Seminar
PMEL/NOAA
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Negative and positive thermodynamic feedbacks in simulated Arctic sea ice

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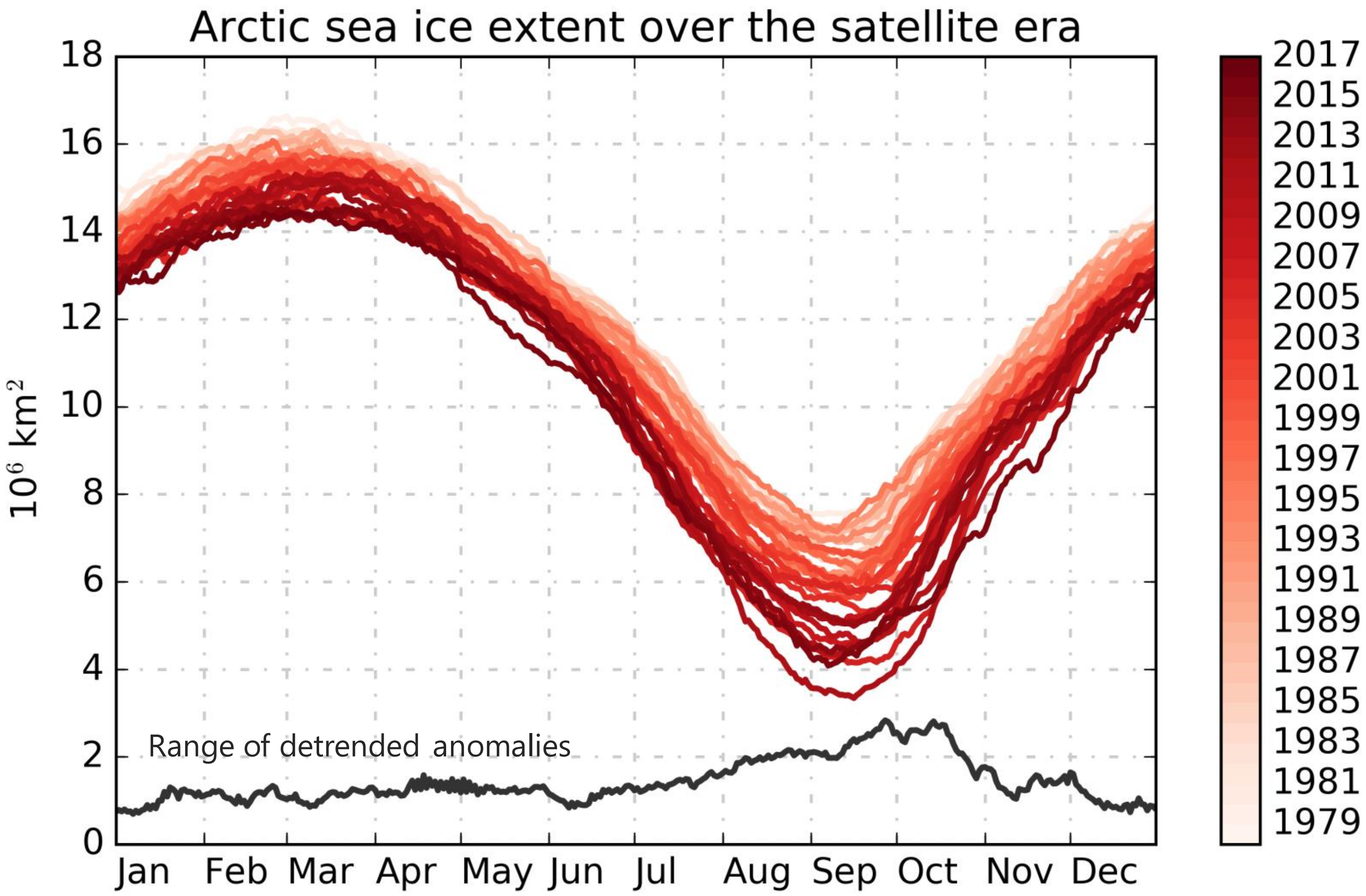
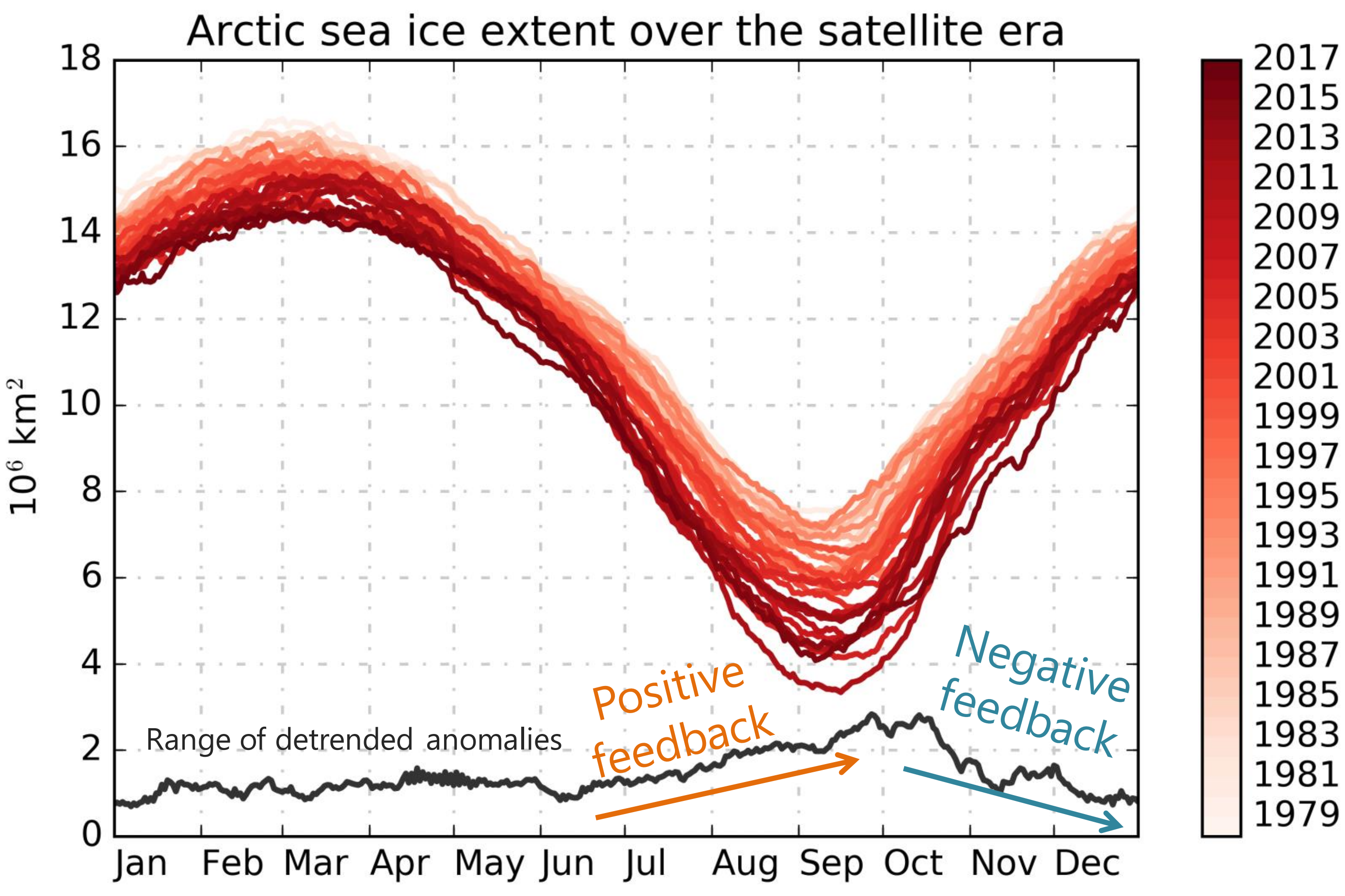
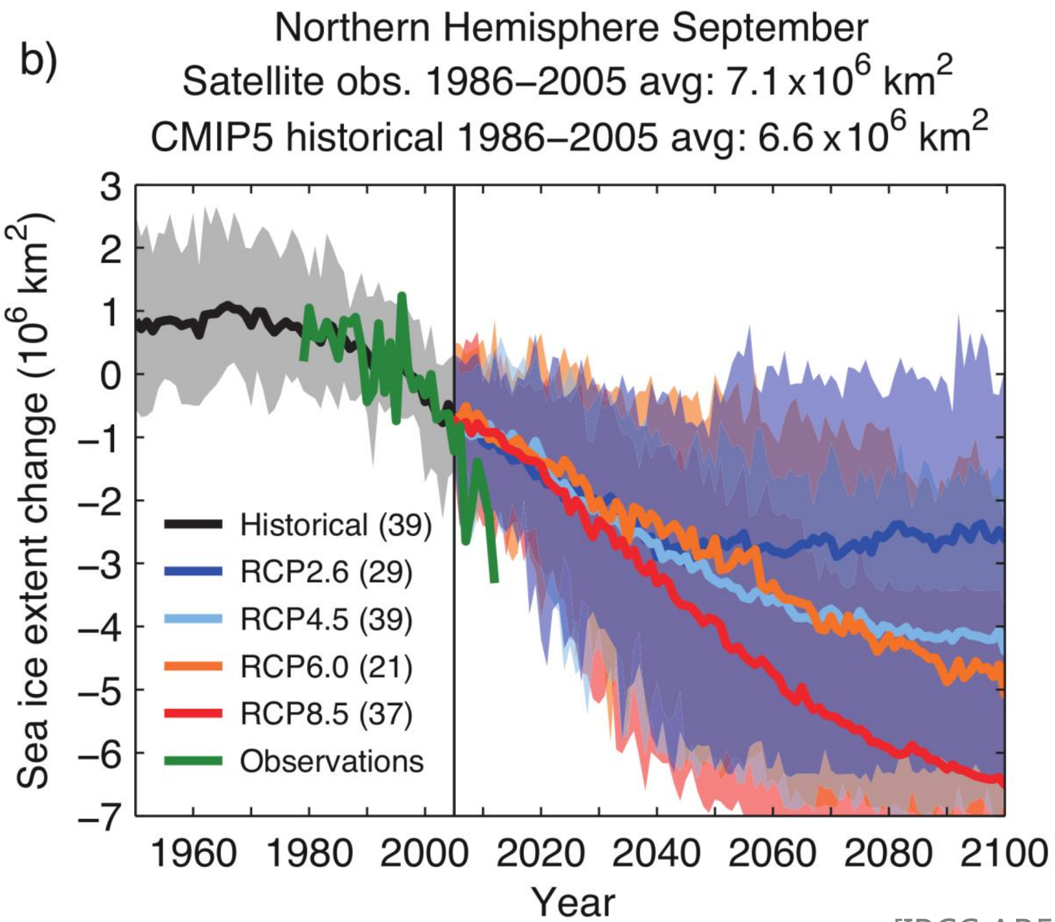
Seasonality, interannual variability and trends in the Arctic sea ice cover



Seasonality, interannual variability and trends in the Arctic sea ice cover



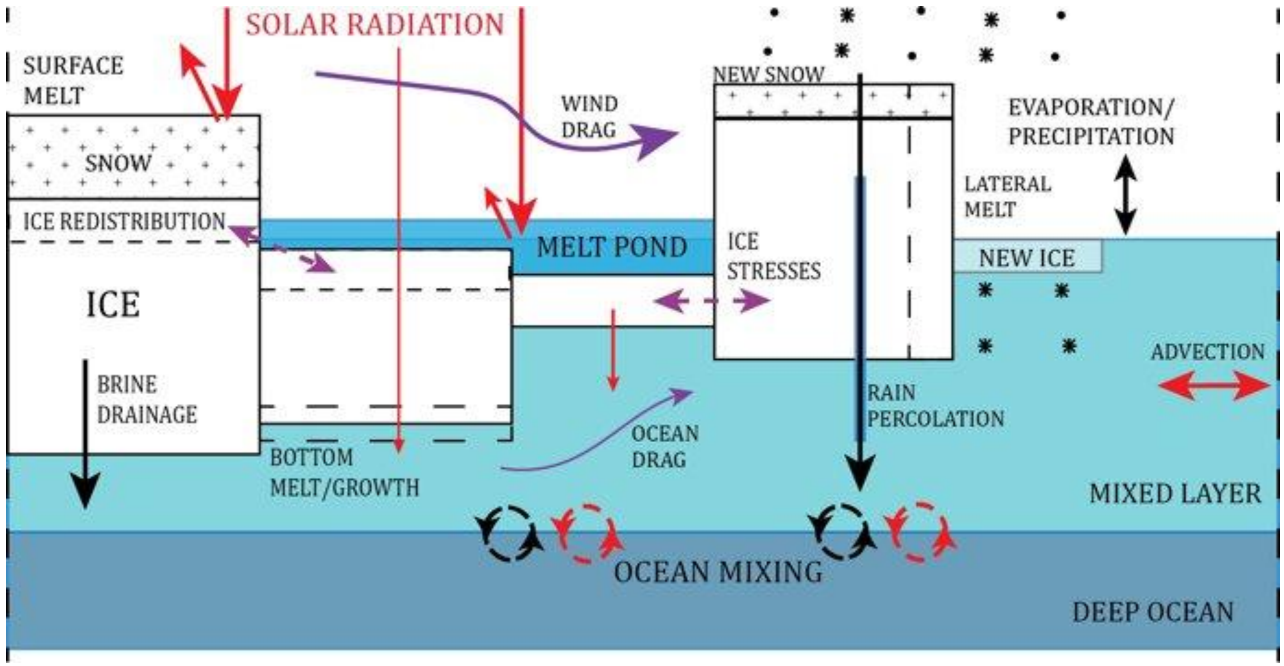
Science Question 1
How can we explain the spread in Arctic sea ice projections?



[IPCC AR5 WG1, 2013, Chapter 12]

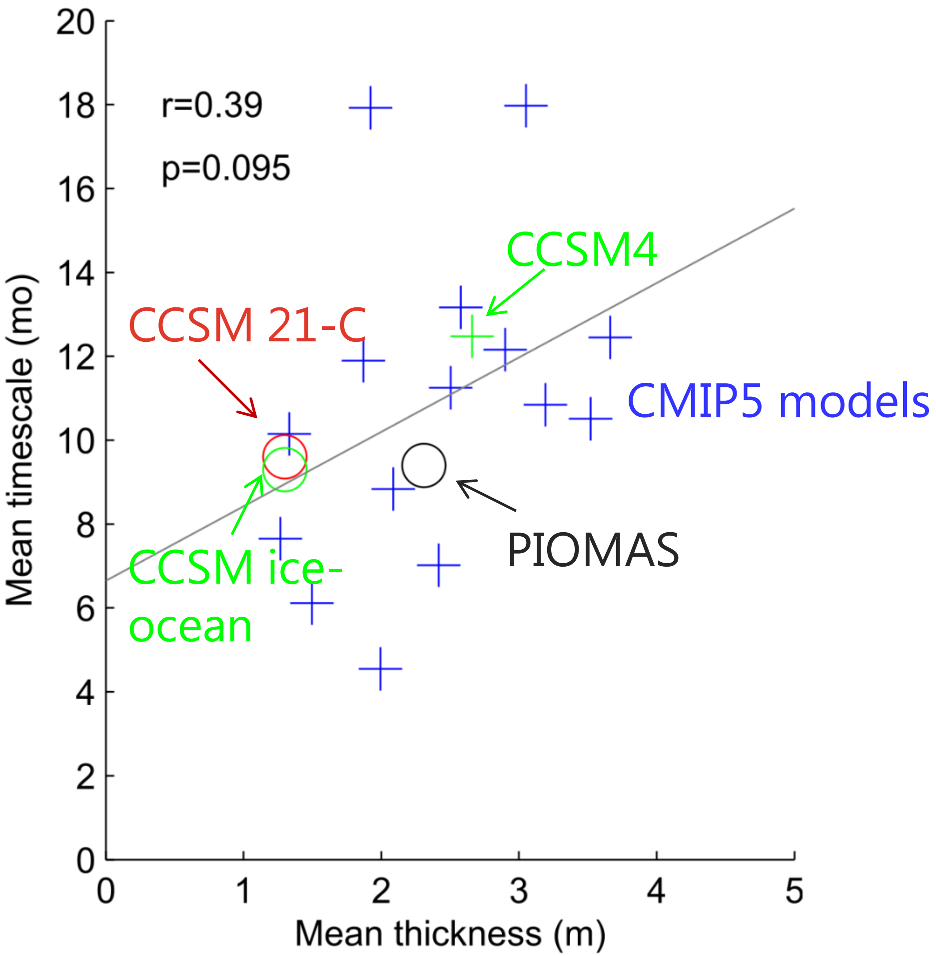
Science Question 2

Is there a link between sea ice model complexity and simulated properties?



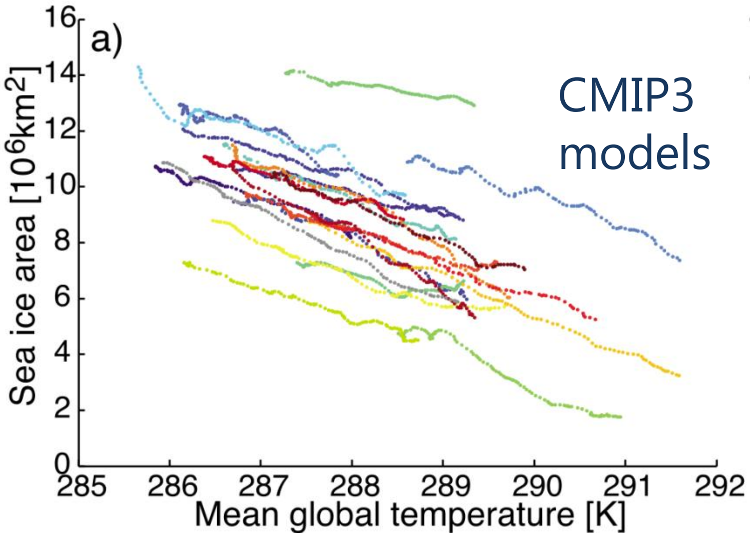
Better sea ice mean state?
Better predictability?
Better variability?
Better trends?

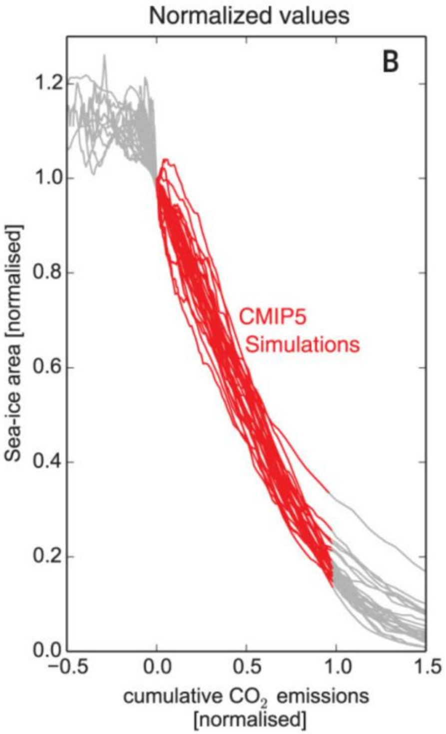
Science Question 3
What controls the predictability of Arctic sea ice? How will it change?



[Blanchard-Wrigglesworth and Bitz, J. Clim., 2014]

Science Question 4
How linear is Arctic sea ice?





[Mahlstein and Knutti, JGR, 2012]

[Notz and Stroeve, Science, 2016]

Arctic sea ice thermodynamics is essentially about

two feedbacks

mostly controlled by the

mean state

1. Estimation of the feedbacks

2. Feedbacks *vs* mean state

3. Feedbacks *vs* variability

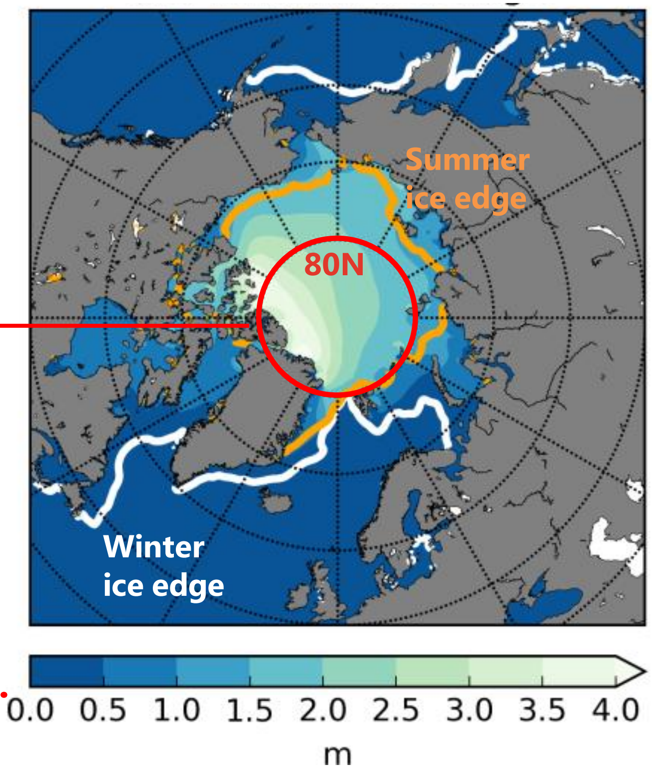
1. Estimation of the feedbacks

2. Feedbacks *vs* mean state

3. Feedbacks *vs* variability

Domain of the study: chosen to investigate sea ice thermodynamics

1979-2015 annual-mean thickness (PIOMAS)



Analyses are conducted north of 80N:
-Large enough to <u>smooth out the effect of dynamics</u> (advection, ridging, rafting, mechanical deformation)
-Small enough to <u>not be influenced by horizontal oceanic heat fluxes</u>
-Retains ice throughout mid-century in projections

The domain is adapted to study sea ice thermodynamics (this will be confirmed a posteriori).

The negative feedback: fundamental safeguard of the sea ice system

Eis dem Wasser entzogen und an die Oberfläche geführt oder, was dasselbe bedeutet, die Kältemenge, welche durch das Eis dem Wasser zugeführt wird. Diese Kältemenge erzeugt eine Schichte Eis von der Dicke dh und ist:

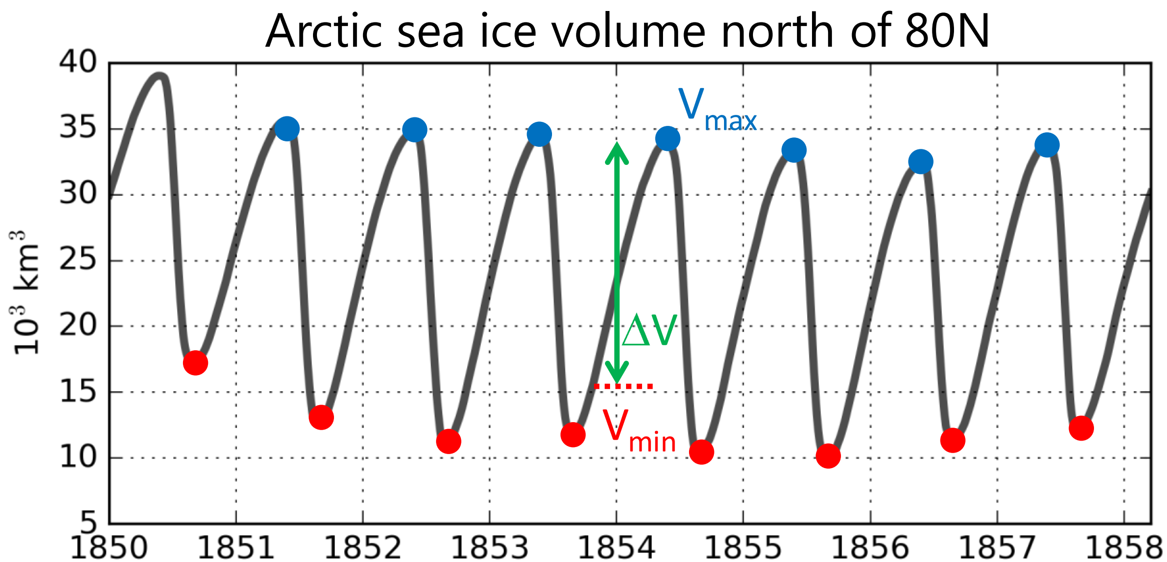
$$\lambda \sigma dh = \frac{Ka}{h} dt. \tag{1}$$

λ bedeutet die latente Wärme, σ das specifische Gewicht des Eises. Aus dieser Gleichung folgt:

« Sea ice grows faster if it is thinner »

[Stefan, 1891]

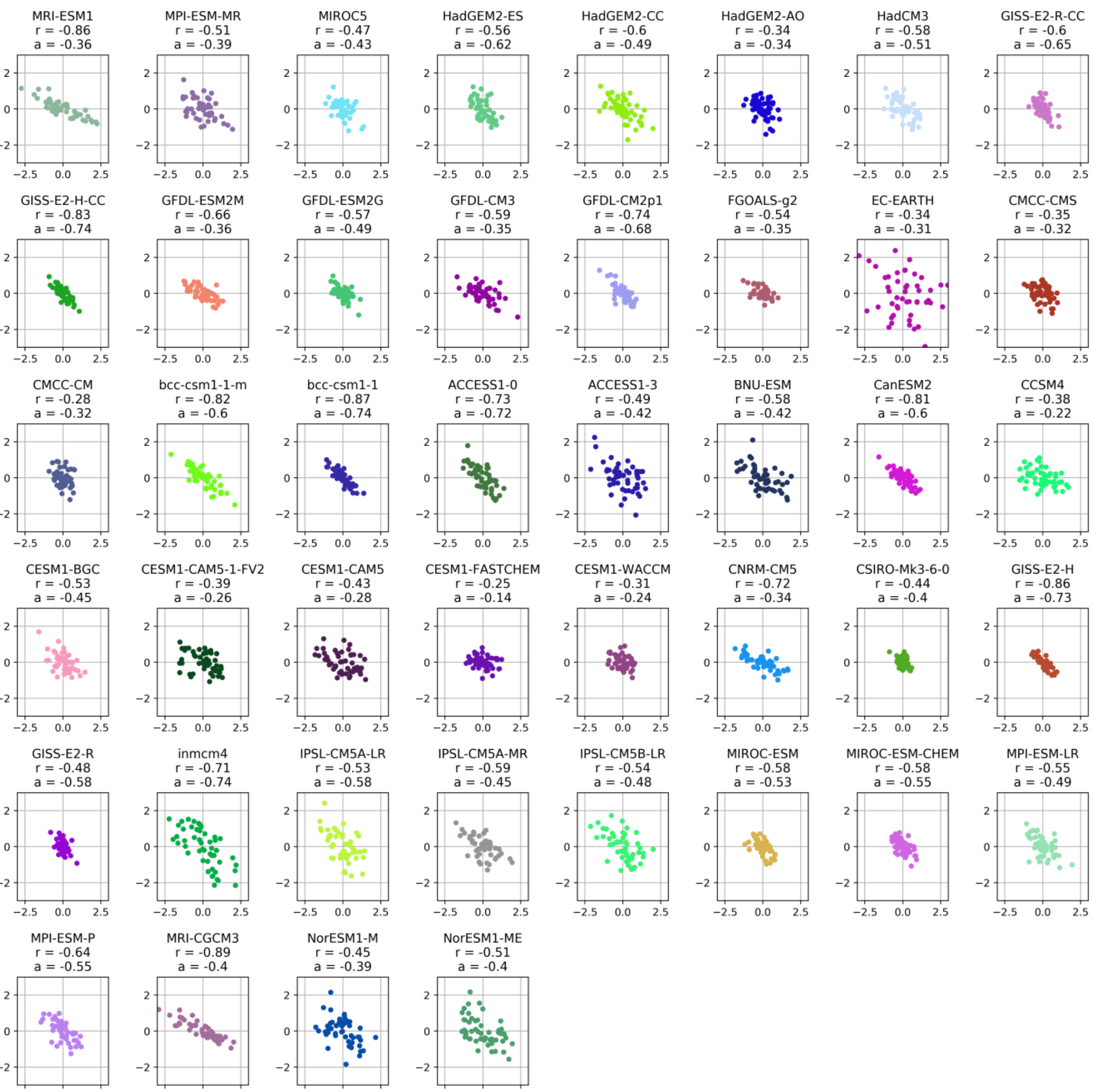
Approach to measure the negative feedback



1. Locate annual minima (V_{min}) and following maxima (V_{max})
2. Estimate the volume production $\Delta V = V_{max} - V_{min}$
3. Regress ΔV on V_{min}
4. Define the feedback factor as the slope of the regression [unitless]

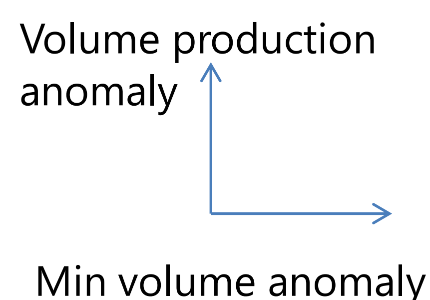
! Signals could contain secular trends. Linear detrending is done prior to the analysis. This does not affect the conclusions

All CMIP5 models have the negative feedback 😊 and they all simulate it differently! 😃



Legend
Model name
r = ... → correlation
a = ... → regression (feedback)

Based on 50 years (1861-1910)



The positive feedback: amplifier of summer sea ice melt

Everyone understands the ice-albedo feedback –conceptually
But definitions vary from study to study
Quantifying it is not straightforward and often requires dedicated experiments

4. Sea ice–albedo feedback

To assess the strength of the sea ice–albedo feedback for the different models, we compare perturbed simulations that include the ice–albedo feedback with the corresponding perturbed simulation that does not include ice–albedo feedback. For the simulations that do

[Curry et al., J. Clim., 1995]

[7] The surface albedo feedback is estimated as:

$$f_{SAF} = \frac{\Delta S_{\alpha\rightarrow\alpha'}}{\Delta T} \quad (3)$$

where $\Delta S_{\alpha\rightarrow\alpha'}$ represents the change in the top-of atmosphere shortwave due to replacing the control run surface albedo, α, with the perturbation run surface albedo, α'. The

[Winton, GRL, 2006]

b. Methods

Following the radiative kernel method, the time (t)-dependent SIRF within a region R (here, the NH) of area A and the SIAF can be estimated separately in two steps (Flanner et al. 2011; Qu and Hall 2006):

$$\mathrm{SIRF}(t,R) = \frac{1}{A(R)}\int_R I(t,r)\frac{\partial\alpha_p}{\partial\alpha_s}(t,r)\alpha_{\mathrm{csi}}(t,r)\,dA(r), \quad (1)$$

$$\mathrm{SIAF} = \frac{\Delta\mathrm{SIRF}}{\Delta T_s}. \quad (2)$$

[Cao et al., J. Clim., 2015]

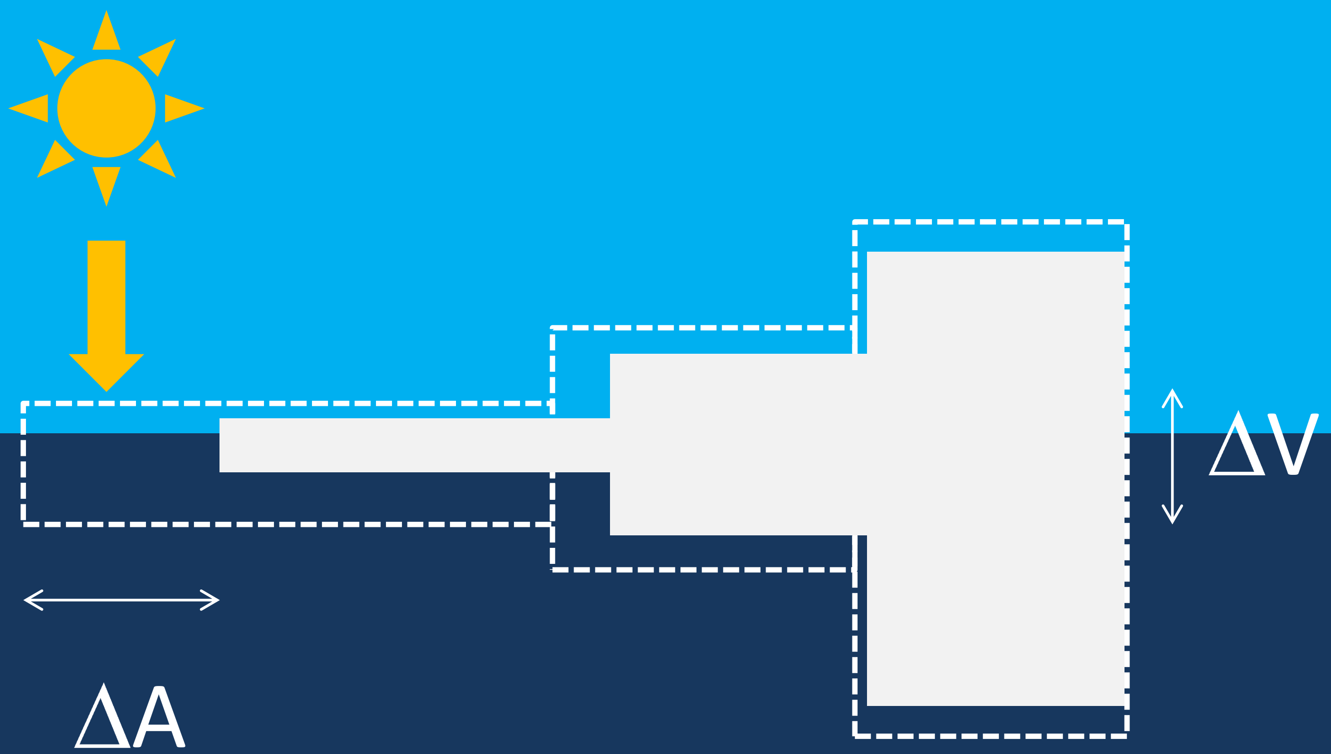
2. Data and Methods

Surface albedo feedback (Y_α) is commonly defined as the change in the net downward top of atmosphere (TOA) shortwave radiative flux per unit surface temperature change caused by changes in surface albedo (α_s):

$$Y_\alpha = \frac{\partial Q_\alpha}{\partial T} = -I\frac{\partial\alpha_p}{\partial\alpha_s}\frac{\partial\alpha_s}{\partial T} \quad (1)$$

[Crook and Forster, GRL, 2014]

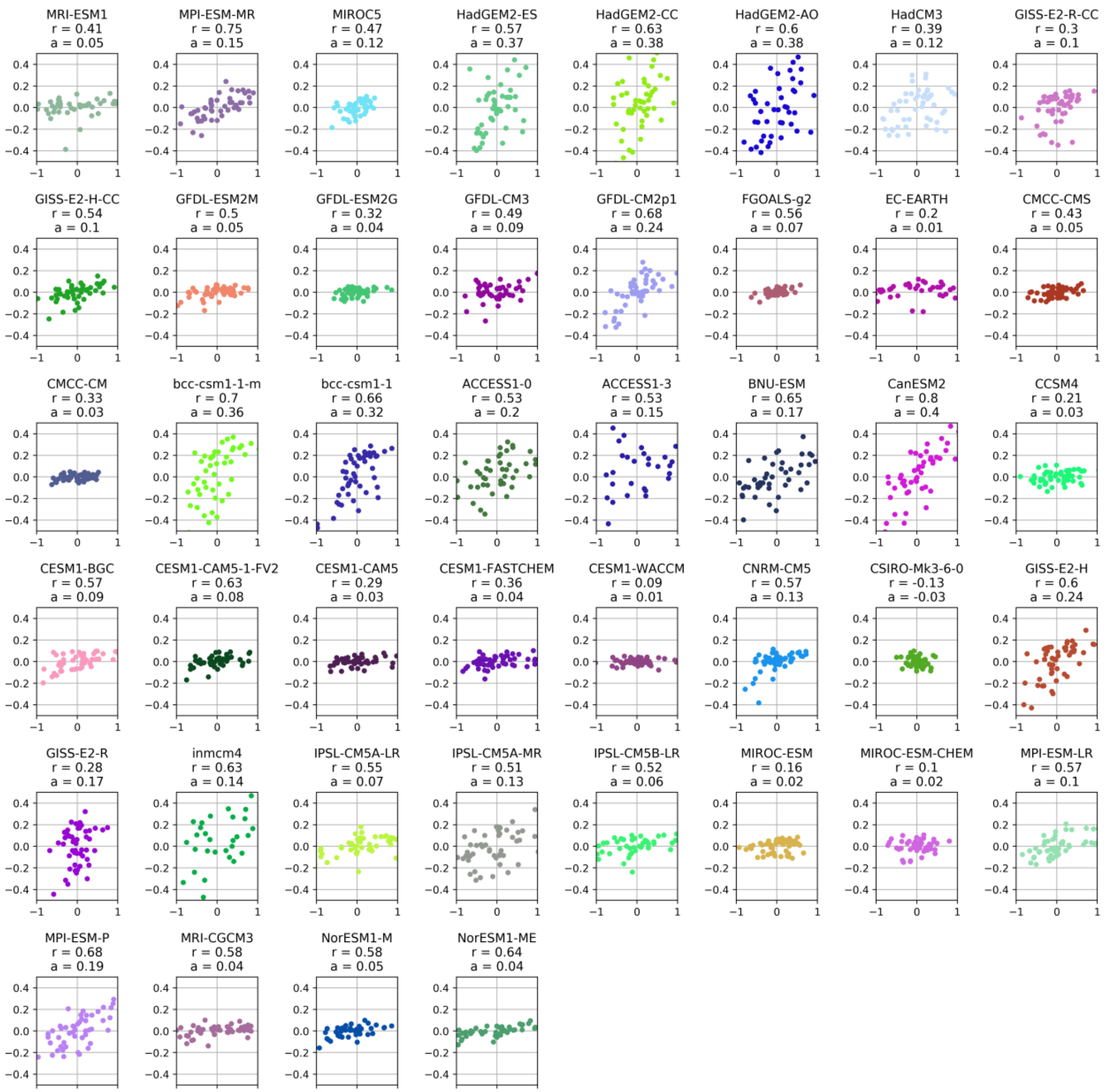
Approach to measure the positive feedback



1. Estimate ΔA and ΔV (max V->min V) for each year
2. Linearly detrend each term to avoid spurious trends
3. Regress (detrended) ΔA on ΔV
4. Units of feedback: [m^{-1}] or [%/cm]

Similar idea as in Holland et al. GRL 2006

All CMIP5 models have the positive feedback and they all simulate it differently!



Legend
Model name

a = … → regression (feedback)

Based on 50 years (1861-1910)

Area loss anomaly

Volume loss anomaly

1. Estimation of the feedbacks

2. Feedbacks *vs* mean state

3. Feedbacks *vs* variability

1. Estimation of the feedbacks

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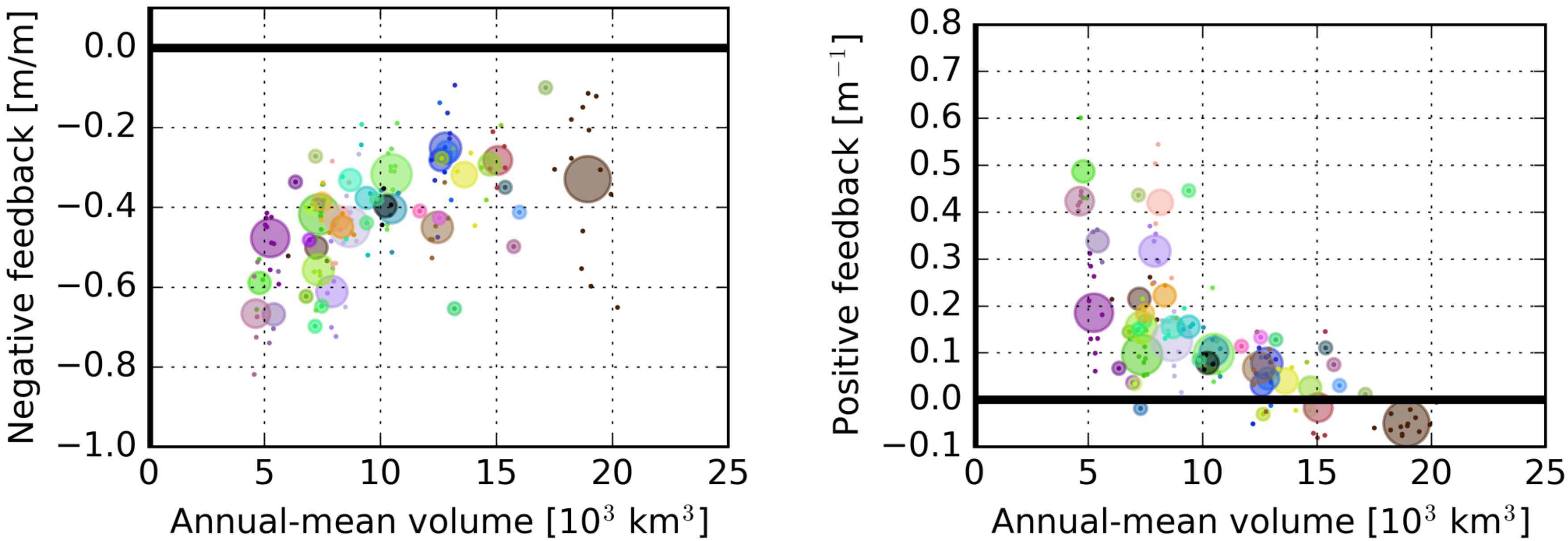
Both feedbacks are related to the mean state

44 CMIP5 models. Reference period: 1861-1910

Diagnostics for one ensemble member of one model

Diagnostics for ensemble mean (bigger if more members)

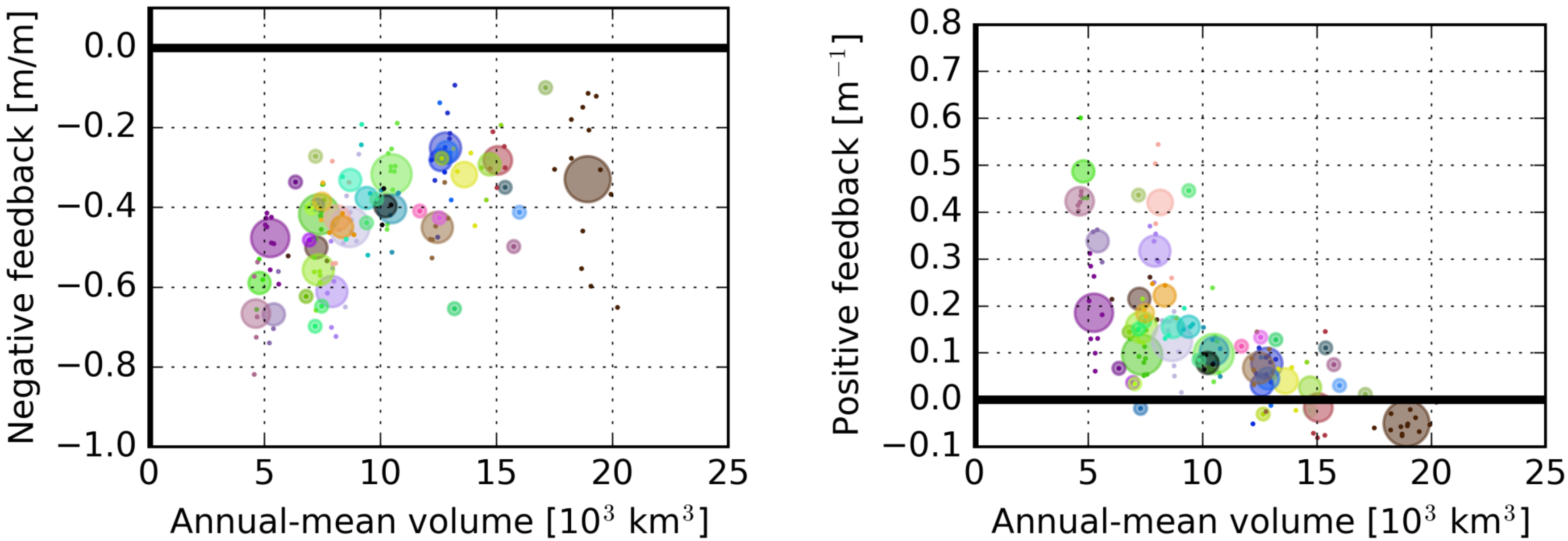


Both feedbacks are <u>strongly</u> related to the mean state

44 CMIP5 models. Reference period: 1861-1910

Diagnostics for one ensemble member of one model

Diagnostics for ensemble mean (bigger if more members)



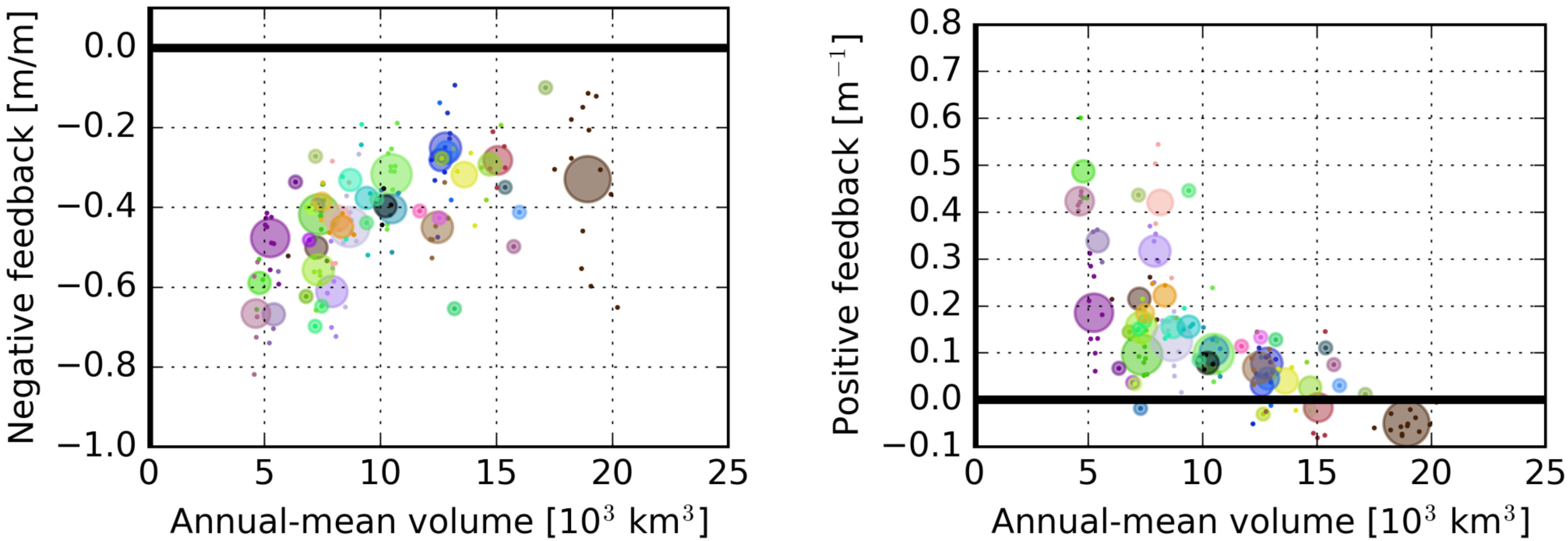
r(x, y)	0.53 ($p<10^{-9}$)	–0.70 ($p<10^{-18}$)

Both feedbacks are strongly, non-linearly related to the mean state

44 CMIP5 models. Reference period: 1861-1910

Diagnostics for one ensemble member of one model

Diagnostics for ensemble mean (bigger if more members)



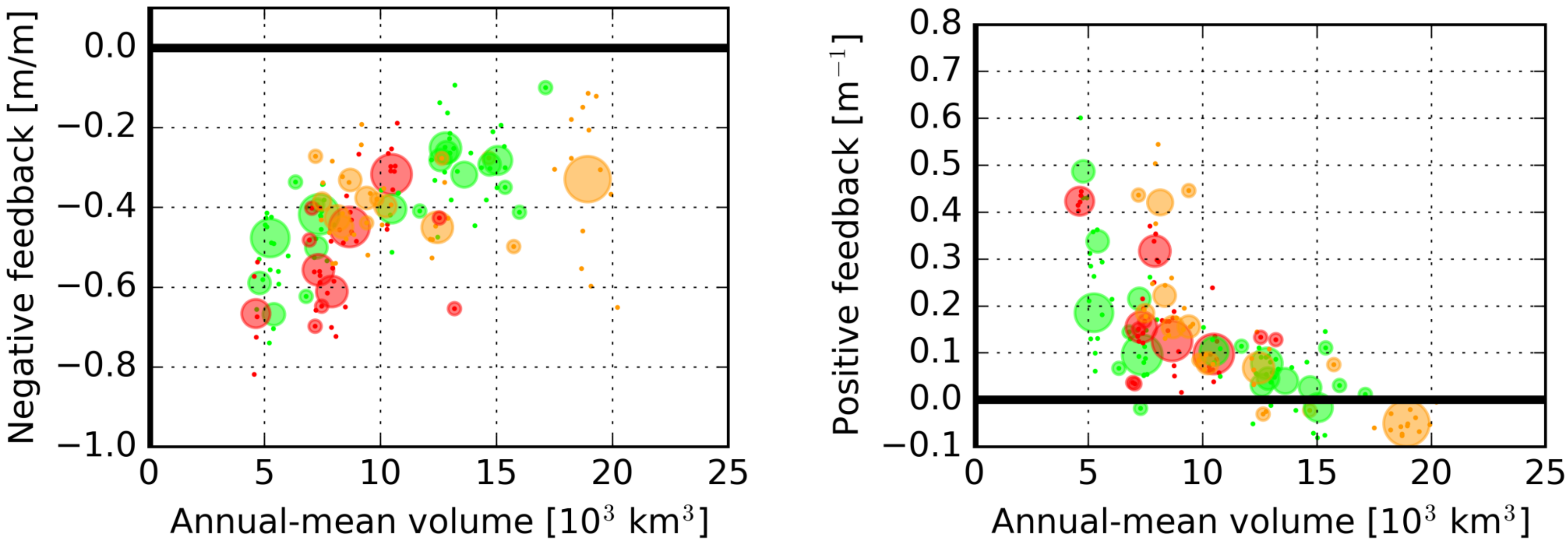
$r(x, y)$	0.53 ($p<10^{-9}$)	–0.70 ($p<10^{-15}$)
$r(1/x, y)$	– 0.58 ($p<10^{-12}$)	0.71($p<10^{-18}$)

Both feedbacks are strongly, non-linearly related to the mean state

44 CMIP5 models. Reference period: 1861-1910

Diagnostics for one ensemble member of one model

Diagnostics for ensemble mean (bigger if more members)



Simple

No ITD, 0-layer

Intermediate

Virtual ITD/no ITD or 0-layer (LIM2, MPI, ...)

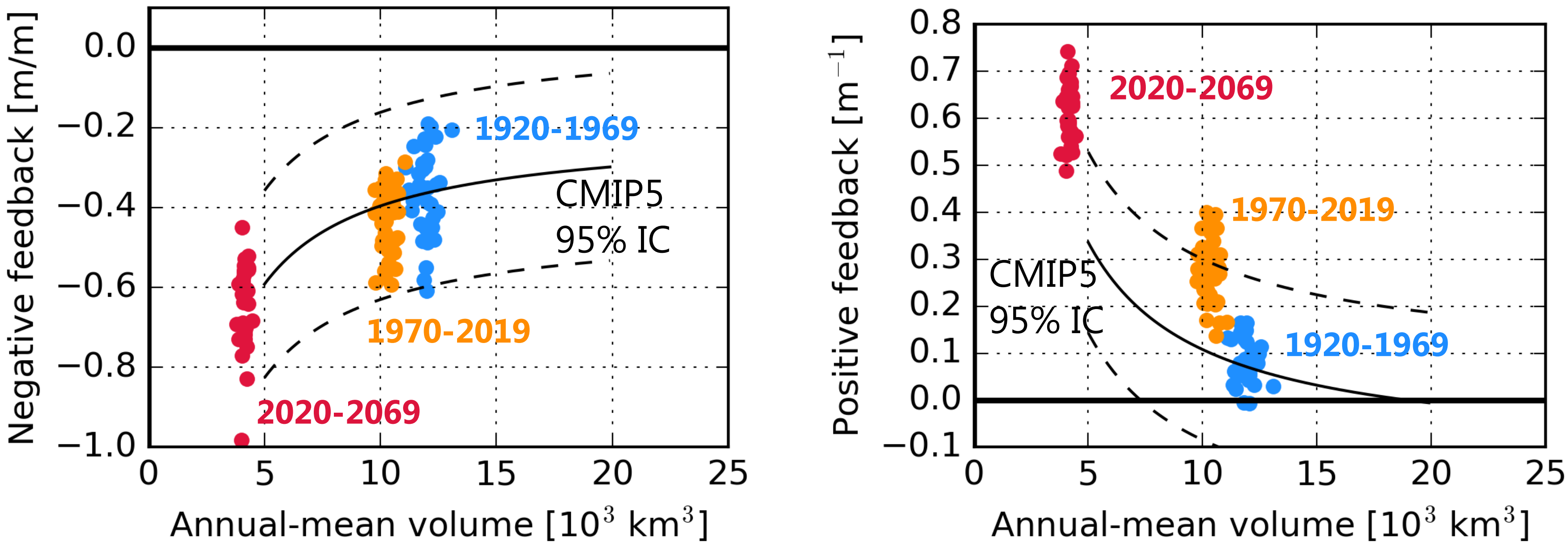
State-of-art

ITD + multi-layer (CICE4, GELATO, SIS)

No clear link between model complexity and mean state/feedbacks

Both feedbacks are <u>strongly</u>, <u>non-linearly</u> related to the mean state

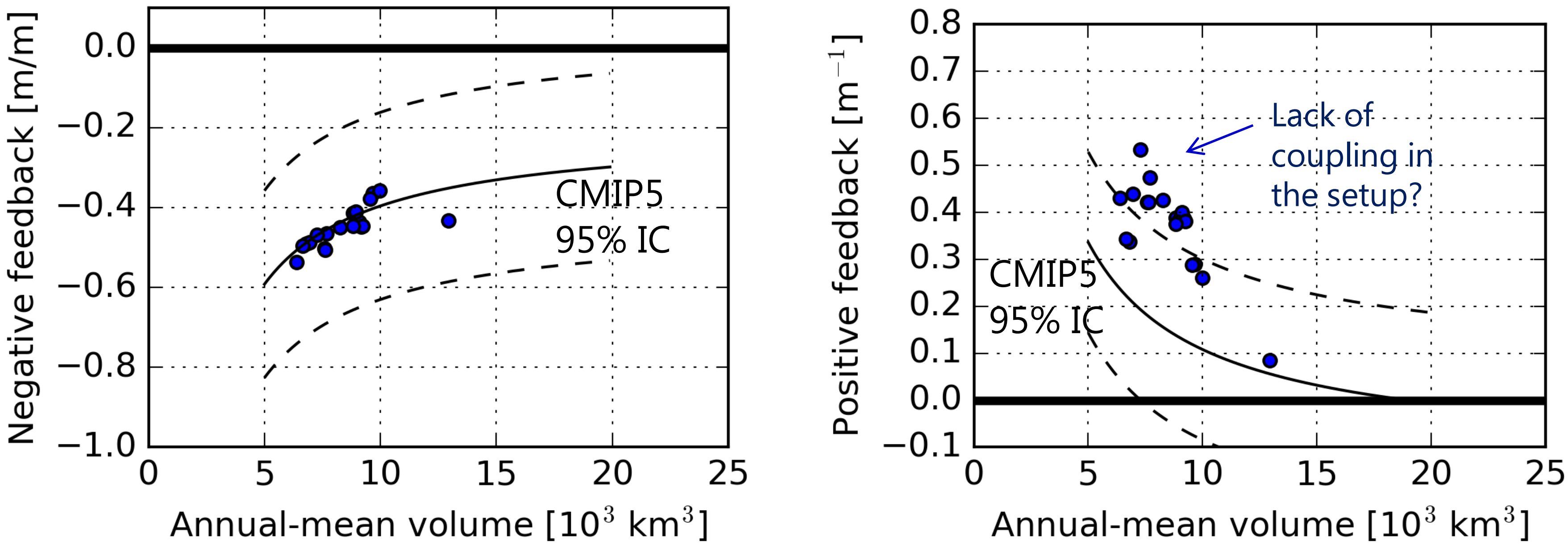
CESM Large Ensemble (35 members, 1920-2100, historical + RCP8.5)



Internal variability is sufficient to explain the spread of CMIP5

Both feedbacks are strongly, non-linearly, almost exclusively related to the mean state

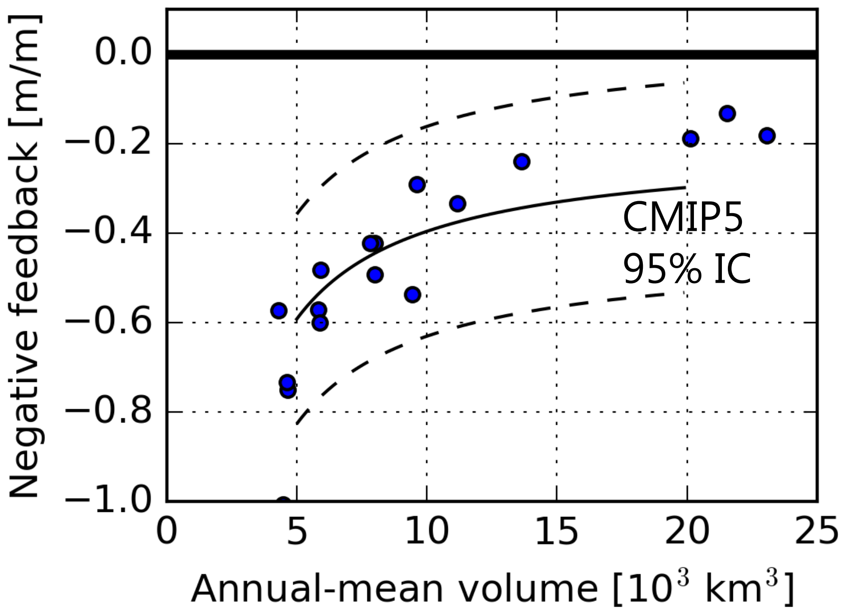
NEMO-LIM3 **ocean – sea ice simulations** (1979-2014) with varying number of ice thickness categories and varying dynamical parameter *P**



Only the mean state is important for the two feedbacks considered – regardless of how you get there

Both feedbacks are strongly, non-linearly, almost exclusively related to the mean state

Semtner 0-layer **1-D sea ice model** (no horizontal fluxes, prescribed ocean and atmospheric fluxes). 50 last years of data from 100-yr run used

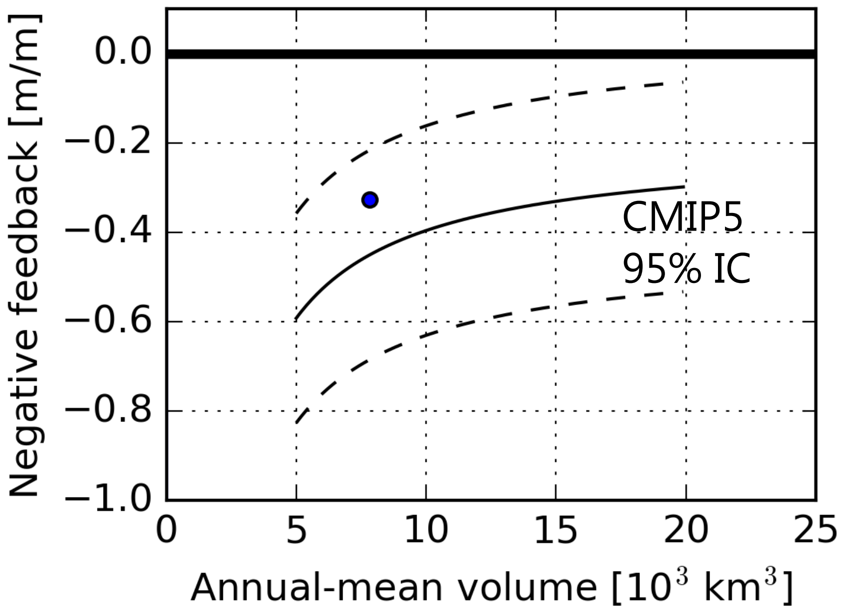


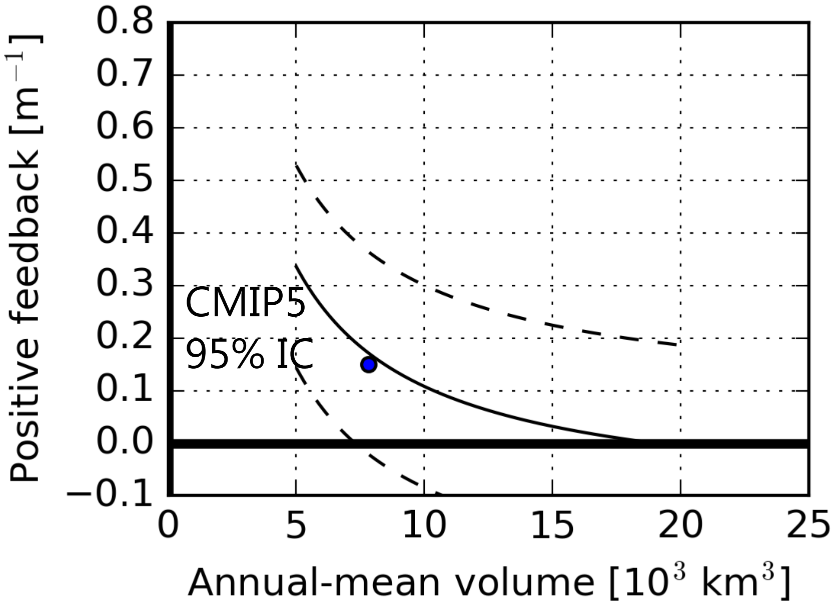
(This simple model has no prognostic sea ice concentration variable)

The most simple and most complex sea ice models agree on something, which must necessarily be fundamental.

Both feedbacks are strongly, non-linearly, almost exclusively related to the mean state in a hierarchy of data sets

Observations (IceSat; Kwok and Cunningham, JGR, 2008 + OSI-SAF; Eastwood et al., 2014). 2003-2008





Don't take those points for granted: large sampling error (5 data points) + large uncertainty on data

1. Estimation of the feedbacks

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3. Feedbacks *vs* variability

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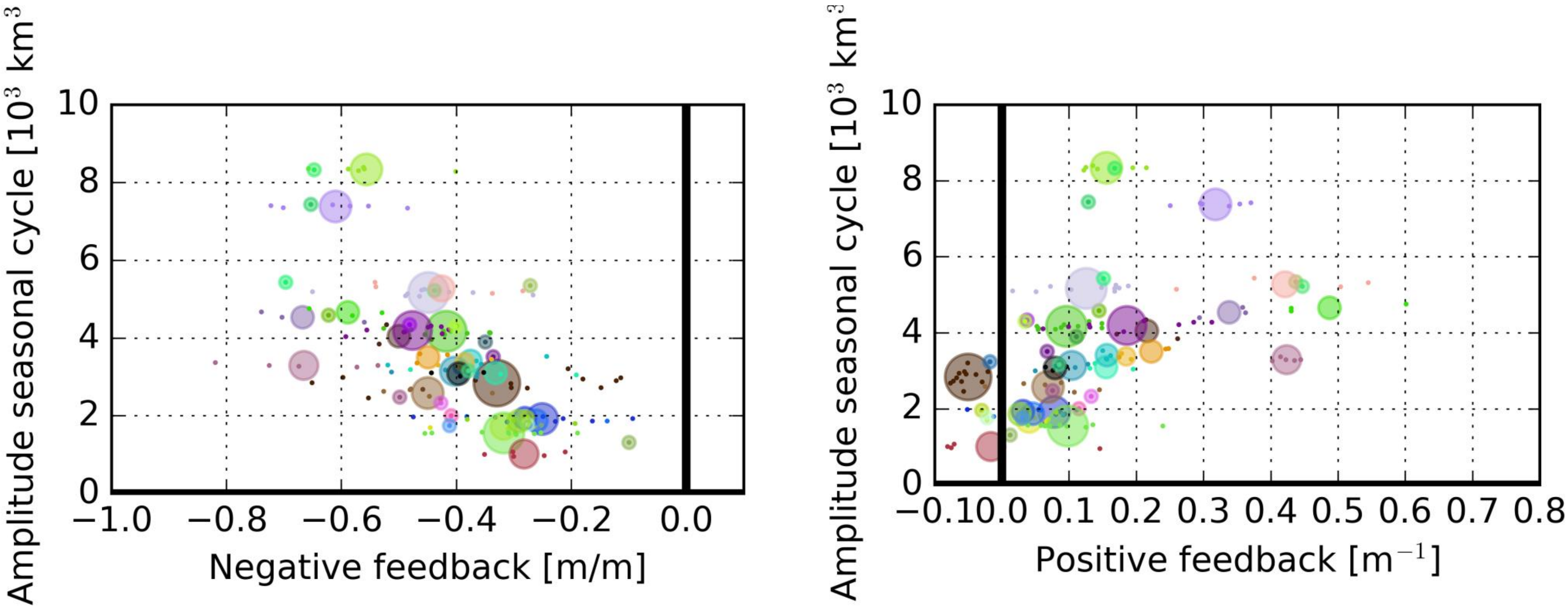
↑

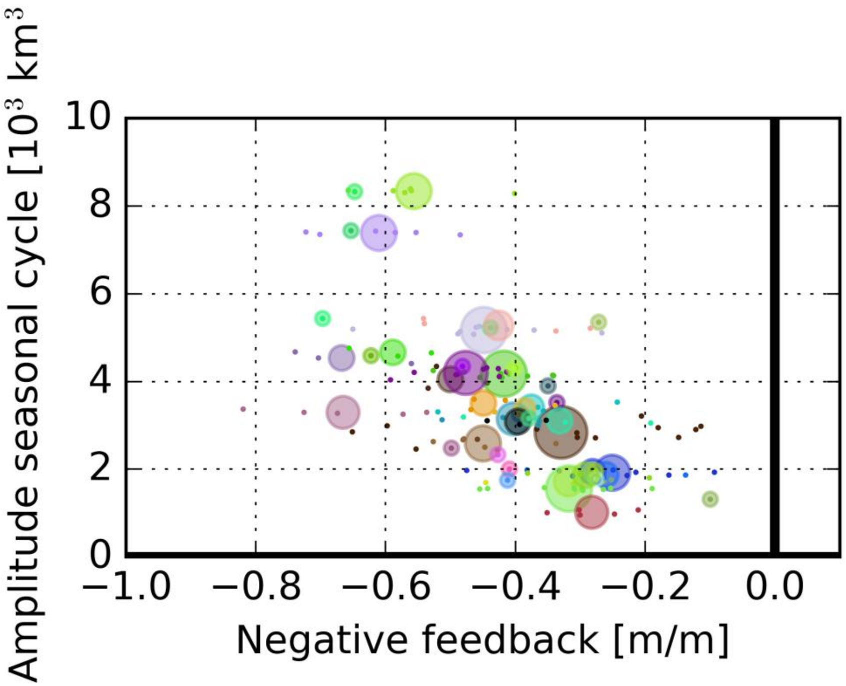
Seasonality
Interannual variability
Predictability
Response to forcing

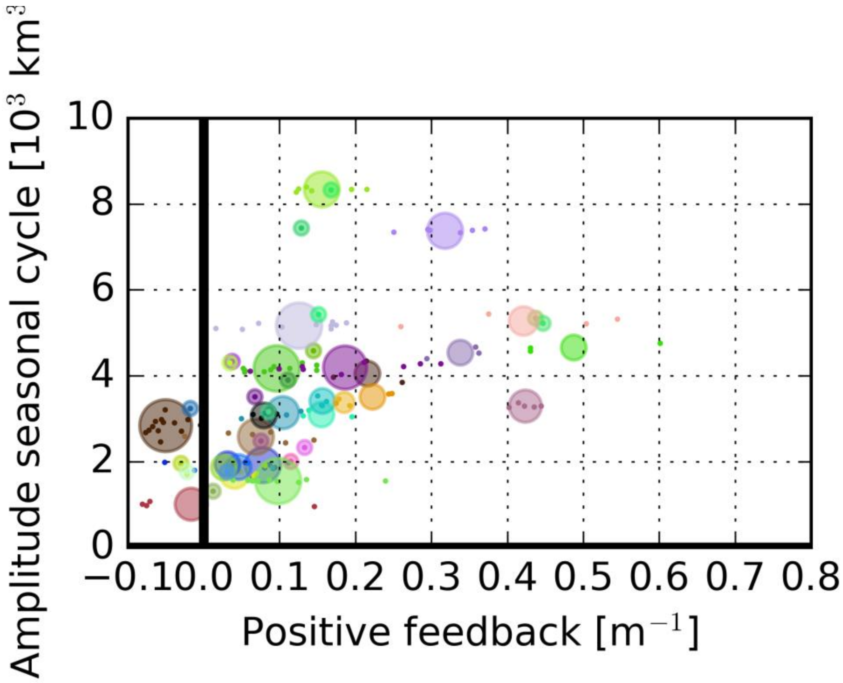
Both feedbacks enhance the seasonality

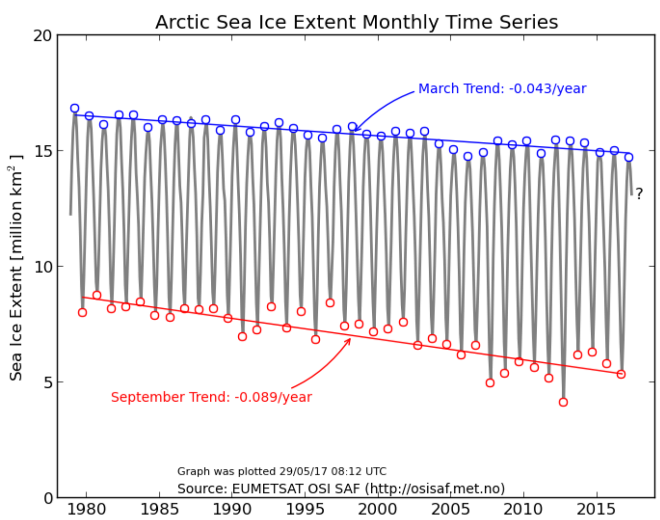


The positive feedback triggers summer anomalies, the negative feedback ensures that these anomalies are damped → large seasonality

Both feedbacks enhance the seasonality

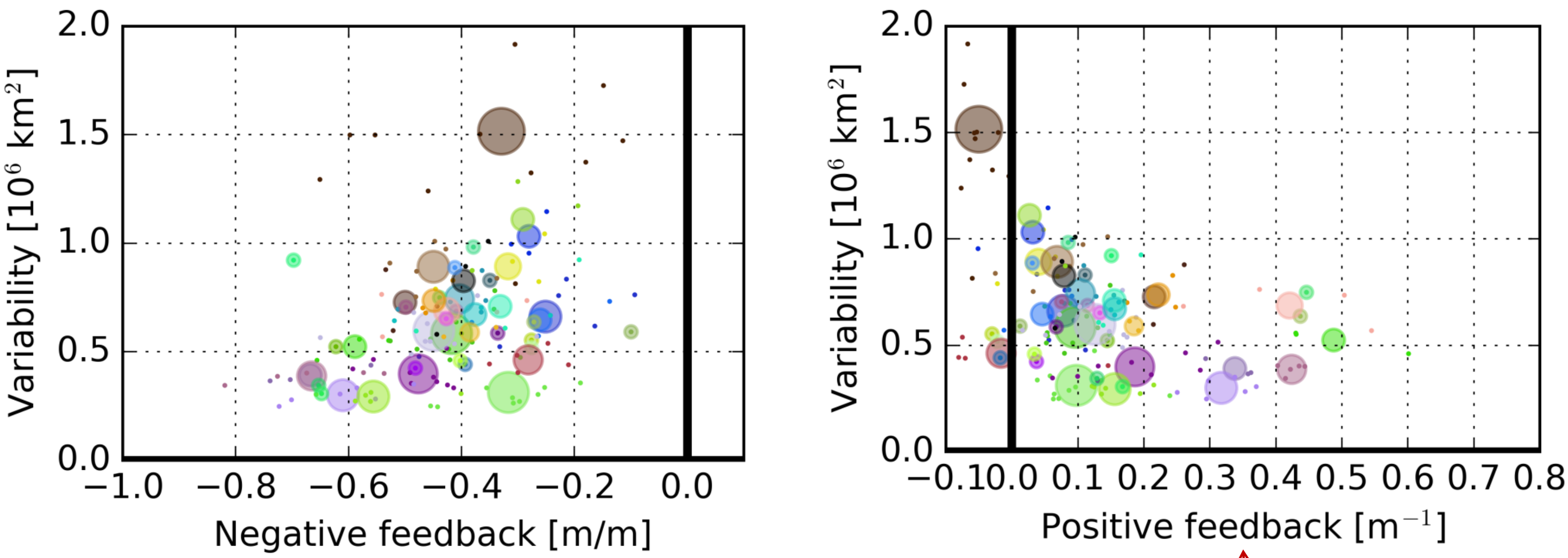






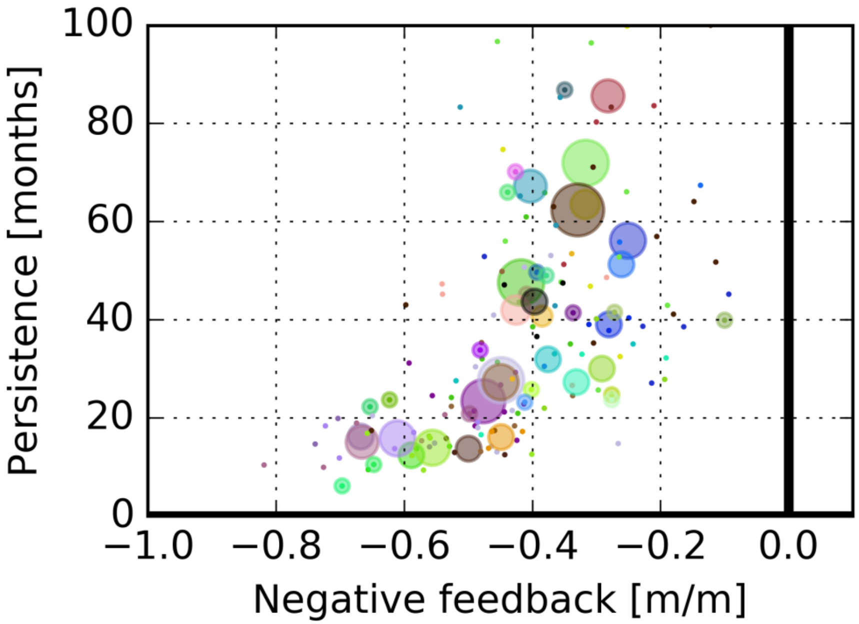
Is this what is going on here?
Mean state ↓ → Feedbacks ↑ →
Seasonality ↑

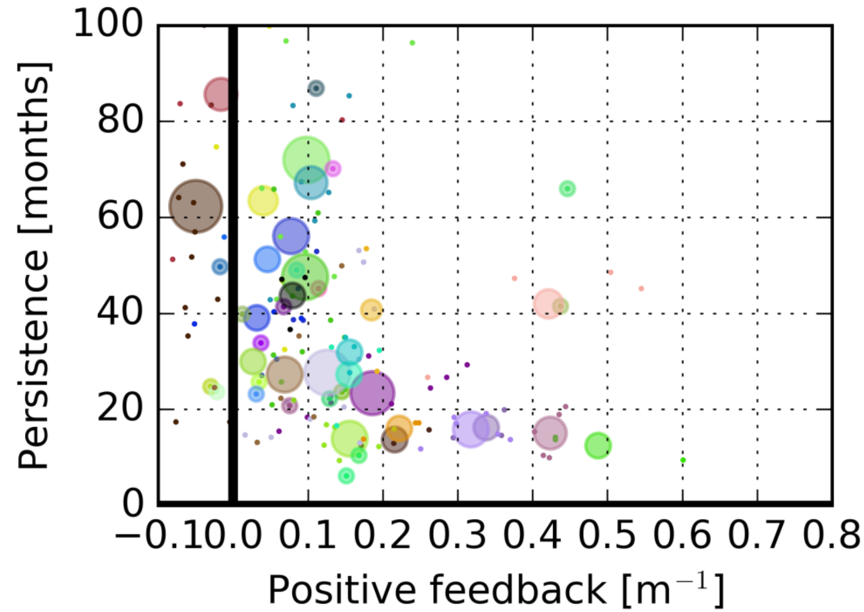
Both feedbacks dampen interannual variability



I'm not sure to understand this (perhaps because the feedback impacts area only?)

Both feedbacks kill predictability





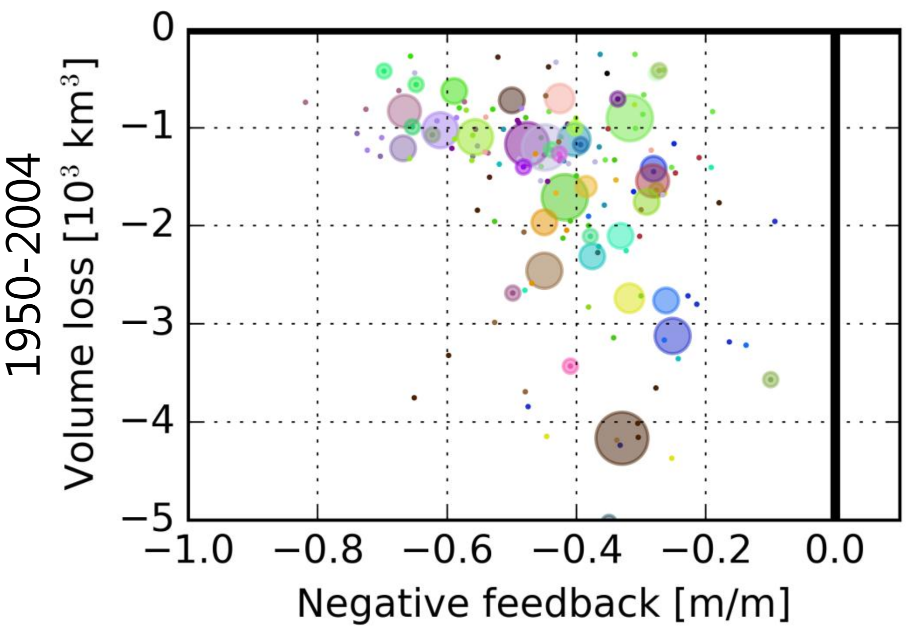
Predictability arises from the ability of anomalies to persist over time.

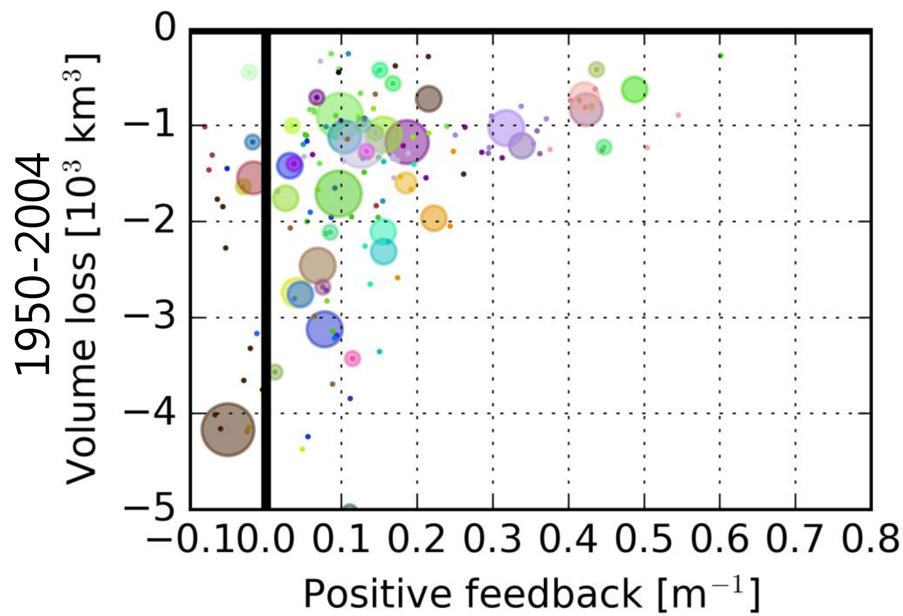
-The positive feedback amplifies the initial anomaly

-The negative feedback erases it

In both cases, predictability is lost.

Both feedbacks mitigate the forced response





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Conclusions

Two thermodynamic
sea ice

Feedbacks

are characterized, quantified and
estimated from multiple data sets

Conclusions

Mean state

Two thermodynamic sea ice

Feedbacks

are characterized, quantified and estimated from multiple data sets

Conclusions

Mean state → Two thermodynamic sea ice Feedbacks are characterized, quantified and estimated from multiple data sets → Variability

Conclusions

Mean state

Two thermodynamic sea ice

Feedbacks

are characterized, quantified and estimated from multiple data sets

Variability

Sea ice model physics/parameters + tuning + atmosphere and ocean biases

Conclusions

Mean state → Two thermodynamic sea ice **Feedbacks** are characterized, quantified and estimated from multiple data sets → Variability

↑

Sea ice model physics/parameters + tuning + atmosphere and ocean biases

And now 7 implications (in descending order of good news)

1. Sea ice thermodynamics is **surprisingly simple**, even in complex models

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2. Sea ice properties scale **non-linearly** with its annual-mean volume (linearly with area, cf. existing studies)

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3. **Variability and mean state are related, but indirectly** and sometimes through a chain of non-linear relationships

1. Sea ice thermodynamics is surprisingly simple, even in complex models
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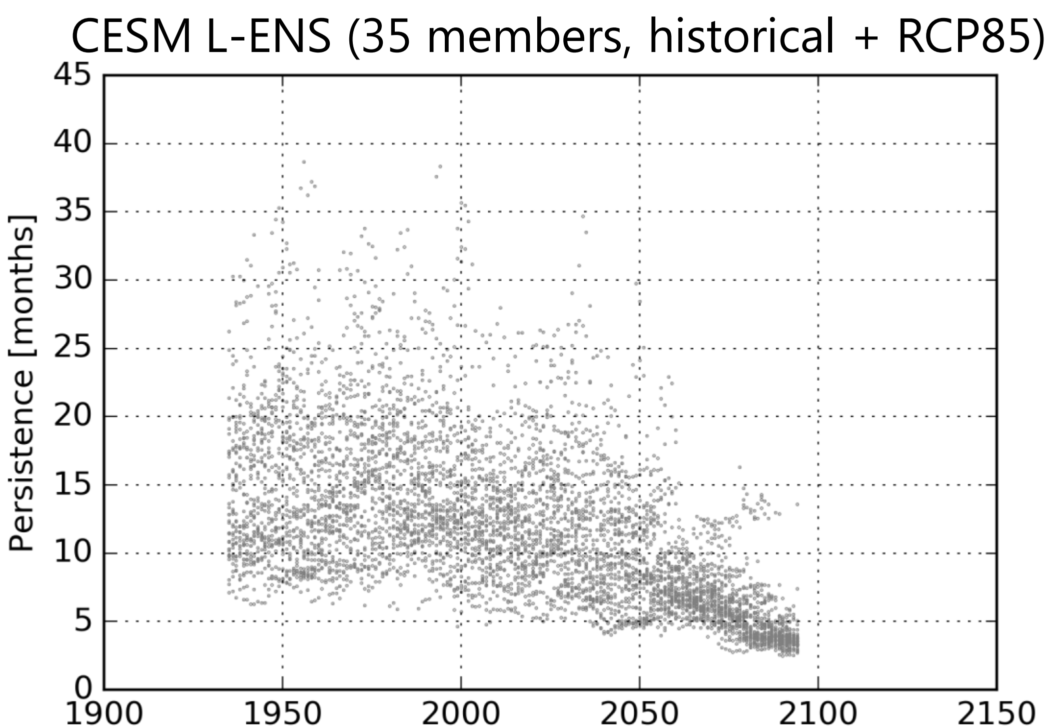
3. Variability and mean state are related, but indirectly and sometimes through a chain of non-linear relationships
4. Sea ice thickness will likely become **less predictable** as the ice thins



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5. You can’t trust the predictability of a biased model, for which post-processing was applied. **Fix your mean state first**.

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6. Comprehensive sea ice models are not sufficient for realistic simulation of the feedbacks. Tuning to mean state may suffice.
7. Two CMIP5 models may resemble each other for **awfully different reasons**