

WGSIP Prediction Capabilities Project: Temperature trends

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WGSIP 22

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WORLD
METEOROLOGICAL
ORGANIZATION



United Nations
Educational, Scientific and
Cultural Organization



Intergovernmental
Oceanographic
Commission



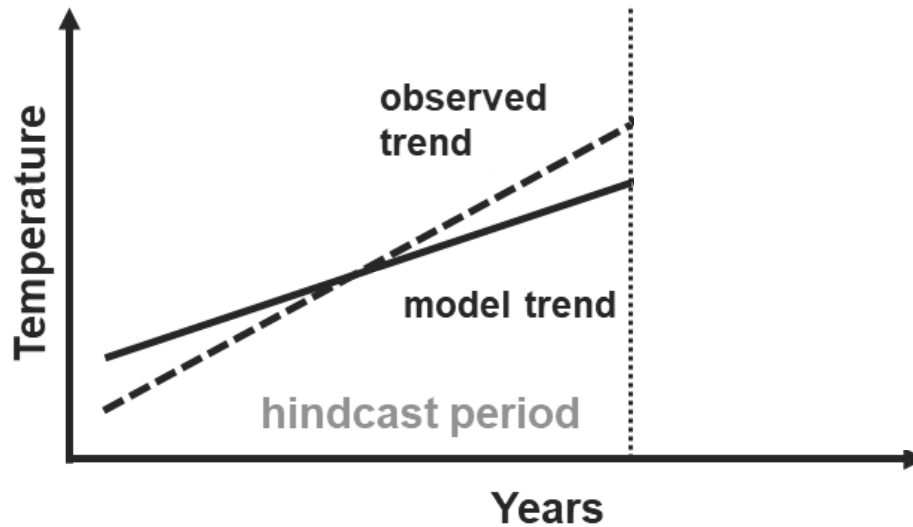
International
Science Council



World Climate Research Programme

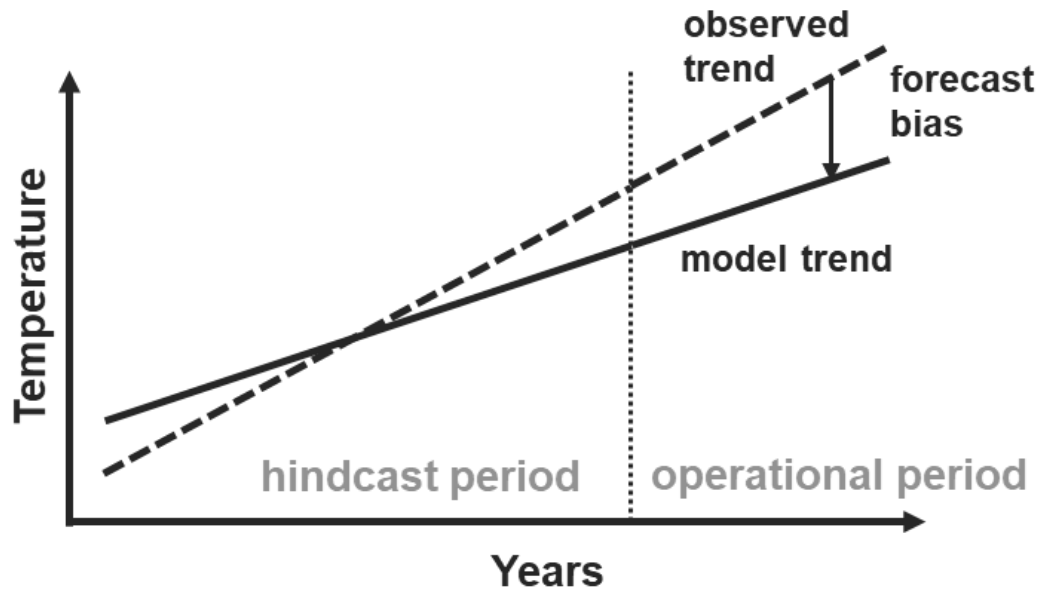
Overview

- Differing treatments of radiative forcings in NWP and climate model-derived prediction systems, along with differing initialization methodologies, may cause long-term temperature trends to deviate from observed.
- Prediction systems may thus systematically over- or under-estimate temperatures in operational forecasts, even after mean biases during the hindcast period have been removed:



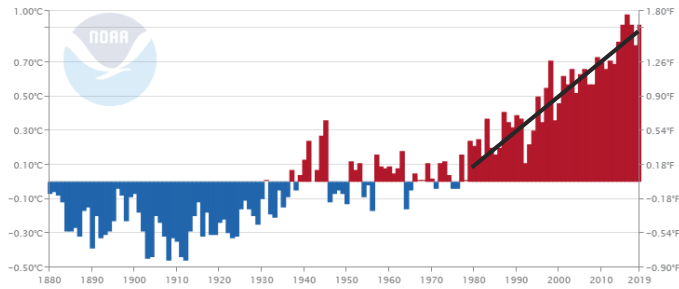
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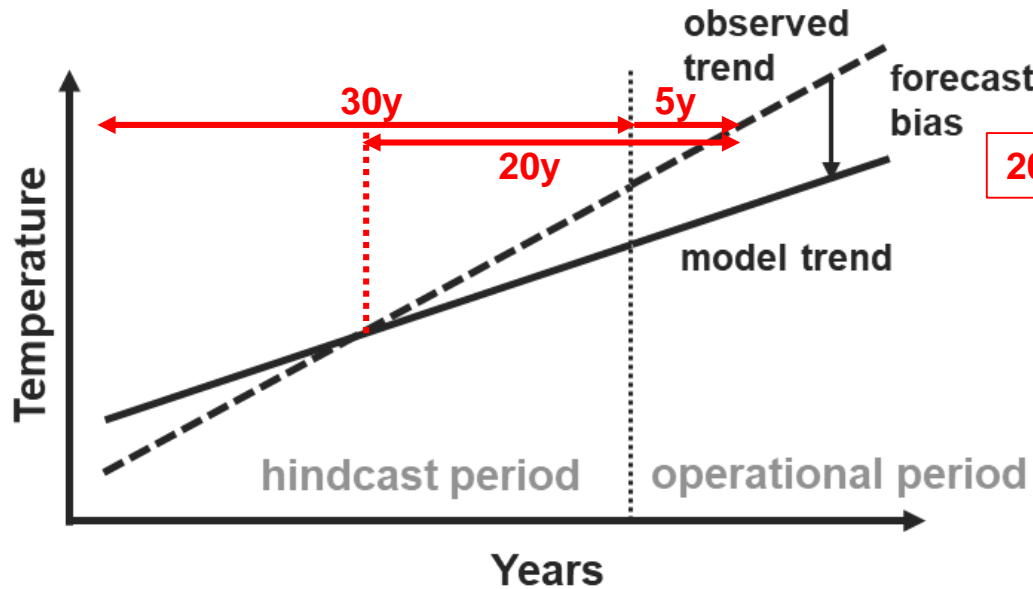


Magnitude of deterministic biases

Global Land and Ocean
August Temperature Anomalies



→ Global temperature trend since 1980 $\sim 0.2^\circ\text{C}/\text{decade}$
($\sim 0.3^\circ\text{C}/\text{decade}$ over land)



Probabilistic forecast Impact: Example

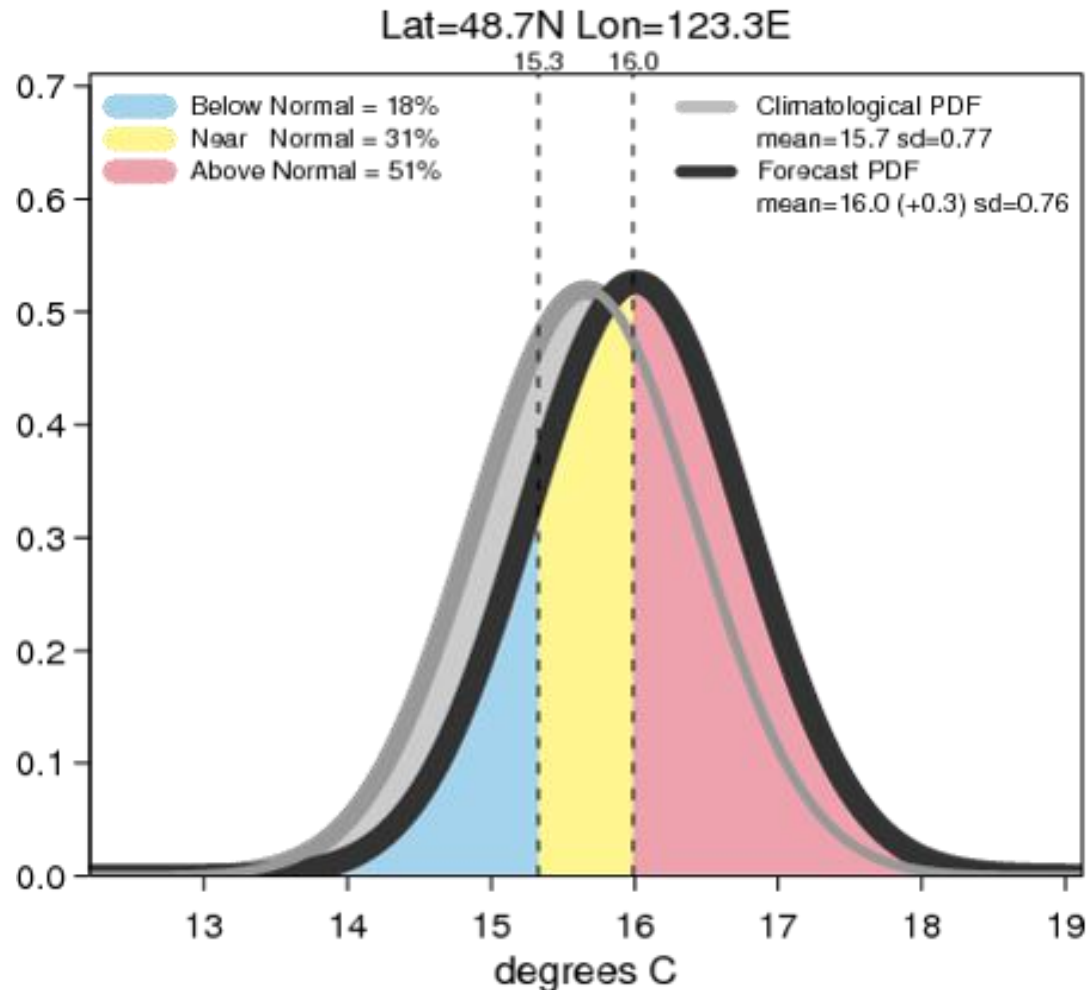
Tercile temperature
forecast for Victoria →

$$\sigma_{\text{clim}} = 0.77^{\circ}\text{C}$$

$$\sigma_{\text{fcst}} = 0.76^{\circ}\text{C}$$

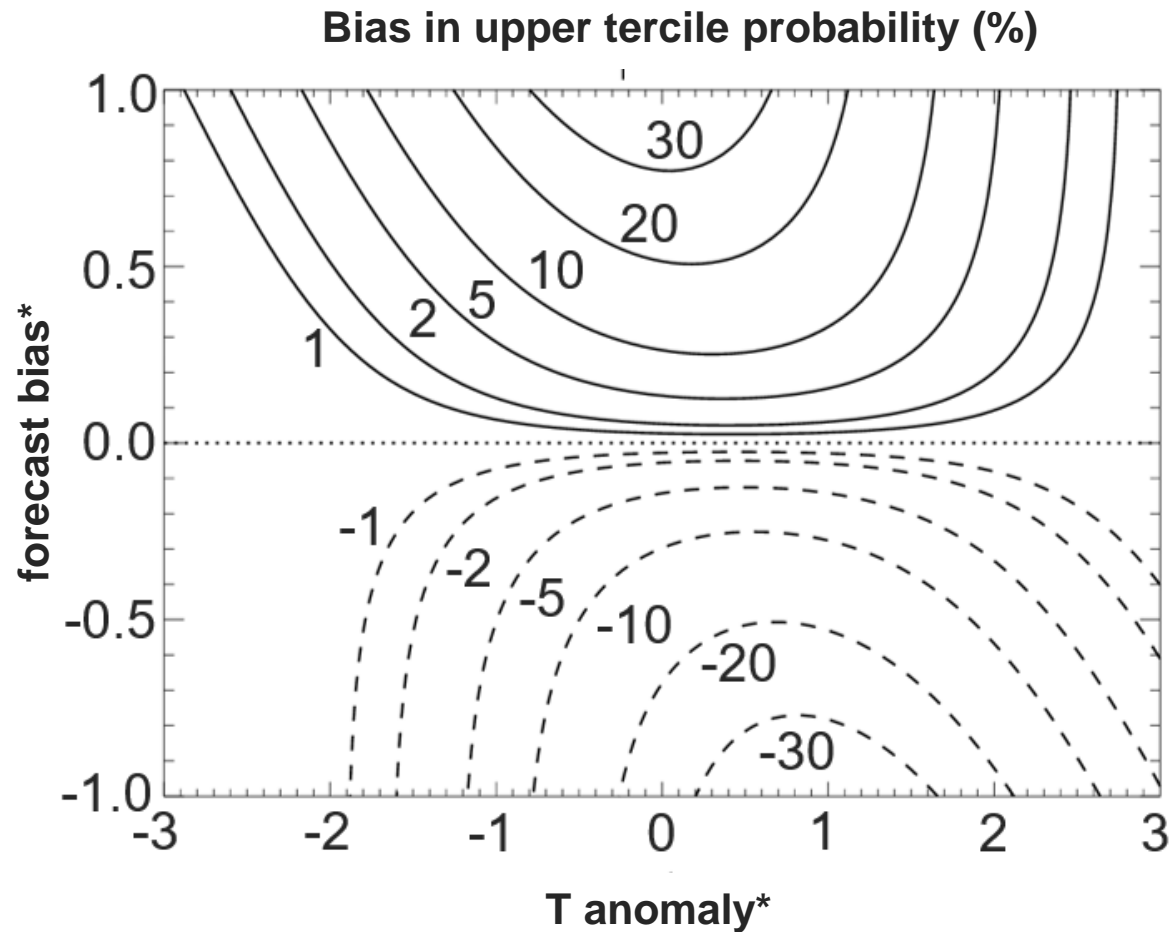
deterministic
anomaly = 0.30°C
 $\approx 0.39 \sigma_{\text{clim}}$

→ examine impact of
under-/overestimation
of trend on tercile
probabilities



Probabilistic forecast impact: Example

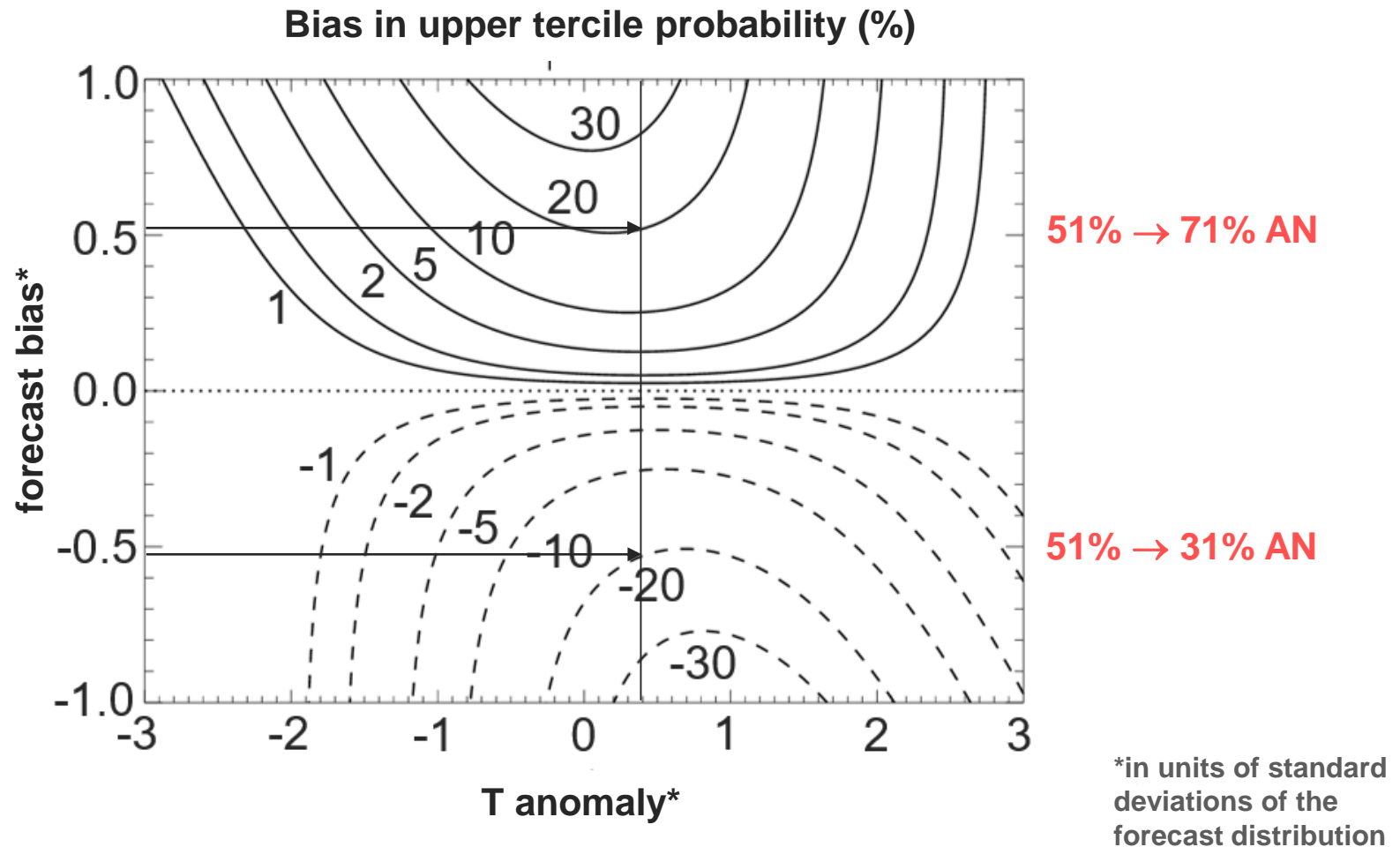
Analytical result based on Gaussian statistics



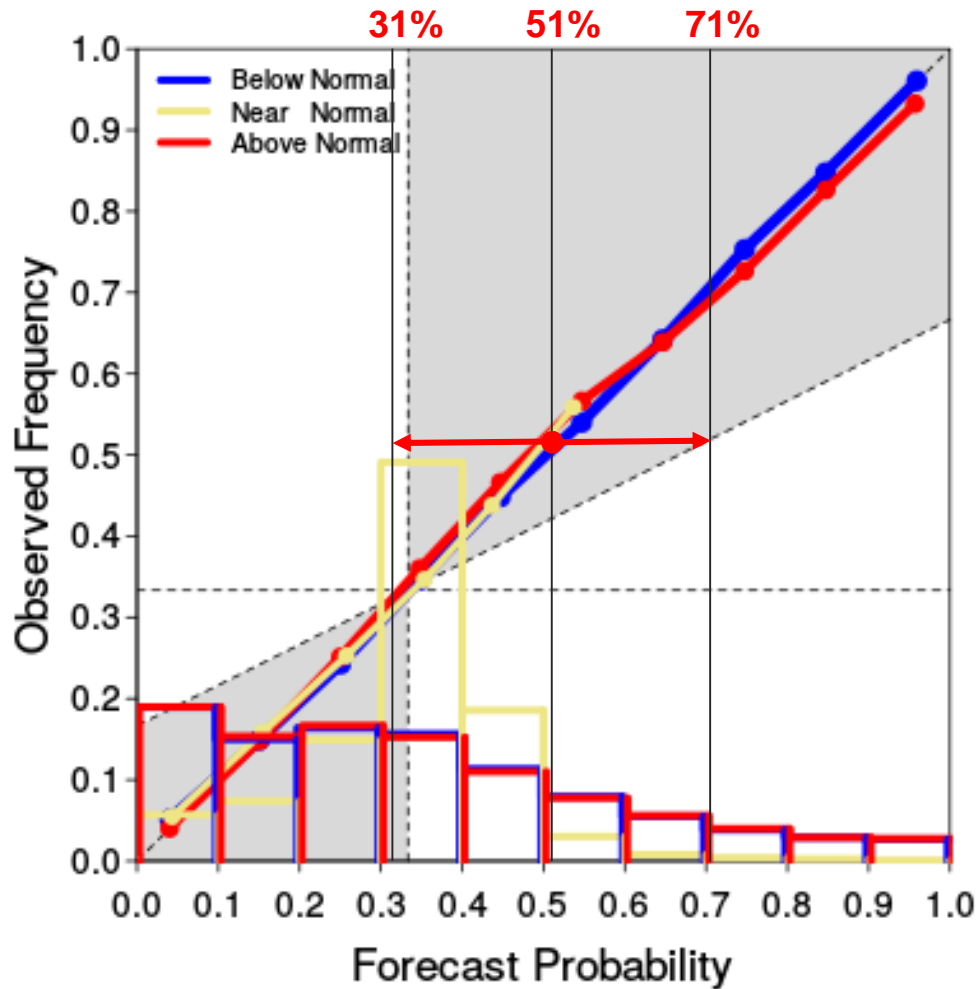
*in units of standard deviations of the forecast distribution

Probabilistic forecast impact: Example

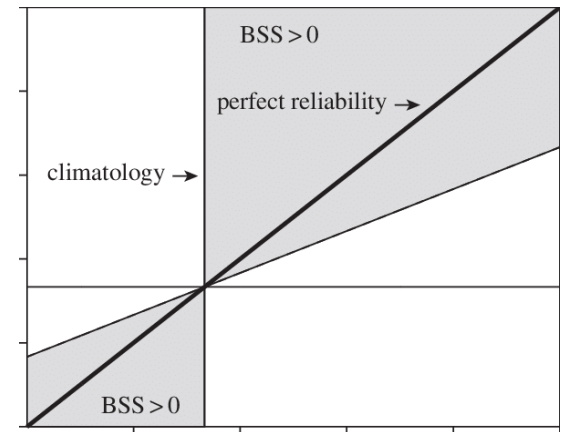
Analytical result based on Gaussian statistics



Probabilistic forecast impact: Example



Perfect reliability → no skill!



Weisheimer and Palmer (2014)

Results from seasonal hindcasts

Consider seasonal hindcasts from

- DEMETER (7 models)
- ENSEMBLES (6 models)
- CHFP (11 models)
- ACCESS-S (GPC Melbourne)

For each model, evaluate differences from observed trends, considering

- 3 observational products (HadCRUT, NOAA, Berkeley)
- as functions of initial month and lead time
- global, land, ocean
- for available hindcast periods

DEMETER and ENSEMBLES

- Global trends in °C/decade
- August initialization (e.g.)
- 1980-2001 (DEMETER), 1981-2005 (ENSEMBLES)

Observed:

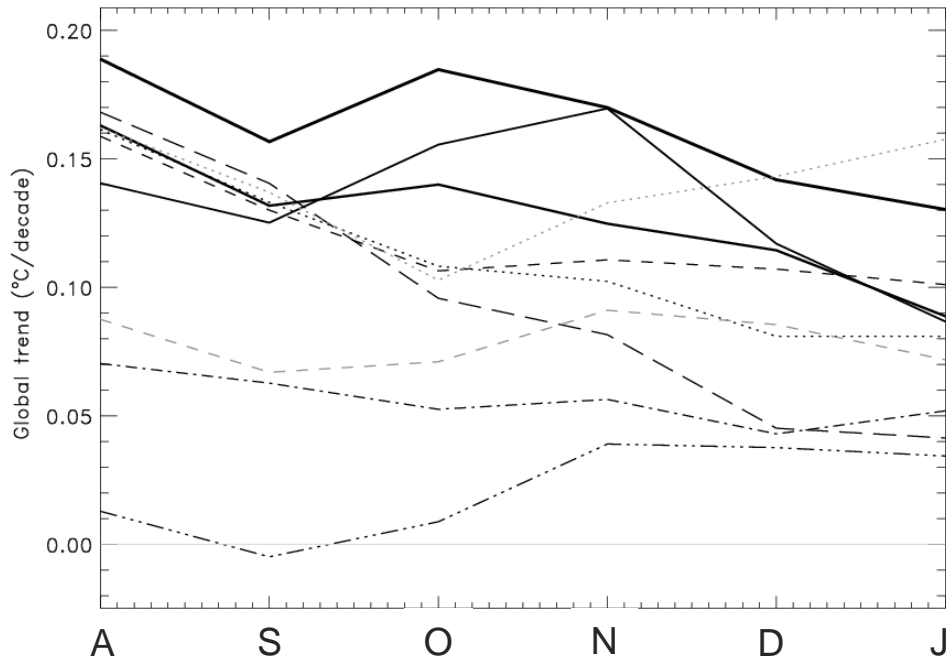
— HadCRUT

— NOAA

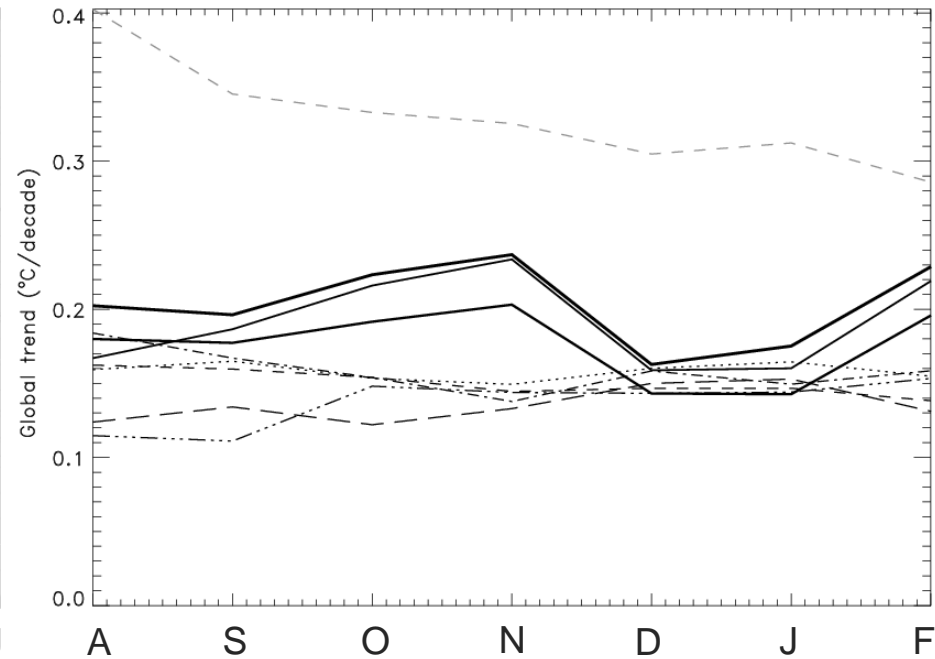
— Berkeley

Other line types: Models

DEMETER models initial month=08 1980-2001



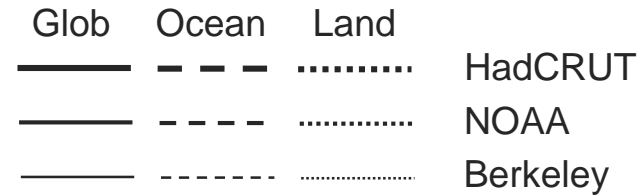
ENSEMBLES models initial month=08 1981-2005



→ most systems underestimate by up to 0.2 °C/decade, one overestimates

CHFP

- Trend differences in °C/decade
- Consider common 1981-2020 hindcast period



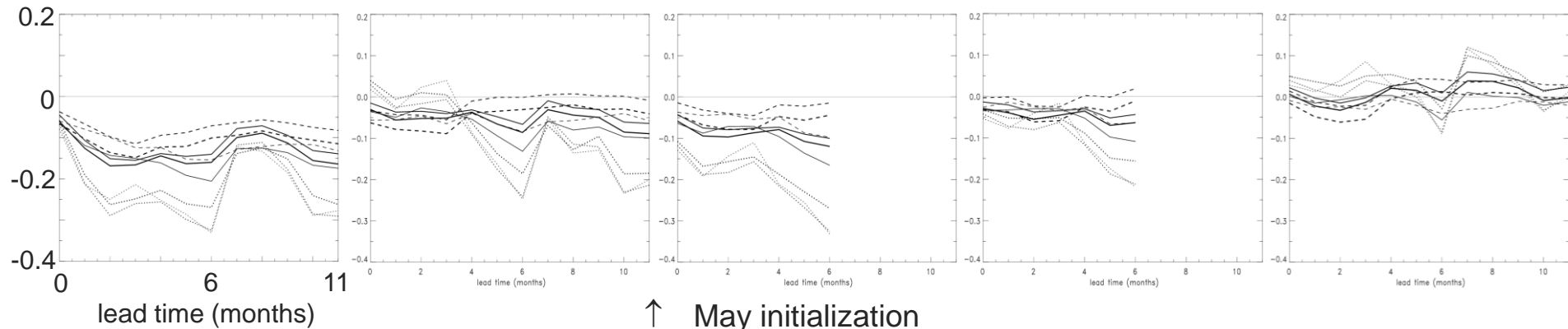
CCCma-CanCM3

CCCma-CanCM4

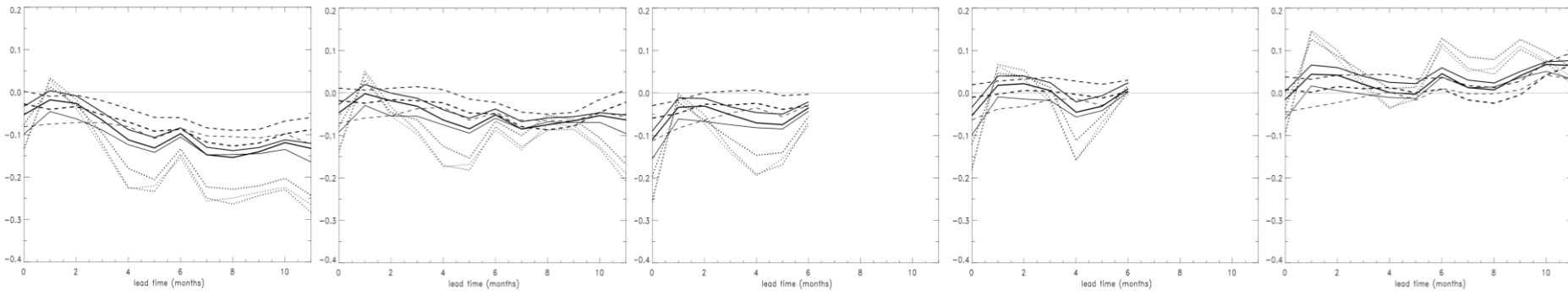
JMAMRI-CGCM1

JMAMRI-CGCM2

MIROC5-v1.0

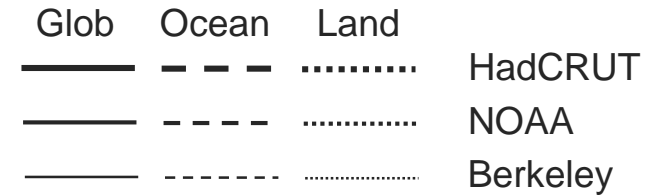


↑ May initialization
↓ Dec initialization

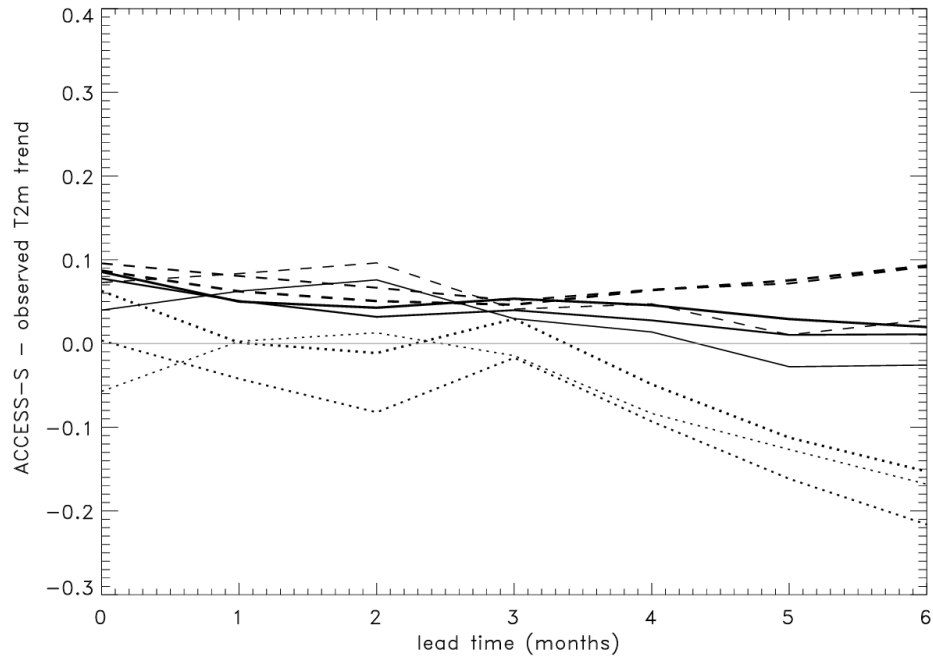


ACCESS-S

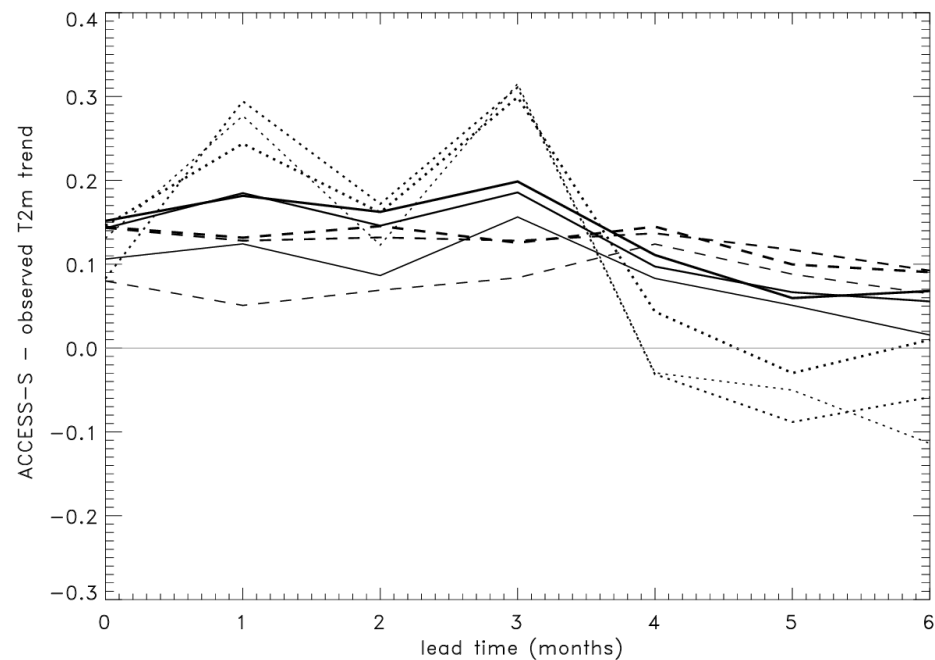
- Current GPC-Melbourne system
- Similarities to GloSea5
- 1990-2012 hindcast period



May initialization



Dec initialization



Conclusions so far

- Temperature trend biases are particularly problematic for operational systems with long hindcast periods
- Trend errors of plausible magnitude can seriously bias tercile probabilities, degrade probabilistic skill
- Global/land/ocean trends evaluated for 25 models vs 3 observational products
- Seasonal hindcasts from older systems (ca. 2010 and earlier) tend to seriously underestimate trends, especially over land → anthropogenic forcings mis- or unrepresented?
- Trend errors in currently operational systems tend to be smaller, but may still affect skill and reliability of real time forecasts

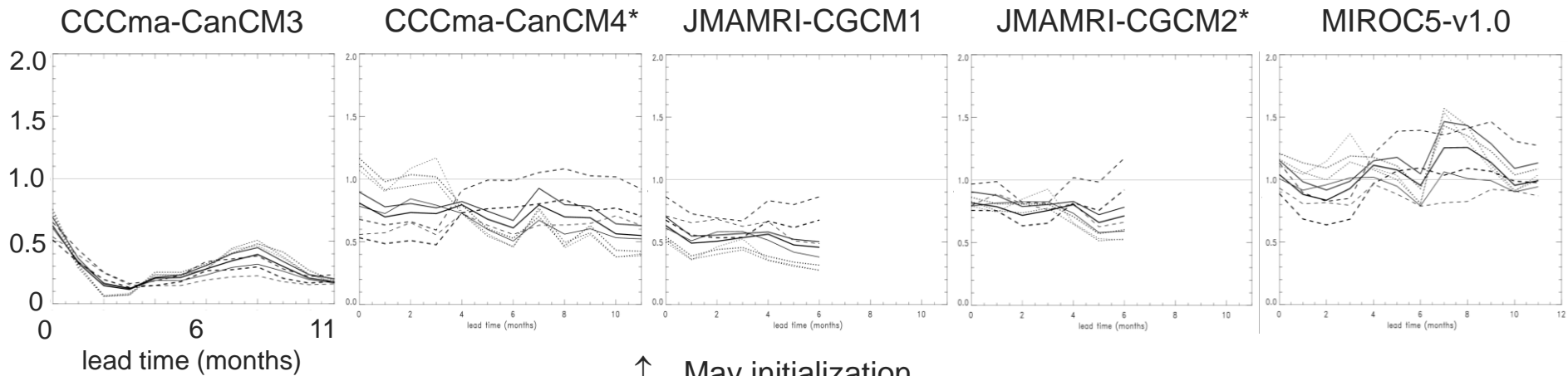
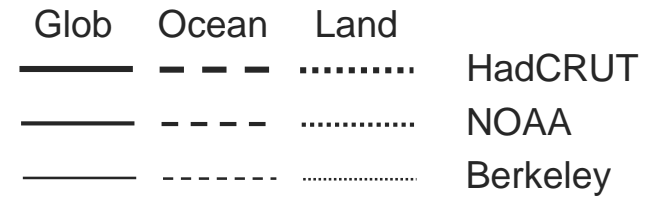
Extra slides

Objectives

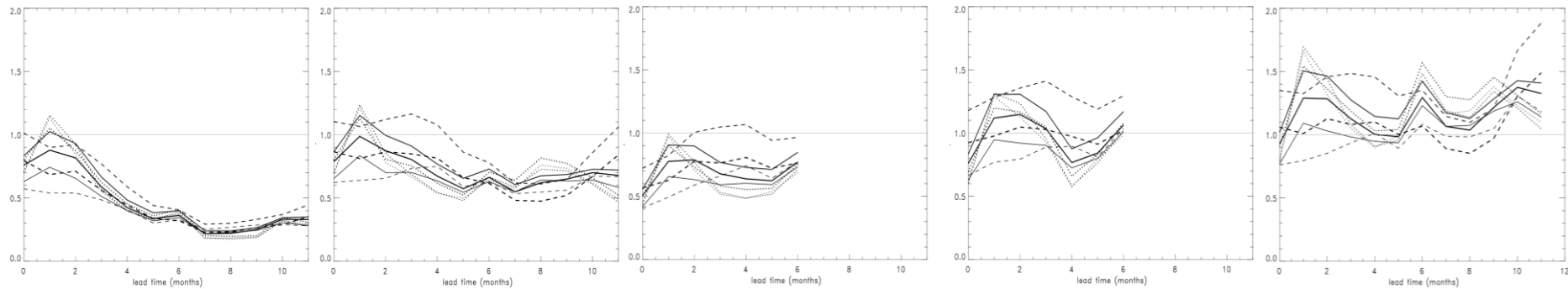
- Assess long-term global and regional temperature trends as a function of lead time in hindcasts across many seasonal prediction systems
- Assess extent to which deficiencies in representing long-term temperature trends impact temperature prediction skill
- Attempt to relate representation of trends to radiative forcing and initialization methodologies employed
- Develop standard diagnostics for temperature trends in hindcasts
- Journal publications and meeting presentations communicating improved knowledge on this topic, synthesizing with previous results

CHFP

- Trend ratios (model/obs)
- Consider common 1981-2020 hindcast period



↑ May initialization
↓ Dec initialization



*currently operational

Some previous results

Liniger et al. (2007)

ECMWF Sys 2 / DEMETER w/ & w/o GHG forcing

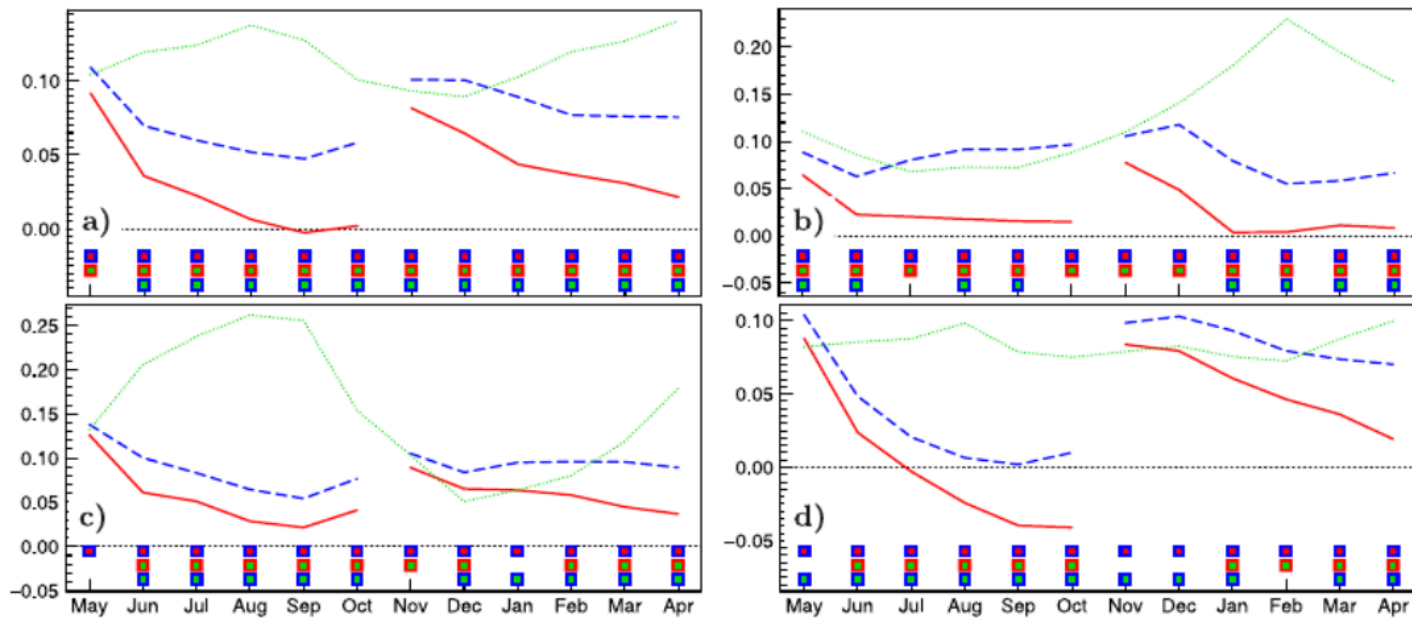
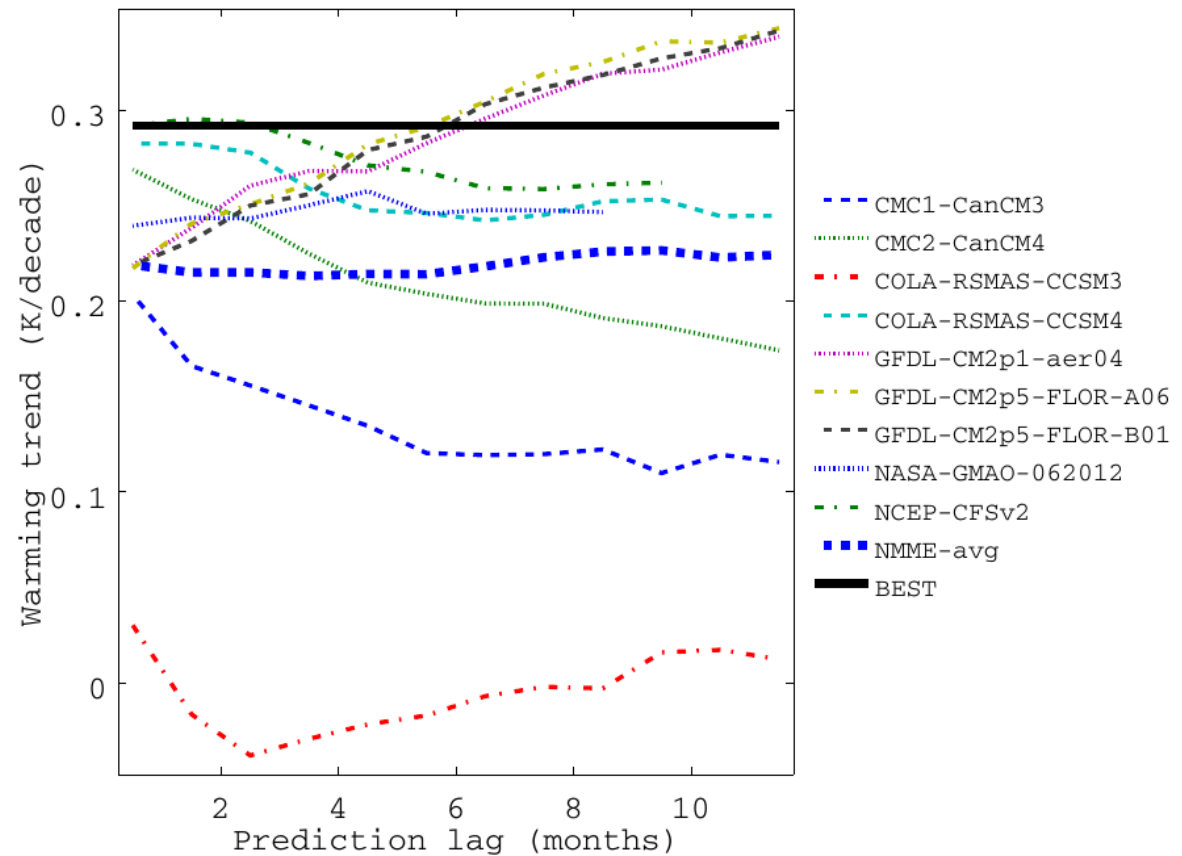


Figure 2. Linear trends of monthly T2 over 1958–2001 in K/decade. Shown are all months of OBS (green, dotted) and corresponding lead months of CONST (red, solid) and INC (blue, long dashed) for (a) global mean, (b) Northern Hemisphere, (c) Southern Hemisphere, and (d) Tropics. The squares in the lower part of the panels indicate significant differences of the trends between CONST and INC (upper row), CONST and OBS (middle row) and CONST and INC (lower row) at a 95%-level.

Some previous results

Krakauer (2019)

Fig. 1 Global (surface air temperature over land) warming rate of NMME model and multimodel mean temperature forecasts for 1982–2015, as a function of forecast lag. The warming rate based on observations (BEST) is also shown for reference



Bibliography (chronological)

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