

# GLACE-2: Impact of land initialization on subseasonal forecasts

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With contributions from the entire GLACE-2 team (see later slide)

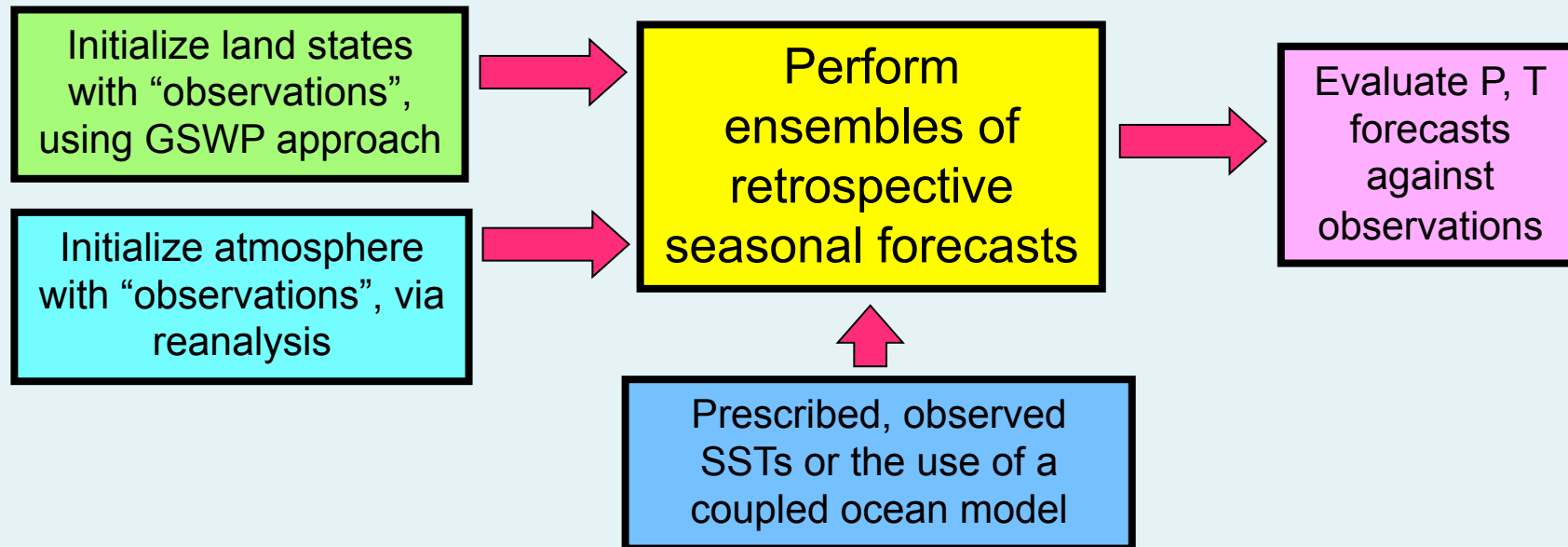
***GLACE-2:*** An international project aimed at quantifying soil moisture impacts on prediction skill.

Overall goal of GLACE-2: Determine the degree to which realistic land surface (soil moisture) initialization contributes to forecast skill (rainfall, temperature) at 1-2 month leads, using a wide array of state-of-the-art forecast systems.



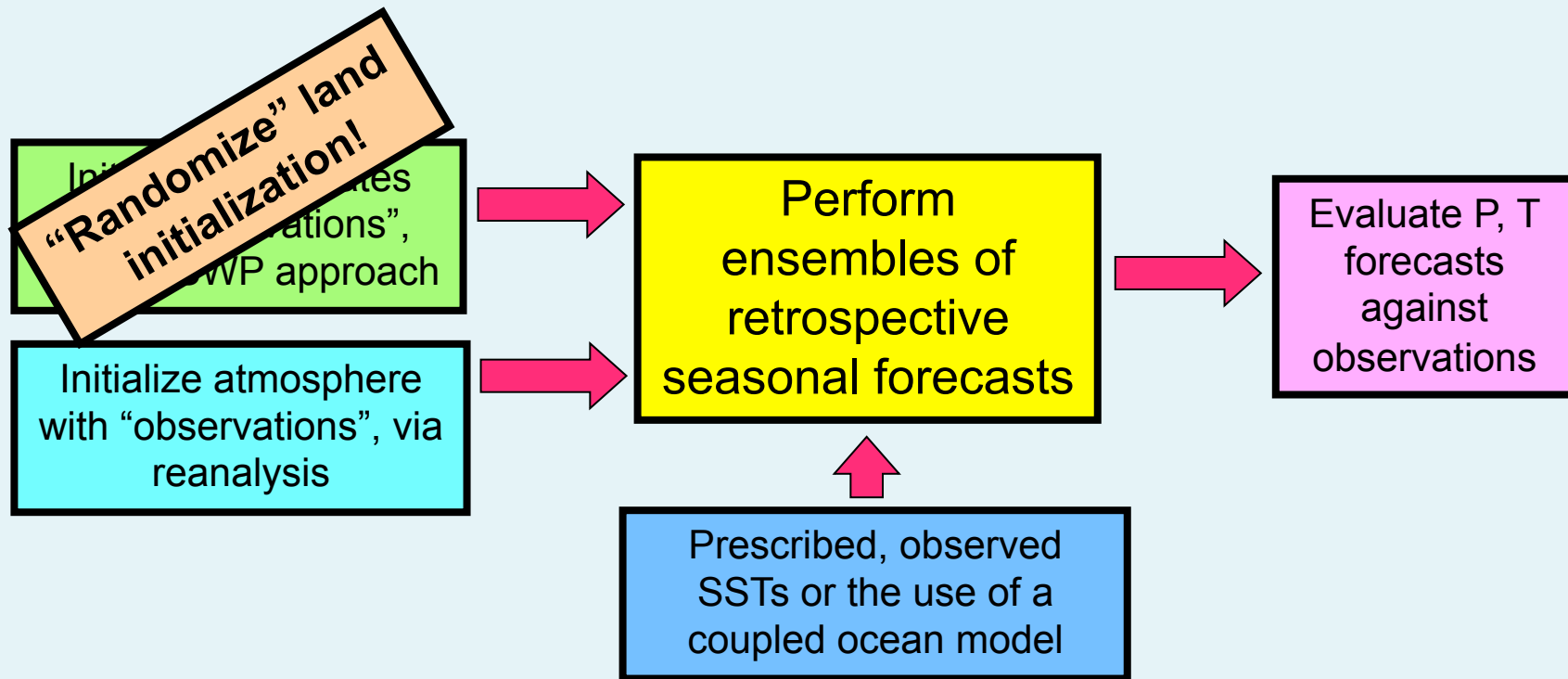
# GLACE-2: Experiment Overview

## Series 1:



# GLACE-2: Experiment Overview

## Series 2:

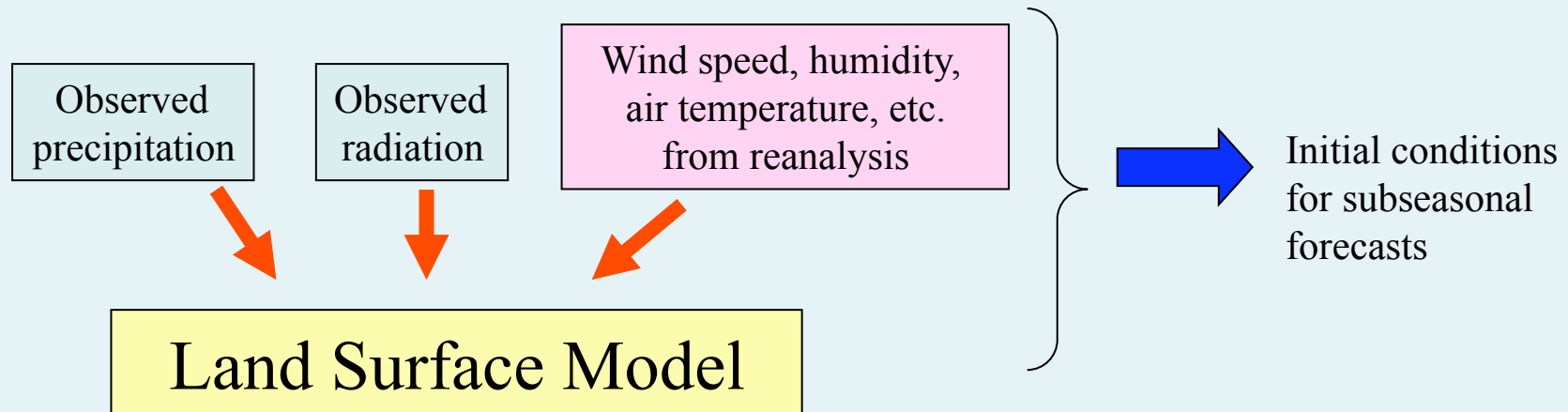


# GLACE-2: Experiment Overview

**Step 3:** Compare skill in two sets of forecasts; isolate contribution of realistic land initialization.



## Land model initialization



## 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.

## Participant List

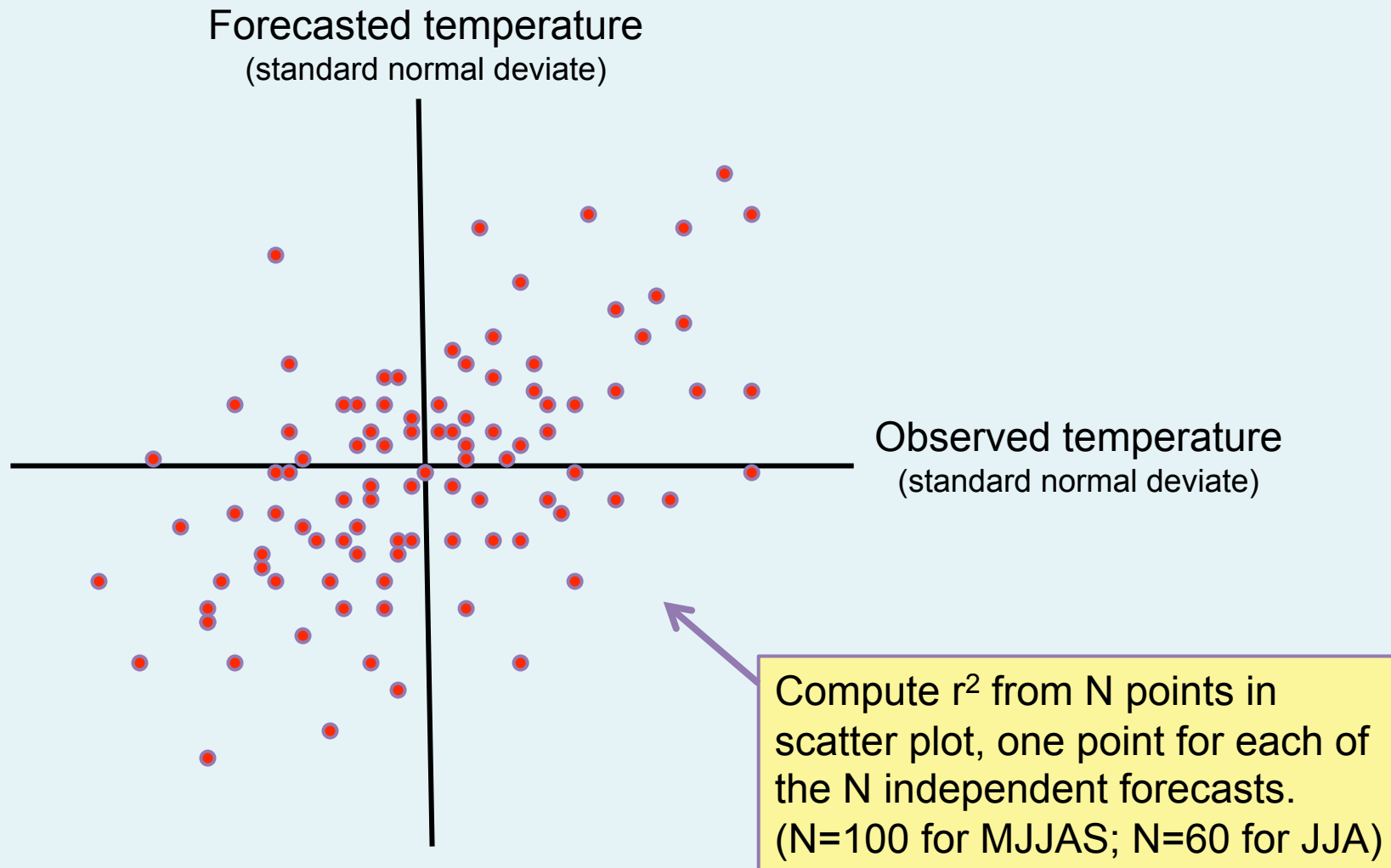
Group/Model	# models	Points of Contact
1. NASA/GSFC (USA): GMAO seasonal forecast system (old and new)	2	R. Koster, S. Mahanama
2. COLA (USA): COLA GCM, NCAR/CAM GCM	2	P. Dirmeyer, Z. Guo
3. Princeton (USA): NCEP GCM	1	E. Wood, L. Luo
4. IACS (Switzerland): ECHAM GCM	1	S. Seneviratne, E. Davin
5. KNMI (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

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13 models



## Skill measure: $r^2$ when regressed against observations



- After first picture, we focus 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

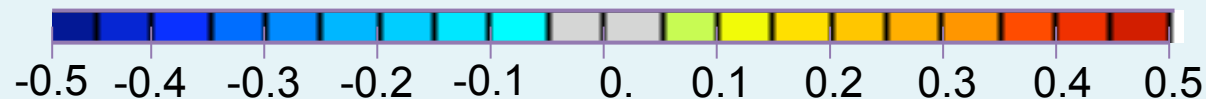
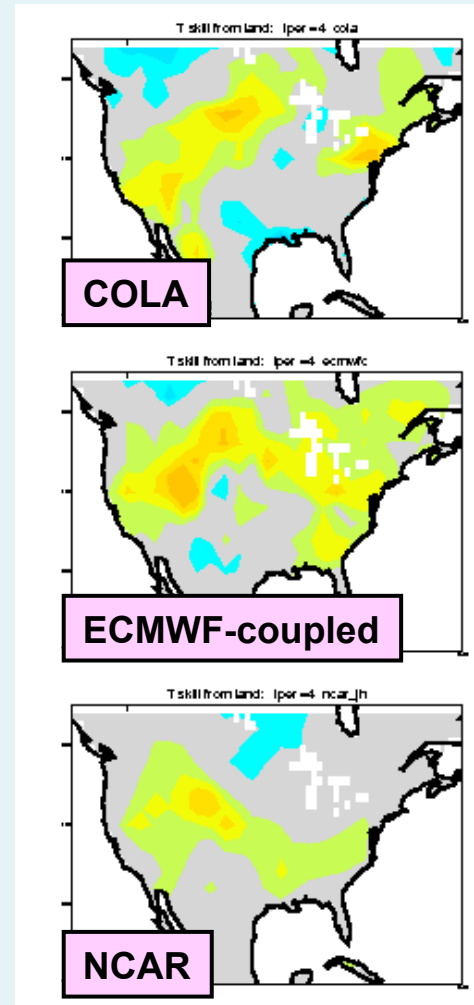
Sample results: Isolated impact of land initialization on  $r^2$  skill score for 3 different models ( $r^2$  from Series 1 minus  $r^2$  from Series 2).

Predicted variable: Air temperature at 16-30 days.

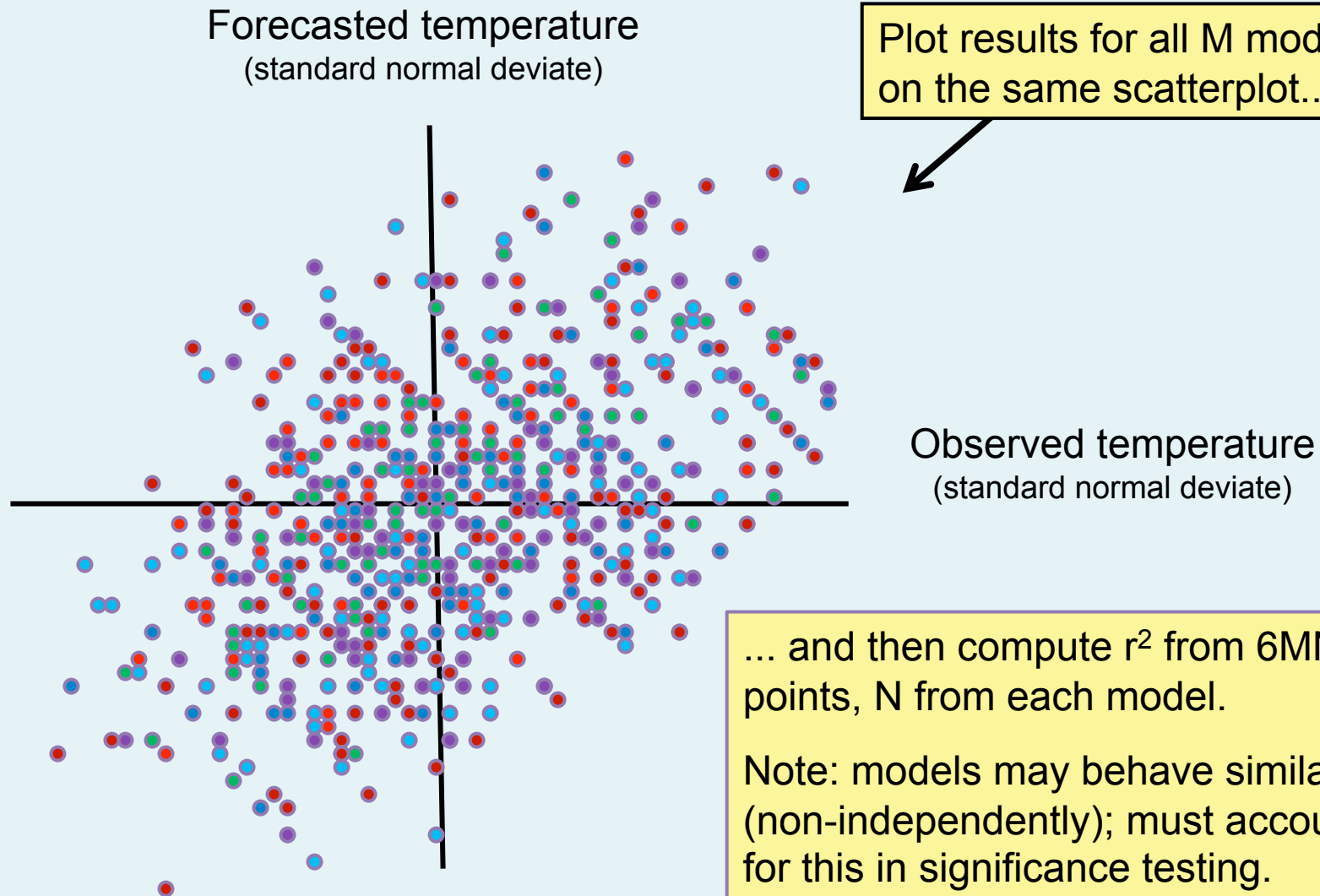
*Models appear to differ in their ability to extract skill from land initialization.*

*Some models (not shown) have almost no skill.*

*Results for precipitation forecasts are much weaker.*



## Multi-model “consensus” measure of skill: a prerequisite to a conditional skill analysis

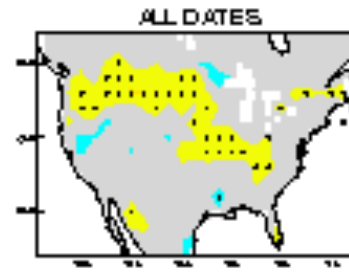
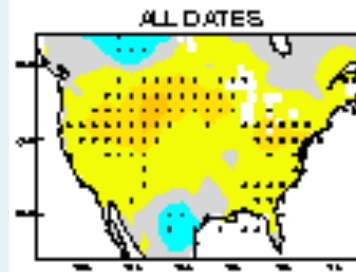


# Forecasts: “Consensus” skill due to land initialization (JJA)

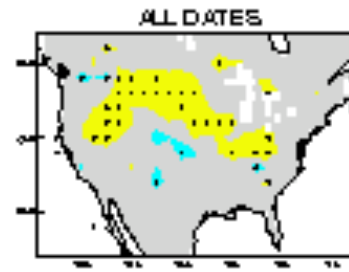
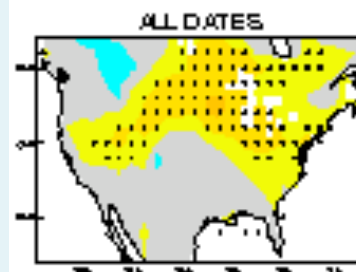
temperature

precipitation

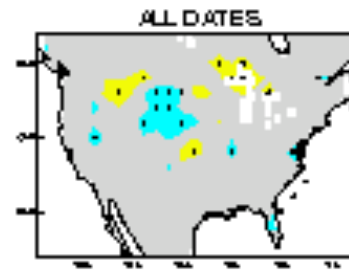
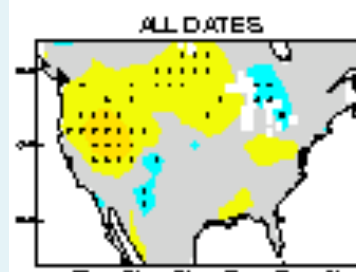
16-30 days



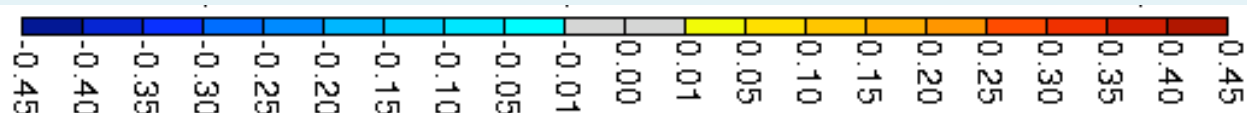
31-45 days



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:

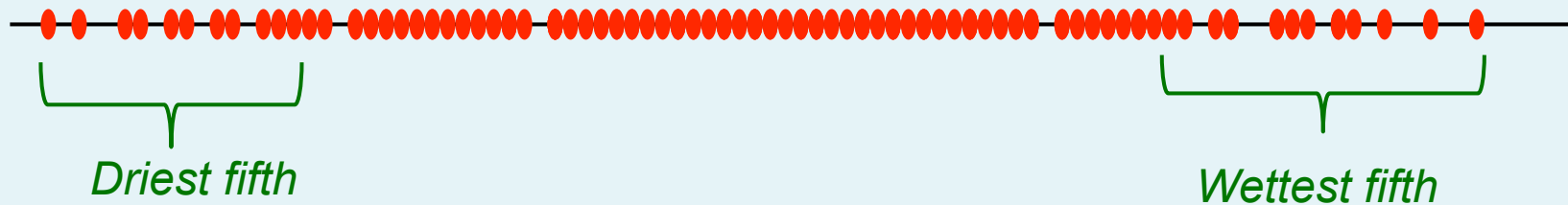


Step 2: Separate into terciles:



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

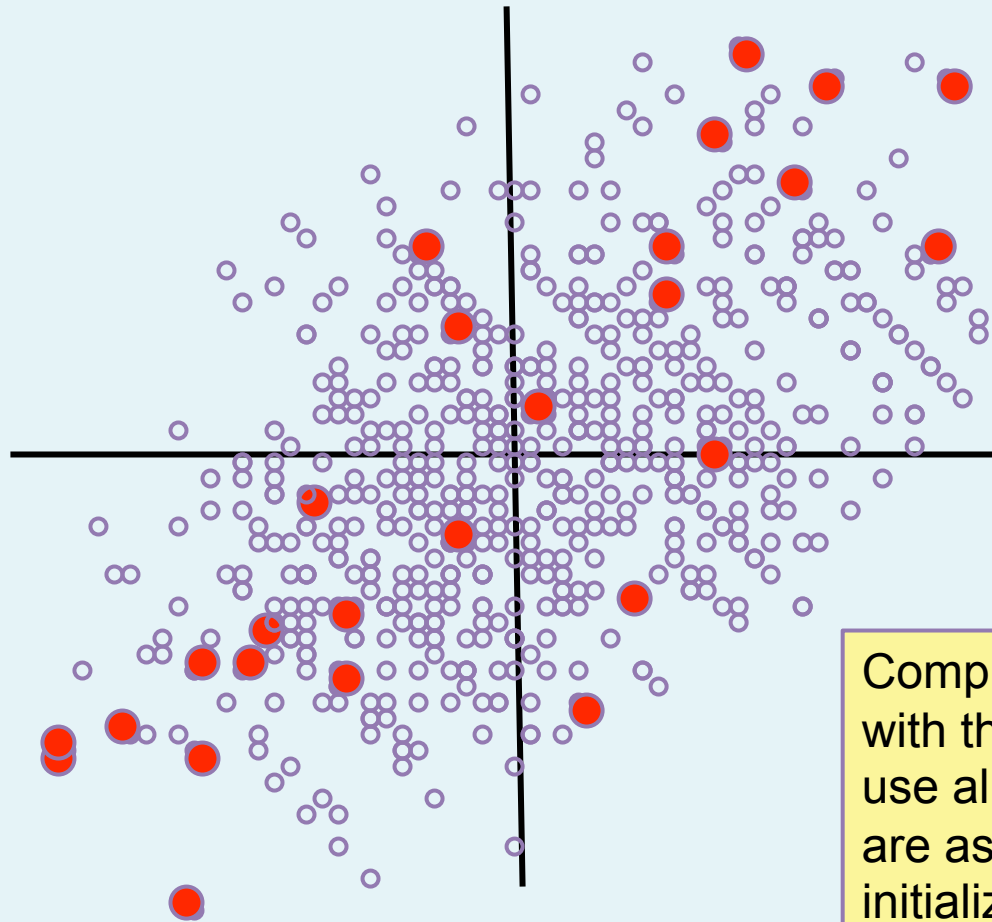
Step 2: Separate into quintiles:



Step 3: Separate into deciles:



Forecasted temperature  
(standard normal deviate)



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



Observed temperature  
(standard normal deviate)

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)

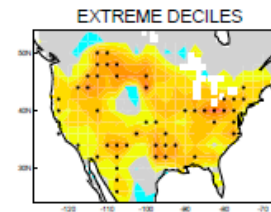
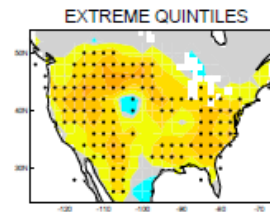
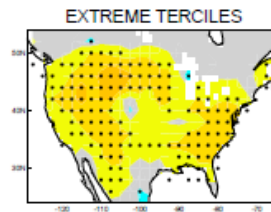
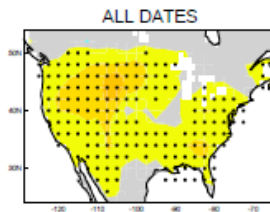
all points

Extreme  
terciles

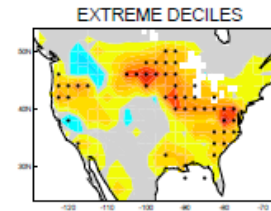
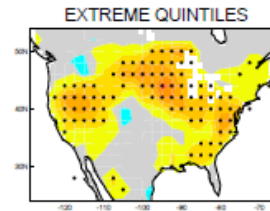
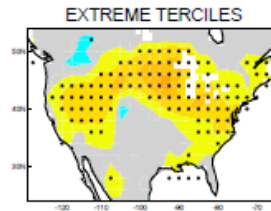
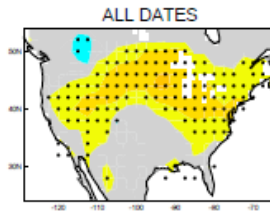
Extreme  
quintiles

Extreme  
deciles

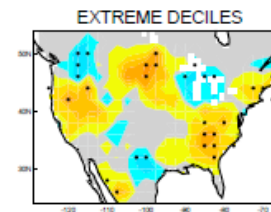
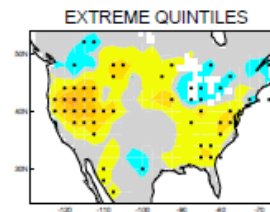
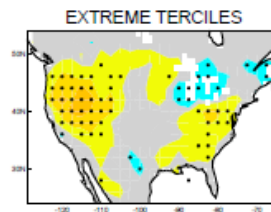
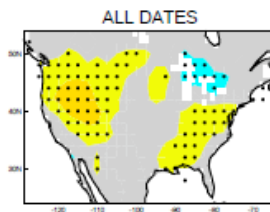
16-30 days



31-45 days



46-60 days

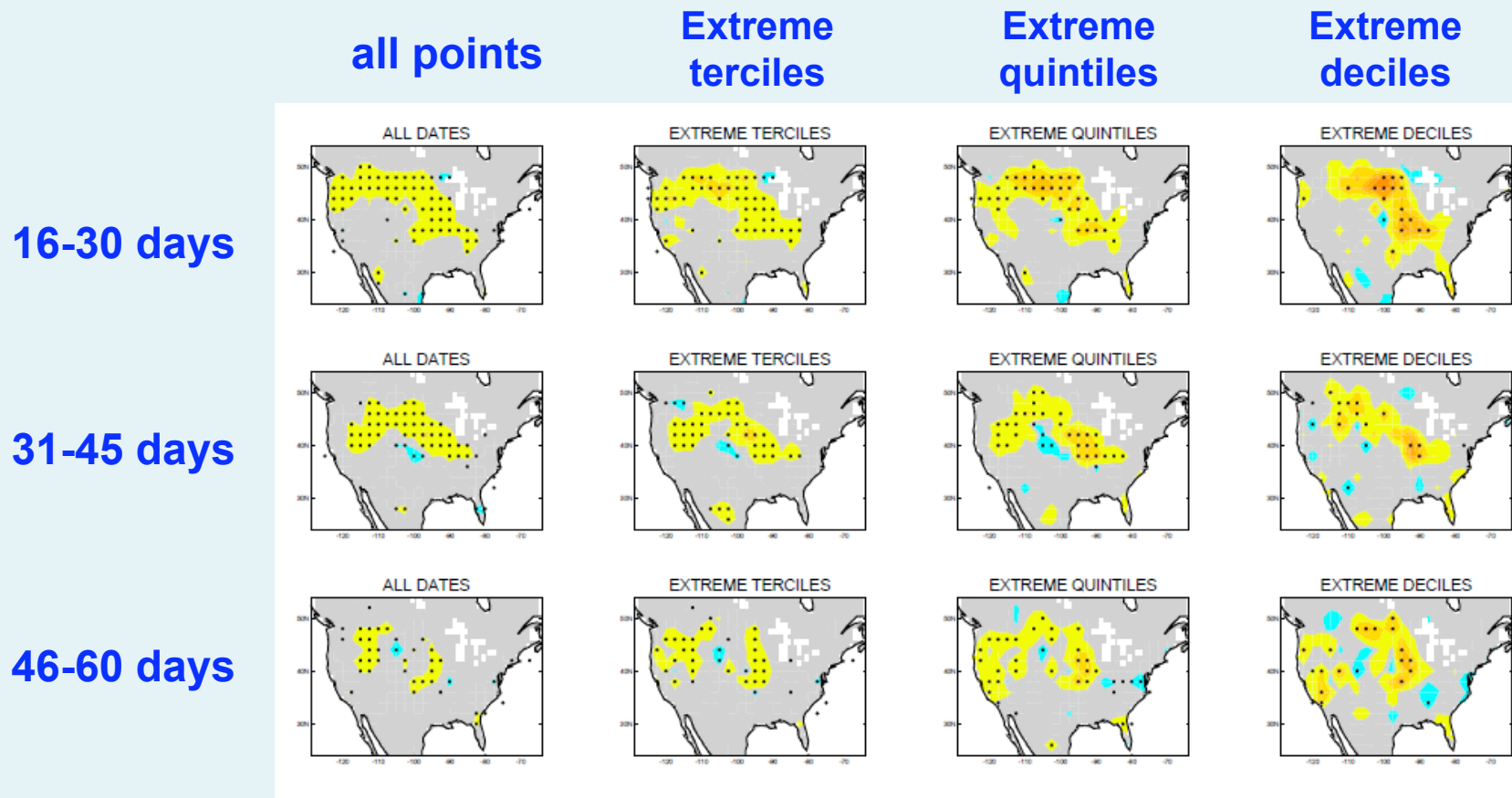


Dates for conditioning vary w/location

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

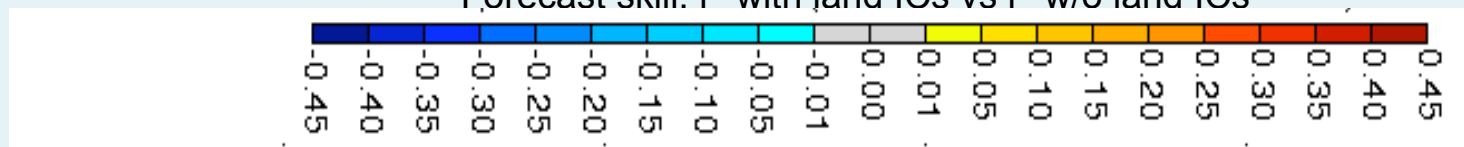


# Precipitation forecasts: Increase in skill due to land initialization (JJA) (conditioned on strength of local initial soil moisture anomaly)



Dates for conditioning vary w/location

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

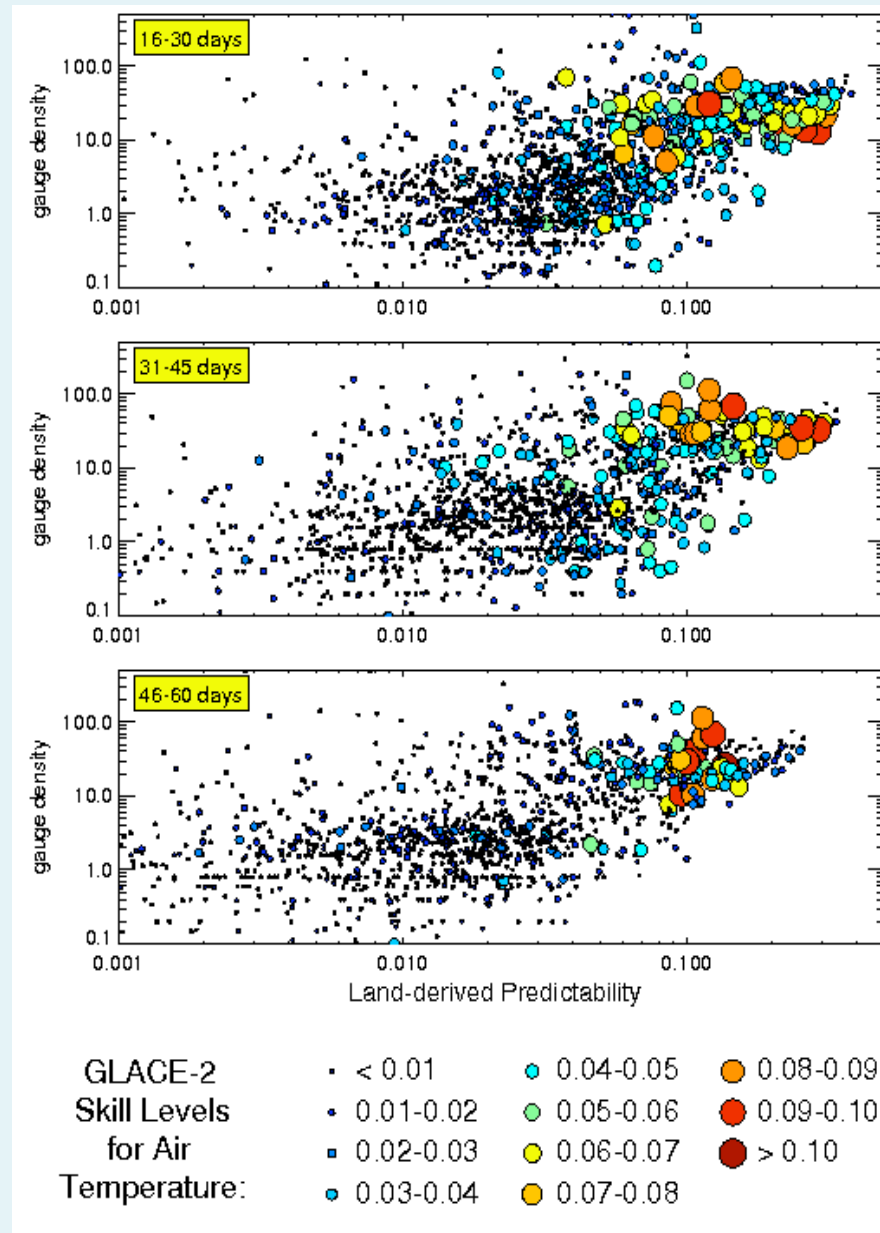


Forecast skill levels are highest in regions with both:

a) some inherent model “predictability”, and

b) an adequate observational network for accurate initialization

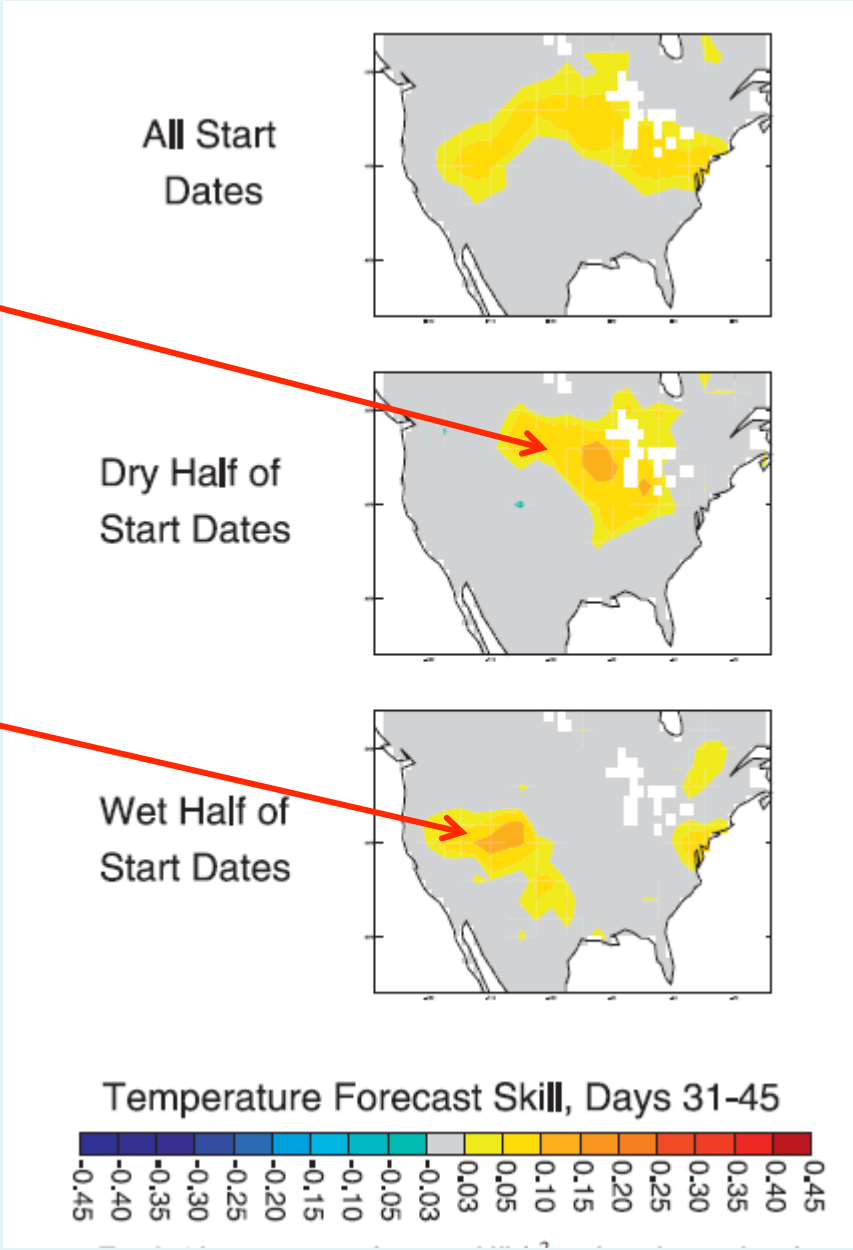
(This is a global analysis.)



# Wet/dry asymmetry in skill contributions

Drier-than-average initial conditions provide skill here...

... whereas wetter-than-average initial conditions provide skill here



## Conclusions of GLACE-2 Analysis

1. The experiments for GLACE-2 were performed with 13 models.
2. The individual models vary in their ability to extract forecast skill from land initialization. In general,
  - Low skill for precipitation
  - Moderate skill (in places) for temperature, even out to two months.
3. Land initialization impacts on skill increase when conditioned on the size of the initial local soil moisture anomaly.



If you know the local soil moisture anomaly at time 0 is large, you can expect (in places) that initializing the land correctly will improve your temperature forecast significantly, and your precipitation forecast slightly, even out to 2 months.

4. The results highlight the potential usefulness of improved observational networks for prediction and provide some indication of wet/dry asymmetry in skill contributions.

## The Second Phase of the Global Land–Atmosphere Coupling Experiment: Soil Moisture Contributions to Subseasonal Forecast Skill

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### ABSTRACT

The second phase of the Global Land–Atmosphere Coupling Experiment (GLACE-2) is a multi-institutional numerical modeling experiment focused on quantifying, for boreal summer, the subseasonal (out to two months) forecast skill for precipitation, temperature, and soil moisture. This paper reports on the initial findings from the precipitation and soil moisture experiments. The precipitation experiment is a 10-year simulation of the Global Land–Atmosphere Coupling Experiment (GLACE-2) using the National Centers for Environmental Prediction (NCEP) Community Climate Model (CCM3) with a 100-day spinup. The soil moisture experiment is a 10-year simulation of the Global Land–Atmosphere Coupling Experiment (GLACE-2) using the National Centers for Environmental Prediction (NCEP) Community Climate Model (CCM3) with a 100-day spinup. The soil moisture experiment is a 10-year simulation of the Global Land–Atmosphere Coupling Experiment (GLACE-2) using the National Centers for Environmental Prediction (NCEP) Community Climate Model (CCM3) with a 100-day spinup.

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