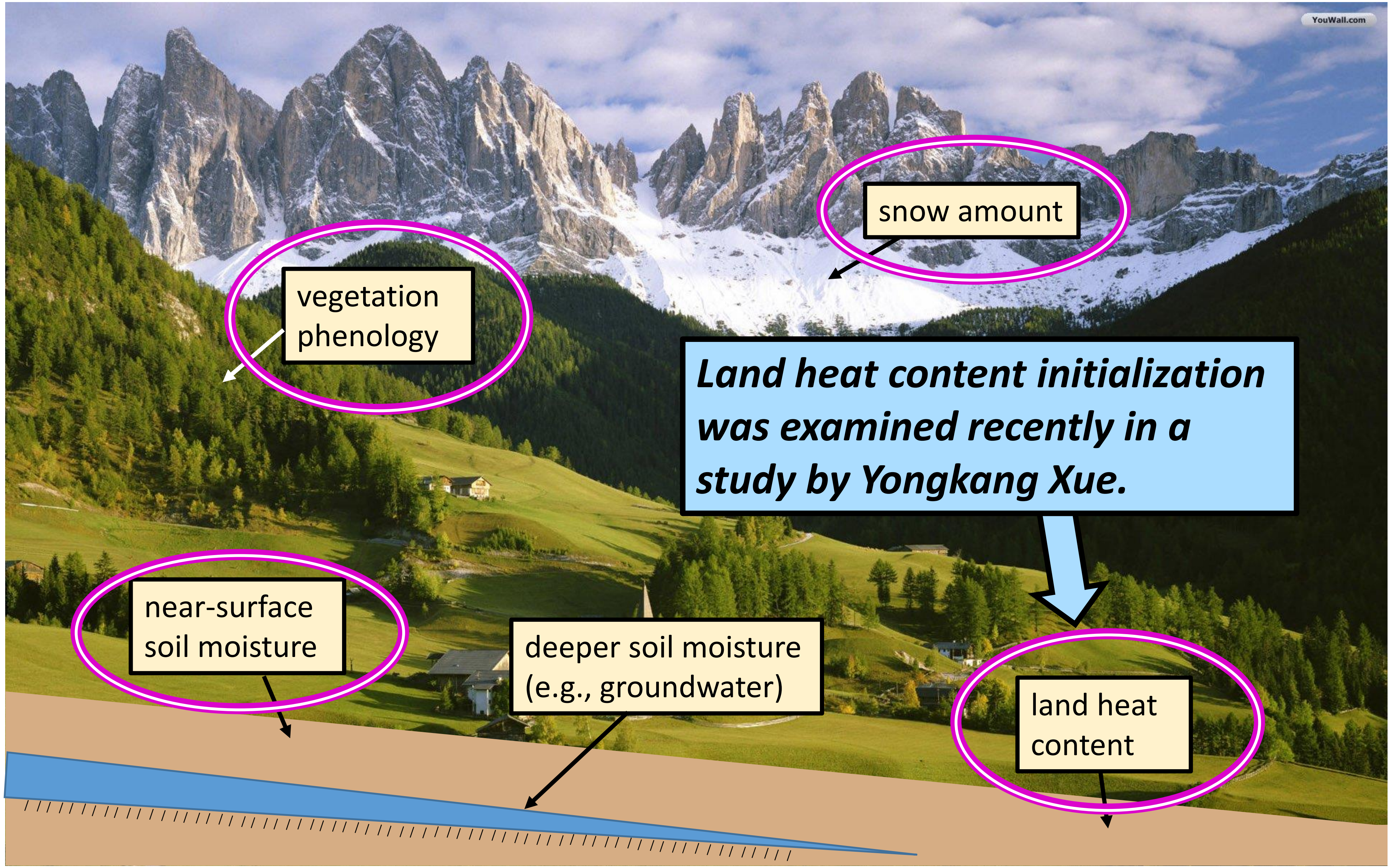


Global averages of contributions over areas with adequate rain gauge density





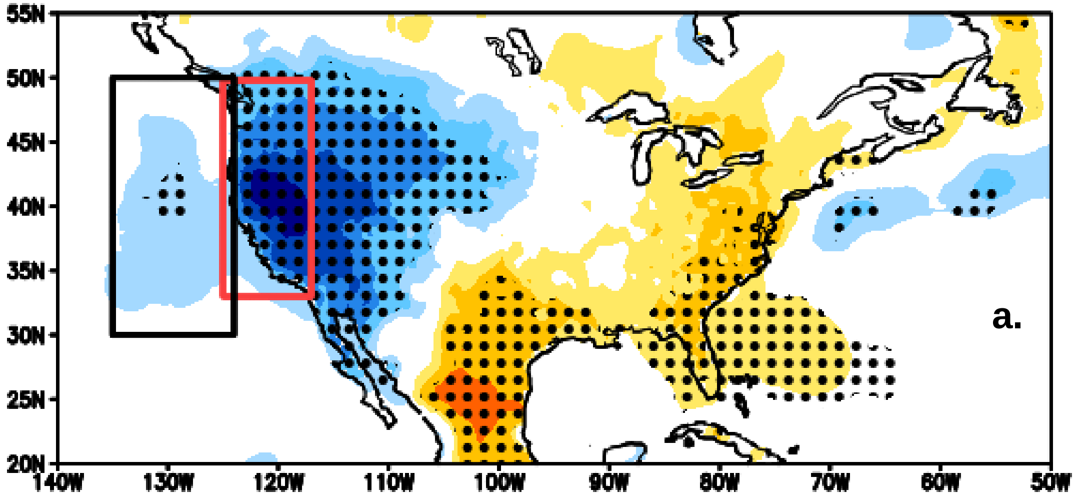
1-month air temperature forecasts



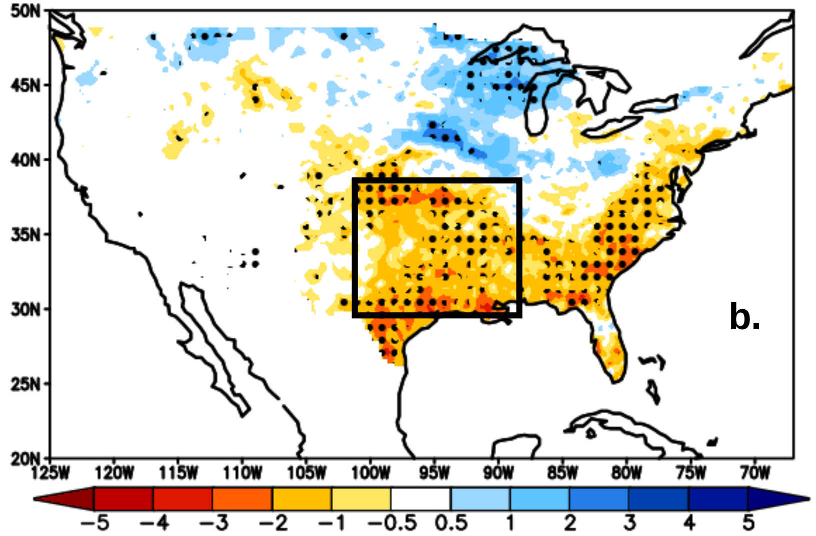
(Image stolen from internet!)

Observed differences between 9 coldest years and 9 warmest years (based on N.W. U.S. & S. E. Canada LST)

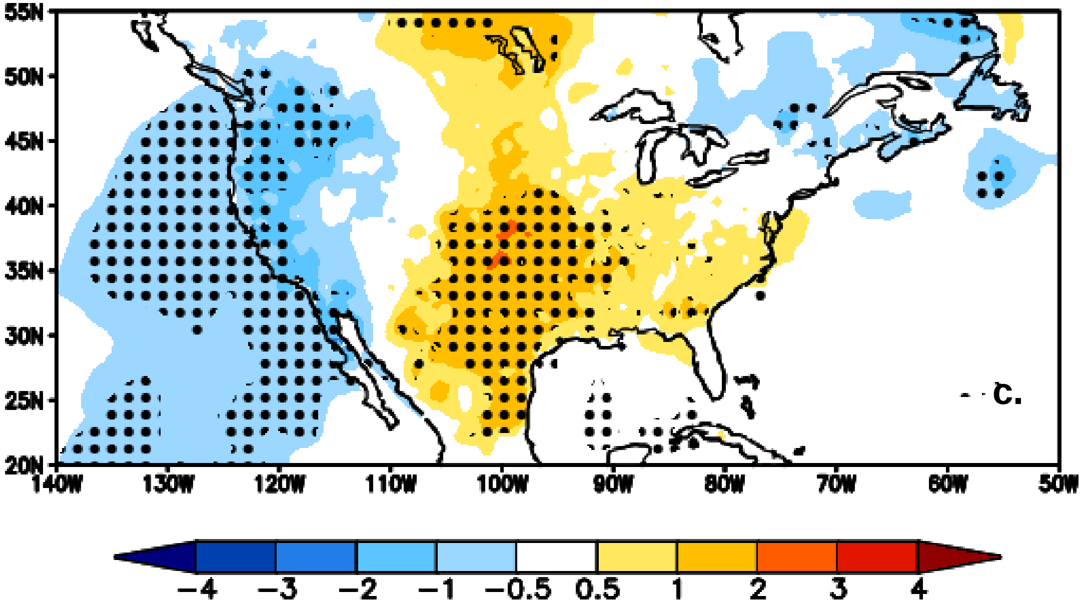
May Observed LST and **SST**



June Observed Precipitation



June Observed LST and SST



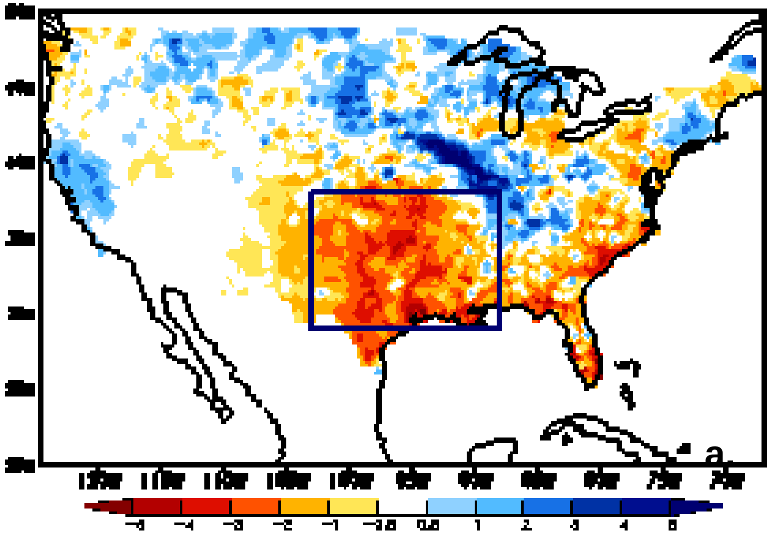
1) LST: land surface temperature

2) The dotted areas denote statistical significance less than α=0.1 level of t-test values.

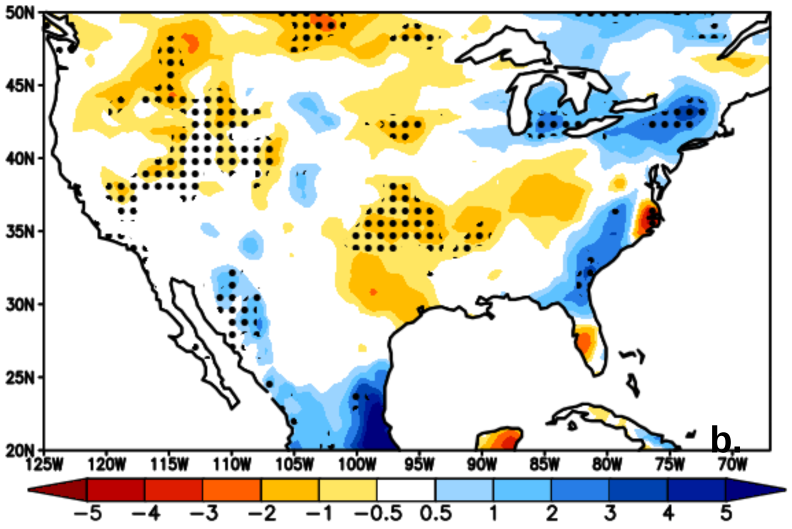
Xue et al., 2012 (JGR), 2016 (ERL)

Observed/WRF-NMM simulated anomaly/difference of 2011 June Precipitation (mm day^{-1})

Observed

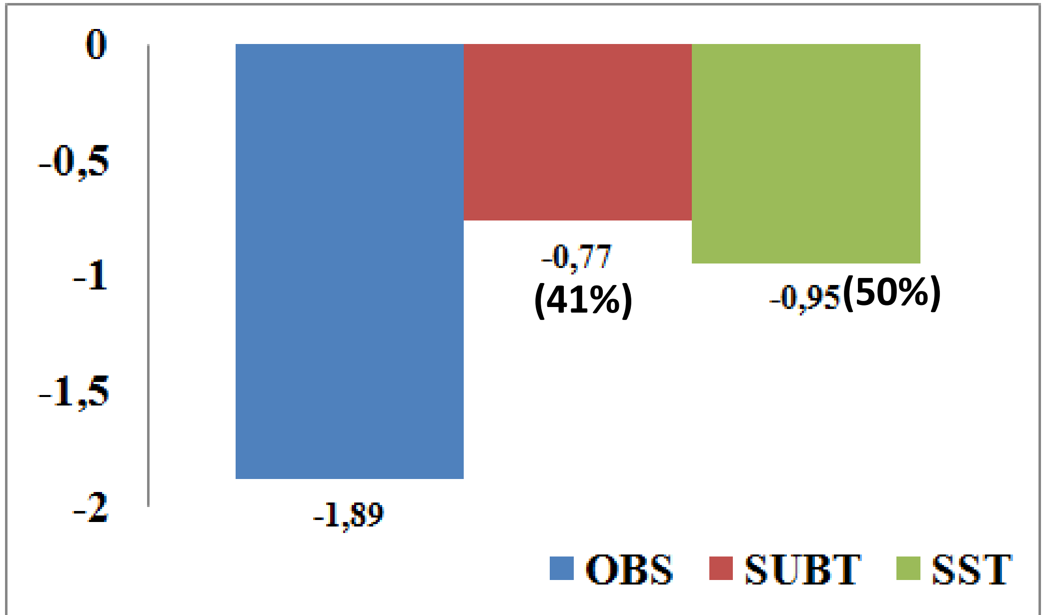


SUBT Effect

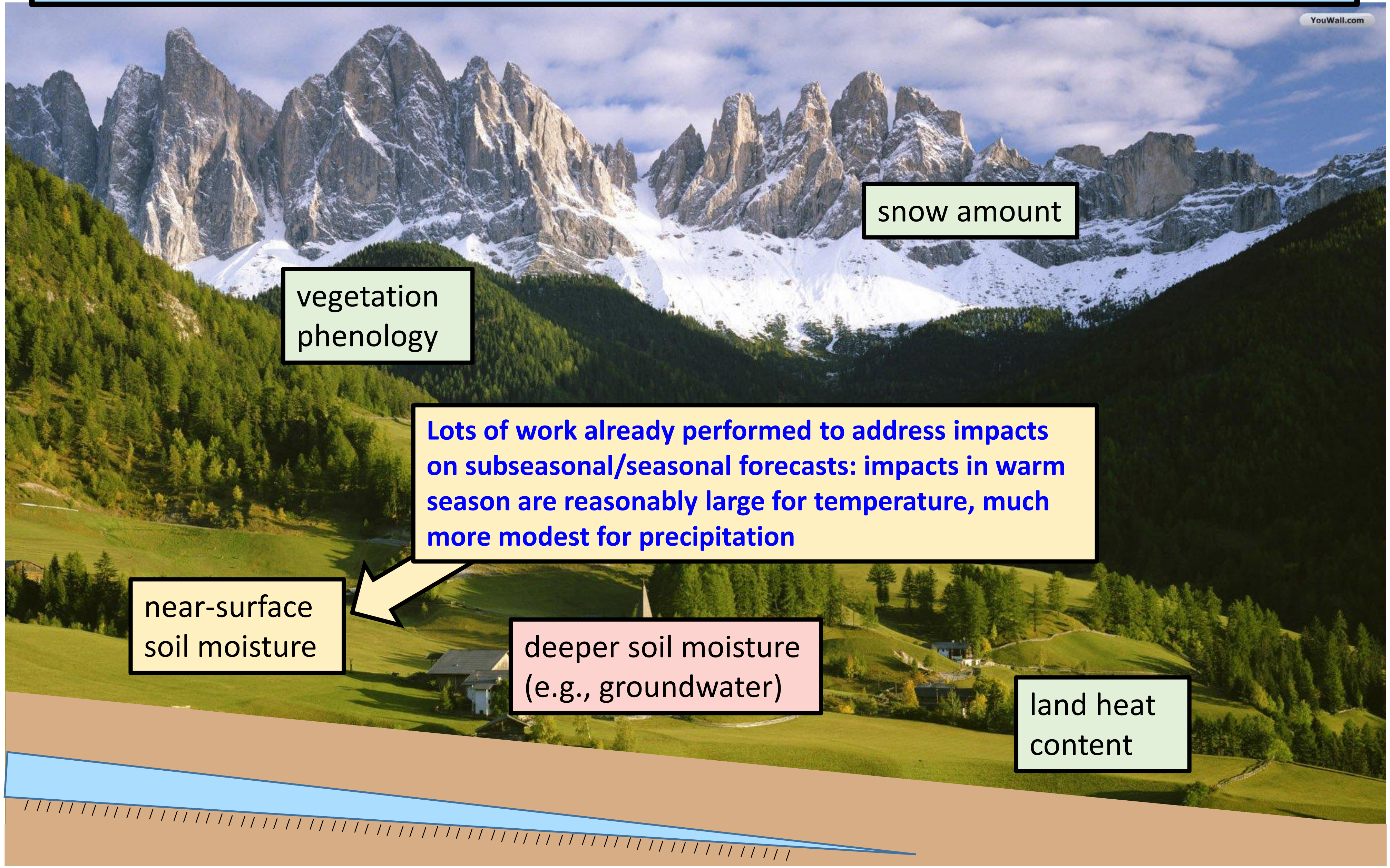


SUBT: Subsurface temperature.
The dotted areas denote statistical significance at the α=0.01 level of t-test values.

Observed/WRF_NMM-Simulated 2011 June Precipitation anomaly/difference over Southern Great Plains

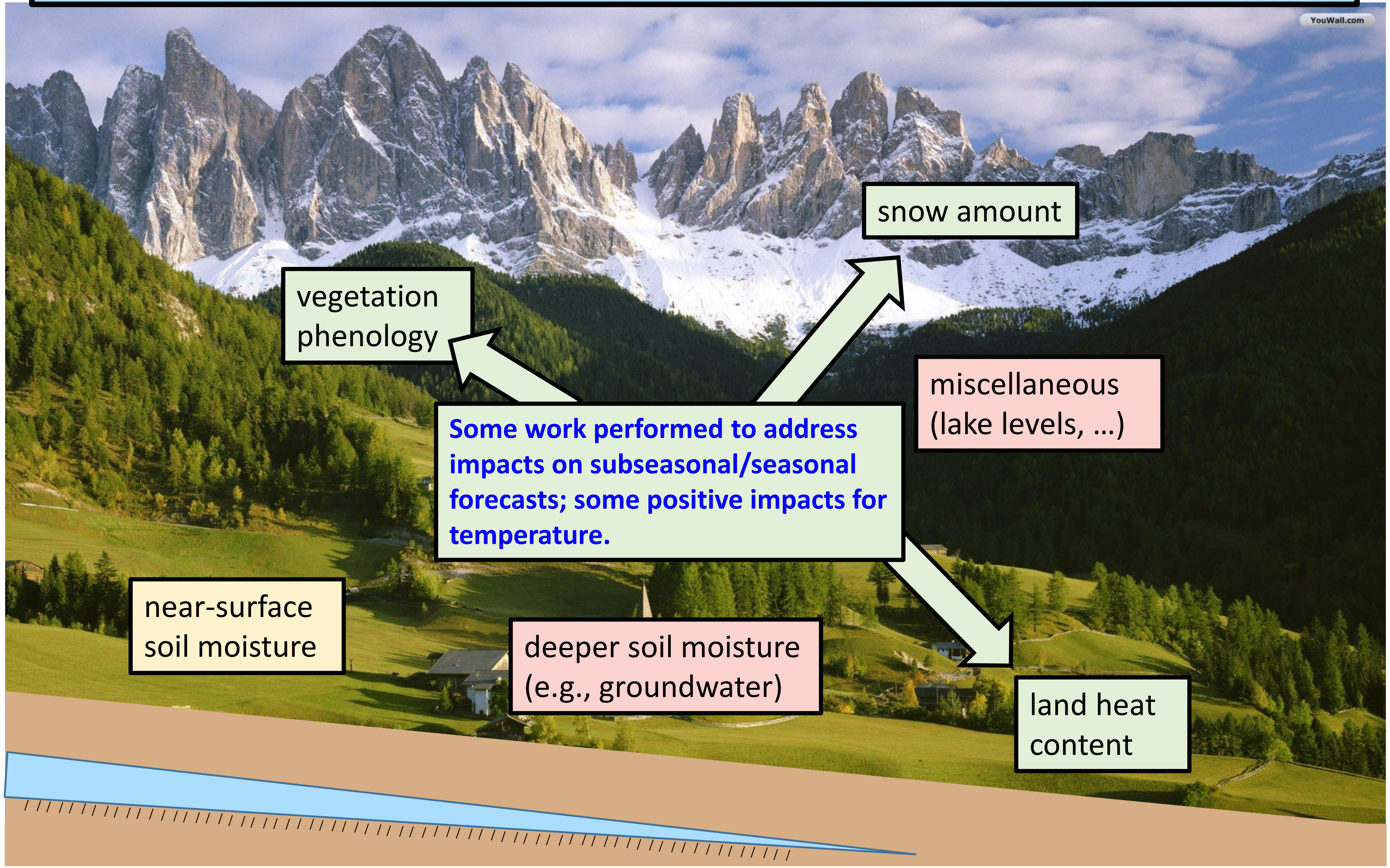


Before we discuss some ongoing challenges, here's a brief summary



(Image stolen from internet!)

So, before we discuss some ongoing challenges, here's a brief summary



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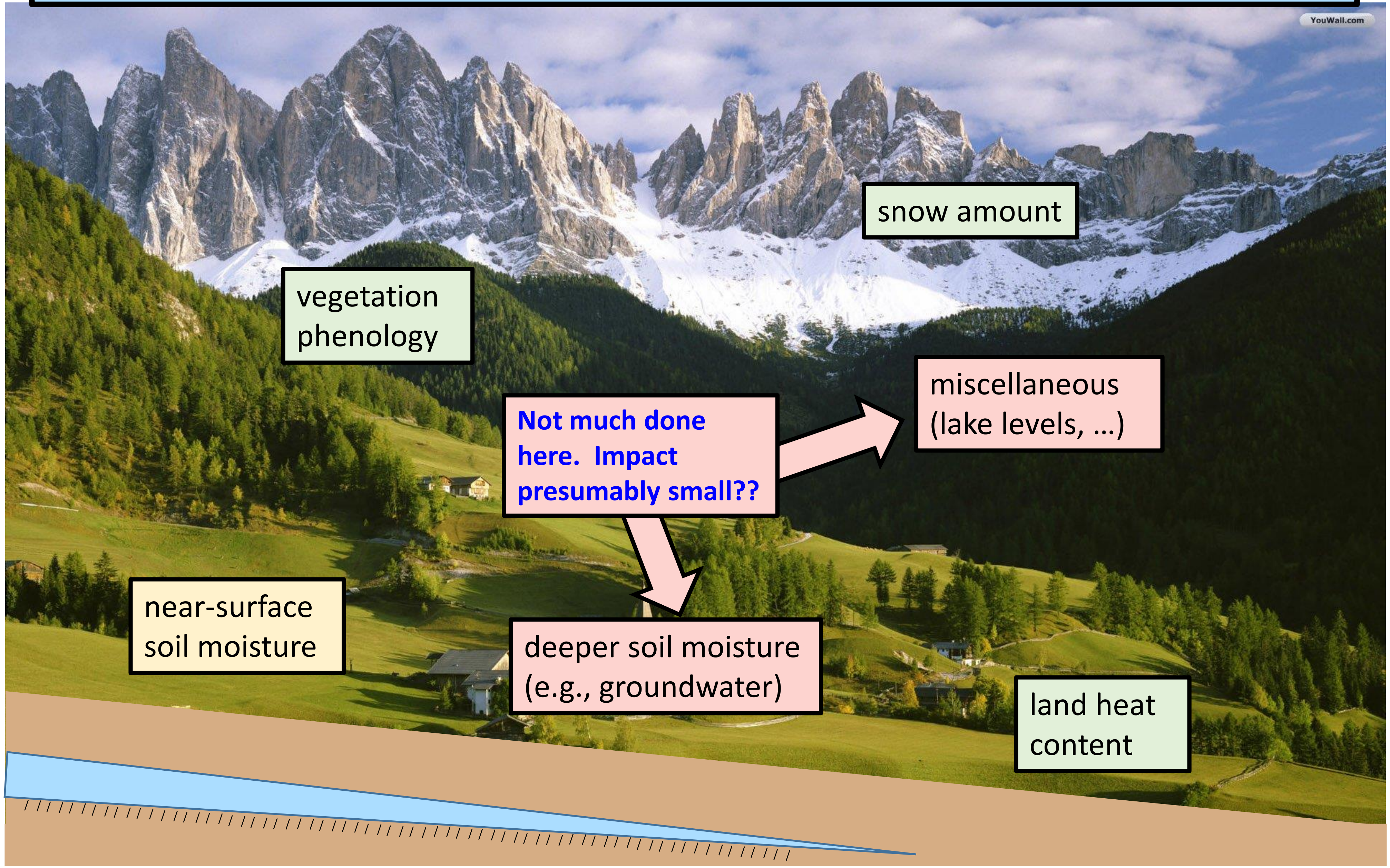
So, before we discuss some ongoing challenges, here's a brief summary



(Image stolen from internet!)

Some current challenges

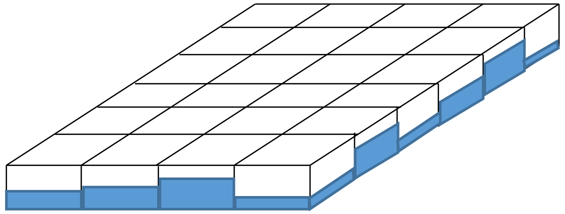
- Quantifying the skill contributions further, with a large complement of models (soil moisture analyses relatively mature, but not other variables)
- More thorough theoretical analysis of memory and feedback mechanisms; characterizing “nature’s” land-atmosphere coupling strength.
- Inclusion of additional variables into operational forecast systems (e.g., phenology)
- Taking advantage of the potential for conditional forecasts
- Need for better data for initialization: optimizing use of limited measurement resources to maximize impact on forecast skill, and tapping into as-yet-unused data sources

Land Initialization in Earth System Models

How can we initialize land conditions, e.g., for forecasts? From direct, in situ observations?

<u>*No.*</u> *In situ observations (certainly across large areas) are sparse to non-existent.*

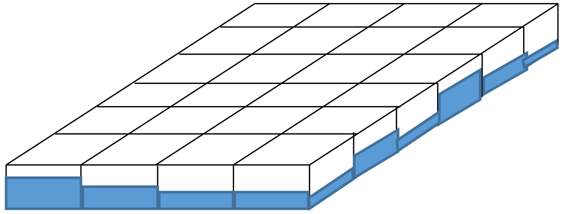
Modeling approach: Force a gridded array of land surface model elements with arrays of observations-based meteorological forcing ⇨ let modeled soil moistures and other states evolve in response to the forcing.



Array of soil moistures at beginning of time period (crude representation)

Force array of land models with arrays of P, R_{net}, etc.

Compute E, Q, etc. at each land element; let all computed fluxes update soil moisture

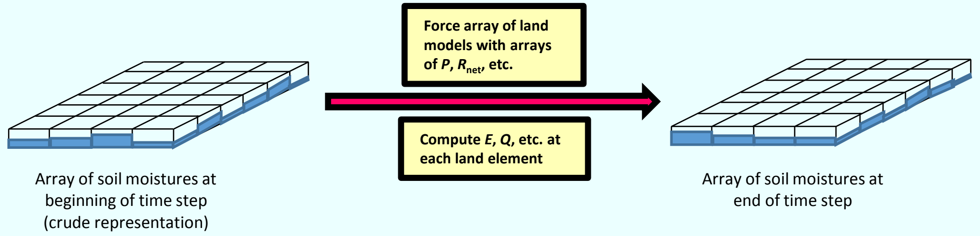


Array of soil moistures at end of time period: reflects antecedent meteorology

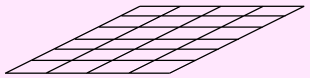
Land Initialization in Earth System Models

Even better approach to initialization: Combine modeling and land state observations (e.g., from satellite) through <u>data assimilation</u>:

Drive array of land elements w/ met. forcing (previous slide)



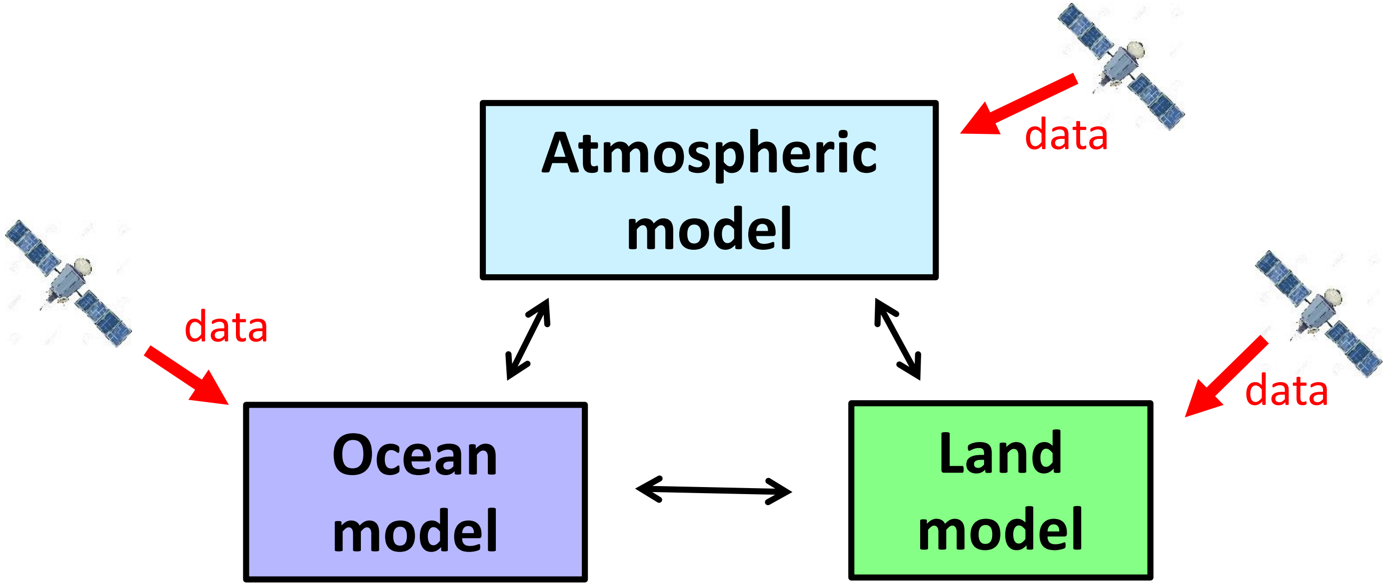
Obtain satellite-based estimate of, e.g., soil moisture in top few centimeters.



Optimally <u>combine</u> these estimates, using rigorous mathematical procedures ⇨ a soil moisture field that is <u>more accurate</u> than either the modeled field or the satellite-based field alone.

Land Initialization in Earth System Models

Even better approach to initialization: Assimilate land, atmosphere, and ocean data together into a fully coupled Earth system model as part of an integrated Earth system analysis.

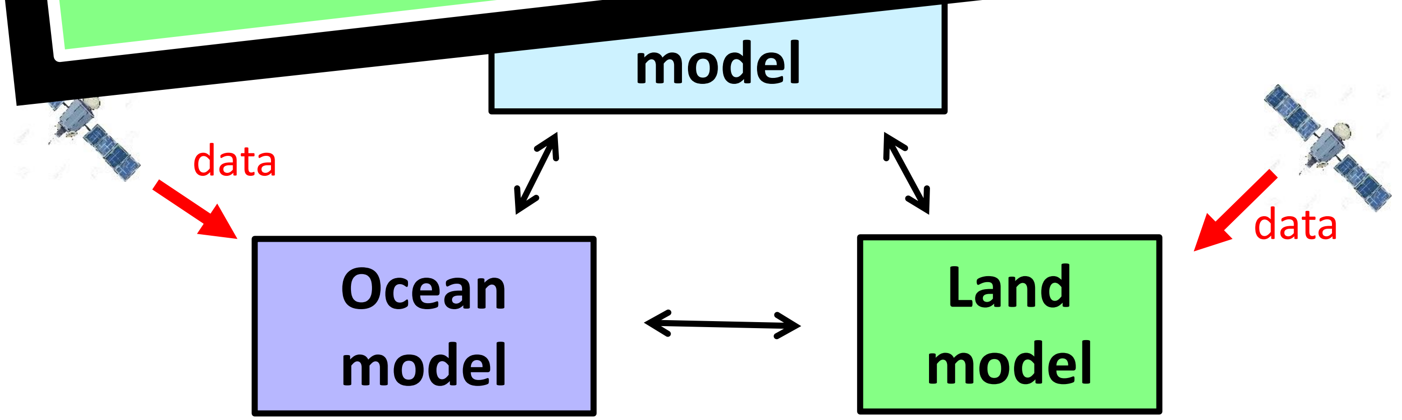


Land Initialization in Earth System Models

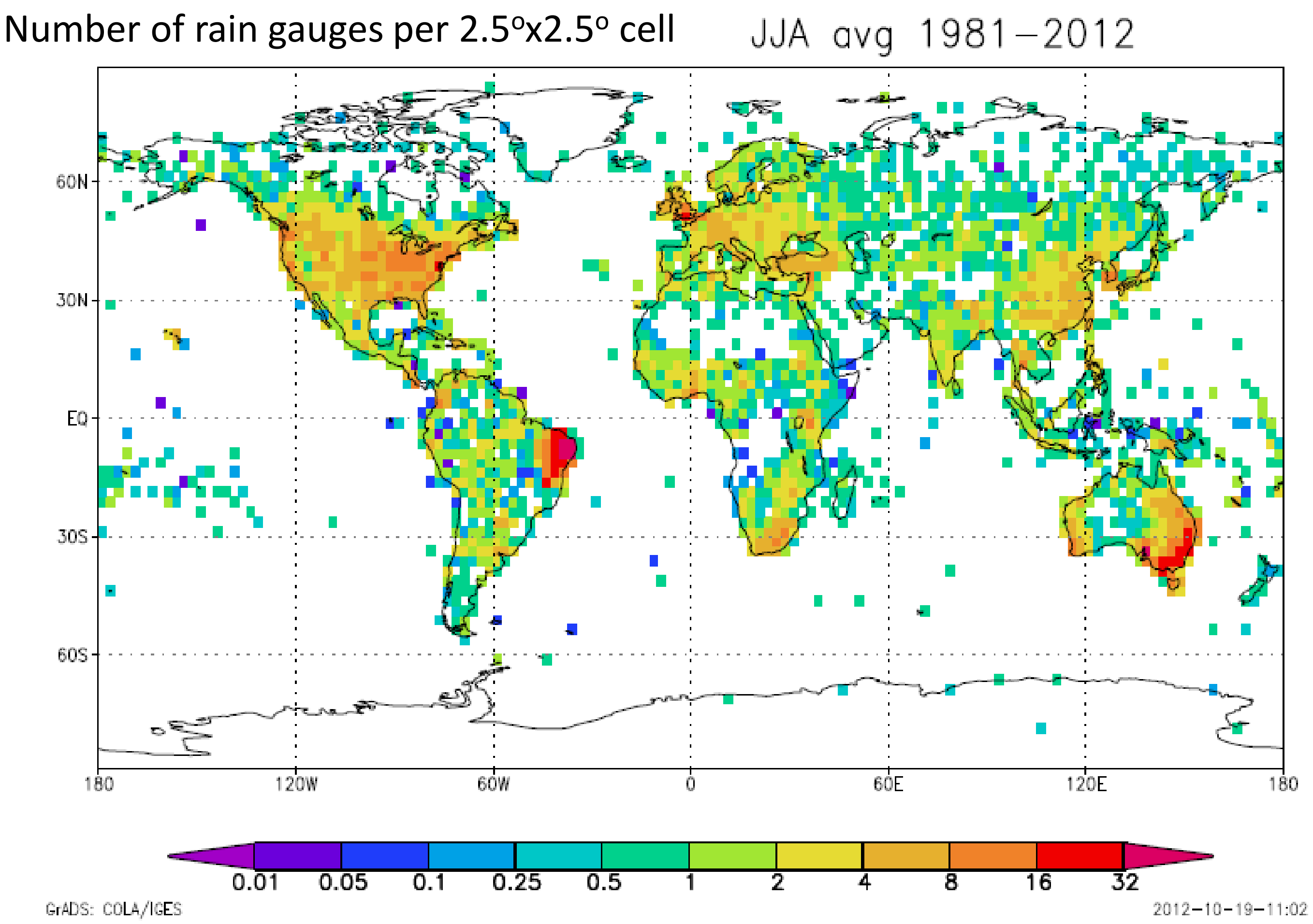
Even be… e, and ocean
data tog… integrated
Earth sy…

With or without data assimilation, accurate initialization is critical for forecasts:

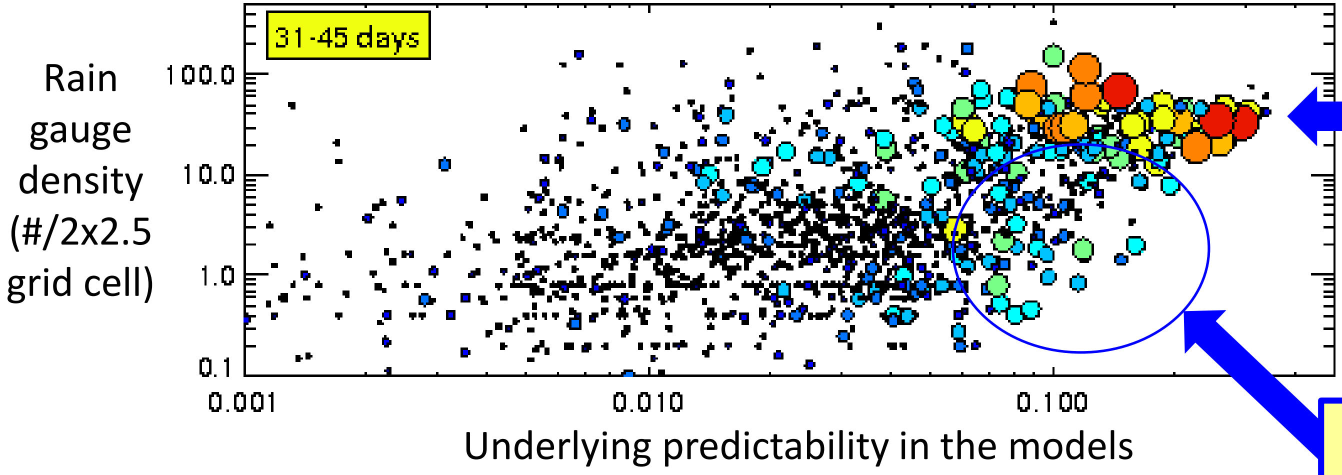
Garbage in → Perfect forecast model → **Garbage out**



Consider the global rain-gauge network used to initialize soil moisture in the GLACE-2 study:



Air Temperature Forecast Skill at 31-45 Days Derived from Soil Moisture Initialization. (Each dot represents a location; size of dot represents skill achieved there.)

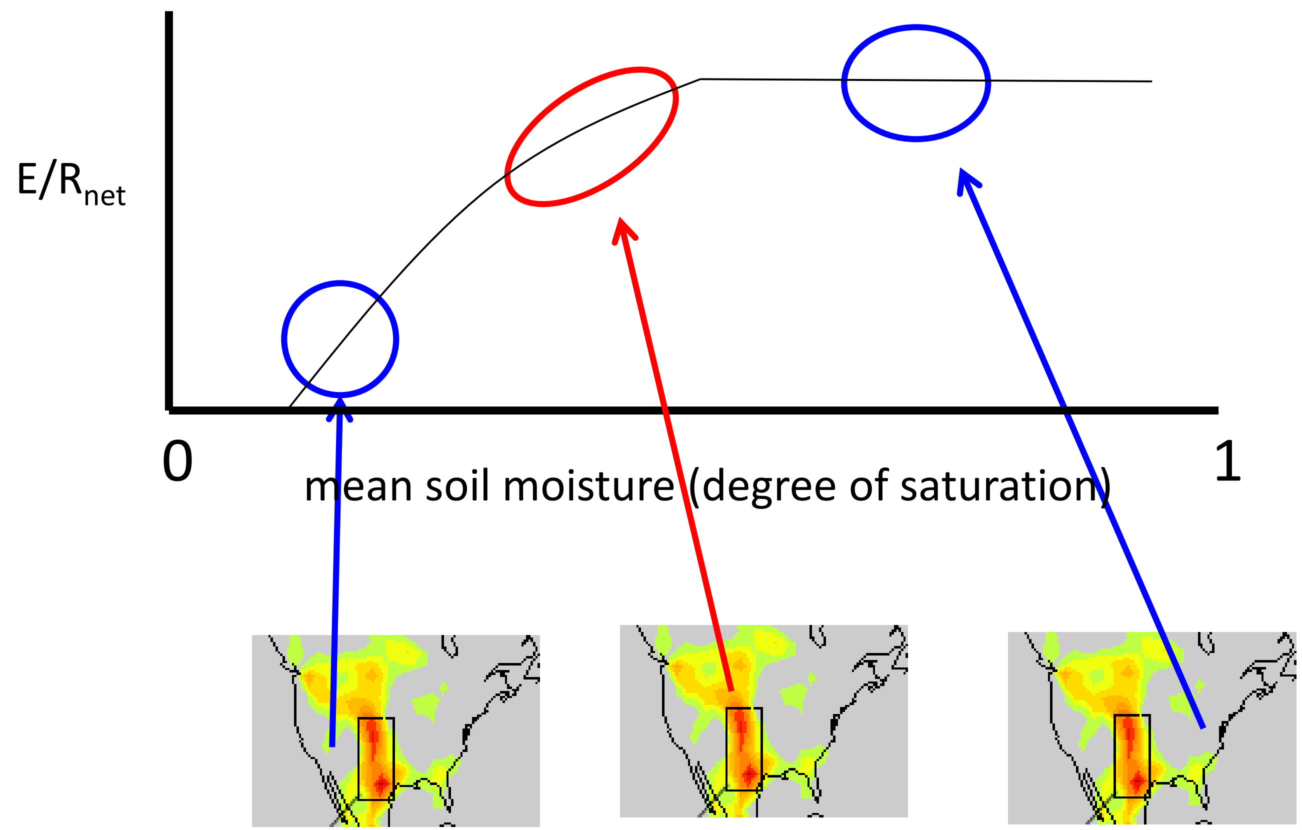


Higher skill levels (larger, “warmer” dots) are achieved only for higher rain gauge density, a proxy for initialization quality.

Skill levels realized at these grid cells would presumably have been larger if obs. network had been more complete there.

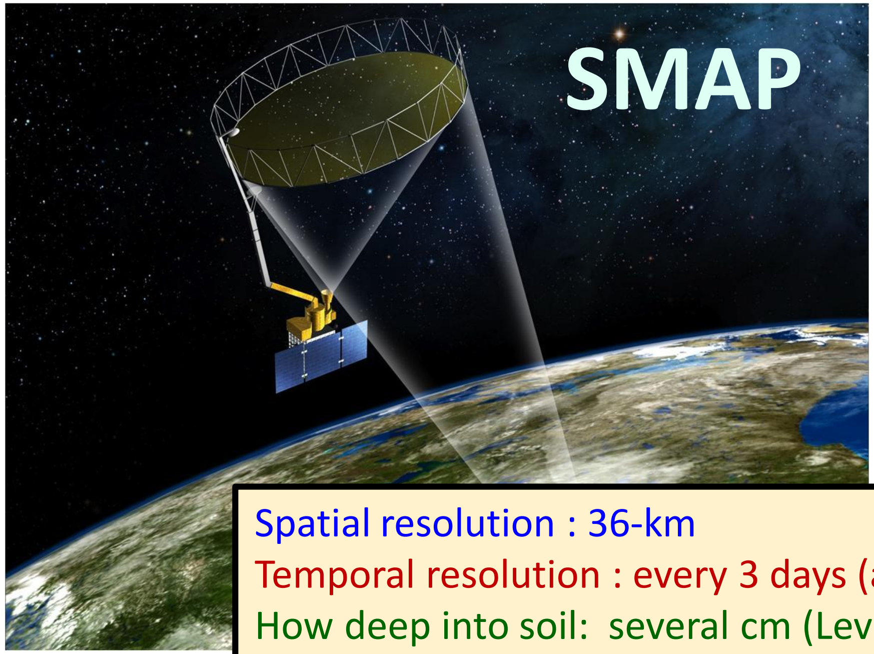
➡ ***The GLACE-2 results speak to the value of improved soil moisture monitoring, either via improved rain measurement or via soil moisture sampling from space.***

Where would new in situ soil moisture measurements have the most impact?
Presumably in the aforementioned transition zones…



We live at a time when satellite-based information can transform the way we do our initializations…

For example: recent satellite-based L-band sensors have the potential to provide valuable global soil moisture data for use in forecast model initialization.

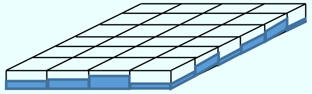


Spatial resolution : 36-km
Temporal resolution : every 3 days (at least)
How deep into soil: several cm (Level 1-3)
1 m (Level 4)
Accuracy: RMSE < 4 volumetric percent
Latency: short! (hours – days)
Baseline mission duration: 3 years

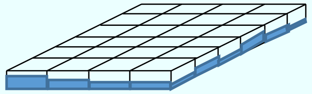
Drive array of land elements w/ met. forcing (previous slide)

Force array of land models with arrays of P, R_{net}, etc.

Compute E, Q, etc. at each land element

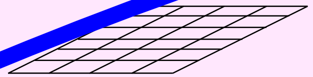


Array of soil moistures at beginning of time step (crude representation)



Array of soil moistures at end of time step

Obtain satellite-based estimate of, e.g., soil moisture in top few centimeters.

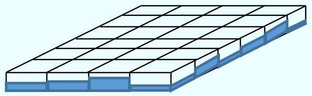


Optimally combine these estimates, using rigorous mathematical procedures ⇨ a soil moisture field that is more accurate than either the modeled field or the satellite-based field alone.

Obvious application: Assimilate L-band soil moisture data

Unexplored (and potentially powerful?) application: Use soil moisture data to improve precipitation forcing

Drive array of land elements w/ met. forcing (previous slide)



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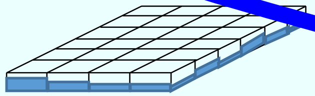

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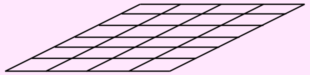
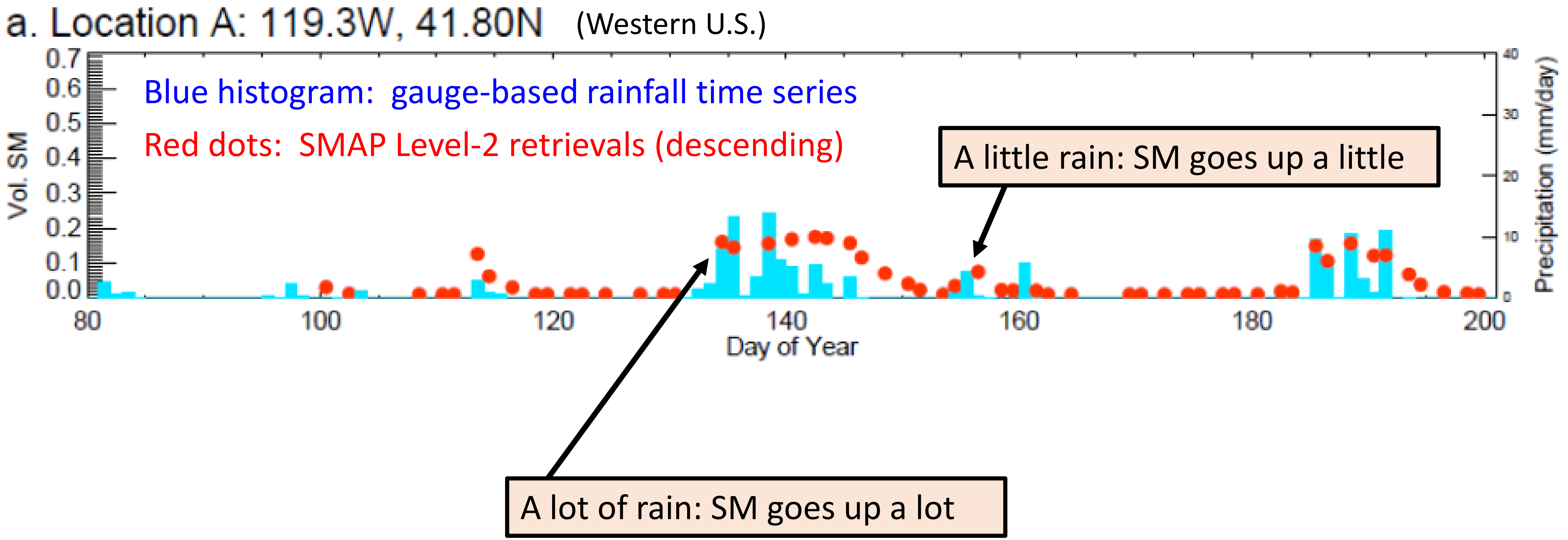


Optimally <u>combine</u> these estimates, using rigorous mathematical procedures ⇨ a soil moisture field that is <u>more accurate</u> than either the modeled field or the satellite-based field alone.

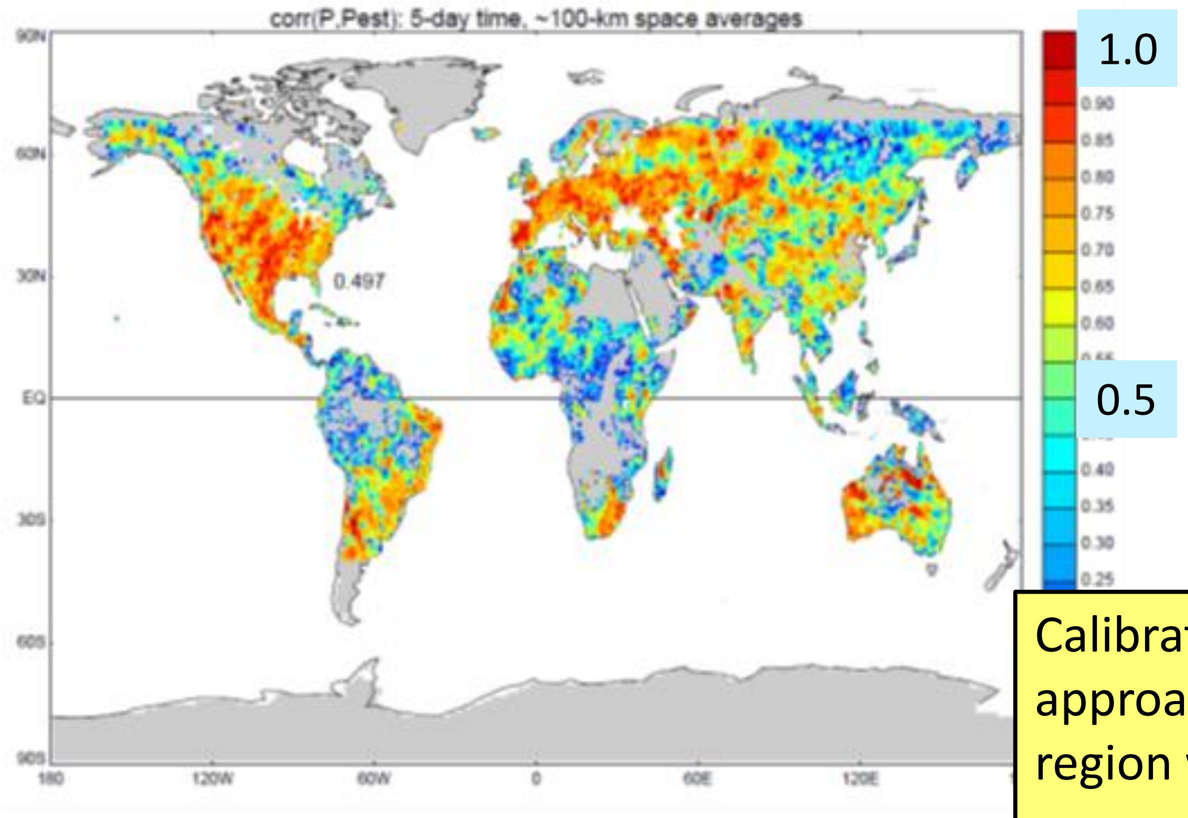
Rainfall estimation from soil moisture data

Rain gauge data and SMAP radiometer data generally look nicely consistent.

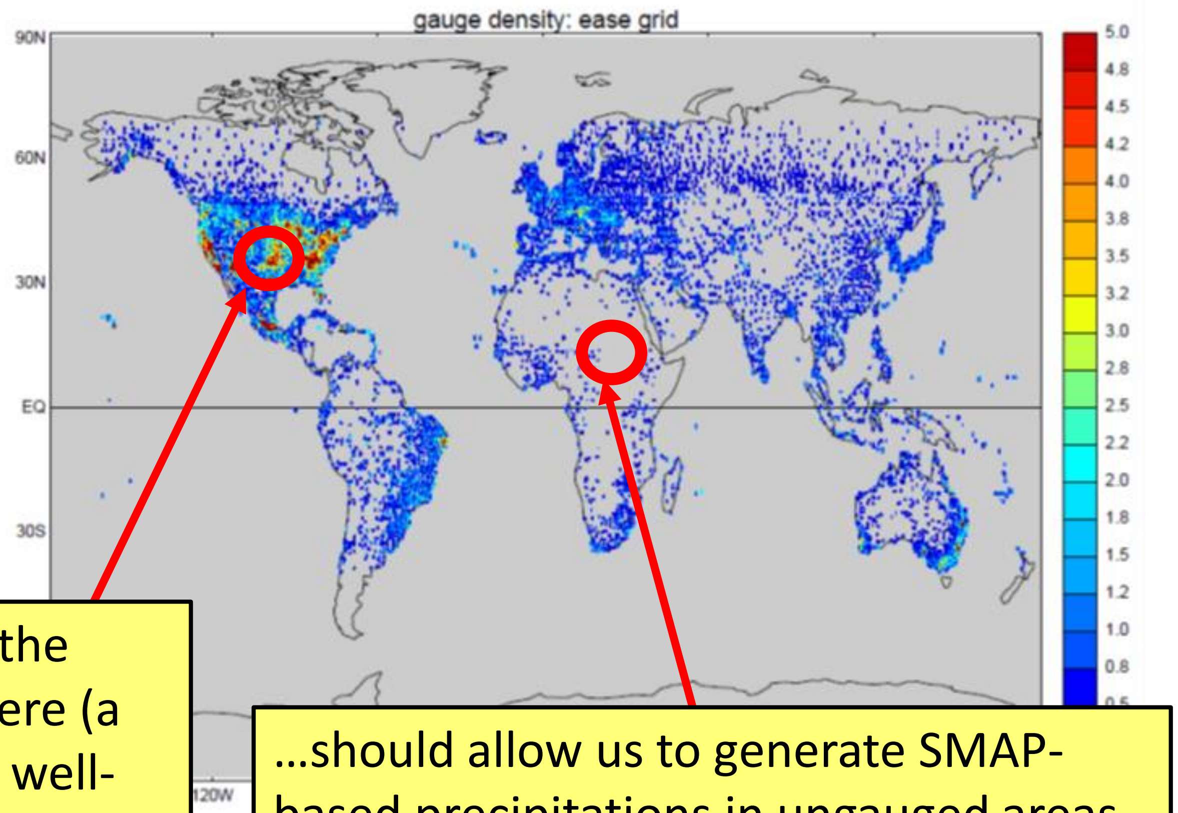


Overall, across much of the globe, the estimation works well!

Temporal correlations, for 5-day, 108-km aggregations

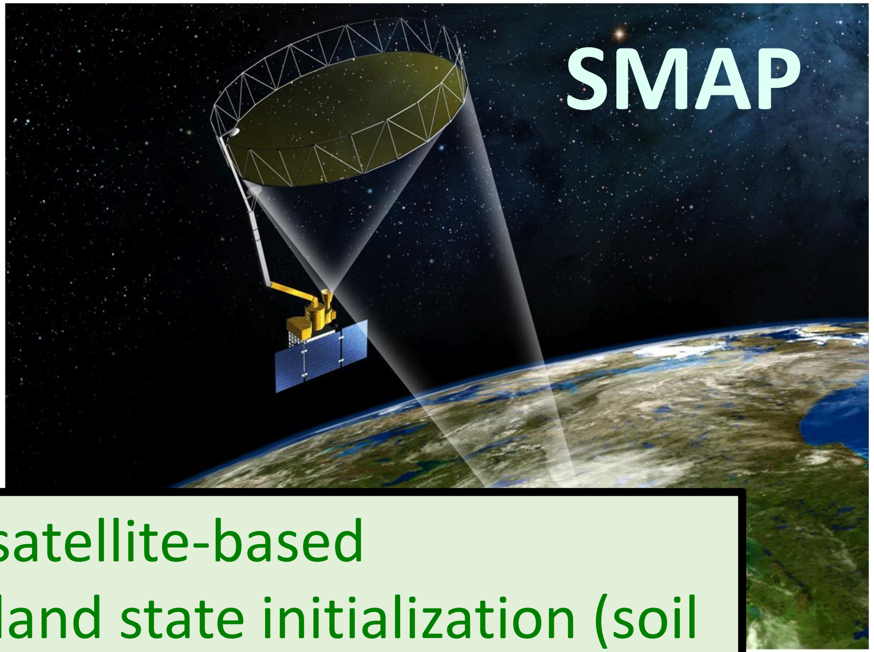


Density of rain gauges underlying the precipitation observations



Calibrating the approach here (a region with well-measured precipitation)…

…should allow us to generate SMAP-based precipitations in ungauged areas that have, e.g., similar soil texture.



The potential for satellite-based improvements in land state initialization (soil moisture, snow, vegetation) in forecast models is largely untapped!

Thank you.

Questions?