Workshop on satellite retrievals
MPI, University of Hamburg
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Observational needs for climate models

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	Observer	Not observer
Modeller		
Not modeller		

	Observer	Not observer
Modeller		**Dirk** **Martin** **Einar** **…**
Not modeller	**Leif** **Stefan** **Gunnar**	

Walt **…**

	Observer	Not observer
Modeller	 	Dirk Martin Einar …
Not modeller	Leif Stefan Gunnar	

Walt …

	Observer	Not observer
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Not modeller	Leif Stefan Gunnar	Myself

Walt ...

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Walt …

Part 1: What I wanted to say initially

Part 2: What came to my mind during the workshop

Observational needs for climate models

Data assimilation and reanalyses

Climate forecast initialization and verification

Tuning

Process verification

Other remarks

Models as guidance for observational network design

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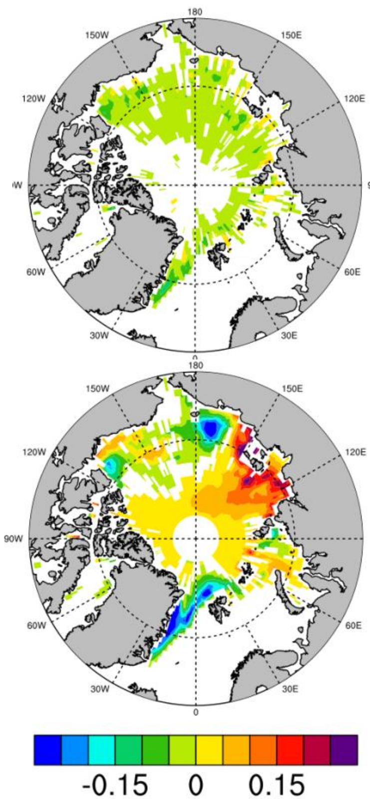
Are observational products available
adapted for reconstructing the sea ice history?

September 1993-2007 mean
sea ice **concentration bias**
(ref: NSIDC/CERSAT/OSISAF)

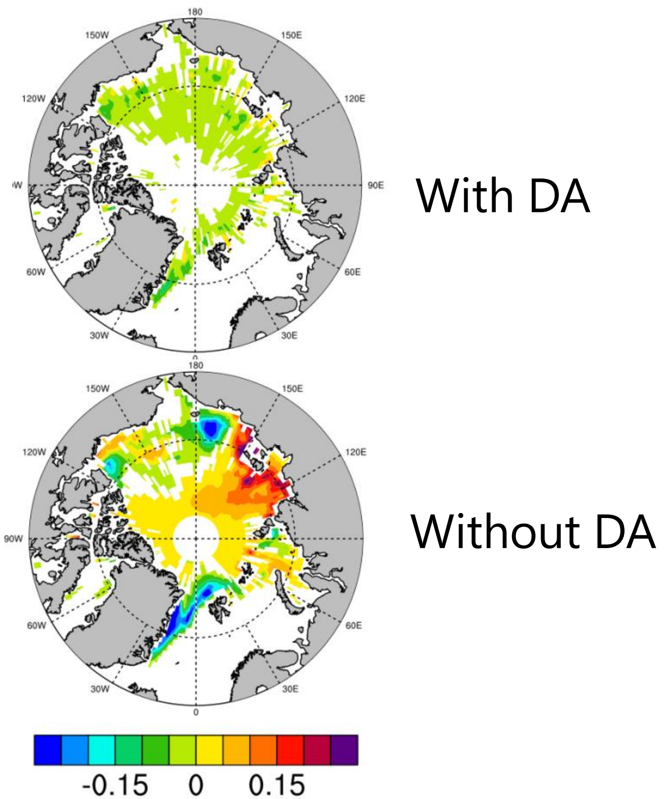


With DA

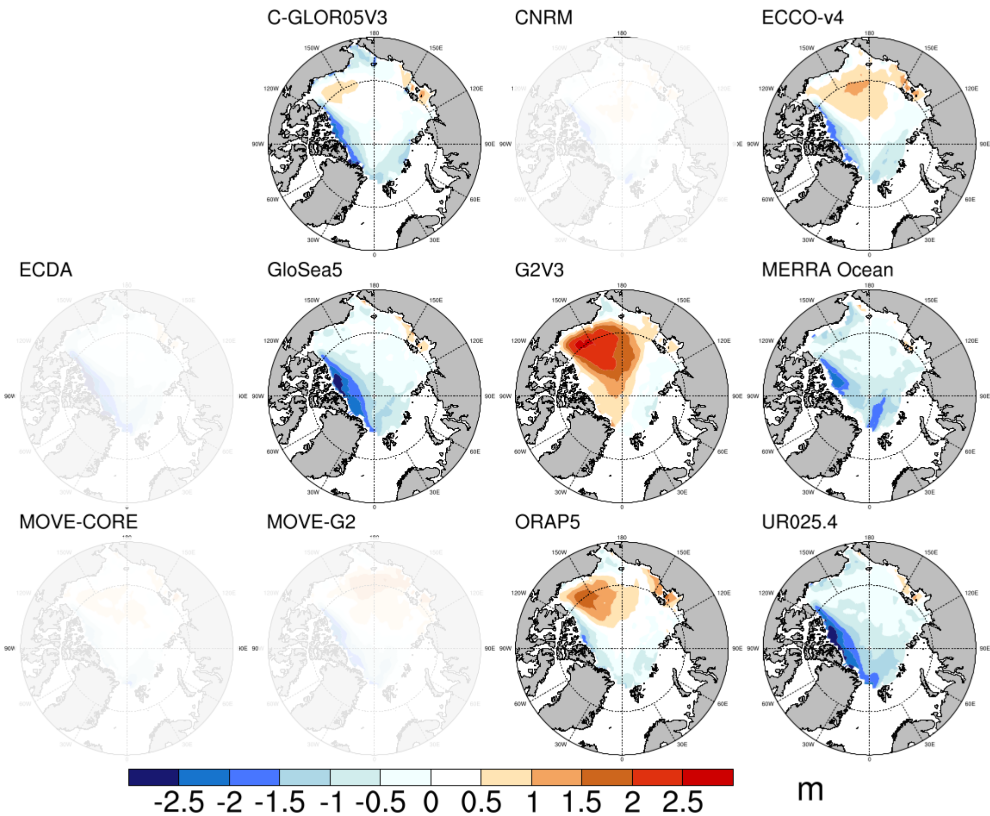
Without DA

[Chevallier et al., 2016]

September 1993-2007 mean sea ice **concentration bias** (ref: NSIDC/CERSAT/OSISAF)



March 1993-2007 mean sea ice **thickness bias** (ref: IceSAT)



[Chevallier et al., 2016]

SIC data assimilation is not enough to constrain SIT

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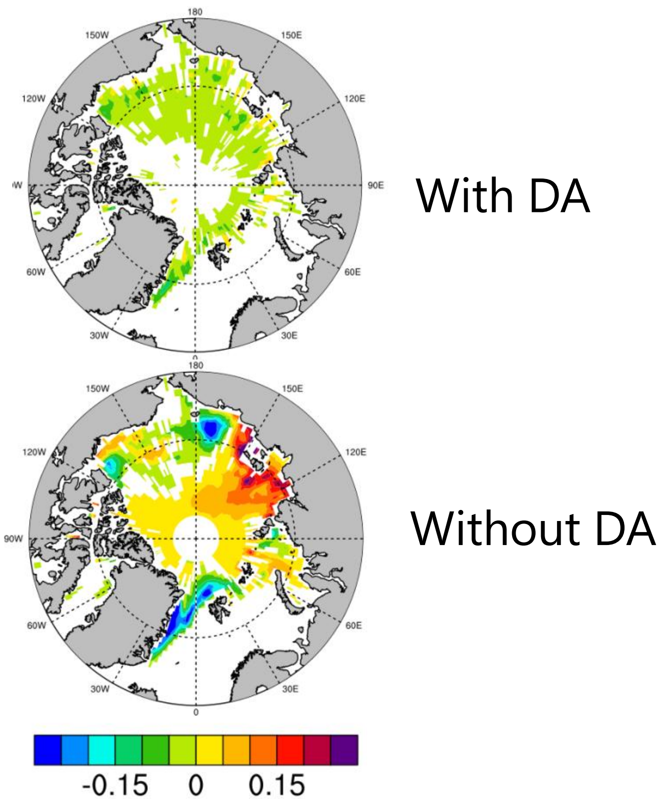

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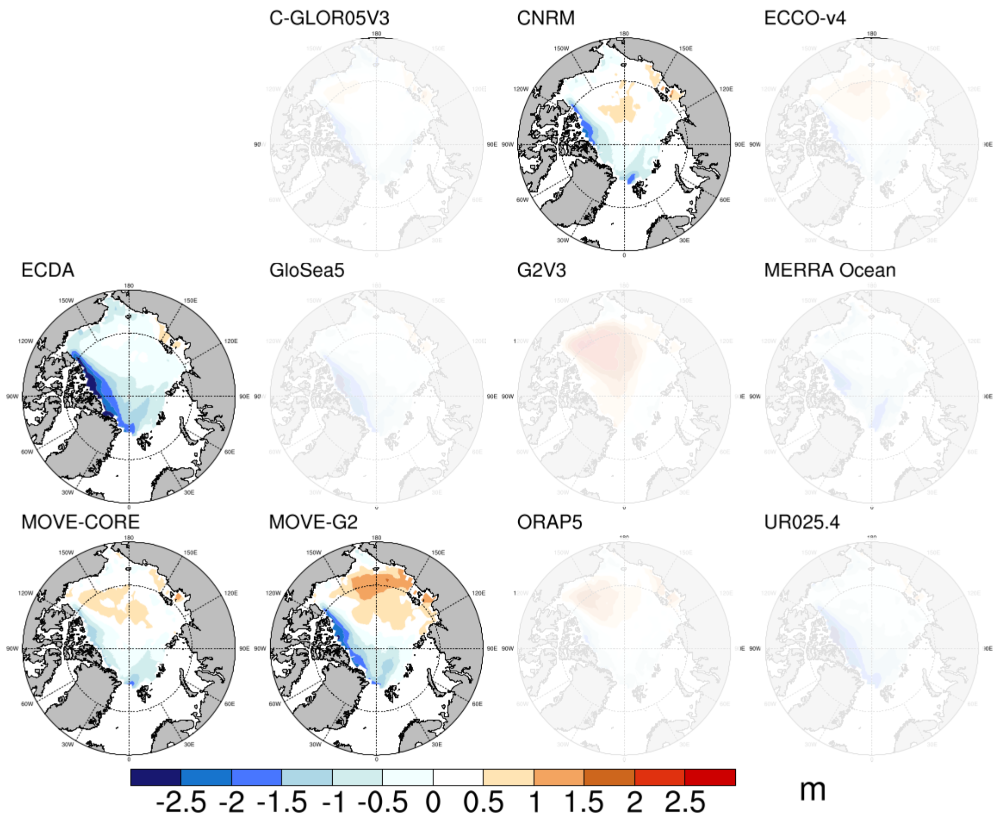


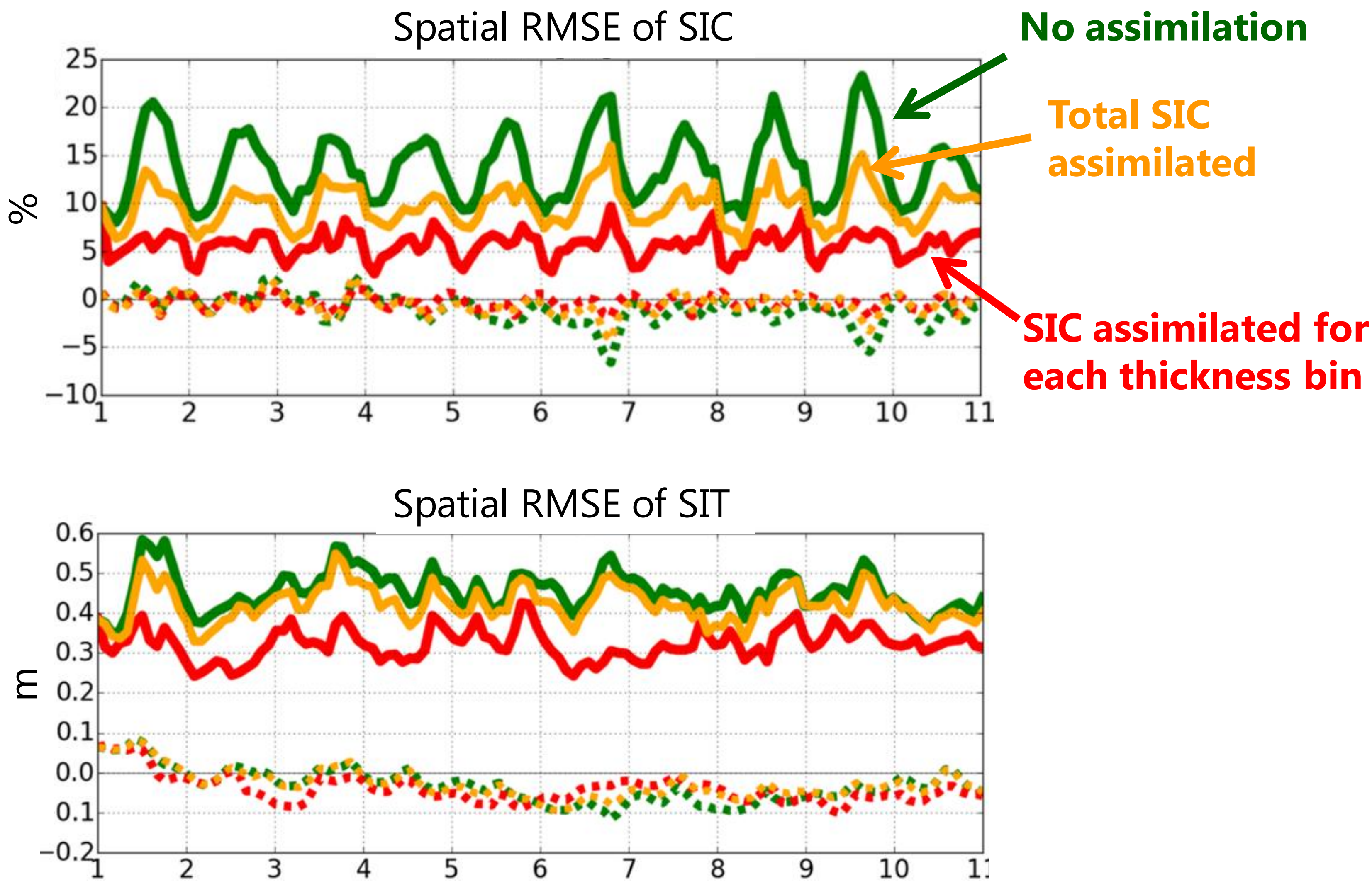
[Chevallier et al., Clim. Dyn., 2016]

Why do sea ice thickness biases remain so large?

1. The models do not adjust SIT when assimilating SIC, or do it inappropriately
2. More data must be assimilated

   e.g. sea-ice thickness: Mathiot et al., 2012; Yang et al., 2014; Xie et al., 2016.

Perfect-model experiments

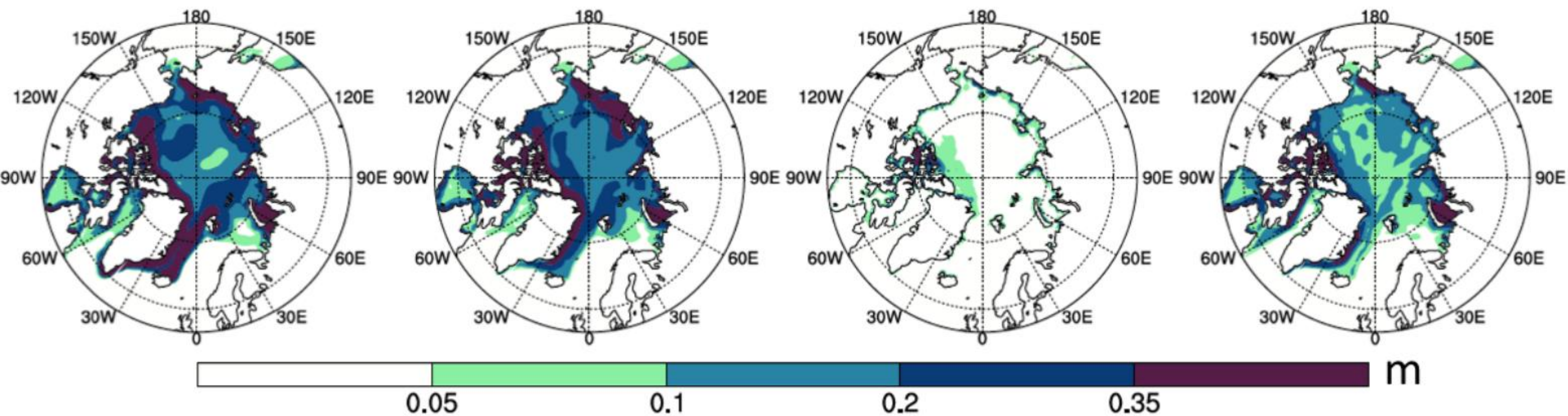


[Kimmritz et al., submitted]

Same result, obtained in a different setup

RMSE of SIT (2001-2003)
Perfect-model experiments

No assimilation | SIC assimilated | SIT assimilated | SIC + MYI SIC assimilated



[Zhang et al., in prep.]

Are observational products available
adapted for reconstructing the sea ice history?

Likely yes.

The models are the ones to blame
-Issues in cross-covariances
-Not a lot assimilate thickness obs. (yet)

But more « per-type » SIC information
would certainly help

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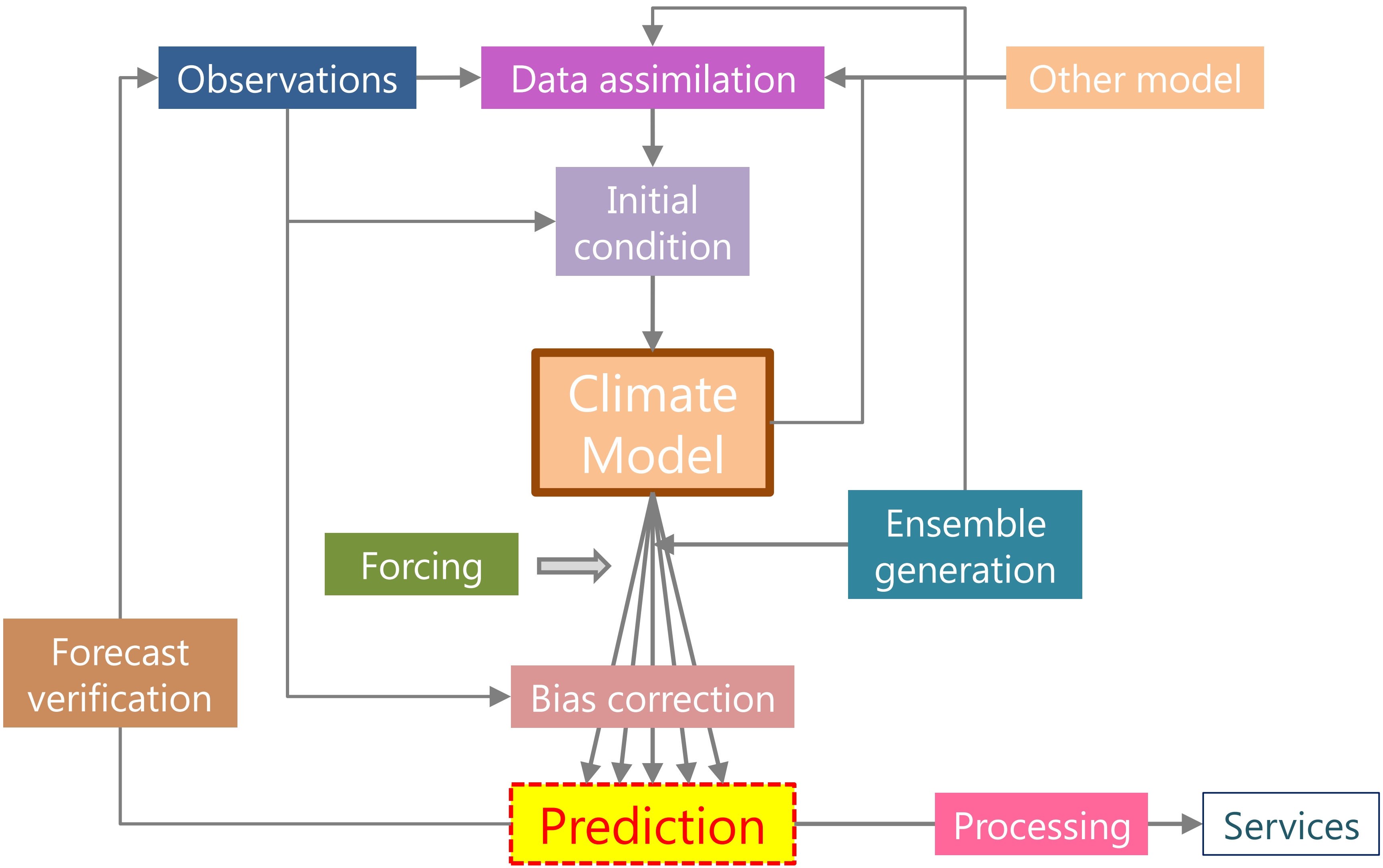
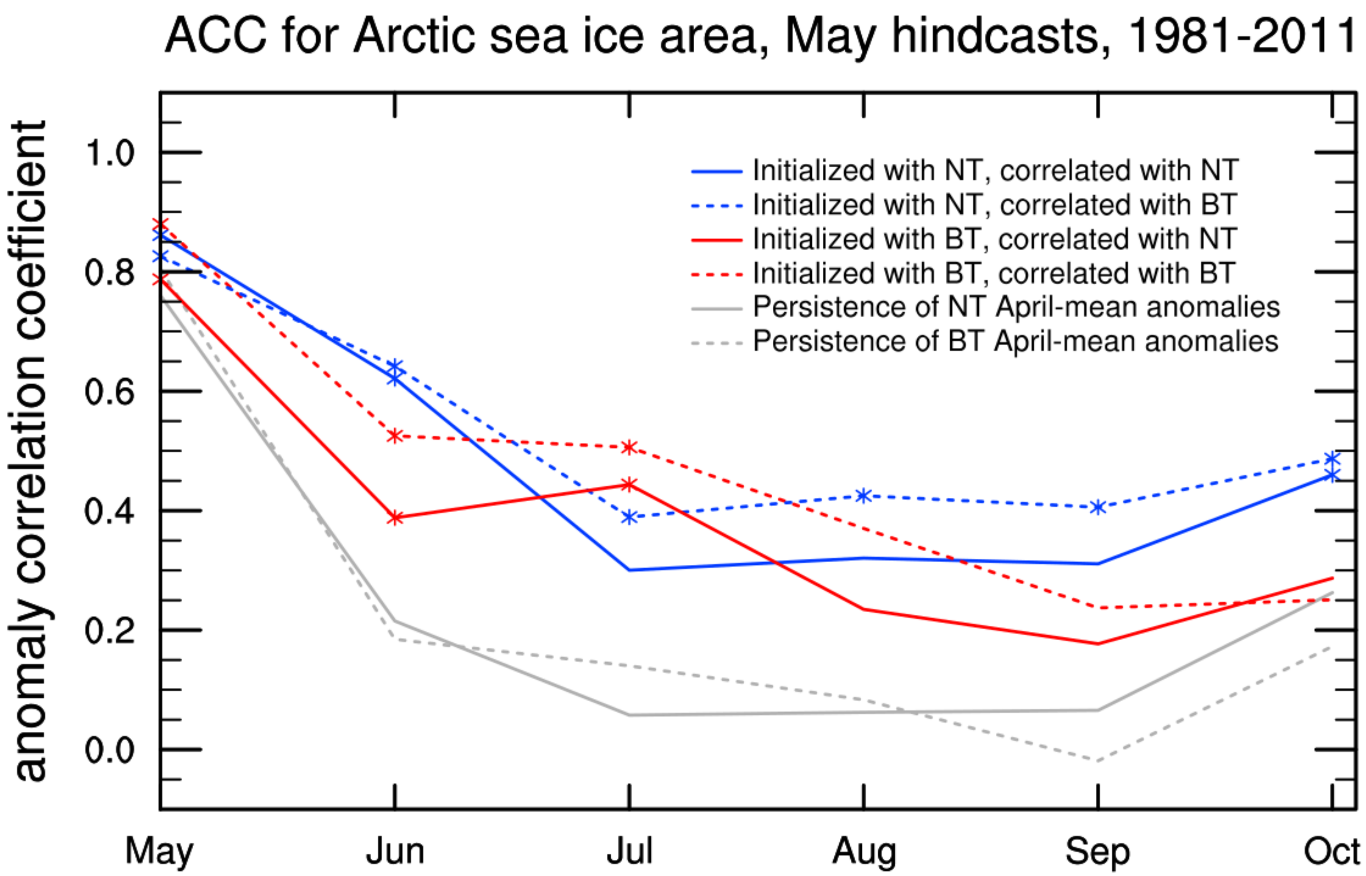
How does observational uncertainty affect the quality of sea-ice forecasts?

Observations are filtered many times in a traditional forecast system



The choice of the observational dataset has an impact on the skill of the forecasts – twice

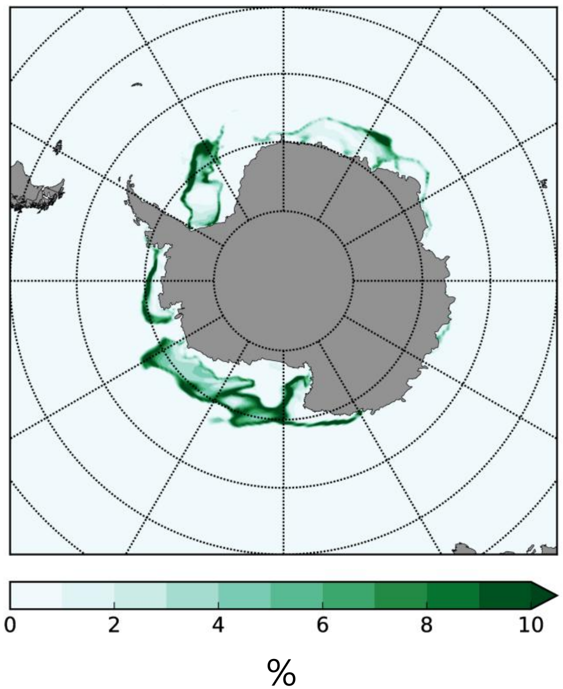


[Bunzel et al., 2016]

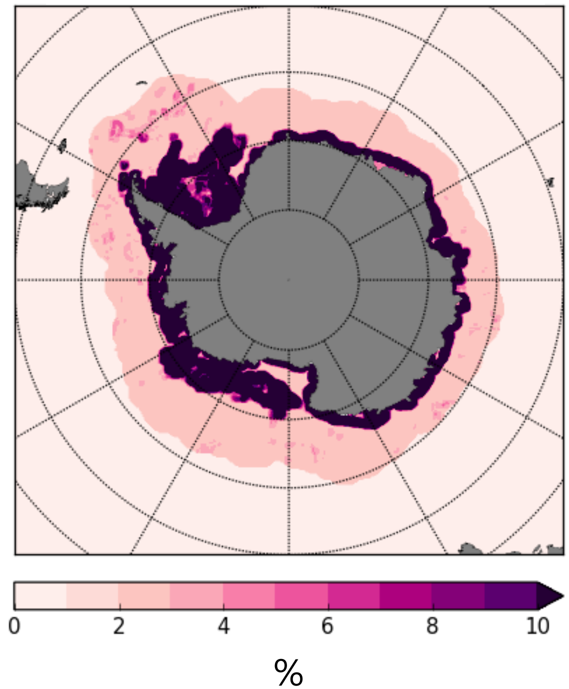
Uncertainty provided with SIC products: much welcome, but how to use them at climate scales?

February 1st, 1993

SIC spread (1σ) of a 25-member ensemble forecast (NEMO)



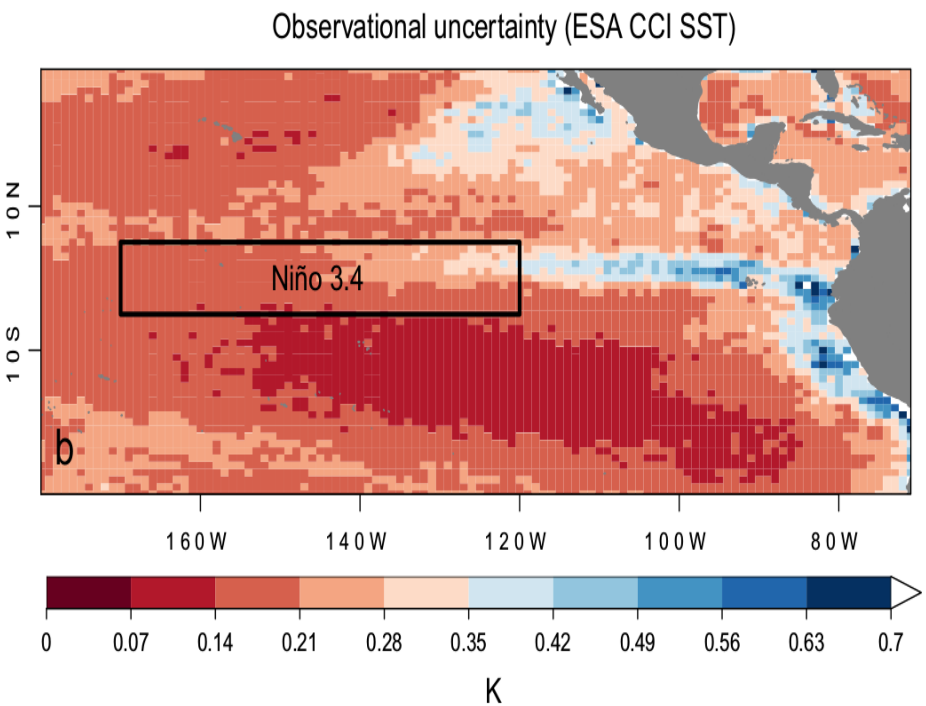
SIC total uncertainty (1σ) from OSI-SAF

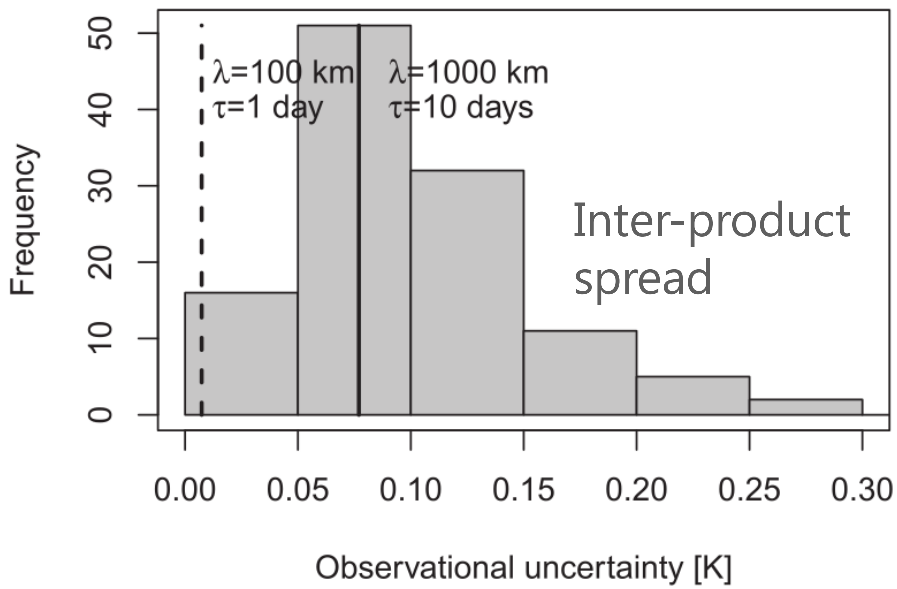


1. How can make a grid-point comparison of model and obs uncertainties?
2. How can I propagate obs uncertainty to climate scales (month, region)?

→ Need characterization of the obs error covariance matrix (explicit or parameterized, e.g. knowing length/time scales of decorrelation)

Propagating uncertainty to climate scales: example of SST





[Bellprat et al., 2017]

How does observational uncertainty affect the quality of sea-ice forecasts?

Greatly.

-First, at initialization.
-Then, at verification.

-Modellers need information on how uncertainty propagates to climate scales (region, month)
-Observational members (e.g. HadISST2)?

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What should be the
tuning target for CMIP6?

Tuning of Arctic sea ice remains a contentious issue

1. Modelling groups do not report <u>how</u> they tune their model [Mauritsen et al., 2012]
2. Modelling groups do not report <u>to what observable</u> they tune their model
3. It is unclear if there is a universal tuning target [Notz, 2015]

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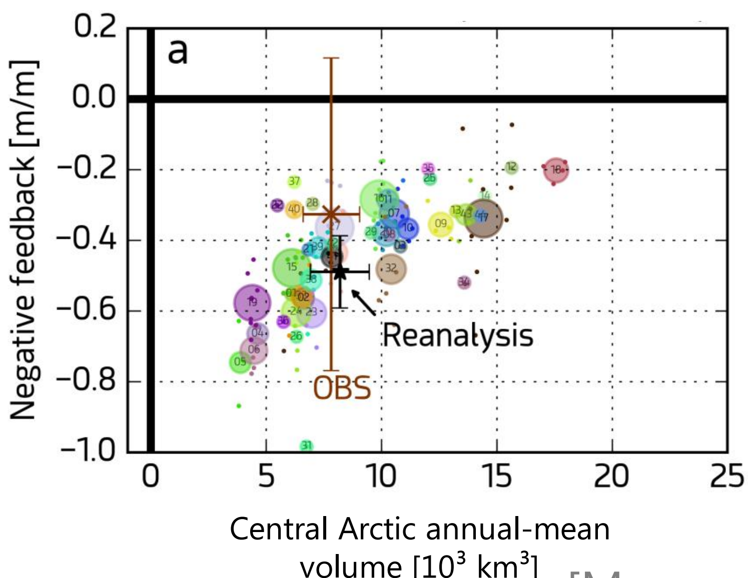
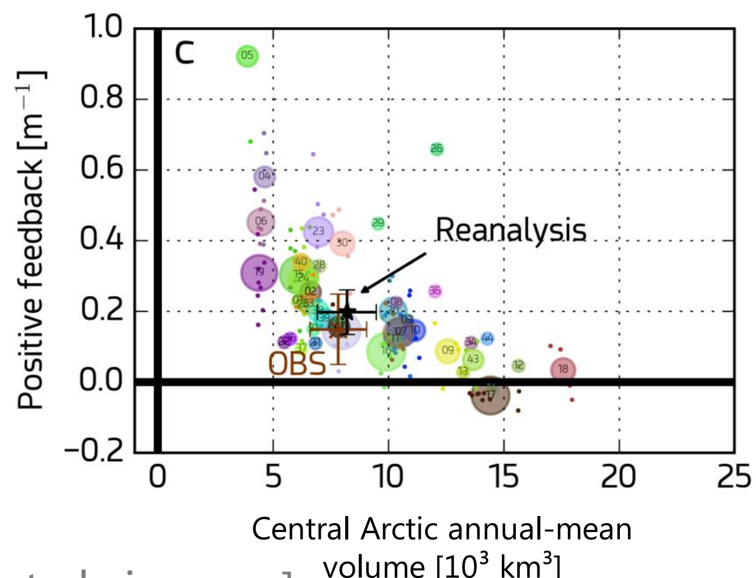
44 CMIP5 models





[Massonnet et al., in prep.]

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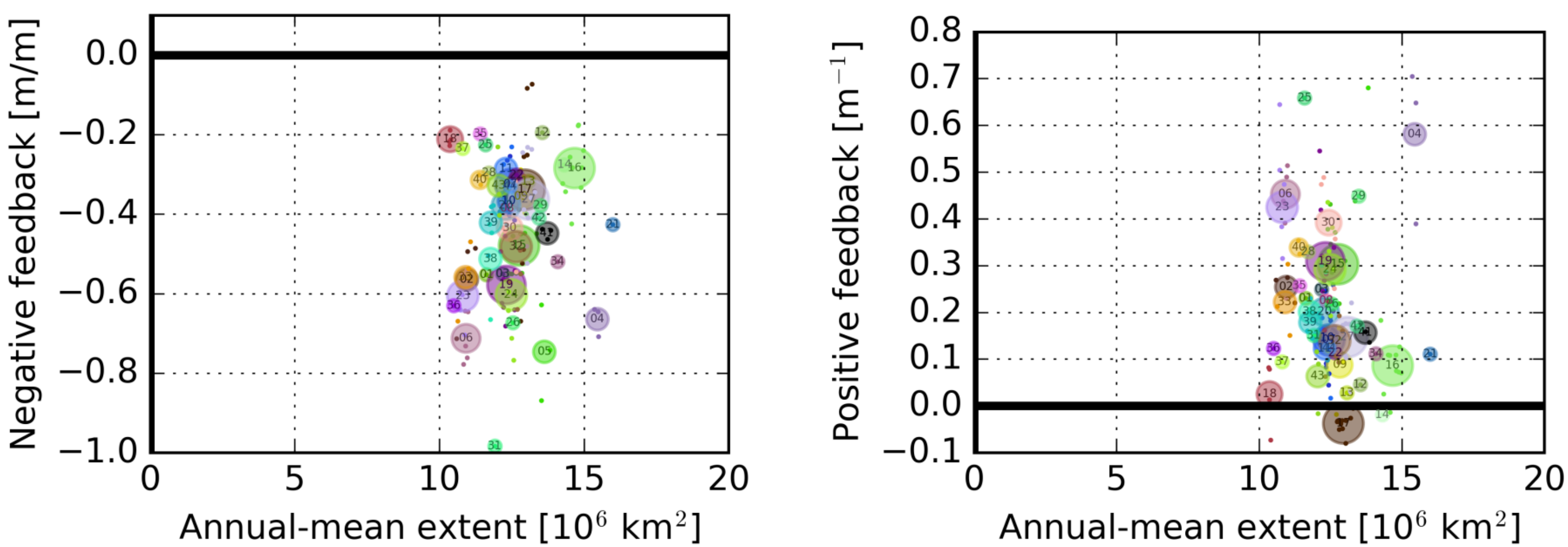
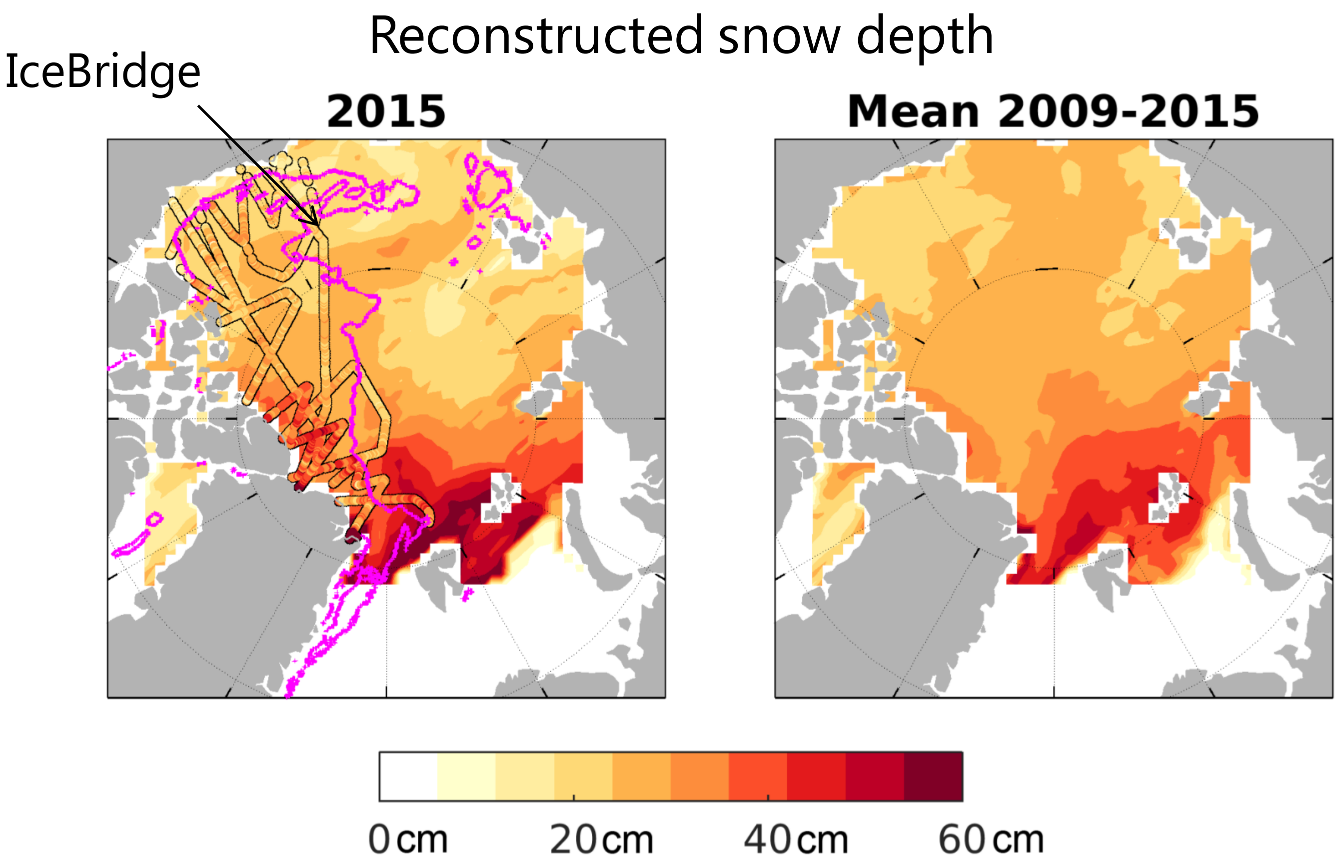
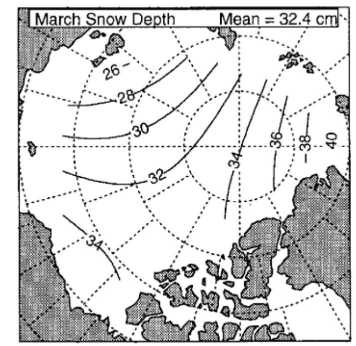


[Massonnet et al., in prep.]

Important to provide updated estimates of snow depth



[Blanchard-Wrigglesworth et al., submitted]



[Warren et al. 1999]

What should be the tuning target for CMIP6?

Depends on purpose.

One cannot be wrong with tuning to thickness

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YOPP

YEAR OF POLAR PREDICTION

Can we evaluate GCMs with one year of data?
If so, based on what data?

- The terms of continuity equation

$$\frac{\partial A}{\partial t} = -\vec{u} \cdot \nabla A - A \cdot \nabla \vec{u}$$

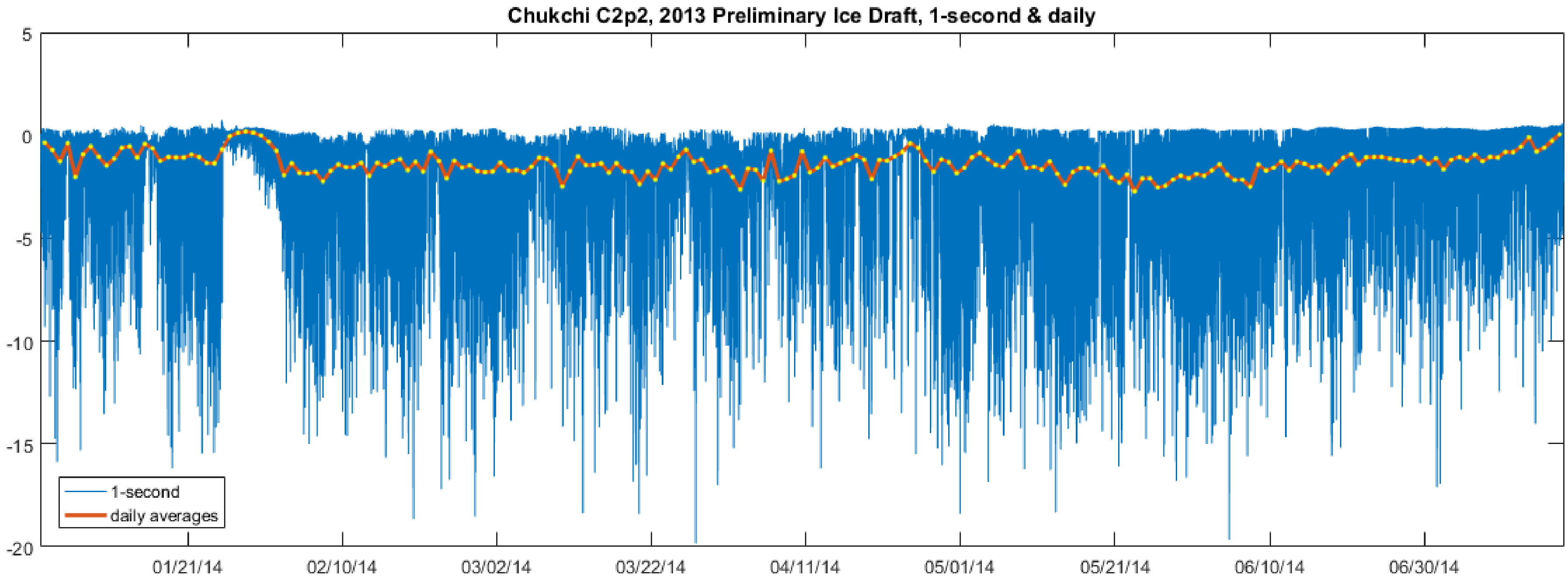
(+ thermo + mech.)

- Statistics of deformation

- Sea Ice Mass Balance and fluxes

[Holland and Kwok, 2014; Lecomte et al., 2016; Rampal et al., 2016; Vancoppenolle et al. 2011]

1-second sea ice draft data from mooring



[Courtesy Peggy Sullivan (PMEL/NOAA)]

Can we evaluate GCMs with one year of data?
If so, based on what data?

Likely yes.

Based on data that can directly be matched to first physical processes/principles

-Continuity

-Deformation

-Thermodynamic growth/melt

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Observational needs for sea ice models
Short note

F. Massonnet*, A. Jahn†

January 25, 2012

1 Scope

This note summarizes discussions held during a 2-day m
Group, in Boulder, CO (31st Oct. – 1st Nov., 2011). It i
identify gaps in the observations of the Arctic sea ice c

Data request from modellers for Antarctic sea ice modelling
Martin Vancoppenolle (Université catholique de Louvain, Louvain-la-Neuve, Belgium) with input from collaborators (T. Fichefet, H. Goosse, F. Massonnet)
Elizabeth Hunke (Los Alamos National Laboratory, Los Alamos, USA)

Sea ice models.
Sea ice models that are used for climate simulation aim at representing the sea ice processes that are relevant at the global scale. The spatial domain typically covers the entire globe and the size of a grid cell ranges, depending on application, from 10 to 100 km. which means that the processes occurring at scales smaller than that

Have we progressed in six years?

Have we progressed in six years?

I think we have.

Consistent definitions (SIMIP)
More data availability
More data readability
More uncertainties available

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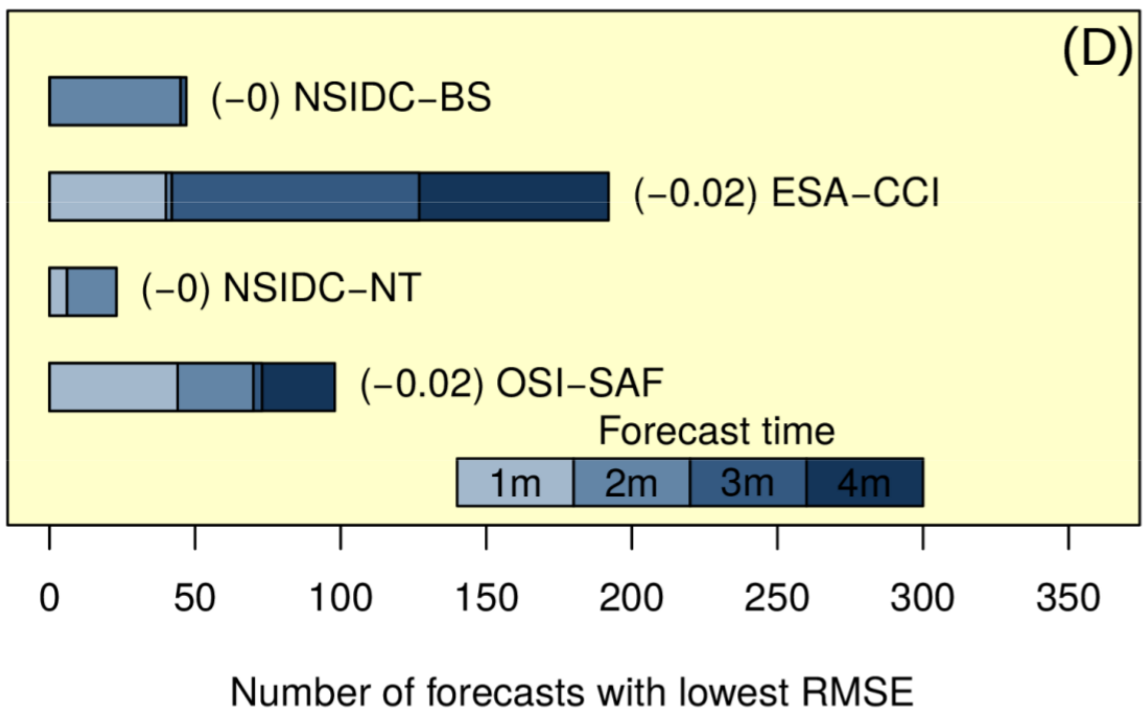
Can climate models be any useful to observational community?

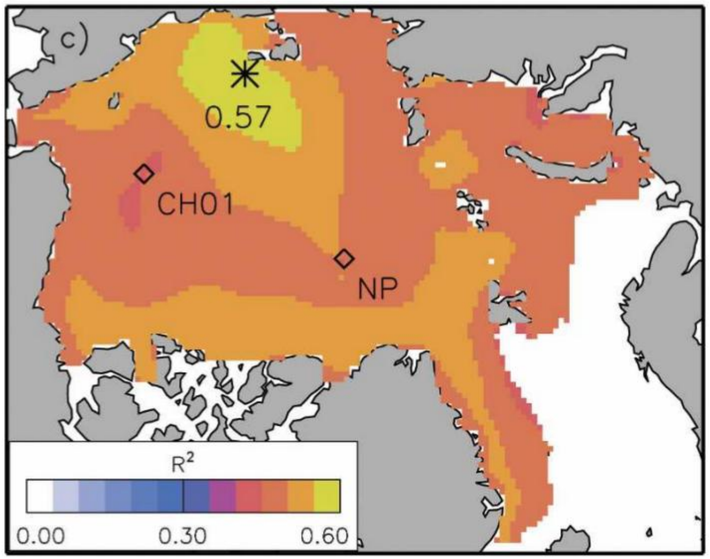
Climate models used to rank observational products



[Massonnet et al., 2016]

Climate models used to optimize deployment of future observational sites

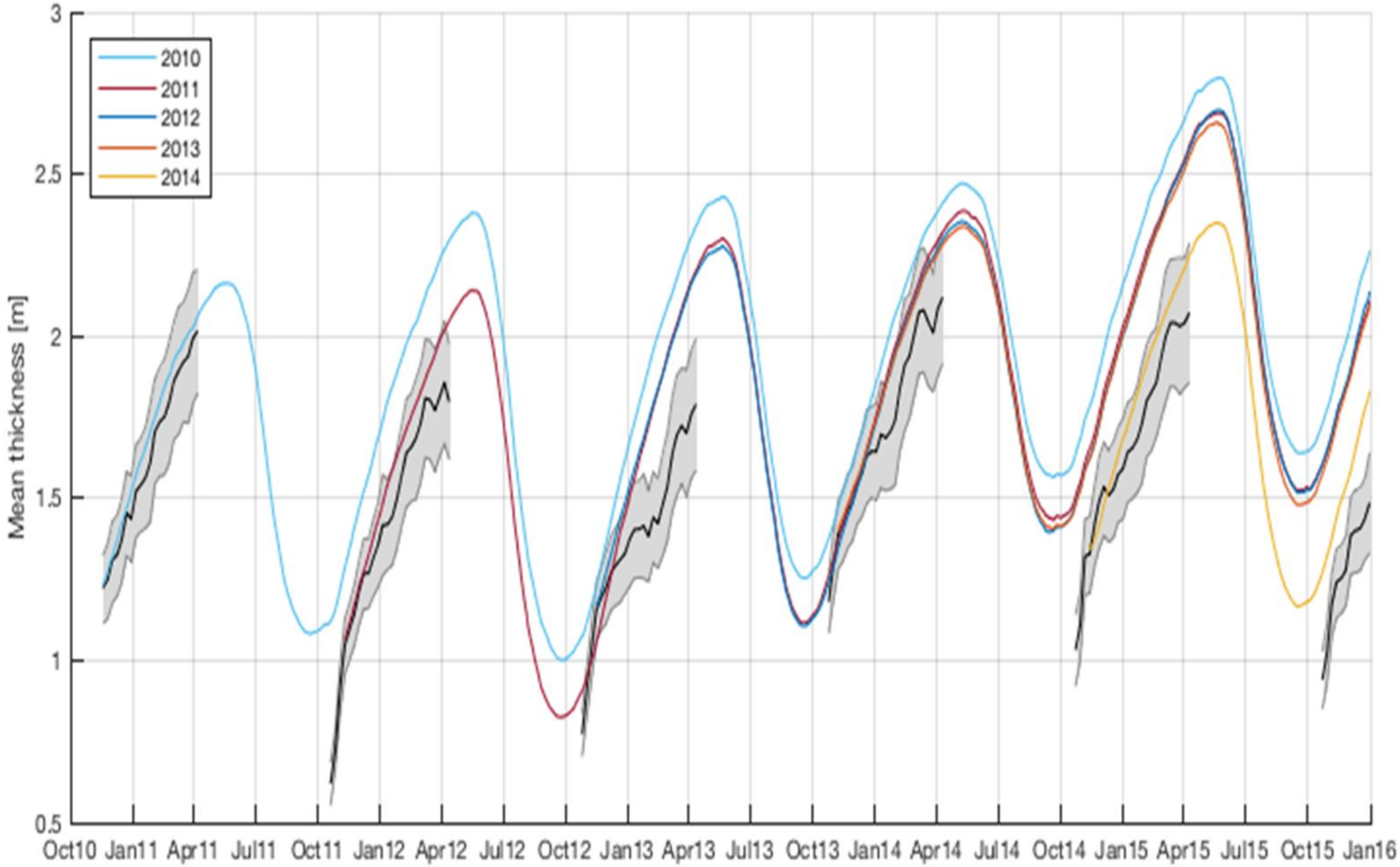
Fraction of SIT variance explained by three points



[Lindsay and Zhang, 2005]

APPLICATE
www.applicate.eu
Advanced prediction in Polar regions and beyond

Climate models used to identify shortcomings in observational errors



[Courtesy P. Rampal & E. Ólason]

Part 1: What I wanted to say initially

Part 2: What came to my mind during the workshop

The workshop's three overarching questions

1. What do we really mean by uncertainty?
2. What can modellers get from observations in terms of reality?
3. How can we best combine model and measurement to understand reality?

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1. What do we really mean by uncertainty?

Earth Syst. Sci. Data Discuss., doi:10.5194/essd-2017-16, 2017
Manuscript under review for journal Earth Syst. Sci. Data
Discussion started: 28 February 2017

Open Access Earth System Science Data Discussions

Uncertainty information in climate data records from Earth observation

Christopher J. Merchant[1,2], Frank Paul[3], Thomas Popp[4], Michael Ablain[5], Sophie Bontemps[6], Pierre Defourny[6], Rainer Hollmann[7], Thomas Lavergne[8], Alexandra Laeng[9], Gerrit de Leeuw[10], Jonathan Mittaz[1,11], Caroline Poulsen[12], Adam C. Povey[13], Max Reuter[14], Shubha Sathyendranath[15], Stein Sandven[16], Viktoria F. Sofieva[11] and Wolfgang Wagner[17].

[Merchant et al., 2017]

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Unknown, perhaps ill-defined concept

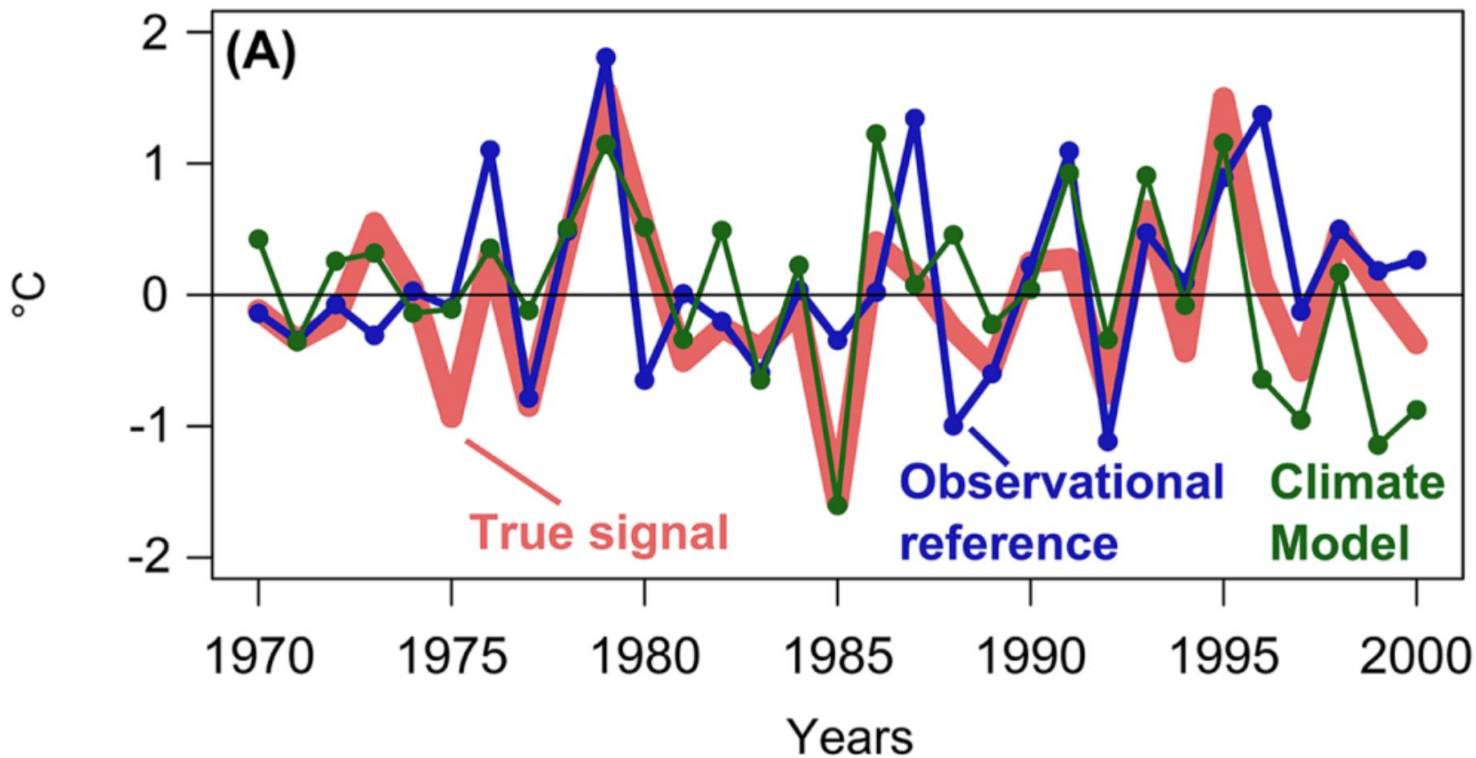
- Error = measured value – truth
- Uncertainty = « parameter characterizing the spread of the quantity values attributed to the measurement, given the measured value and an understanding of the measurement »

The **PDF of measured values** fully embraces the definition of uncertainty (includes error std and co-variates)

[Merchant et al., 2017]

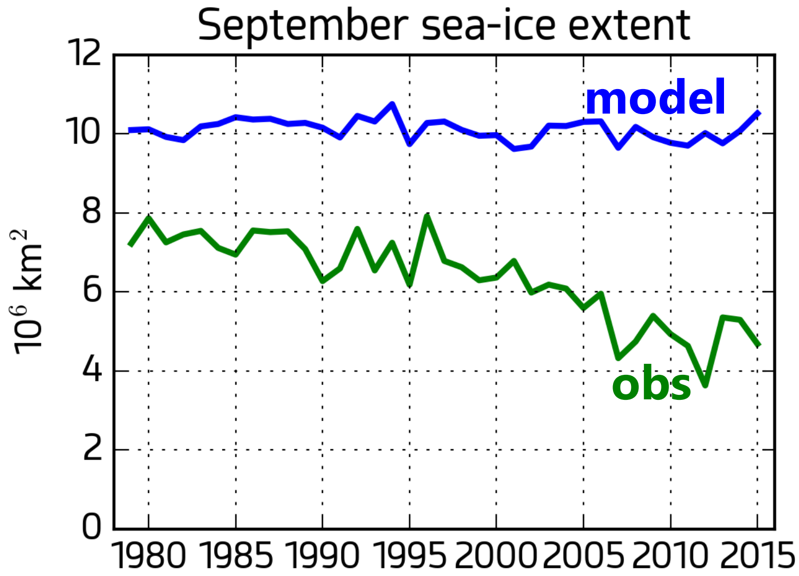
Models and observations are two sides of the same coin

SST anomalies in the Niño3.4 box (fictious example)



[Massonnet et al., 2016]

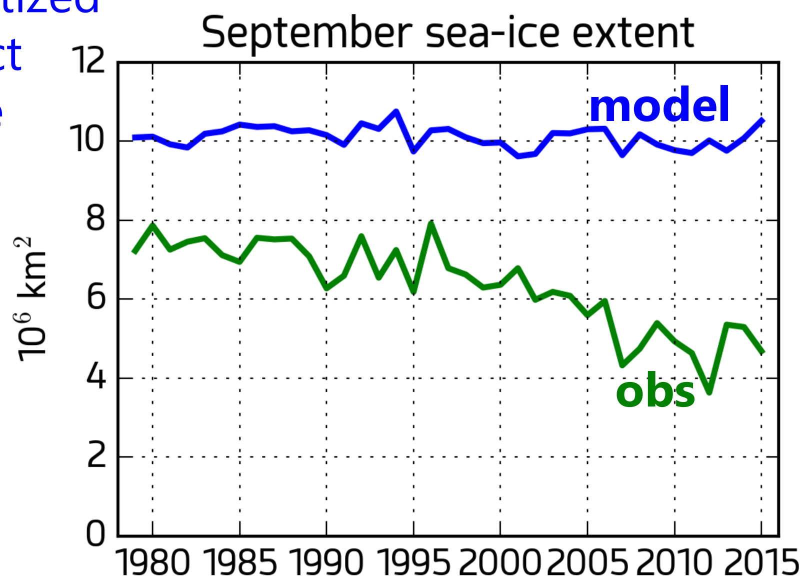
Why don't models and observations match?



Why don't models and observations match?

It's the modellers fault

- -Physical equations are wrong
- -Equations are discretized
- -Forcing is not correct
- -Initial conditions are not correct
- -Parameterizations
- -HPC error



[Orrell et al., 2001]

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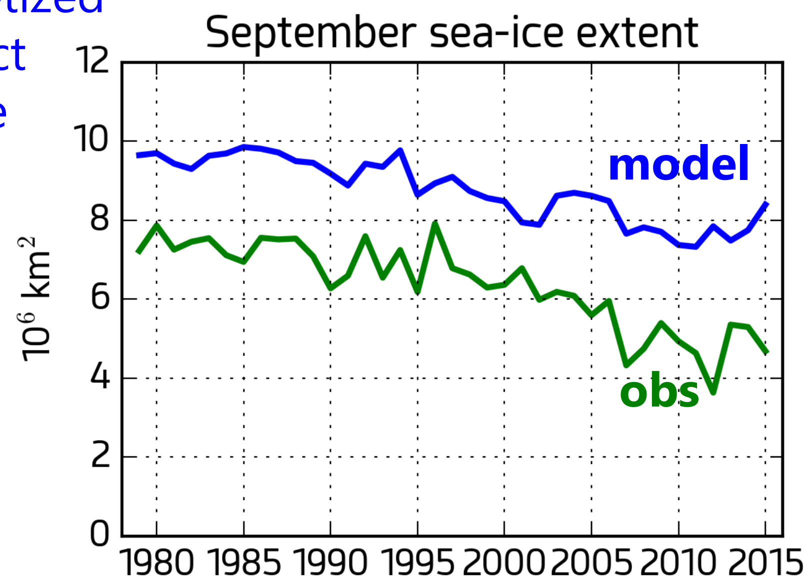

[Orrell et al., 2001]

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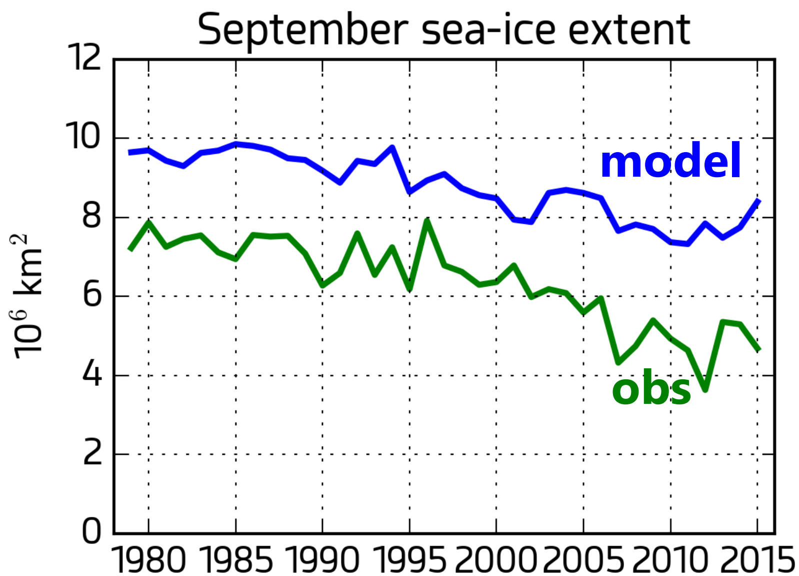
It's the observers fault

Instrumental error
Algorithm error
Assumptions (e.g. hydrostatic)
Sampling error



[Ivanova et al., 2014; Zygmuntowska et al., 2014; Worby et al., 2008]

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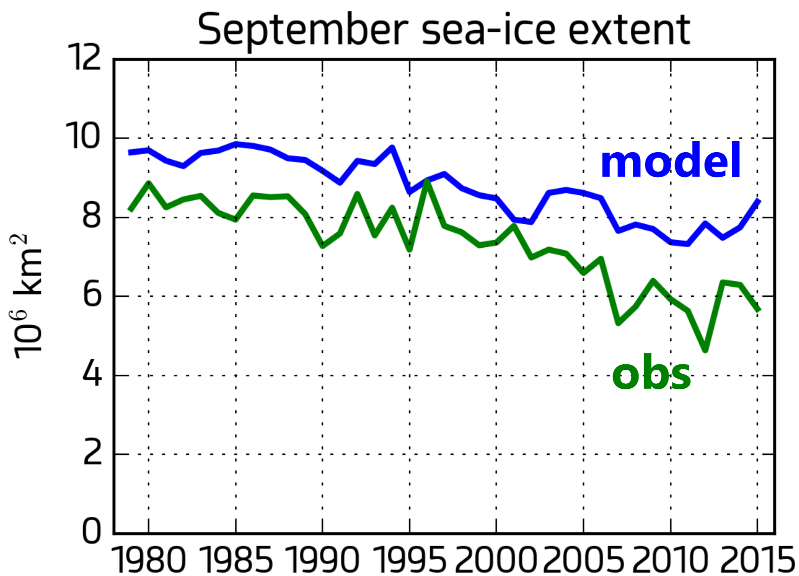

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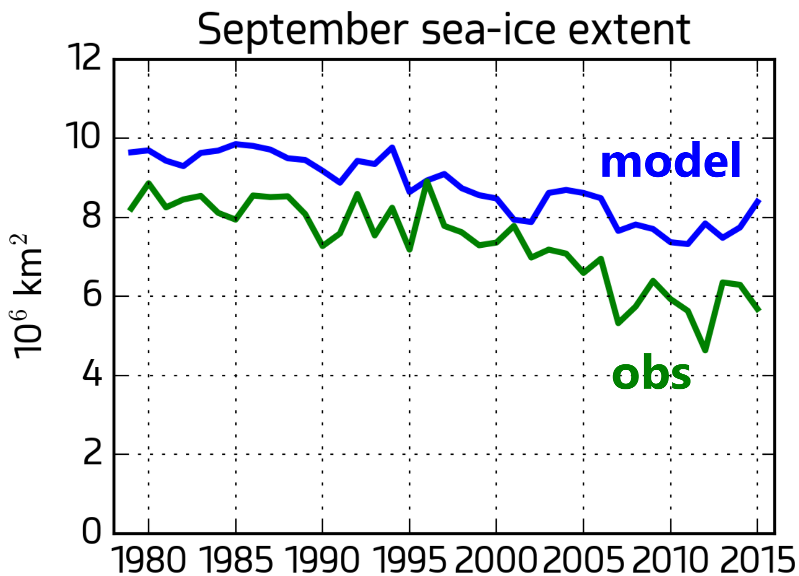

It's my fault

No scale-awareness

No definition-awareness

[Kay et al., 2016]

Why don't models and observations match?

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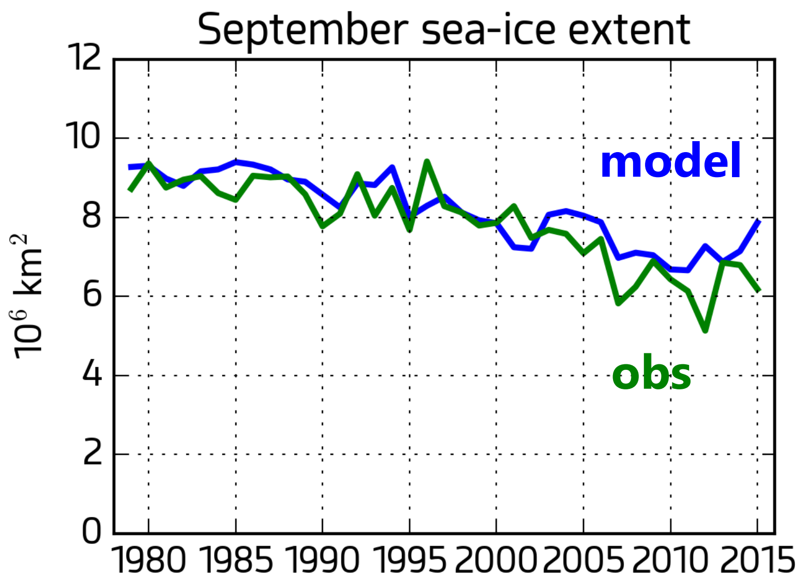

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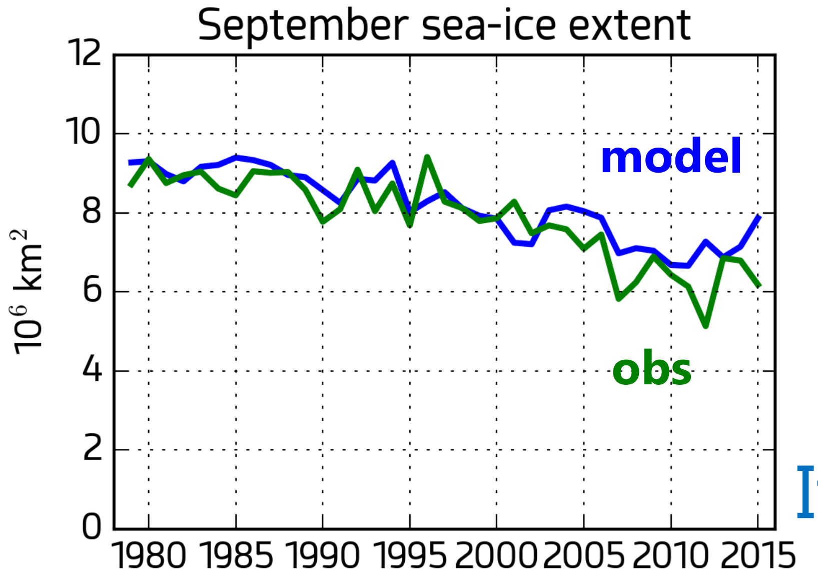

It's my fault

It's no one's fault

Internal variability

Interannual variability

[Notz, 2015]

- Ban the word « validation » from our vocabulary – use « evaluation » instead
- Ban the word « observations » - use « observational reference » instead

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