Skillful Decadal Climate Prediction in the Atlantic Sector using CESM

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Experimental Setup

CESM Large Ensemble of decadal predictions (**DP**; Yeager et al. 2017):

- Fully coupled CESM1.1:
  - atm: CAM5 (FV dycore, 1º, 30lvl) ocean: POP2 (1º, 60lvl)
  - ice: CICE4 (1º) land: CLM4
- 40-member ensembles initialized each Nov. 1 from 1954-2015
- 122 month simulations ➔ 40 x 62 x 10.17 = ~25,200 sim-years in total
- Full field initialization
- Ocean/sea-ice initial conditions from **CORE**-forced POP-CICE run
- Atmosphere/land initial conditions from 40-member CESM Large Ensemble of 20th Century (**20C**) simulations (Kay et al. 2015)
- **20C** represents "uninitialized" counterpart to **DP** (both experiments use same model, external forcings, and comparable ensemble sizes)

Skill Metrics

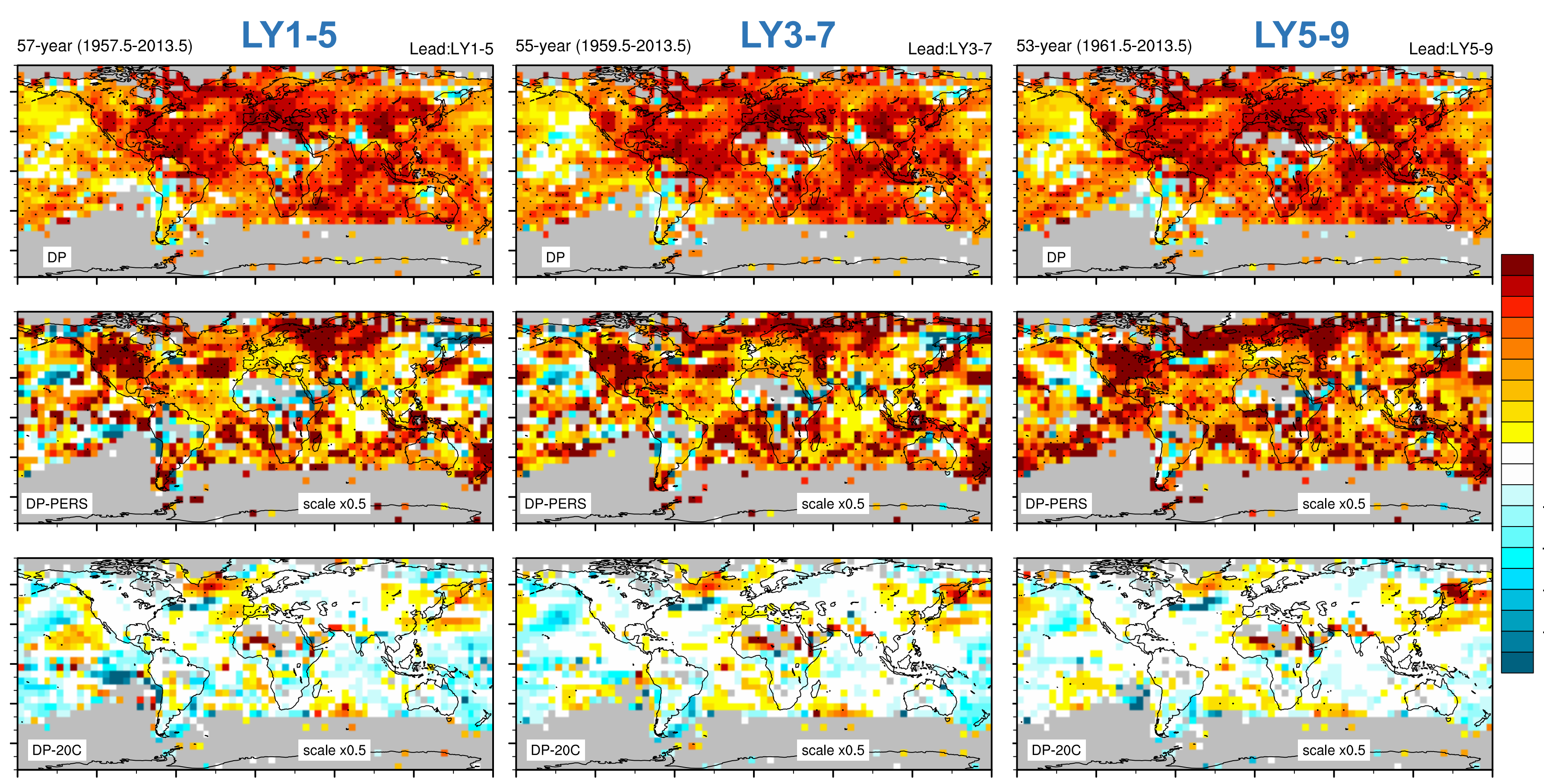
- Anomaly correlation coefficient (**ACC**) and mean square skill score (**MSSS**): $MSSS = 1 - MSE/MSE_{ref}$, $MSE = \frac{1}{n}\sum_{j=1}^{n}(F_j - O_j)^2$, where F_j and O_j represent forecasted and observed anomalies at time j. MSSS measures skill relative to a reference forecast (e.g., uninitialized **20C**).
- Significance of positive scores assessed at 90% confidence level using a non-parametric bootstrap method (Goddard et al. 2013).

Surface Air Temperature (SAT)

1,**2** : ACC between seasonal, 5-year-average SAT forecasts and HadCRUT4.5.0 (Morice et al. 2012) data. No detrending. Top panels show ACC(DP,obs) for various forecast lead year (**LY**) averages. Middle (bottom) panels show ΔACC relative to persistence (20C).

3,**4** : MSSS for seasonal, 5-year-average SAT anomalies using 20C as reference forecast (positive values indicate where DP hindcasts are more accurate than 20C).

1 JJA



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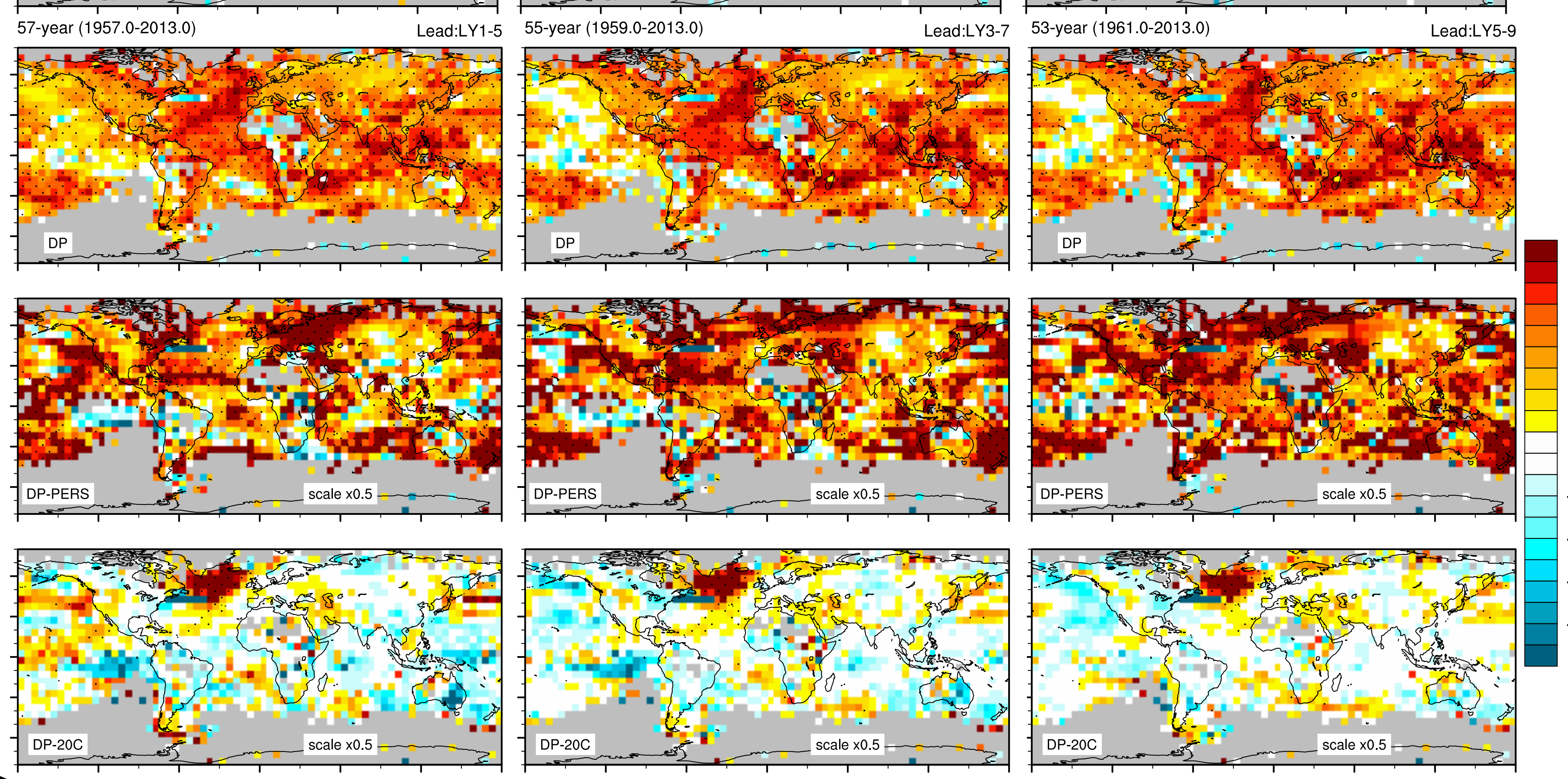

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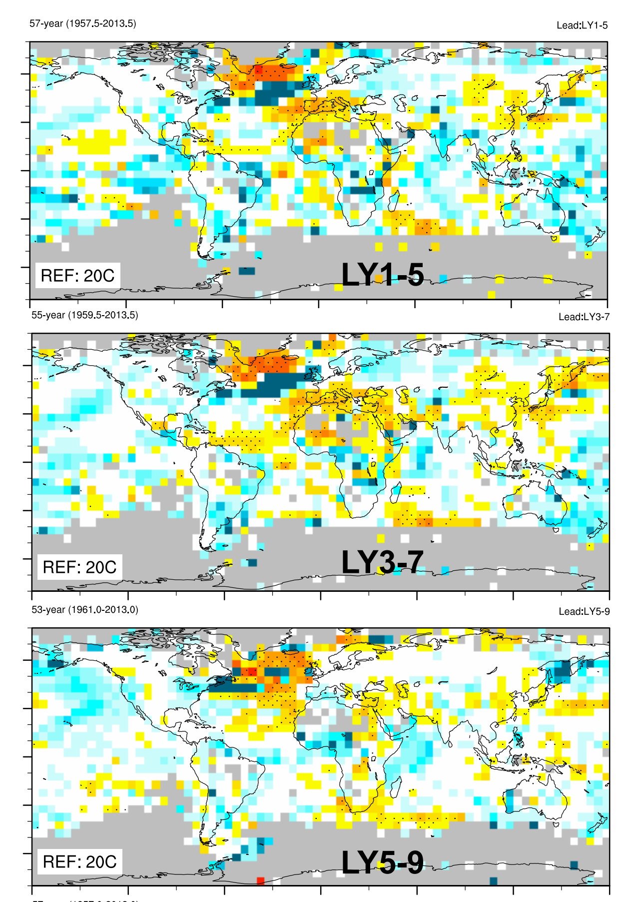

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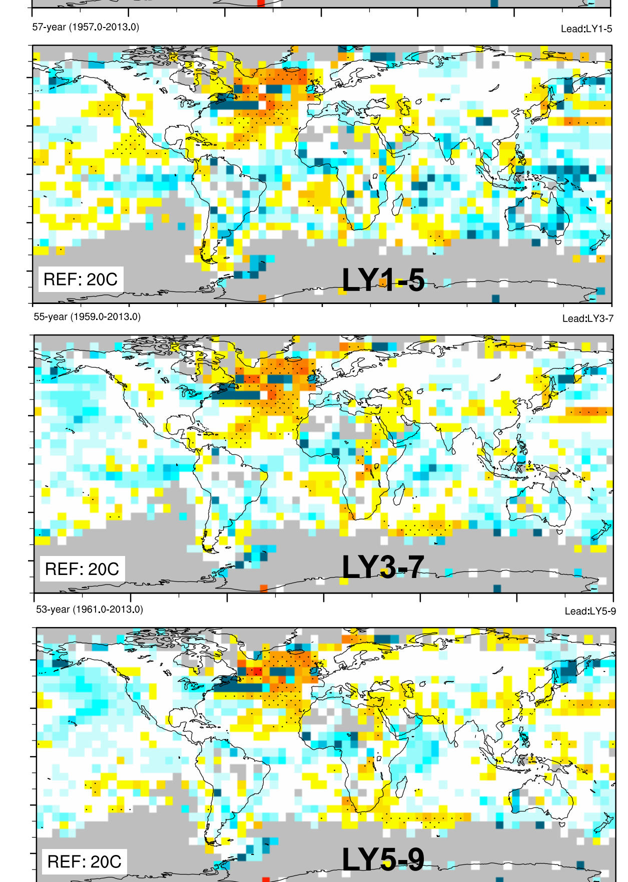
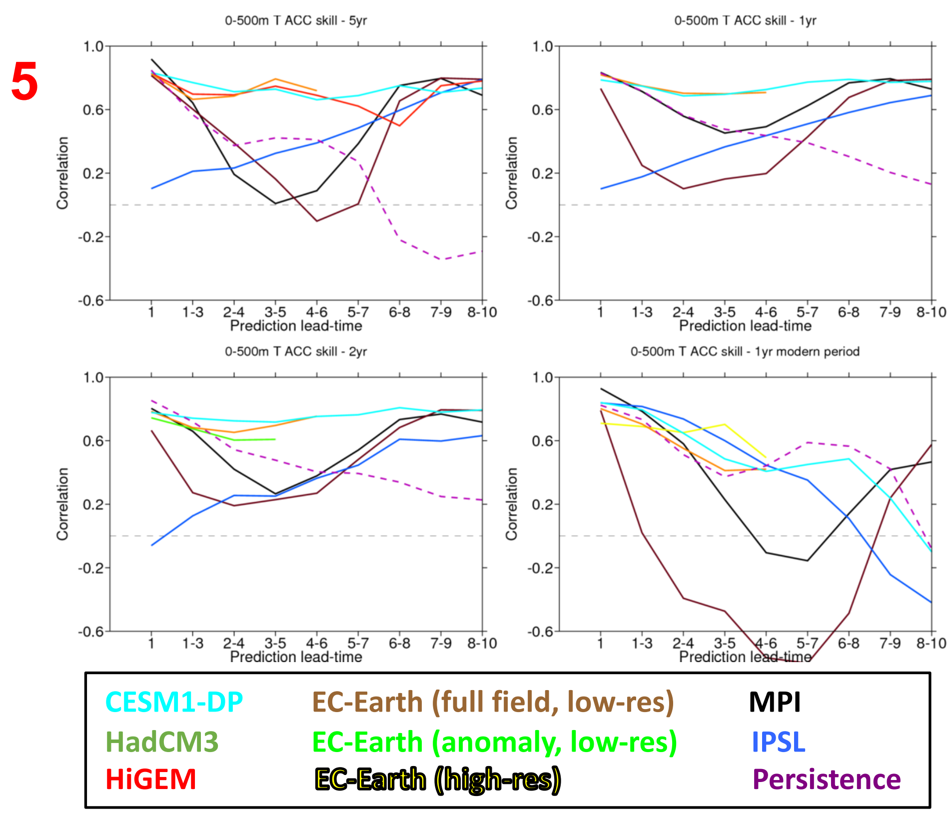


The Subpolar North Atlantic (SPNA)

5



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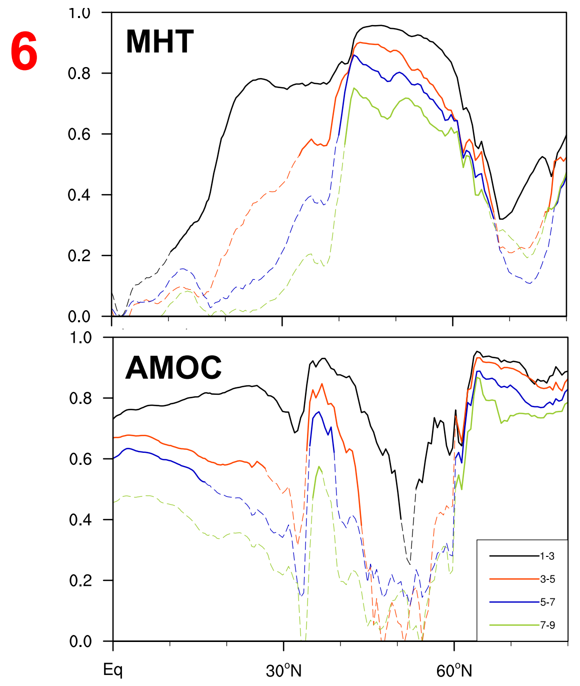

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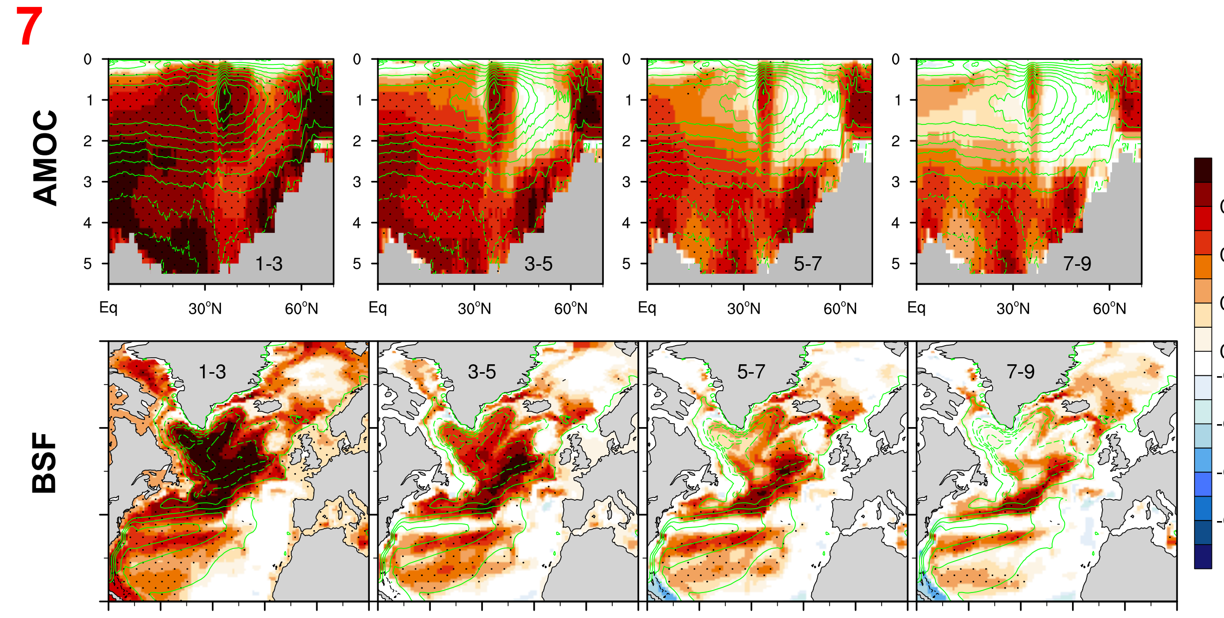
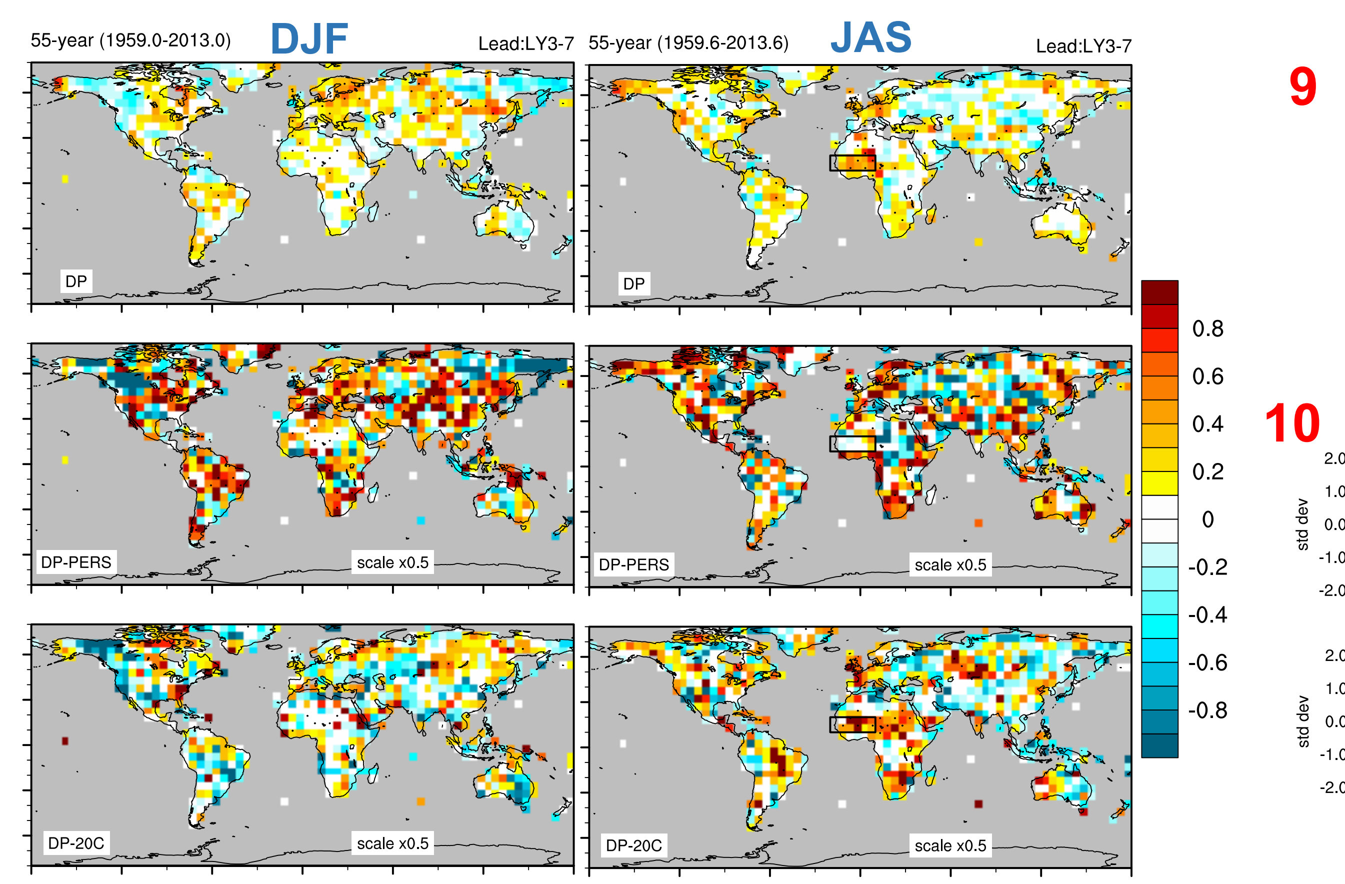


5 : ACC between predicted annual upper 500m ocean heat content in the SPNA (50º-65ºN, 60º-10ºW) and Met Office EN4 data. The different systems have different start date sets. (*Figure courtesy J. Robson*)

6 : ACC between 3-year-average Atlantic meridional heat transport (**MHT**) and overturning strength (**AMOC**) from DP and CORE at various lead times. **7** : ACC between 3-year-average AMOC and barotropic streamfunction (**BSF**) from DP and CORE.

Precipitation (PREC) over land

8



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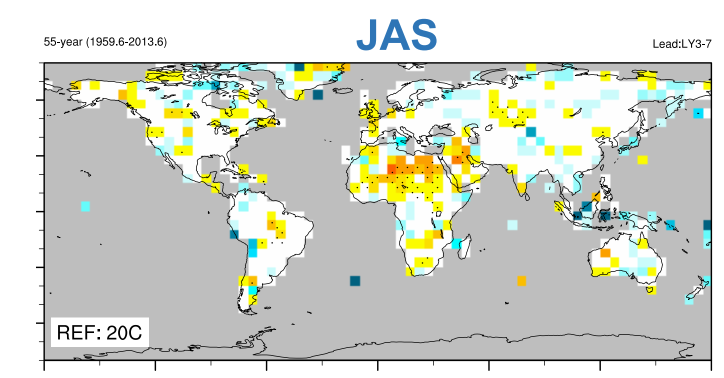

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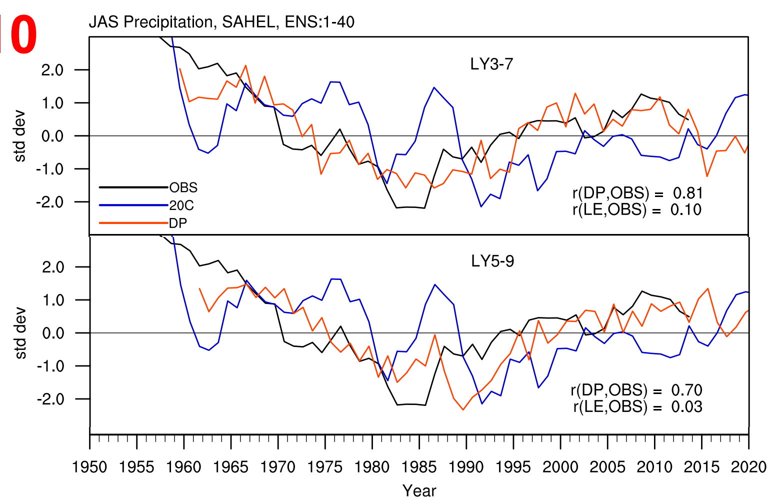

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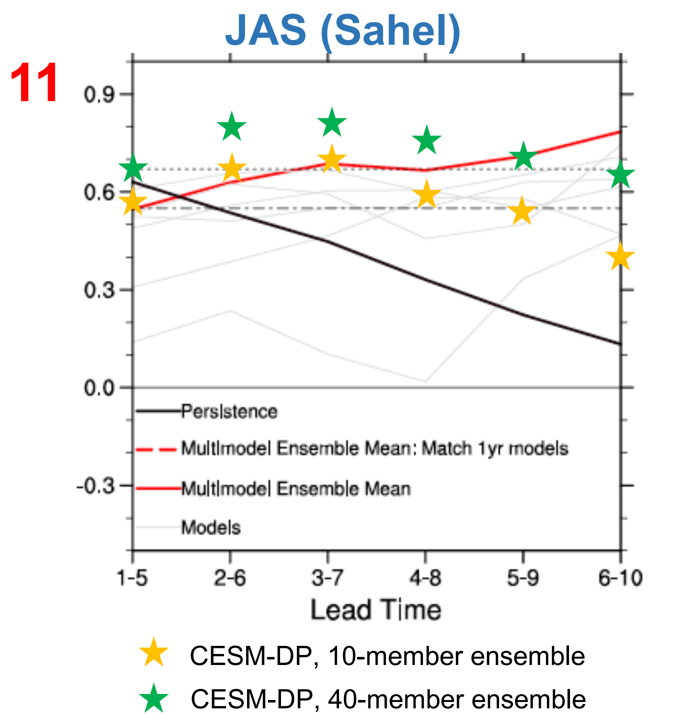

8 : ACC between seasonal, 5-year-average PREC forecasts and CRU TS3.24 data (Harris et al. 2013). No detrending. Middle (bottom) panels show ΔACC relative to persistence (20C). **9** : MSSS for 5-year-average summer (JAS) PREC using 20C as reference forecast (LY 3-7).

10 : Normalized time series of 5-year-average JAS PREC averaged over the Sahel (10º-20ºN, 20ºW-10ºE; see **8**). **11** : Modified from Figure 2b of Martin & Thorncroft (2014). Red line shows ACC skill for JAS Sahel PREC from a multi-model CMIP5 prediction ensemble (52-member). CESM-DP results are indicated with stars.

Key Points

1-4: CESM-DP shows high skill at predicting 5-year-mean winter & summer SAT anomalies at decadal lead times over most of the globe. DP beats persistence almost everywhere, but significant improvement over 20C is largely confined to N. Atlantic sector, particularly SPNA and Southern (Northern) Europe in summer (winter).

5-7: CESM-DP exhibits higher skill than most current prediction systems for SPNA heat content. High skill scores in this region appear to derive from long-lasting skill at predicting MHT north of 40ºN, even though AMOC is not well-predicted. MHT skill appears to be related to long lead time gyre predictability, although $\bar{V}T'$ probably contributes.

8-11: High SPNA SAT skill appears to underpin long lead time skill at predicting summer PREC over the Sahel and Brazil. Skill improves with ensemble size. Winter PREC skill is less compelling, but eastern US and northern Eurasia show improvement with initialization.

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