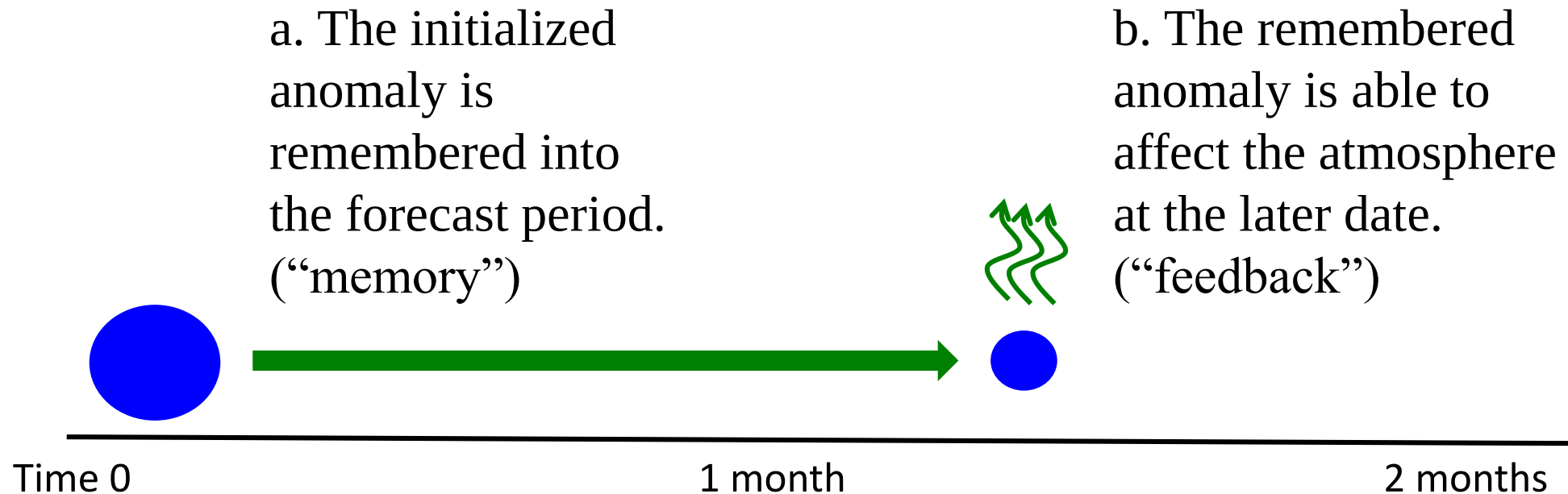


Contribution of Land Surface States to Sub-seasonal Predictability

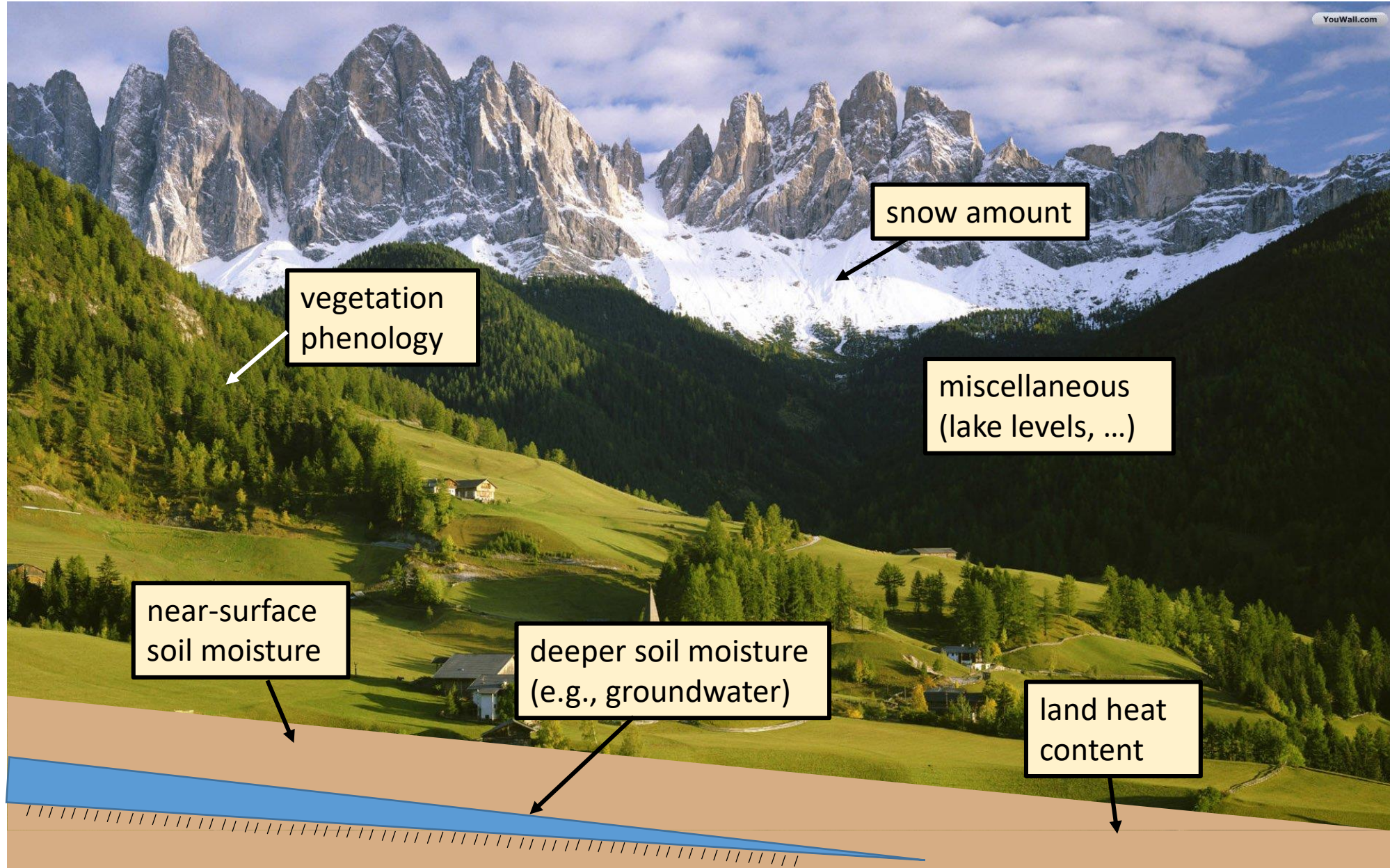
Randal Koster
Global Modeling and Assimilation Office
NASA/GSFC
Greenbelt, MD USA

Theoretical Underpinning

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

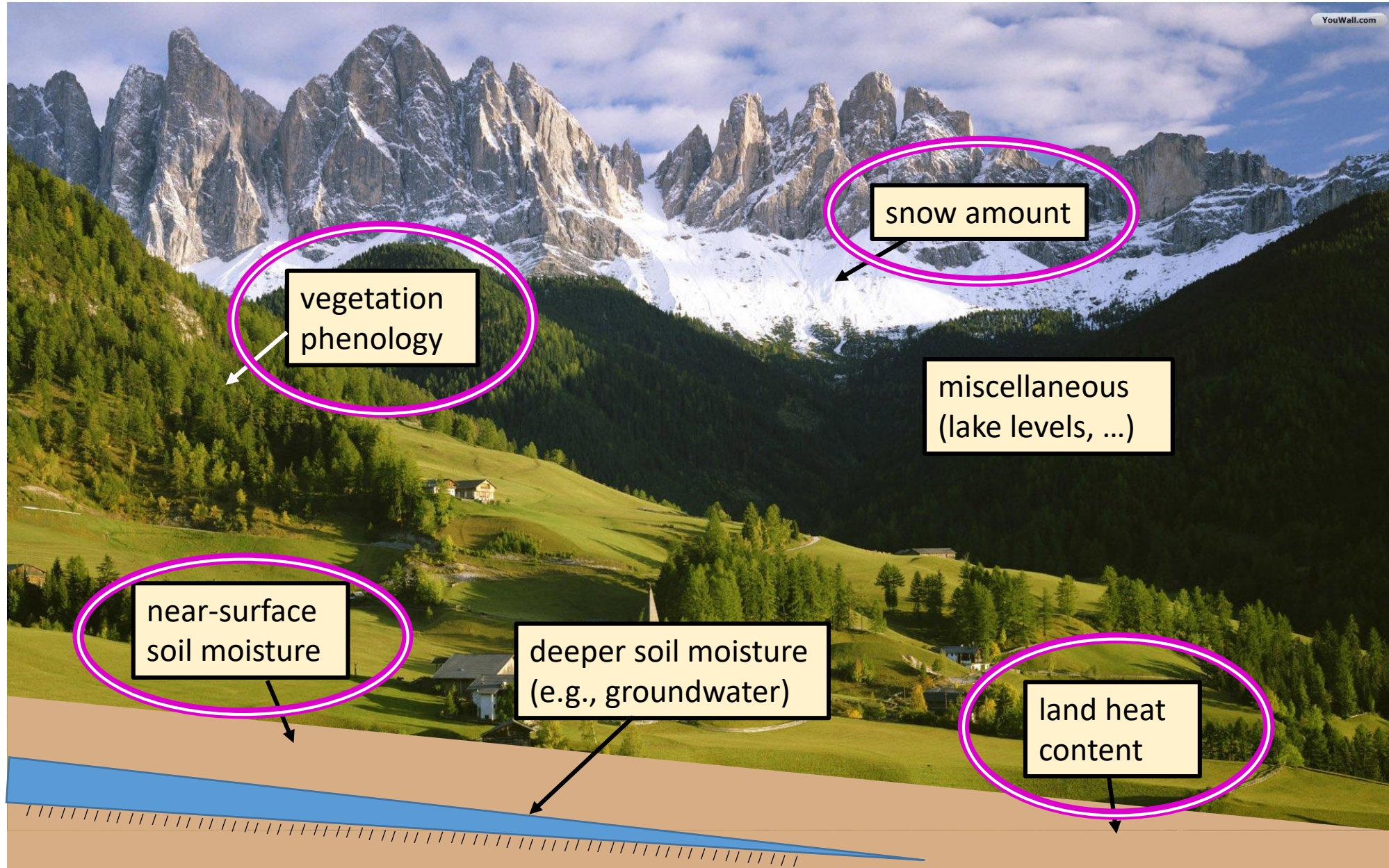


Which land states might have usable memory?



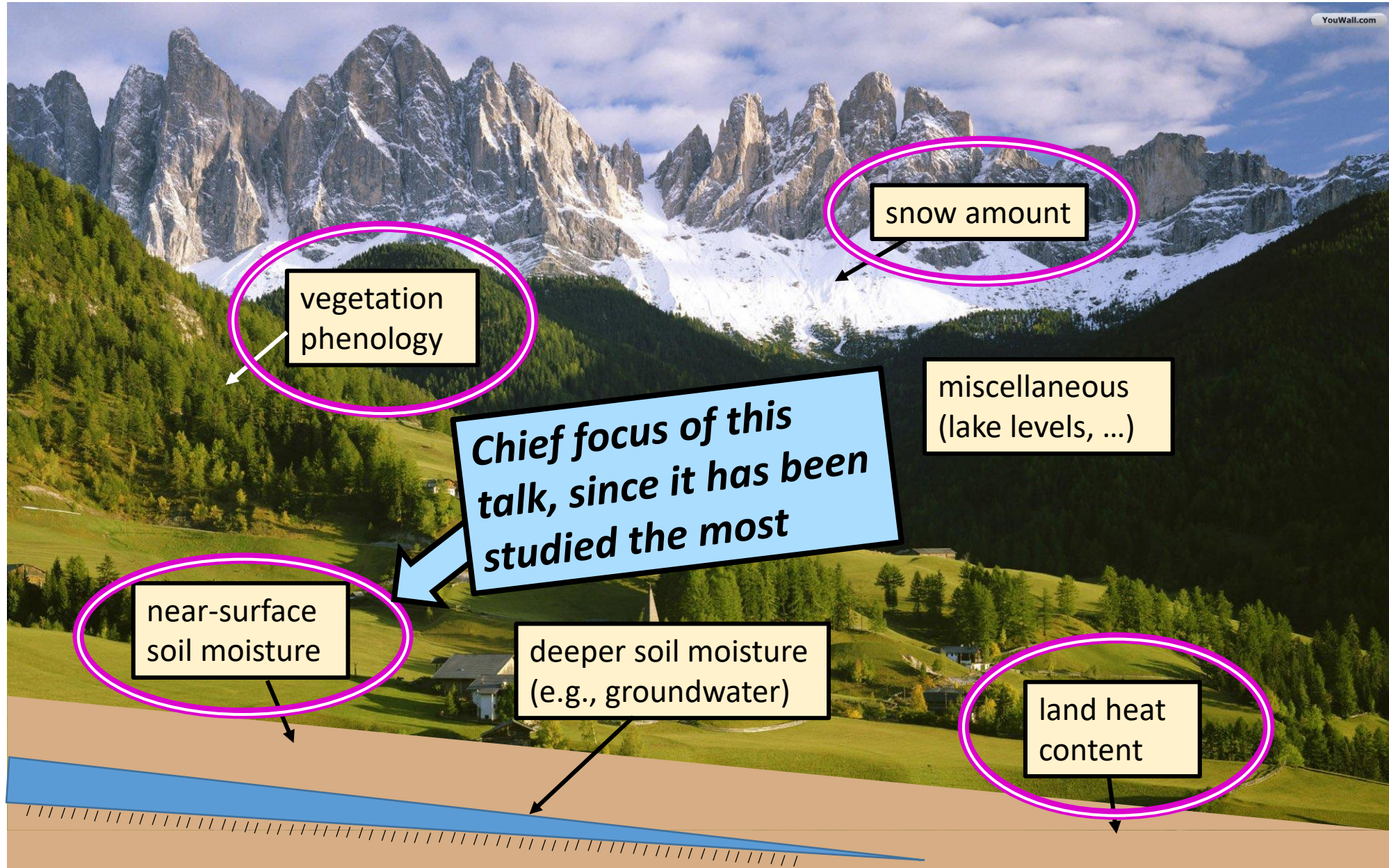
(Image stolen from internet!)

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



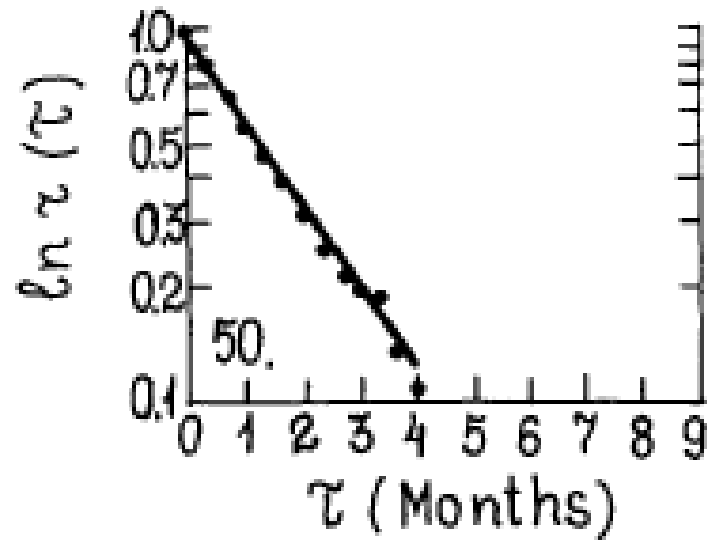
(Image stolen from internet!)

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



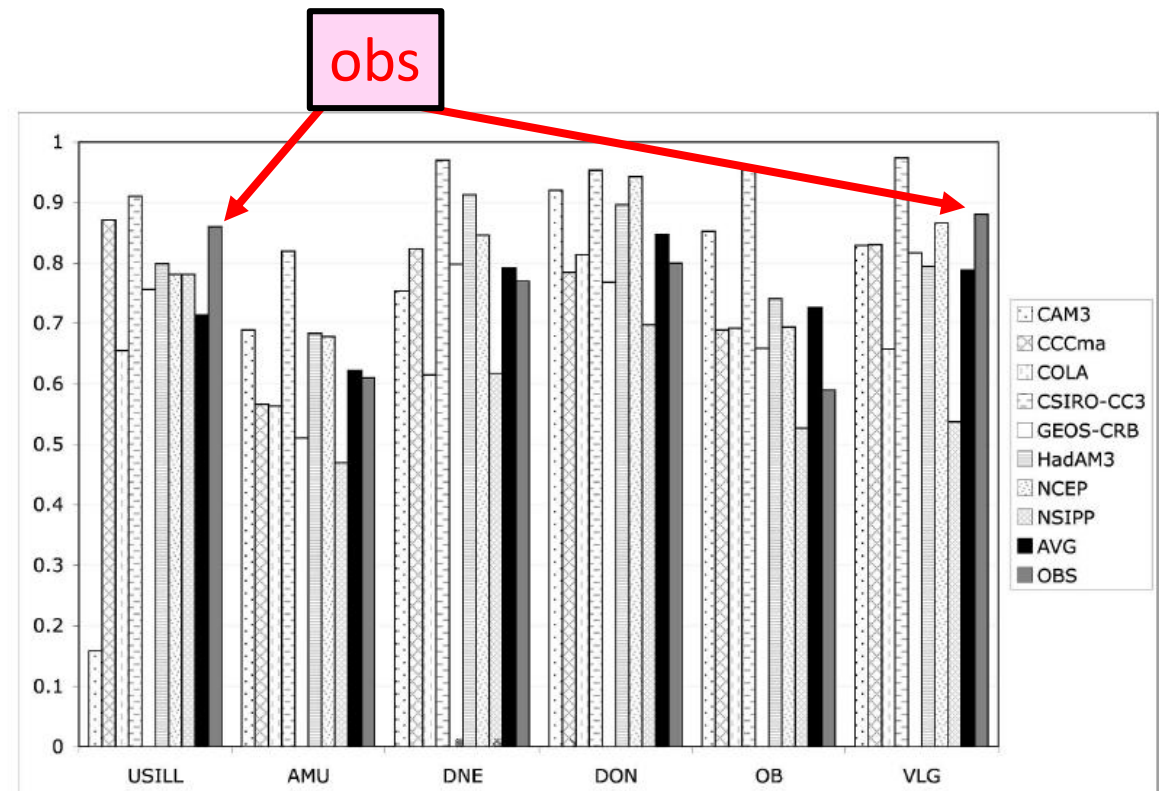
(Image stolen from internet!)

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



“empirical autocorrelation function”

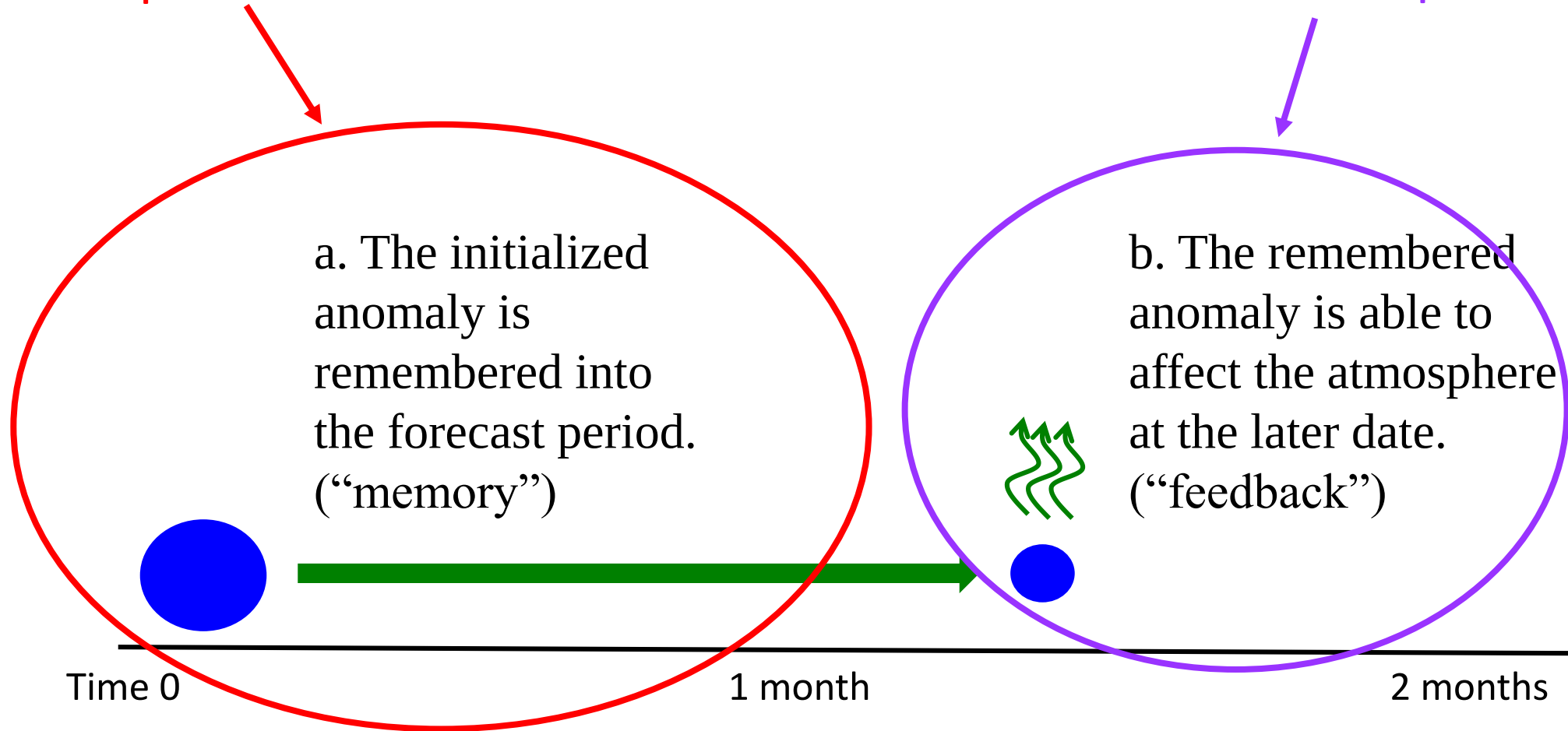
Vinnekov and Yeserkepova, J. Climate, 4, 66-79, 1991



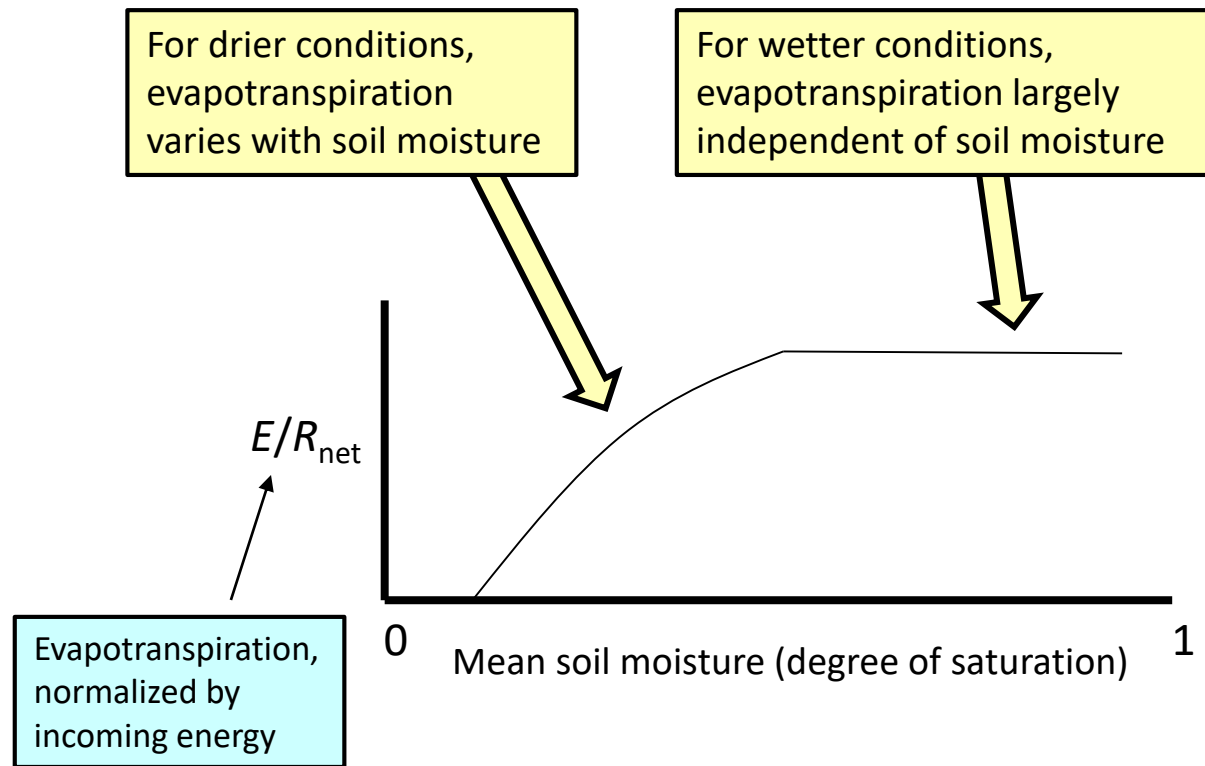
~1-month-lagged autocorrelations of soil moisture (boreal summer)

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

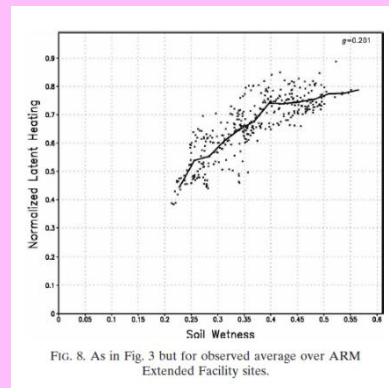
So for soil moisture, we have this part.



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



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

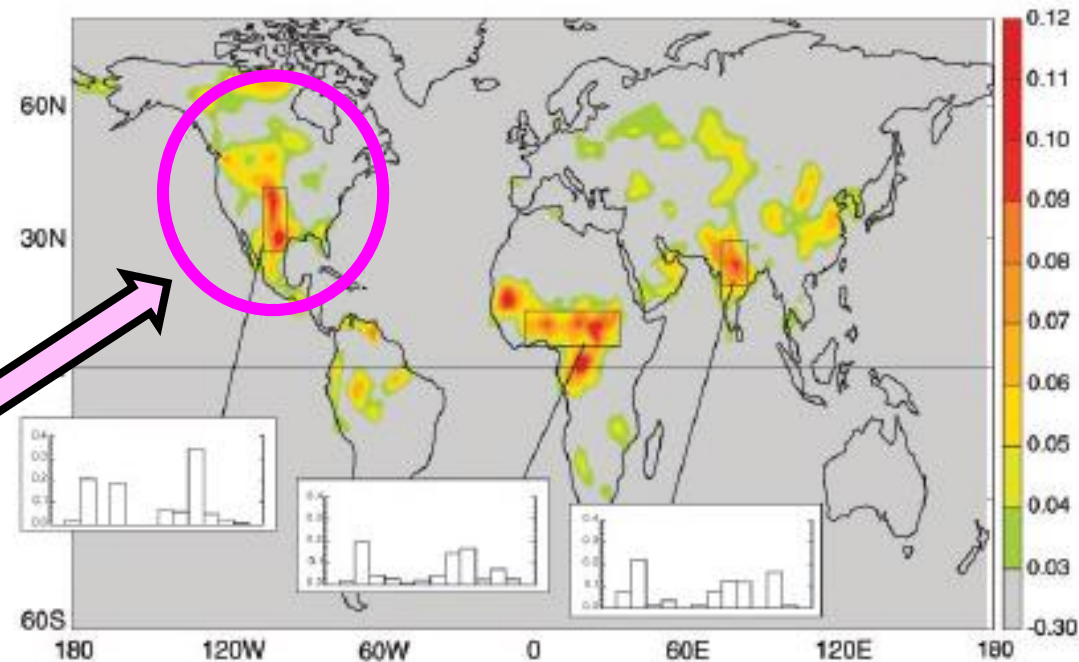


Dirmeyer *et al.*, *J. Hydromet.*, 7, 1177–1198, 2006

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.

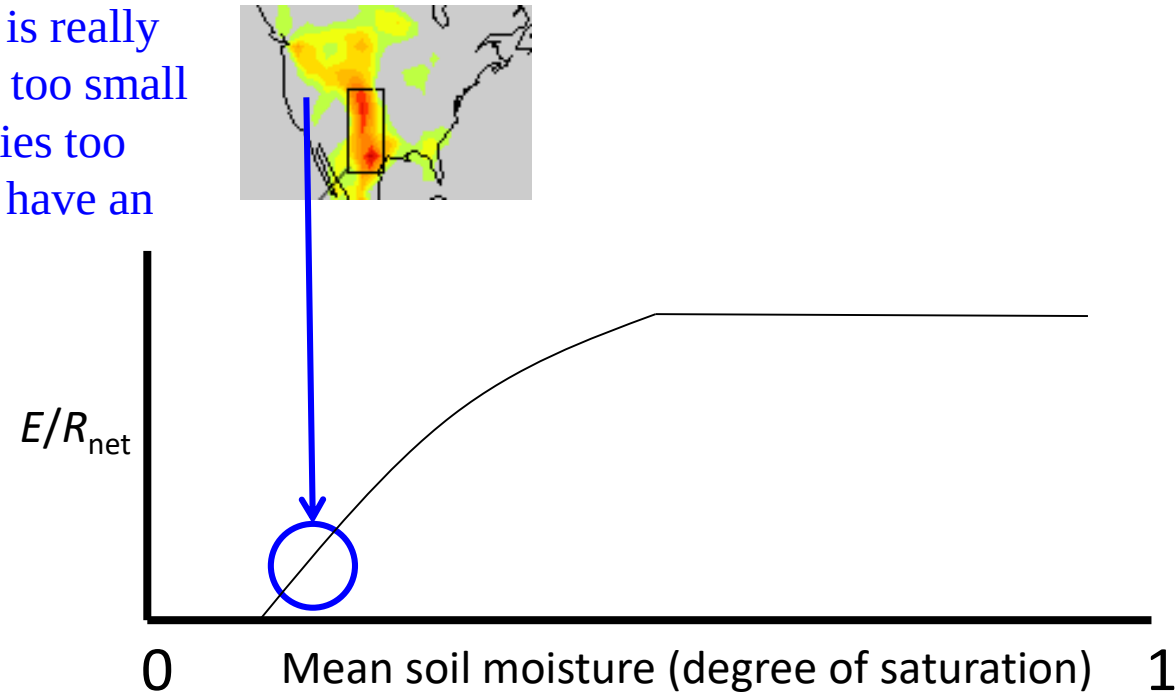
Why are the transition areas important? See next slide, which focuses on North America...



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

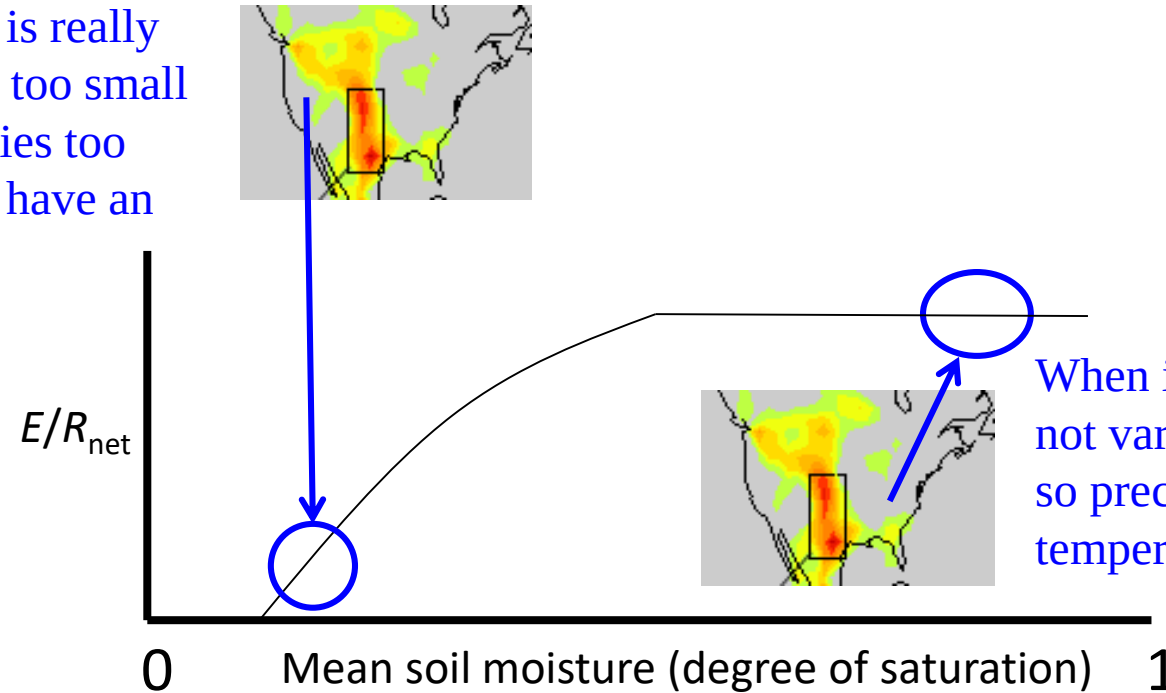
Explanation for why soil moisture feedback on the atmosphere is strongest in transition zones

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



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

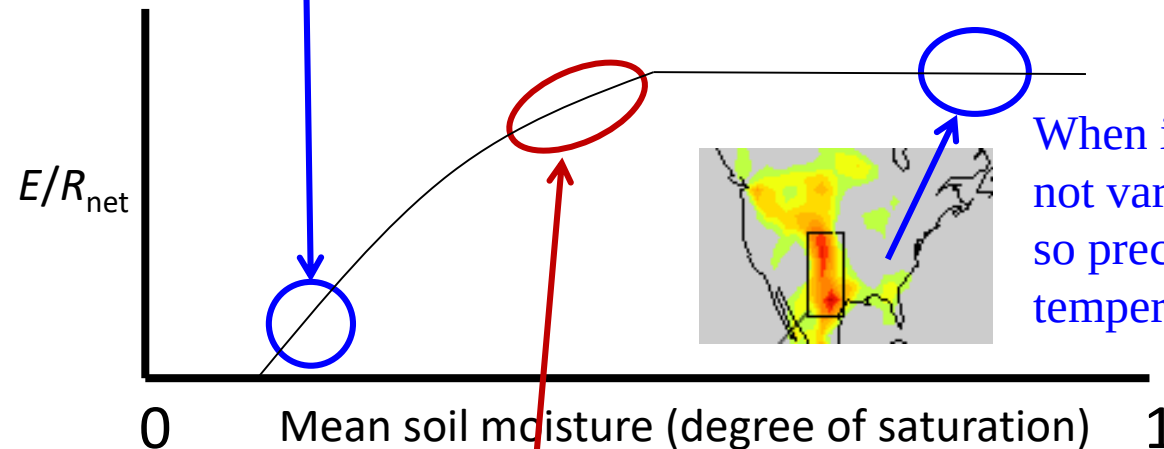
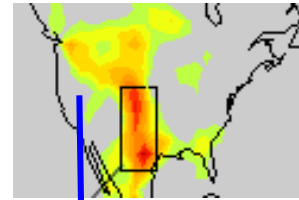
When it is really dry, E is too small (and varies too little) to have an effect.



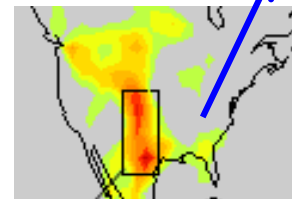
When it is really wet, E does not vary with soil moisture, so precipitation and temperature cannot, either.

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

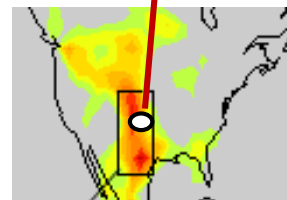
When it is really dry, E is too small (and varies too little) to have an effect.



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

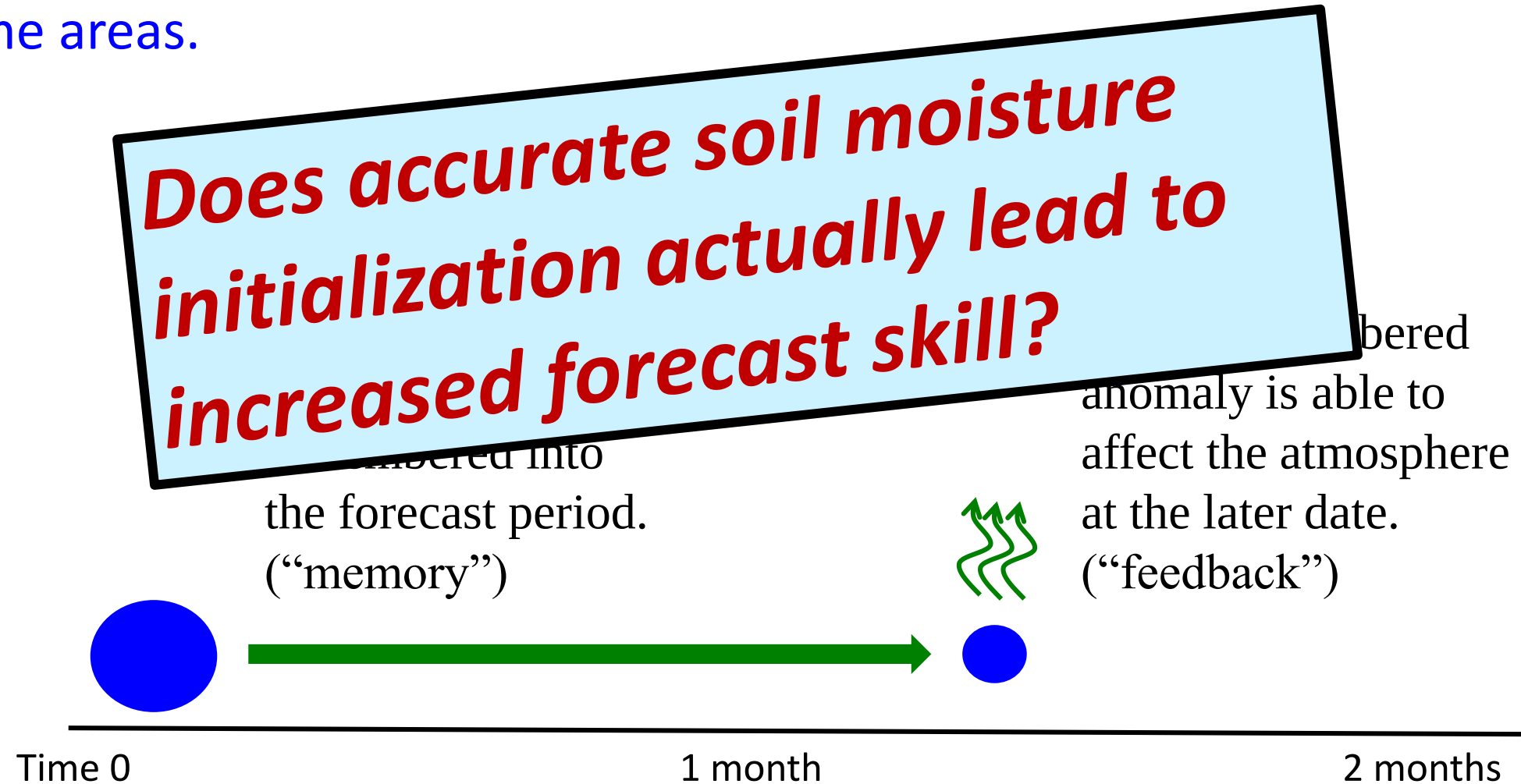


You mainly get an impact in the “sweet spot” in between:



...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.



Estimations of forecast skill associated with soil moisture initialization

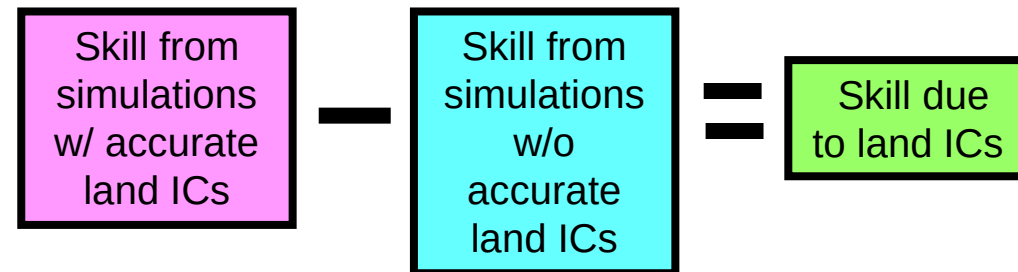


The second phase of the
Global Land-Atmosphere Coupling Experiment
(an international, multi-institution project)

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:



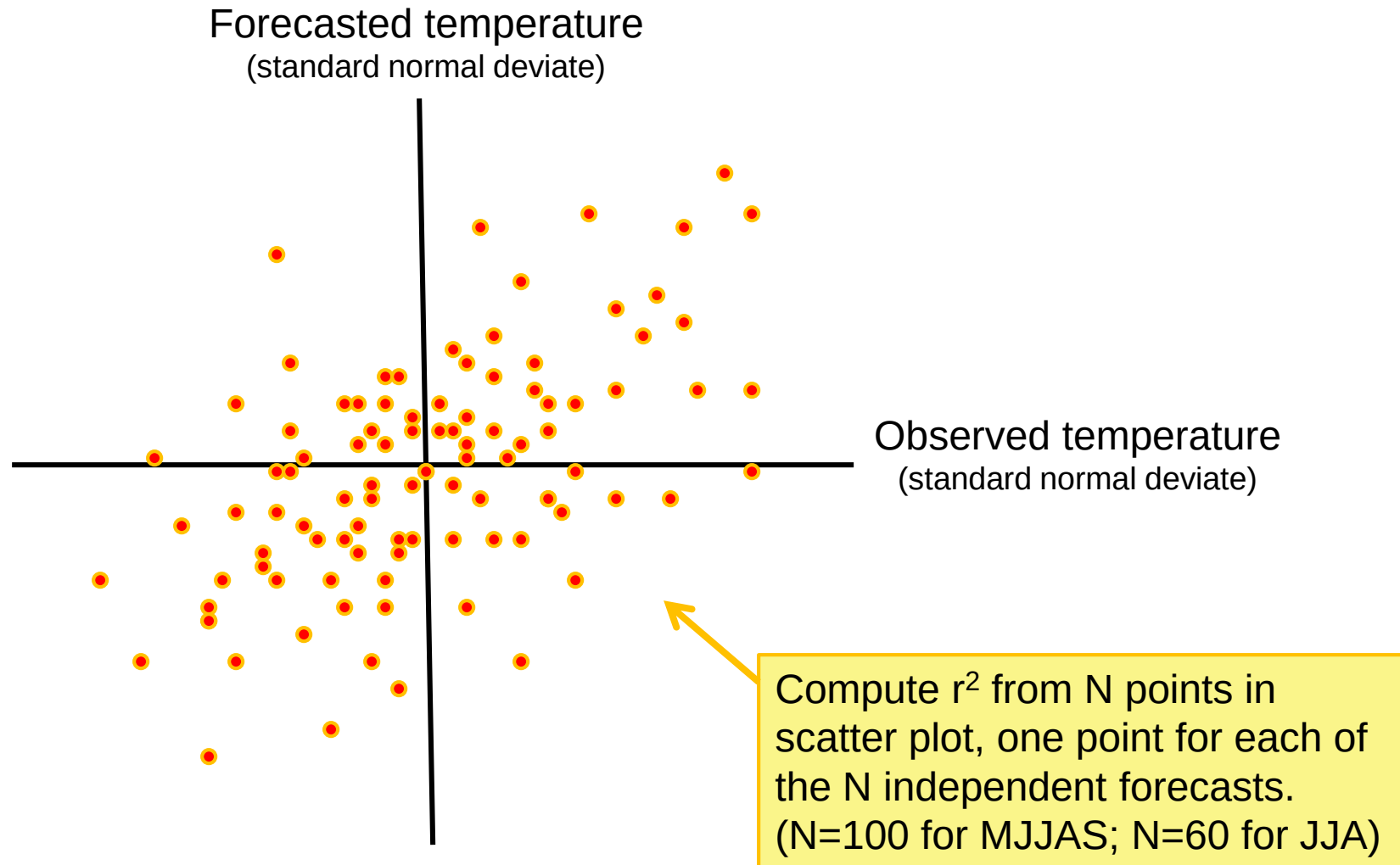
Baseline: 100 Forecast Start Dates

	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.

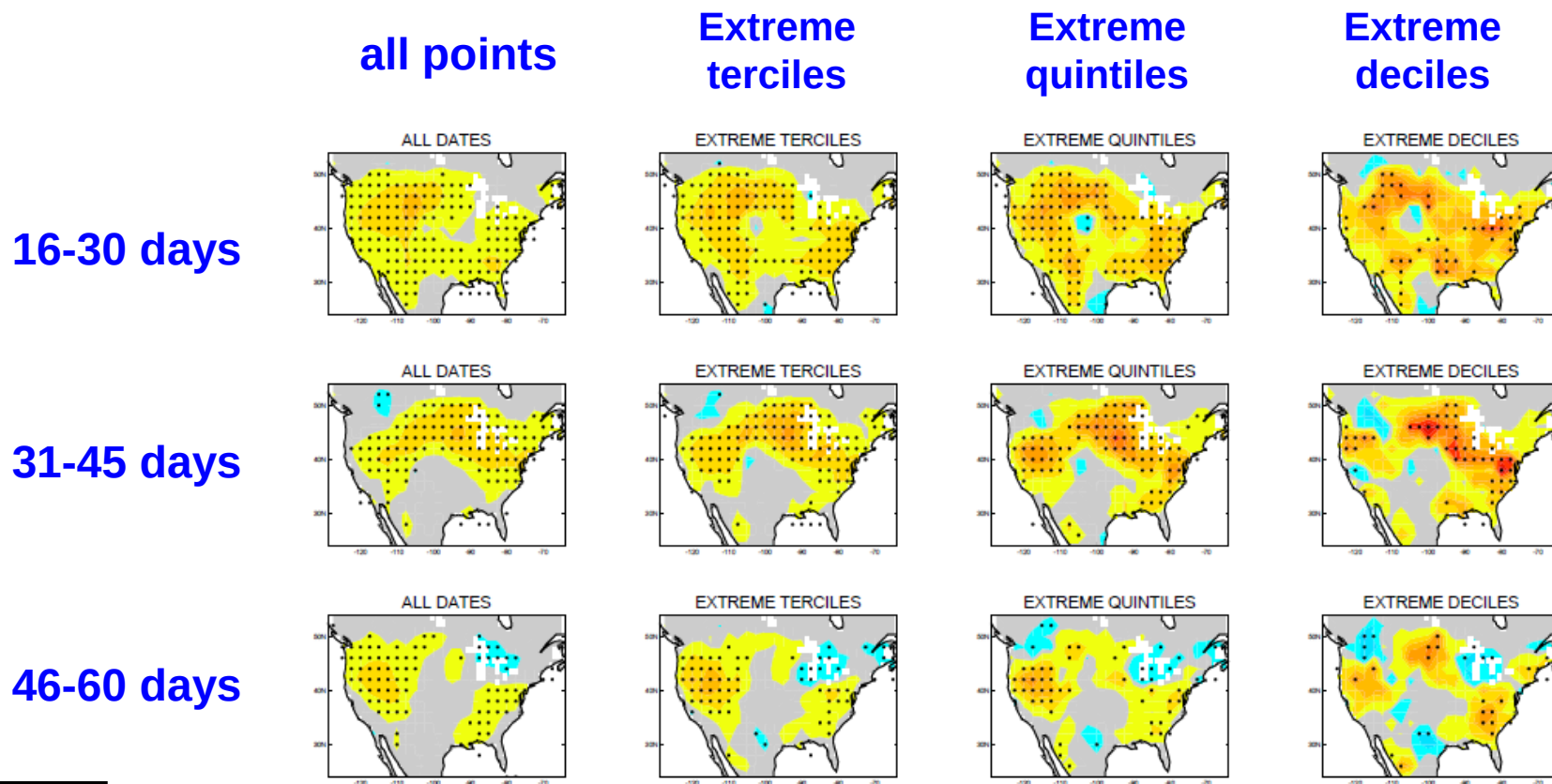
➡ 1000 2-month simulations.

Skill measure: r^2 when regressed against observations



- 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

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



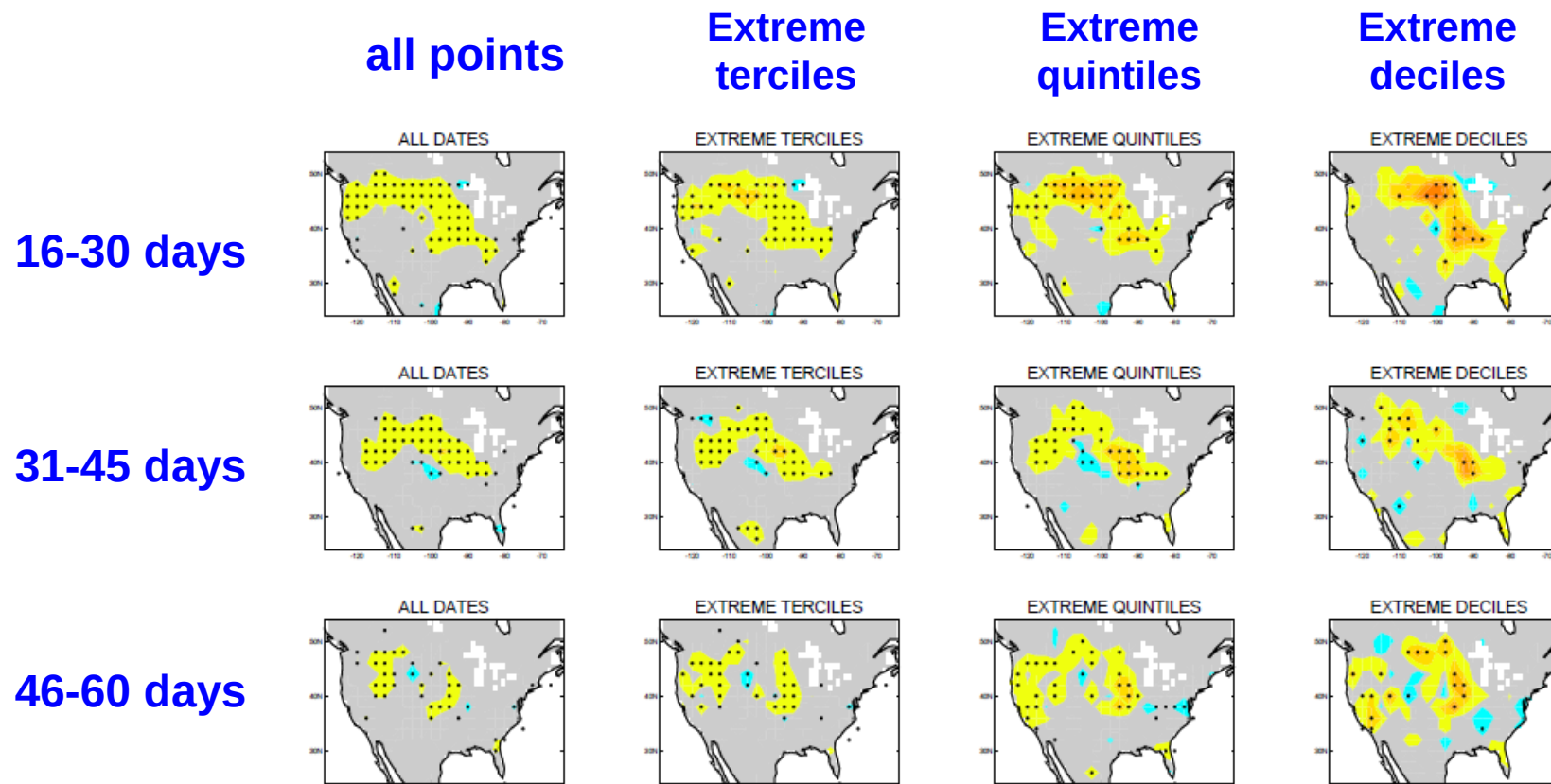
Dates for conditioning vary w/location

“Weaker” models are averaged in with “stronger” ones.

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

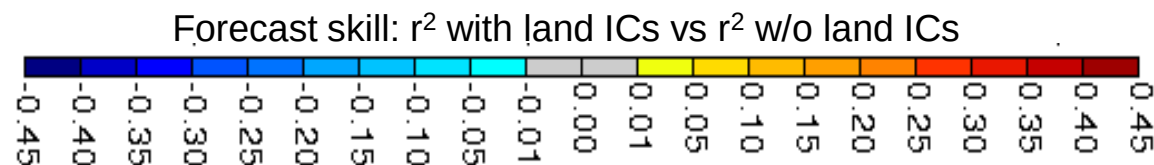


Precipitation forecasts: Increase in skill due to land initialization (JJA) (conditioned on strength of local initial soil moisture anomaly)



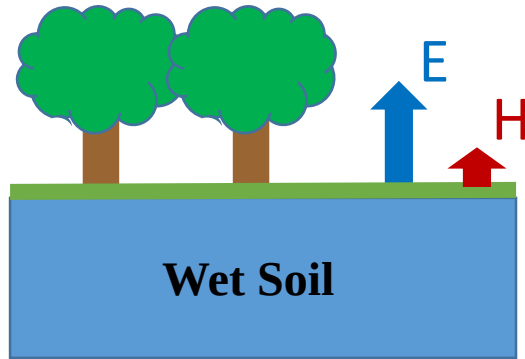
“Weaker” models are averaged in with “stronger” ones.

Dates for conditioning vary w/location



Local vs. Remote Soil Moisture Impacts on the Atmosphere

1. Consider local effects.



For example:

Wet soil $\Rightarrow$ higher evap., lower sensible heat flux

This can affect local air temperature:

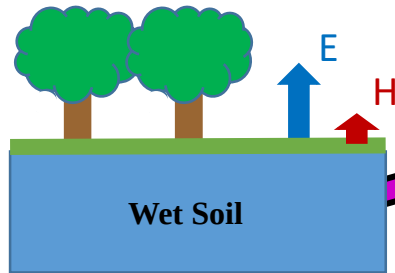
- $\Rightarrow$ more evaporative cooling
- $\Rightarrow$ lower air temperature

It can also affect local precipitation:

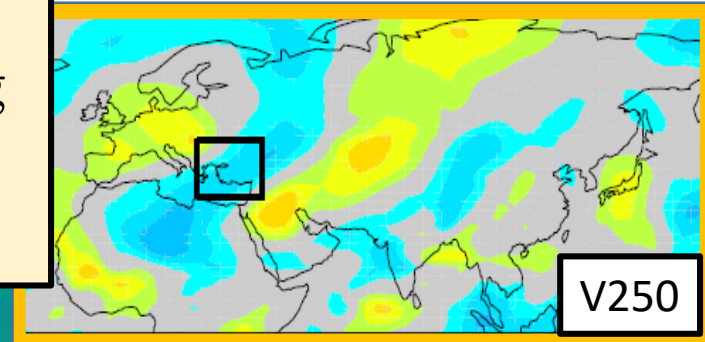
- $\Rightarrow$ boundary layer modification
- $\Rightarrow$ conditions more conducive
(or perhaps less conducive)
to onset of moist convection

2. Now consider potential remote effects:

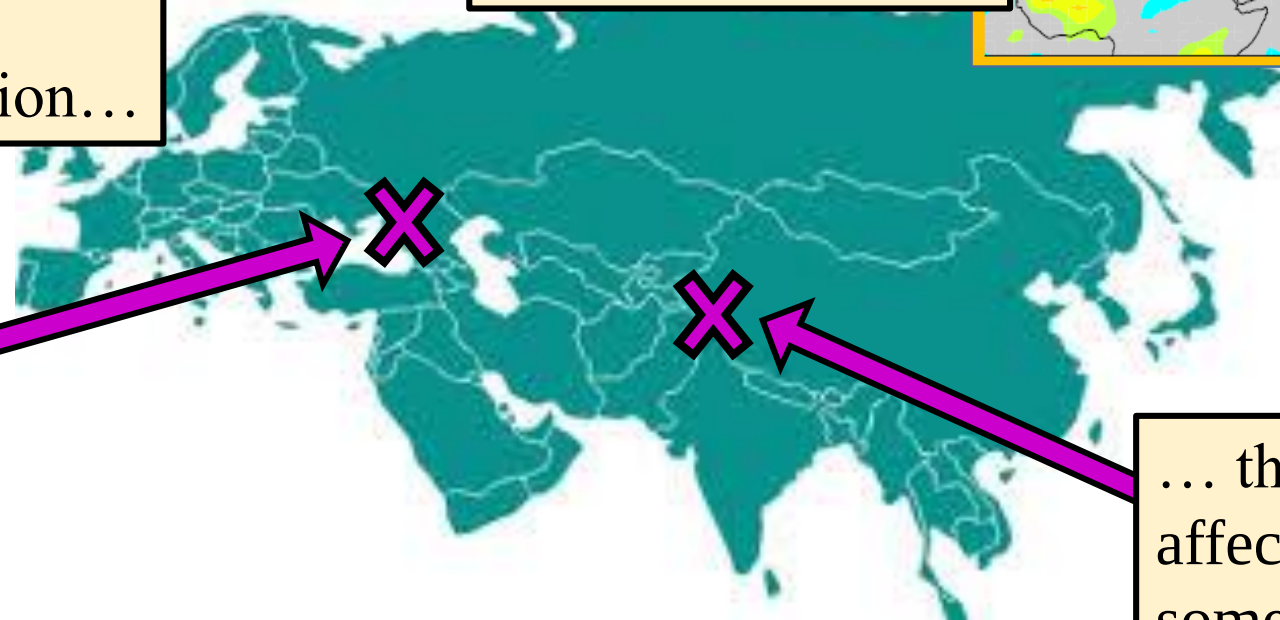
Consider the possibility that a soil moisture anomaly in one location...



... can “phase-lock” an overlying planetary wave into position...



... that in turn can affect conditions at some other location.



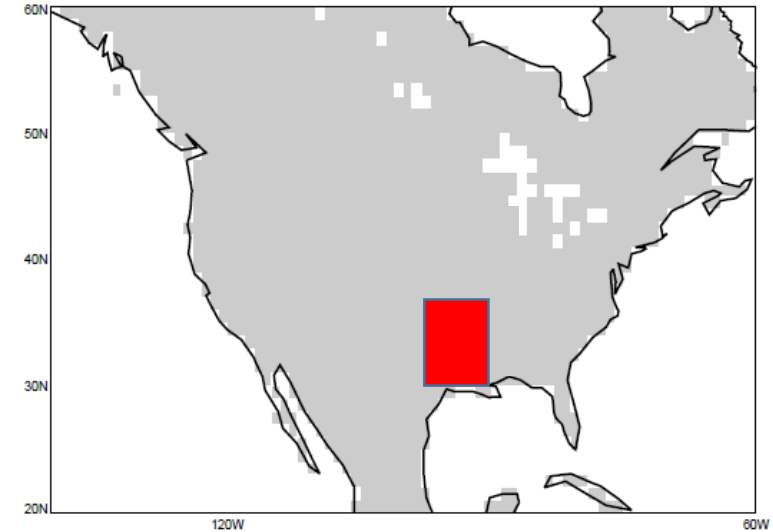
Experimental Design

Control: Ensemble (768 members) of April-July simulations using atmosphere-land components of the GEOS-5 system, at $1^\circ \times 1^\circ$ resolution.

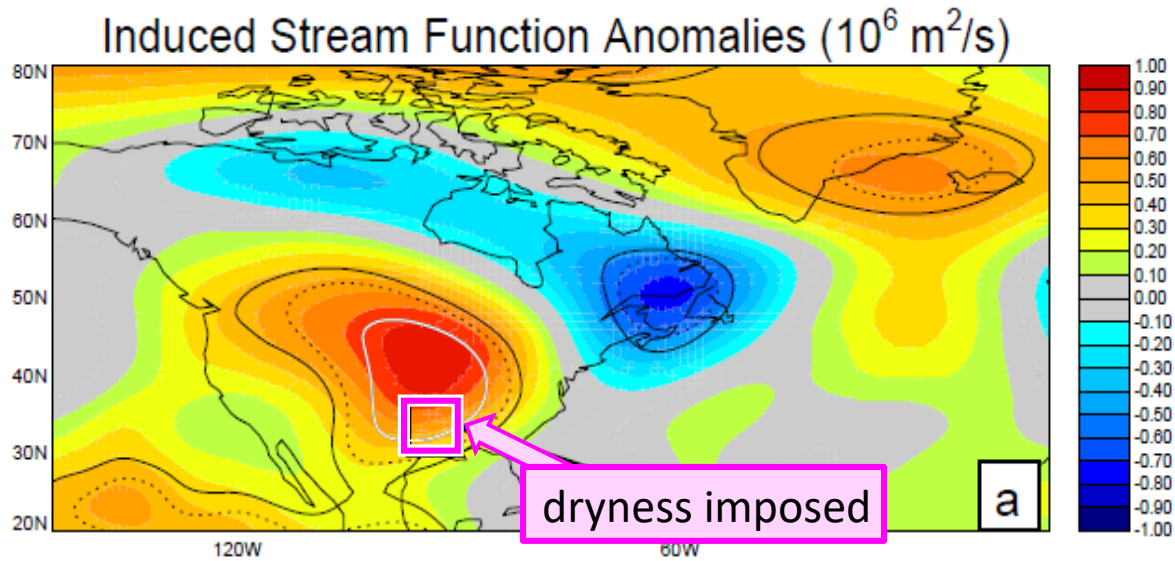
Experiment: Same as control, except:

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

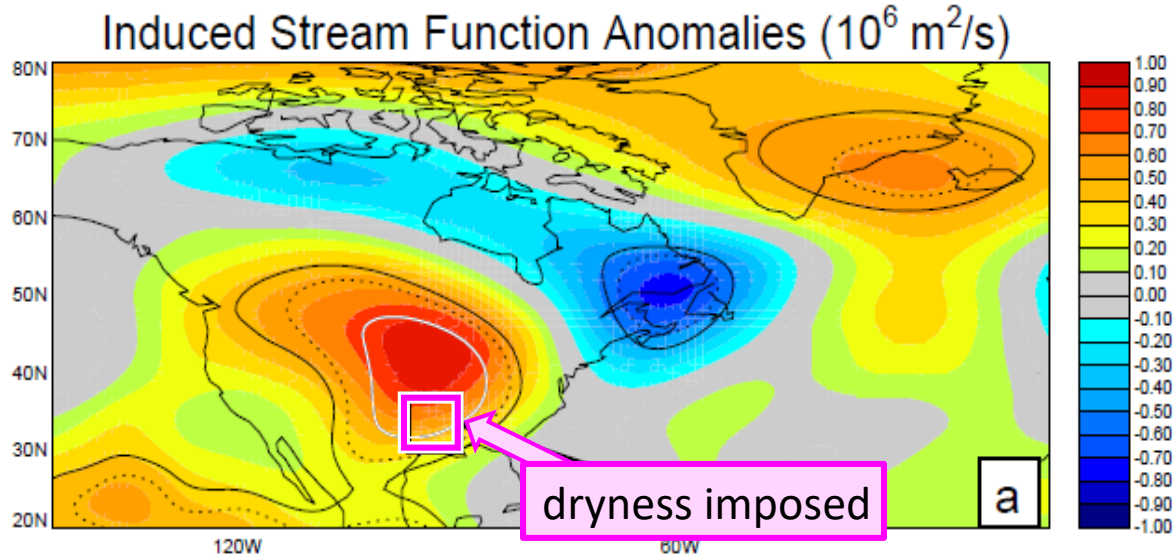
(b) Precipitation in a selected region is not allowed to hit the surface during April-June, *forcing the surface to become dry there.*



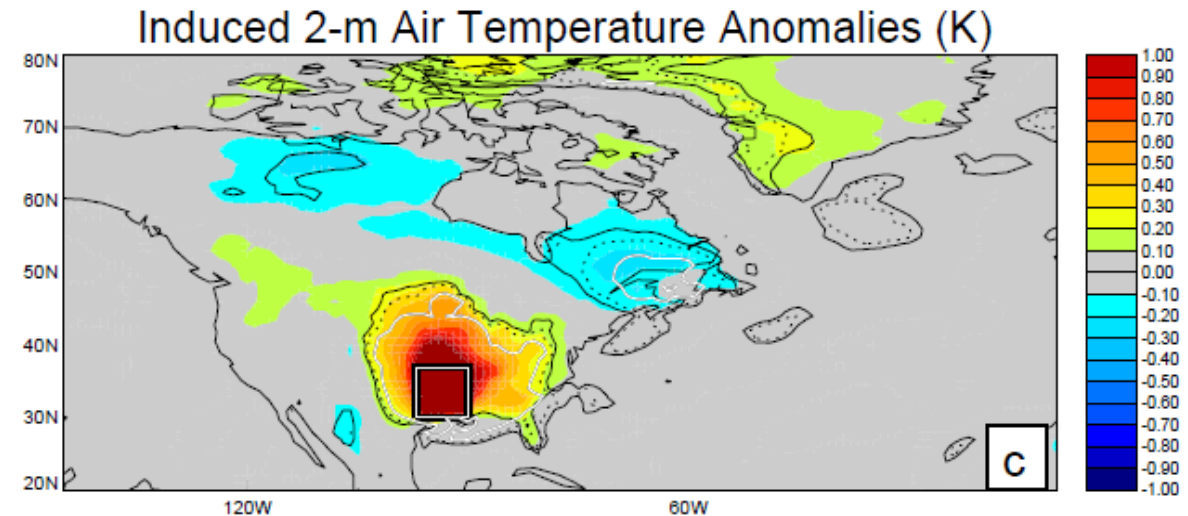
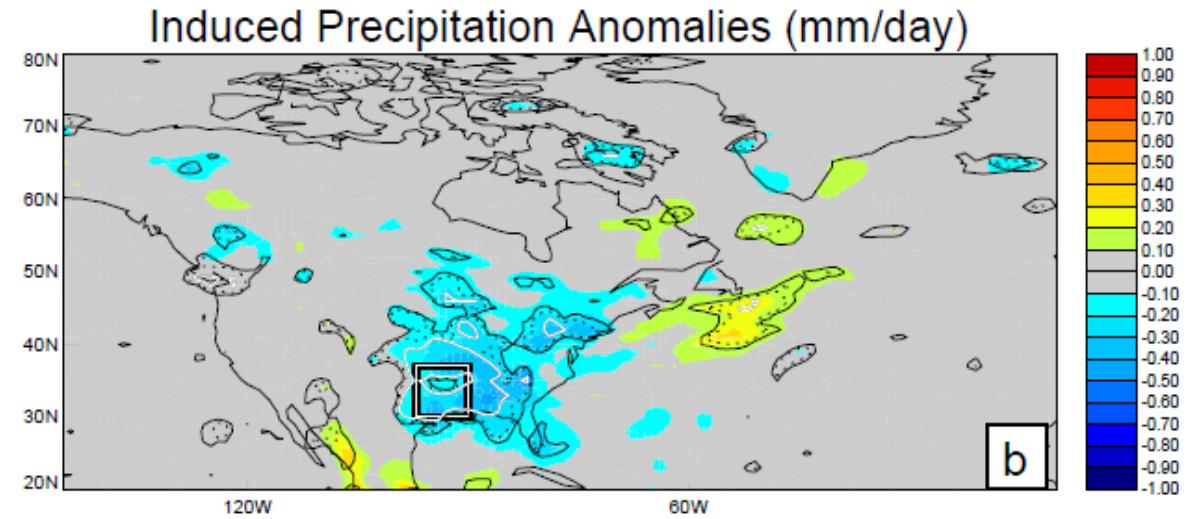
The dry surface anomaly does (on average)
induce a wave pattern in June-July...



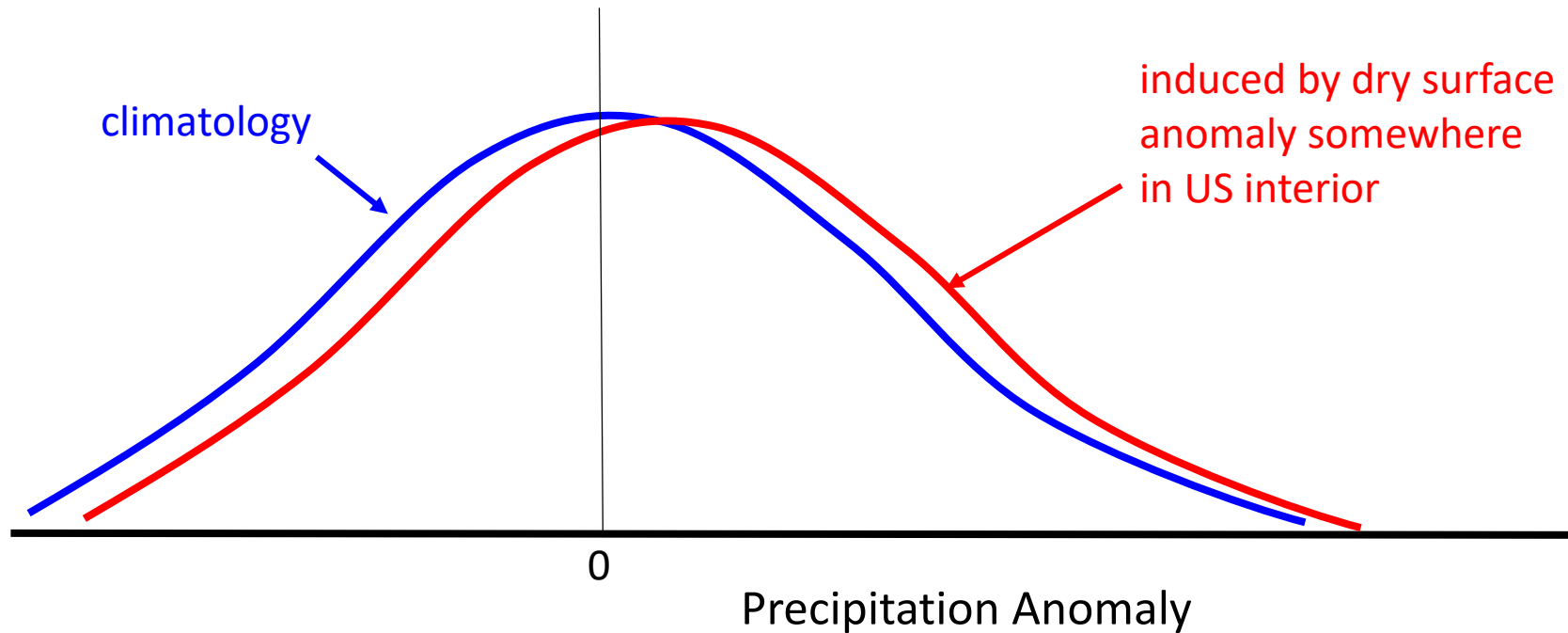
The dry surface anomaly does (on average)
induce a wave pattern in June-July...



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



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.



***Enough about soil moisture.
How about snow initialization
in forecasts?***

snow amount

vegetation
phenology

miscellaneous
(lake levels, ...)

near-surface
soil moisture

deeper soil moisture
(e.g., groundwater)

land heat
content

(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,

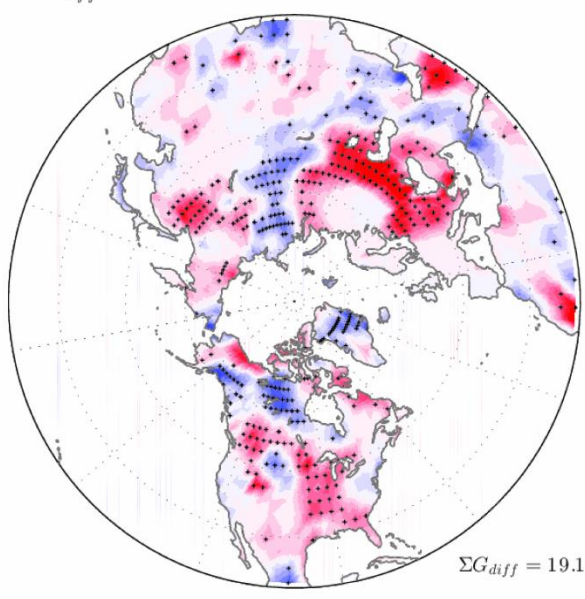
The diagram illustrates the calculation of skill due to land initial conditions (ICs). It consists of three rectangular boxes connected by a minus sign and an equals sign. The first box is pink and contains the text 'Skill (r^2) from simulations w/ accurate land ICs'. A minus sign is positioned between this box and the second box, which is cyan and contains the text 'Skill (r^2) from simulations w/o accurate land ICs'. An equals sign is positioned between the second box and the third box, which is green and contains the text 'Skill due to land ICs'.

$$\text{Skill } (r^2) \text{ from simulations w/ accurate land ICs} - \text{Skill } (r^2) \text{ from simulations w/o accurate land ICs} = \text{Skill due to land ICs}$$

Snow and soil water contributions to skill:

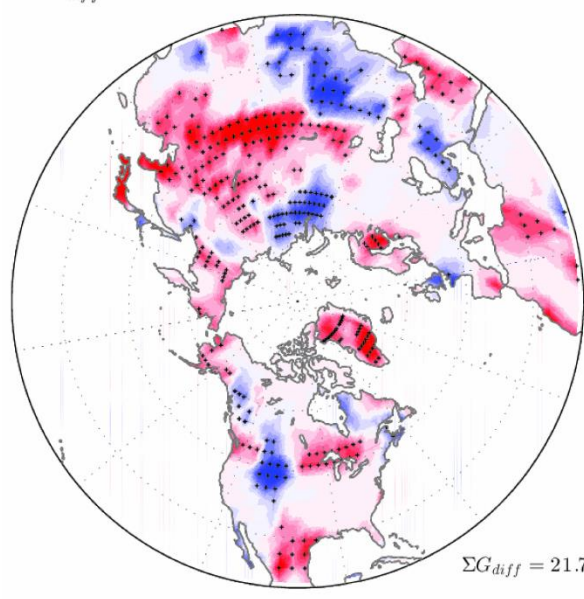
r^2 differences
(15-day lead)

(a) r_{diff}^2 [April, 15 day]: CanCM3 2m-Temperature



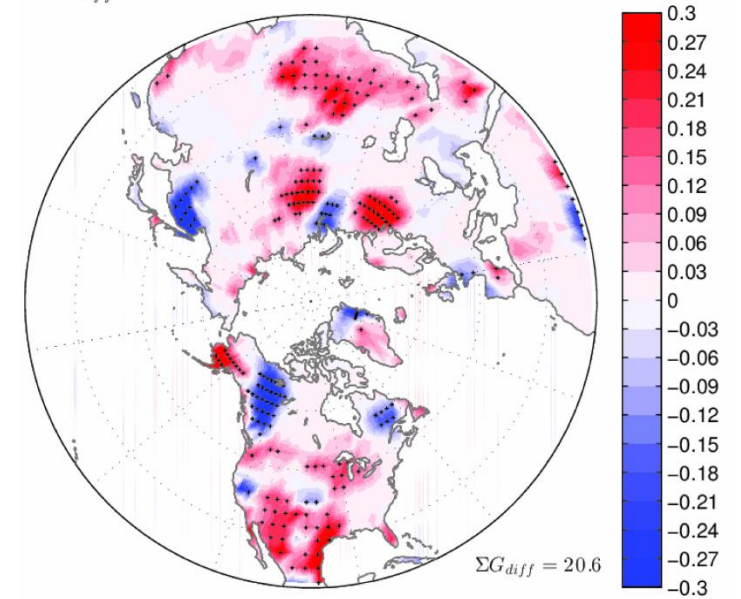
r^2 differences
(30-day lead)

(b) r_{diff}^2 [April, 30 day]: CanCM3 2m-Temperature



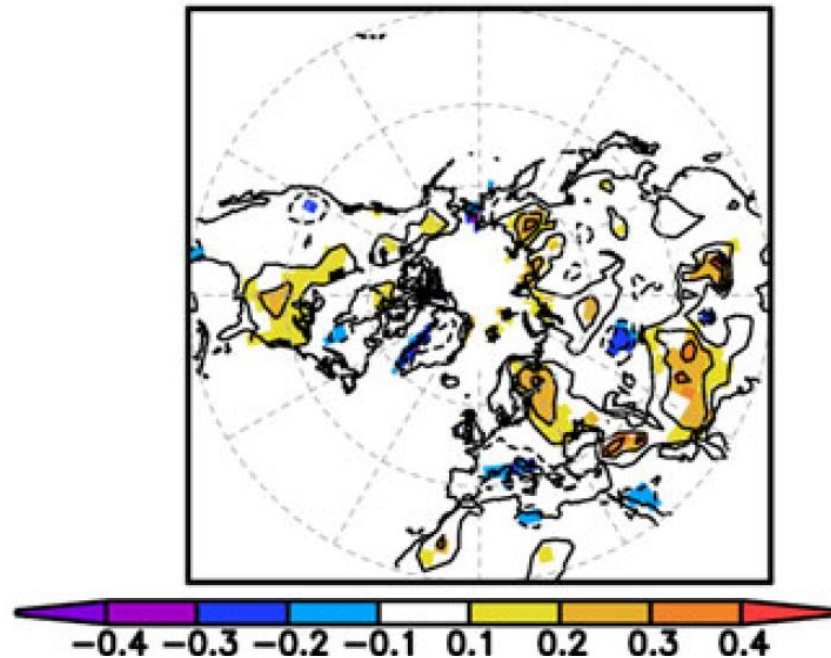
r^2 differences
(45-day lead)

(c) r_{diff}^2 [April, 45 day]: CanCM3 2m-Temperature



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)

Lin et al. (GRL, 43, doi:10.1002/2016GL070966) examined the additional forecast skill achievable through the use of remote sensing in the initialization process.

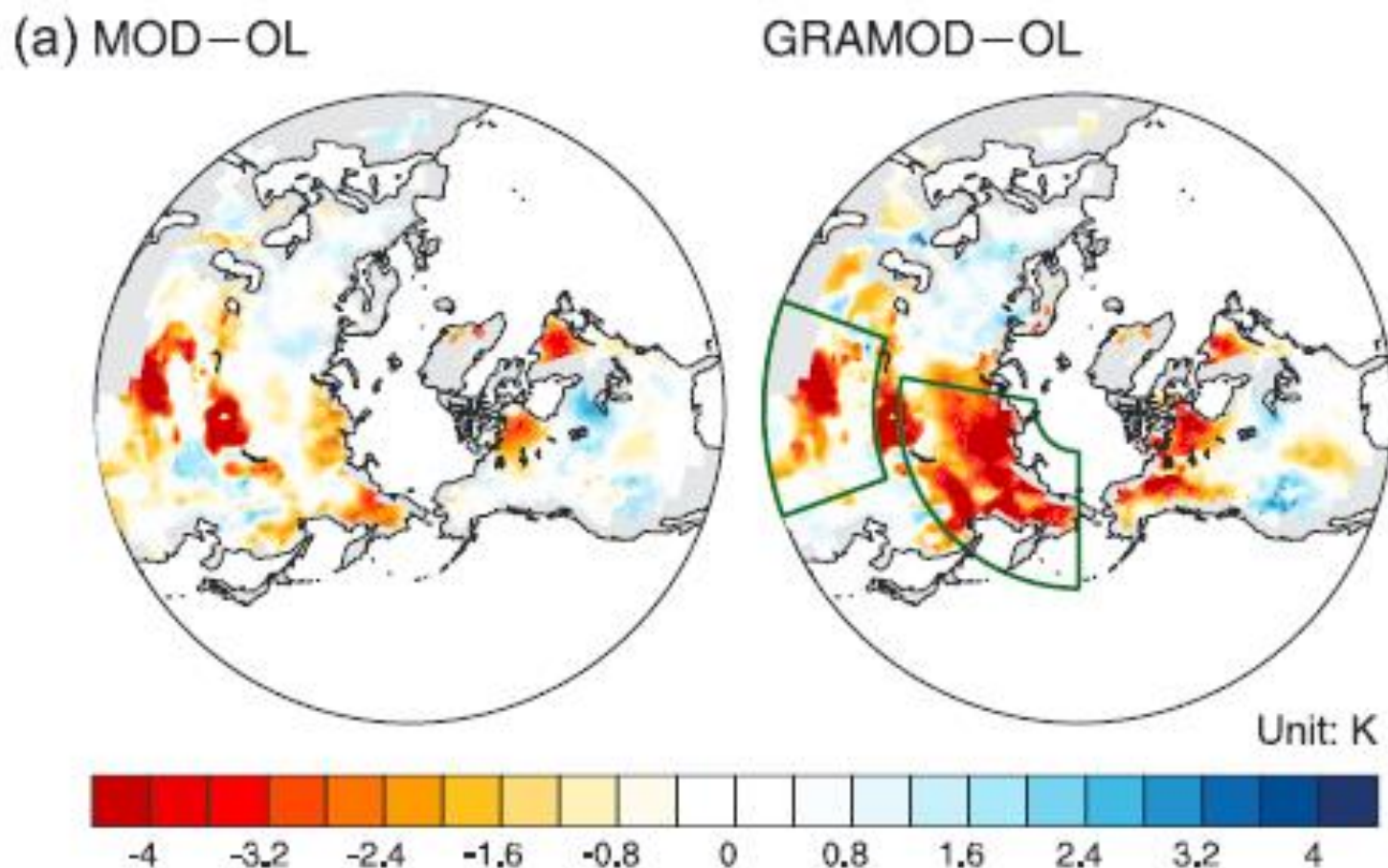


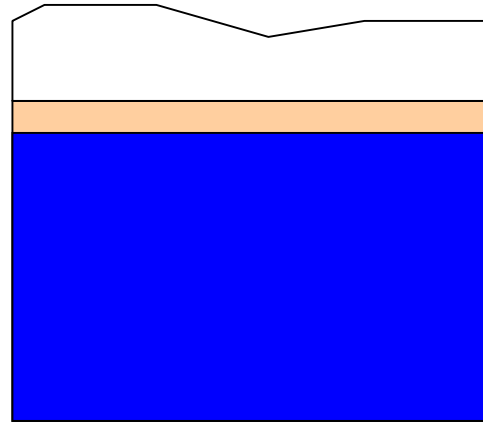
Figure 2. The temperature prediction cumulative RMSE (cRMSE) difference between DA and OL. (a) Absolute value difference (K); (b) Percentage difference (%). Figures 2a (left) and 2b (left) (Figures 2a (right) and 2b (right)) show the difference between MOD (GRAMOD) and OL. The forecasts are initialized on 1 March. Negative values indicate reduced prediction errors and improved temperature predictions after using snow DA-constrained land initializations. The green boxes encompass two regions of interest for a further analysis in section 3.3.

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

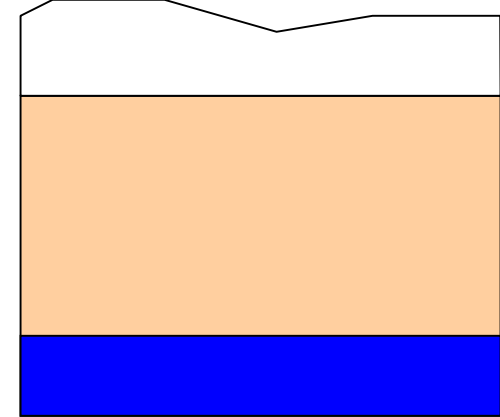
Obvious: Larger snowpack $\Rightarrow$ Increased streamflow during snowmelt season.

Less obvious: Impact of soil moisture...

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



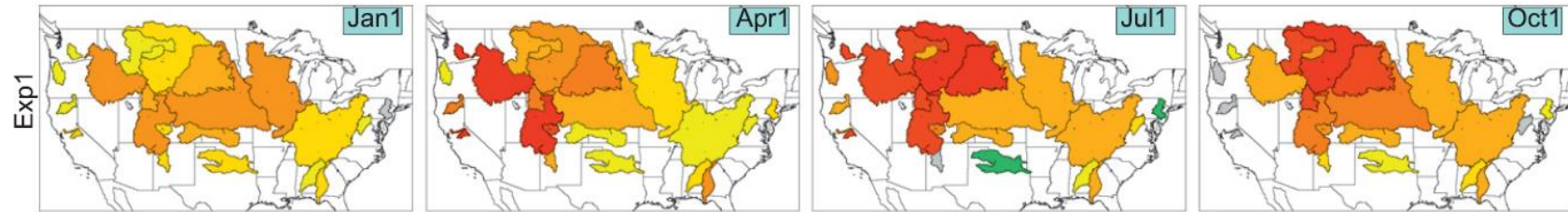
Snow (or rainfall) over dry soil: most of the meltwater infiltrates the soil and is lost to water resources



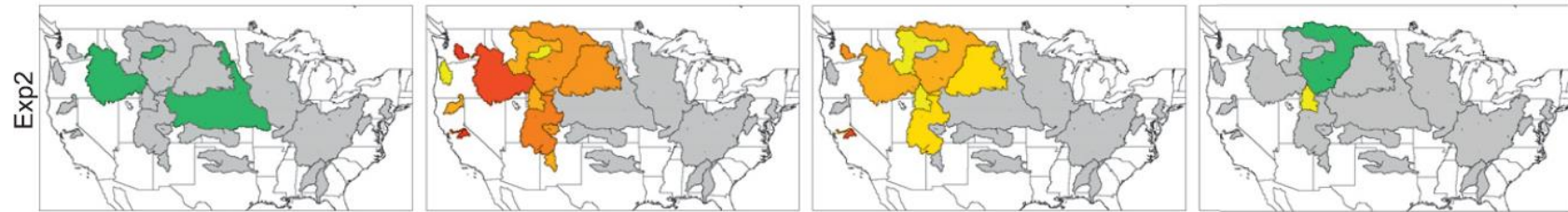
Knowledge of winter snow, soil moisture $\Rightarrow$ streamflow forecast skill

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

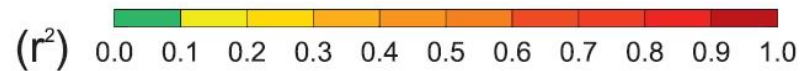
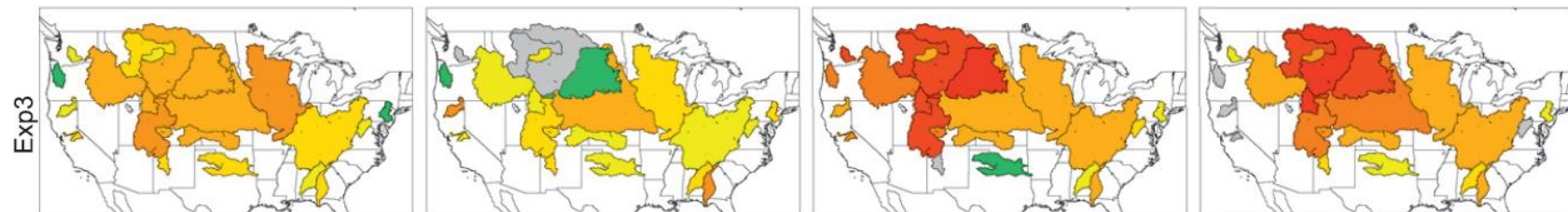
From both
snow and soil
moisture ICs

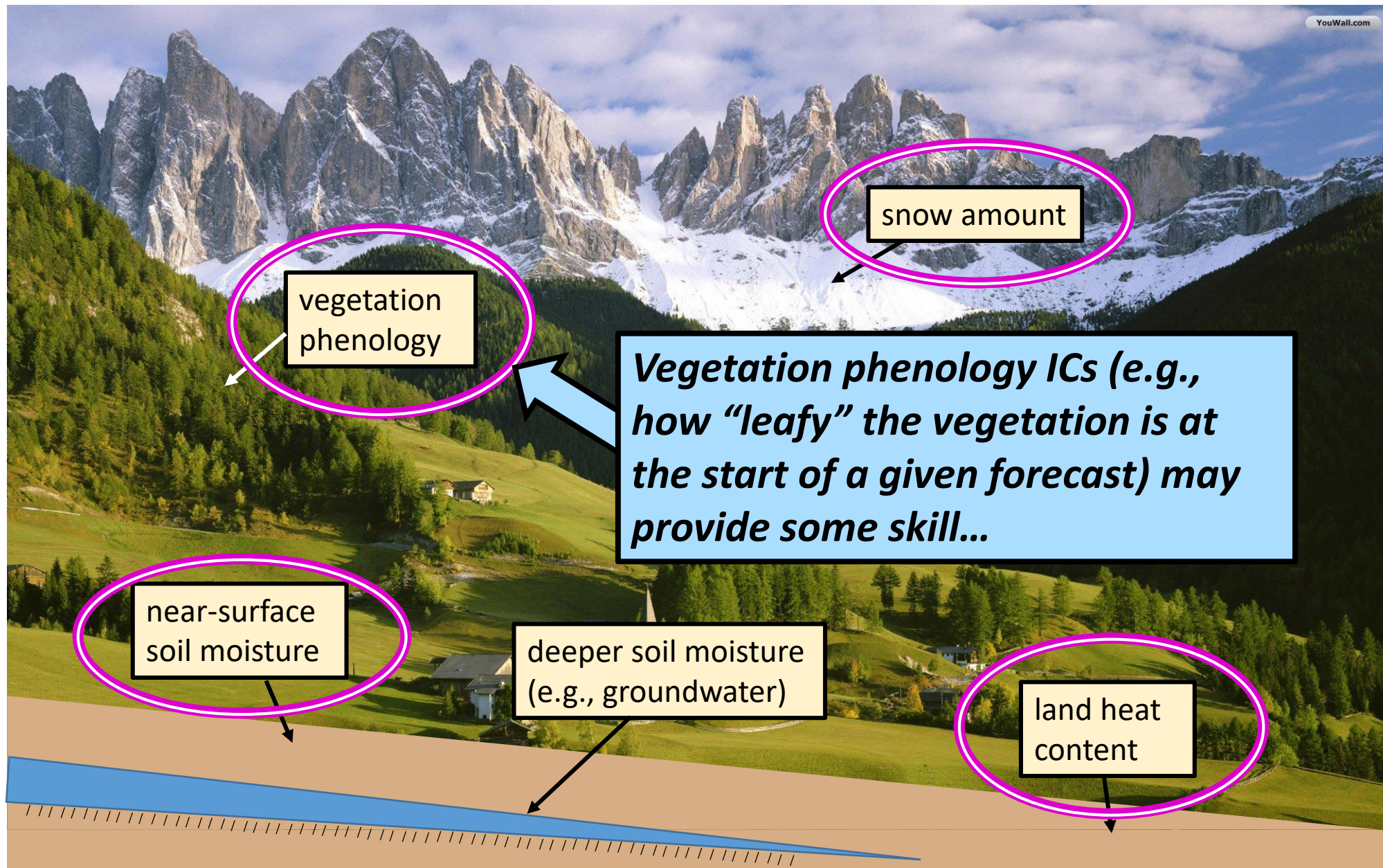


From snow ICs



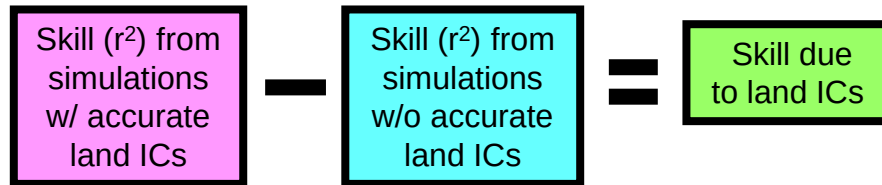
From soil
moisture ICs



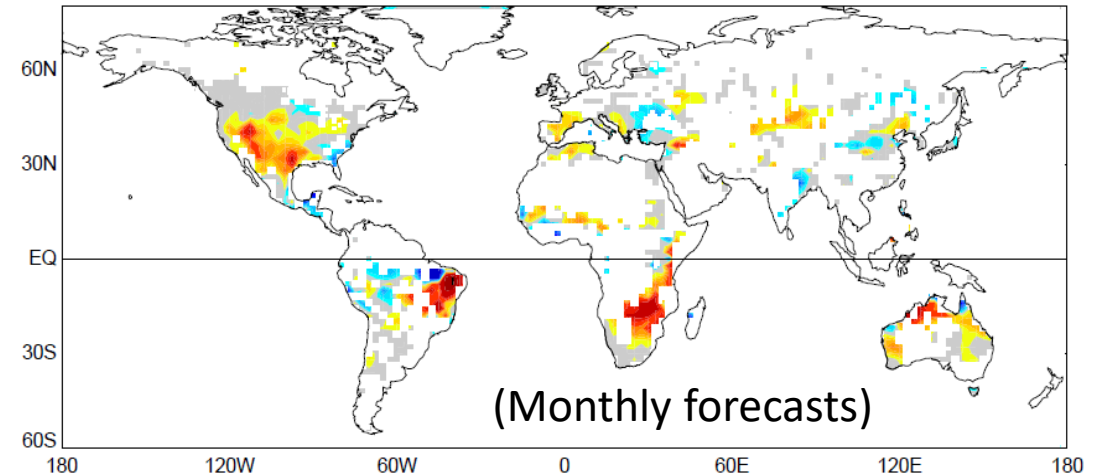


(Image stolen
from
internet!)

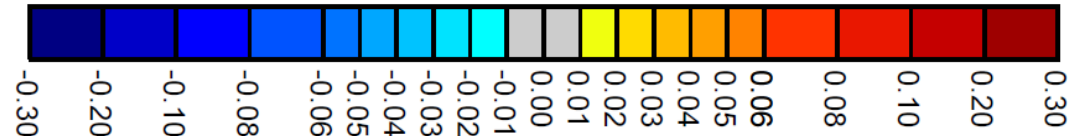
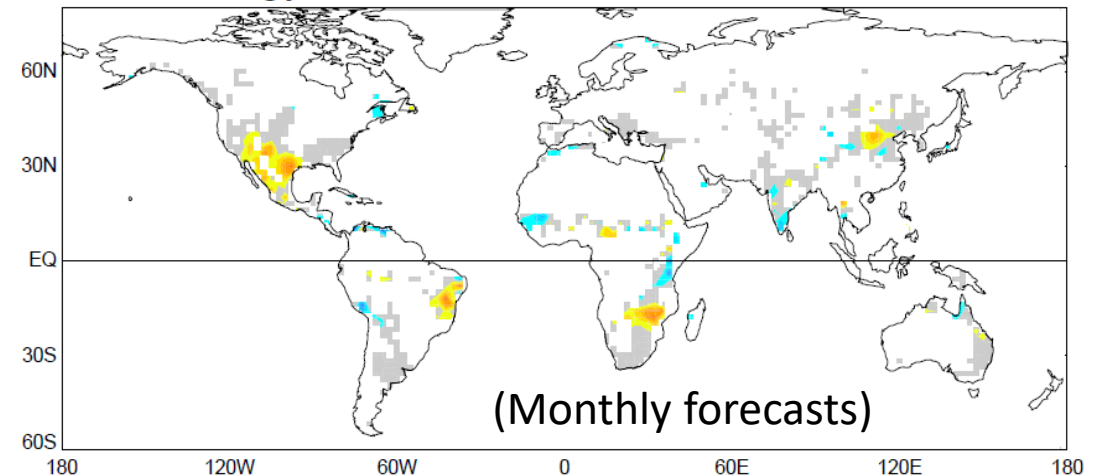
Vegetation state. An experiment similar to GLACE-2, but focusing on the impacts of initialized vegetation state on monthly forecast skill (using a land model with dynamic phenology) was recently performed. In fact, the effects of both soil moisture and vegetation initialization were quantified with the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



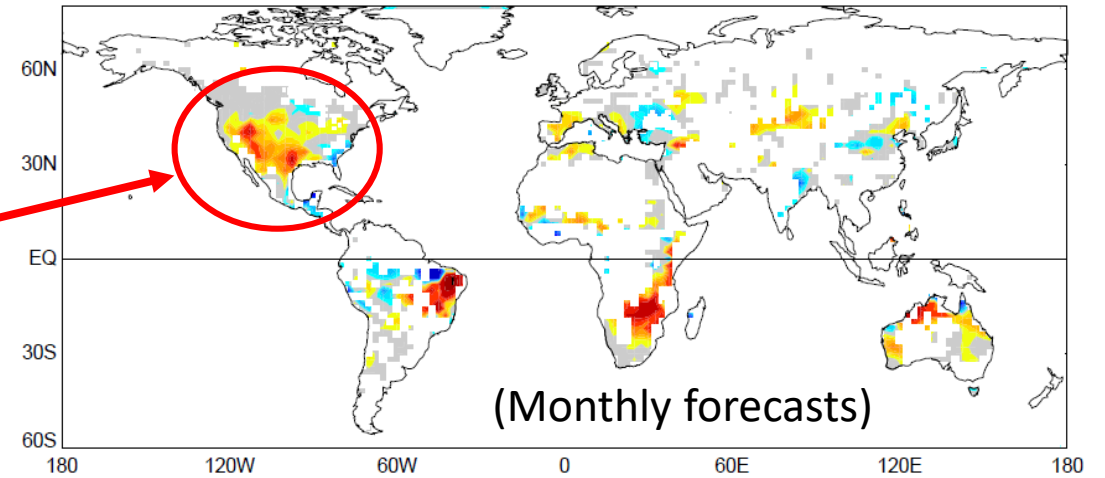
a. Soil Moisture Contribution to Forecast Skill: T-air



b. Phenology Contribution to Forecast Skill: T-air

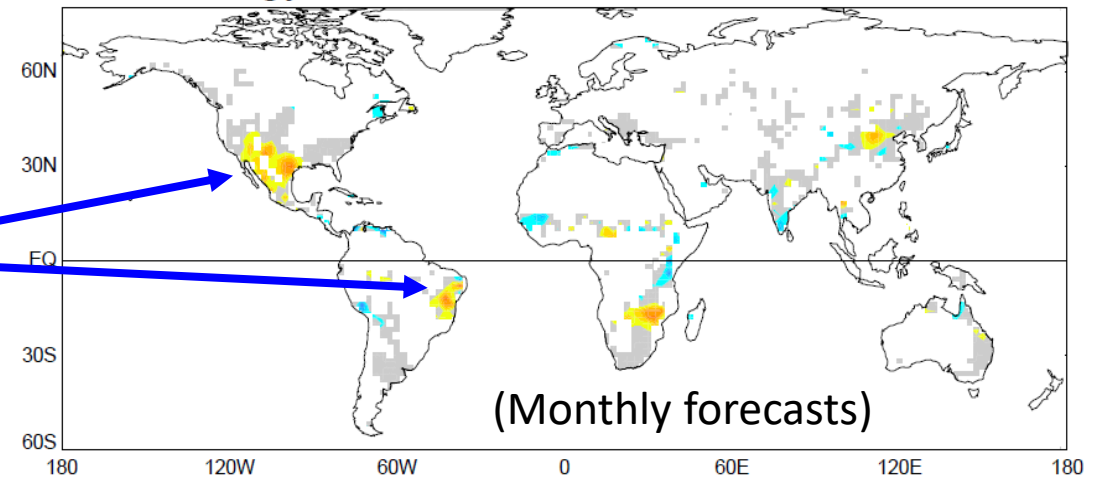


a. Soil Moisture Contribution to Forecast Skill: T-air

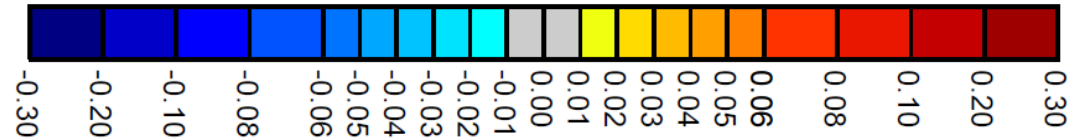


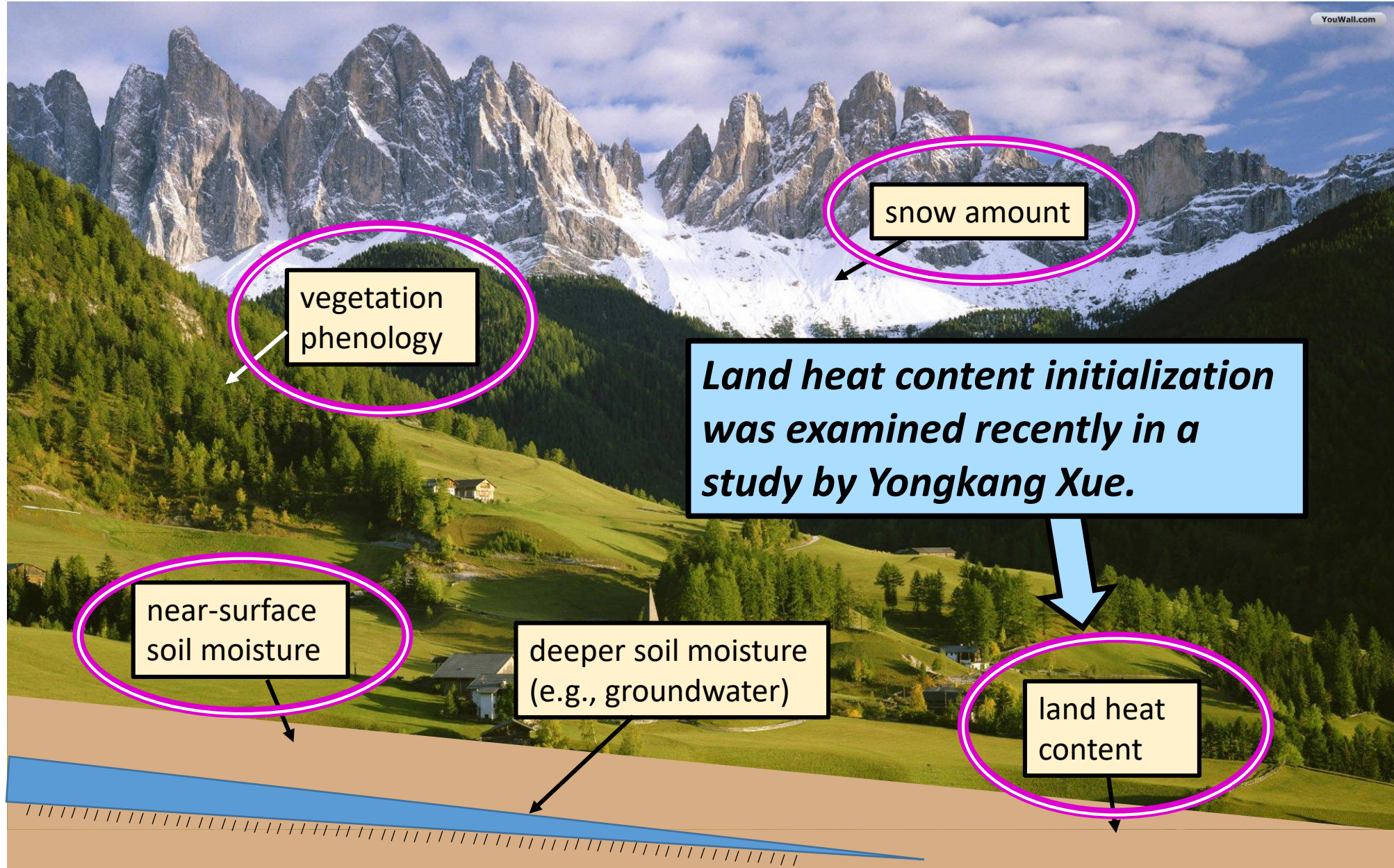
Note: some differences between this pattern (for single model) and that for multi-model GLACE-2 results

b. Phenology Contribution to Forecast Skill: T-air



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

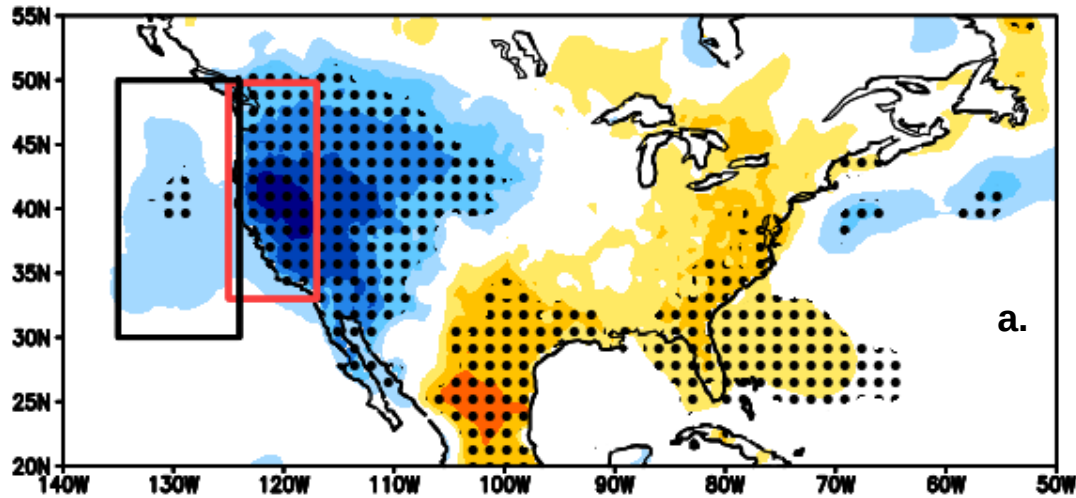




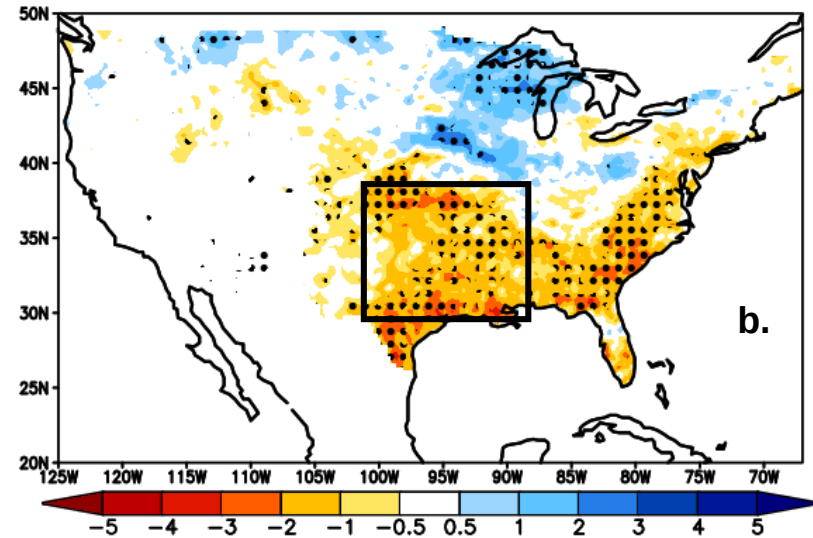
(Image stolen from internet!)

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

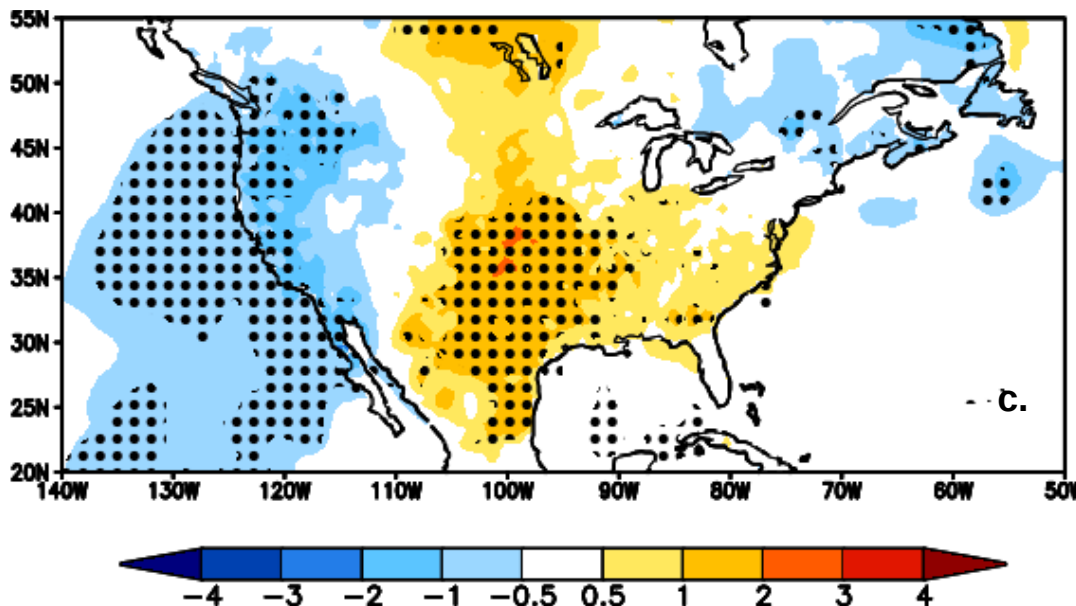
May Observed LST and SST



June Observed Precipitation



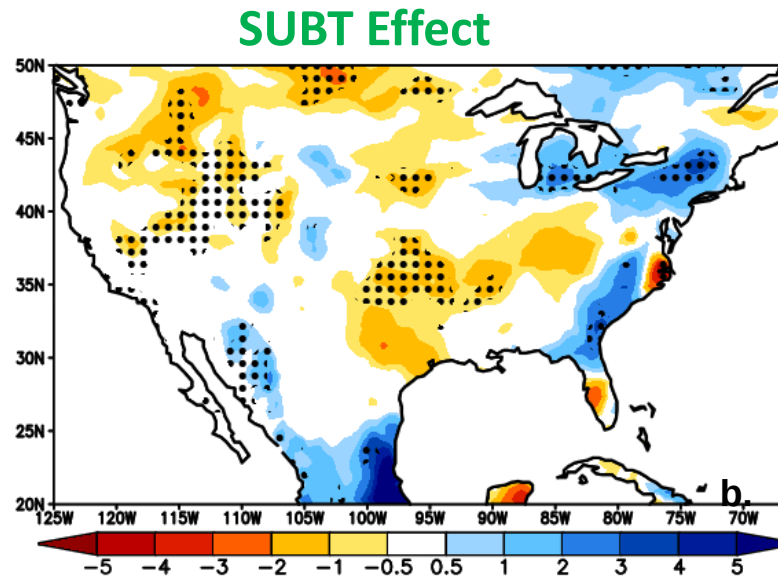
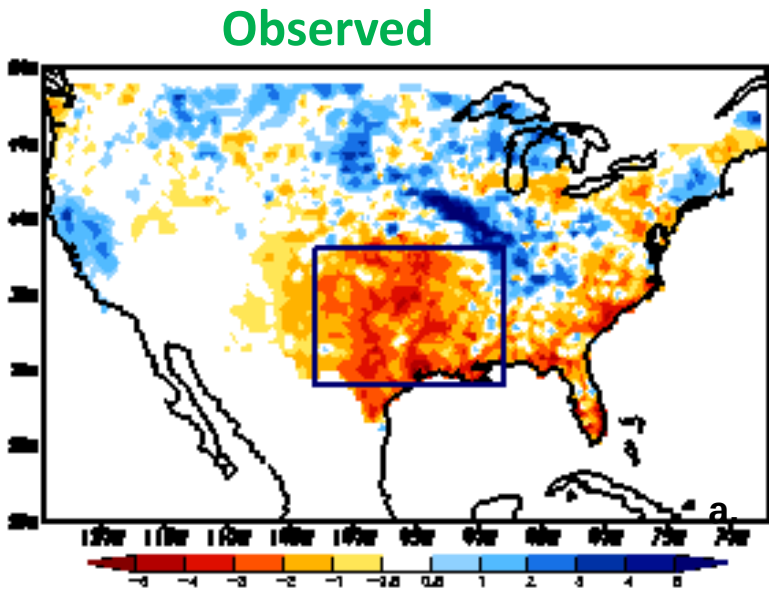
June Observed LST and SST



- 1) LST: land surface temperature
- 2) The dotted areas denote statistical significance less than $\alpha=0.1$ level of t-test values.

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

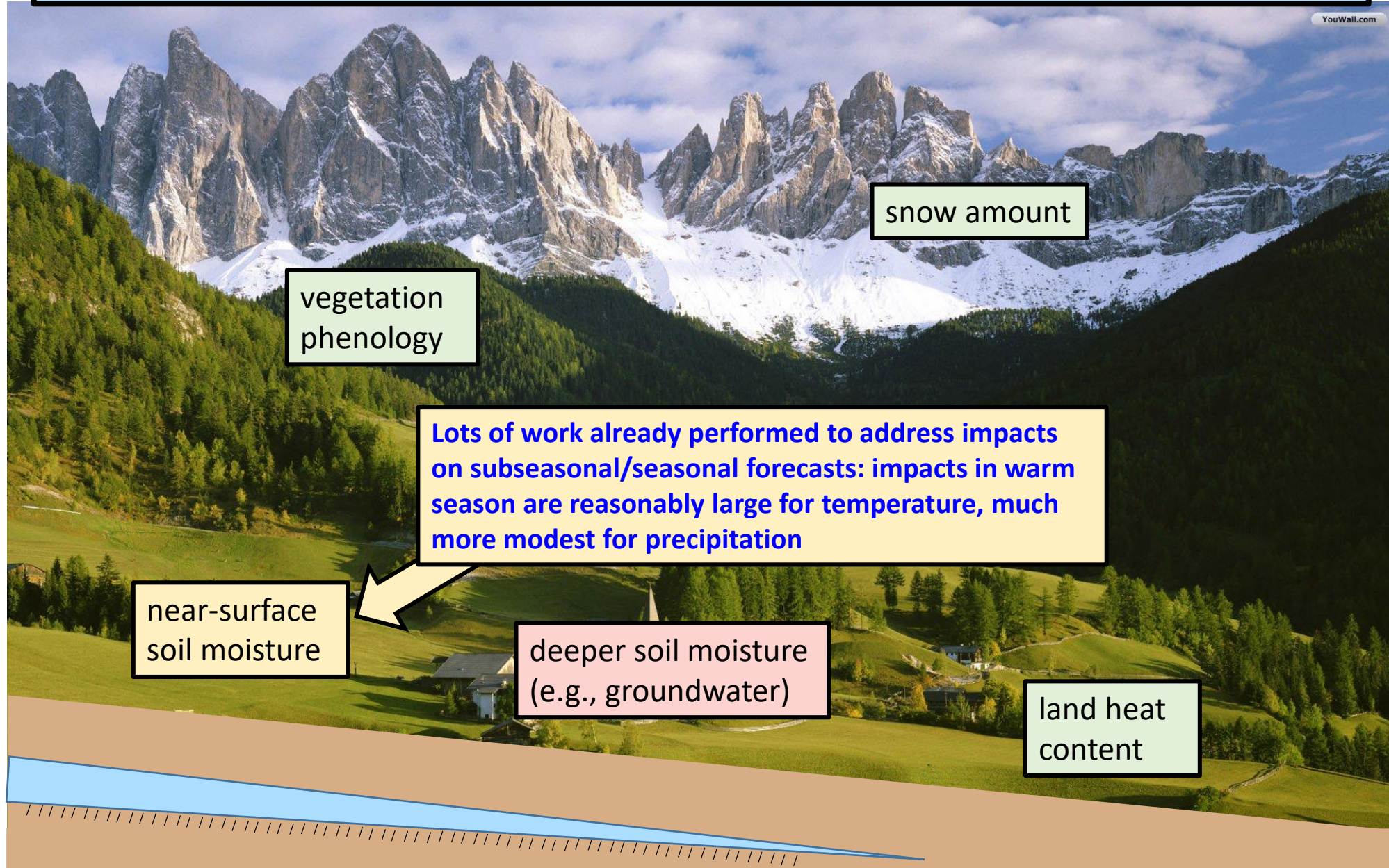
Observed/WRF-NMM simulated anomaly/difference of 2011 June Precipitation (mm day⁻¹)



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

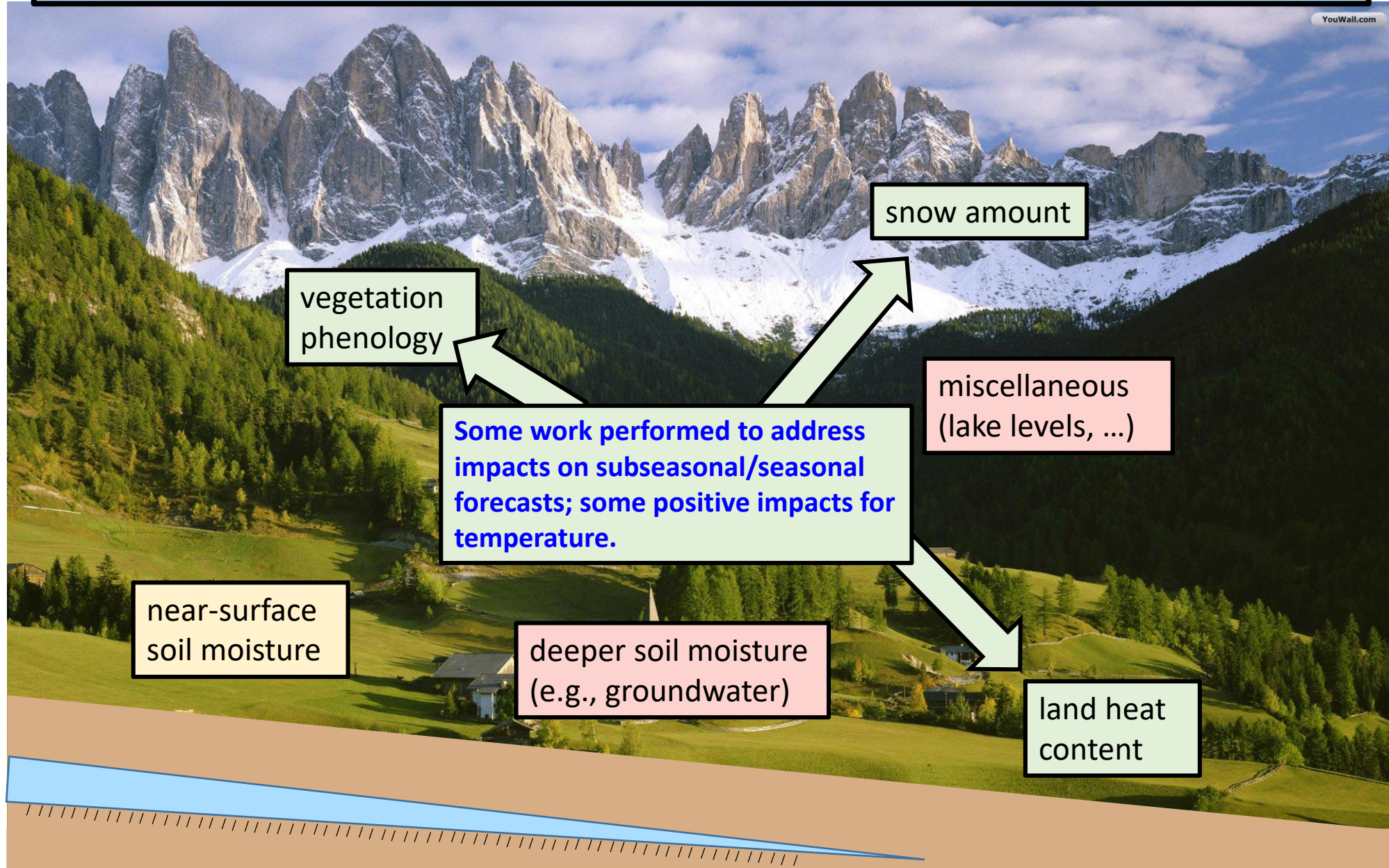
Xue et al., Env. Res. Lett., 11, 044018, 2016.

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



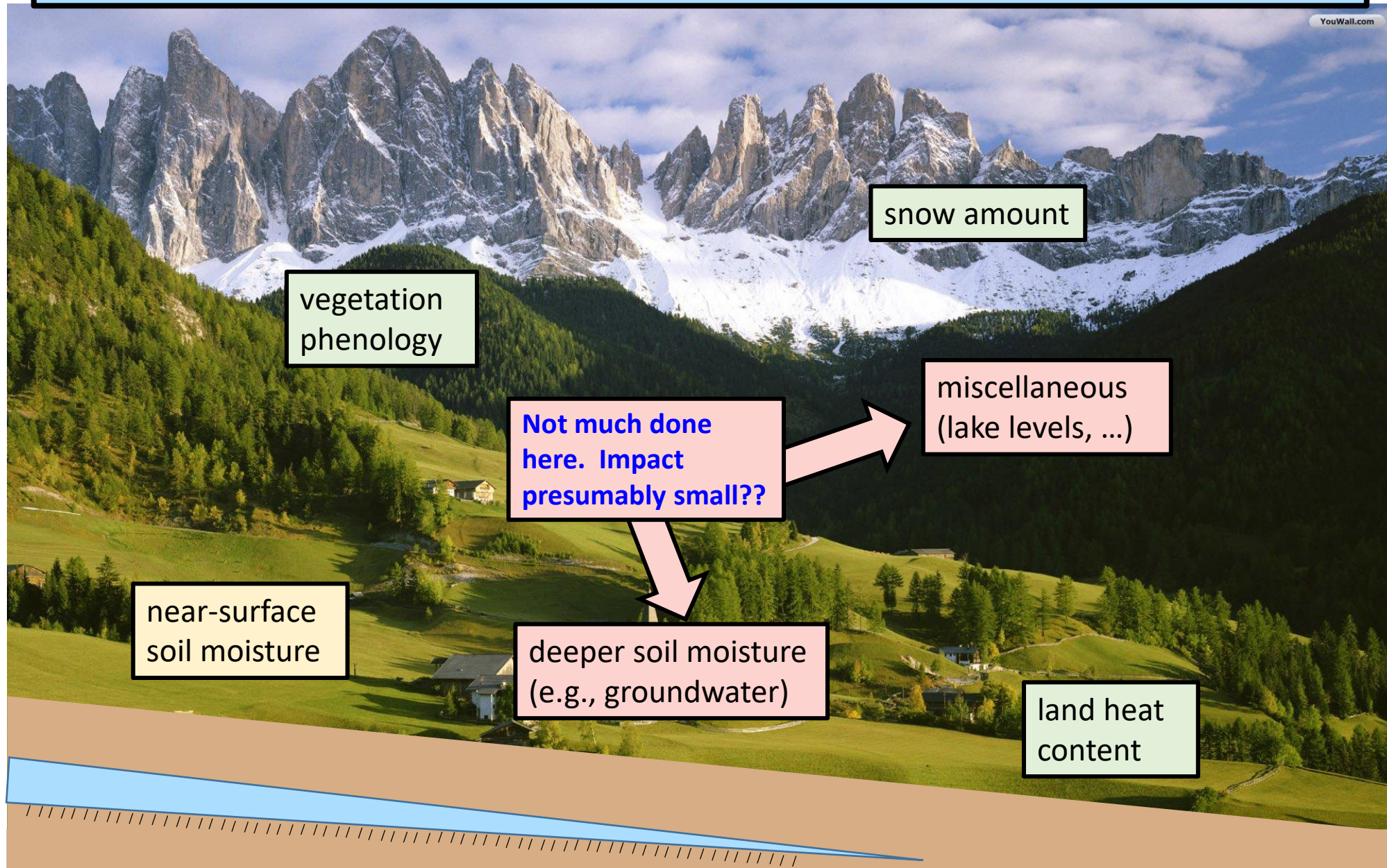
(Image stolen from internet!)

So, 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



(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

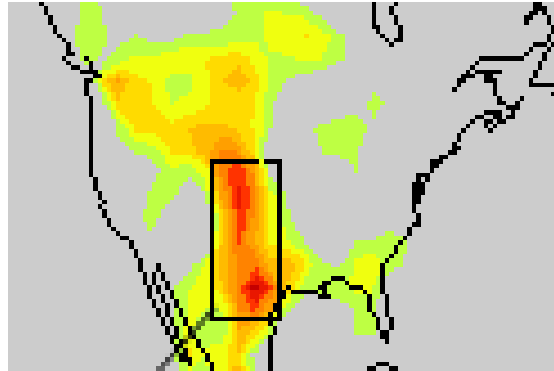
Thank you.

Questions?

Extra Slides

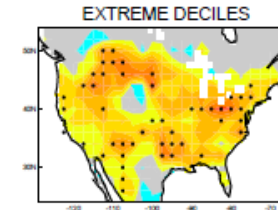
Note the contradiction between diagnosed coupling strength locations (from earlier) and locations where skill appears:

Coupling strength

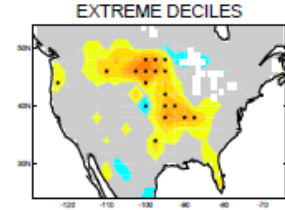


Skill levels (extreme deciles)

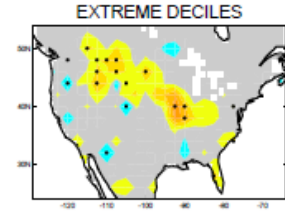
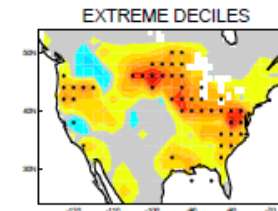
temperature



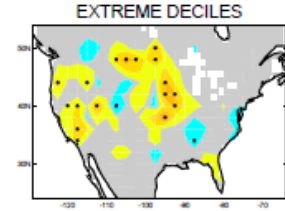
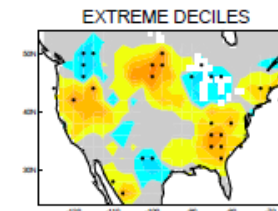
precipitation



16-30 days



31-45 days

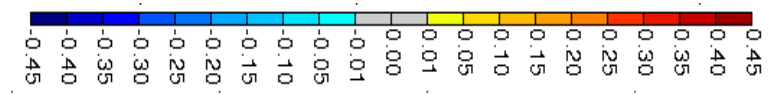


46-60 days

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

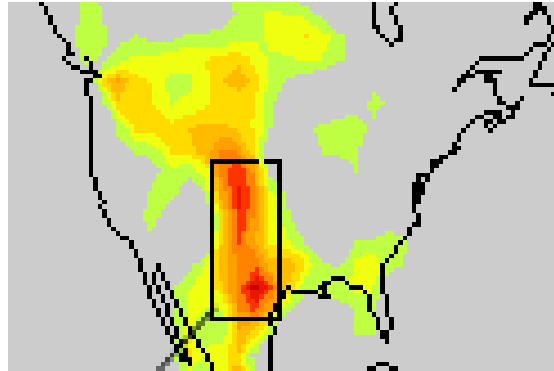
- different set of models, with different biases (different transition zones)
- spatial differences in memory
- ability to produce a feedback loop (“coupled mode”) in the forecast system

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



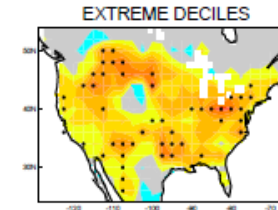
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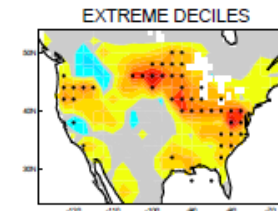


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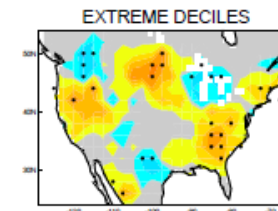
temperature



16-30 days

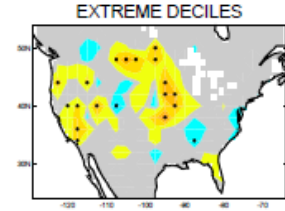
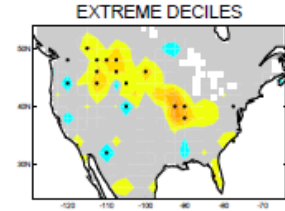
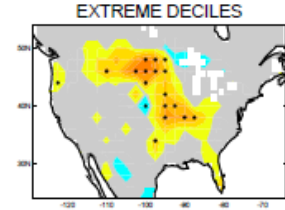


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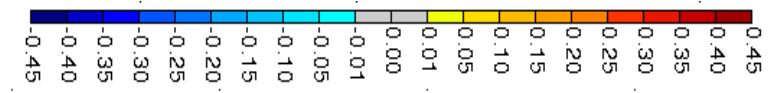
precipitation



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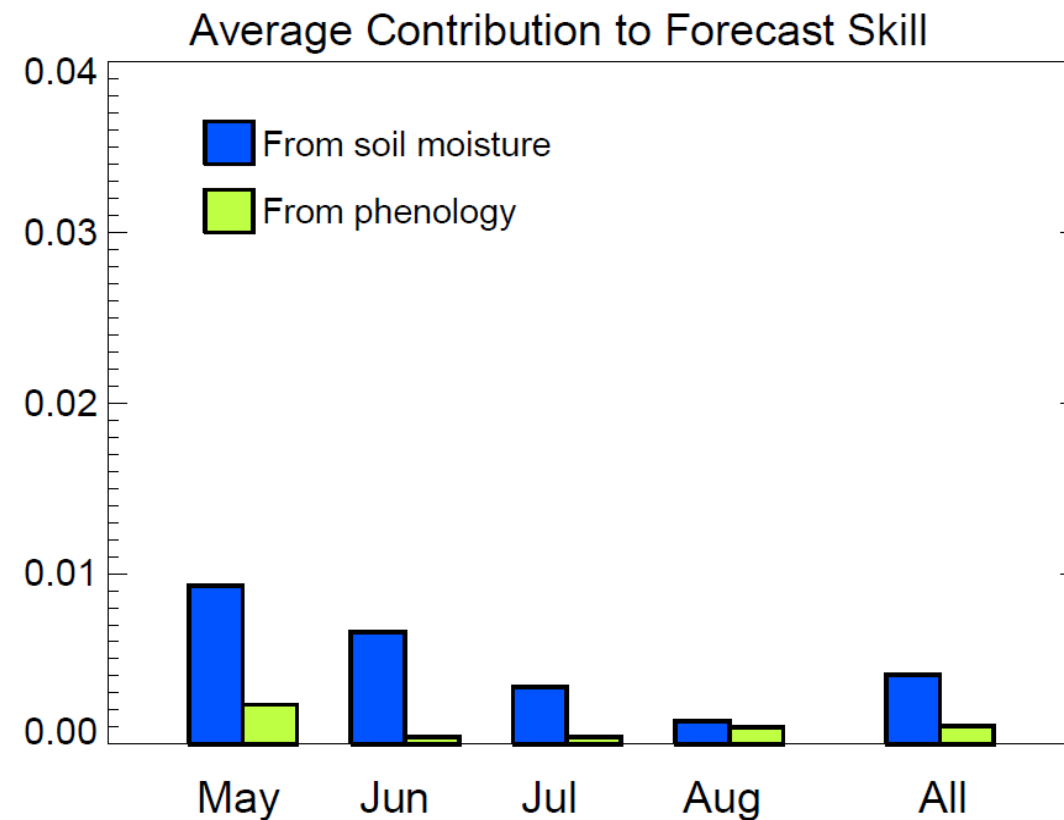
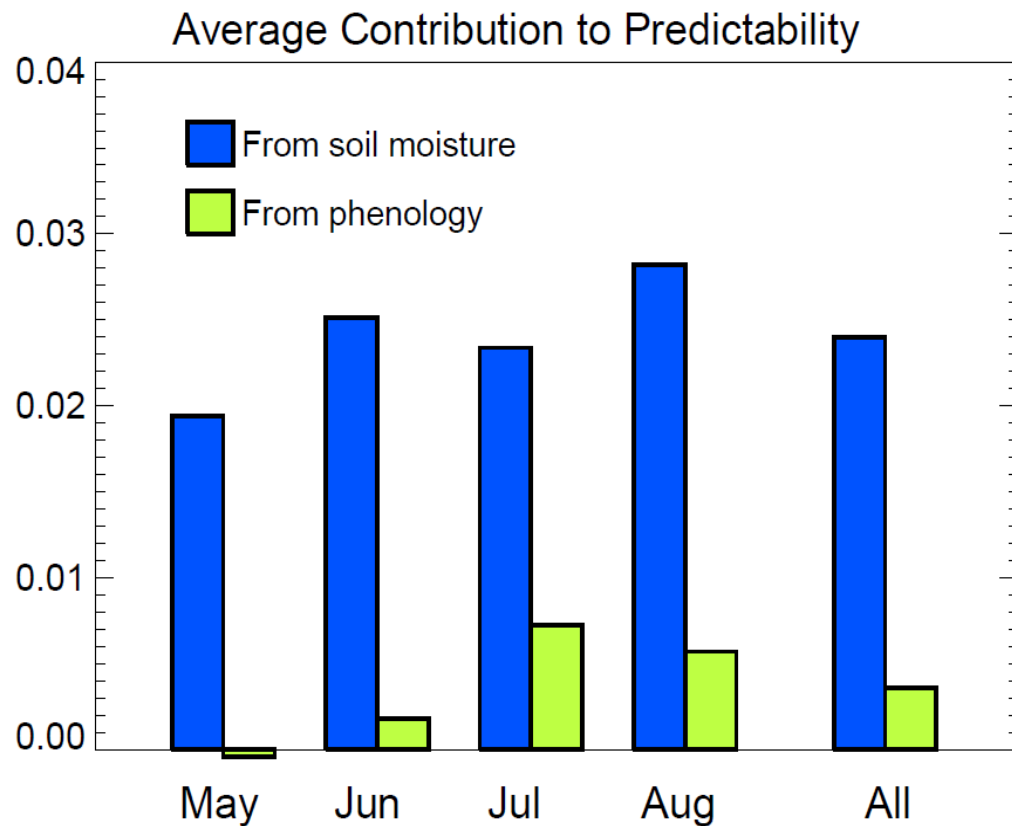
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Forecast skill: r^2 with land ICs vs r^2 w/o land ICs



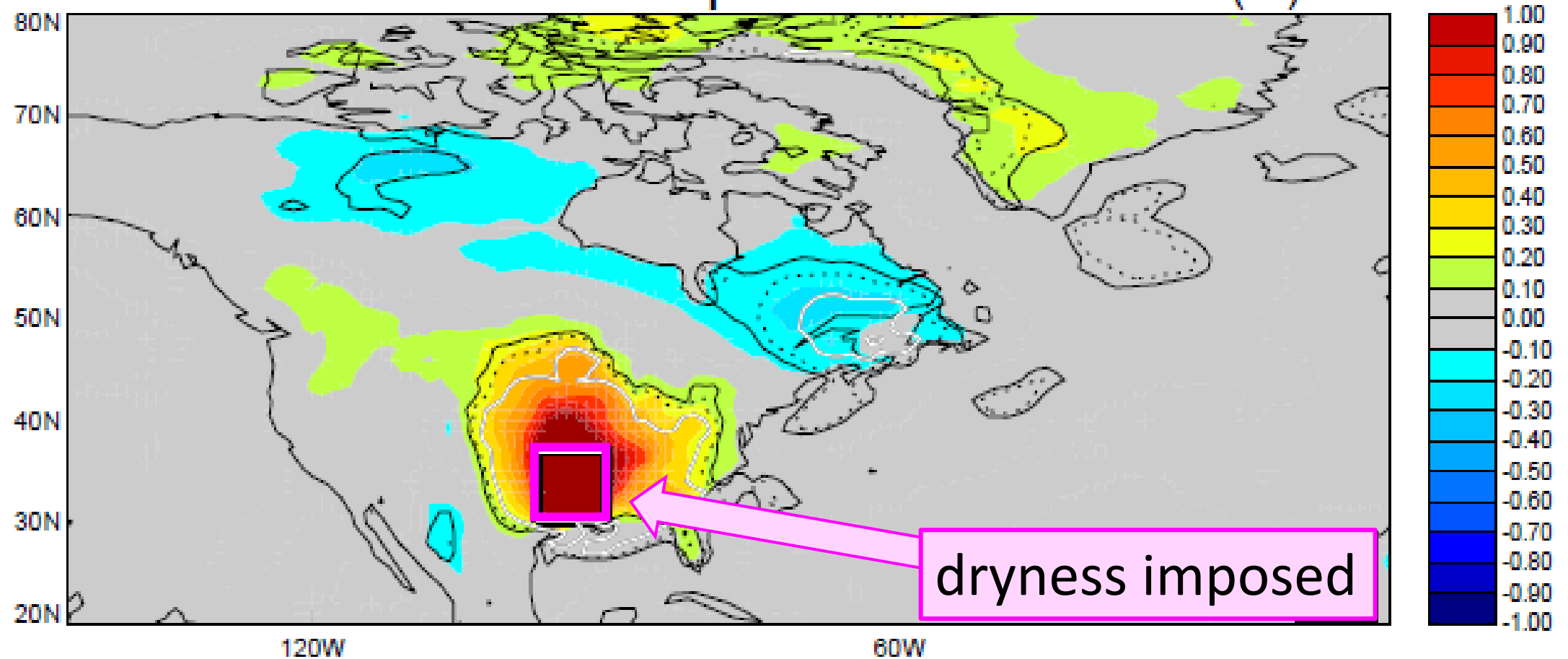
perhaps not the primary reason, but scientifically exciting – worth a quick look!

Global averages of contributions over areas with adequate rain gauge density

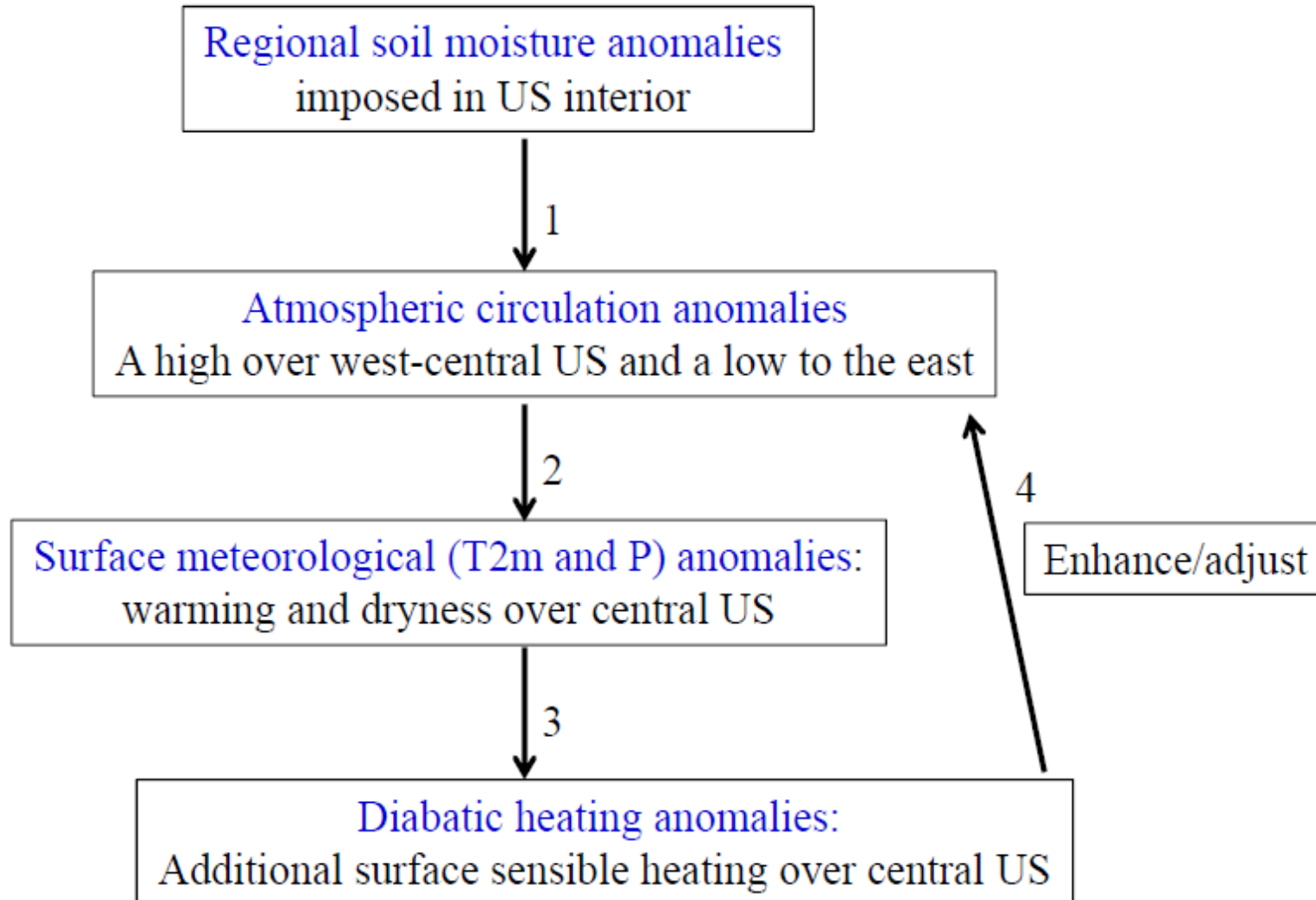


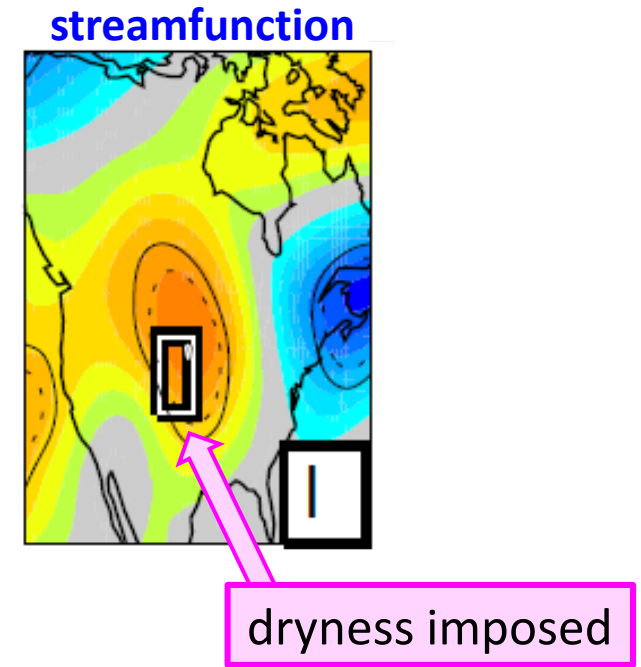
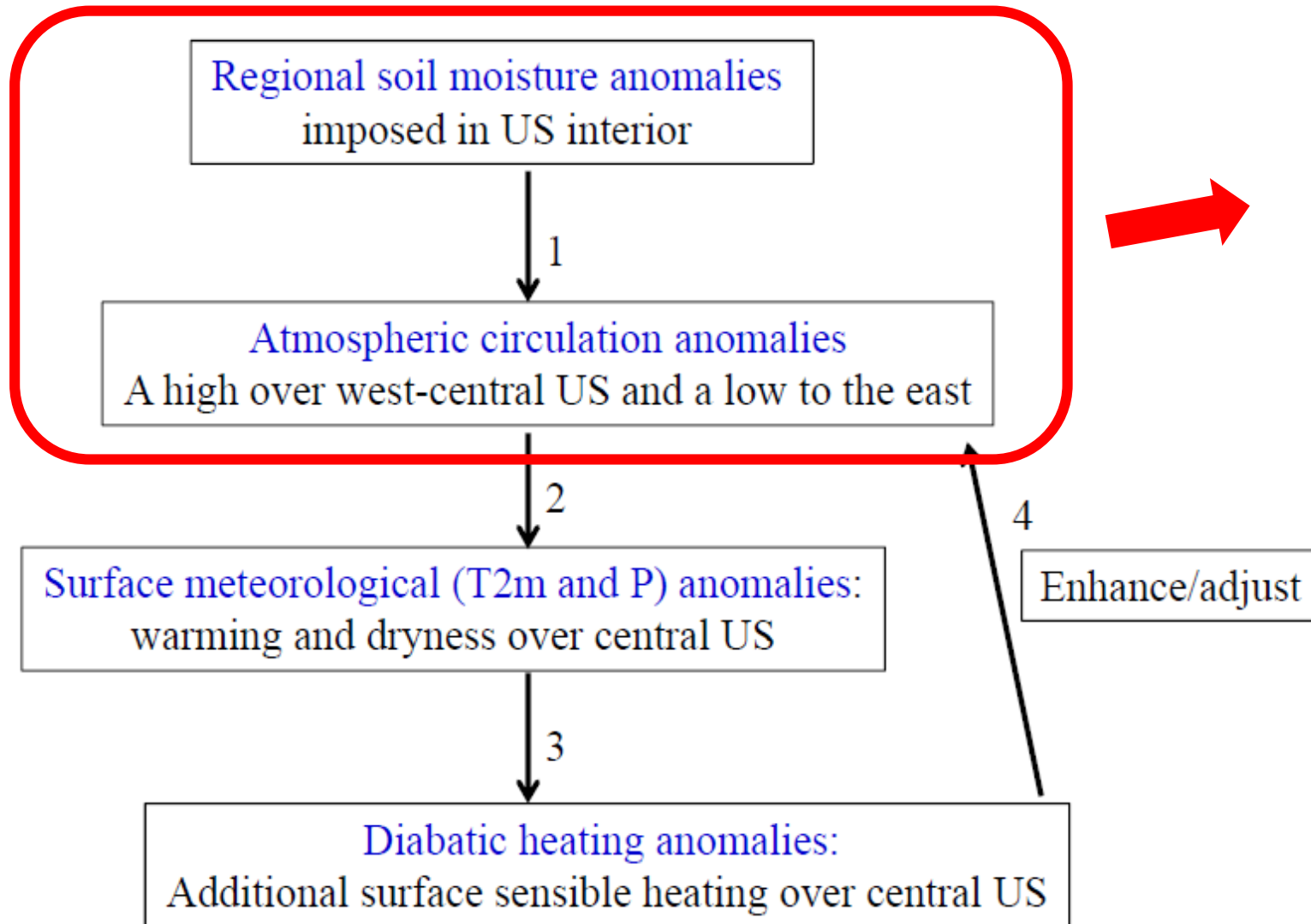
1-month air temperature forecasts

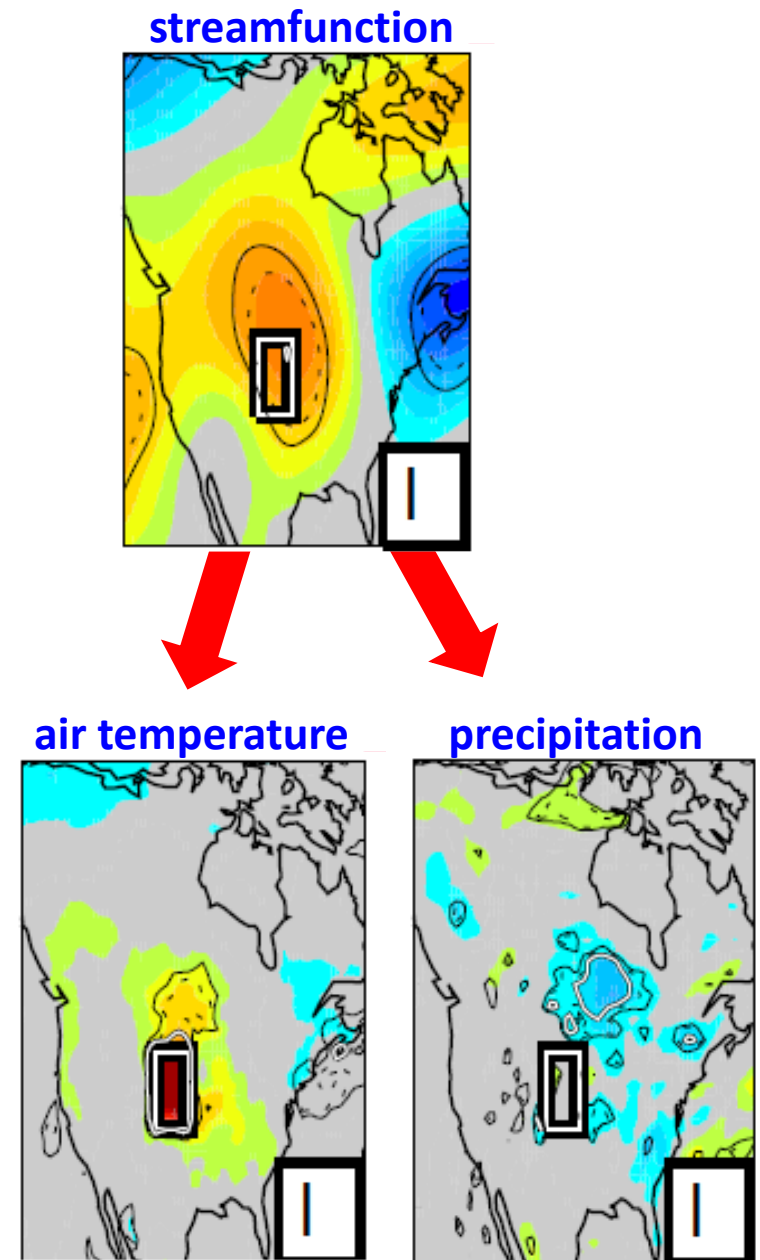
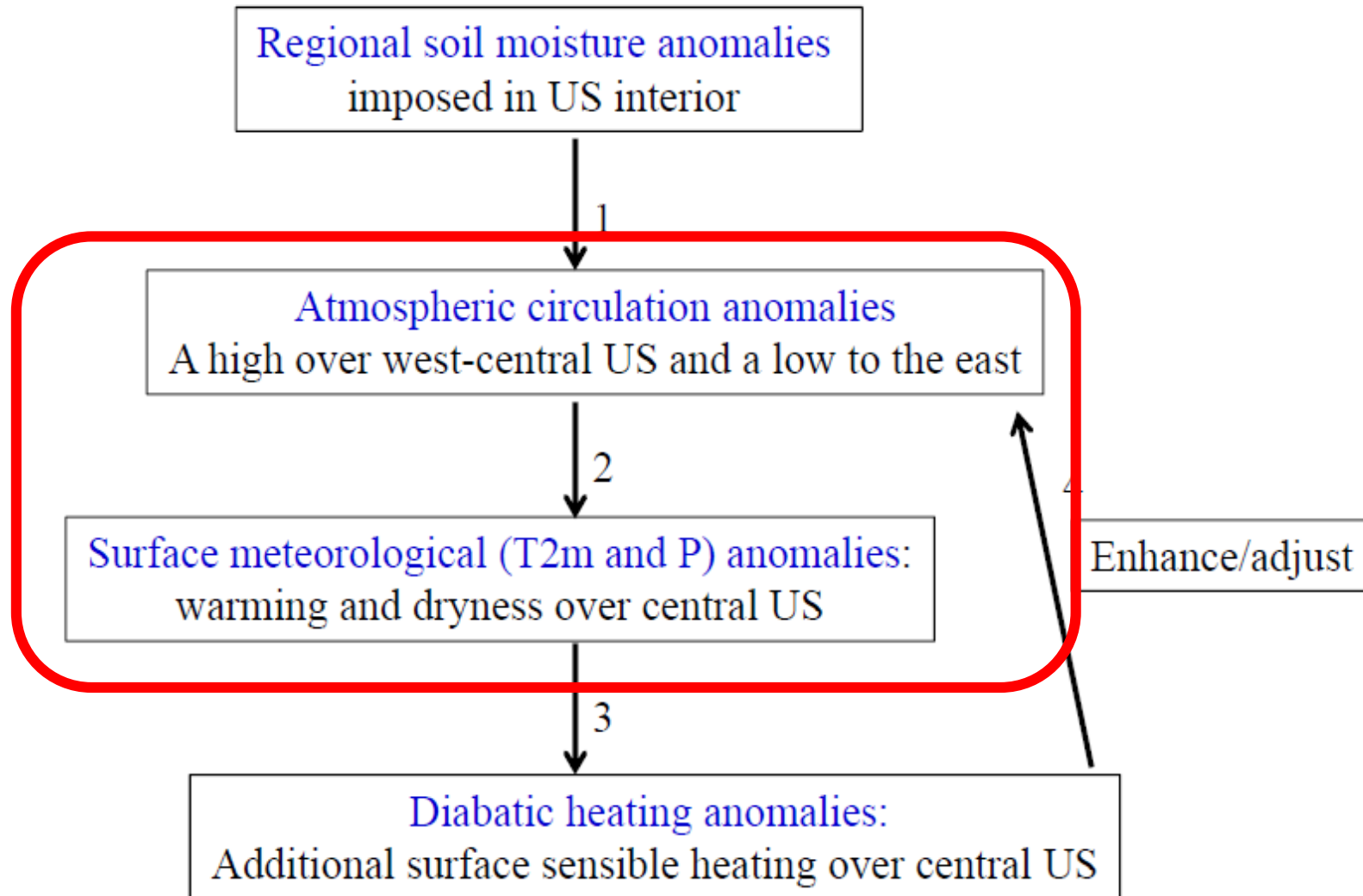
Induced 2-m Air Temperature Anomalies (K)



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



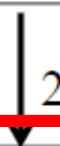




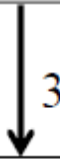
Regional soil moisture anomalies
imposed in US interior



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



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



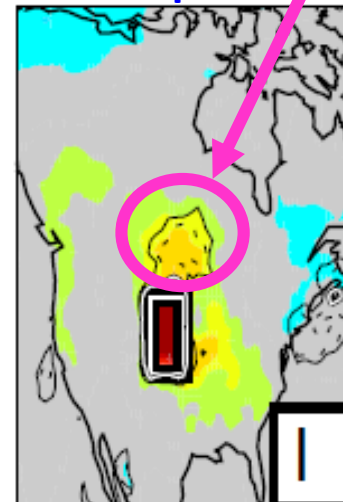
Diabatic heating anomalies:
Additional surface sensible heating over central US

Enhance/adjust

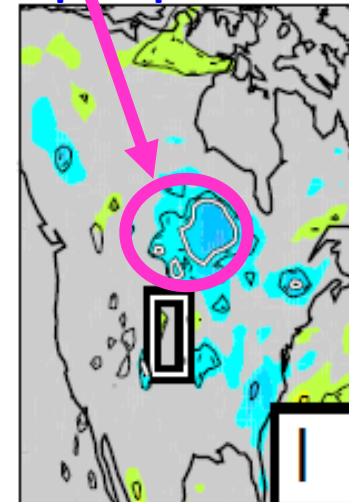


Notice drying and
warming even
outside of original
selected region

air temperature



precipitation



Regional soil moisture anomalies
imposed in US interior

1

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

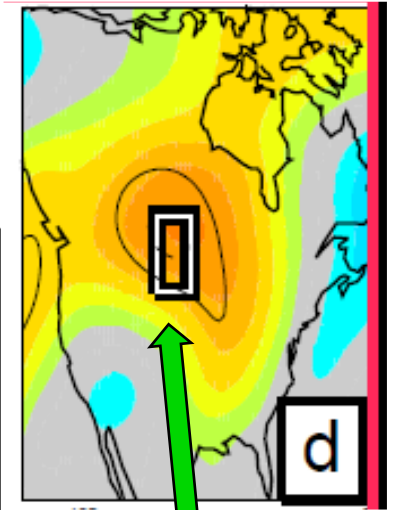
2

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

3

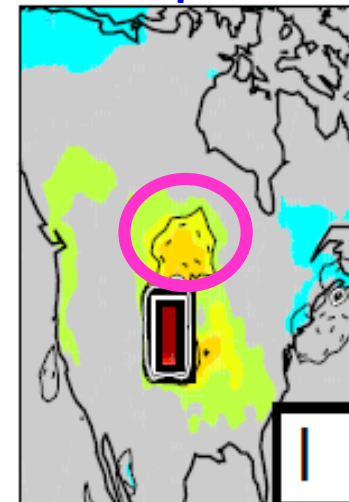
Diabatic heating anomalies:
Additional surface sensible heating over central US

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



Enhance/adjust

air temperature



precipitation

