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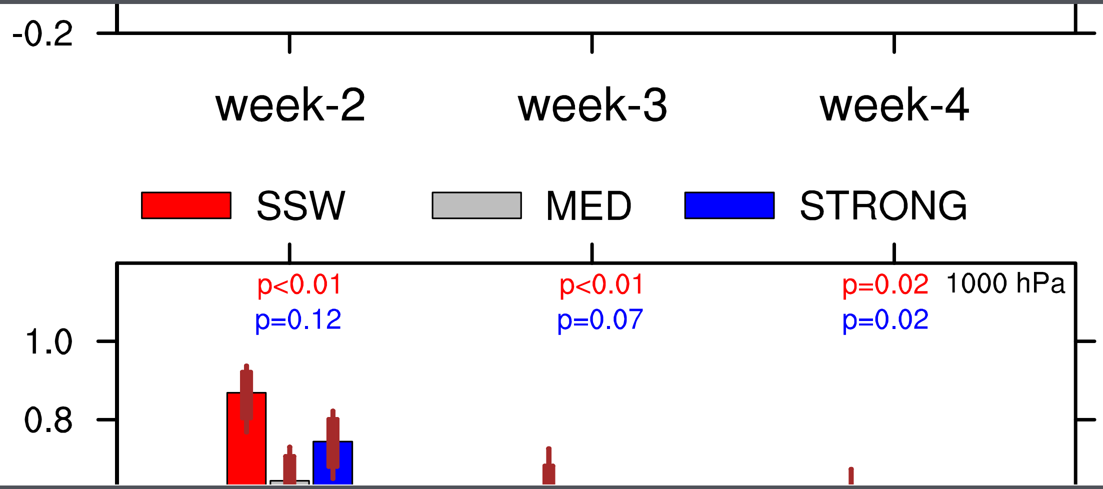
A SIGNAL AND NOISE VIEW OF STRATOSPHERE-TROPOSPHERE COUPLING



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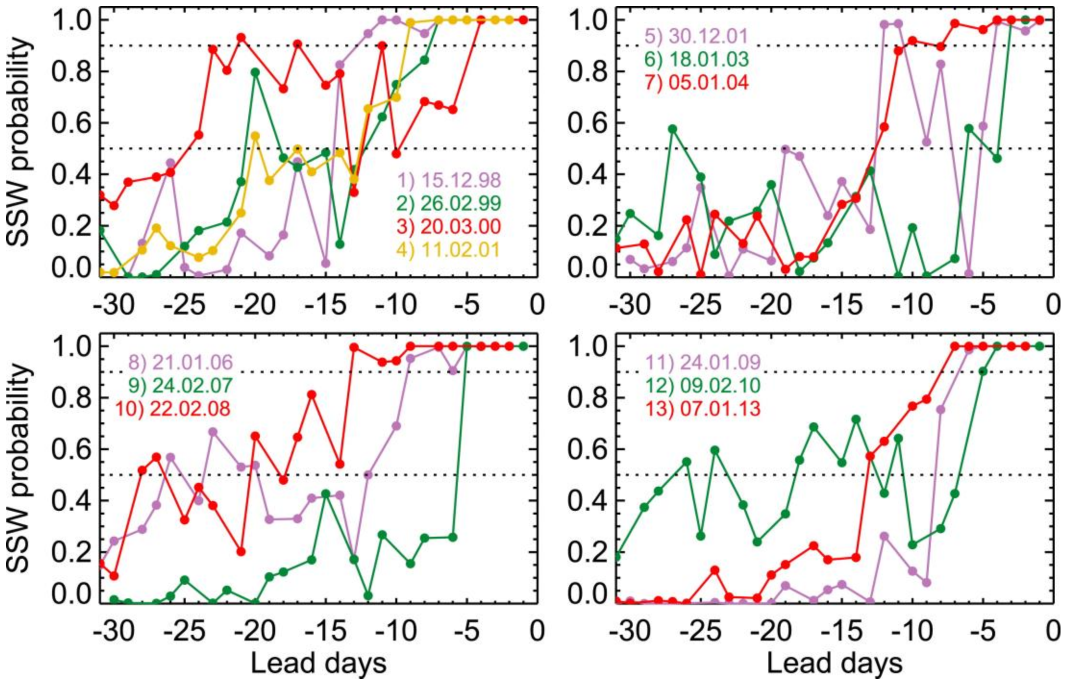
IS STRATOSPHERIC VARIABILITY PREDICTABLE?

- Typically some indication of SSW occurrence 10-15 days before the event (e.g. Tripathi et al., 2013, Karpechko, 2017).
- For some events, early indications of SSW occurrence are not a good predictor of the dynamics of the resulting SSW (Tripathi et al., 2016).

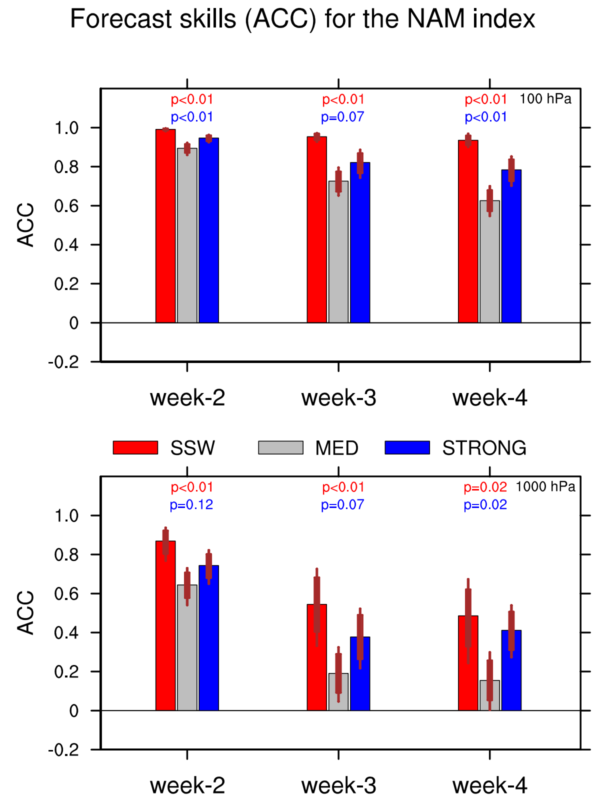


Source: Karpechko
doi: 10.1175/MWR-D-17-0317.1

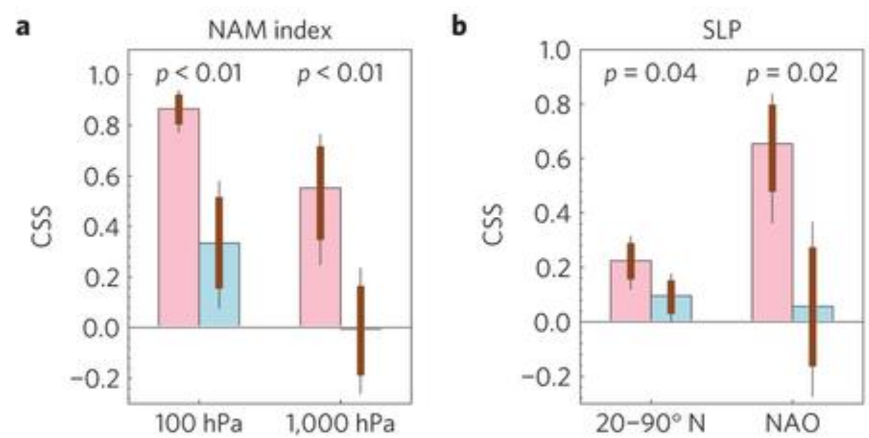
The predictability of key tropospheric precursors limits stratospheric predictability in some cases – Poster by Simon Lee

SKILL LINKED TO STRATOSPHERIC ANOMALIES

On sub-seasonal and seasonal timescales forecasts initialised during SSWs or when the vortex is anomalously strong are significantly more skillful in the troposphere.



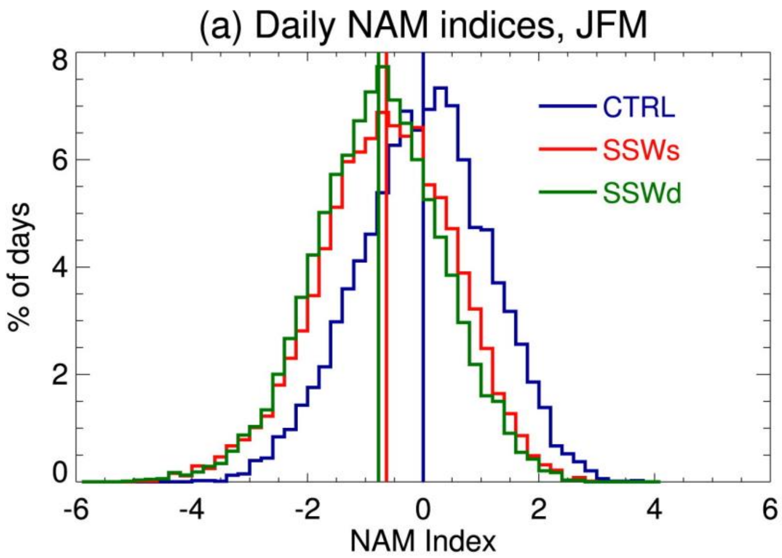
Source: Tripathi et al., doi:10.1088/1748-9326/10/10/104007



Source: Sigmond et al., doi: 10.1038/ngeo1698

TROPOSPHERIC FEEDBACKS

- Even for the same stratospheric event there is significant variation in the tropospheric response (see also 2018 and 2019 SSW events).
- Eddy feedbacks are critical (DCWEF, Song and Robinson, 2004)
- Could also be a role for regime thinking (Charlton-Perez et al., 2018, Beerli et al., 2019).
- Even high-resolution GCMs(~0.35°) may be unable to capture these feedbacks (Scaife et al., 2019)



Source: Hitchcock and Simpson, doi: 10.1175/JAS-D-14-0012.1

If you are interested in exploring more in comprehensive forecasting systems chat to me later (SNAP/QBOi experiment)

General understanding of stratospheric predictability and downward coupling to the troposphere on sub-seasonal timescales can be explored in greater detail than in the past using the S2S database (see WCRP/SPARC SNAP project and later talks).

In this talk, develop more detailed understanding of the properties of stratosphere-troposphere coupling in models by fitting a statistical model to hindcasts of multiple S2S models.

Key questions:

- Is the predictable signal in the troposphere and stratosphere coupled?
- Do models capture the same predictable signal?
- How does the predictable signal at the surface arise?
- What is the local response to the predictable signal?

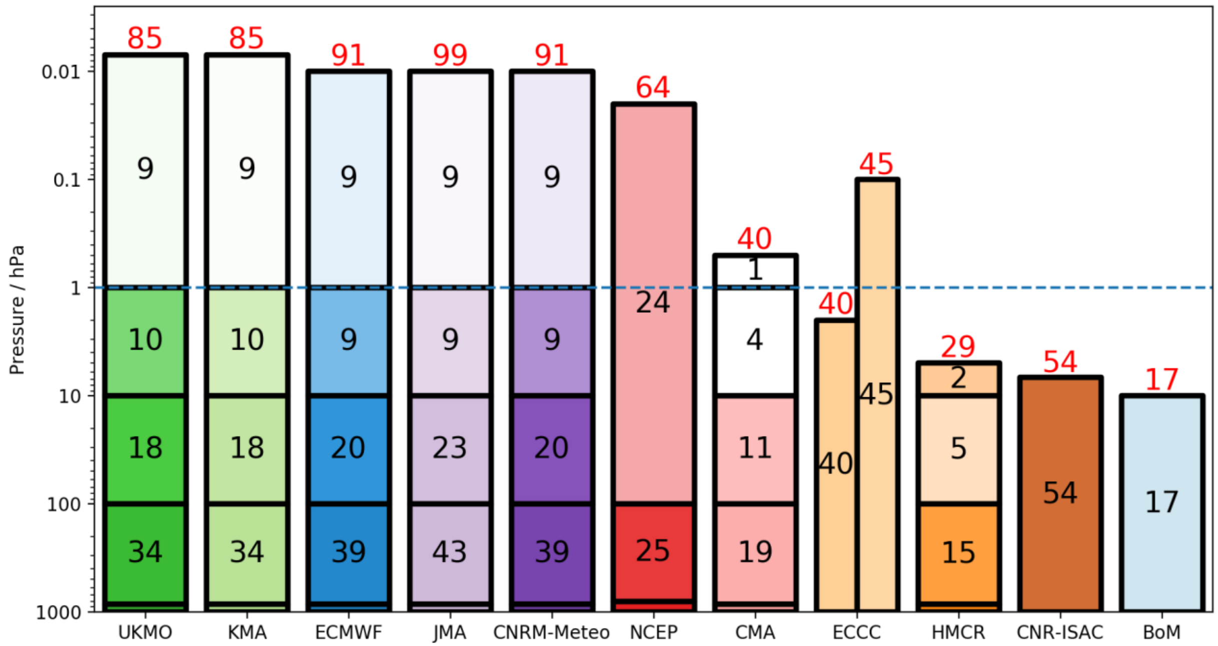
S2S MODELS

Centre	Model	Hindcast			Real-time		
		Years	Ens. Size	N_{forc}	Years	Ens. Size	N_{forc}
BoM	poama	1981-2013	33	792	2015-2019	33	112
CMA	bcc_cps_s2sv1	1994-2014	12	818	2015-2019	12	174
ISAC-CNR	cnr-isac	1981-2010	5	720	2015-2019	41	48
ECCC	gem1	1995-2014	4	840	2016-2018	21	42
ECCC	gem2	1998-2017	4	360	2018-2019	21	17
ECMWF	cy43r1	1996-2016	11	560	2016-2017	51	27
ECMWF	cy43r3	1997-2017	11	680	2017-2018	51	34
ECMWF	cy45r1	1998-2018	11	700	2018-2019	51	33
HMCR	rums	1985-2010	10	1222	2016-2019	20	58
JMA	geps1701	1981-2013	5	384	2017-2019	50	33
KMA	glosea5_gc2	1991-2010	3	320	2016-2019	12	117
Meteo-France	cnrm-cm_6.0	1993-2014	15	352	2016-2019	51	46
NCEP	cfsv2	1999-2009	12	428	2015-2019	48	175
UKMO	glosea5_gc2	1993-2016	7	384	2015-2019	12	146

- Significant variation in hindcast construction in addition (daily or weekly; on-the-fly; initialization)

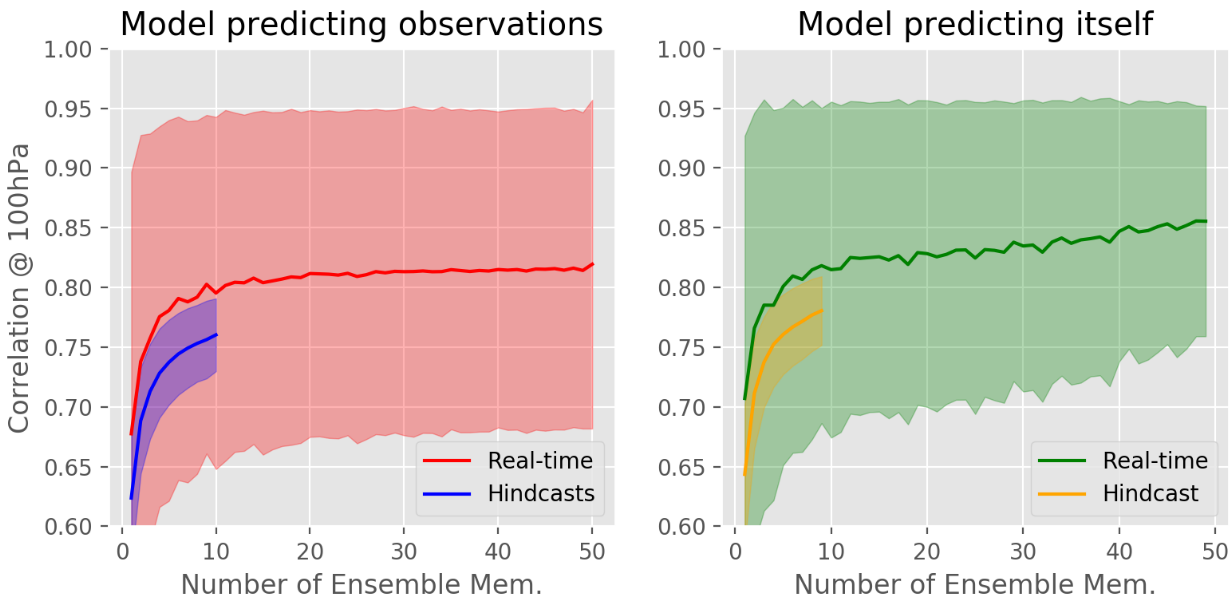
VERTICAL RESOLUTION

- Number of levels in different parts of the atmosphere
- Shading proportional to resolution



- A number of the S2S models have low vertical resolution or are 'low-top'
- Does this restrict their ability to capture stratosphere-troposphere coupling?

- We would like to use the hindcast dataset for each model since this covers a broader range of start dates – but does the hindcast have similar properties to the full ensemble?
- Test by bootstrapping ensemble (cf Eade et al., 2004).
- Example below for ECMWF cy45r1



SIGNAL/NOISE MODEL

- Based on model of Siegert et al. (2016):

$$Y(t) = \mu_y + \beta_y S(t) + \epsilon O(t)$$
$$X_k(t) = \mu_x + \beta_x S(t) + \eta P_k(t) \qquad \text{for } k = 1, \dots, K$$

Y(t) – observation

$X_k(t)$ – forecast member

S(t) – predictable signal; N(0,1)

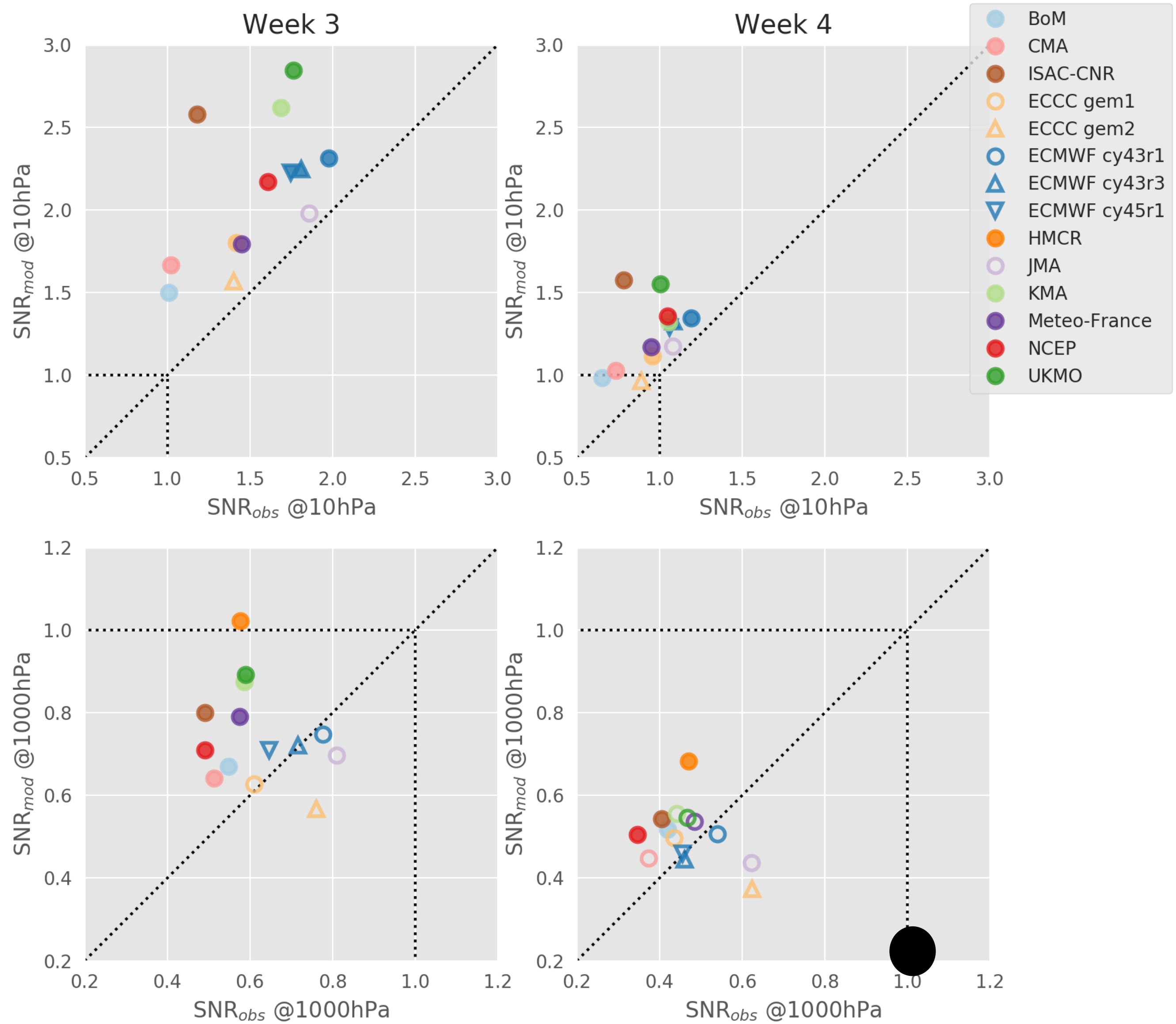
O(t), $P_k(t)$ – unpredictable noise; N(0,1)

$\beta_{x,y}$ – amplitude of shared predictable signal in observations and model

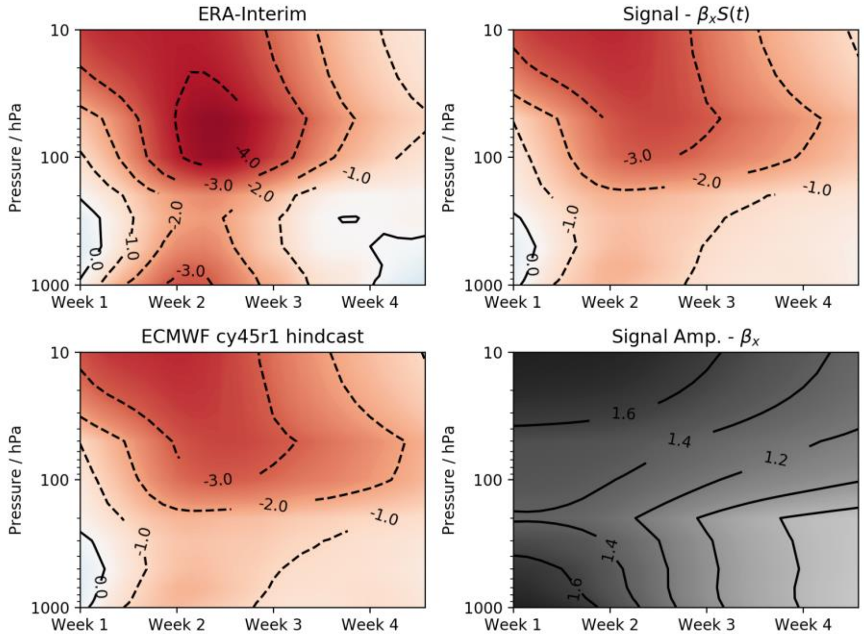
ε,η – amplitude of uncorrelated noise terms

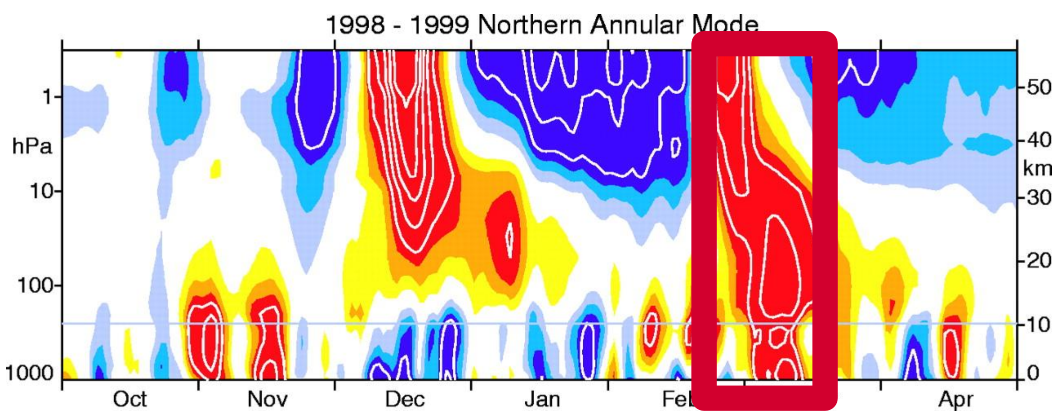
Fit statistical model to forecast data using Maximum-Likelihood Estimate with bootstrapping to estimate confidence intervals

- Dots show cases where SNR for model and obs. Are significantly different at p-value of 0.05
- No evidence for sub-seasonal forecasts of the NAM of model under-confidence or a signal-to-noise paradox.
- For the N. Atlantic sector evidence in some models on longer timescales (see SNAP papers)



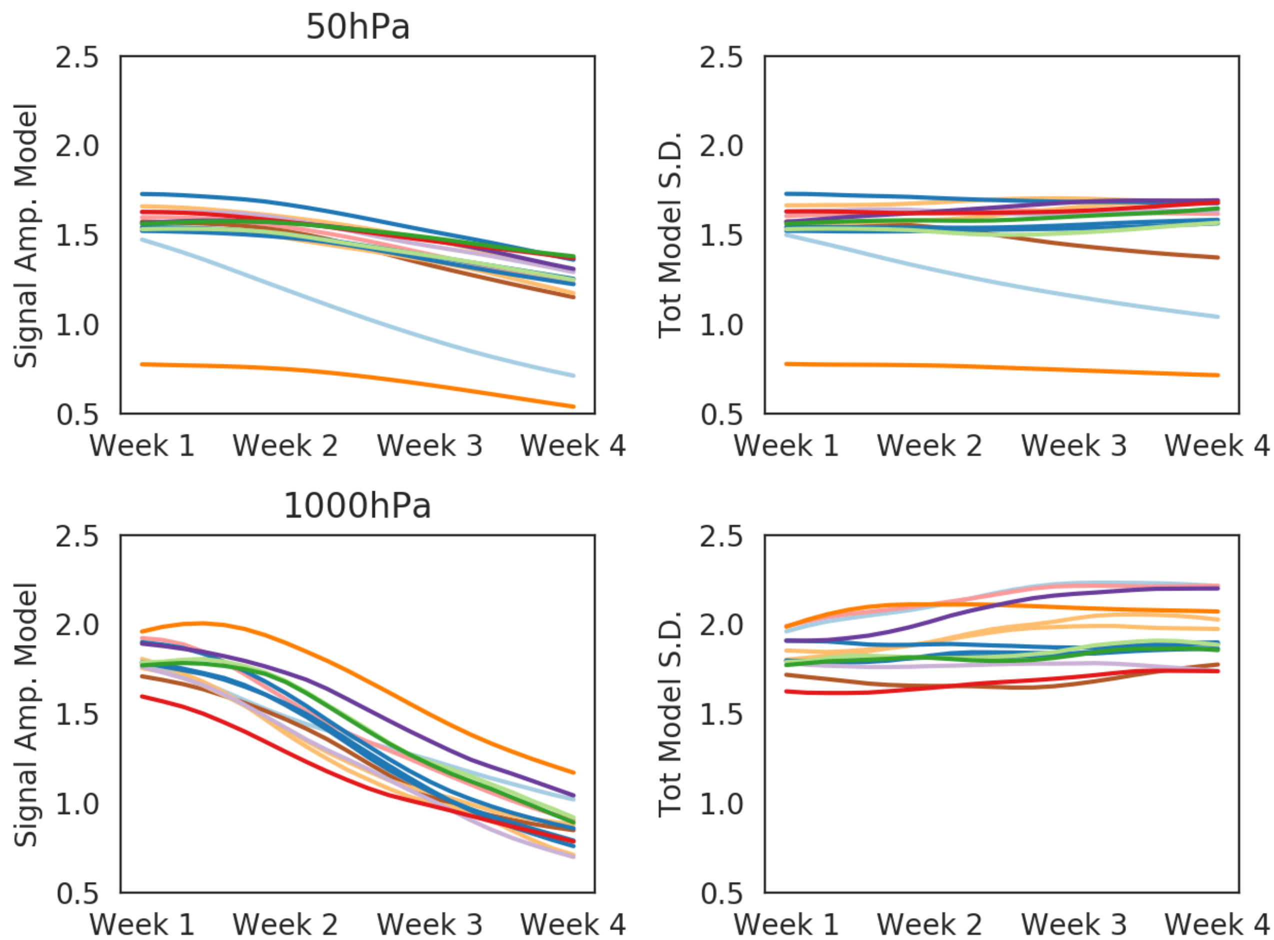
What are the properties of the signal in the models?



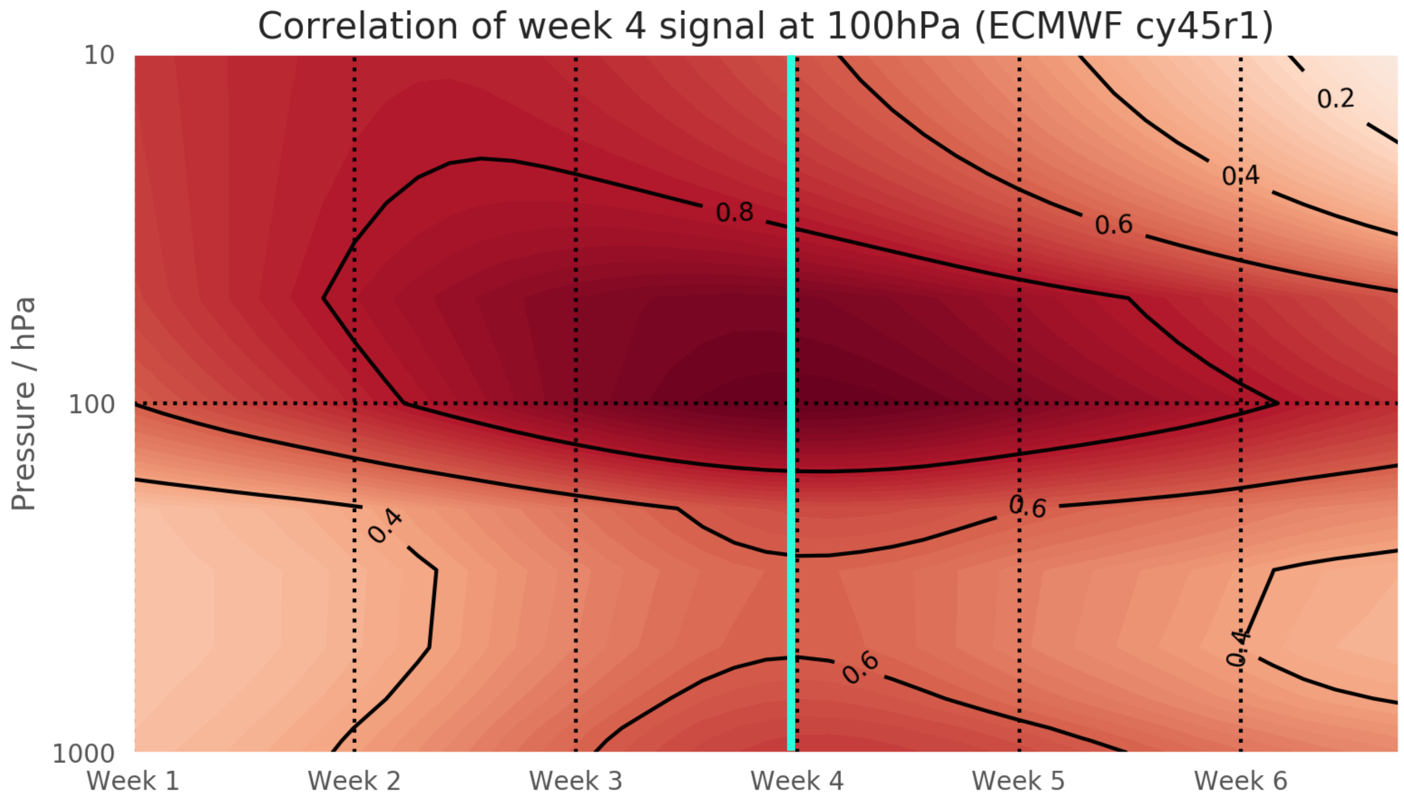


- Signal term as diagnosed for model forecasts of the major SSW during February 1999.
- Amplitude of the signal in the model decays rapidly in the troposphere and more slowly in the stratosphere

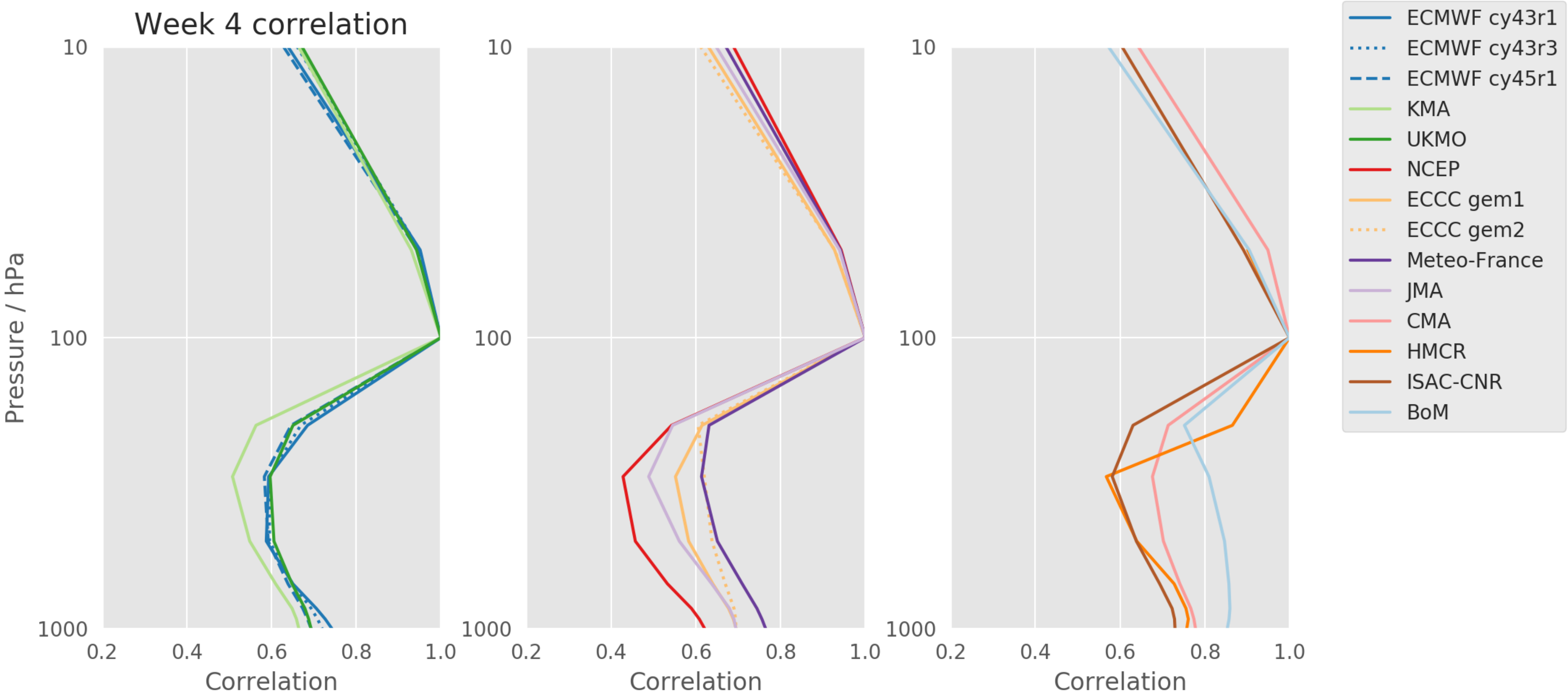
- Pattern of signal decay in ECMWF model is very similar in all models
- Low-top models are an exception due to their limited stratospheric variability



Is the signal in the stratosphere and troposphere coupled?



- Signal on sub-seasonal timescales at the surface is strongly correlated with signal in the lower stratosphere.



- Comparing all the models with the same metric, they have similar properties – but some differences in the amplitude of the coupling.

Do models capture the same signals?

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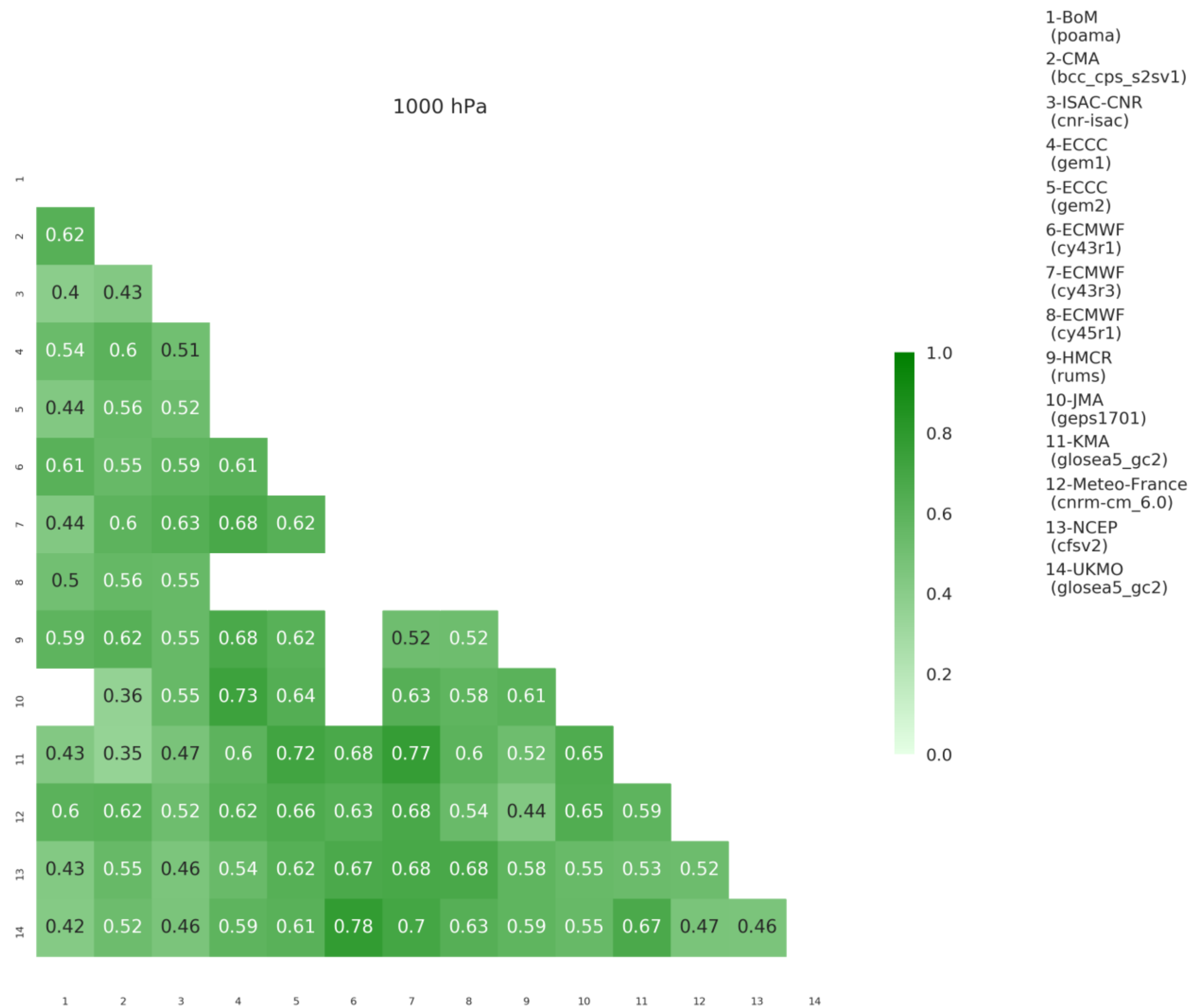
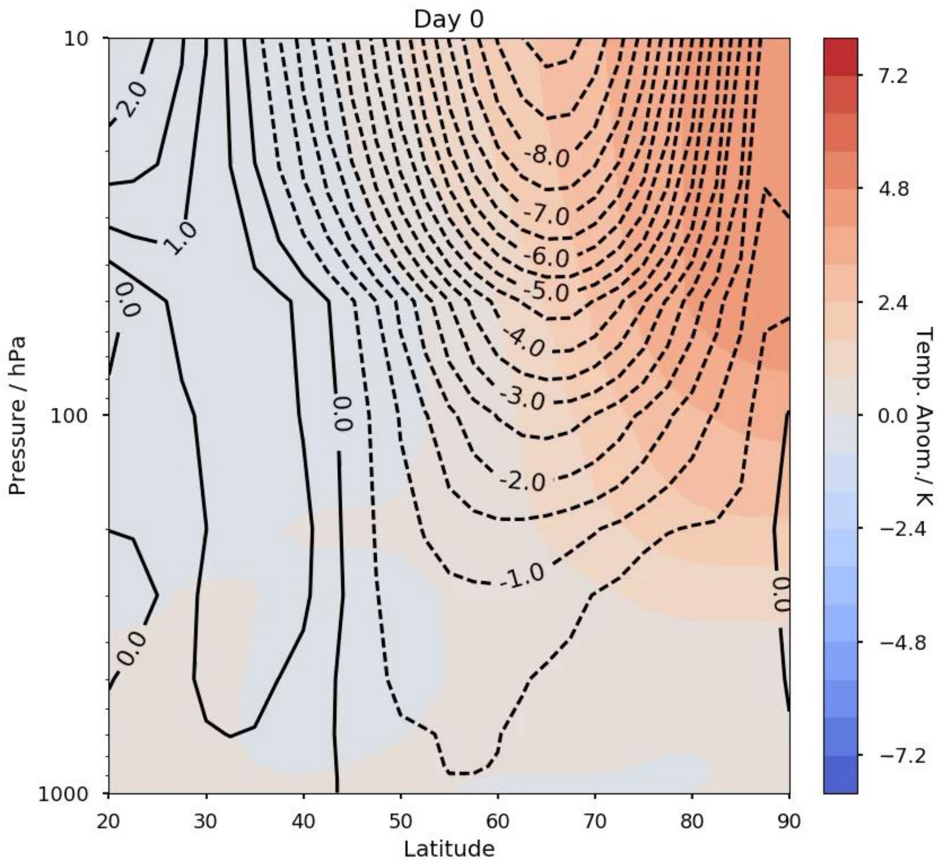
Correlation between the Week 4 signal term for paired forecasts from each hindcast set

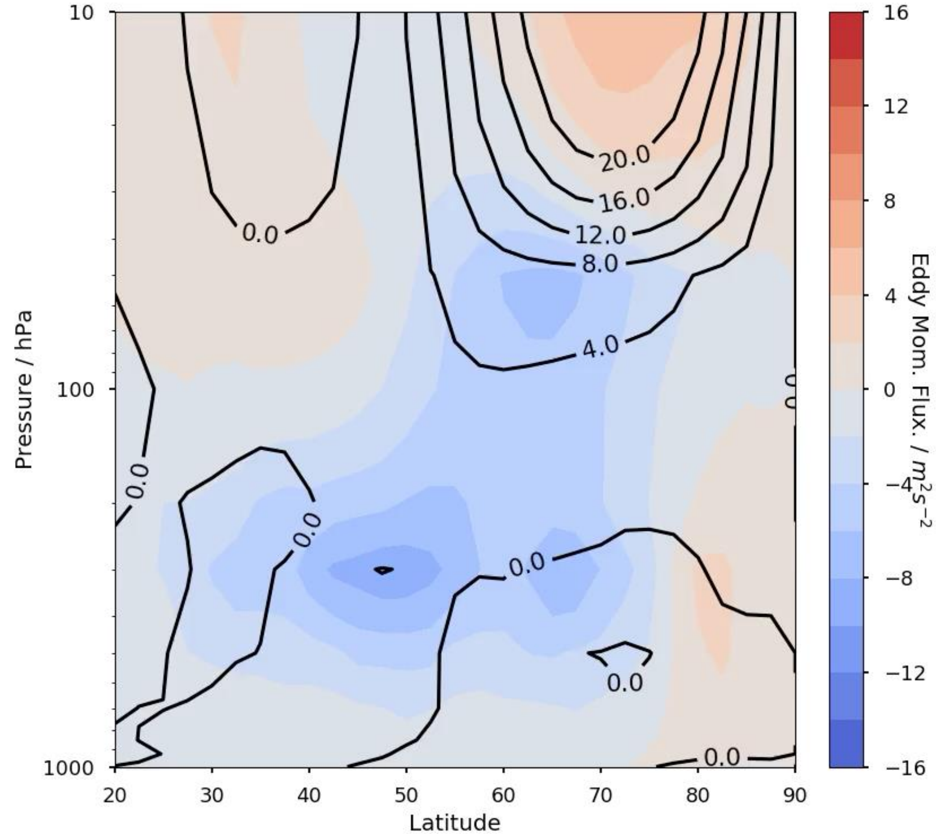
- In the stratosphere – yes
- In the troposphere, mostly but with more variation between models

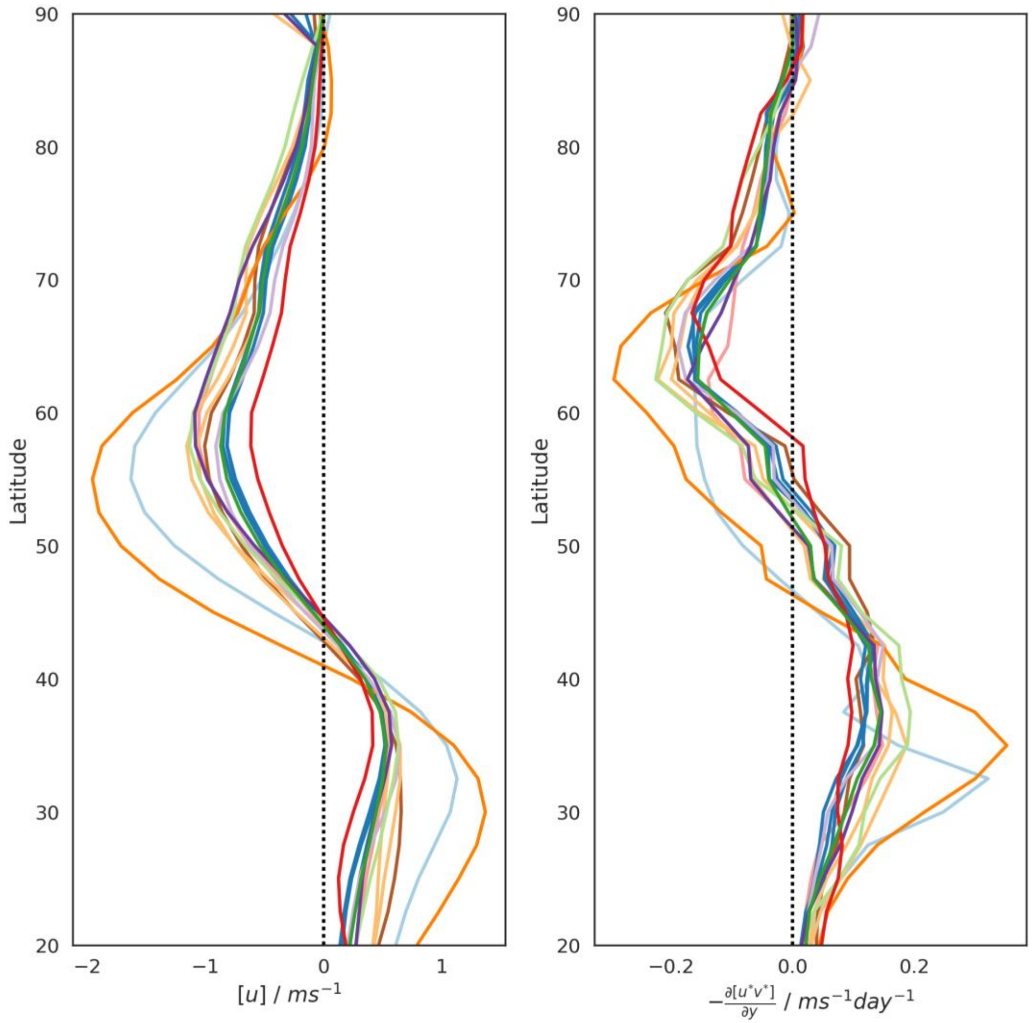


How does the predictable signal at the surface arise?

- The week 4 signal at 100hPa is linked to tropospheric amplification of a pre-existing Annular Mode pattern







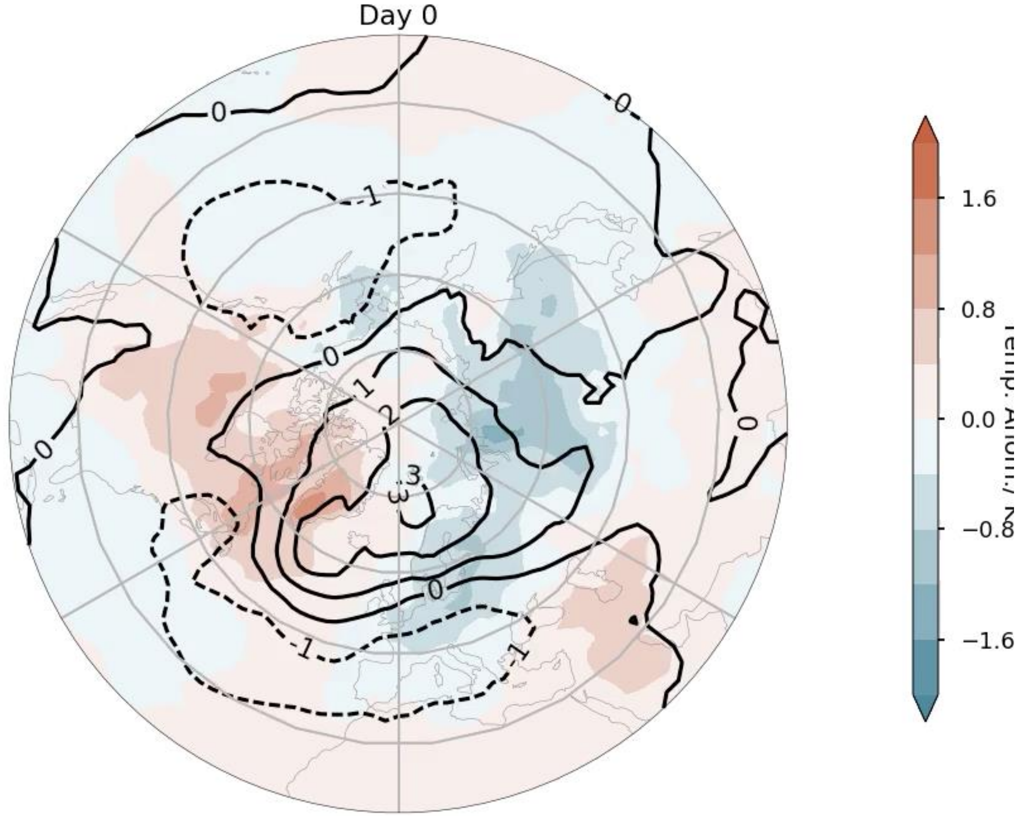
- Consistency in structure of eddy momentum convergence and tropospheric jet response – (HMCR excluded).

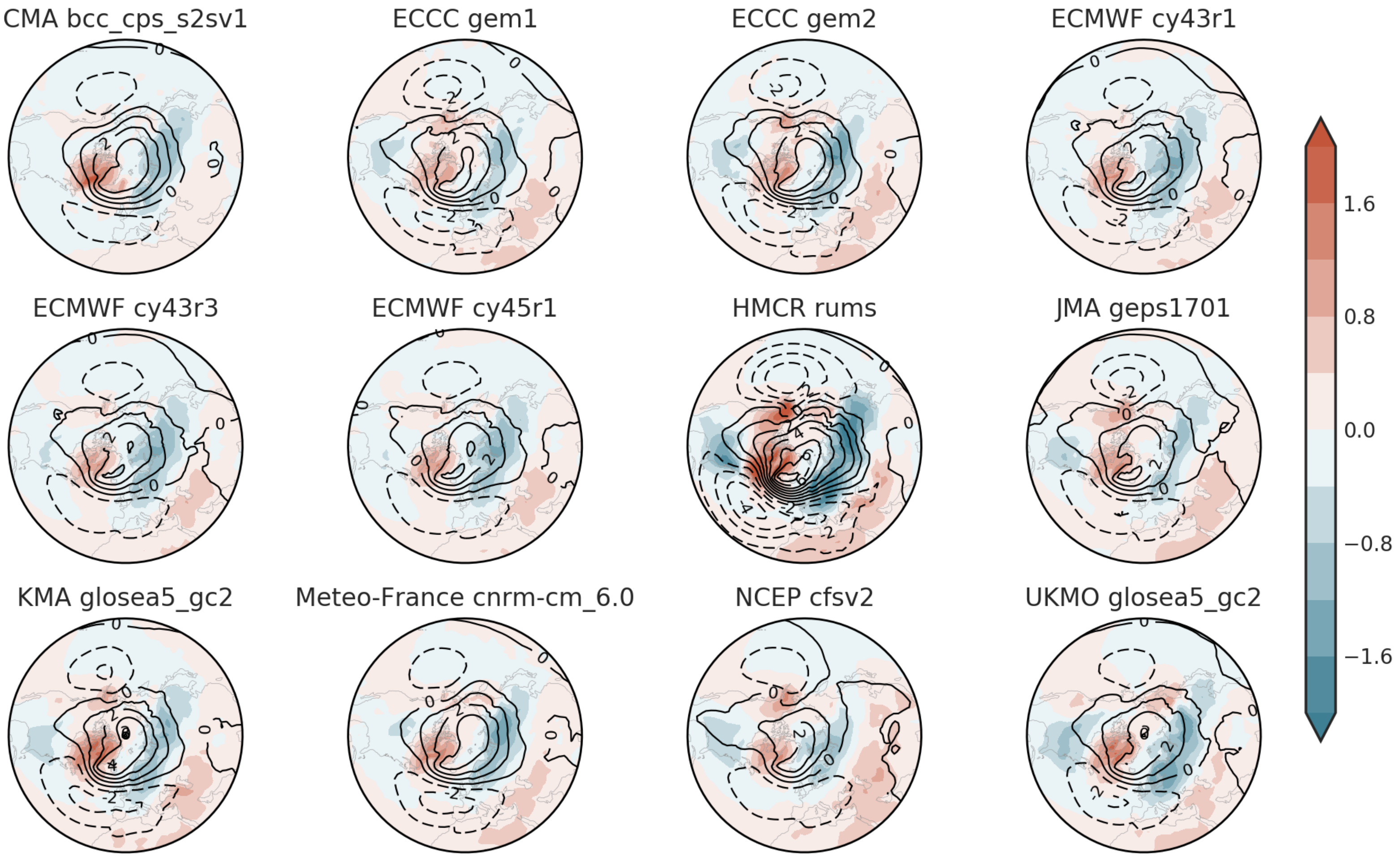
Vertical average (300-1000hPa) of regression between dynamical terms and Week 4 100hPa signal

What is the local response to the coupled signal?

- Associated surface signal is an intensification of NAM- pressure and temperature pattern with emphasis on N. Atlantic response.
- Cold temperatures through N. Europe and mid-Atlantic N. America

ECMWF cy45r1





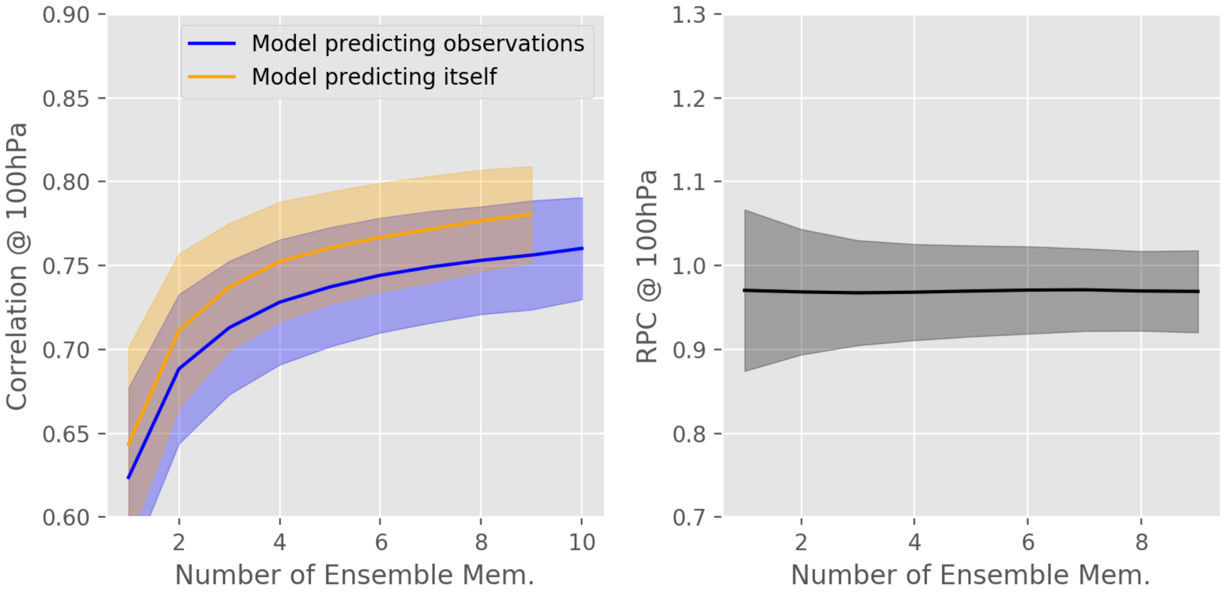
- Structure and amplitude of surface response has significant dependence on model.

CONCLUSIONS

- For the Northern Annular Mode (NAM), a good metric for diagnosis of stratosphere-troposphere coupling there is little evidence of anomalously low signal-to-noise ratio for sub-seasonal forecasts.
- Predictable signals for the NAM decay quickly in the troposphere and more slowly (into the sub-seasonal range) in the stratosphere.
- Predictable signals propagate downwards through the stratosphere and influence the troposphere on the sub-seasonal timescale.
- The predictable signal in the stratosphere is strongly correlated between models, in the troposphere there is greater disagreement; likely link to other influences on the tropospheric state.
- Internal tropospheric dynamics in the models influence the expression of stratosphere-troposphere coupling at the surface.

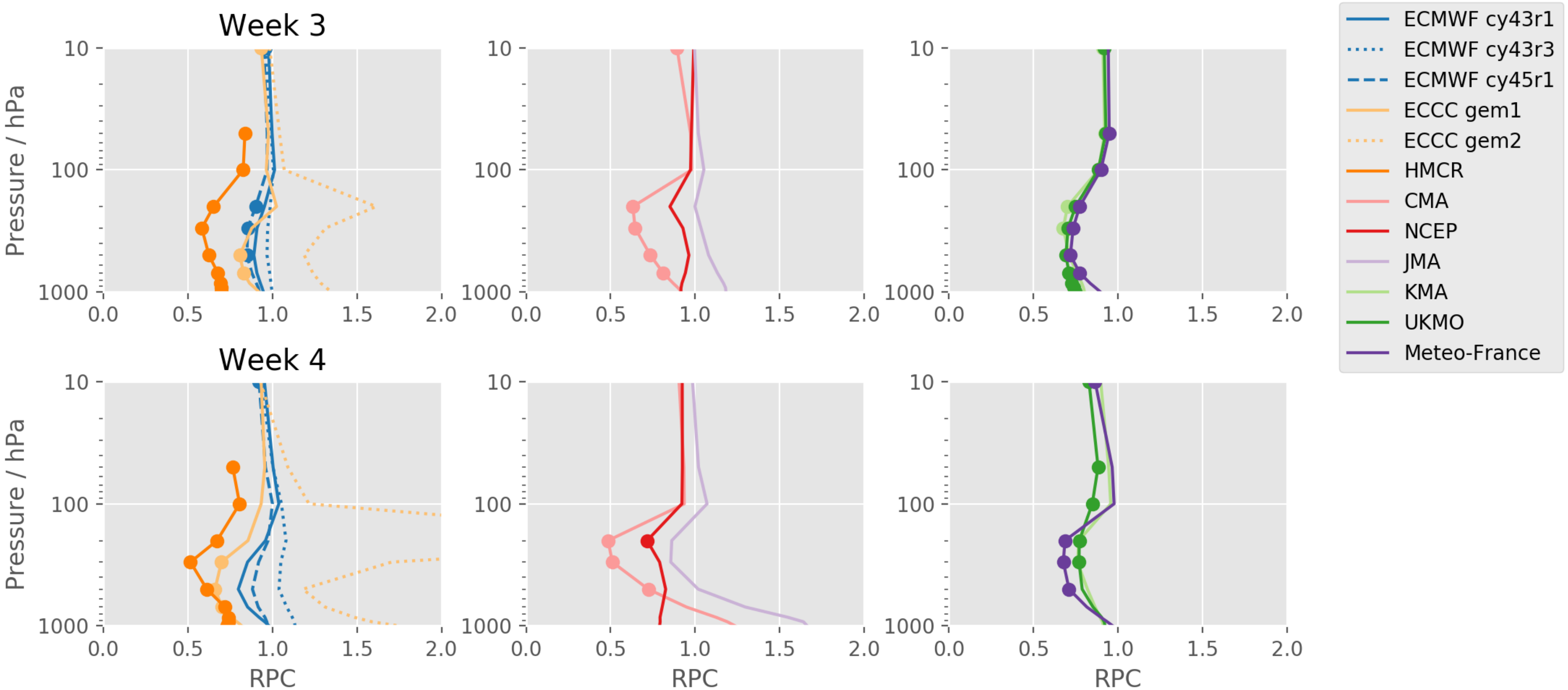
EXTRA SLIDES

RATIO OF PREDICTABLE COMPONENTS



$$\mathrm{RPC}^2 = R^2_{\mathrm{mo}}/R^2_{\mathrm{mm}}$$

- A simple test of the signal-to-noise properties of the models is to construct the ratio of predictable components.



- Dots show cases where the RPC is significantly different from 1 at a p-value of 0.05.
- No evidence for sub-seasonal forecasts of the NAM of model under-confidence or a signal-to-noise paradox.

MLE METHOD

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- Introduce transformed variables, m and ξ.
- **w** – a set of R-1 orthonormal 'contrasts'

$$m(t) = \frac{1}{K}\sum_{k=1}^{K} X_k(t)$$

$$\zeta_l(t) = \langle \mathbf{w}^{(l)}, \mathbf{X}(t)\rangle \qquad \text{for } l = 1, \ldots, K-1$$

Covariance matrix, M is:

$$M = \begin{pmatrix} \beta_y^2 + \epsilon^2 & \beta_y\beta_x \\ \beta_y\beta_x & \beta_x^2 + \sigma_m^2 \end{pmatrix}$$

$$\sigma_m^2 := \eta^2/K$$

MLE estimates for m and M are then:

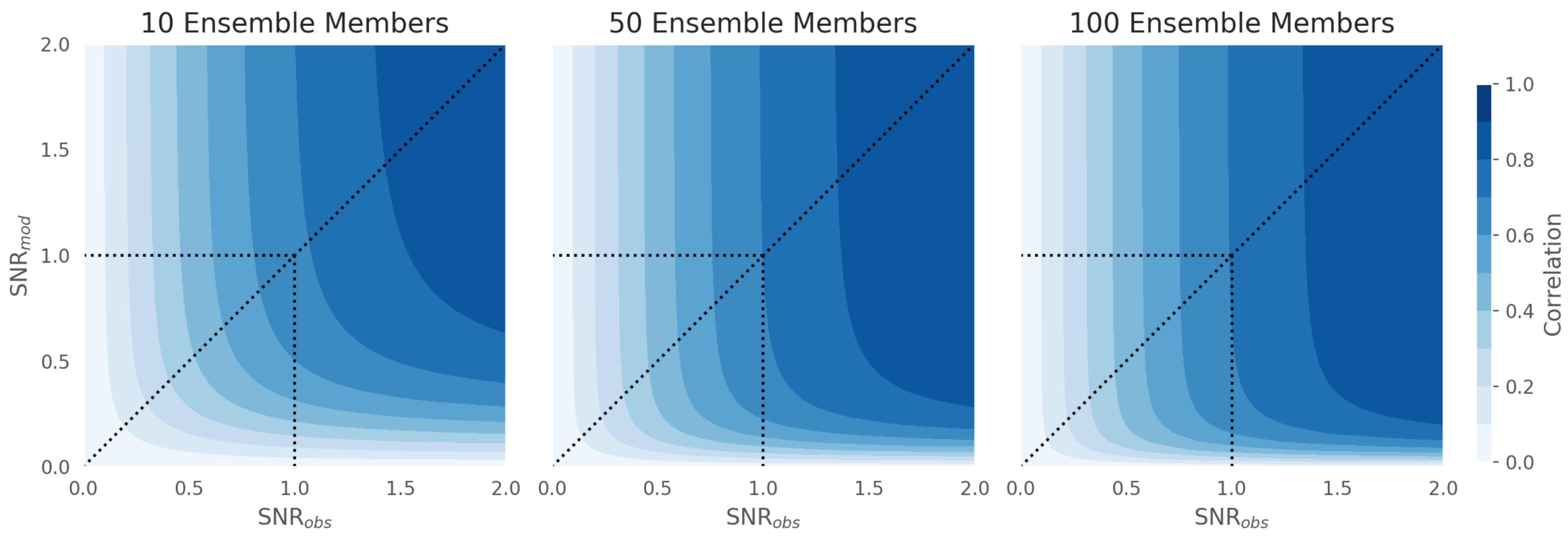
$$\hat{\sigma}_m^2 = \frac{1}{K(K-1)N}\sum_{l\le K-1, t\le N} \zeta_l^2(t)$$

$$\hat{M} = \frac{1}{N}\sum_{t\le N} Z(t)Z^{\mathrm{T}}(t) - \left(\frac{1}{N}\sum_{t\le N} Z(t)\right)\left(\frac{1}{N}\sum_{t\le N} Z(t)\right)^{\mathrm{T}}$$

Bootstrapping:

In the present example, the distributions of $\hat{M}$ and $\hat{\sigma}_m$ are known structurally except for the parameters M and σ_m^2. Namely, $\hat{M}$ follows a Wishart distribution with N degrees of freedom and scale matrix M which we estimate by $\hat{M}$, so samples of $\hat{M}$ are drawn from a Wishart distribution with N degrees of freedom and scale matrix $\hat{M}$. Similarly, samples for $\hat{\sigma}_m^2$ are calculated by randomly drawing from a χ–square distribution with $(K-1)\cdot N$ degrees of freedom and multiplying with $\hat{\sigma}_m^2$. Note also that the resulting bootstrap samples for $\hat{M}$ and $\hat{\sigma}_m^2$ do not only have the correct distribution but are furthermore independent.

How does the signal-to-noise ratio link to the correlation?



$$\mathrm{SNR}_y = \frac{\beta_y}{\epsilon},$$
$$\mathrm{SNR}_x = \frac{\beta_x}{\eta}$$

$$R(Y(t), m(t)) \leq \sqrt{\frac{K \cdot \mathrm{SNR}_x^2}{1 + K \cdot \mathrm{SNR}_x^2}} \cdot \sqrt{\frac{\mathrm{SNR}_y^2}{1 + \mathrm{SNR}_y^2}}$$