Decadal predictability of the North Atlantic eddy-driven jet in winter within CMIP6

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Introduction

Smith et al. (2020, hereafter S20) have shown that North Atlantic climate is more predictable than models imply.

Models show skill in predicting winter NAO, though amplitude is critically underestimated.

Here, we look at the skill in decadal prediction of the North Atlantic eddy-driven jet (latitude and speed, see Figure 1), in order to assess its predictability on such timescales.

The indices

- NAO: difference in pressure between Azores and Iceland
- JLI: latitude of the eddy-driven jet, measured as peak in 850hPa zonal winds, zonally averaged over 0°–60°W
- JSI: speed of the jet, measured as the windspeed at the peak (Woollings et al., 2010)

Change in skill

Skill in the NAO for CMIP6 models is consistent with that found in S20 for a mix of CMIP5 and CMIP6 models (compare their 0.48 to our 0.55).

There seems to be more skill in predicting the strength of the jet (0.71 for the lagged ensemble mean) over its latitude (0.52).

Highest level of skill is achieved when March is included in the definition of winter and is especially true for JLI (see table).

Skill appears to deteriorate if we include latest period (2010s, ACC shown in brackets in Figure 1).

Preliminary analysis shows a degradation of the skill of CMIP6 models in predicting surface temperatures over most of the North Atlantic ocean (Figure 2), which arguably has a stronger influence on the atmospheric circulation above.

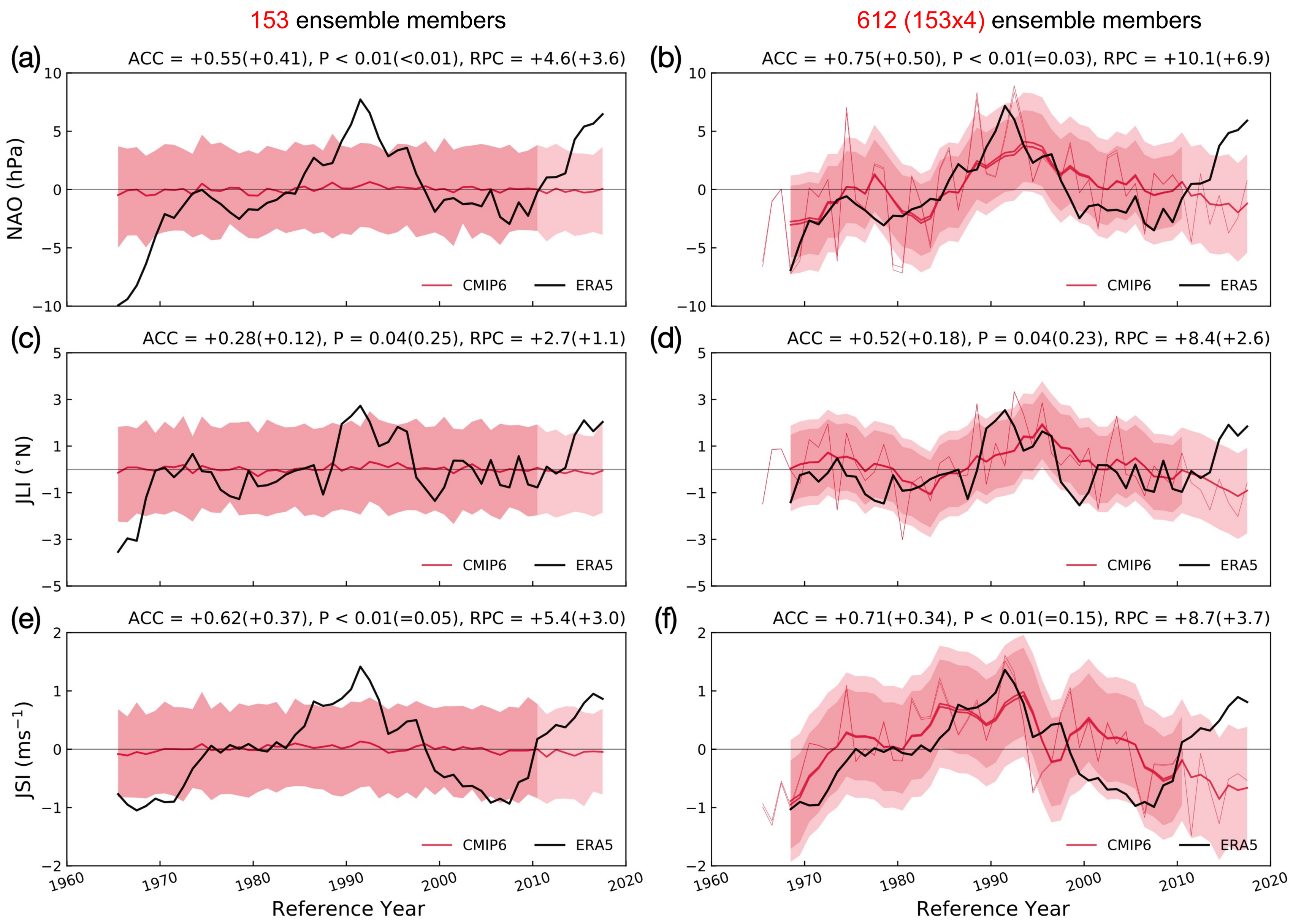


Figure 1: Observed (black) and forecast (red, year 2–9) 8-yr running means for the DJFM NAO (a,b), Jet Latitude (c,d) and Speed (e,f) Indices. Shading represents 5th-95th confidence interval. Panels on the right are as on the left but for lagged multi-model ensemble means (see Methods). Below we include a table with skill from different seasons (and the relative change with respect to DJFM).

		DJF			DJFM			JFM			DJFM – DJF		DJFM – JFM	
		Short	Long	Change (L – S)	Short	Long	Change (L – S)	Short	Long	Change (L – S)	Short	Long	Short	Long
Non Lagged	NAO	**0.45**	0.26	-0.19	**0.55**	**0.41**	-0.14	**0.51**	**0.39**	-0.12	0.10	0.15	0.04	0.02
	JLI	0.06	-0.10	-0.16	**0.28**	0.12	-0.16	0.20	0.09	-0.11	**0.22**	**0.22**	0.08	0.03
	JSI	**0.60**	0.32	**-0.28**	**0.62**	0.37	**-0.25**	**0.54**	0.34	**-0.20**	0.02	0.05	0.08	0.03
Lagged	NAO	**0.73**	0.31	**-0.42**	**0.75**	**0.50**	**-0.25**	**0.8**	**0.57**	**-0.23**	0.02	0.19	-0.05	-0.07
	JLI	0.14	-0.20	**-0.34**	**0.52**	0.18	**-0.34**	0.45	0.21	**-0.24**	**0.38**	**0.38**	0.07	-0.03
	JSI	**0.78**	0.33	**-0.45**	**0.71**	0.34	**-0.37**	**0.62**	0.31	**-0.31**	-0.07	0.01	0.09	0.03
Change (L – nL)	NAO	**0.28**	0.05	**-0.23**	0.2	0.09	-0.11	**0.29**	0.18	-0.11				
	JLI	0.08	-0.10	-0.18	**0.24**	0.06	-0.18	**0.25**	0.12	-0.13				
	JSI	0.18	0.01	-0.17	0.09	-0.03	-0.12	0.08	-0.03	-0.11				

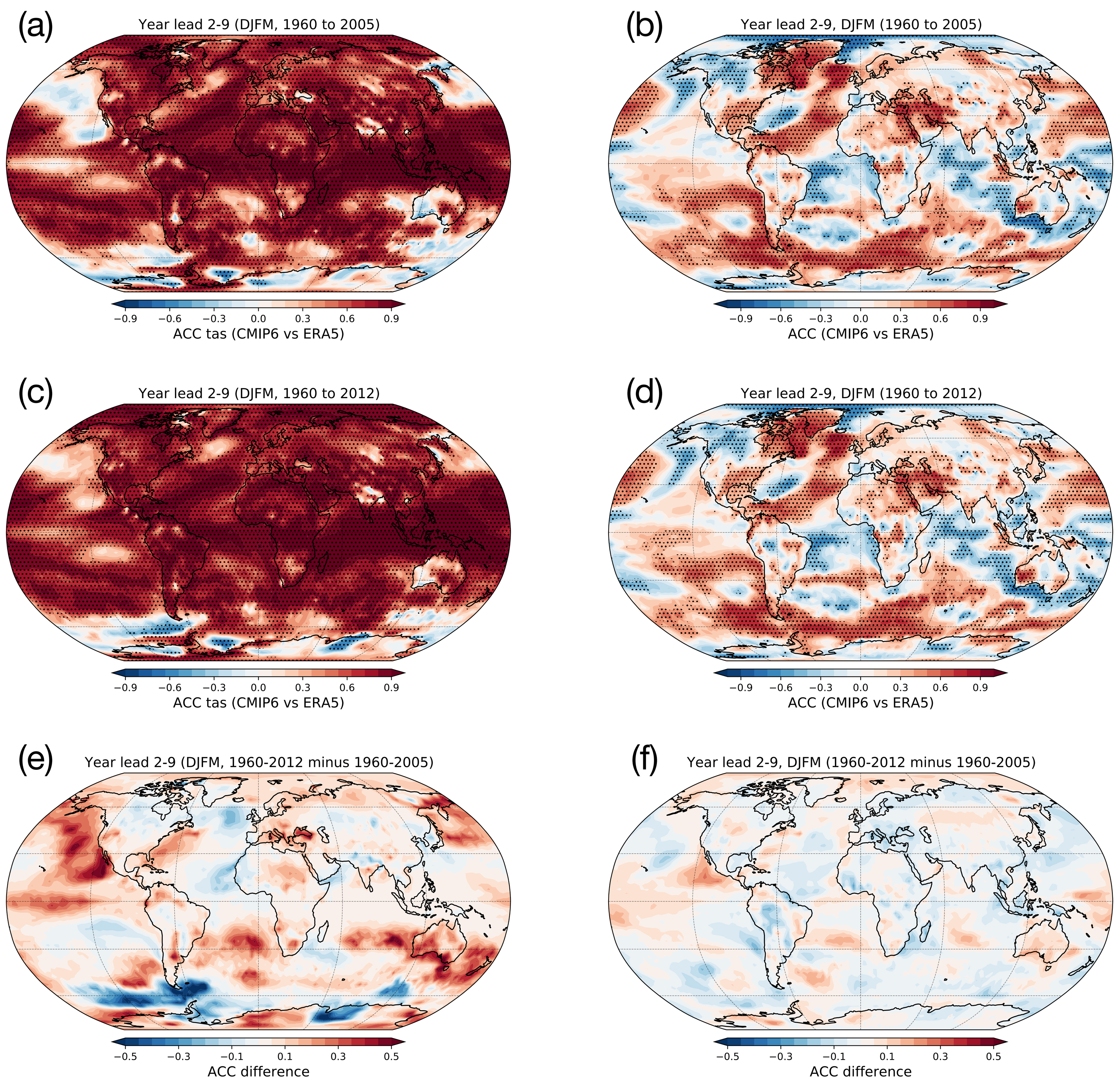
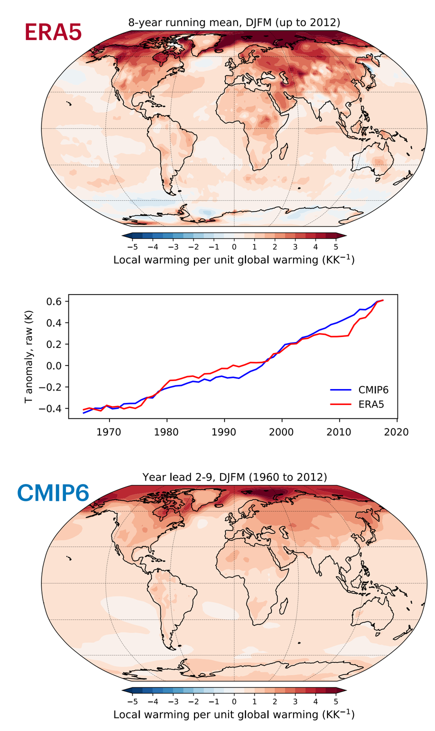


Figure 2: Skill of year 2–9 hindcasts from CMIP6 as measured by ACC of temperature at the surface (TAS). Panels on the left represent ACC for raw TAS (not detrended), while panels on the right show skill for TAS detrended via removal of global mean temperature trend. (a,b) refer to shorter period (up until 2005), (c,d) to longer period (up until 2012) and (e,f) the difference between the two periods. Below we show regression of surface temperature over global mean temperature that we used for detrending.



Possible explanations to skill degradation

We are currently looking into how the model representation of drivers of atmospheric circulation might have changed over the past decade and whether these changes can explain the degradation in skill.
Lower skill may also be due to lower natural predictability of the atmospheric circulation (models not capturing longer-timescale variability).

Data & Methods

We examine data from climate models of the Decadal Climate Prediction Project (DPCC) contributing to CMIP6 (Eyring et al., 2016). The multi-model ensemble has 153 members from 10 different institutions. We focus on years 2–9 of each hindcast.

Data from the ERA5 reanalysis (Hersbach et al., 2020) is used as observations to evaluate model skill against.

Lagged ensembles are obtained by conflating the previous 3 start dates in the computation of the multi-model ensemble means, artificially inflating the number of members by a factor 4, and then rescaling the variance to match it with observations.

We measure skill by the Pearson Anomaly Correlation Coefficient (ACC) between model data and observations. The Ratio of Predictable Components is estimated as the ratio between ACC and the ratio between signal and total variance in the hindcasts.

We test for significance via block bootstrapping (blocks of 5 years, iterating 1,000 times).

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