Trend Errors in Seasonal Forecast Models and Their Links to Climate Model Errors

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Introduction

It has become increasingly apparent that historical climate model simulations have some trends that do not match recent observations, but it has been unclear whether these represent model errors in the forced response or in internal variability. In this study, we show that many of these trend errors are also found within initialised seasonal hindcasts.

Data and methods

- Multi-decade hindcasts from eleven seasonal forecast models: ECMWF SEAS5, DWD GCFS2.1, ECCC CanCM4i, ECCC GEM5-NEMO, CMCC SPS3.5, GFDL-SPEAR, NASA GEOS-S2S, UKMO GloSea6-GC3.2, Meteo-France System 8, NCEP CFSv2 and JMA CPS3
- CMIP6 historical (1994-2014) and SSP245 (2015-2016) simulations from 38 models
- Note that the hindcasts also use CMIP5/6 forcings over the same historical period
- Hindcast trends are determined by linear fit to the hindcasts at each location, separately as a function of lead time and verification month/season
- Trend errors are computed relative to observed linear trends, which are computed monthly/seasonally using ERA5 (SST) and GPCP (precipitation) data for 1994-2016
- Significance is calculated using the Hamed and Rao modification to the Mann-Kendall trend test to account for serial autocorrelation (5% significance threshold)

Results

1) Seasonal forecast models have significant and systematic trend errors in many variables, including SST and precipitation

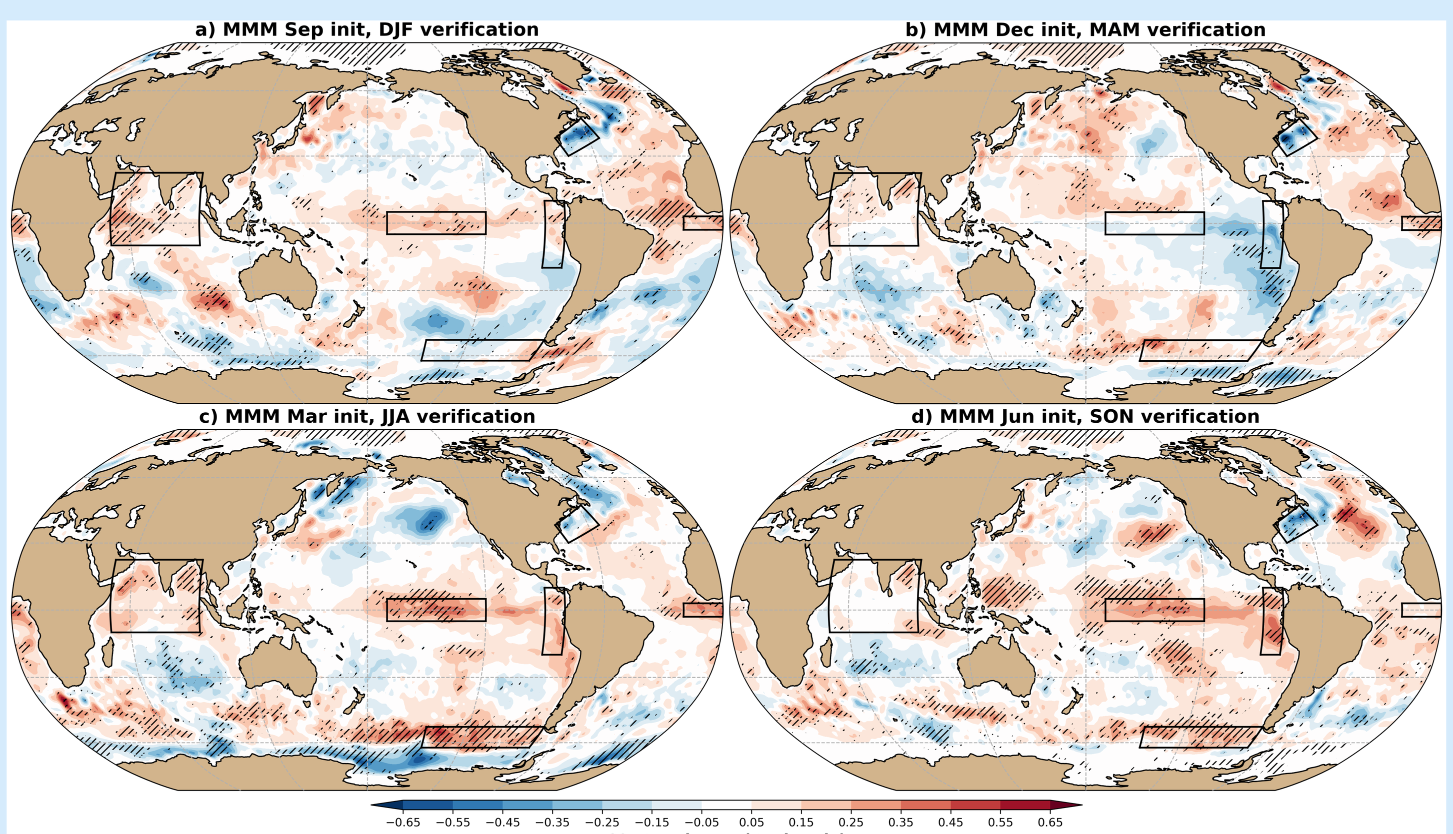

Figure 1: Multi-model mean SST trend error relative to ERA5 (1994-2016) for four different initialisations averaged over leads +4 to +6 months for (a) DJF (b) MAM (c) JJA and (d) SON. Positive values indicate that the model trend is more positive (or less negative) than ERA5, and vice versa. Hatching indicates significance at the 5% level.

- Seasonal forecast models exhibit systematic, seasonally-dependent trend errors in both SST (Figure 1) and precipitation (Figure 2)
- These often resemble common climate model trend errors (e.g. an El Niño-like SST error in the tropical Pacific in DJF, JJA and SON)

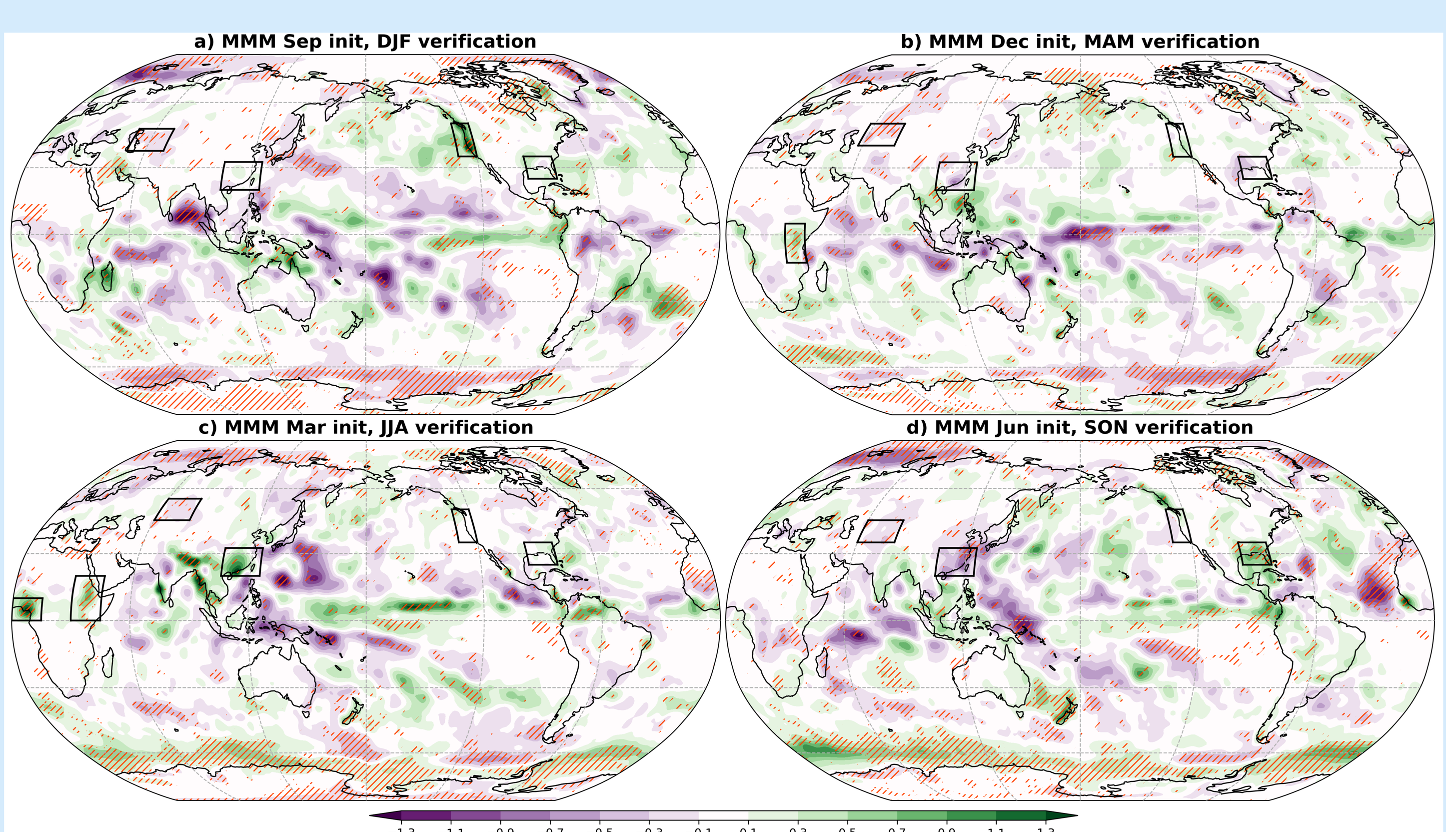

Figure 2: Same as Figure 1, but for precipitation (relative to the GPCP trend).

2) Hindcast trend errors match common CMIP6 historical trend errors

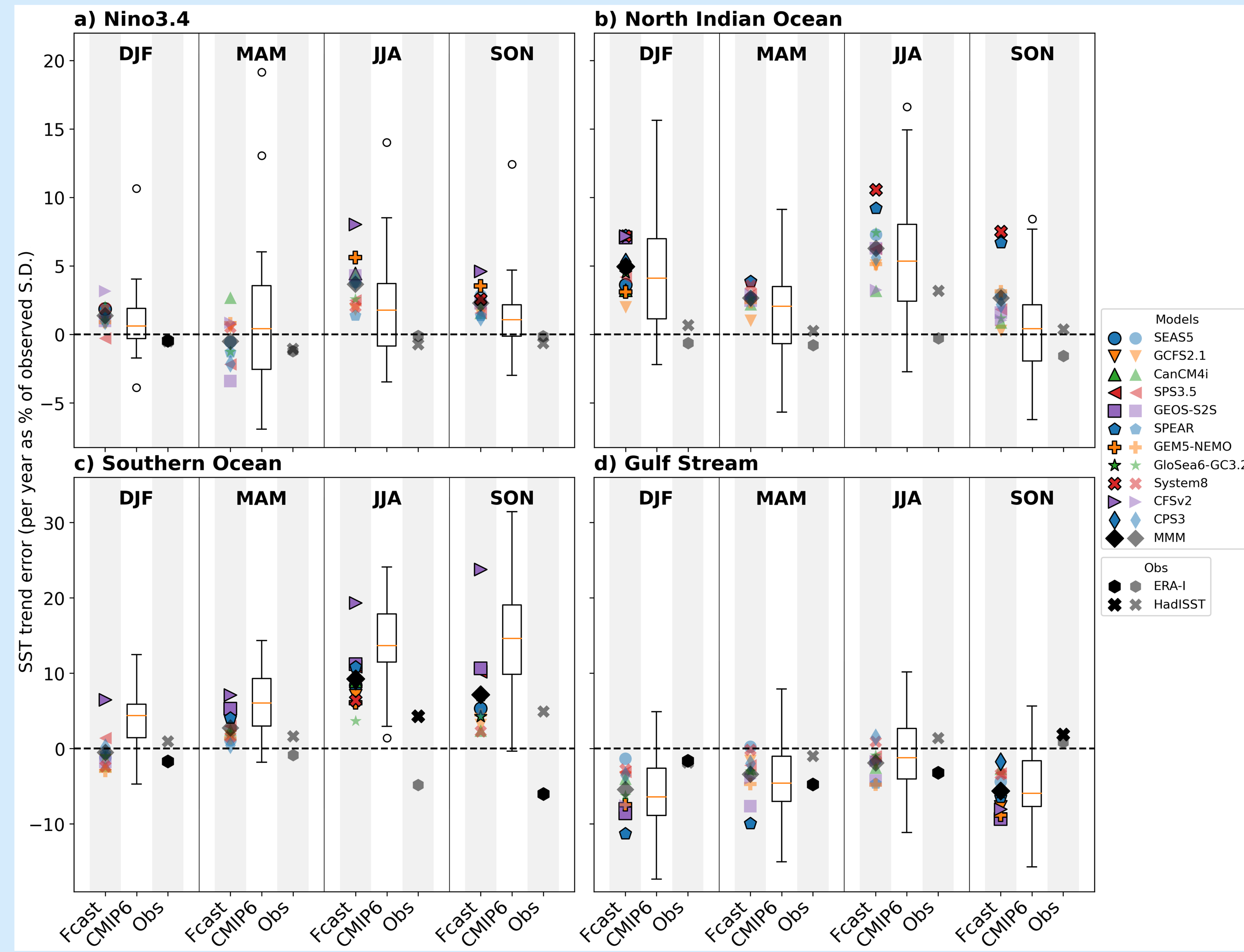

Figure 3: Seasonal SST trend error for (a) Niño3.4 (b) North Indian Ocean (c) Southern Ocean and (d) Gulf Stream (regions shown on Figure 1). For each season, the first column shows the individual seasonal forecast models and the multi-model mean, the second column shows the CMIP6 model distribution and the third column shows two other observations-based datasets, relative to ERA5. As in Figure 1, these are averaged over leads +4 to +6 months for the forecasts. Units are trend error per year as a percentage of the ERA5 index standard deviation.

- Area-averaged SST (Figure 3) and precipitation (Figure 4) trend errors are similar to those from CMIP6 simulations
- Seasonal dependence of the trend errors for the forecast models and the CMIP6 models are strikingly similar, which is particularly noticeable for precipitation (e.g. western US, southeast Asia, Figures 4a, b)

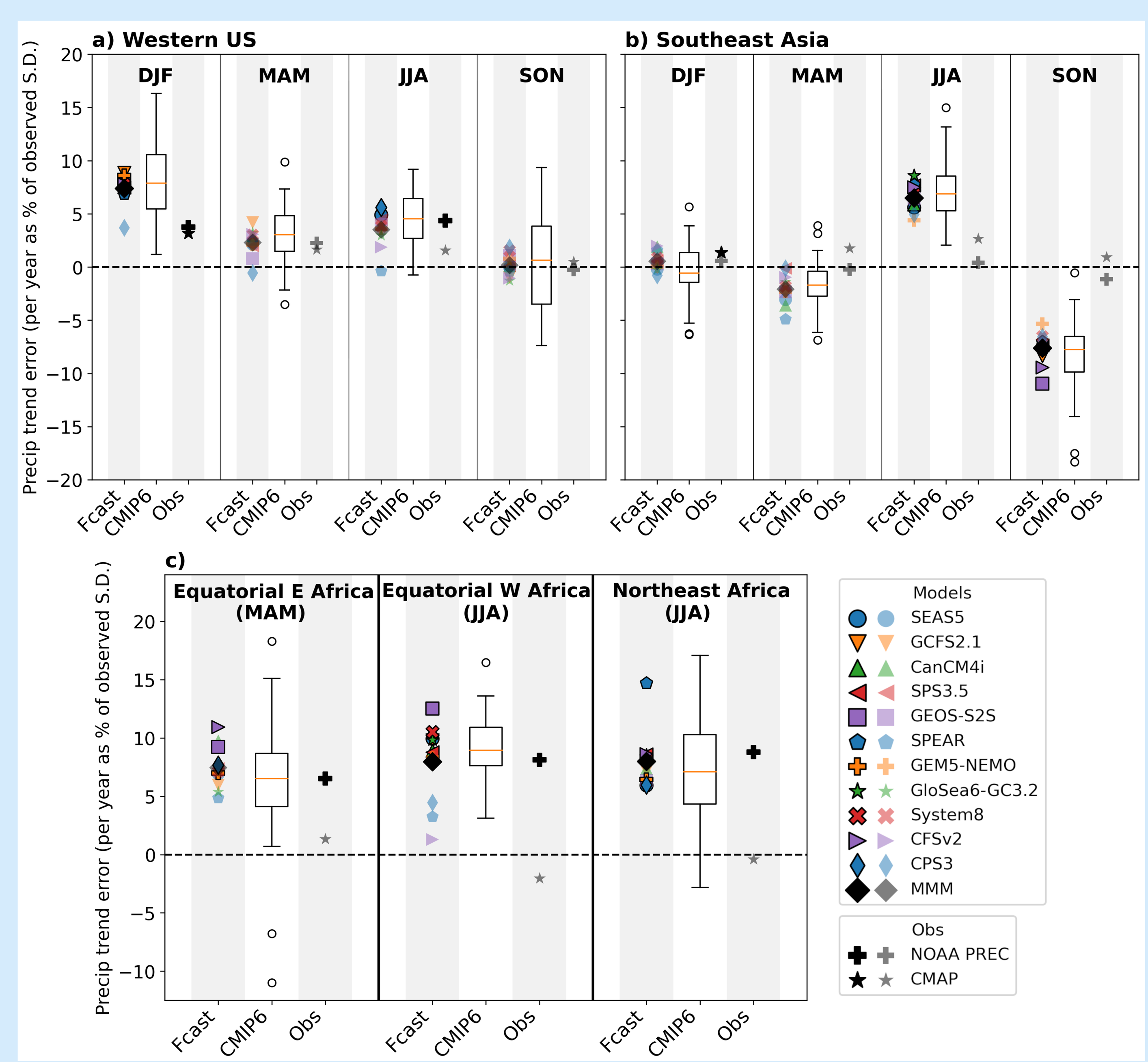

Figure 4: Same as Figure 3, but for precipitation trend error relative to GPCP for (a) the western US (b) southeast Asia and (c) equatorial east Africa (MAM), equatorial west Africa (JJA) and northeast Africa (JJA) (regions shown on Figure 2).

3) Hindcast trend errors develop rapidly and are seasonally-dependent

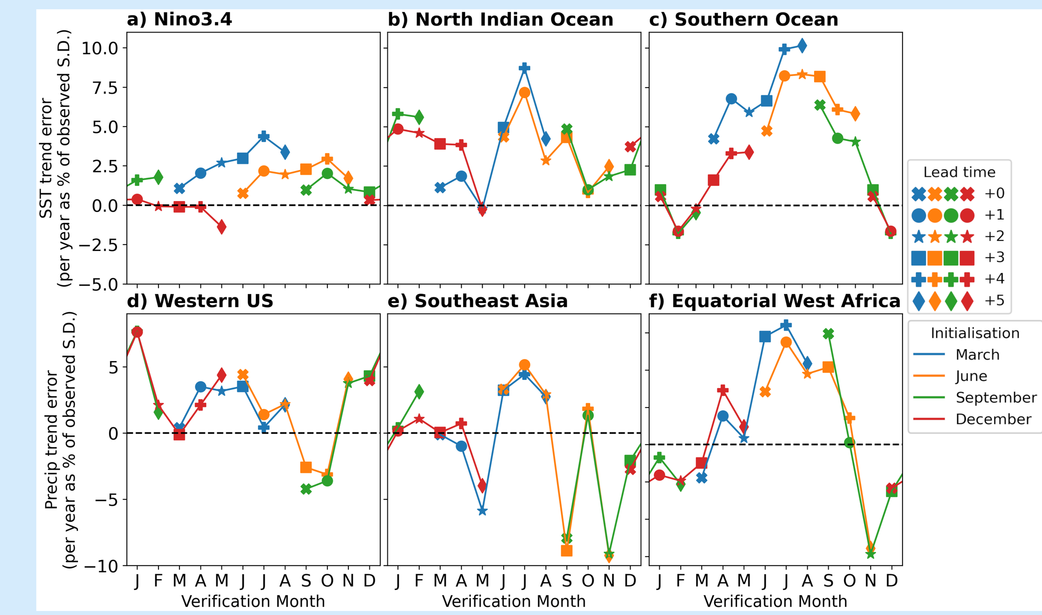

Figure 5: Area-averaged monthly (a-c) SST and (d-f) precipitation trend error for several of the regions shown on Figures 1 and 2. Four different initialisations are shown by the different colours, with the x-axis indicating the verification month.

- Forecast trend errors often develop large amplitude within 1—2 months after forecast initialisation (Figure 5)
- They are also more dependent on the seasonal cycle than on lead time, consistent with each model rapidly transitioning to its own (model) attractor
- The stronger seasonality of precipitation than SST also suggests that the errors may be developing faster in the atmospheric model component

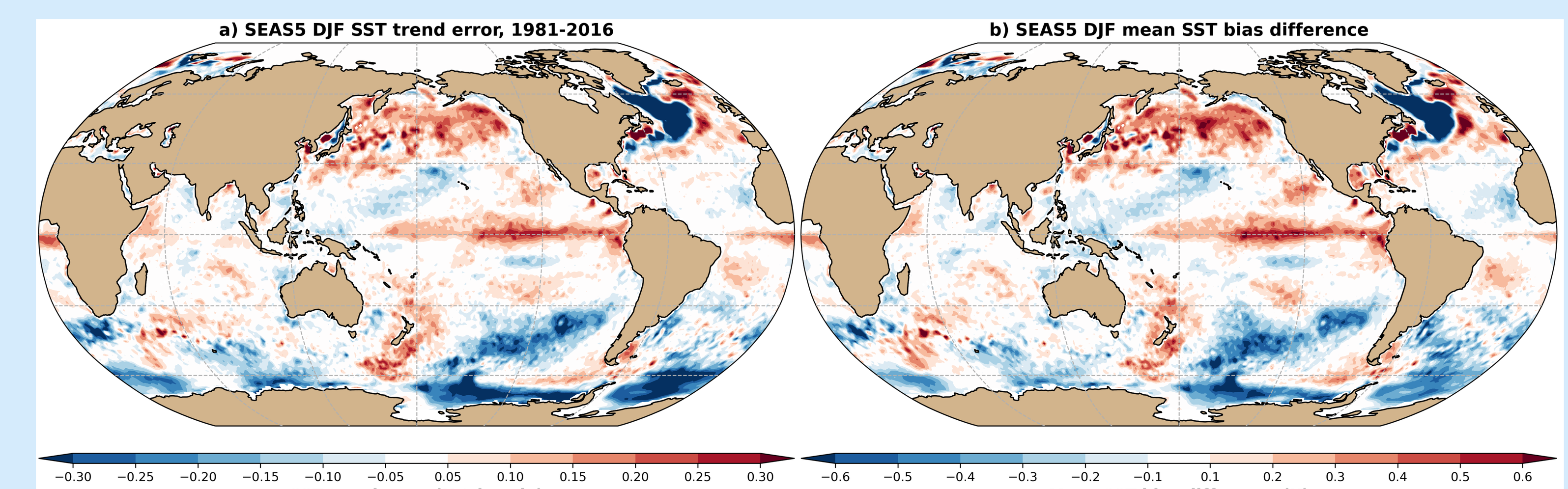

Figure 6: (a) September initialisation, DJF verification SST trend error in ECMWF SEAS5 (1981-2016). (b) Difference in mean DJF SST bias (September initialisation) between the early (1981—1998) and late (1999—2016) periods.

- The pattern of trend error in individual models is very closely related to the difference in the mean bias between the first and second half of the hindcast period – this is more clearly seen for the longer hindcast period available for ECMWF SEAS5
- Also, both mean biases and trend errors develop very rapidly (at short leads) within the hindcasts
- This suggests that the trend errors may represent (roughly) linear change in the mean bias, due to the time-evolving radiative conditions present in each hindcast run, as opposed to an erroneous forced response

Summary and conclusions

- **Seasonal forecast models exhibit significant, systematic trend errors in both SST and precipitation in many regions**
- **The forecast errors develop rapidly and are tied to the seasonal cycle, typical of the rapid evolution of climate drift in forecast models as they transition from nature's attractor to the climate model attractor, and may be developing faster in the atmospheric than the oceanic component of the model**
- **Hindcast and CMIP6 trend errors are similar in both magnitude and seasonality, suggesting that simulation trend errors may be due to sensitivity of model mean bias to changes in radiative forcing, rather than unrepresented internal variability or erroneous forced response**
- **Diagnosis of climate model simulation trend errors may be made by diagnosing trend errors in seasonal forecast model hindcasts**

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