FUTURE CHANGES IN SEASONAL CLIMATE PREDICTABILITY

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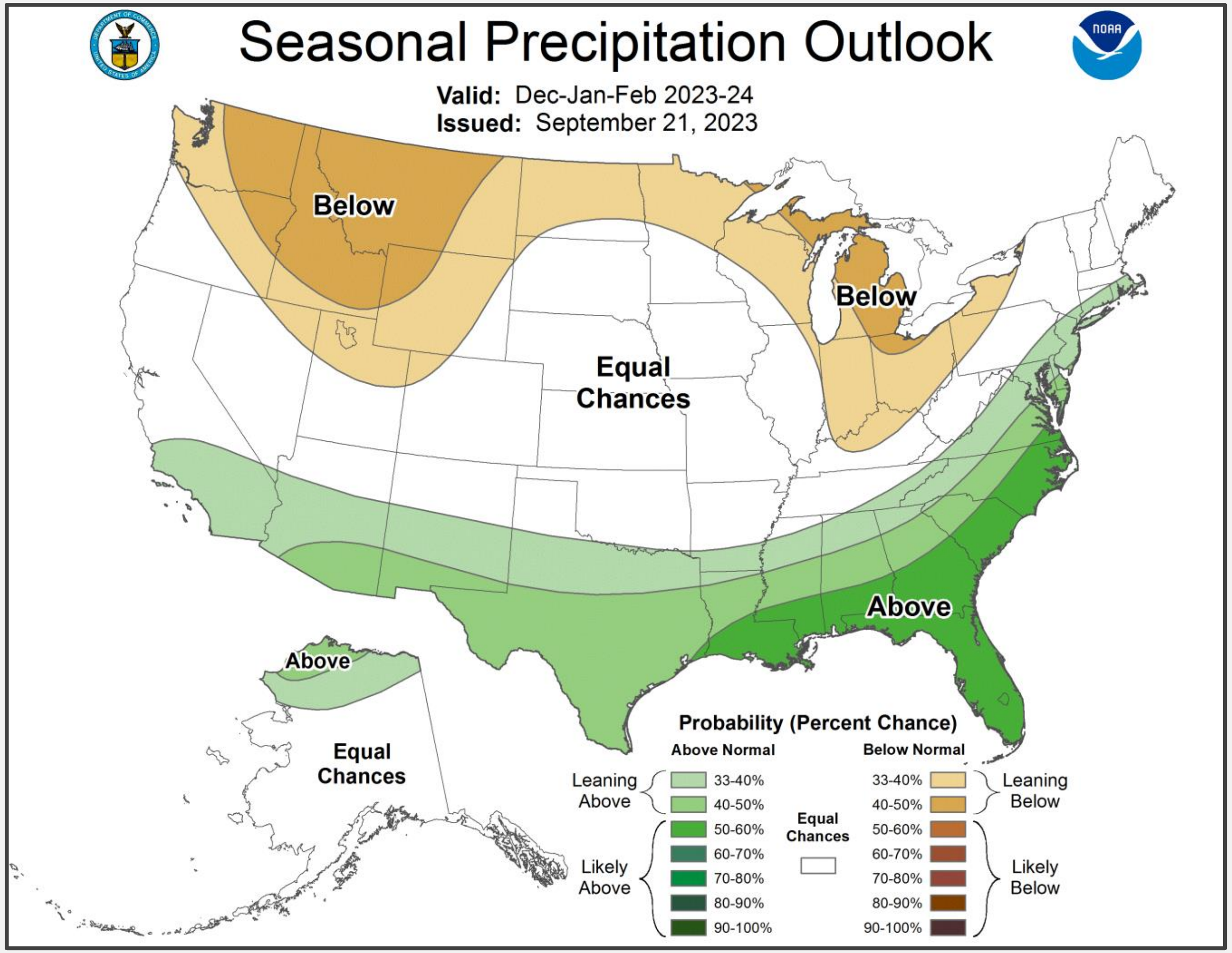
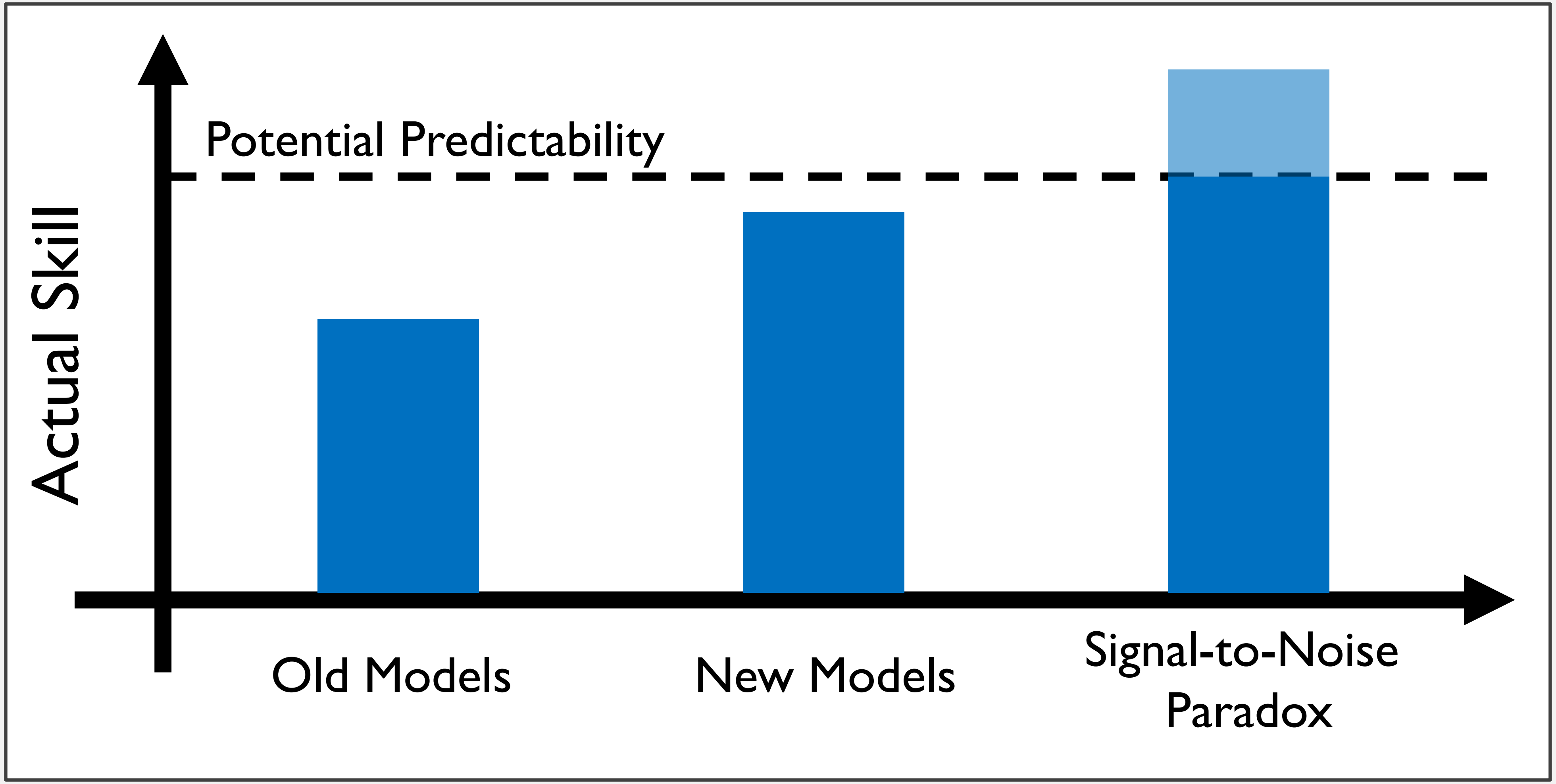
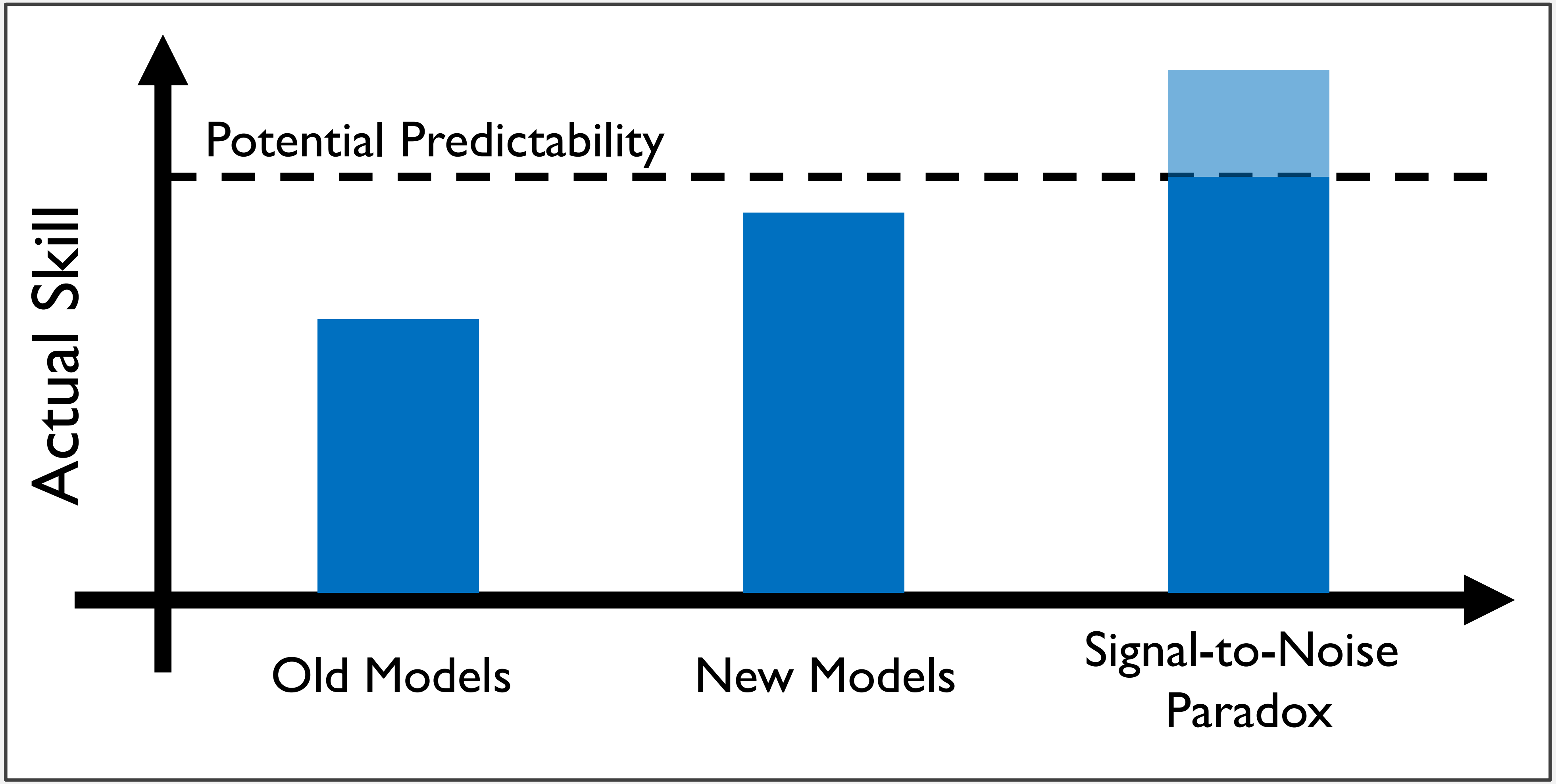


Seasonal outlooks based on historical skill relationships are extremely useful...but

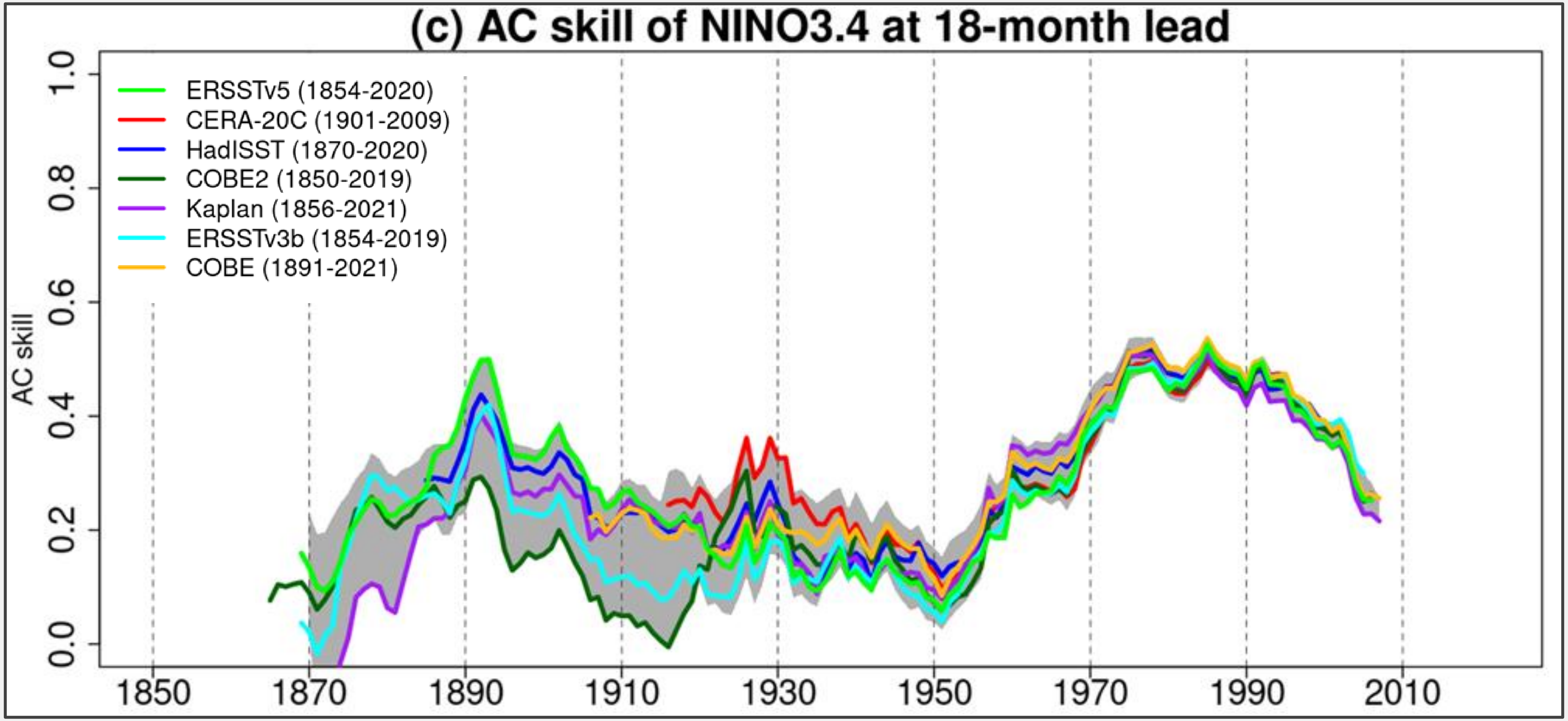


Actual skill – forecast skill derived from dynamical or statistical hindcasts of the real world

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



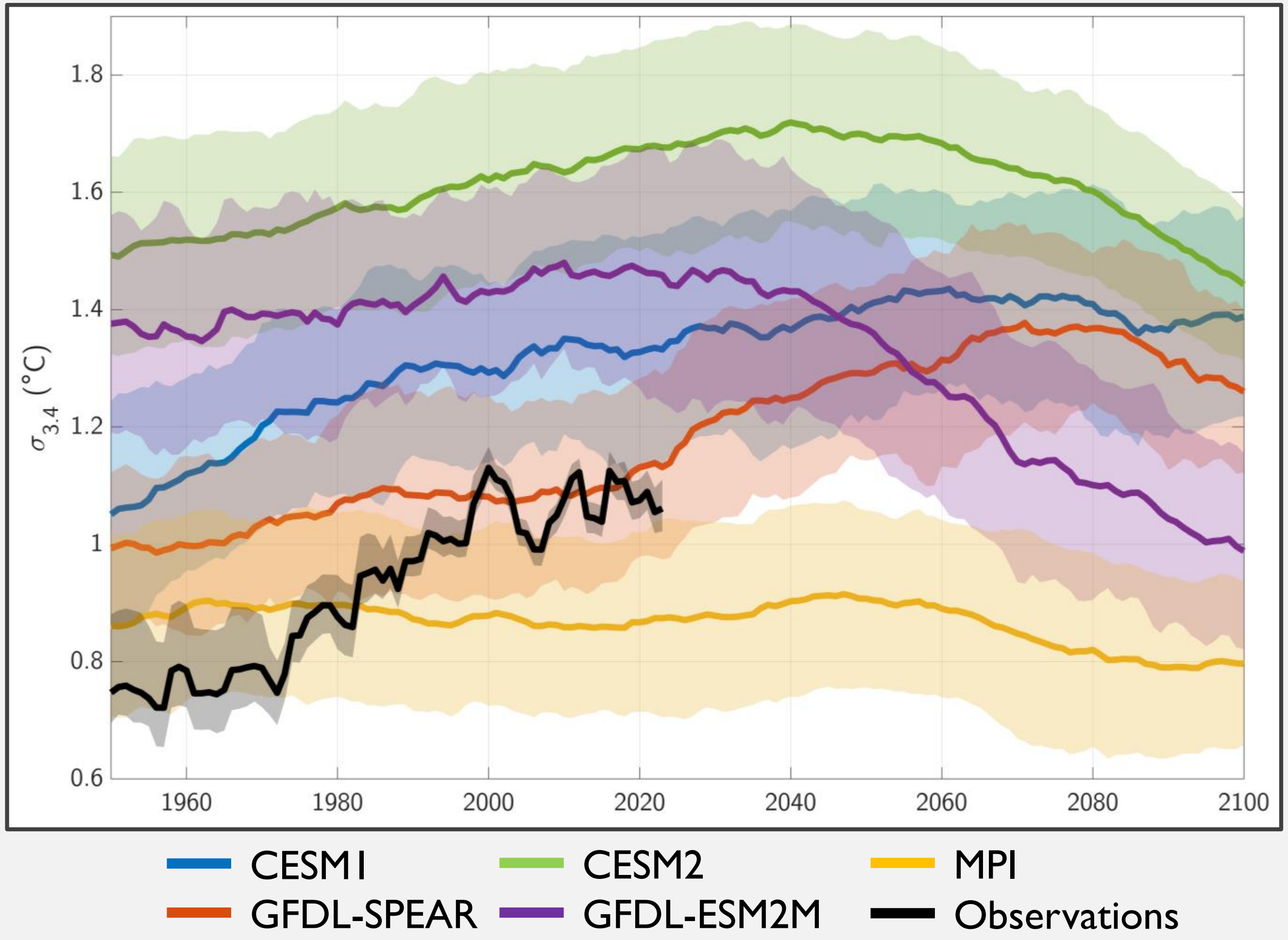
Lou et al. (2023)

Will seasonal climate predictability change in the future?

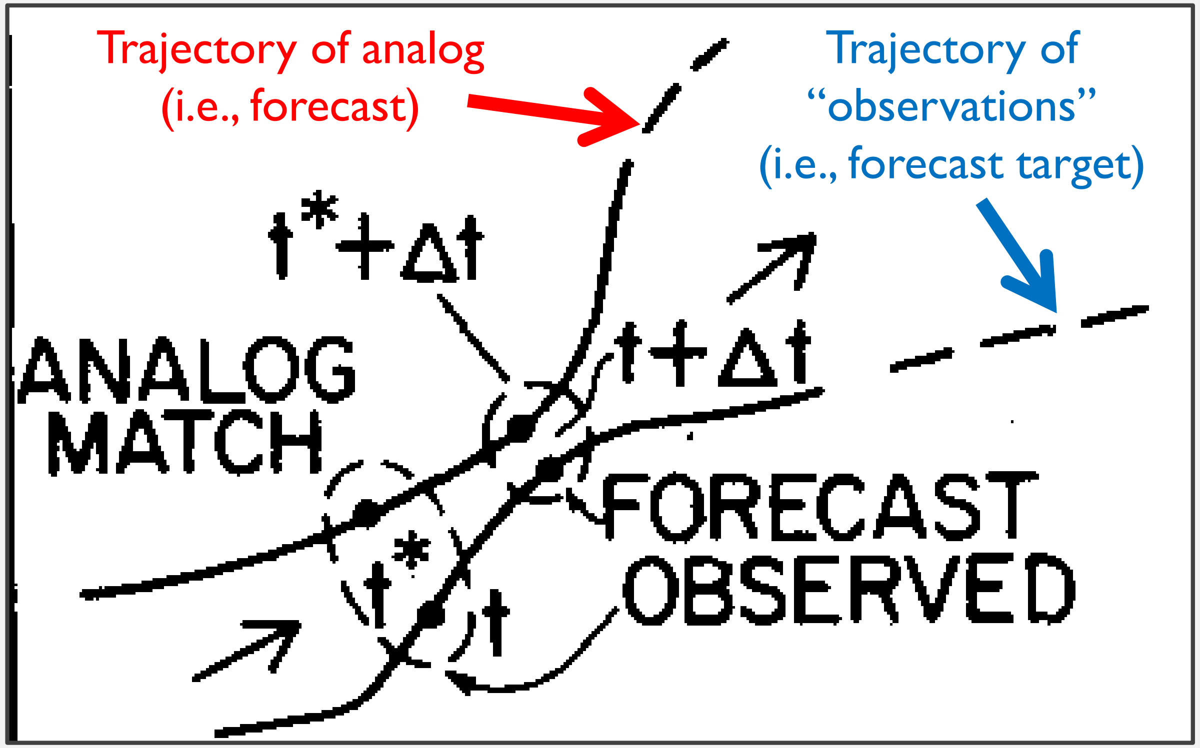
Climate models project significant changes to ENSO and its teleconnections

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

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



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.

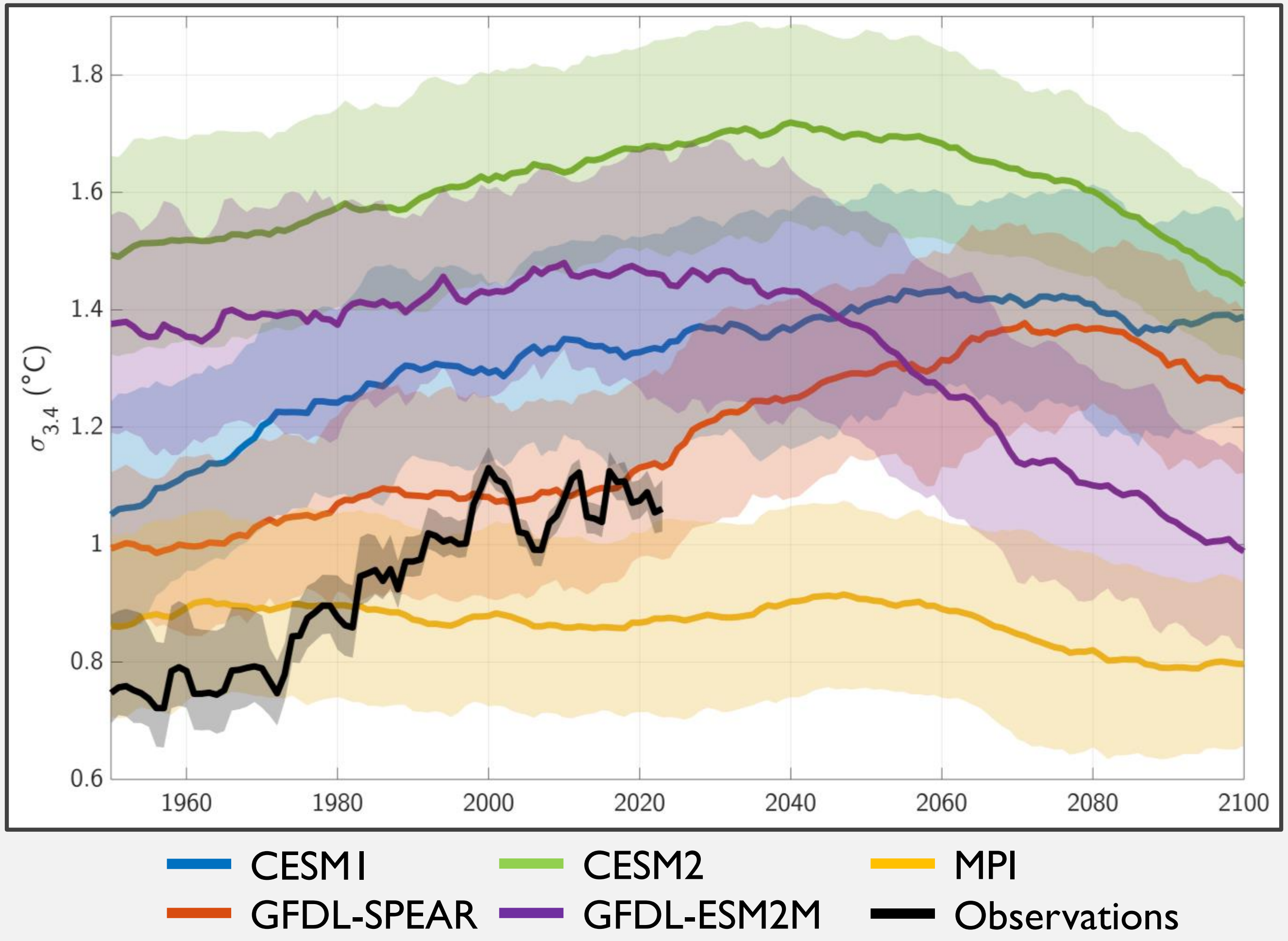
Date and Methods

<u>Single model initial condition large ensembles (SMILEs):</u>

<u>Nino3.4σ trend:</u>

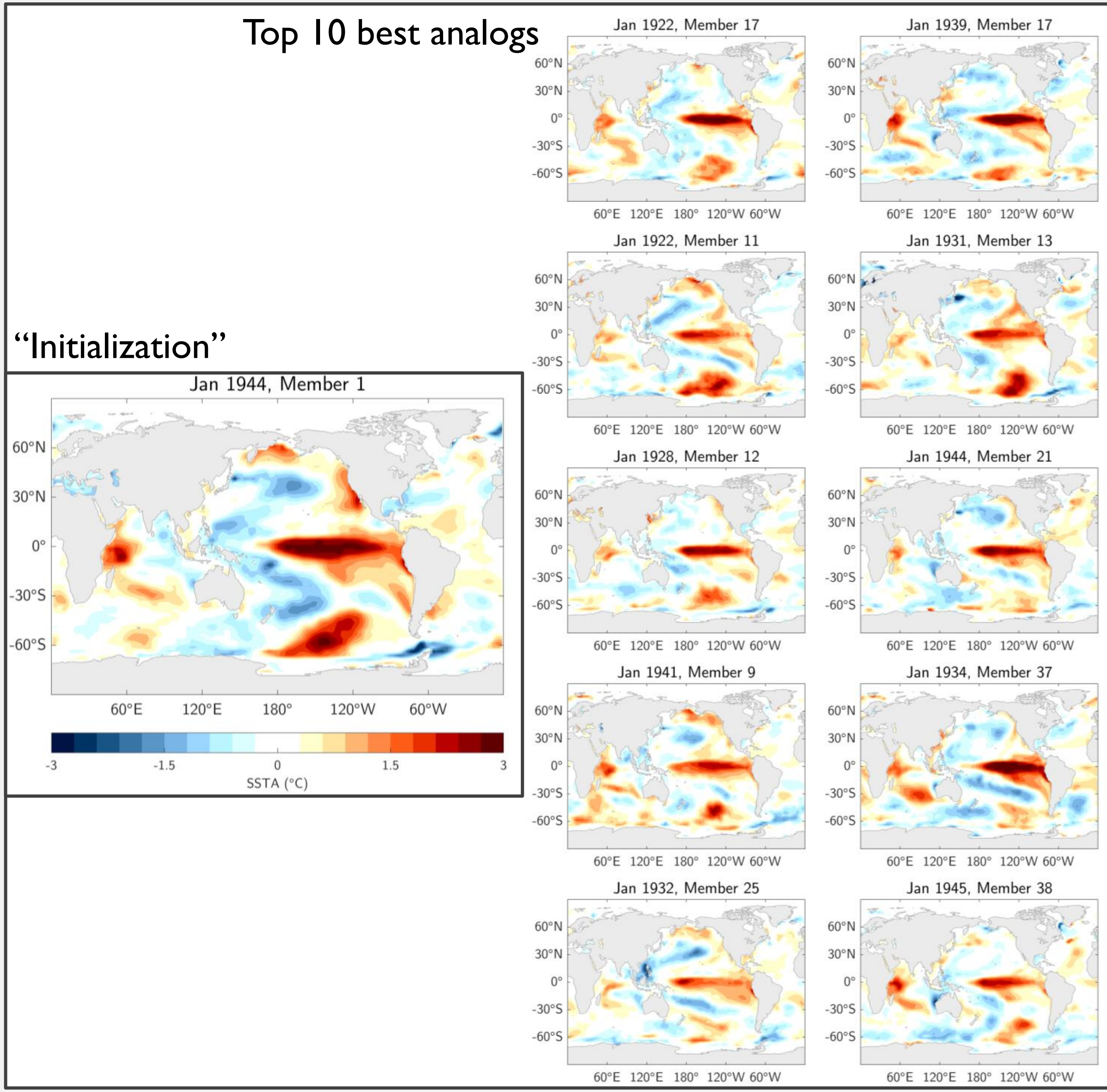
- CESM1 – 40 members ↑ →
- CESM2 – 100 members ↑ ↓
- GFDL-SPEAR – 30 members → ↑
- GFDL-ESM2M – 30 members → ↓
- MPI – 100 members → →
- All data 2.5° x 2.5°, 1920-2100
- Will refer to potential predictability/skill simply as "predictability" or "skill"

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



Perfect model-analog forecast workflow:

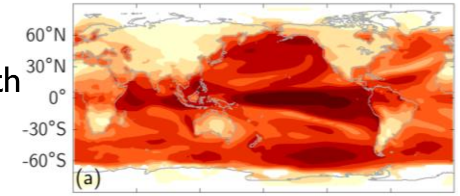
1. Extract SST for 30 year period (e.g., 1921-1950) in all large ensemble members.
2. Remove seasonal cycle. Remove ensemble mean.
3. Arbitrarily take 1st ensemble member as "truth".
4. Construct data libraries using other members. For example, all Januarys, all Februarys, etc.
5. "Initialize" with global 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. CESM1: 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).



Surface temperature

CESM1
1921-1950

0-month lead



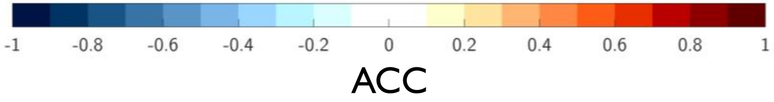
Temp. predictability increases, especially in tropics/at long leads

Shading: Change in ensemble mean potential skill (ΔACC)

Stippling: 80% members agree on ΔACC sign

Shading: Ensemble mean potential skill (ACC)

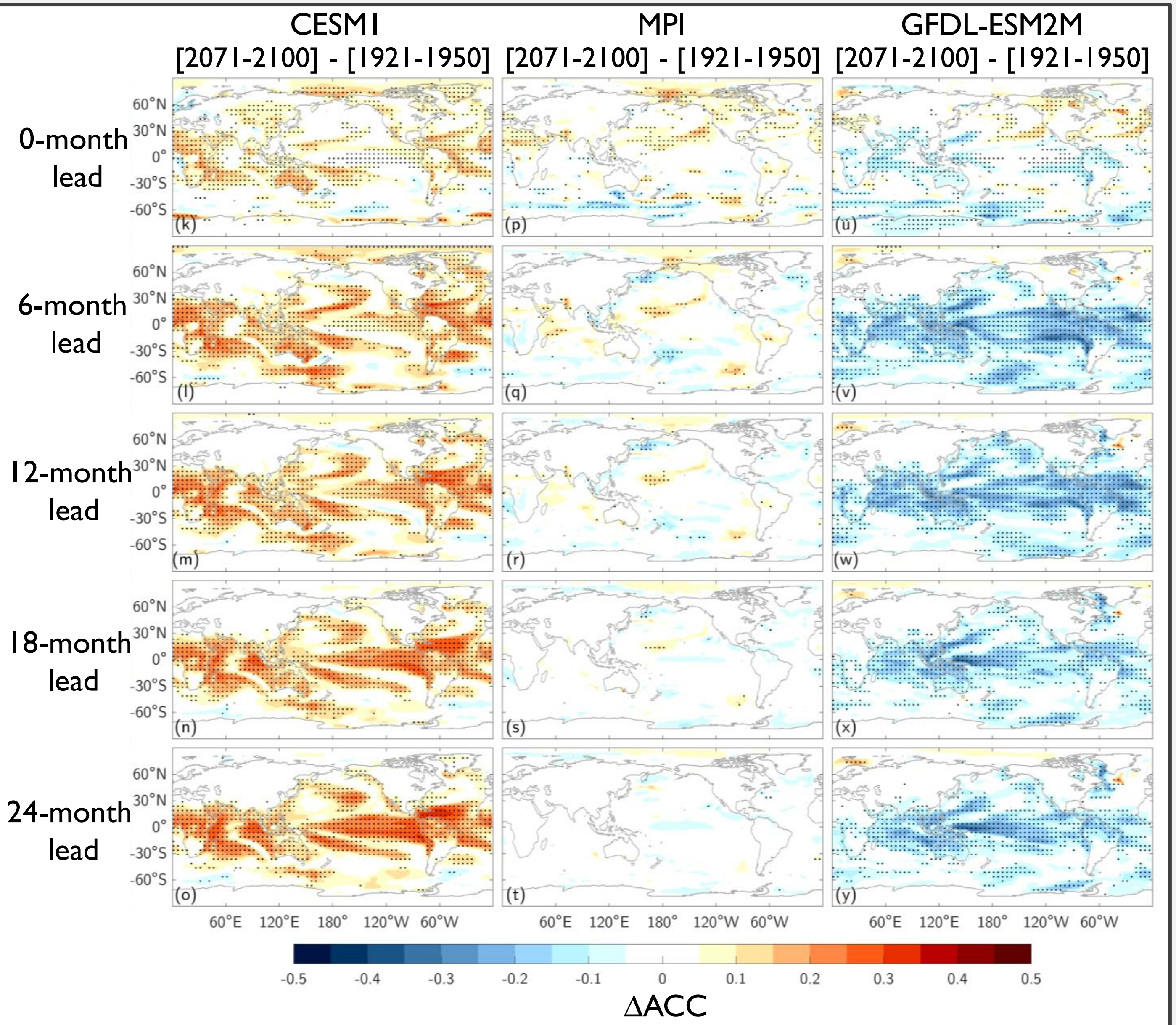
Shading: Ensemble mean potential skill (ACC)



Surface temperature

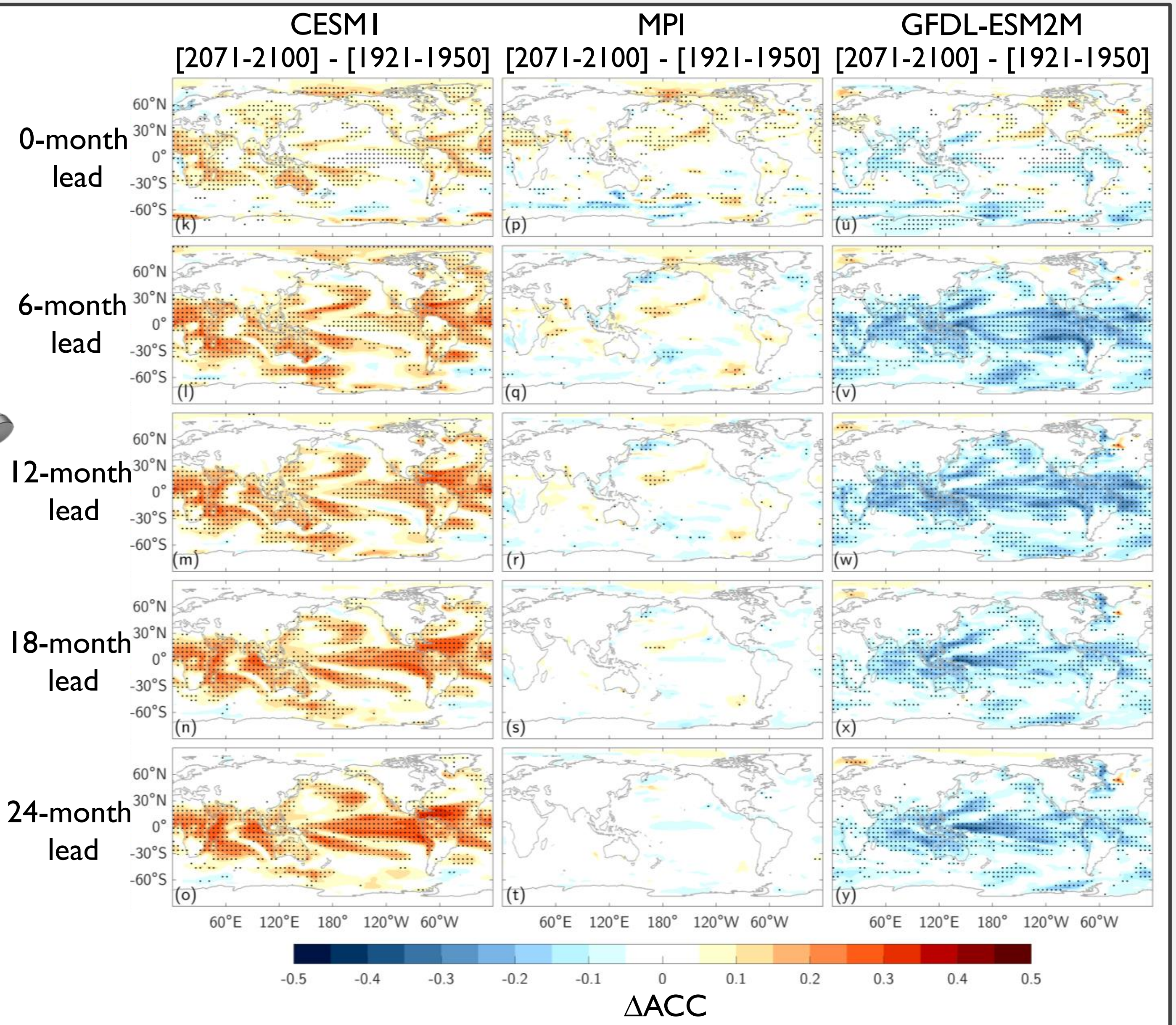
Sign/intensity of predictability changes are highly model dependent

Changes consistent for probabilistic skill metrics and other variables

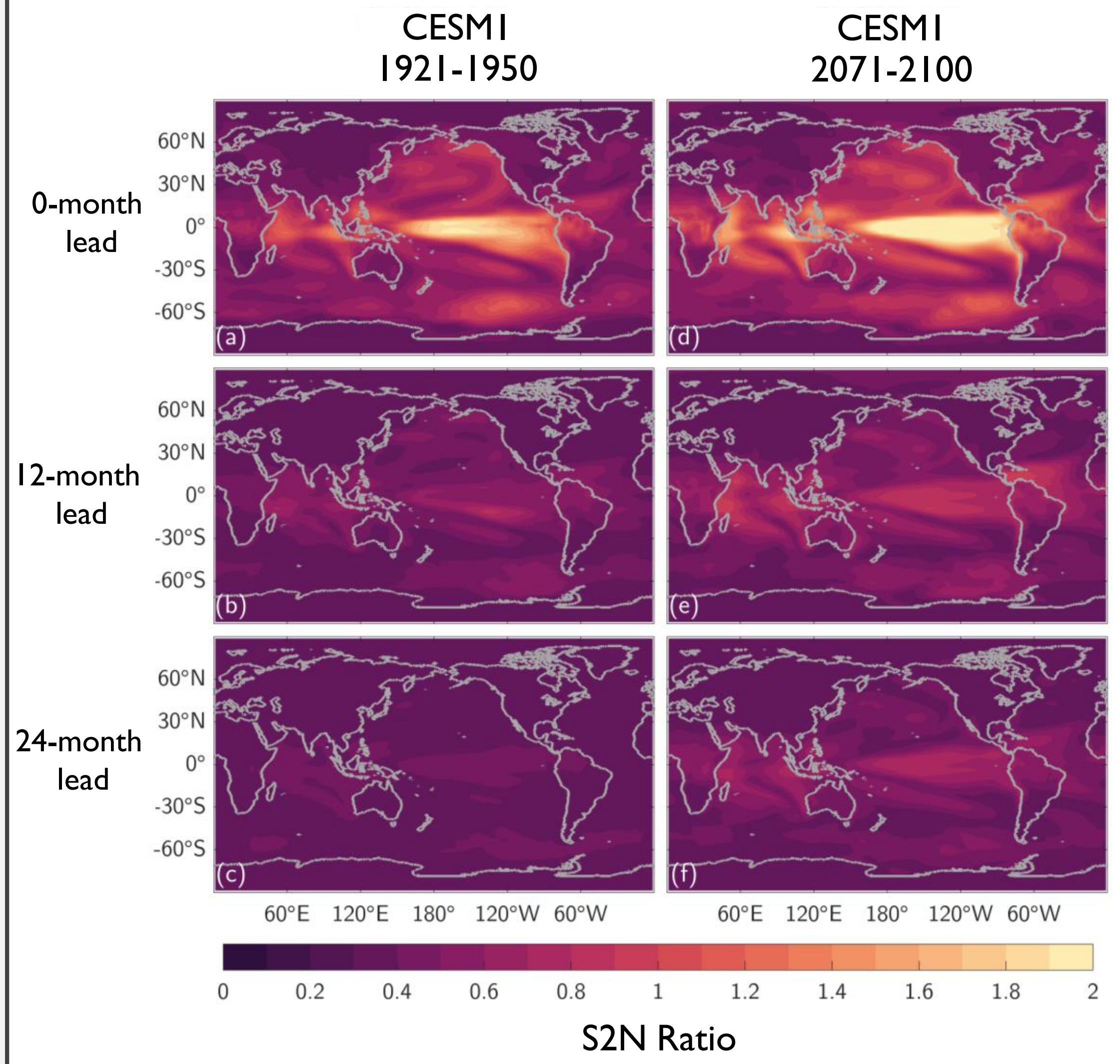


Surface temperature

Nino3.4σ trend:

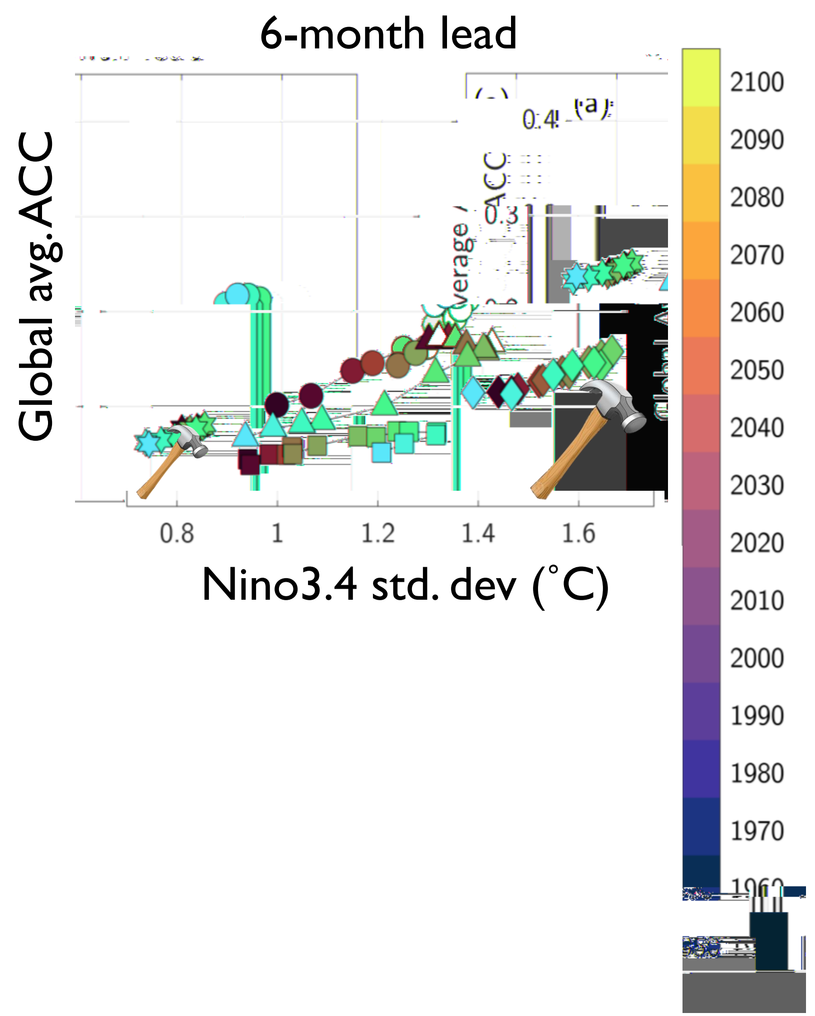


Nino3.4σ trend:



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

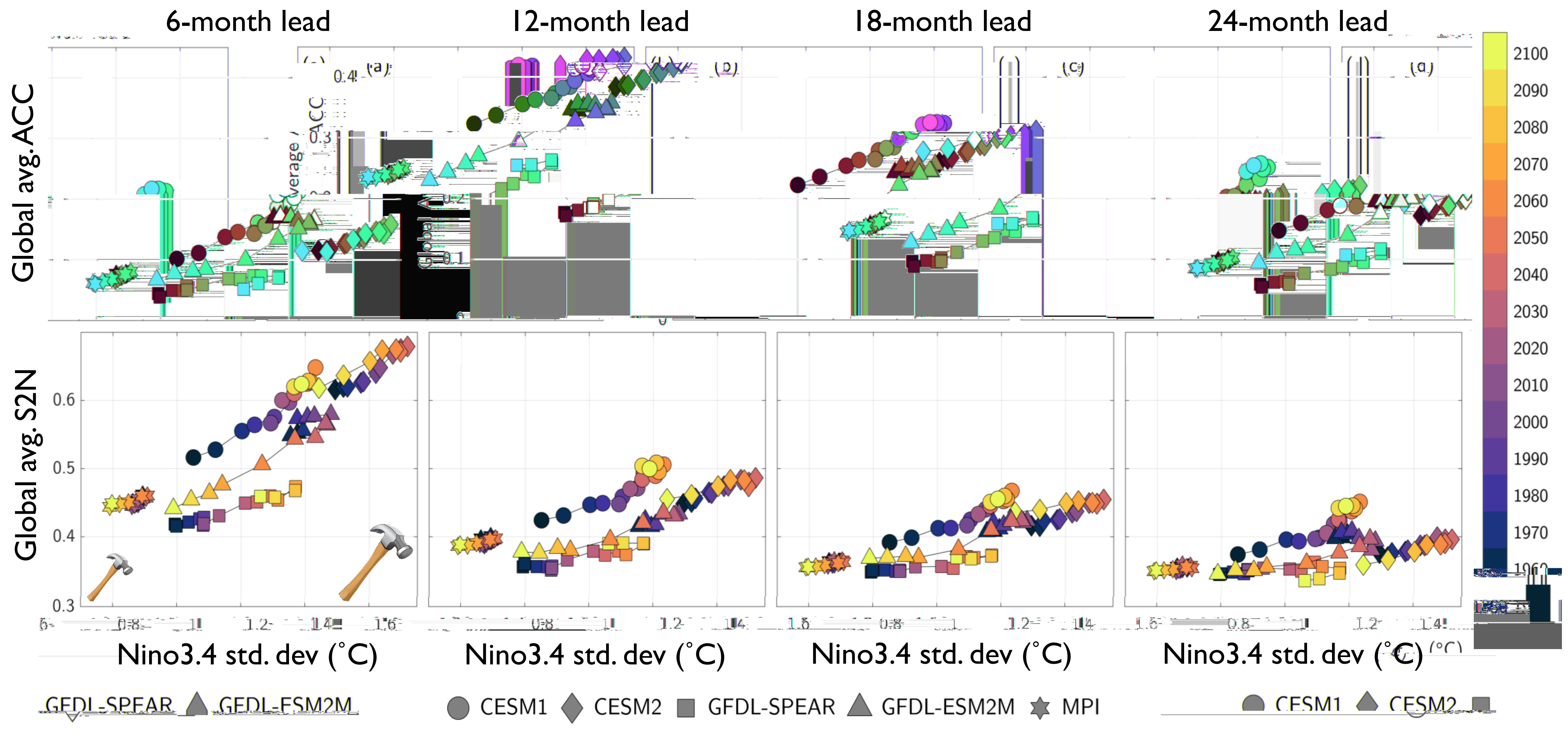


GFDL-SPEAR

CESM1 CESM2 GFDL-SPEAR GFDL-ESM2M MPI

CESM1 CESM2

Sea surface temperature



Sea surface temperature

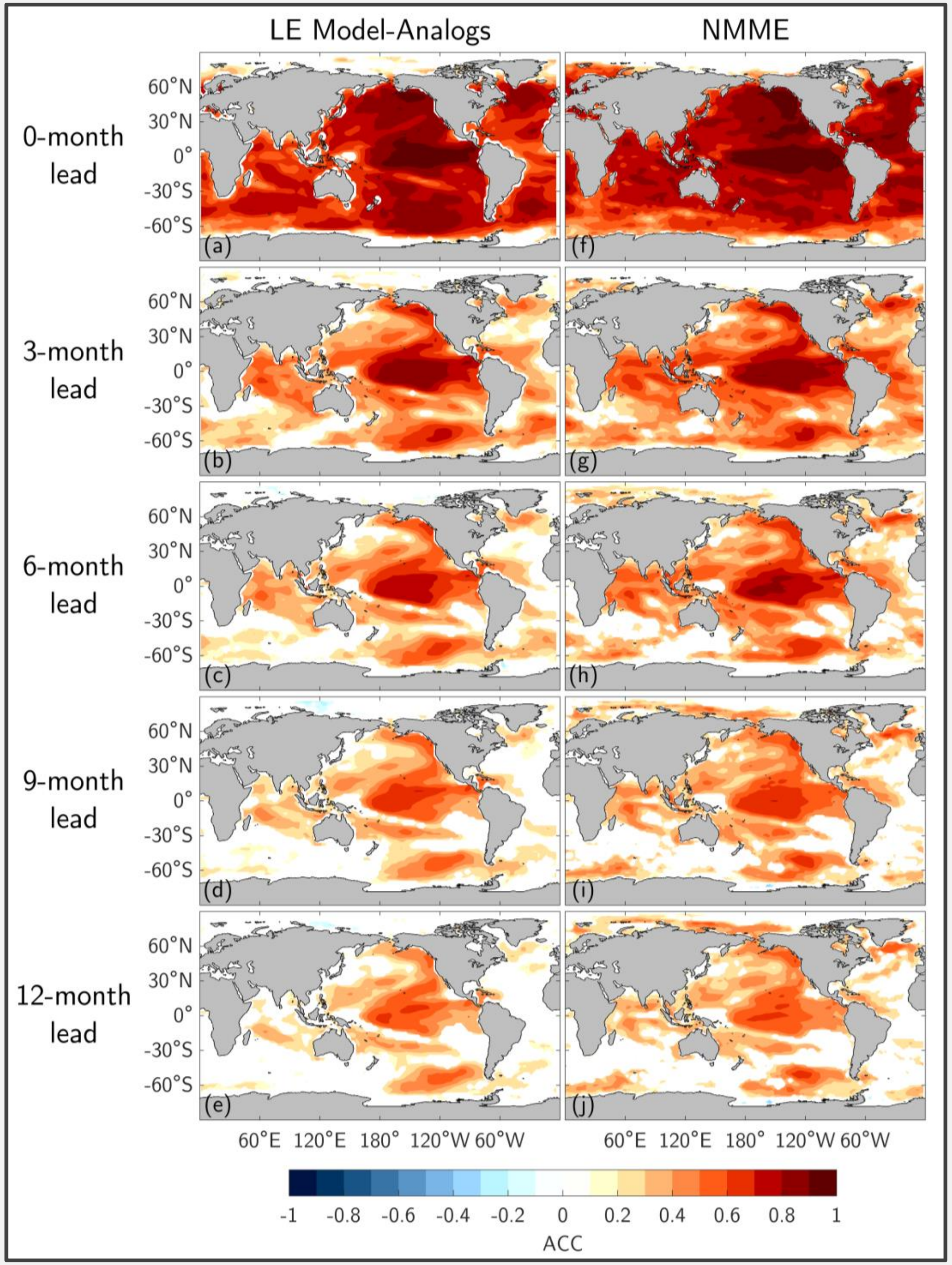
Summary:

- 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.

One more thing…

How well can model large ensembles predict the real world?



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?

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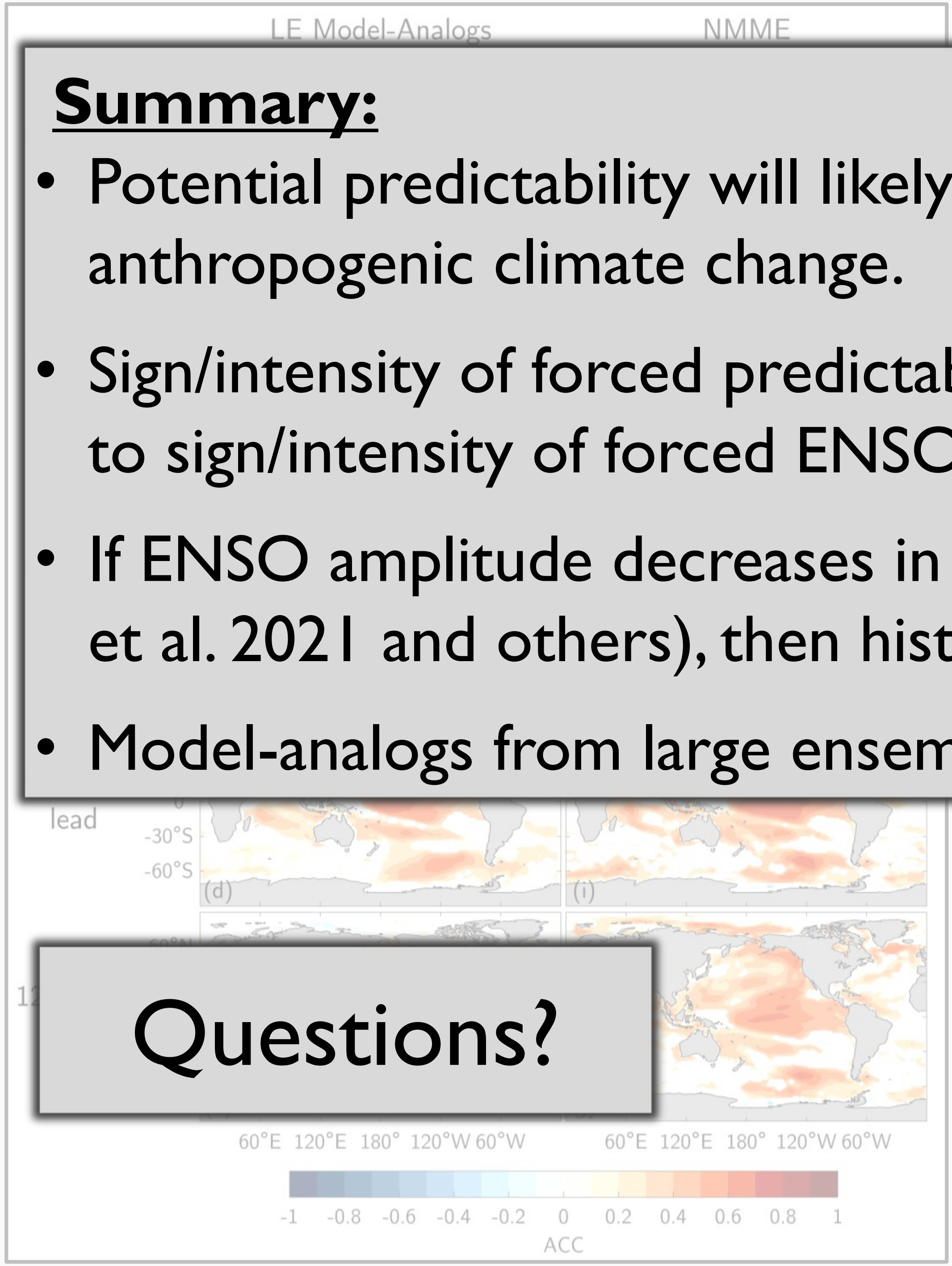
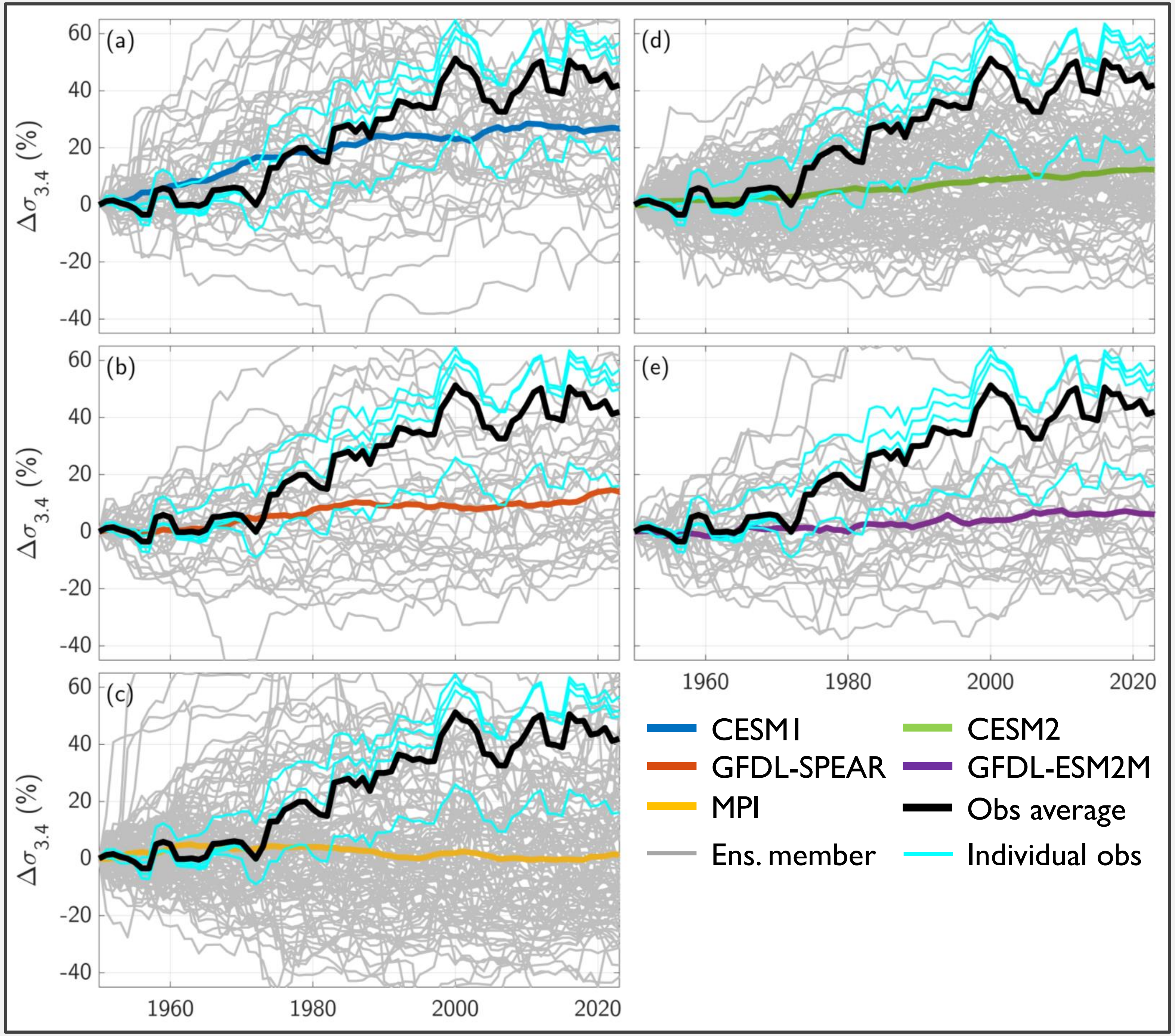


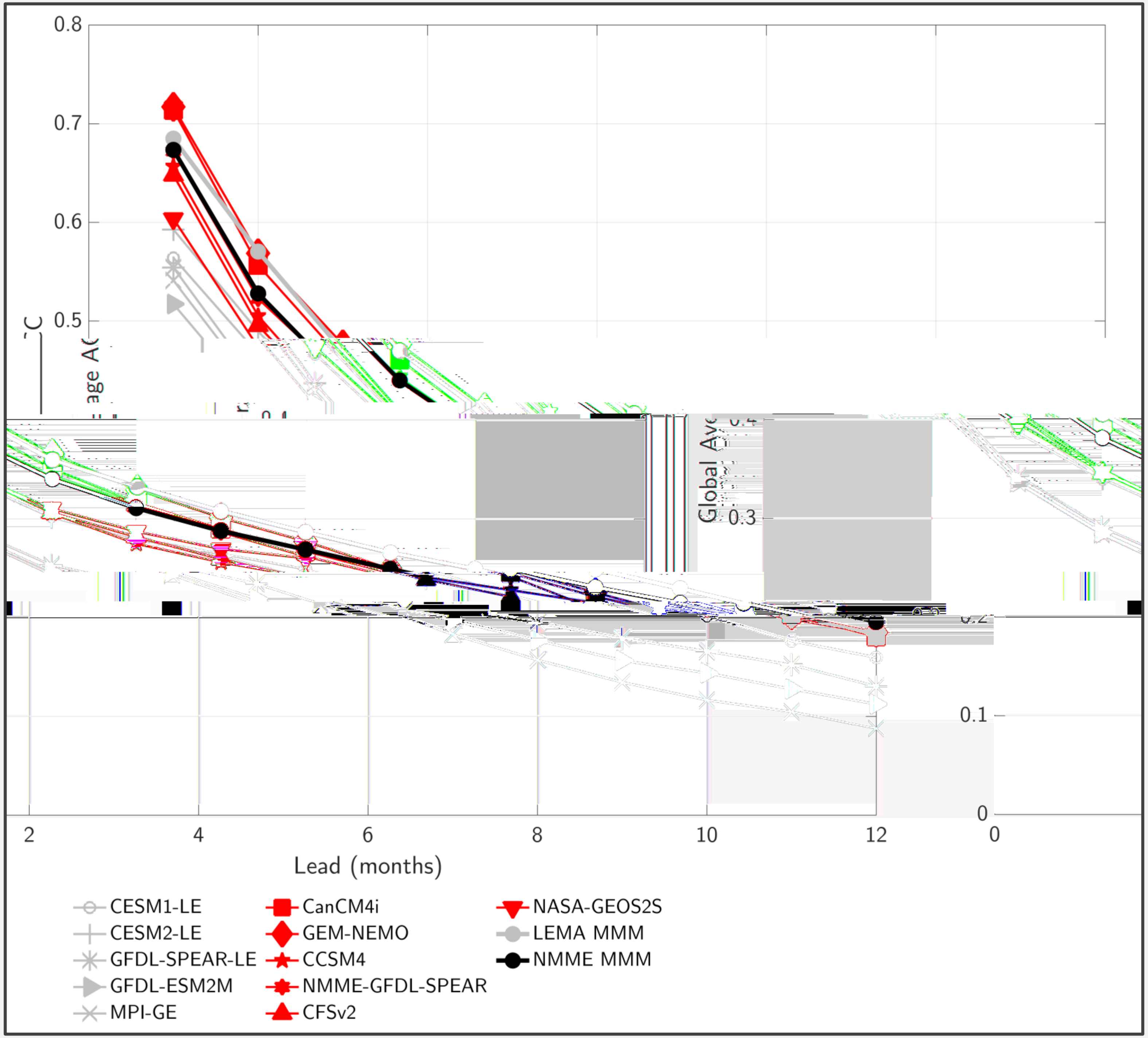
Model-analogs forecasts are as skillful as dynamical forecasting models, at a

Shading: Skill shown where significant with 95% confidence

Extra Slides

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





Global Average ACC
Lead (months)
CESM1-LE
CESM2-LE
GFDL-SPEAR-LE
GFDL-ESM2M
MPI-GE
CanCM4i
GEM-NEMO
CCSM4
NMME-GFDL-SPEAR
CFSv2
NASA-GEOS2S
LEMA MMM
NMME MMM

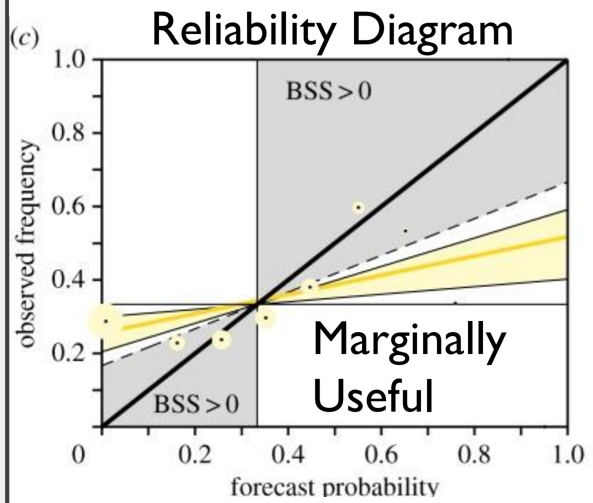
Forecast reliability

<u>Reliability Categories:</u>
Category 5: *Perfect*
Category 4: *Very Useful*
Category 3: *Marginally Useful*
Category 2: *Not Useful*
Category 1: *Dangerously Useless*

Brier Skill Score = BSS

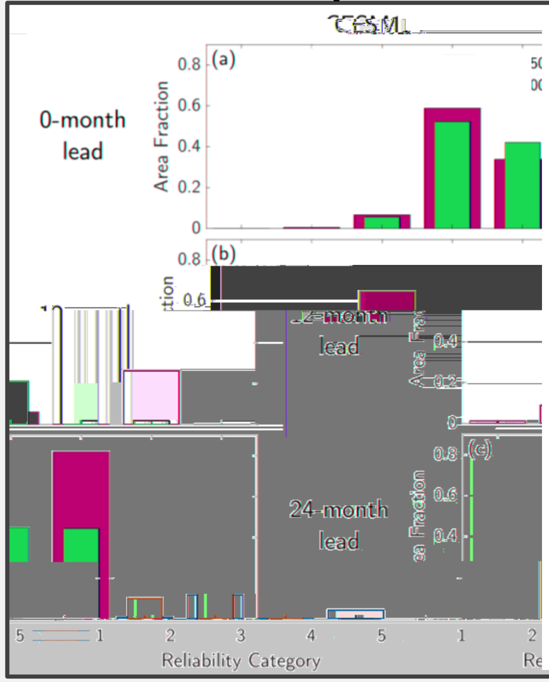
Forecast probability = fraction of forecast members in given tercile

Observed frequency = fraction of timesteps with observed event in tercile



Weisheimer and Palmer (2014)

Surface temperature, upper tercile



Fraction of globe in each category

1921-1950 2071-2100

Reliability Categories:

Category 5: *Perfect*

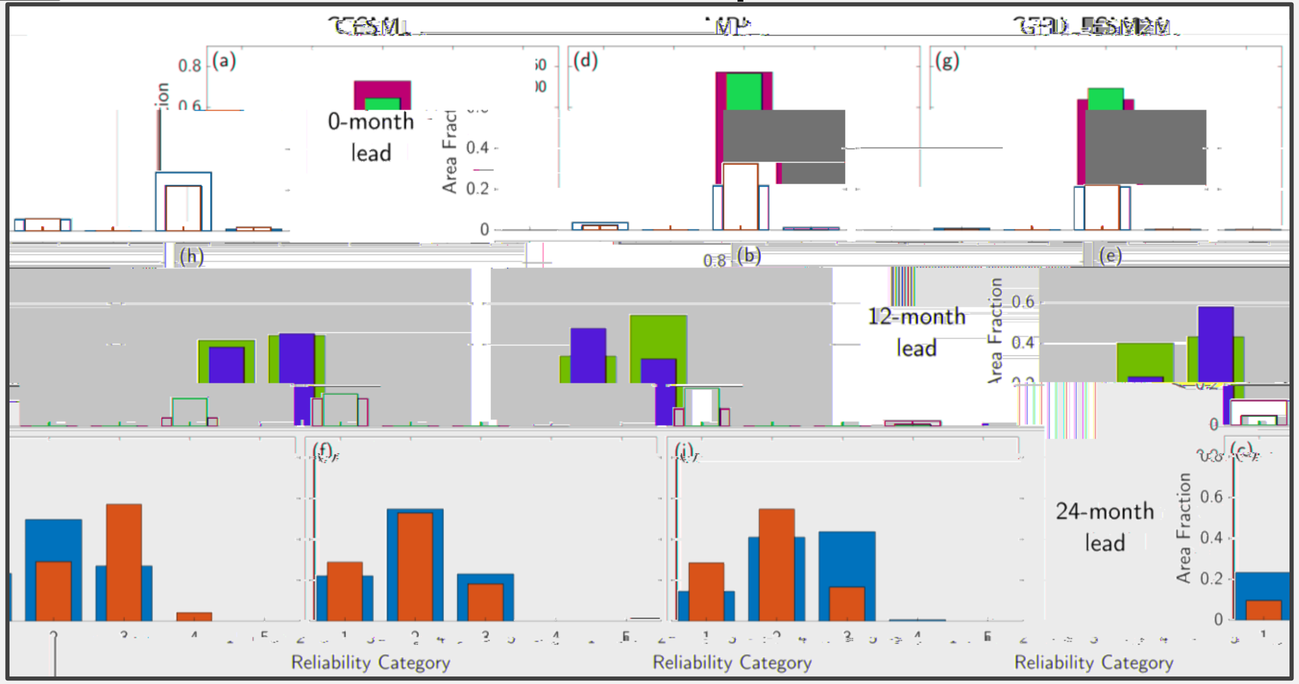
Category 4: *Very Useful*

Category 3: *Marginally Useful*

Category 2: *Not Useful*

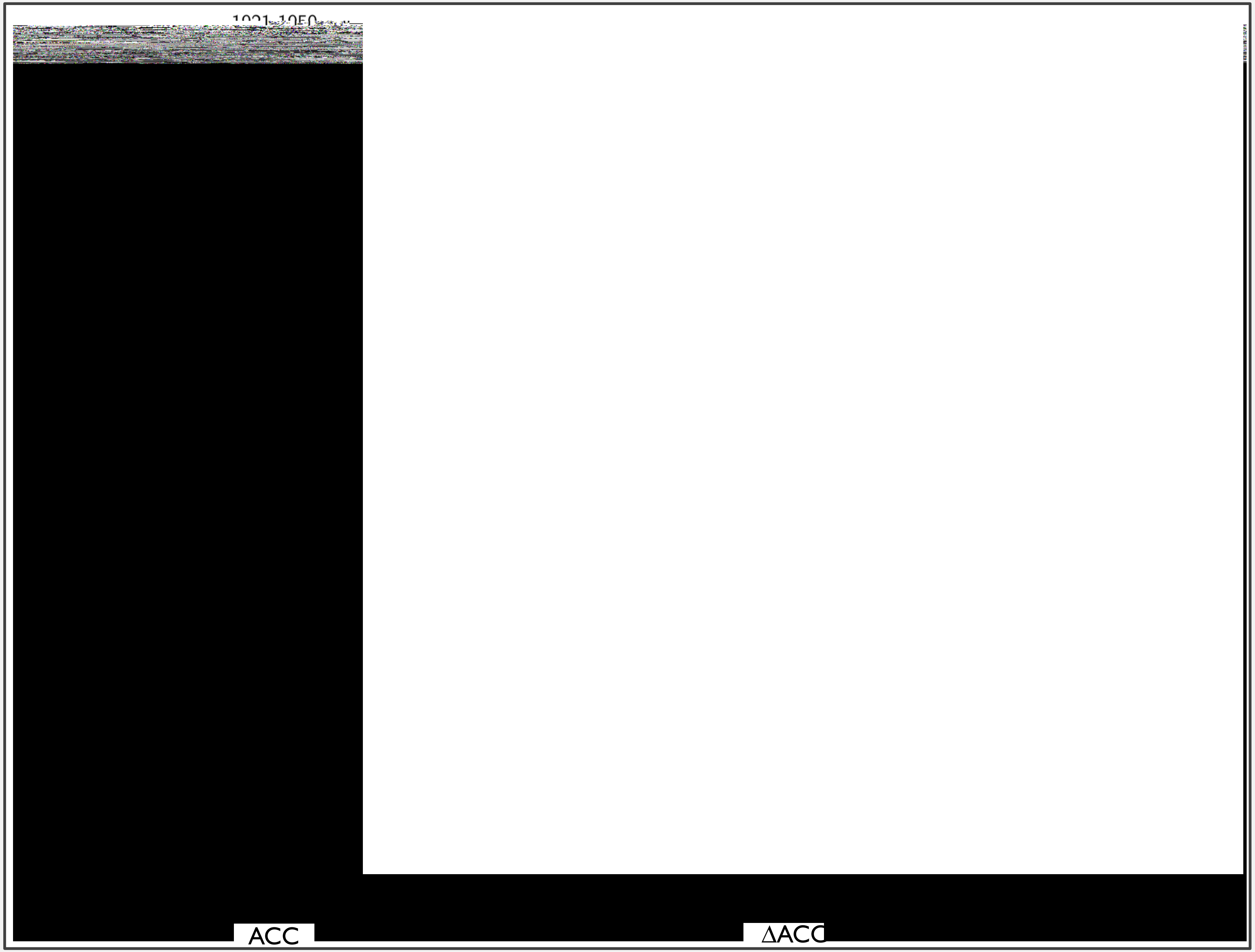
Category 1: *Dangerously Useless*

Precipitation, lower tercile



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

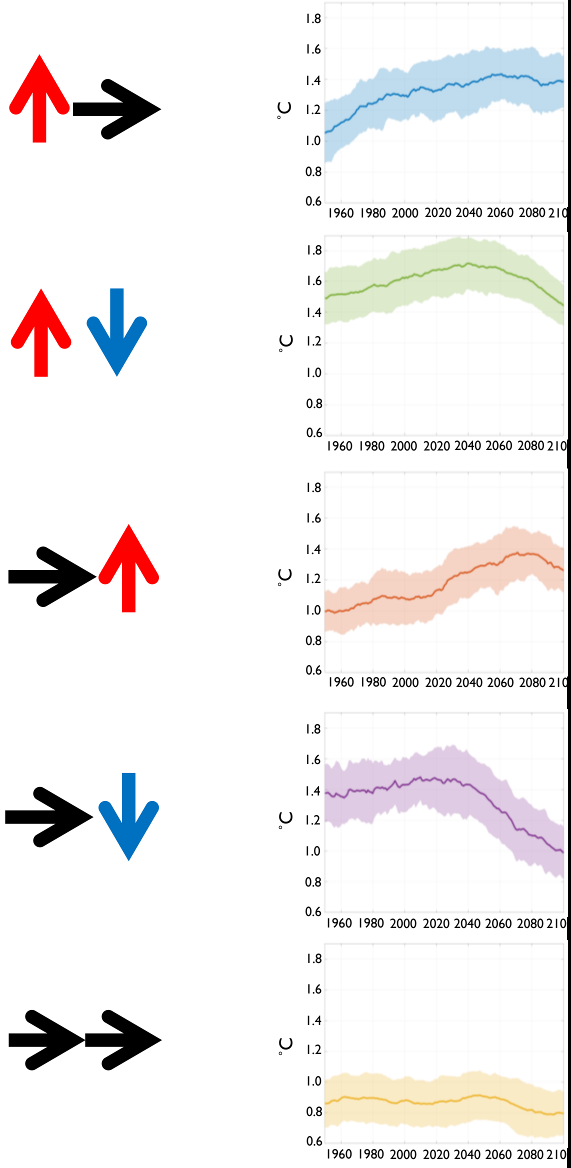
ENSO skill



Shading: Ensemble mean ACC across all months
Stipples: 80% members agree on ΔACC sign

Trend:

DJF Nino3.4 std. dev.



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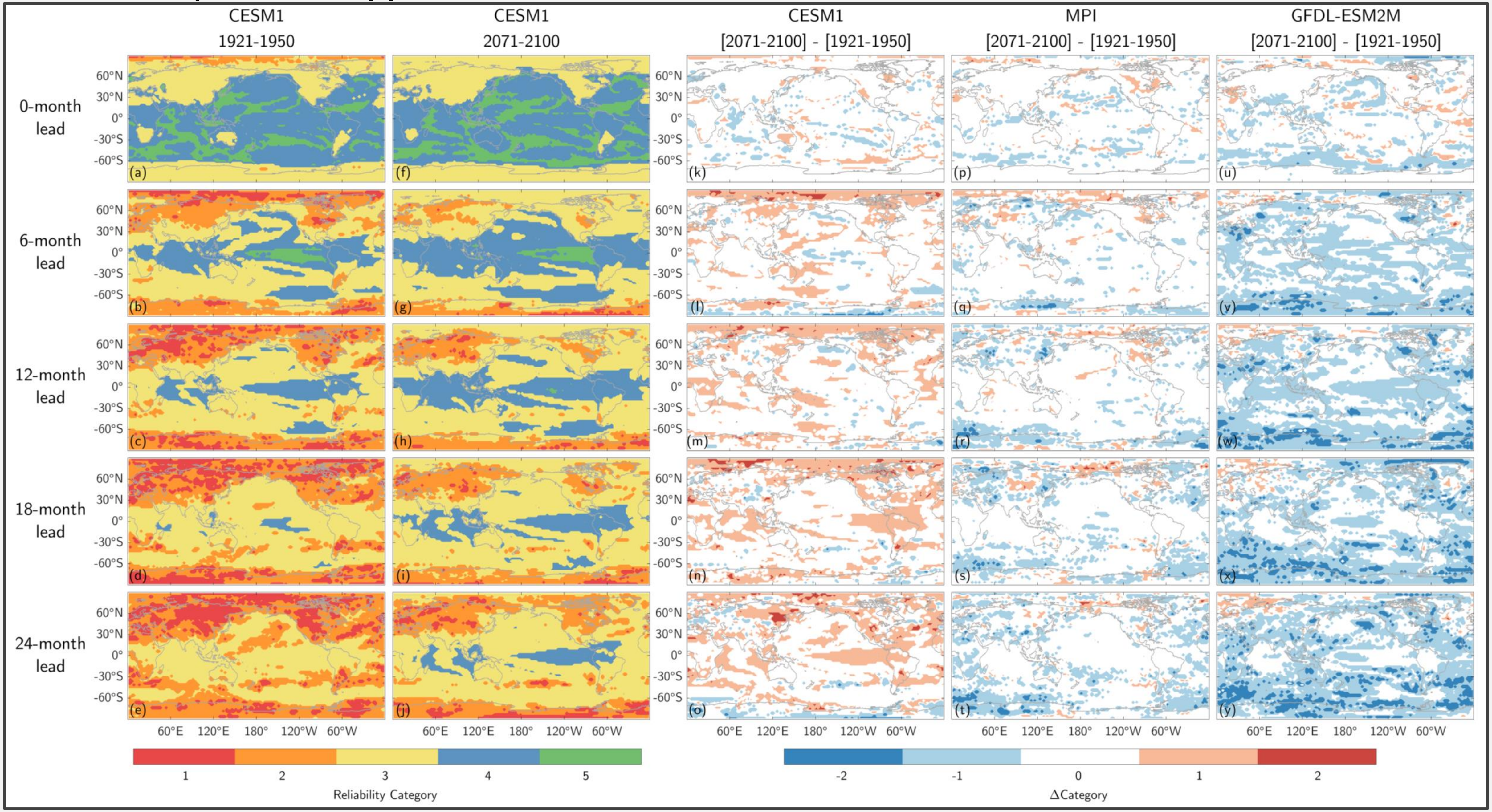
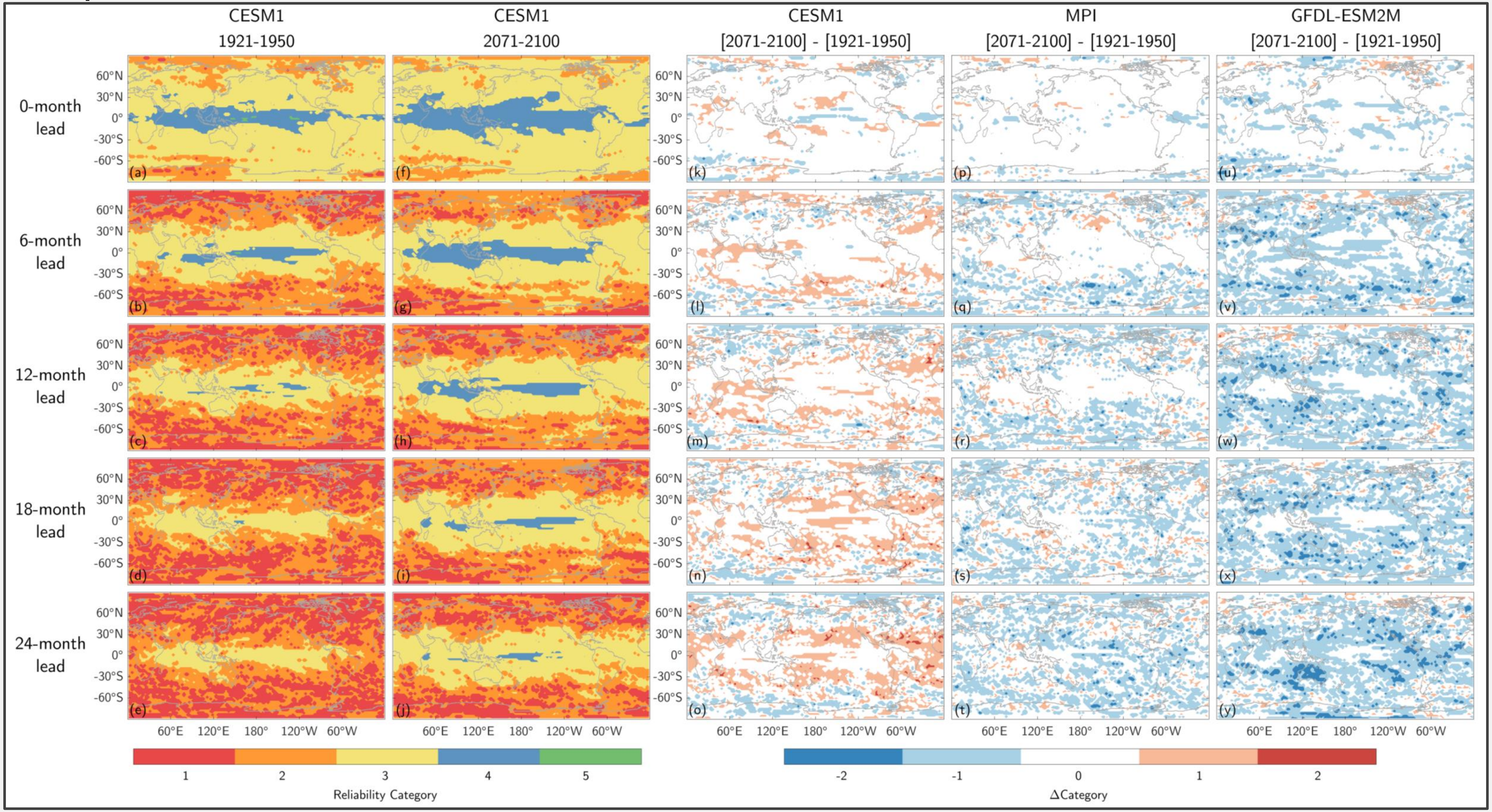
ACC

ΔACC

Surface temperature, upper tercile

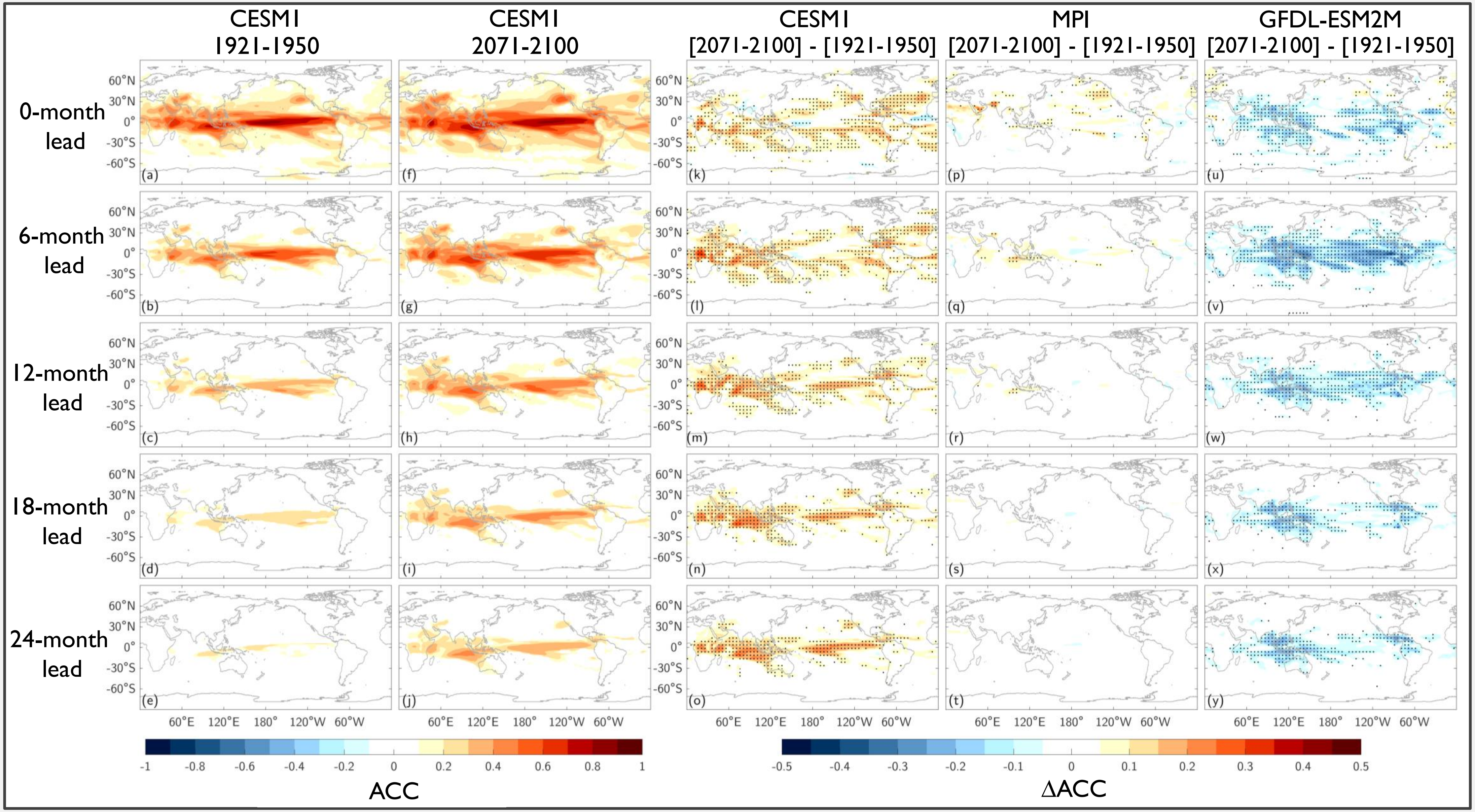


Precipitation, lower tercile



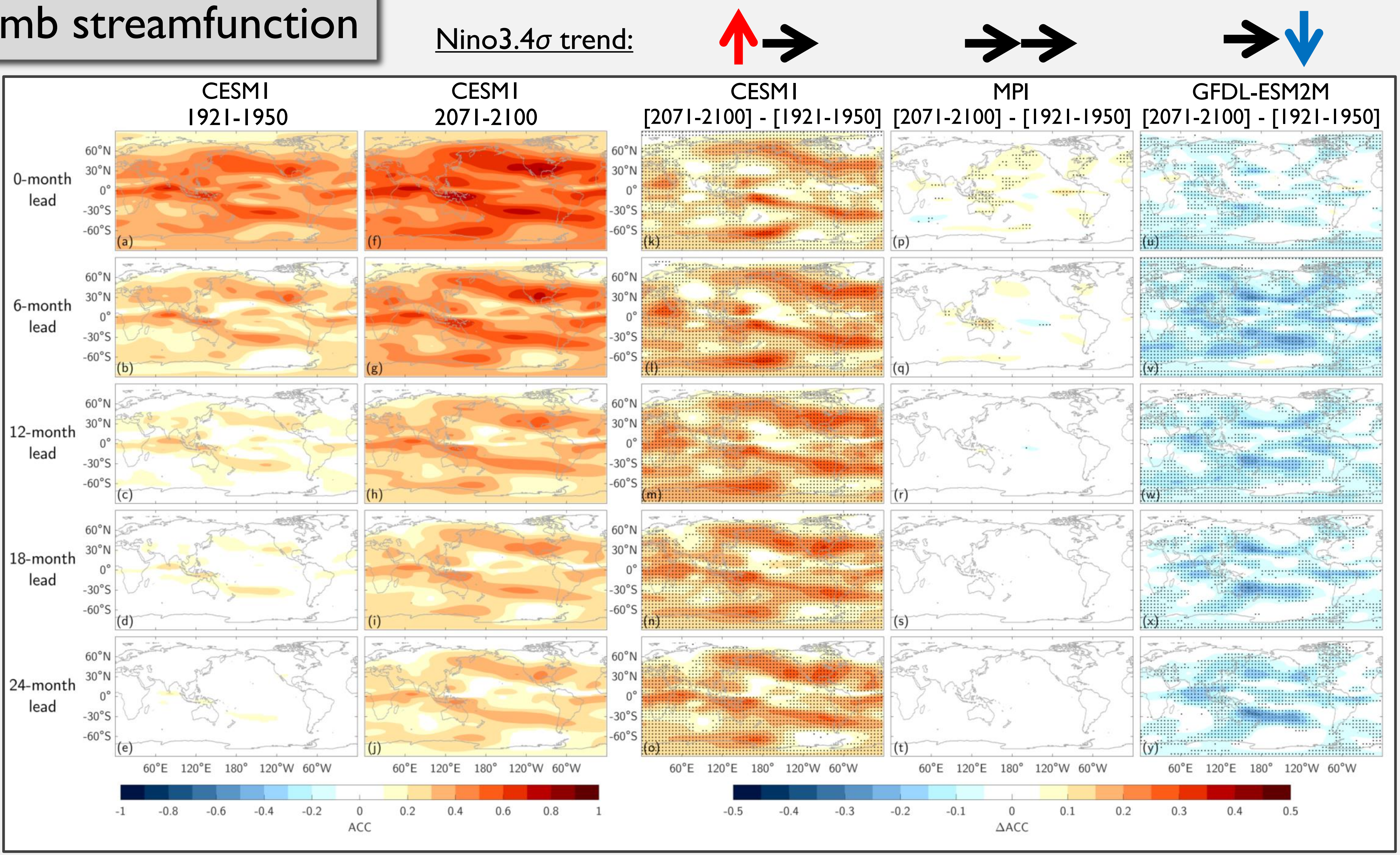
Precipitation

Nino3.4σ trend:

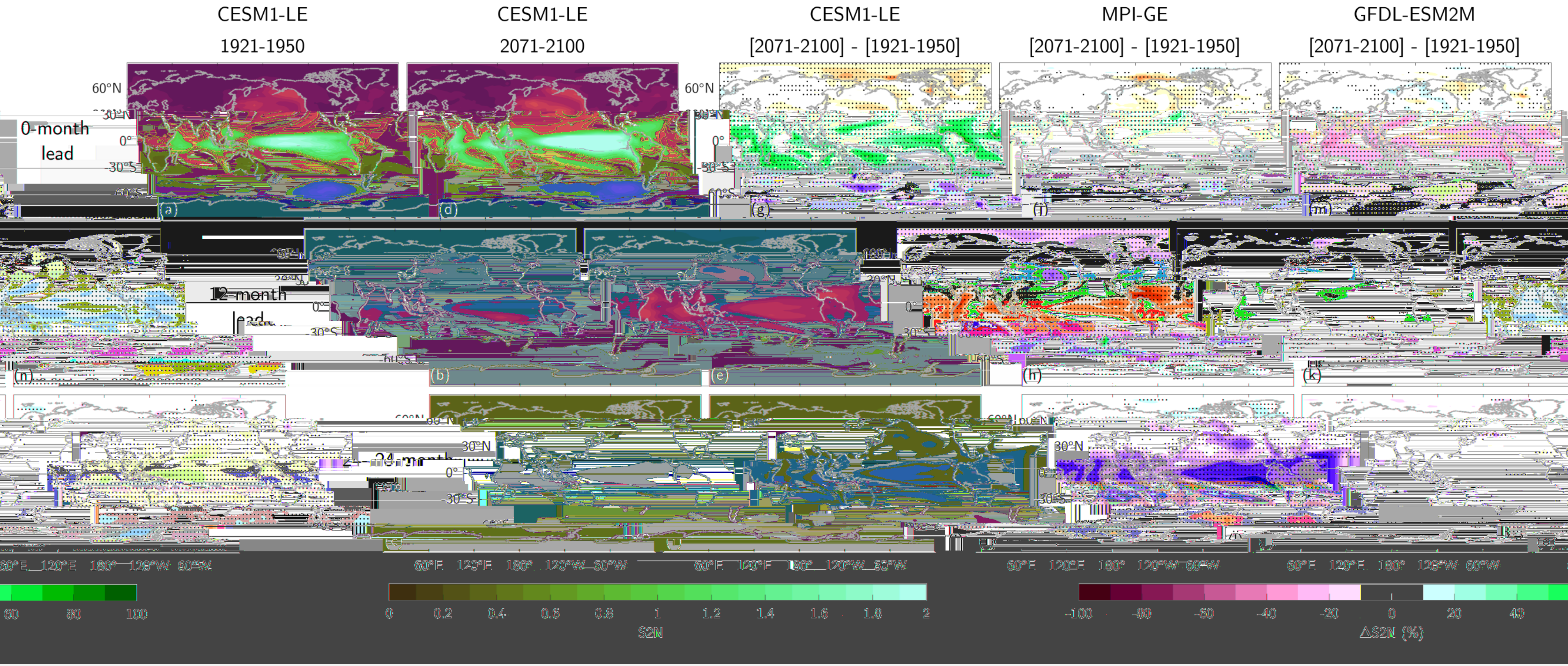


500mb streamfunction

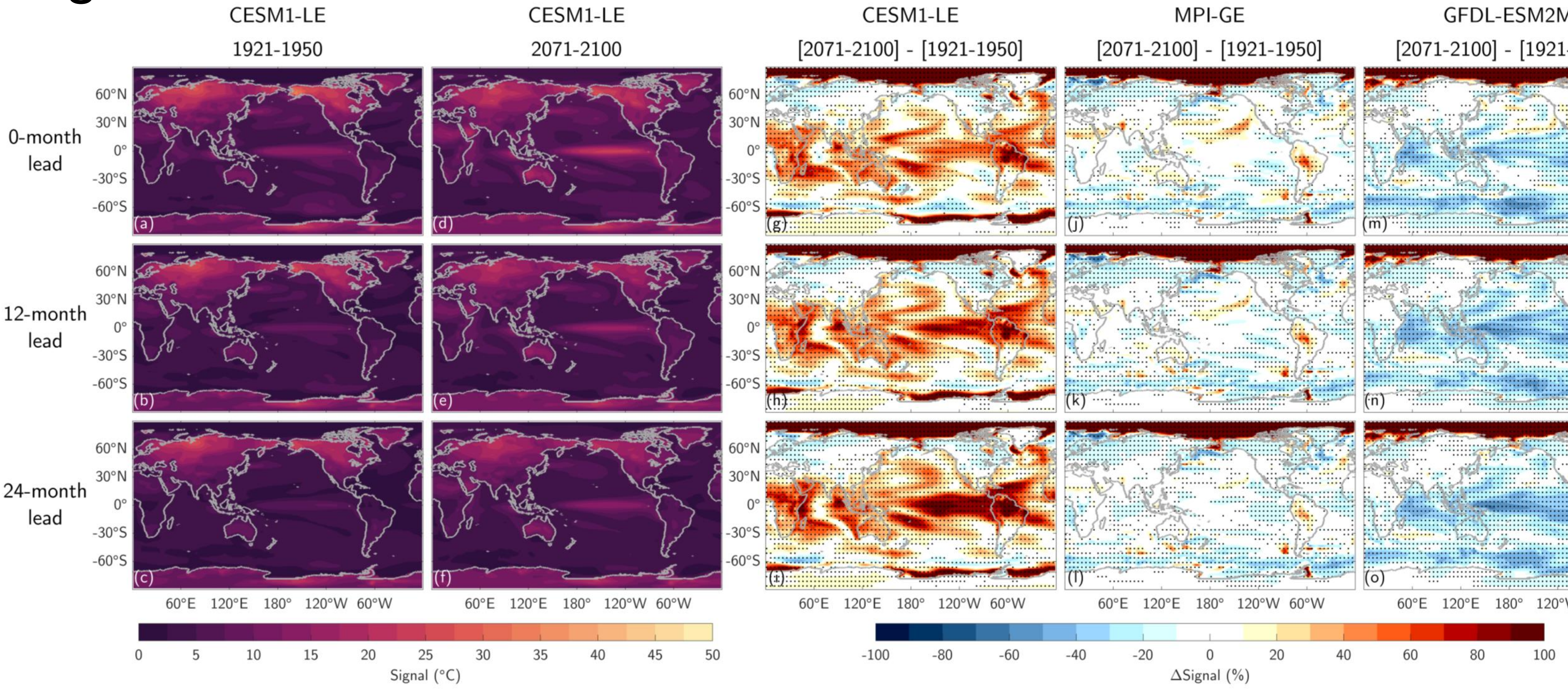
Nino3.4σ trend:



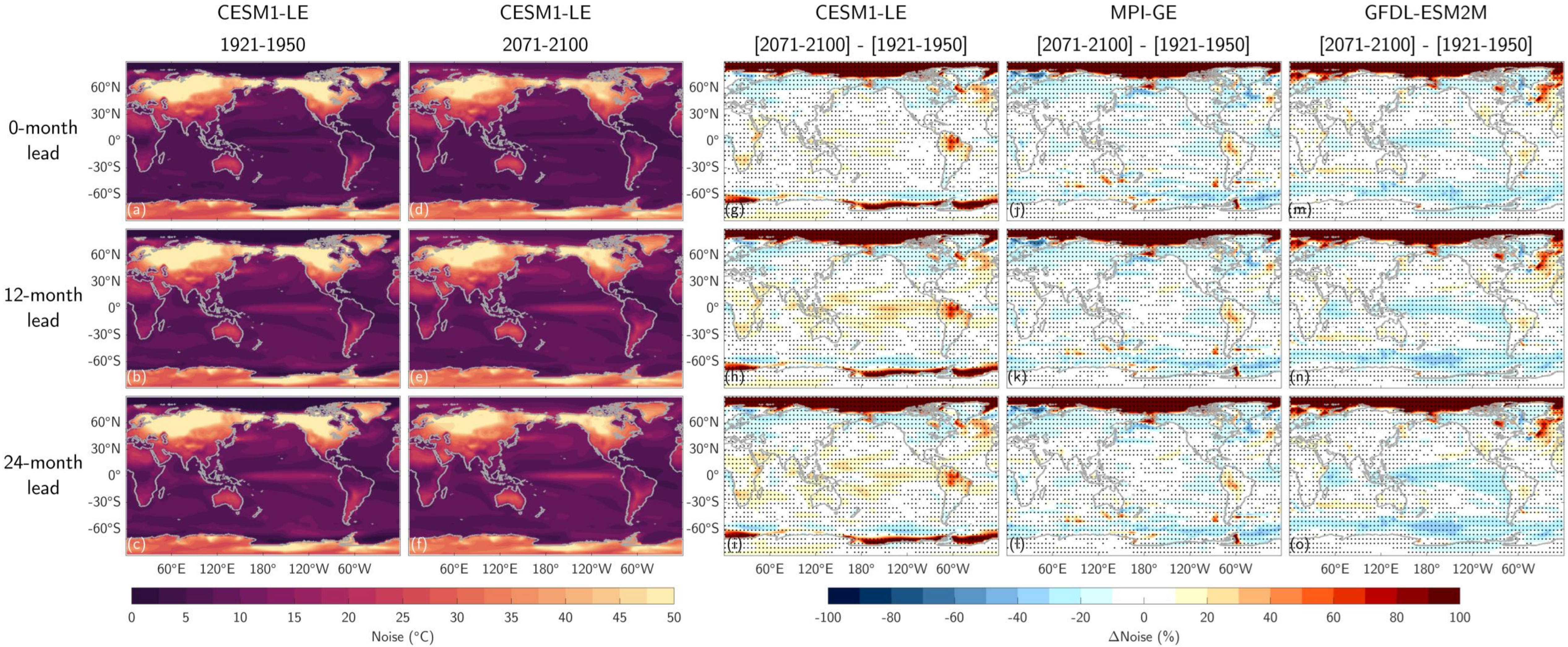
S2N Ratios


CESM1-LE
1921-1950
CESM1-LE
2071-2100
CESM1-LE
[2071-2100] - [1921-1950]
MPI-GE
[2071-2100] - [1921-1950]
GFDL-ESM2M
[2071-2100] - [1921-1950]
0-month
lead
S2N
ΔS2N (%)

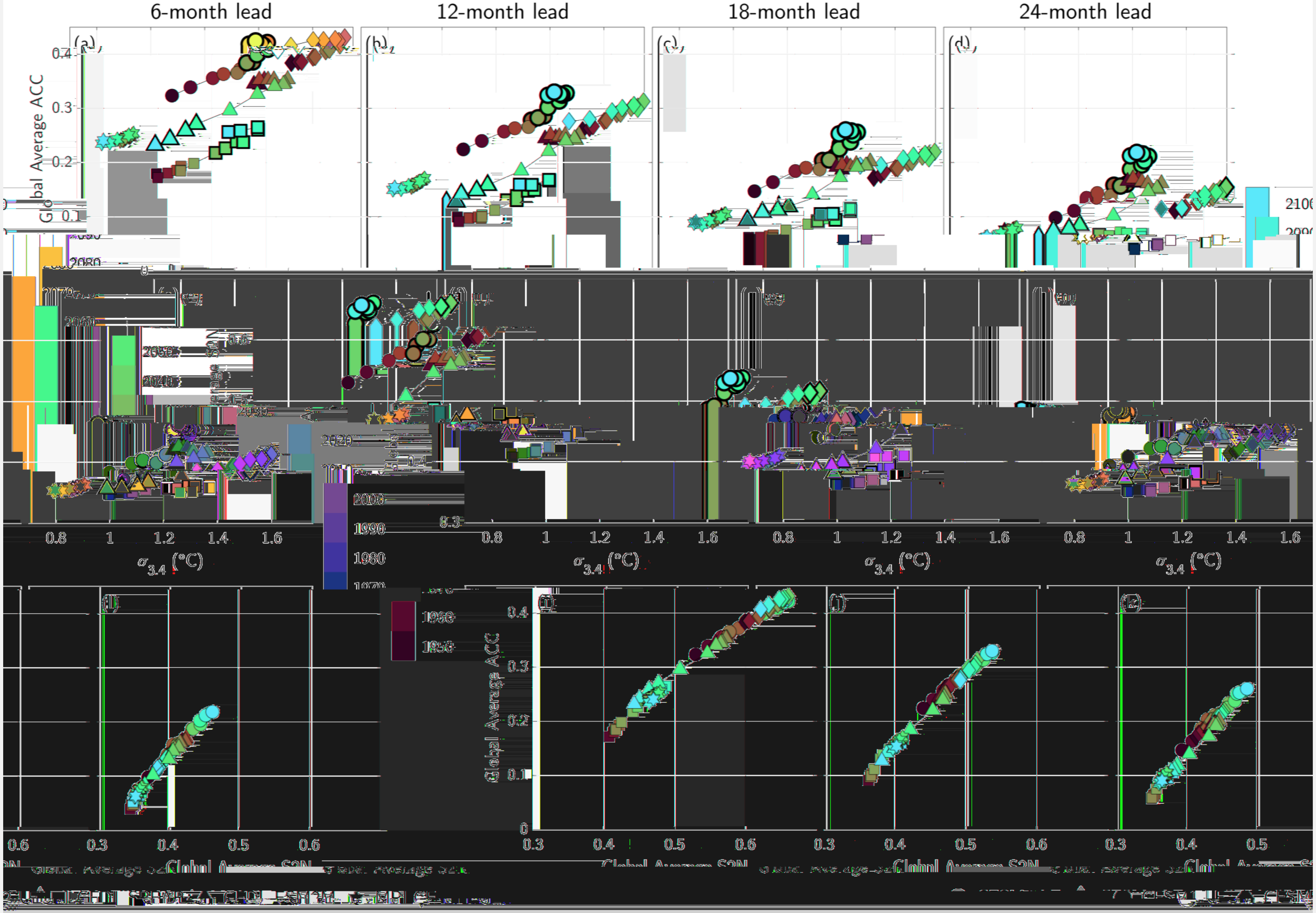
Signal

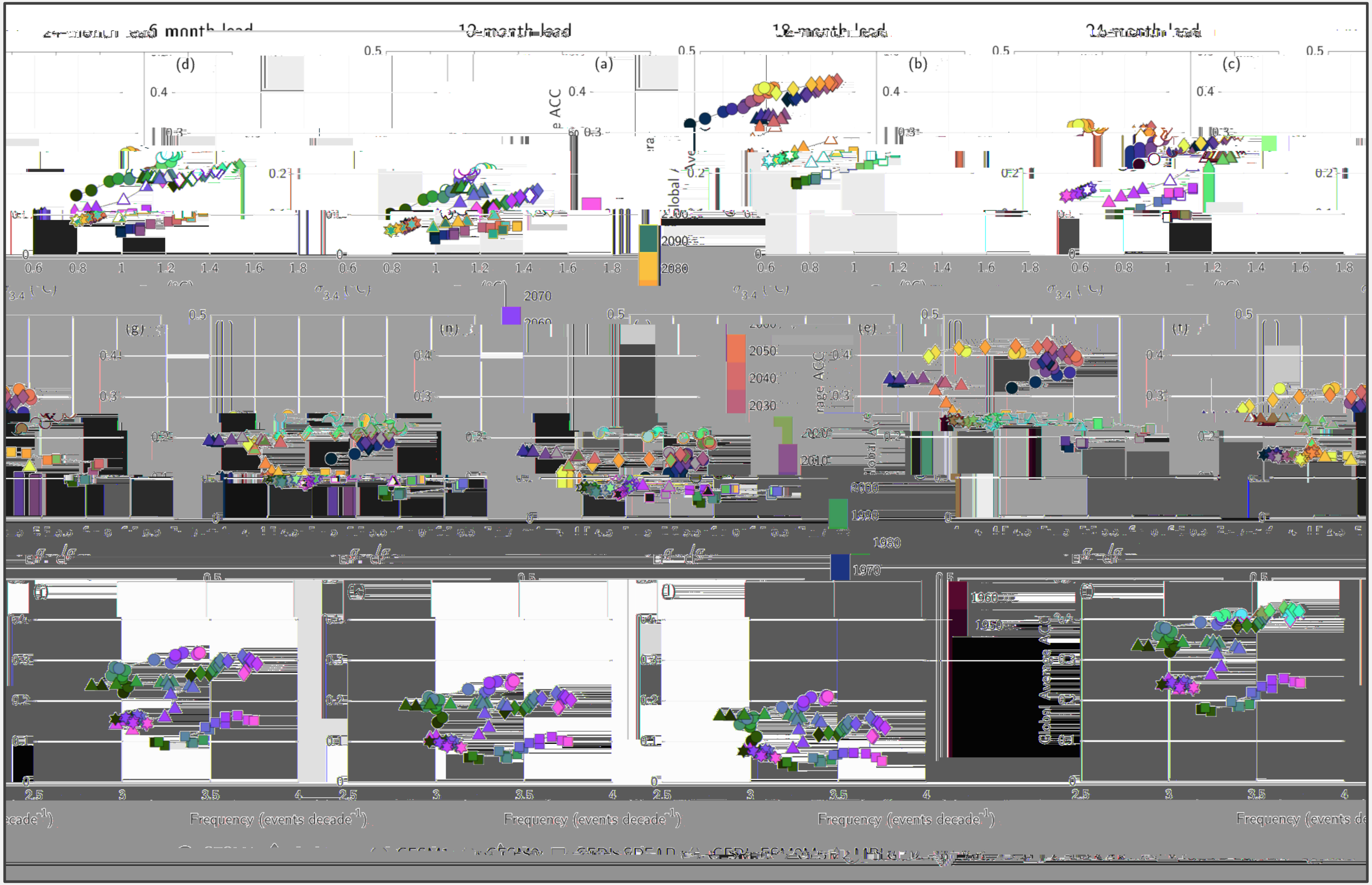

CESM1-LE
1921-1950
CESM1-LE
2071-2100
CESM1-LE
[2071-2100] - [1921-1950]
MPI-GE
[2071-2100] - [1921-1950]
GFDL-ESM2M
[2071-2100] - [1921-1950]
0-month lead
12-month lead
24-month lead
60°N
30°N
0°
-30°S
-60°S
60°E 120°E 180° 120°W 60°W
(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l) (m) (n) (o)
0 5 10 15 20 25 30 35 40 45 50
Signal (°C)
-100 -80 -60 -40 -20 0 20 40 60 80 100
ΔSignal (%)

Noise



CESM1-LE
1921-1950
CESM1-LE
2071-2100
CESM1-LE
[2071-2100] - [1921-1950]
MPI-GE
[2071-2100] - [1921-1950]
GFDL-ESM2M
[2071-2100] - [1921-1950]
0-month lead
12-month lead
24-month lead
60°N
30°N
0°
-30°S
-60°S
60°E
120°E
180°
120°W
60°W
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)
(j)
(k)
(l)
(m)
(n)
(o)
0
5
10
15
20
25
30
35
40
45
50
Noise (°C)
-100
-80
-60
-40
-20
0
20
40
60
80
100
ΔNoise (%)


6-month lead
12-month lead
18-month lead
24-month lead
(a)
(b)
(c)
(d)
Global Average ACC
0.4
0.3
0.2
0.1
0.8
1
1.2
1.4
1.6
0.3
0.4
0.5
0.6
2100
2080
2060
2050
2040
2030
2020
2000
1990
1980
1960
1950



6-month lead
12-month lead
18-month lead
24-month lead
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
Global Average ACC
Frequency (events decade-1)

ΔACC relative to 1921-1950, averaged in Nino3.4