

FUTURE CHANGES IN SEASONAL CLIMATE PREDICTABILITY

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Mike Alexander, Matt Newman, Juliana Dias, and Jiale Lou



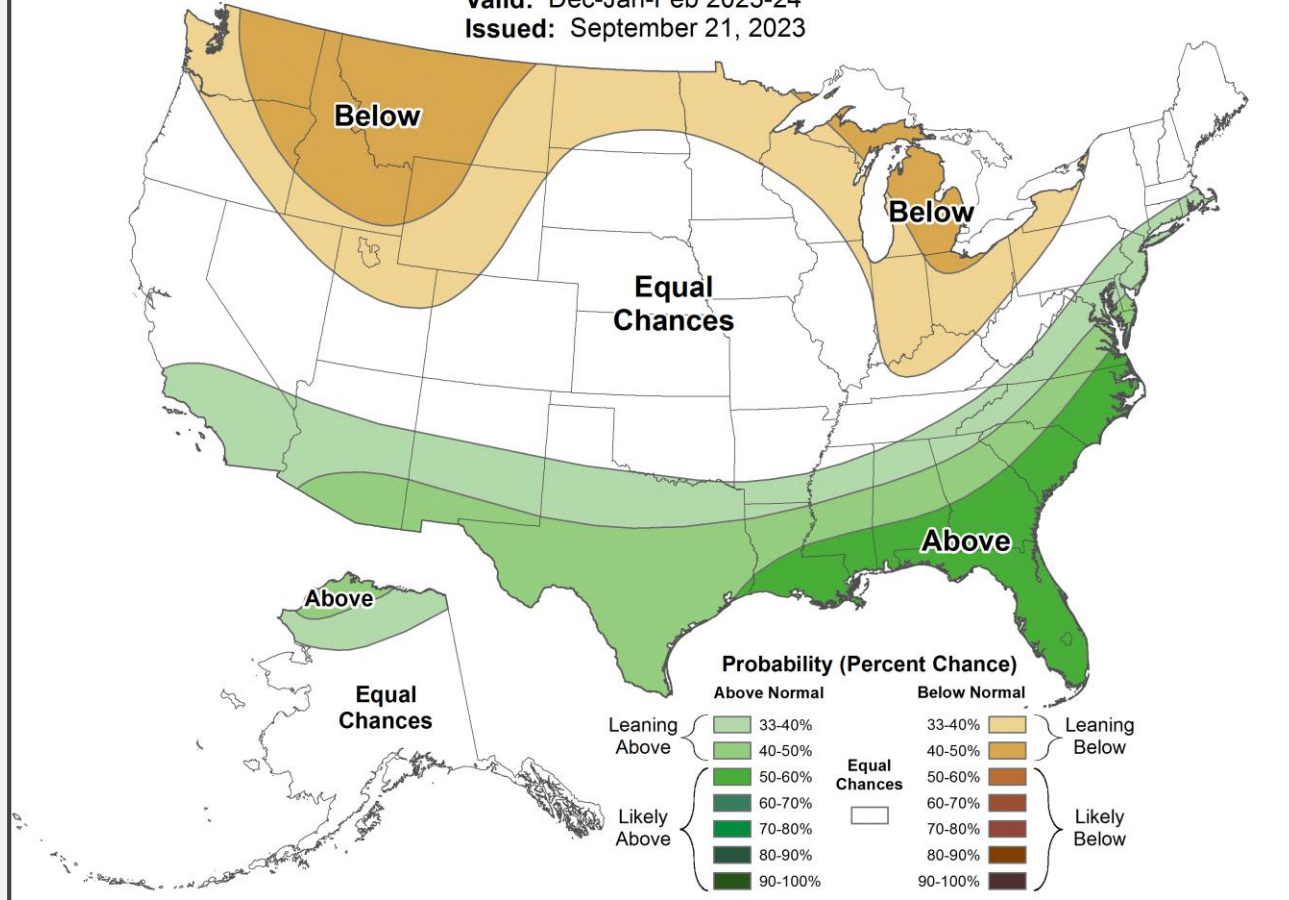
April 1, 2024



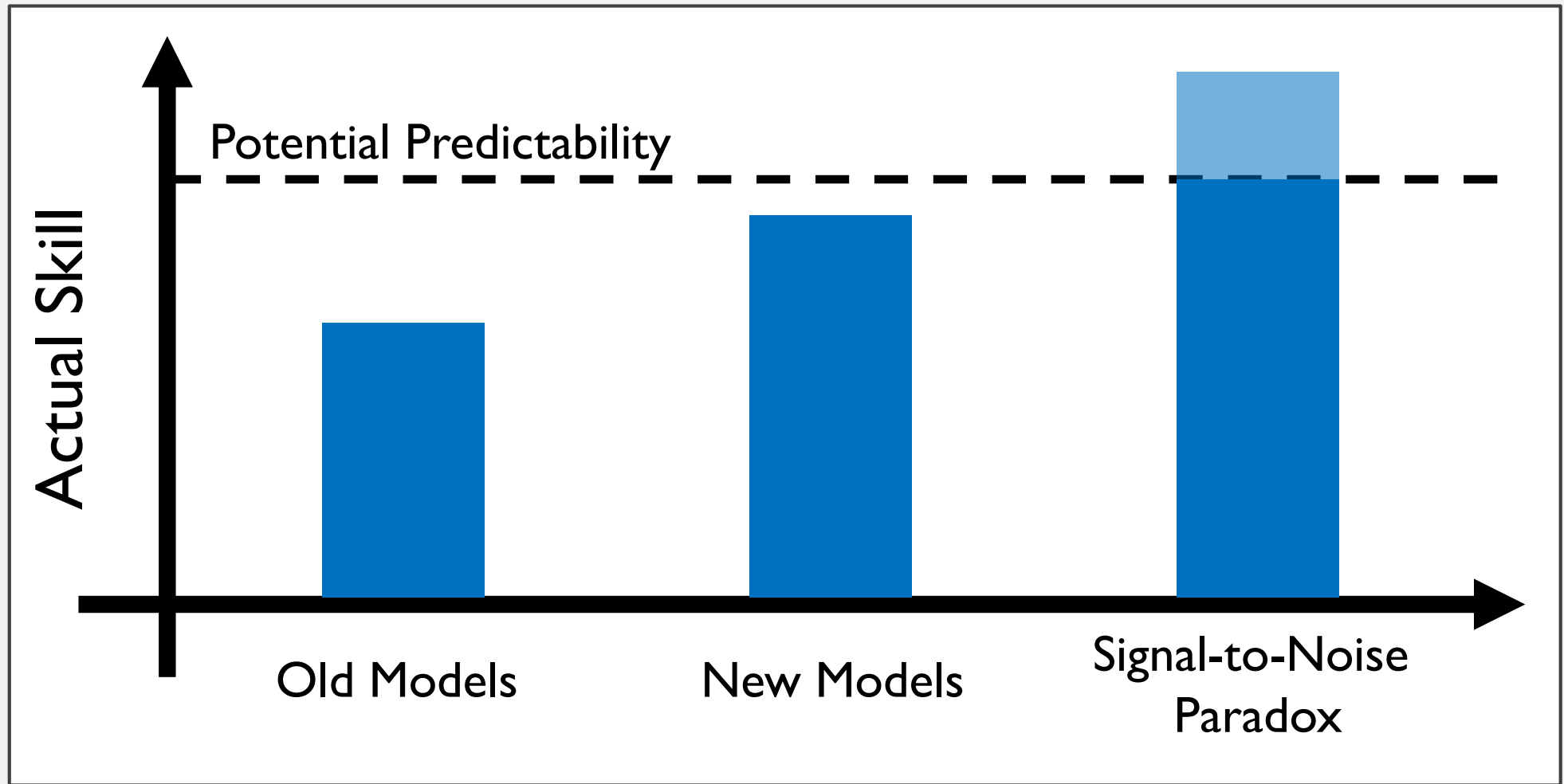
Seasonal Precipitation Outlook



Valid: Dec-Jan-Feb 2023-24
Issued: September 21, 2023

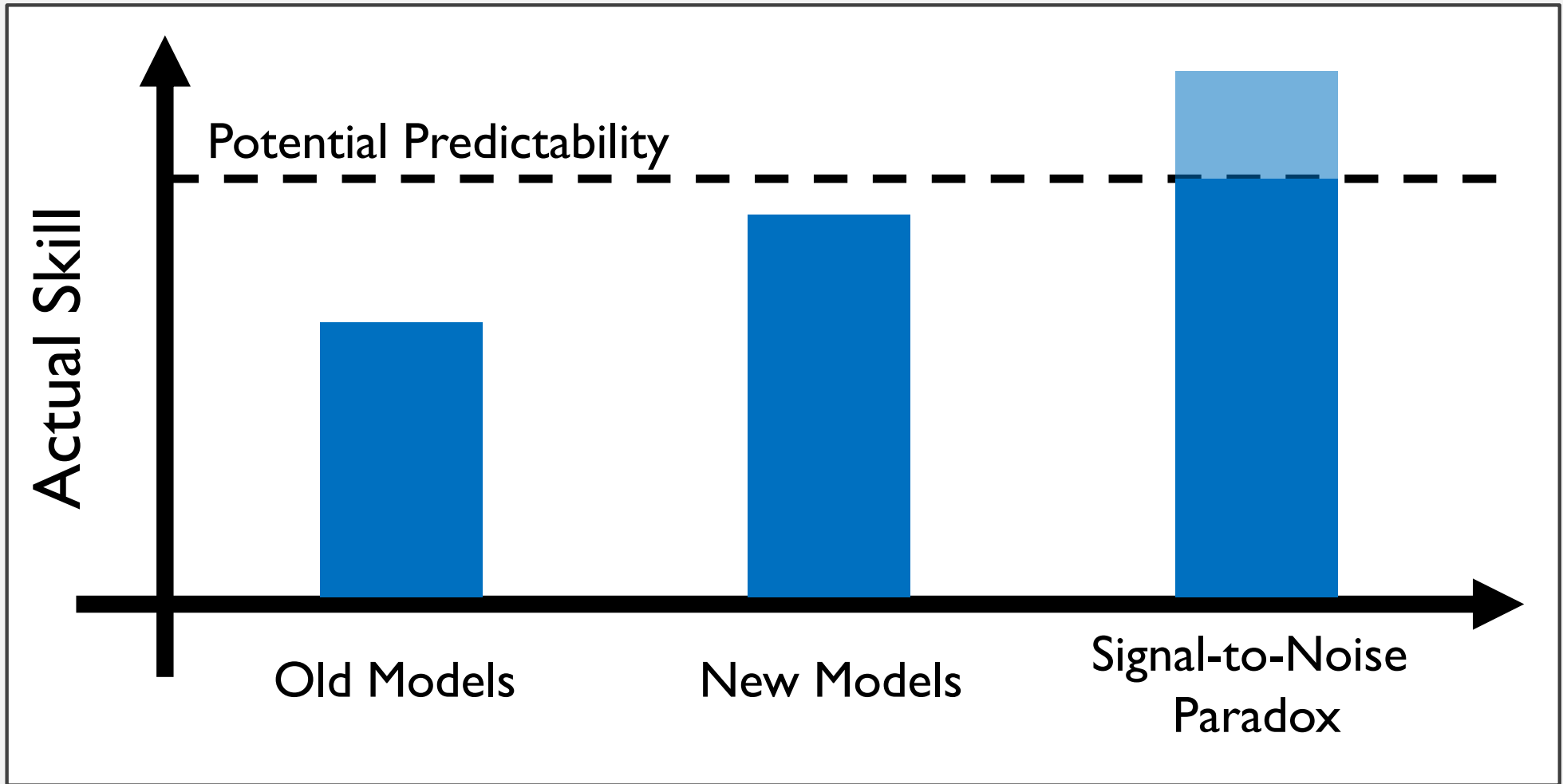


Seasonal outlooks based on historical skill relationships are extremely useful...but



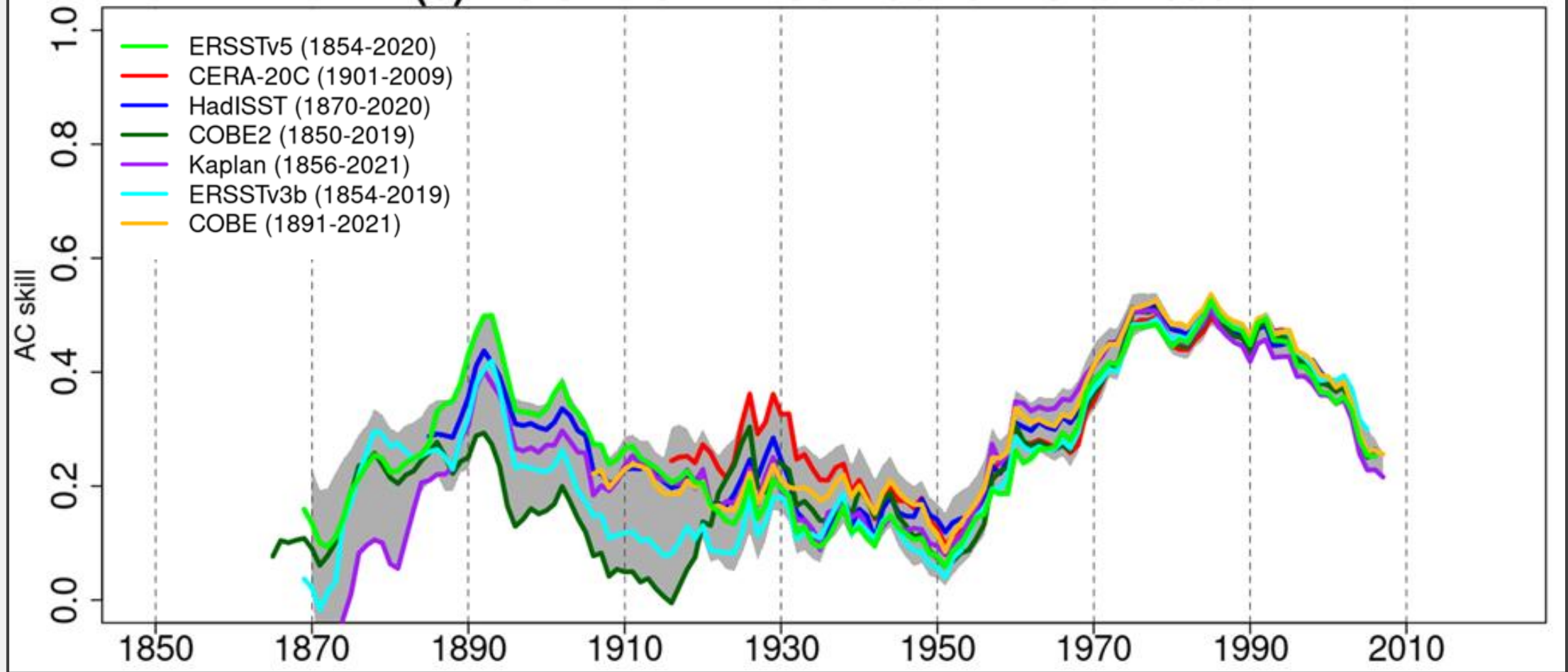
Actual skill – forecast skill derived from dynamical or statistical hindcasts of the real world

Potential predictability (or “potential skill”) – a “hard” predictability limit intrinsic to the chaotic nature of the climate system



Predictability has varied substantially in the past

(c) AC skill of NINO3.4 at 18-month lead



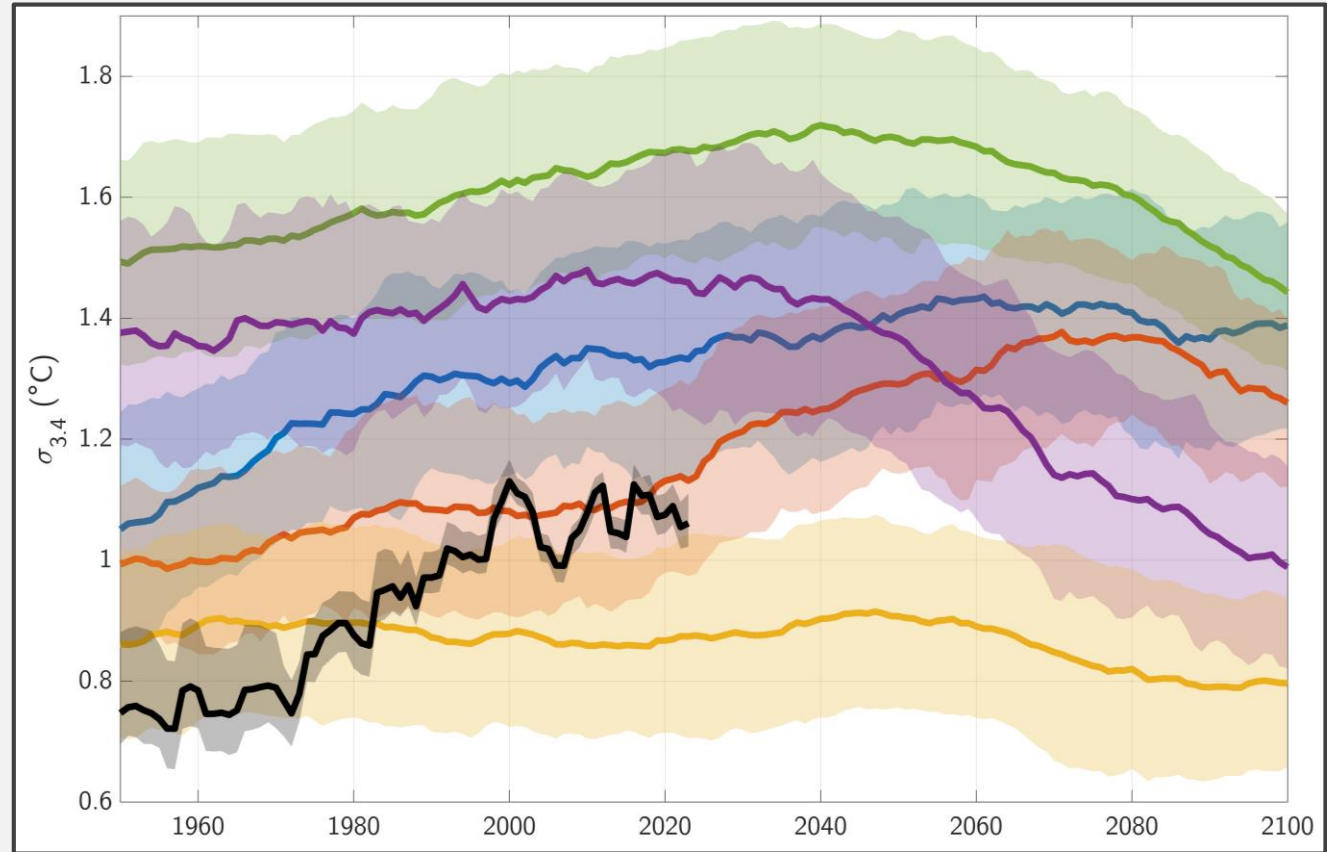
Lou et al. (2023)

Will seasonal climate predictability change in the future?

Climate models project significant changes to ENSO and its teleconnections

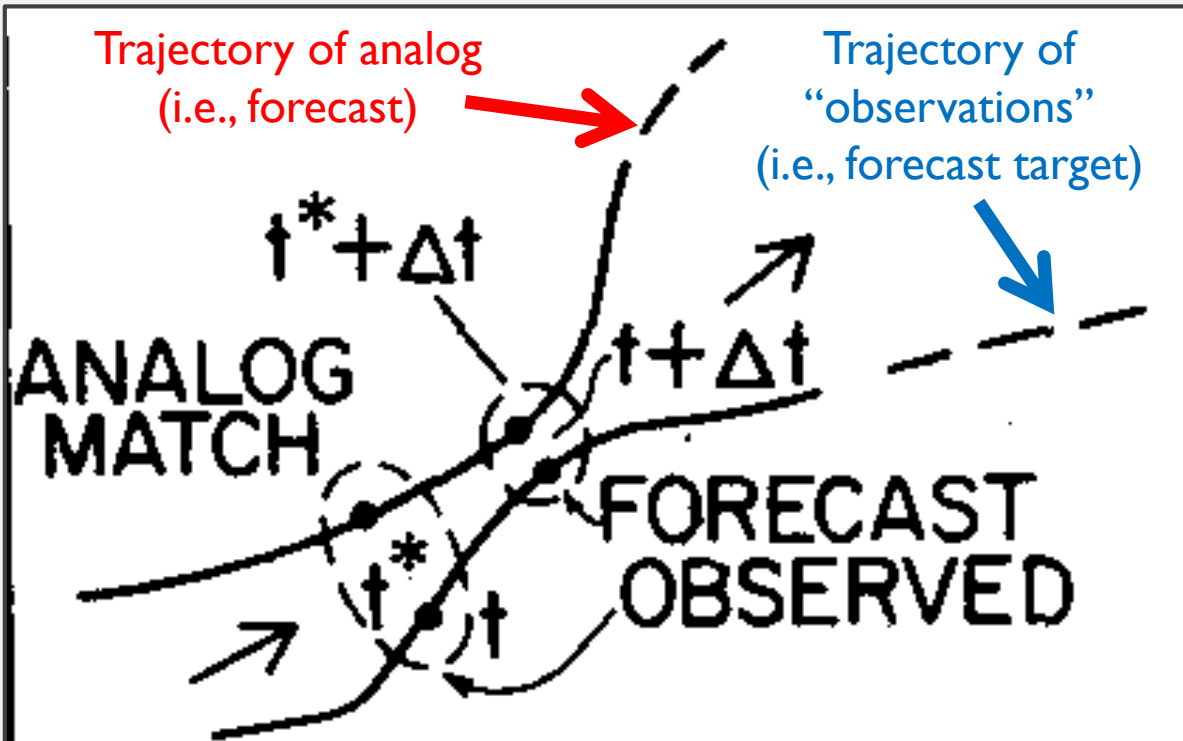
(e.g., Maher et al. 2023; O'Brien and Deser 2022)

Ensemble mean DJF Nino3.4 std. dev. in 30-year windows



— CESM1 — CESM2 — MPI
— GFDL-SPEAR — GFDL-ESM2M — Observations

Model-analog framework



Barnett and Preisendorfer (1978)

If two states in the climate system are very close to each other, they can be called each other's "analog"

Model-analog:

- Using a model to predict the real world.

Perfect model-analog:

- Use a model to predict the same model.
- "Perfect" because resulting forecasts have no unconditional or conditional biases.
- Estimates limits to climate predictability.

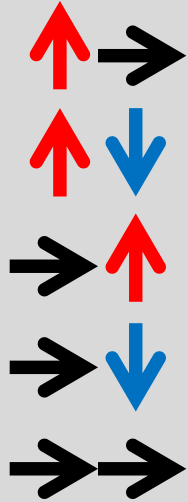
Objective: Estimate anthropogenically forced changes in potential predictability using perfect model-analogs from large ensembles.

Date and Methods

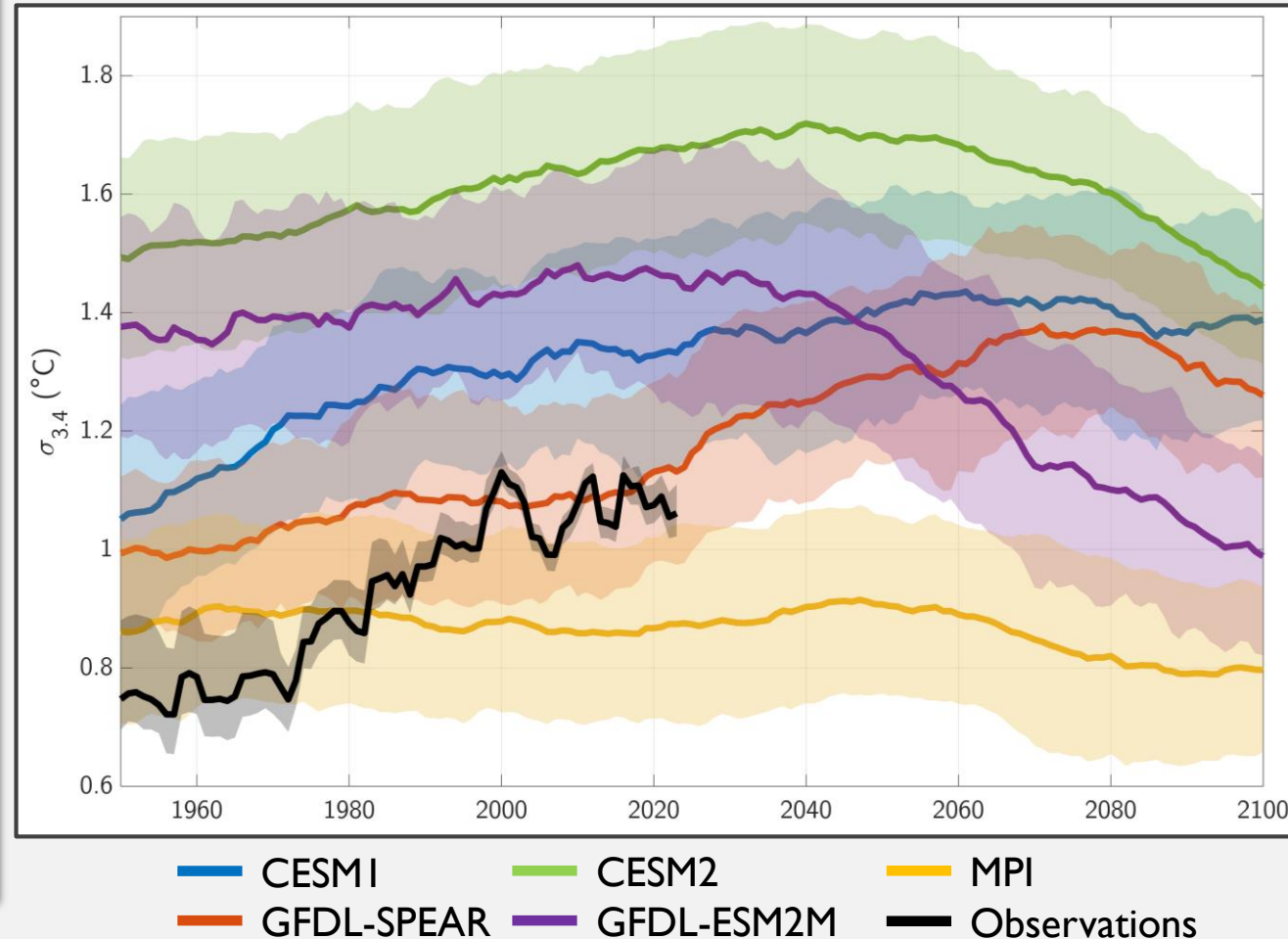
Single model initial condition large ensembles (SMILEs):

- **CESM1 – 40 members**
- CESM2 – 100 members
- GFDL-SPEAR – 30 members
- **GFDL-ESM2M – 30 members**
- MPI – 100 members
- All data $2.5^\circ \times 2.5^\circ$, 1920-2100
- Will refer to potential predictability/skill simply as “predictability” or “skill”

Nino3.4 σ trend:



Ensemble mean DJF Nino3.4 std. dev. in 30-year windows

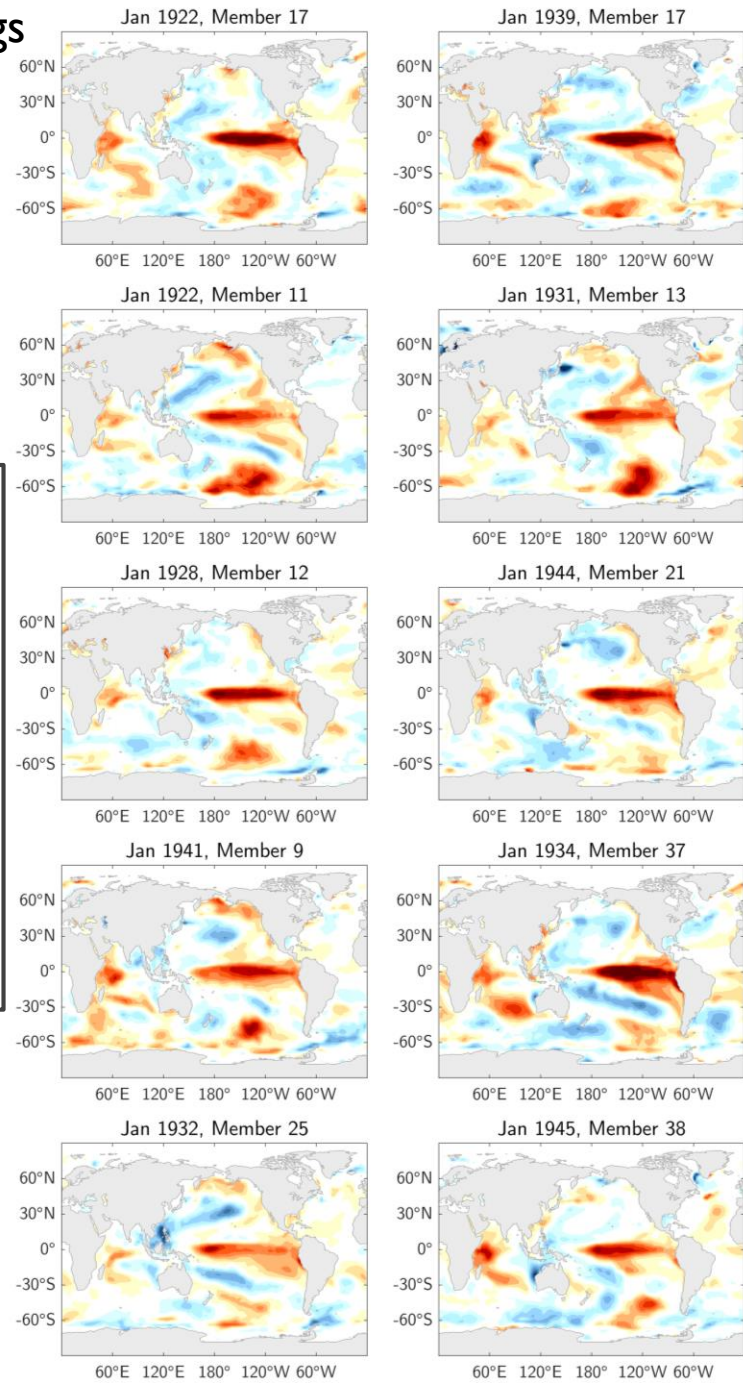
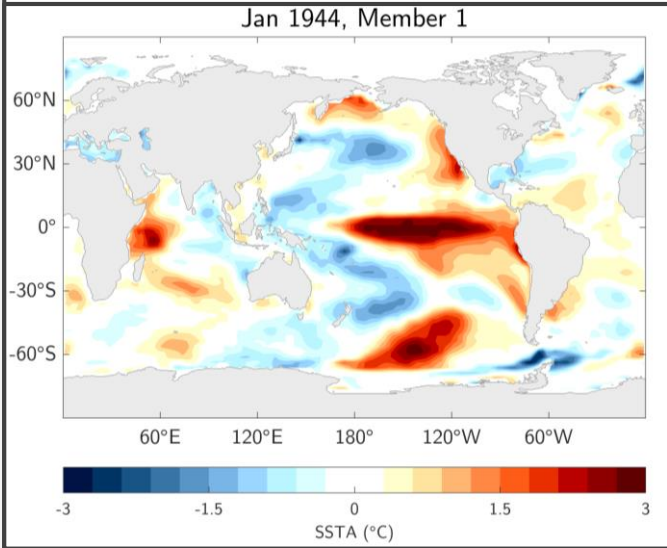


Perfect model-analog forecast workflow:

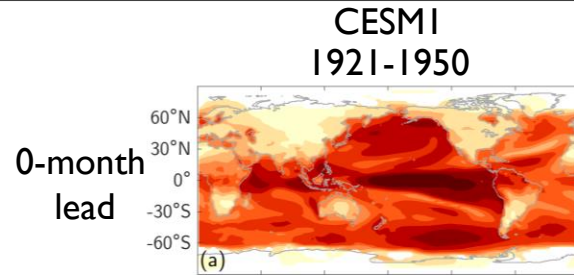
1. Extract SST for 30 year period (e.g., 1921-1950) in all large ensemble members.
2. Remove seasonal cycle. Remove ensemble mean.
3. Arbitrarily take 1st ensemble member as “truth”.
4. Construct data libraries using other members. For example, all Januarys, all Februarys, etc.
5. “Initialize” with global SSTA and keep subsequent 24 months as the forecast target.
6. Choose analogs from library using RMSE.
7. Keep top 10 matches and subsequent 24 months as forecasts.
8. Repeat steps 3-7, treating each remaining ensemble member as “truth”.
9. CESMI: 40 members x 12 months x 28 years = 13,400 forecasts with 10 members each
10. Repeat steps 3-8 for new 30 year period (e.g., 2071-2100).

Top 10 best analogs

“Initialization”



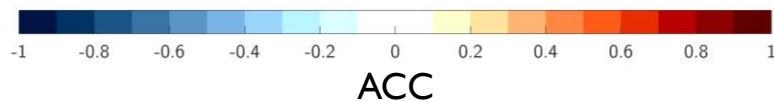
Surface temperature



Temp. predictability
increases, especially in
tropics/at long leads

Shading: Ensemble mean potential skill (ACC)

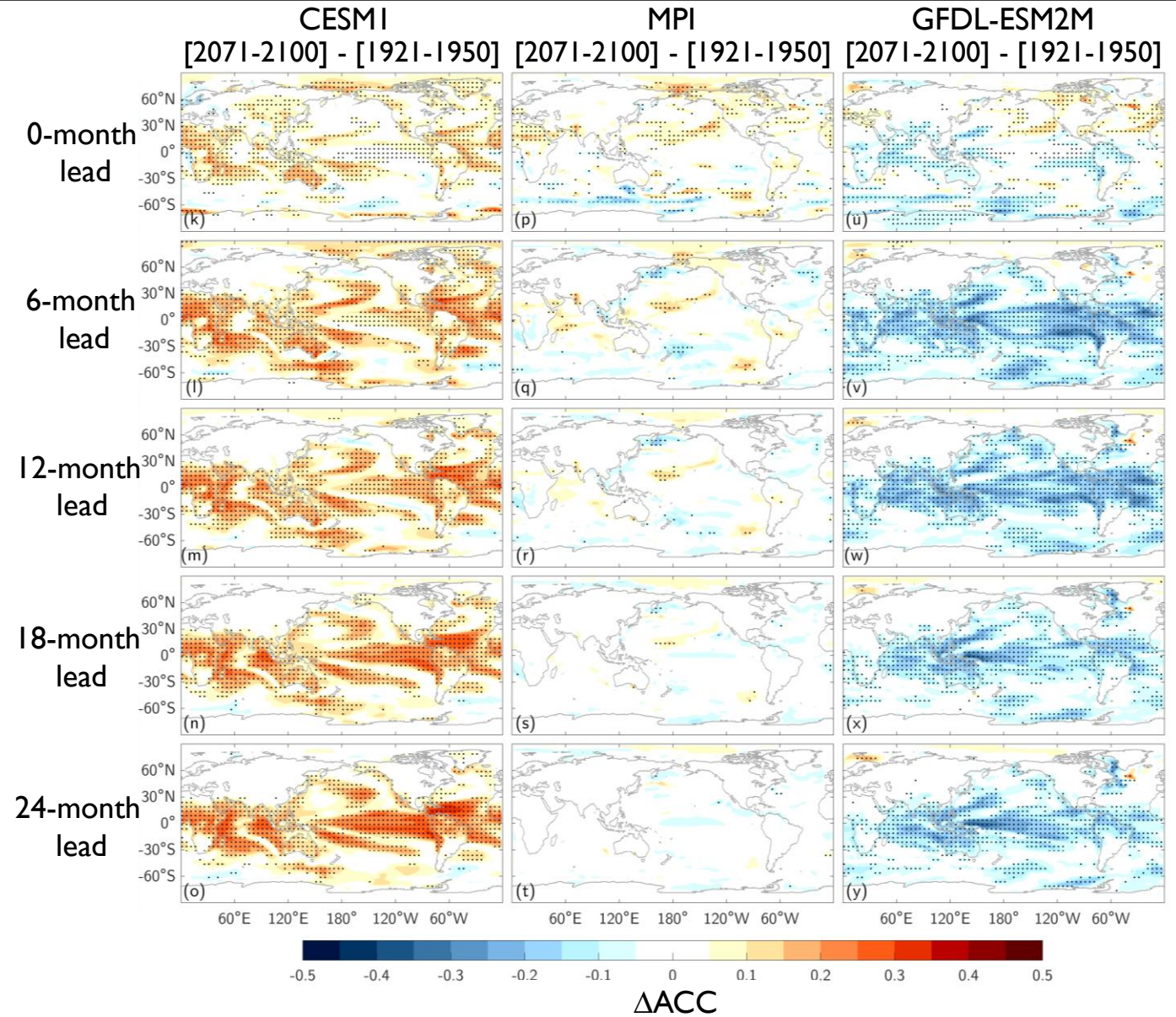
Stippling: 80% members agree on Δ ACC sign



Surface temperature

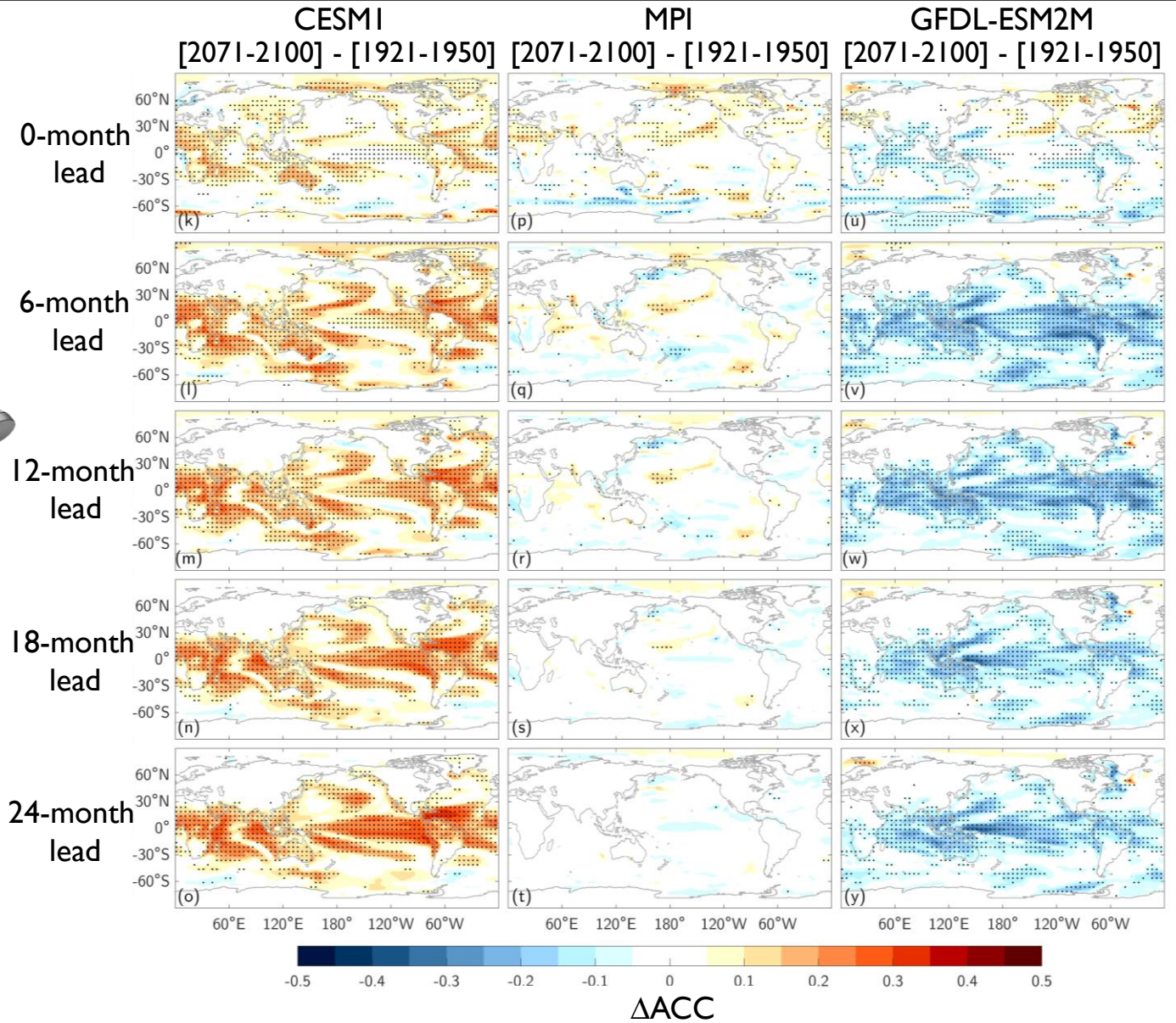
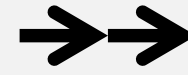
Sign/intensity of predictability changes are highly model dependent

Changes consistent for probabilistic skill metrics and other variables

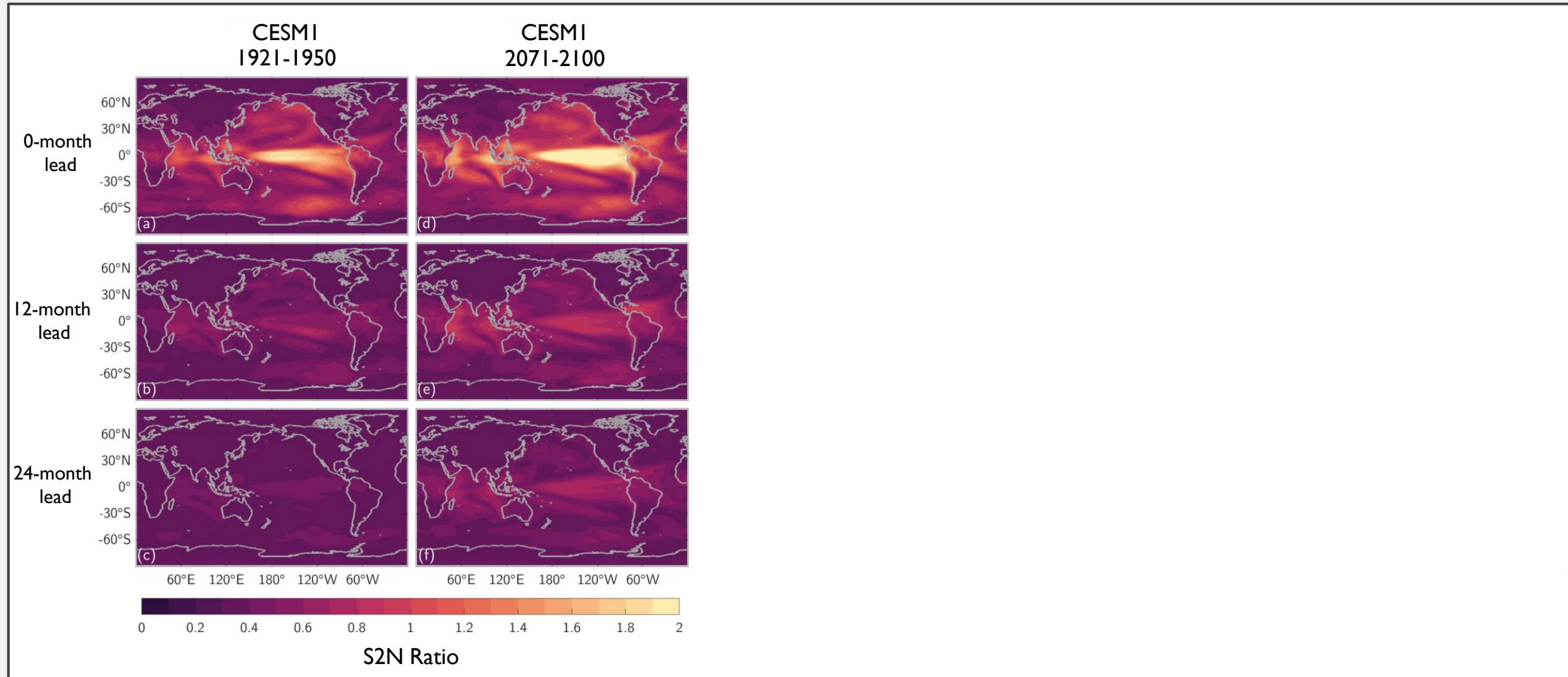


Surface temperature

Nino3.4σ trend:

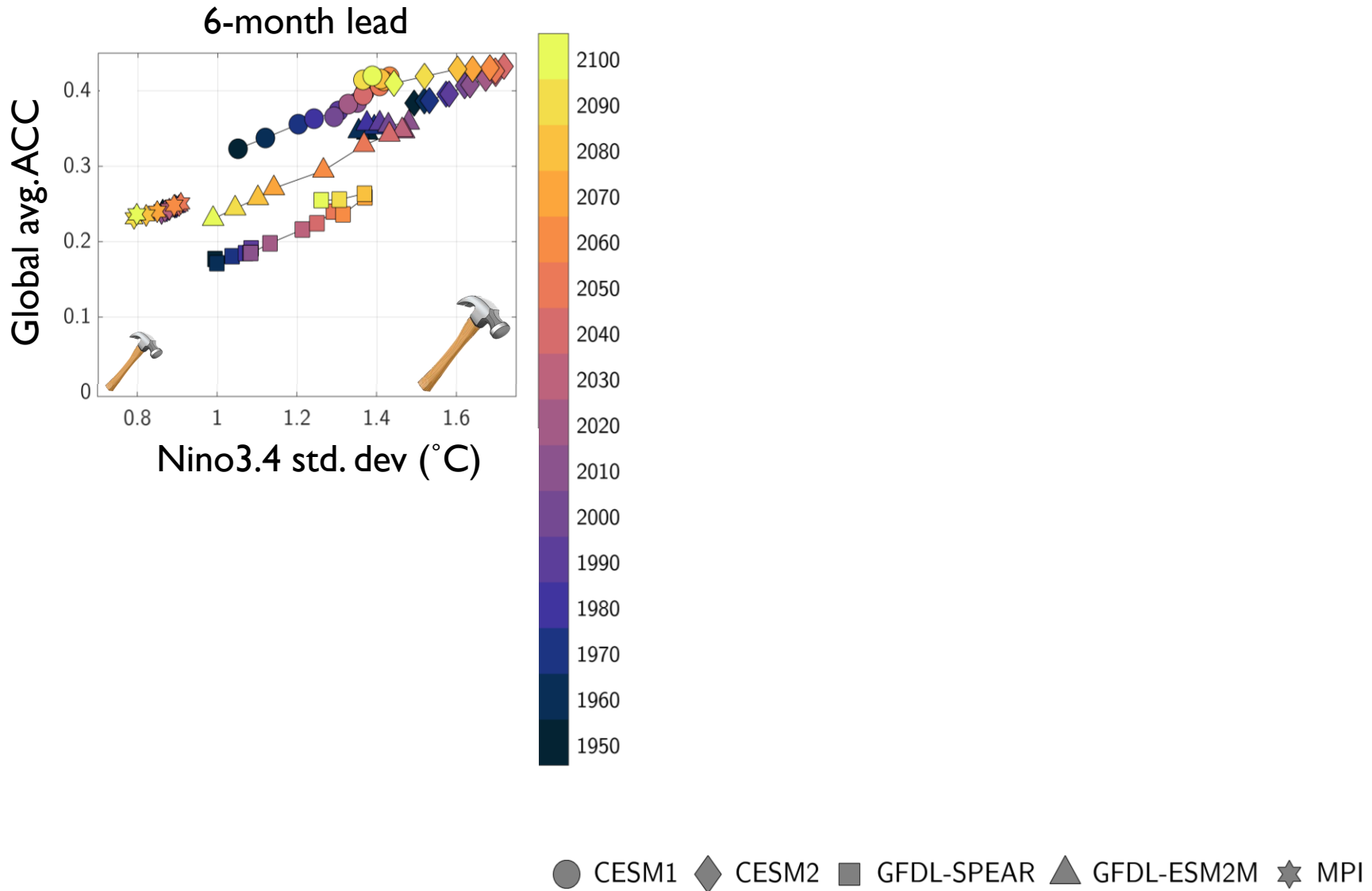


Nino3.4 σ trend:

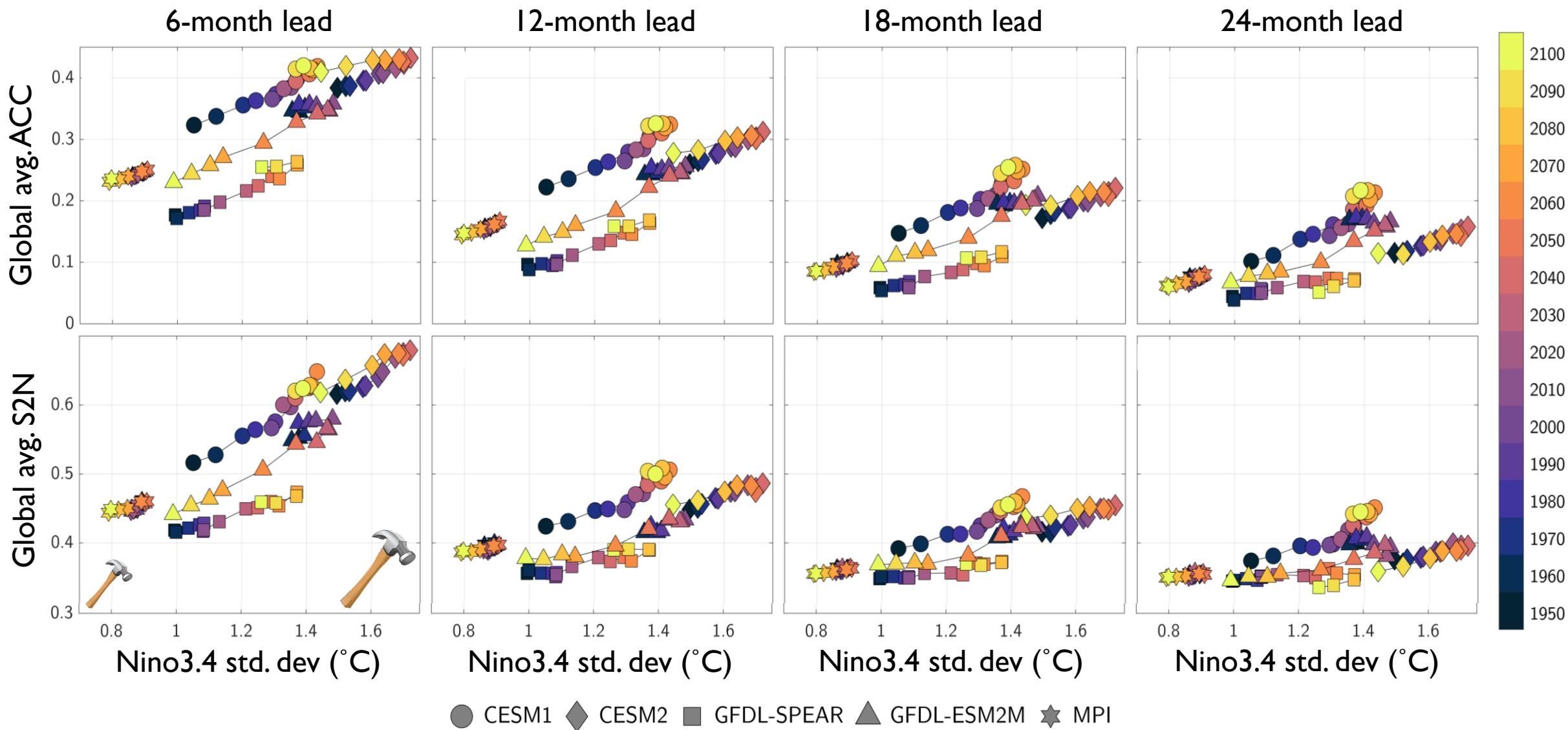


Analog forecast = $f_i(t, x, y) = \bar{f} + f'_i$ Signal-to-noise = $\left(\frac{\sum \bar{f}^2}{\sum f'^2} \right)^{1/2}$

Sea surface temperature



Sea surface temperature



Summary:

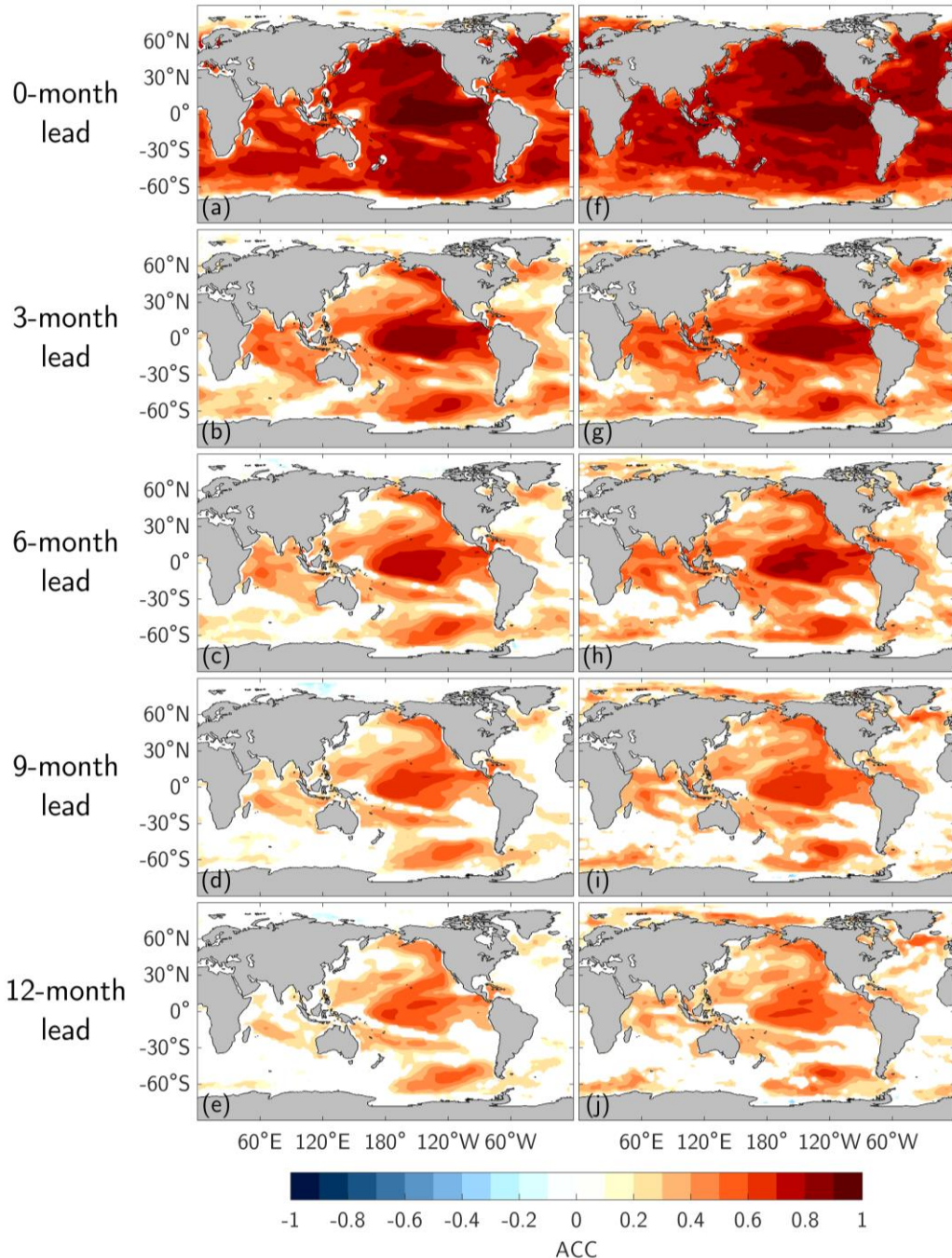
- Potential predictability will likely change in the future as a distinct response to anthropogenic climate change.
- Sign/intensity of forced predictability changes are linked to sign/intensity of forced ENSO variability changes.
- If ENSO amplitude decreases in response to future climate change (e.g., Wengel et al. 2021 and others), then historical forecast skill relationships may not hold.



How well can model large
ensembles predict the real world?

LE Model-Analogs

NMME



Predicting the real world:

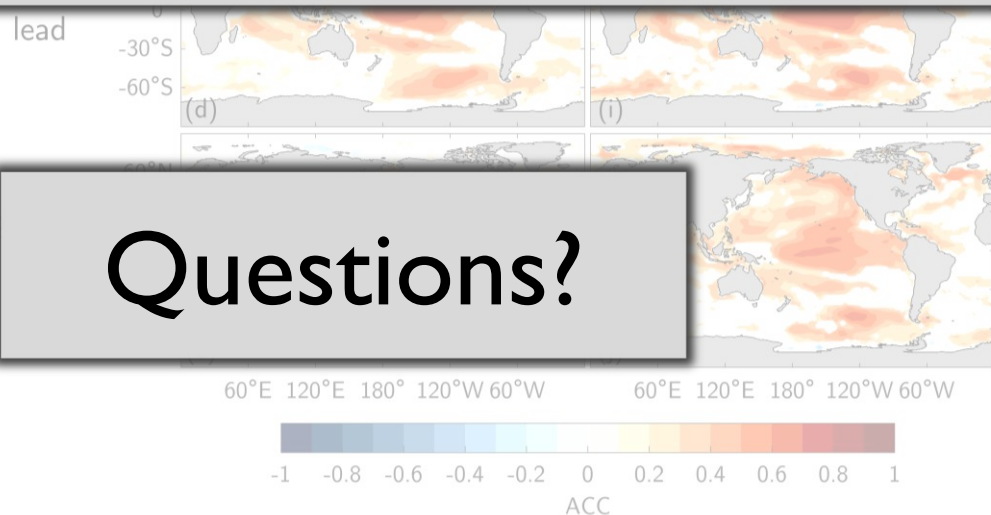
- Multi-model mean (MMM) SST skill from:
 - Dynamical forecasts from 6 NMME models.
 - Model-analogs forecasts from 5 model LEs.
- Predicting ERSSTv5 from 1991-2020.

Model-analogs forecasts are as skillful as dynamical forecasting models, at a fraction of the computational cost

Shading: Skill shown where significant with 95% confidence

Summary:

- Potential predictability will likely change in the future as a distinct response to anthropogenic climate change.
- Sign/intensity of forced predictability changes are linked to sign/intensity of forced ENSO variability changes.
- If ENSO amplitude decreases in response to future climate change (e.g., Wengel et al. 2021 and others), then historical forecast skill relationships may not hold.
- Model-analogs from large ensembles are cheap and as skillful as NMME.



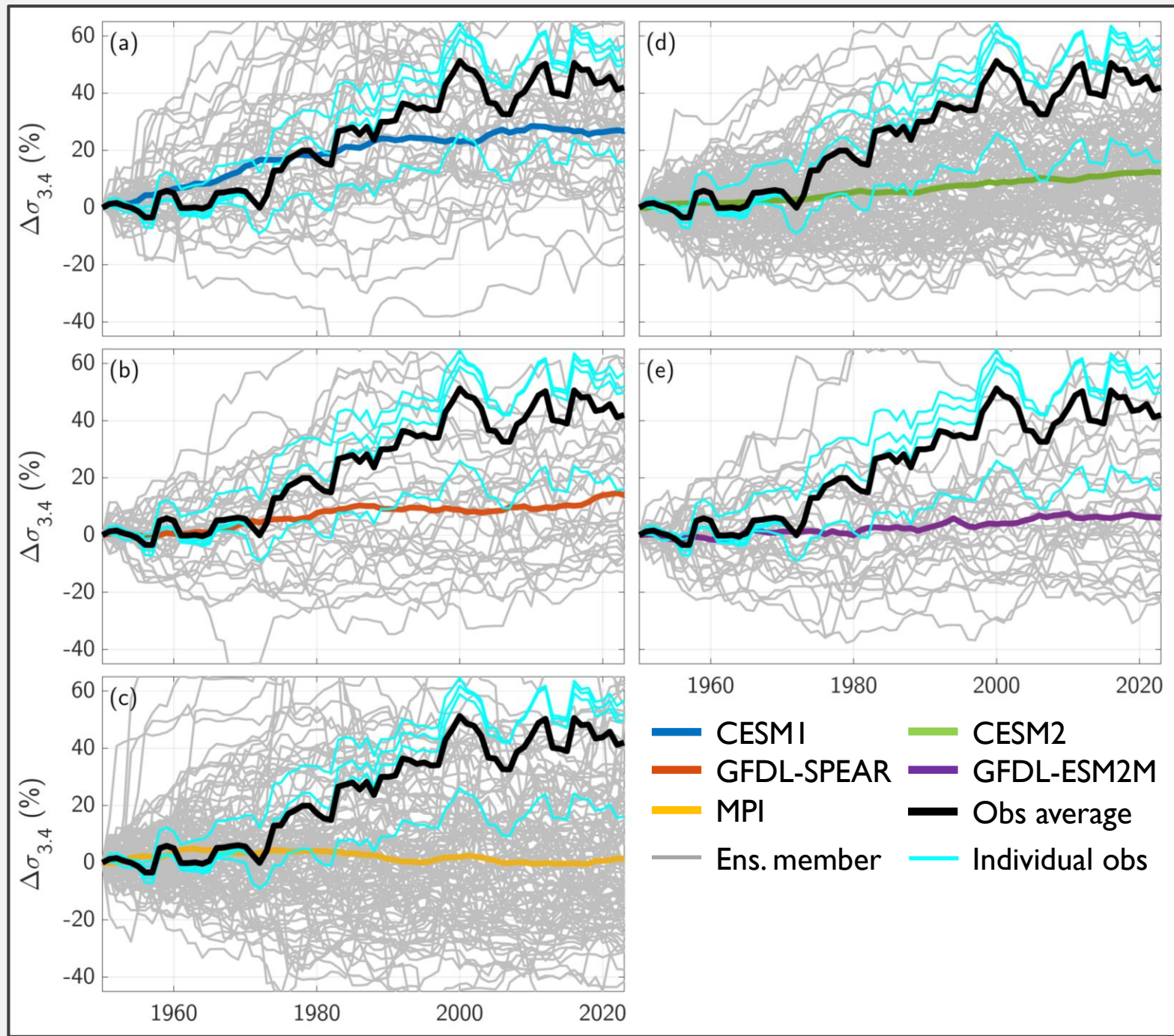
Questions?

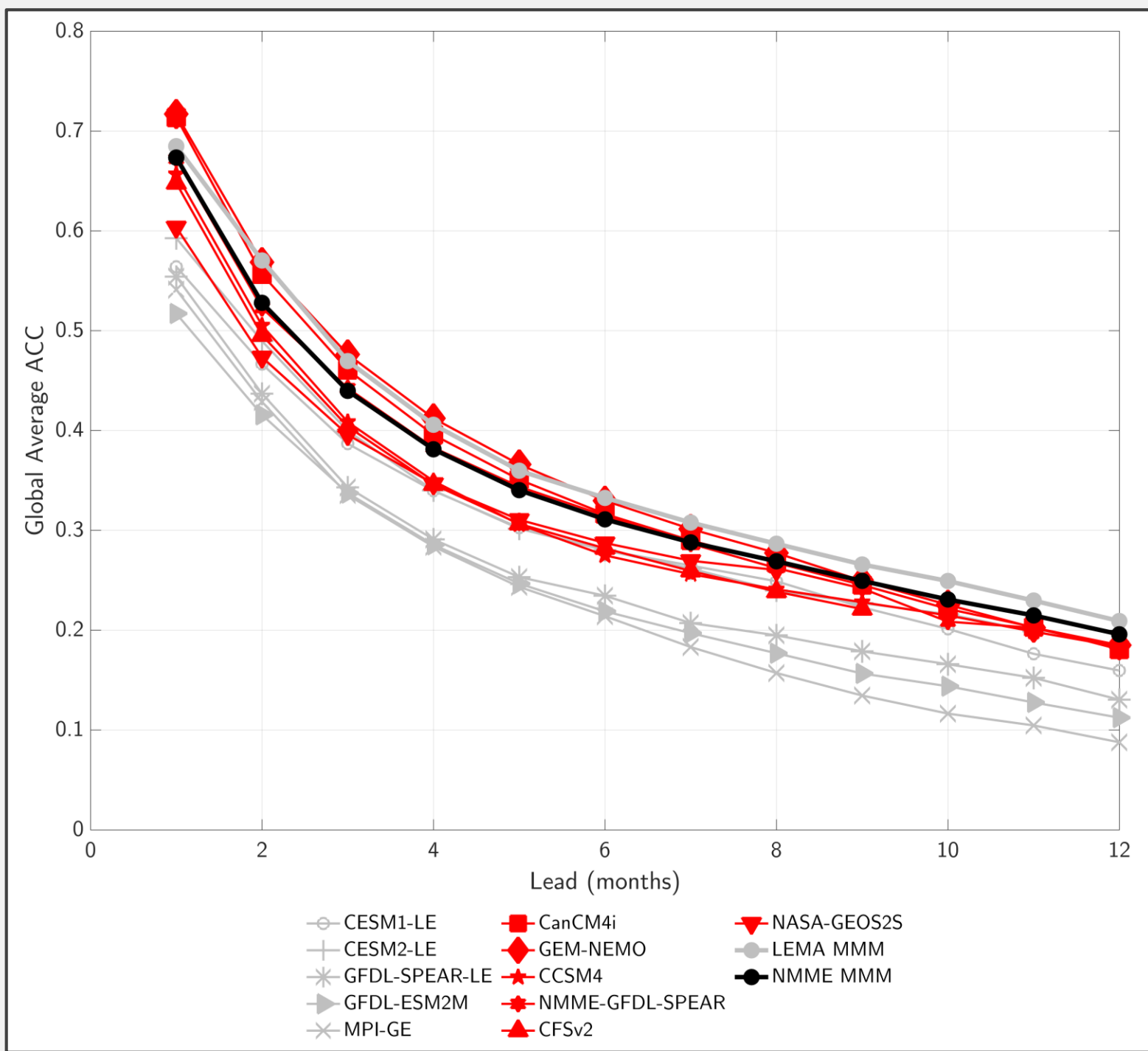
Email: dillon.amaya@noaa.gov

Shading: Skill shown where significant with 95% confidence

Extra Slides

Observed changes in Nino3.4 amplitude are captured by model large ensembles





Forecast reliability

Reliability Categories:

Category 5: *Perfect*

Category 4: *Very Useful*

Category 3: *Marginally Useful*

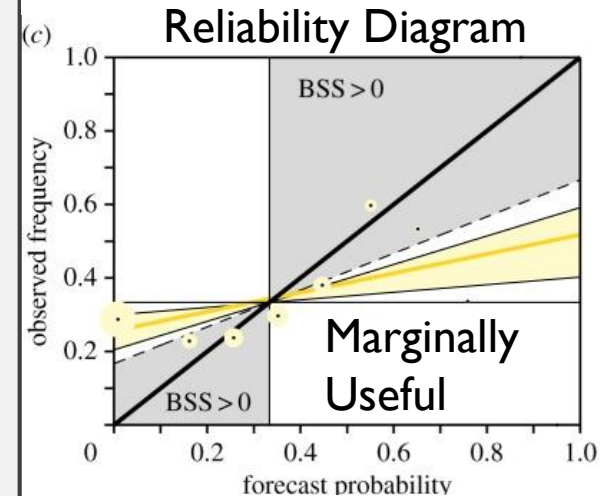
Category 2: *Not Useful*

Category 1: *Dangerously Useless*

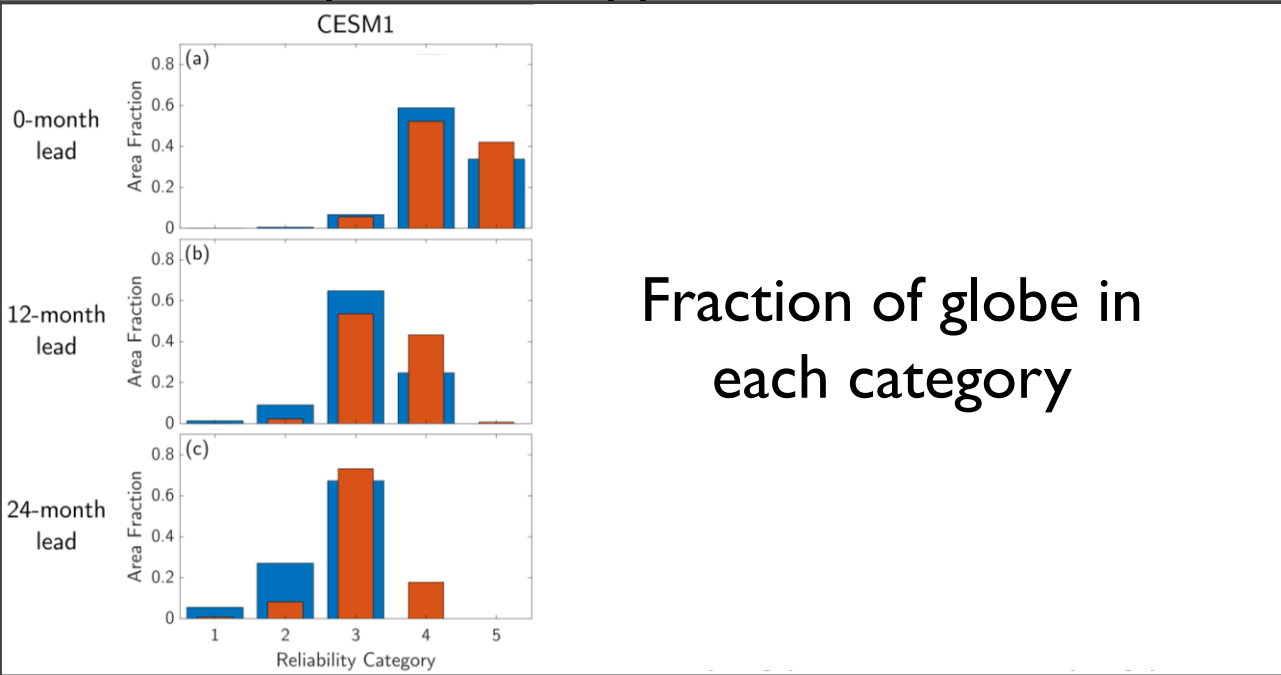
Brier Skill Score = BSS

Forecast probability = fraction of forecast members in given tercile

Observed frequency = fraction of timesteps with observed event in tercile



Surface temperature, upper tercile



Fraction of globe in each category

■ 1921-1950 ■ 2071-2100

Forecasts become more reliable/useful in CESM1, less reliable/useful in GFDL-ESM2M

Reliability Categories:

Category 5: *Perfect*

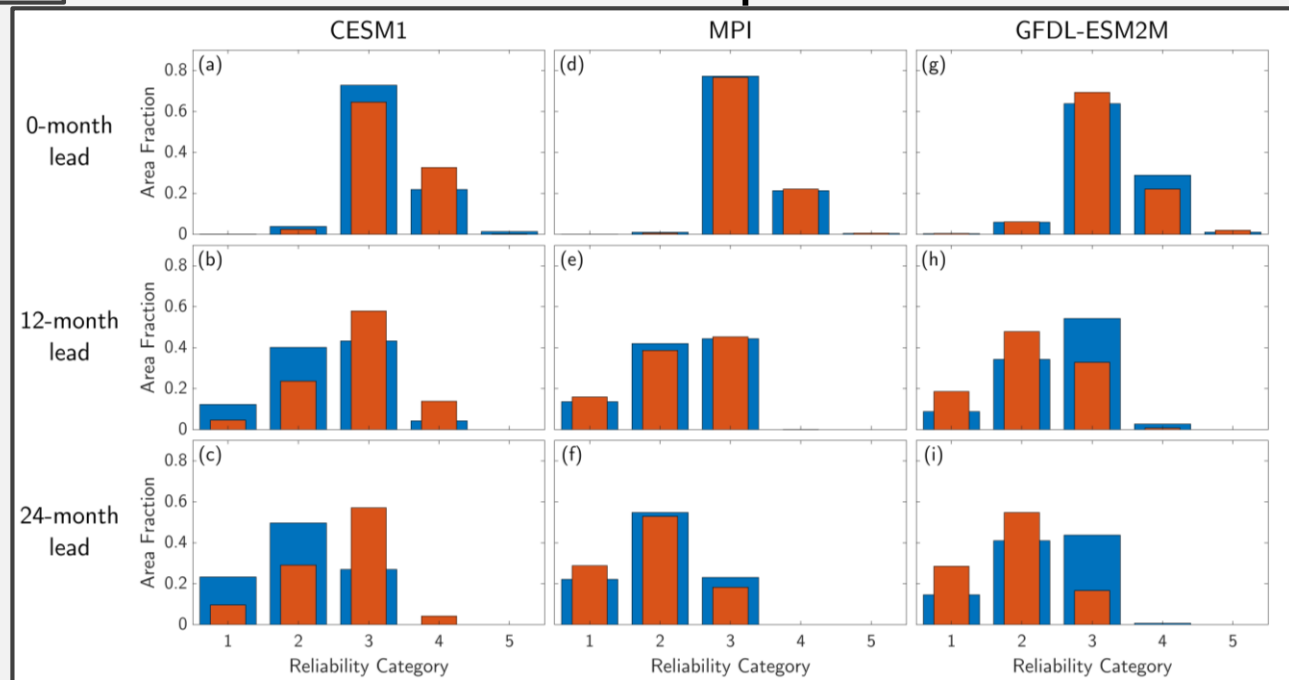
Category 4: *Very Useful*

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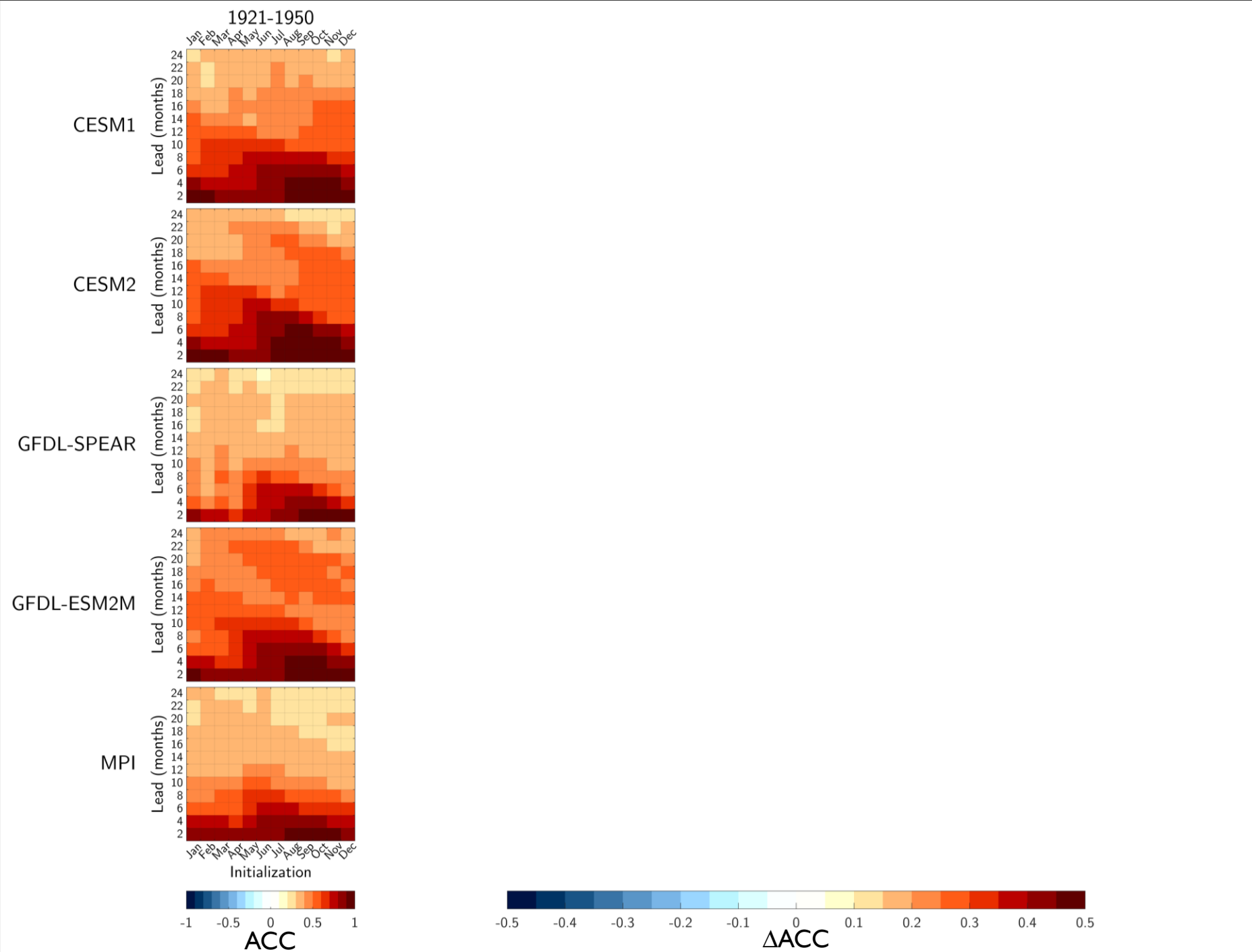
Category 2: *Not Useful*

Category 1: *Dangerously Useless*

Precipitation, lower tercile



ENSO skill

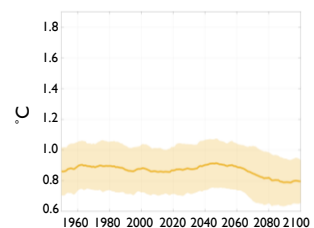
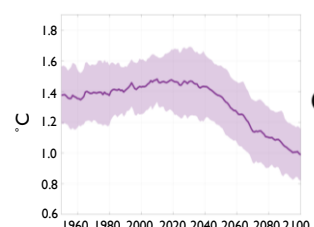
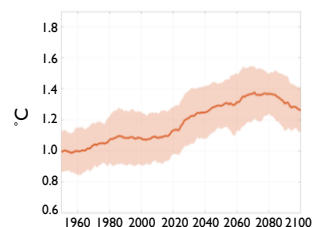
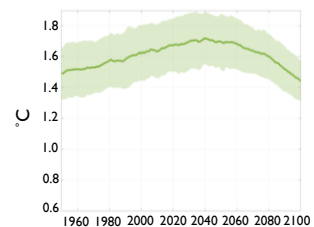
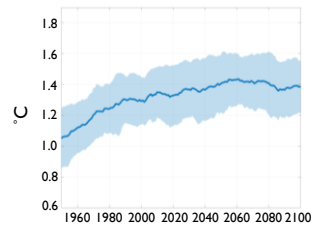
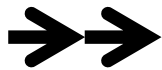


Shading: Ensemble mean ACC across all months

Stipples: 80% members agree on ΔACC sign

Trend:

DJF Nino3.4 std. dev.



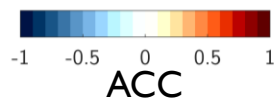
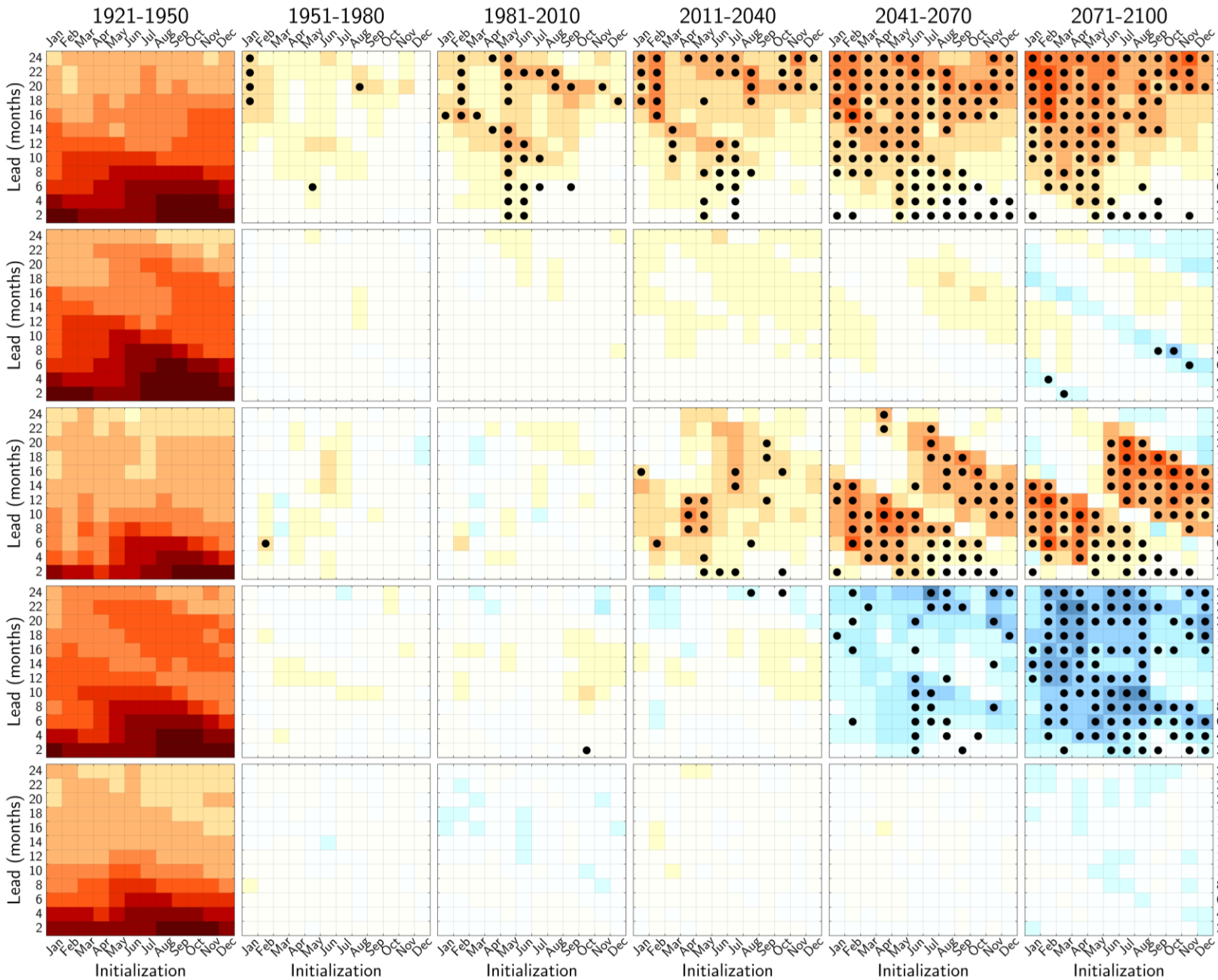
CESM1

CESM2

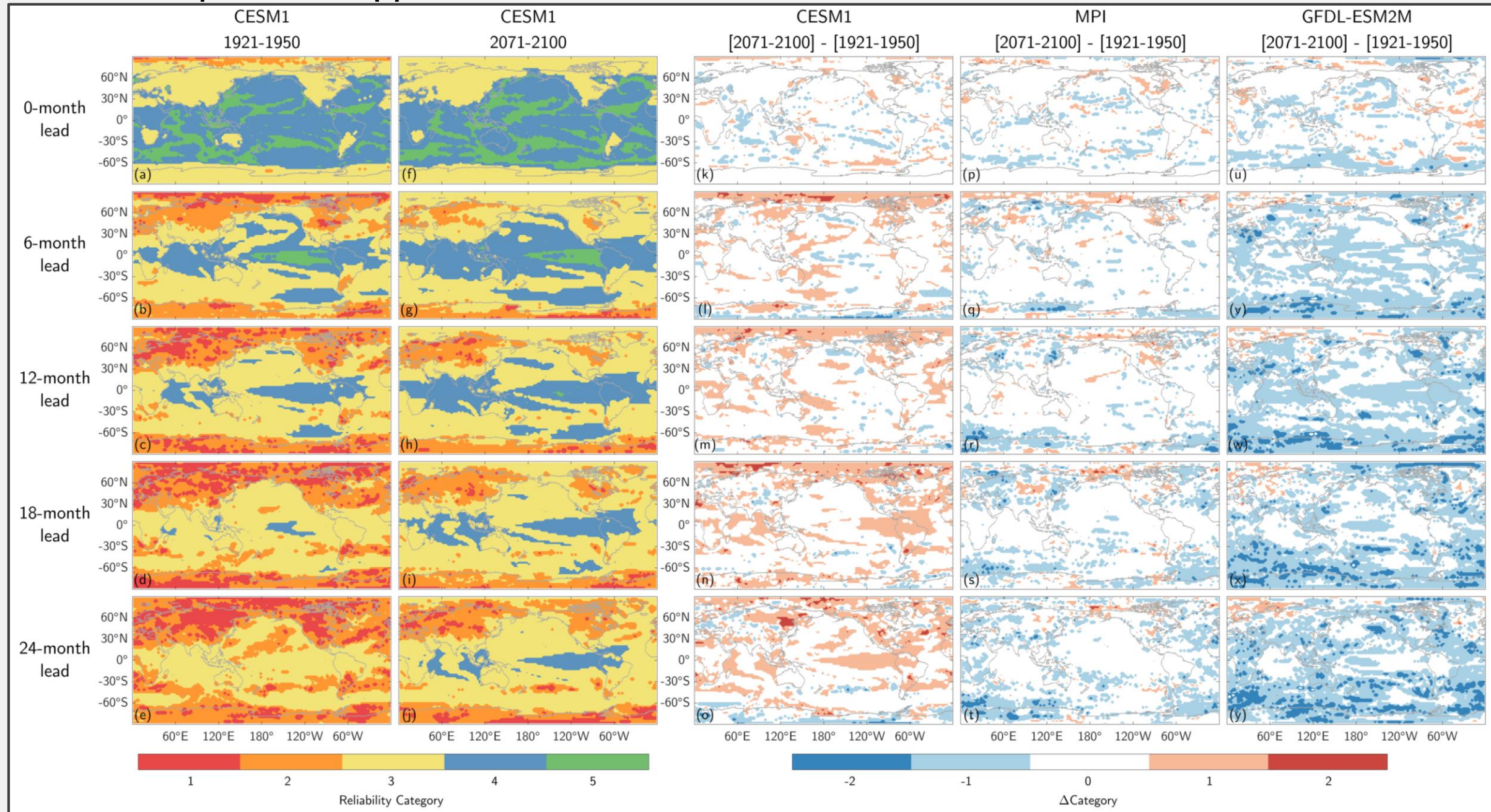
GFDL-SPEAR

GFDL-ESM2M

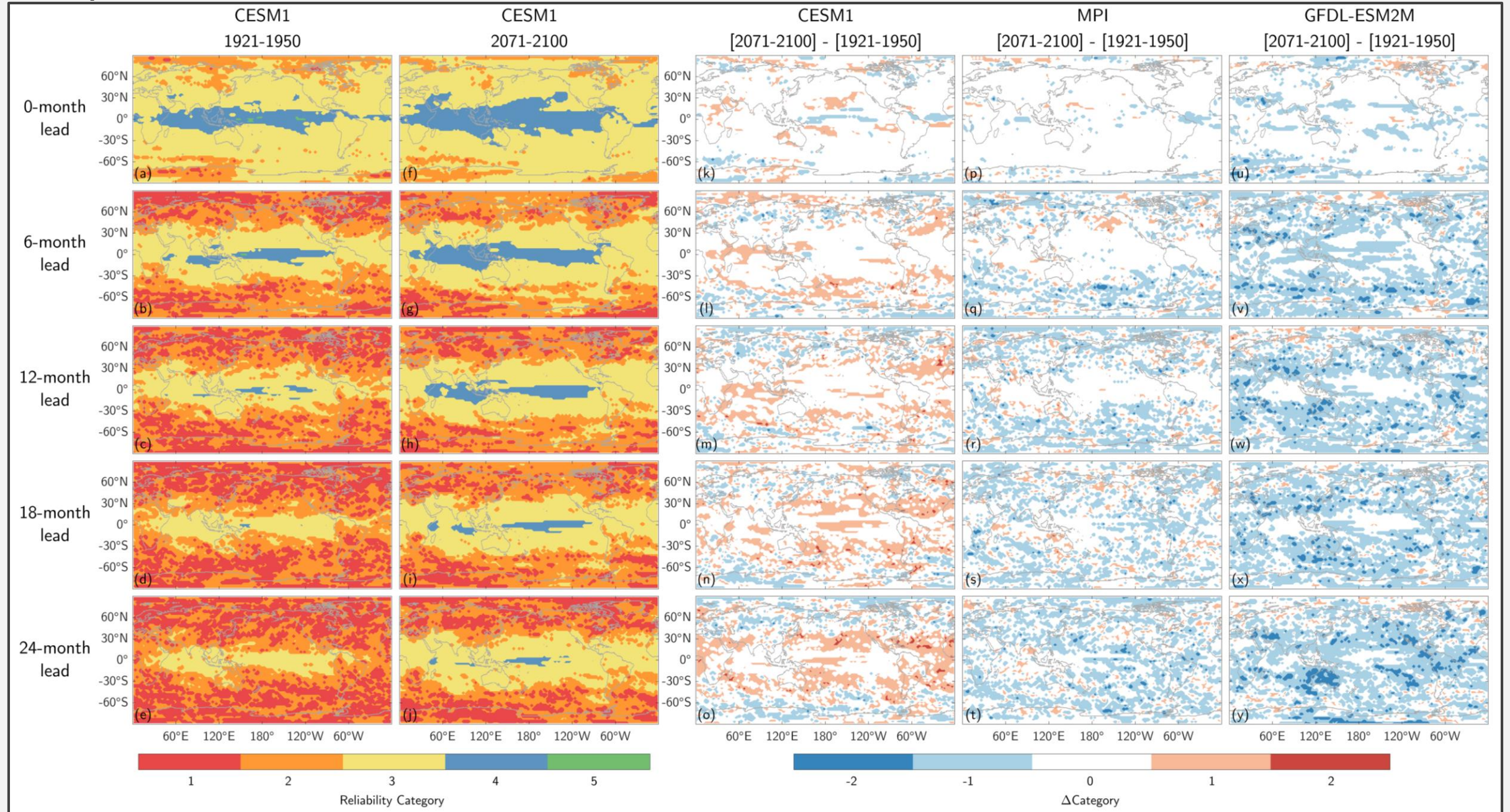
MPI



Surface temperature, upper tercile

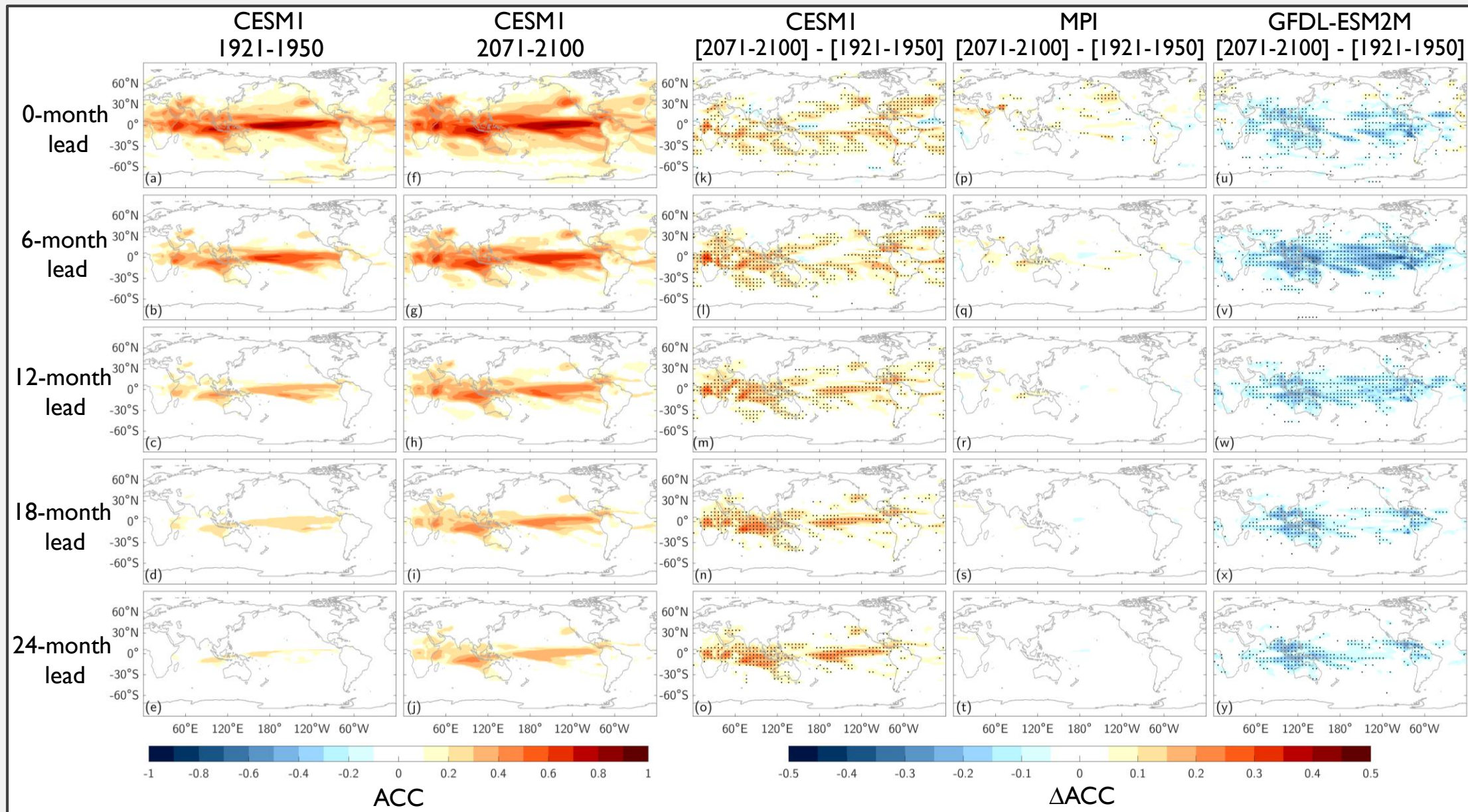
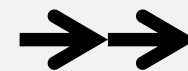


Precipitation, lower tercile



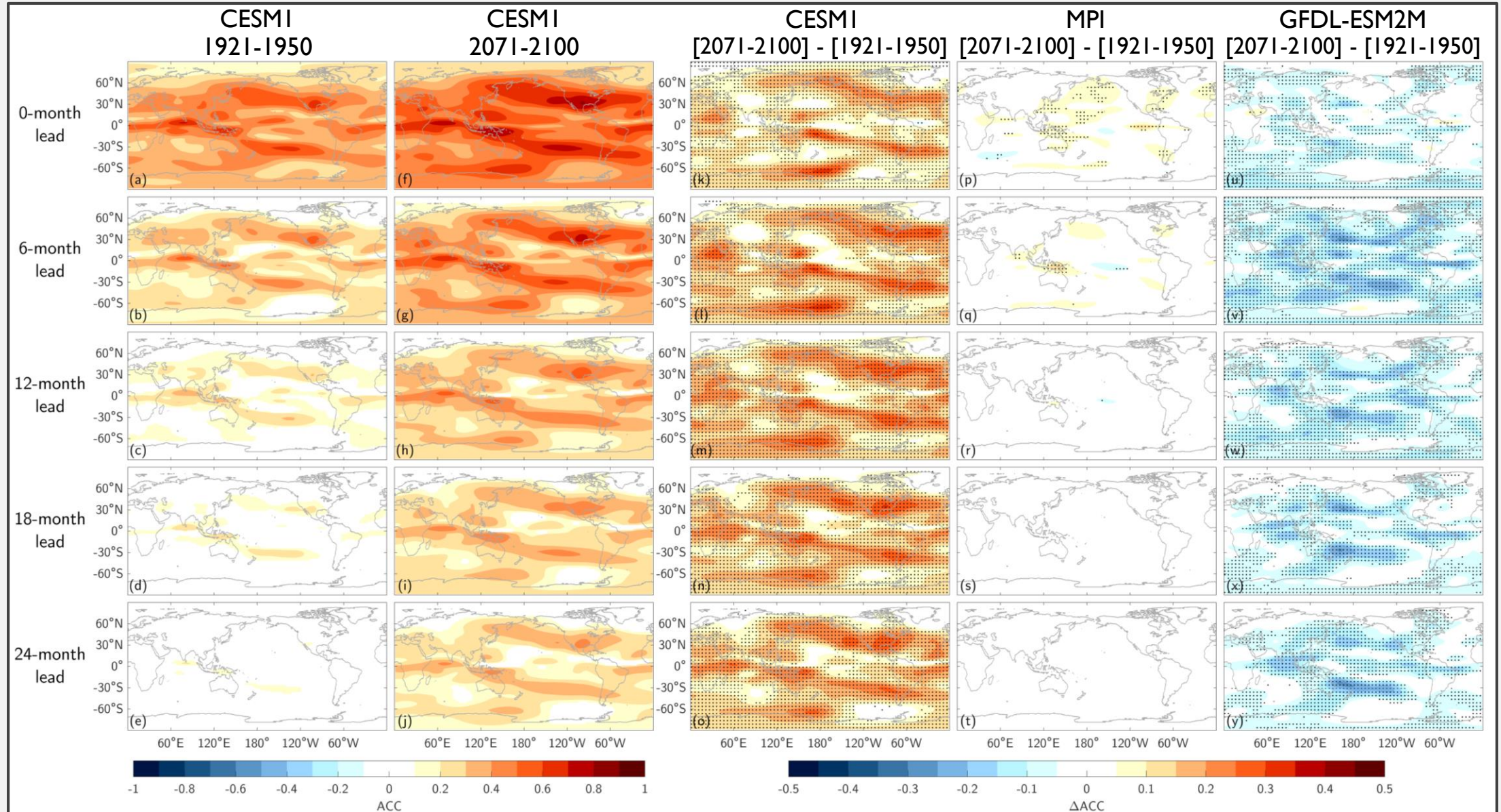
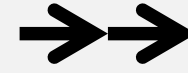
Precipitation

Nino3.4 σ trend:

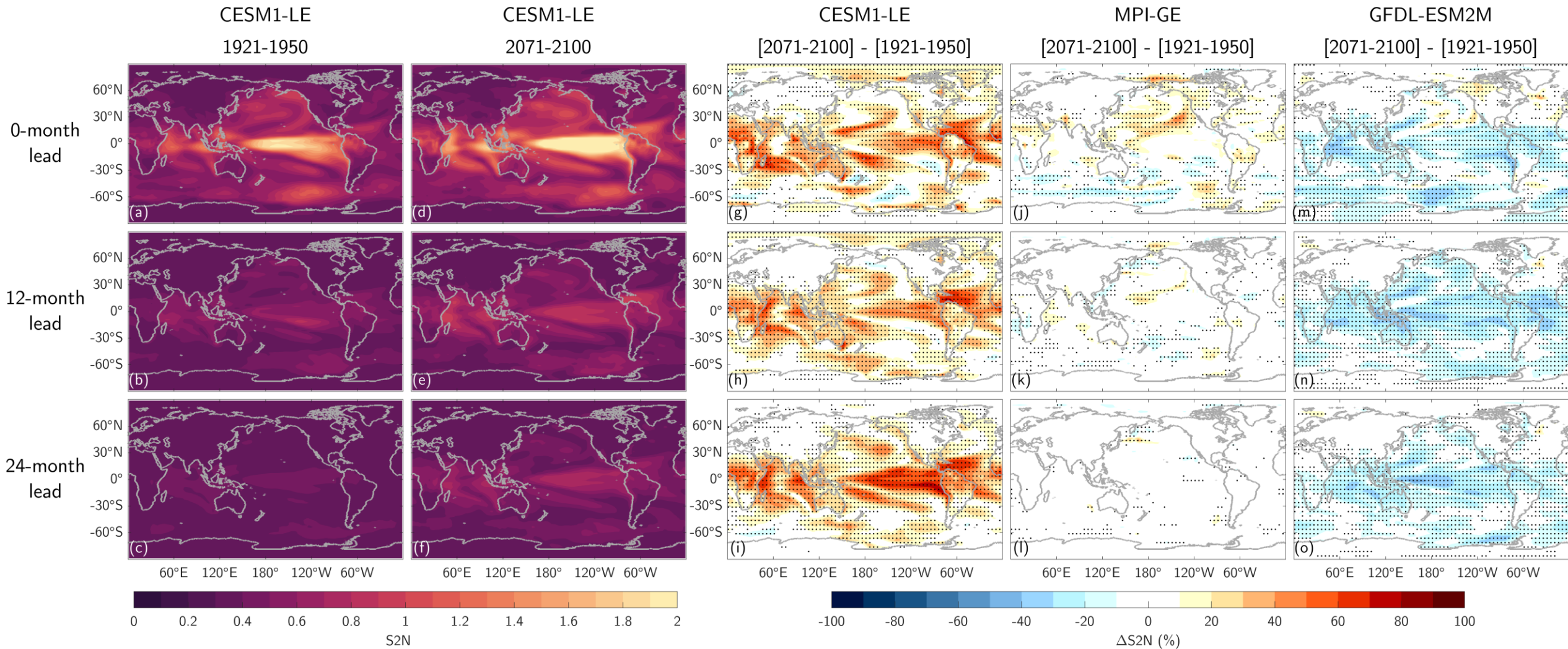


500mb streamfunction

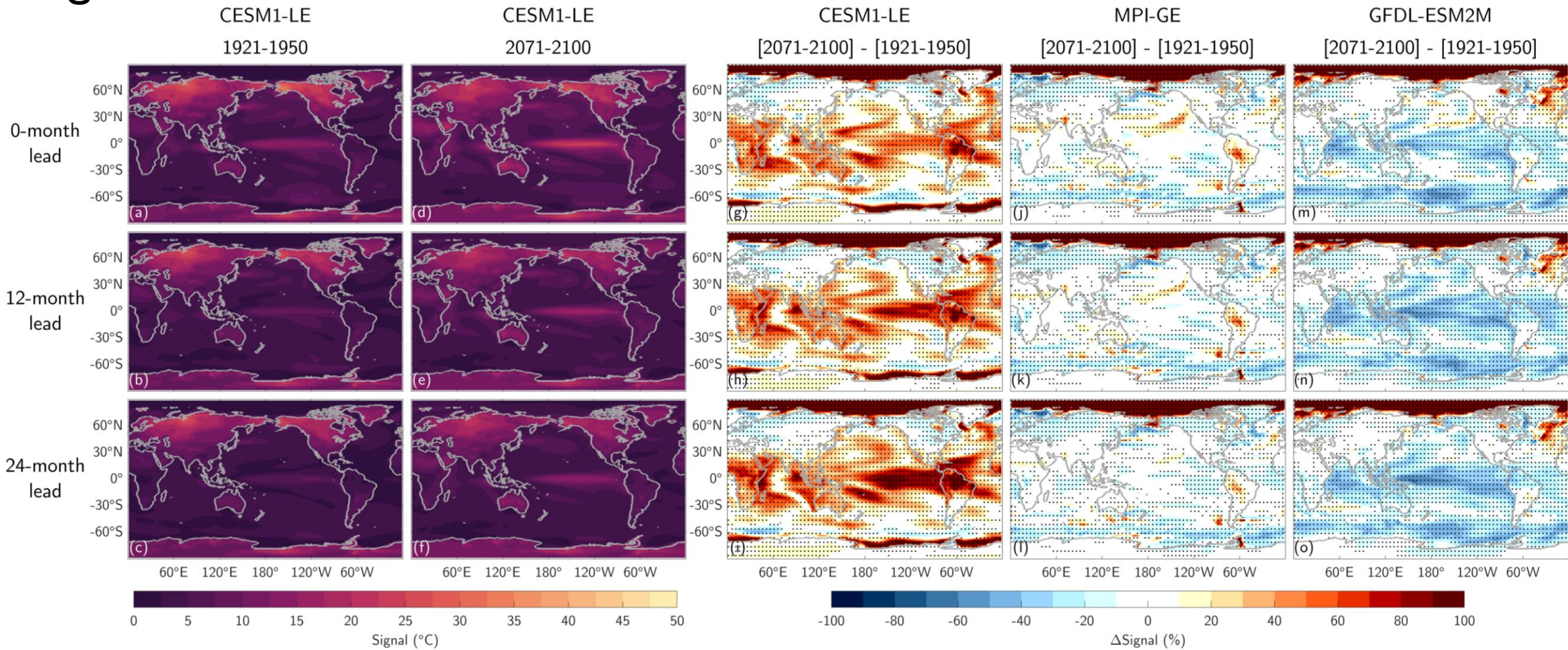
Nino3.4 σ trend:



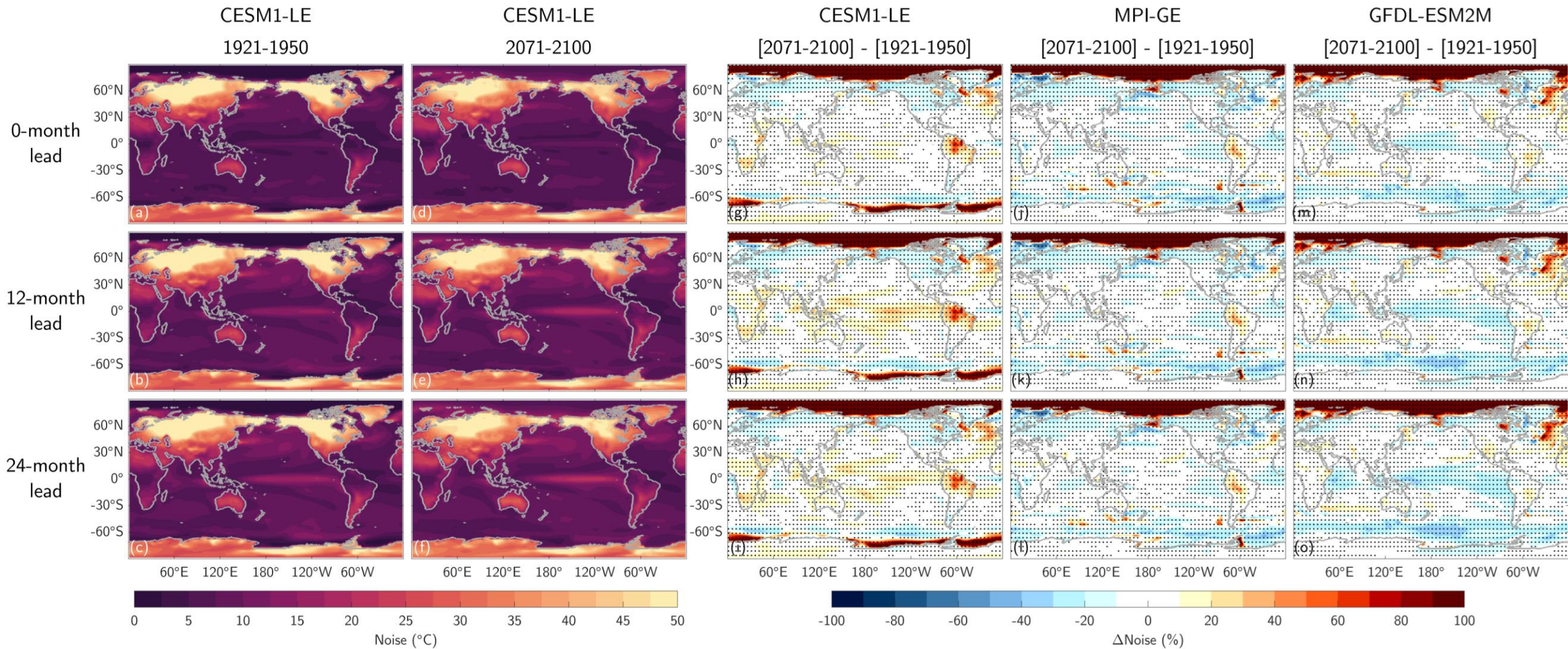
S2N Ratios

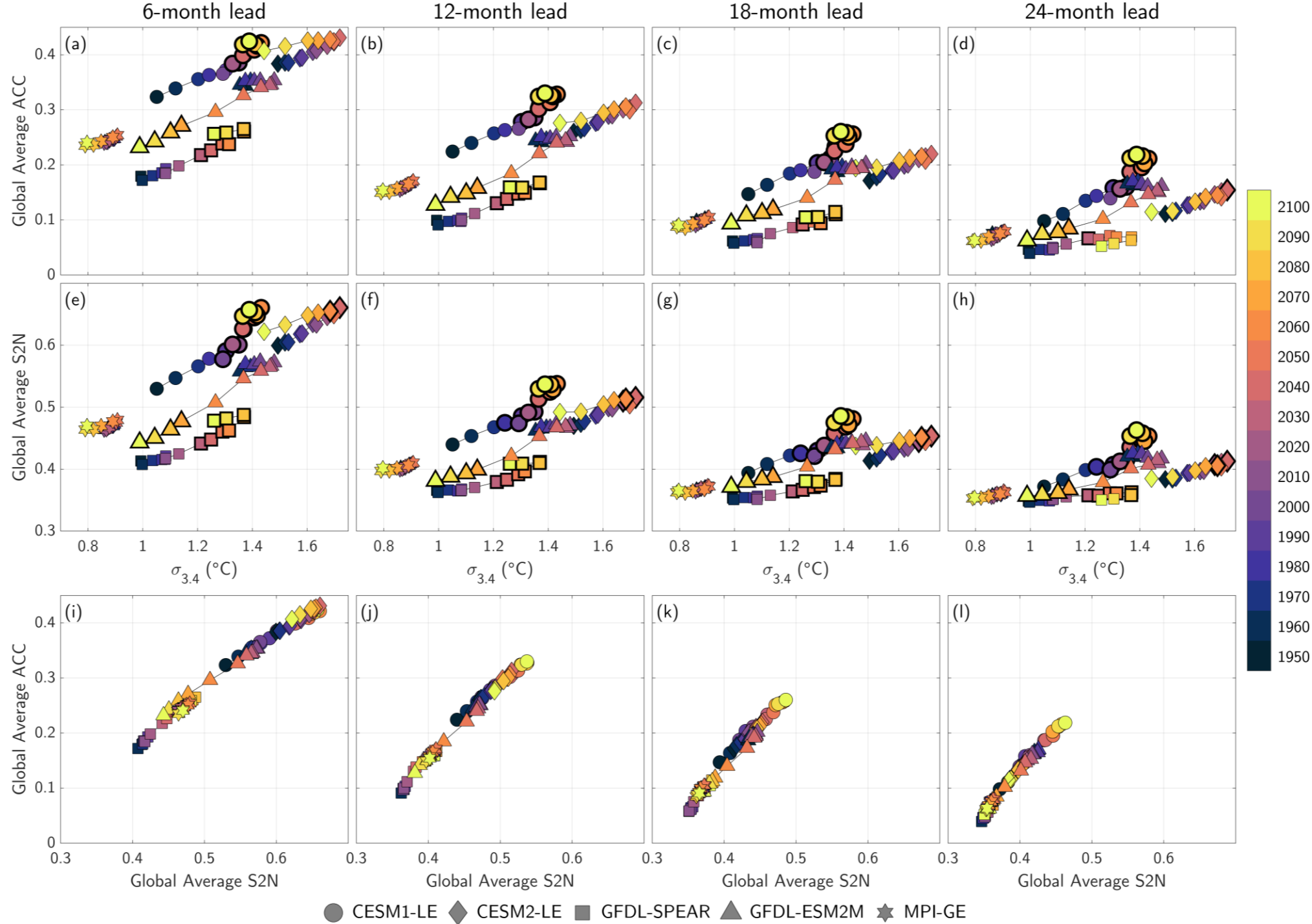


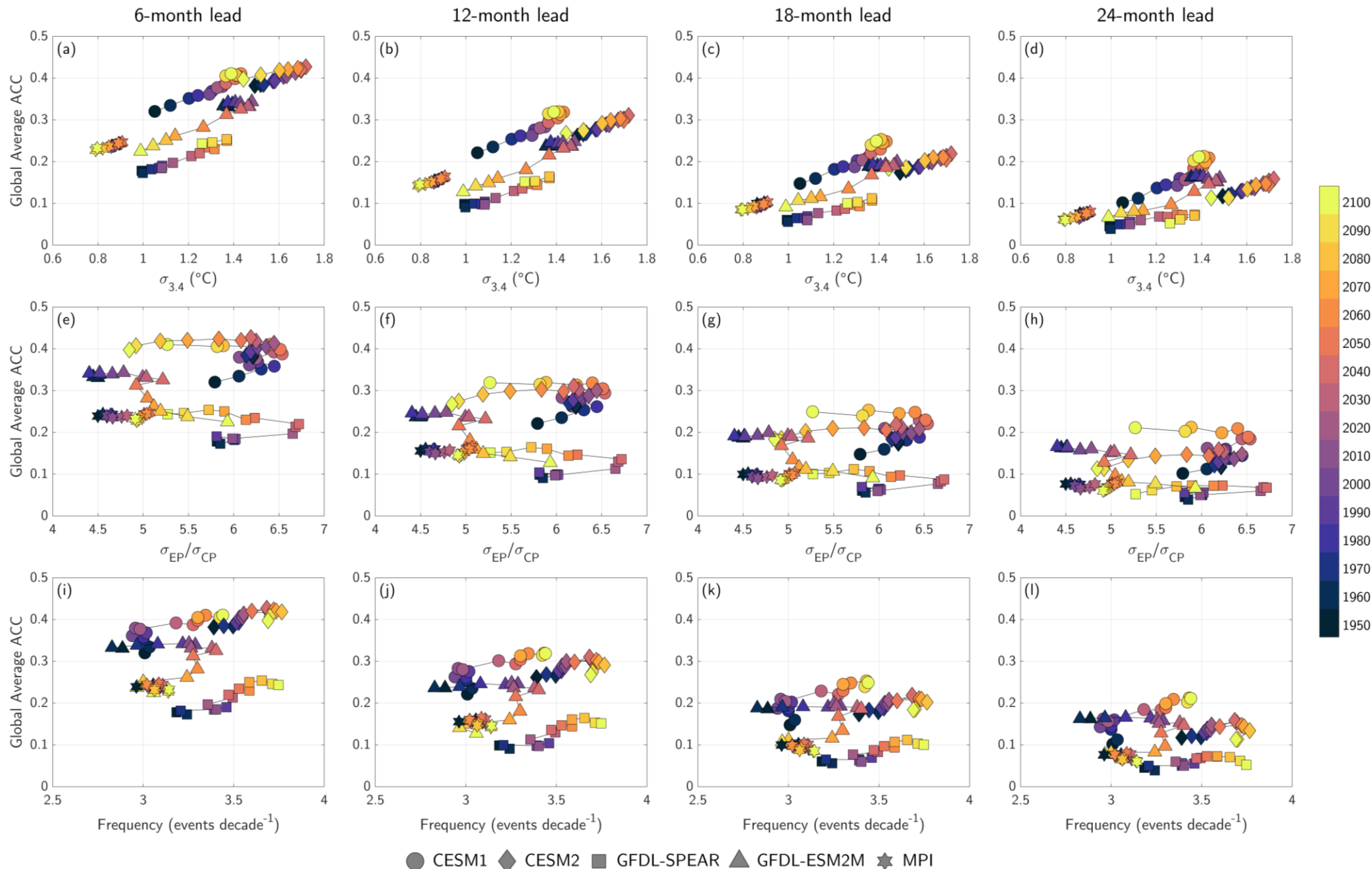
Signal



Noise







Δ ACC relative to 1921-1950, averaged in Nino3.4

