

Linear response of Barents Sea ice cover to upstream ocean conditions

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CHUNCHENG GUO AND ALEKSI NUMMELIN

NORCE CLIMATE BJERKNES CENTRE FOR CLIMATE RESEARCH











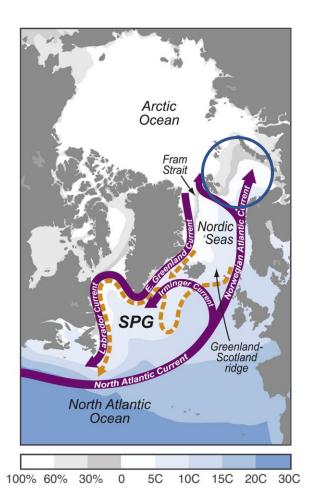
Take home messages

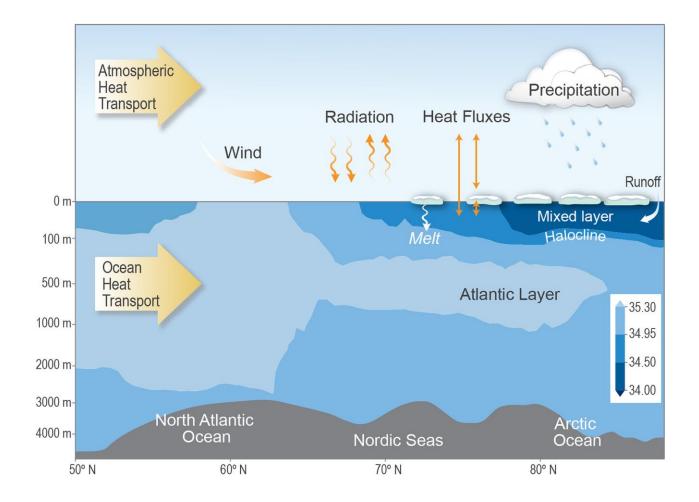
> [useful] SST -> Sea ice response functions have finite timescales.

> Predictability of the Barents Sea ice cover increases [beyond pure chance] when we use information from along the entire path of the Norwegian Atlantic current.



Introduction: the coupled system





OHT-sea ice linkage: Årthun et al. (2012), Onarheim et al. (2015), Li (2017) + many more

Li and Born (2019)

A bit of theory

Assume a linear stochastic system governed by a response function *G* and a forcing *F*.

We can write this system in a matrix form and solve for *G*

Finally, we can estimate the original timeseries C by convolving *G* and *F*.

$$C = G \cdot F$$
$$G = C \cdot F^{-1}$$

 $\hat{C}(t) = \int_{t-\tau} G(t-\tau)F(\tau)d\tau$

 $C(t) = \int_{0}^{\tau_{max}} G(\tau) F(t-\tau) d\tau$

If we have more than one forcing (predictor), we can use multiple linear regression to solve for a combined estimate

$$B = C \cdot \hat{\mathbf{C}}^{-1}$$
$$\hat{C}_c = B \cdot \hat{\mathbf{C}}$$

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Details

Linear trend removed from both the sea ice and the forcing (predictor).

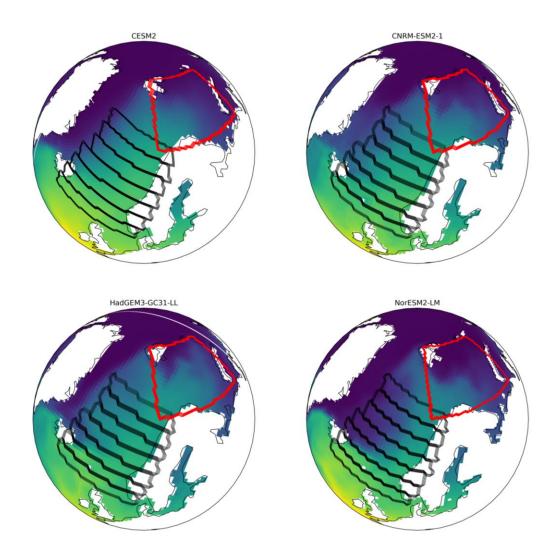
The analysis is done on a monthly basis, i.e. we recover one response function for each month.

We focus on March, but the results are similar for other months, although predictability is weaker in summer (as expected – little to no ice in the Barents Sea).

All results are normalized by standard deviations.

DATA

- Predictors: SST anomalies at given sections in the Nordic Seas
 - SST enables the use of observations
 - Also tested: salinity, surface heat flux, and ocean heat transport
- CMIP6 (piControl, control-1950, omip1, omip2) + OI-SST (observations)
- Target: Barents Sea ice cover (concentration, volume)

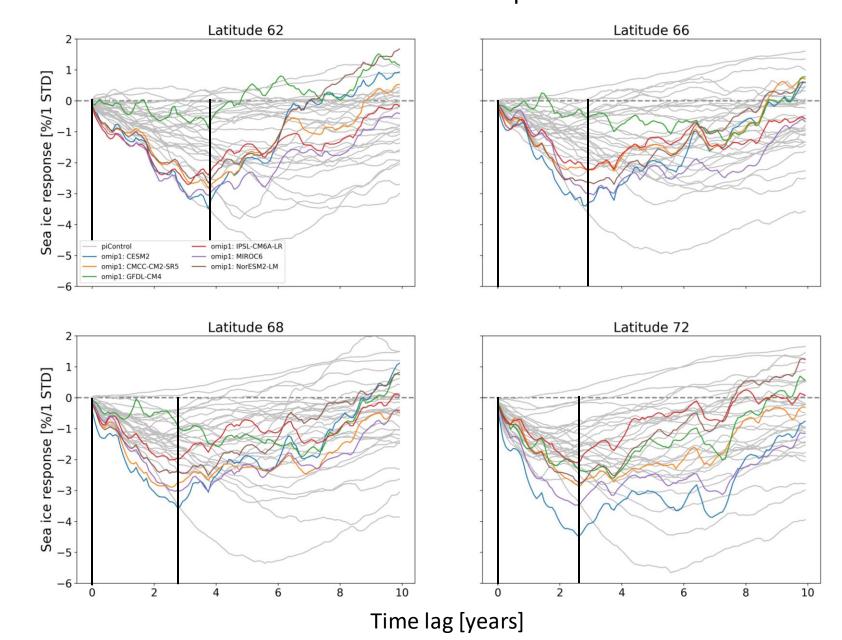


Model response functions (G_{Step}, March)

OMIP based response functions show 3-4 year response timescale

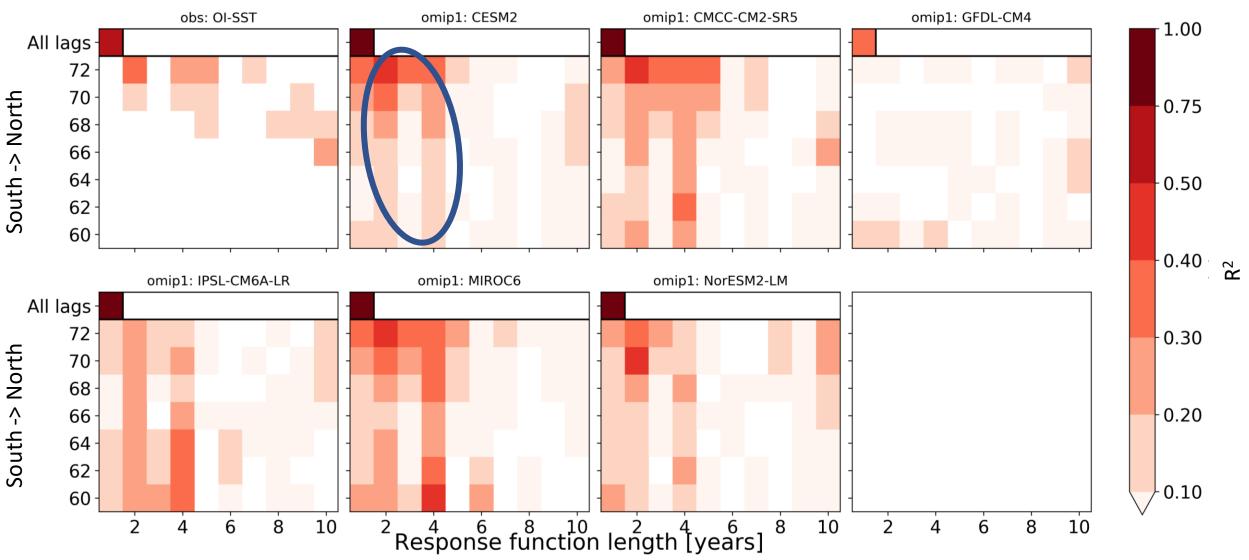
PiControl based response functions (grey) have a large spread in response timescales especially further south.

Note that 62N is close to the Greenland-Scotland Ridge, whereas 72N is roughly at Barents Sea Opening



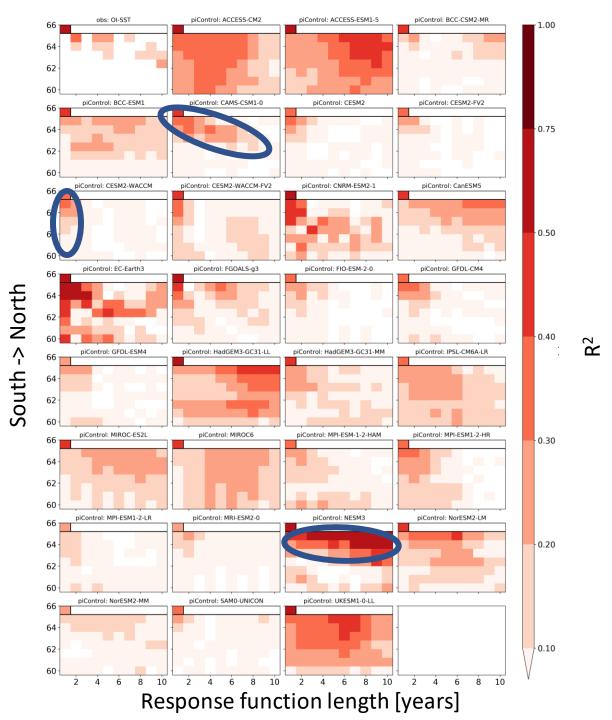
Reconstructing modelled sea ice (OMIP, March)

- High correlation is concentrated close to the ice edge
- Dominated by short timescales



Reconstructing modelled sea ice (PiControl, March)

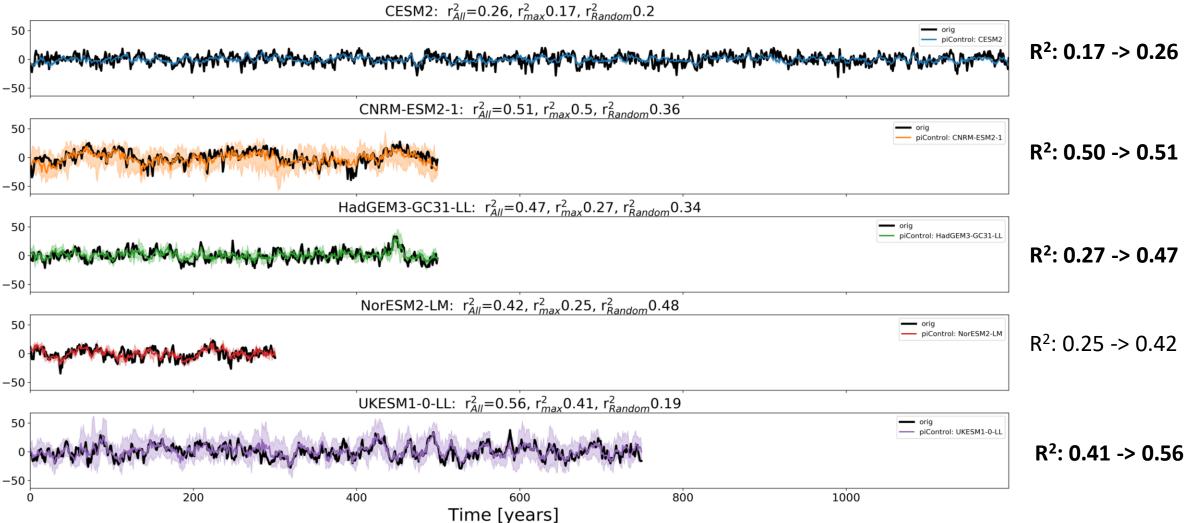
- In most cases high correlation is concentrated close to the ice edge
- Large spread in timescales from few years to 10 years (probably longer)
 - blue ellipses highlight different examples



Reconstructing modelled sea ice (selected PiControl examples, March)

concentration [%]

Sea ice



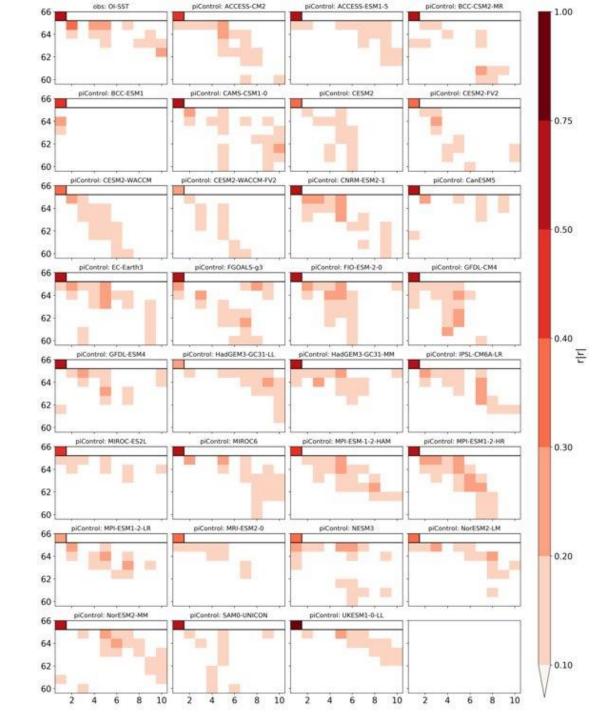
Change in R² when more than one section is used. Bold if increase is more than expected from adding random data.

Reconstructing observed sea ice (piControl, March)

All models have some skill, but the skill is weak and at most explains <30% of the variance at individual sections

High correlations concentrated close to the ice edge

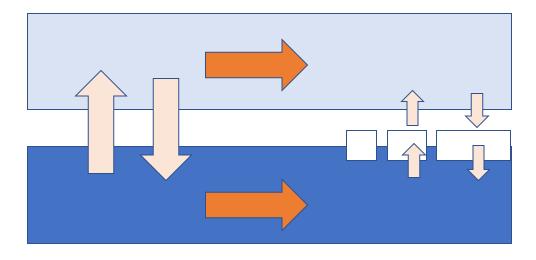
Combining all sections is hardly useful because of overfitting



Summary & further development

- SST based response functions reveal a lagged signal along the Norwegian Atlantic current
 - 3-4 year timescales in OMIP-I
 - Somewhat larger spread in piControl
- The model-based response functions have limited skill in reconstructing the observed sea ice concentration at individual sections (<30%)
- Open Questions
 - Do the response functions represent causal physical relations?
 - Why does a combination of the different sections seem to provide extra information?
 - Reduces noise?
- Idealized 1.5-D channel model provides insight into the physics (extra-slides)

Simple model



Setup

Ua = 5 m/s
Uo = 5 cm/s
Ha = 1km
Ho = 50m
Da = 1E5 m2/s
Do = 5E2 m2/s

The model is run for 1000 years with monthly mean output using white noise and NAO-type forcing that enters the model through the heat flux term.

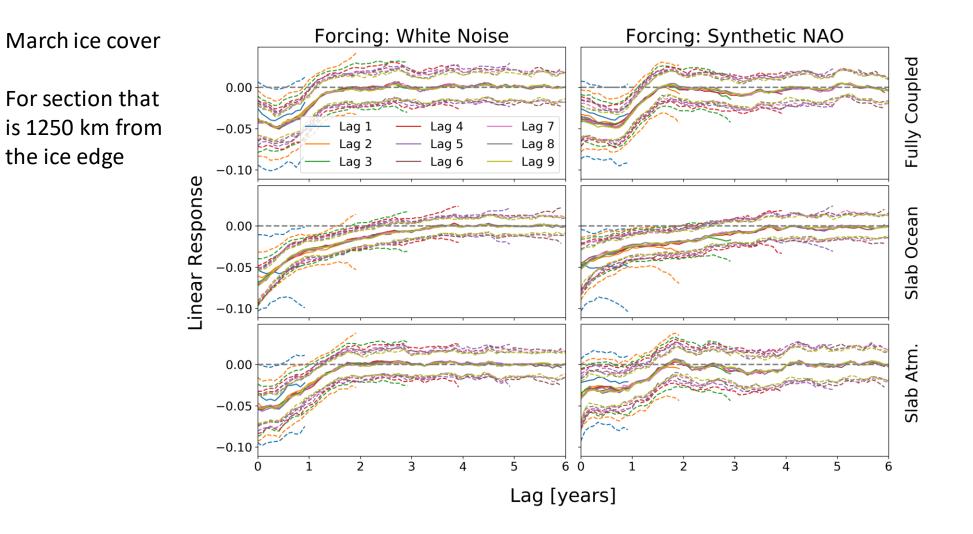
$$\frac{\partial T_a}{\partial t} = -u_a \frac{\partial T_a}{\partial x} + D_a \frac{\partial^2 T_a}{\partial x^2} + \frac{F}{H_a \cdot C_{pa} \cdot \rho_a} - \frac{\alpha \epsilon T_a^4}{H_a \cdot C_{pa} \cdot \rho_a}$$
$$\frac{\partial T_o}{\partial t} = -u_o \frac{\partial T_o}{\partial x} + D_o \frac{\partial^2 T_o}{\partial x^2} - \frac{F}{H \cdot C_{po} \cdot \rho_o} + \frac{T_{AW} - T_o}{\tau} + \frac{F_{SW}}{H \cdot C_{po} \cdot \rho_o}$$

Sea ice is diagnosed from the heat budget: cooling below freezing point produces ice, warming above freezing point only after all the ice is melted.

See also

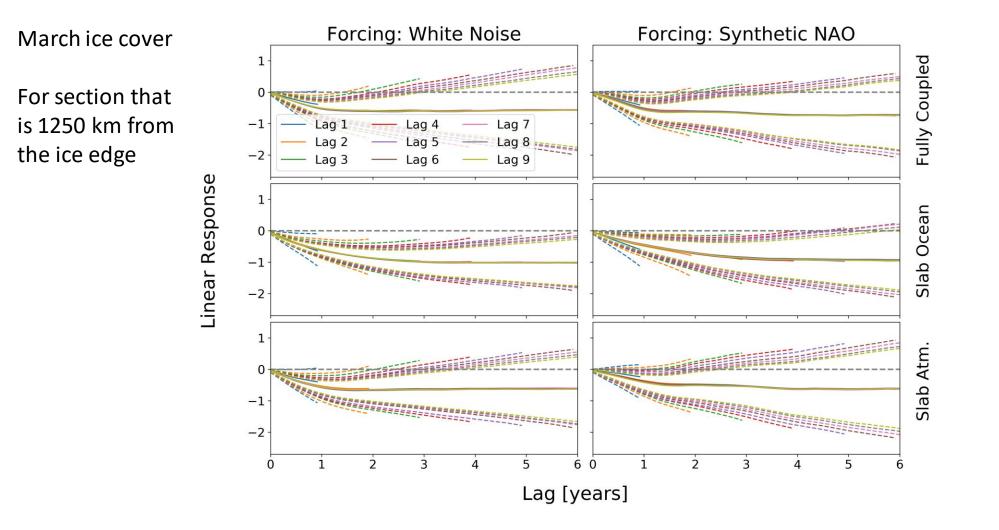
Nilsson (2001) Jeffress and Haine (<u>2014</u>) Broome and Nilsson (2018)

Effect of coupling on G in a simple model

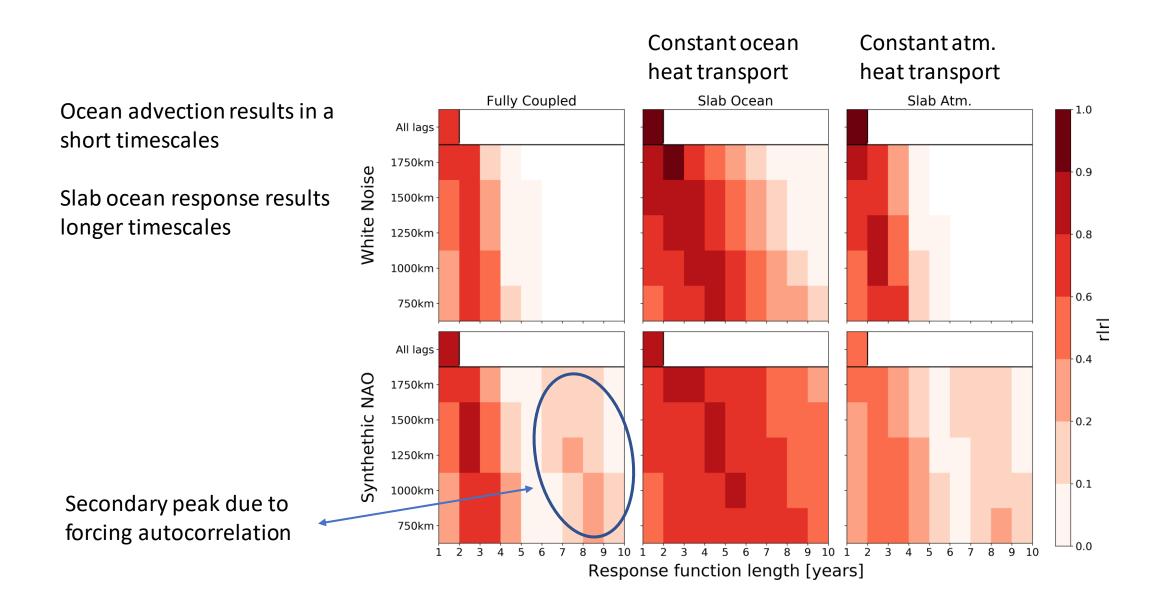


Note that in theory the envelope should go to zero at some long lag – here it stays the same

Effect of coupling on G_{step} in a simple model



Correlation suggest that length of G matters!



Summary from simple model results

- Response timescale:
 - Relatively short and distinct in ocean dominated system.
 - Longer and wider when atmosphere (mixed layer) dominate.
- For prediction purposes the response functions should be of some finite length!
 - Otherwise noise will decrease the correlation
- Auto-correlated forcing influences the response function.