The Future of Earth System Modeling: Polar Climates
Caltech, 28-30 November 2018

Using numerical models to design the future of the Arctic observing system

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FREEDOM TO RESEARCH

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A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing

Christopher J. Roy [a,*], William L. Oberkampf [b]

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[b] Consulting Engineer, 5112 Hidden Springs Trail, Georgetown, Texas 78633, USA

Roy and Oberkampf, *Comput. Methods Appl. Mech. Engrg.*, 2011

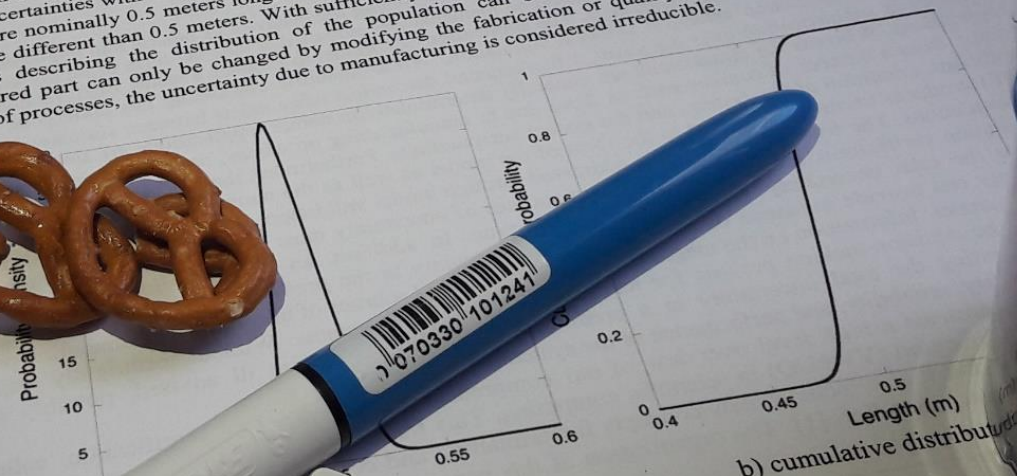
uncertainty are discussed; aleatory and epistemic uncertainty. Then the key sources of uncertainty in scie
computing are identified: model inputs, numerical approximations, and model form uncertainty. A comprehens
framework for treating all sources of uncertainty in scientific computing is then described. The framework includ
the identification of all sources of uncertainty, characterization of model input uncertainties, elimination o
estimation of code and solution verification errors, propagation of model input uncertainties through the model to obtain
uncertainties in the system response quantities, quantification of model form uncertainty, and estimation of model
form uncertainty due to extrapolation to application conditions of model form uncertainty, and estimation of model
the paradigm shift from deterministic to nondeterministic simulations and the impact of this shift on the decision-
making process.

II. Types of Uncertainty

While there are many different ways to classify uncertainty, we will use the taxonomy prevalent in the risk assessment community which categorizes uncertainties according to their fundamental essence [2-5]. Thus, uncertainty is classified as either a) *aleatory* – the inherent variation in a quantity that, given sufficient samples of the stochastic process, can be characterized via a probability distribution, or b) *epistemic* – where there is insufficient information concerning the quantity of interest to specify either a fixed value or a precisely known probability distribution. In scientific computing, there are many sources of uncertainty including the model inputs, the form of the model, and poorly-characterized numerical approximation errors. All of these sources of uncertainty can be classified as either purely aleatory, purely epistemic, or a mixture of aleatory and epistemic uncertainty.

A. Aleatory Uncertainty

Aleatory uncertainty (also called irreducible uncertainty, stochastic uncertainty, or variability) is uncertainty due to inherent variation or randomness and can occur among members of a population or due to spatial or temporal variations. Aleatory uncertainty is generally characterized by a probability distribution, most commonly as either a probability density function (PDF) – which quantifies the probability density at any value over the range of the random variable – or a cumulative distribution function (CDF) – which quantifies the probability that a random variable will be less than or equal to a certain value (see Figure 1). Here we will find it more convenient to describe aleatory uncertainties with CDFs. An example of an aleatory uncertainty is a manufacturing process which produces parts that are nominally 0.5 meters long. Measurement of these parts will reveal that the actual length for any given part will be different than 0.5 meters. With sufficiently large number of samples, both the form of the CDF and the parameters describing the distribution of the population can be determined. The aleatory uncertainty in the manufactured part can only be changed by modifying the fabrication or quality control processes; however, for a given set of processes, the uncertainty due to manufacturing is considered irreducible.



b) cumulative distribution

Figure 1. Example of probability distributions

Classification of uncertainty

Uncertainty

« Aleatoric »

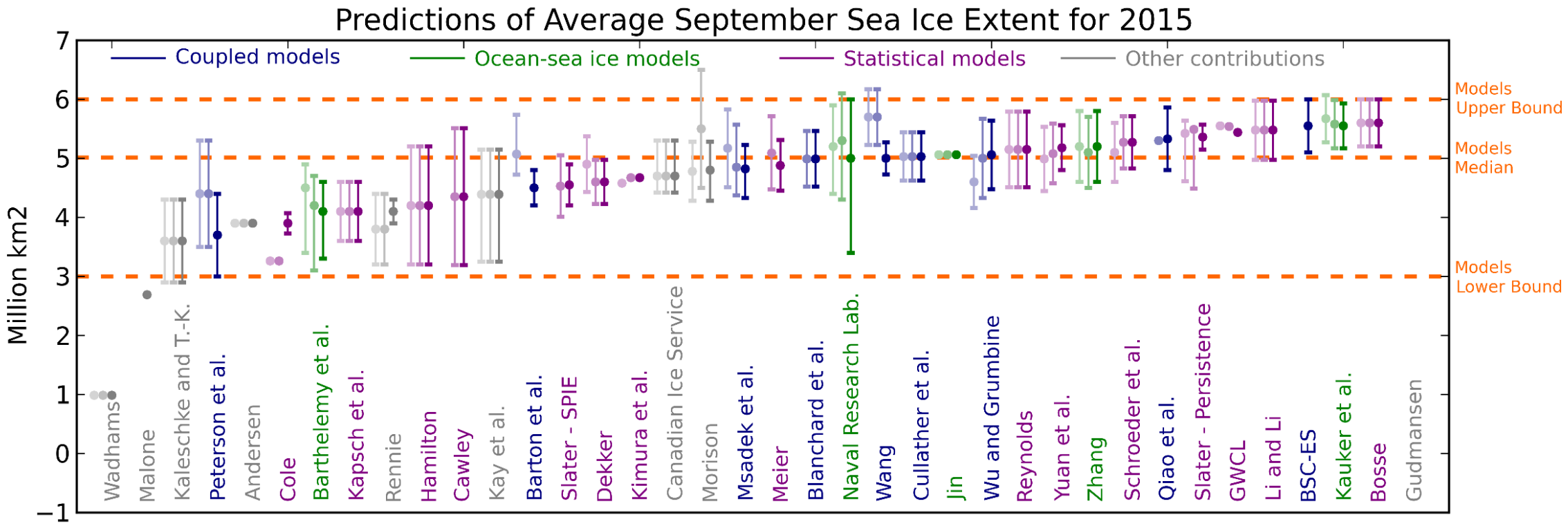
- Due to random effects
- Characterized by a PDF (frequentist interpretation)
- Irreducible

« Epistemic »

- Due to ignorance
- Characterized by an interval
- Can, in principle, be eliminated

Roy and Oberkampf, *Comput. Methods Appl. Mech. Engrg.*, 2011

Aleatoric *vs* epistemic uncertainy in the Sea Ice Outlooks



https://www.arcus.org/sipn/sea-ice-outlook/2015/post-season

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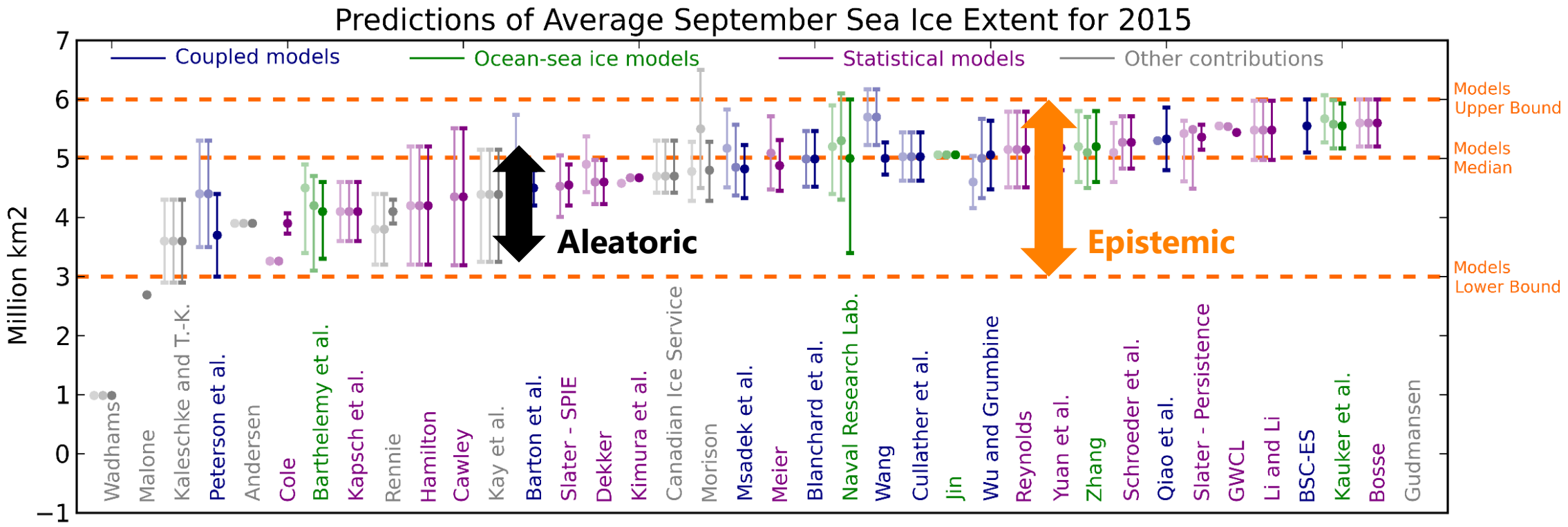

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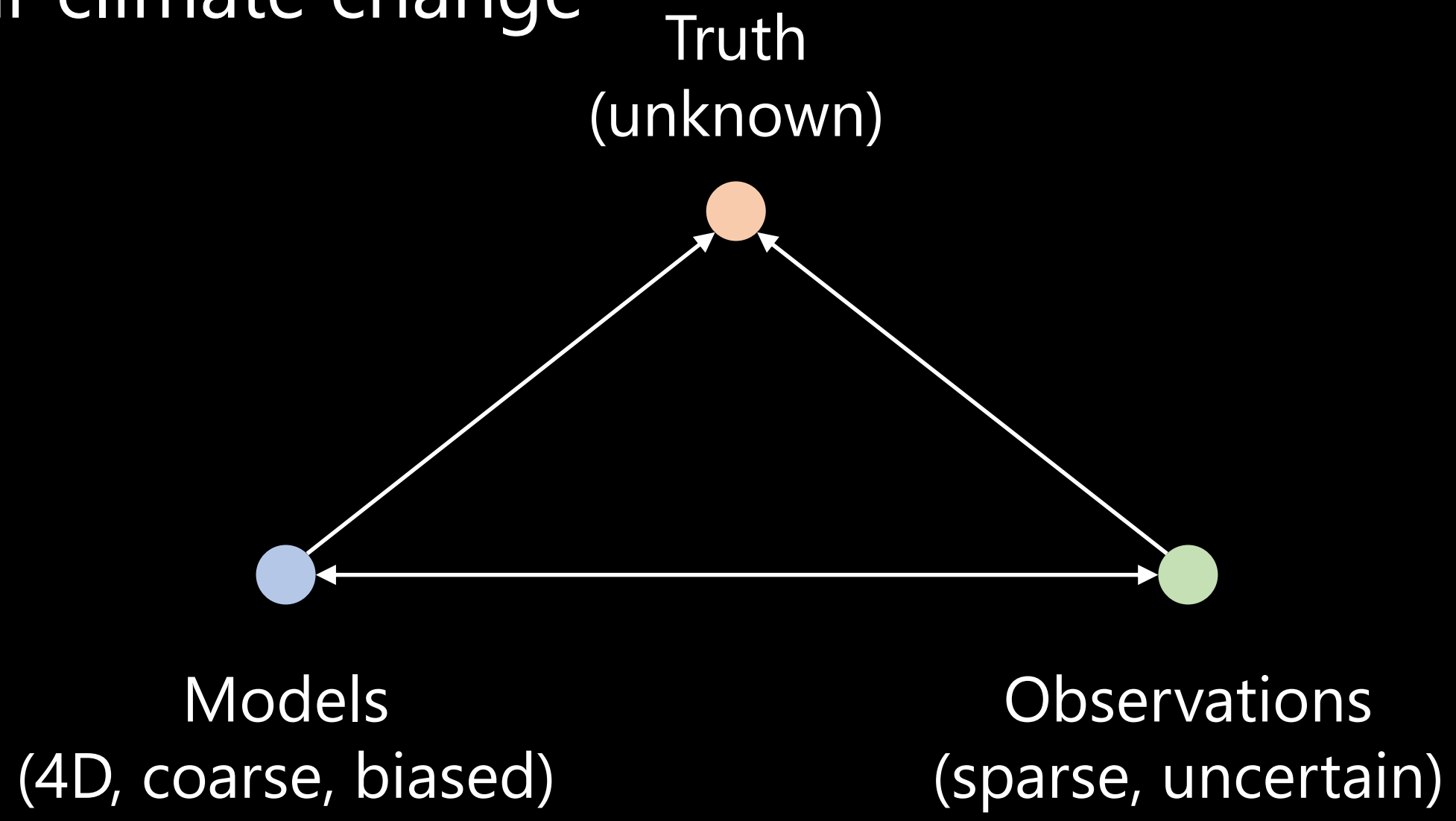
Roy and Oberkampf, *Comput. Methods Appl. Mech. Engrg.*, 2011

The Trinity of understanding polar climate change



A sea ice climate change perspective on the running questions of the workshop

1. How should we design a climate model to obtain better predictions of polar climates on timescales of decades?
2. How can we integrate observations better with models?
3. What additional observations would help improving models?

A sea ice climate change perspective on the running questions of the workshop

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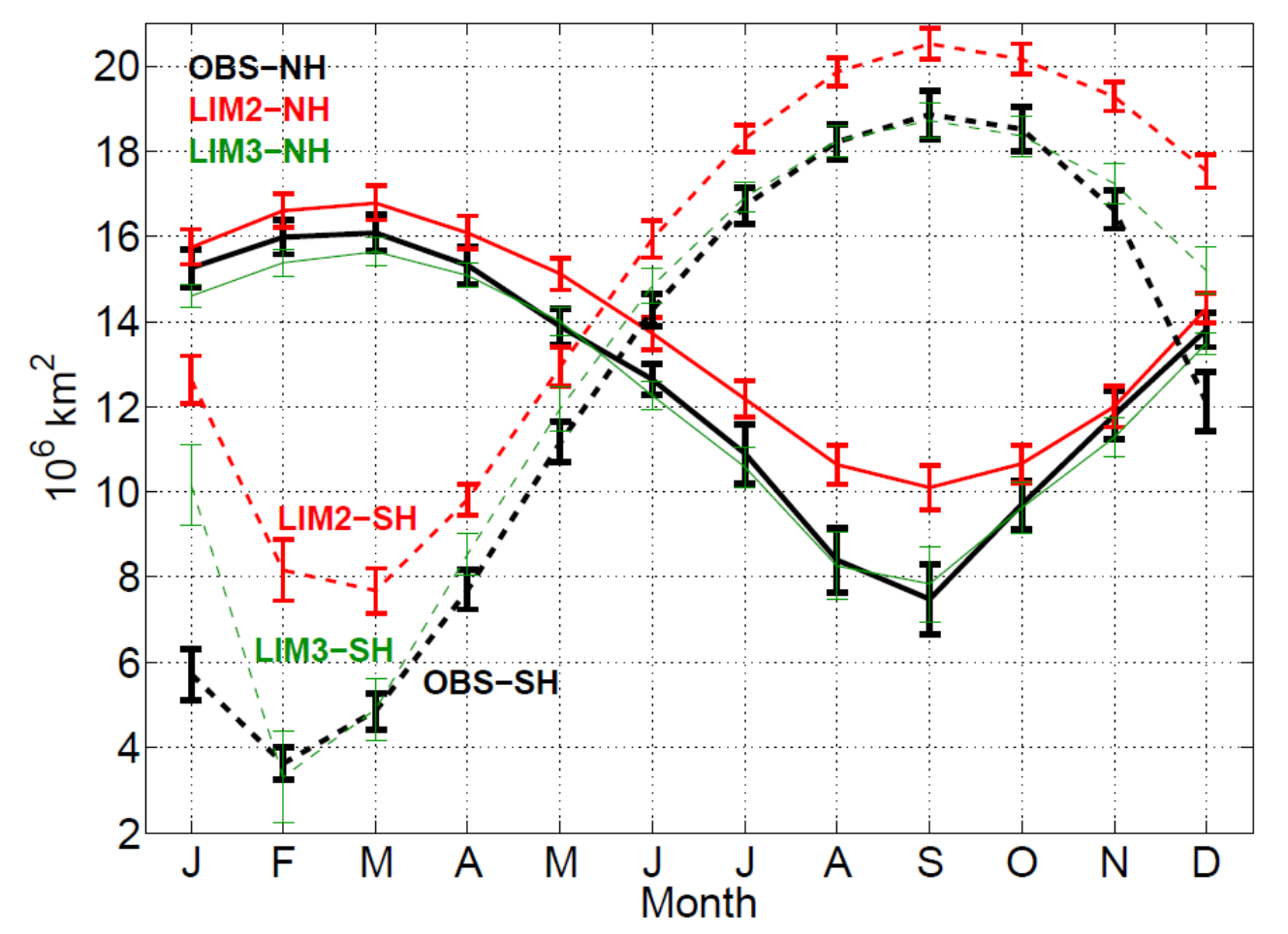
Adding complexity to a sea ice model leads to improved Arctic mean sea ice state (and variability)

Seasonal cycles of sea ice extent (1983-2007)



tion, extent and thickness. We suggested that the inclusion of a detailed ice thickness distribution (ITD) in one of the model enhanced the interannual variability of sea ice extent, and significantly improved and reduced the simulated ice thickness in the Arctic. We also emphasized that the ex-

Massonnet et al., *The Cryosphere*, 2011

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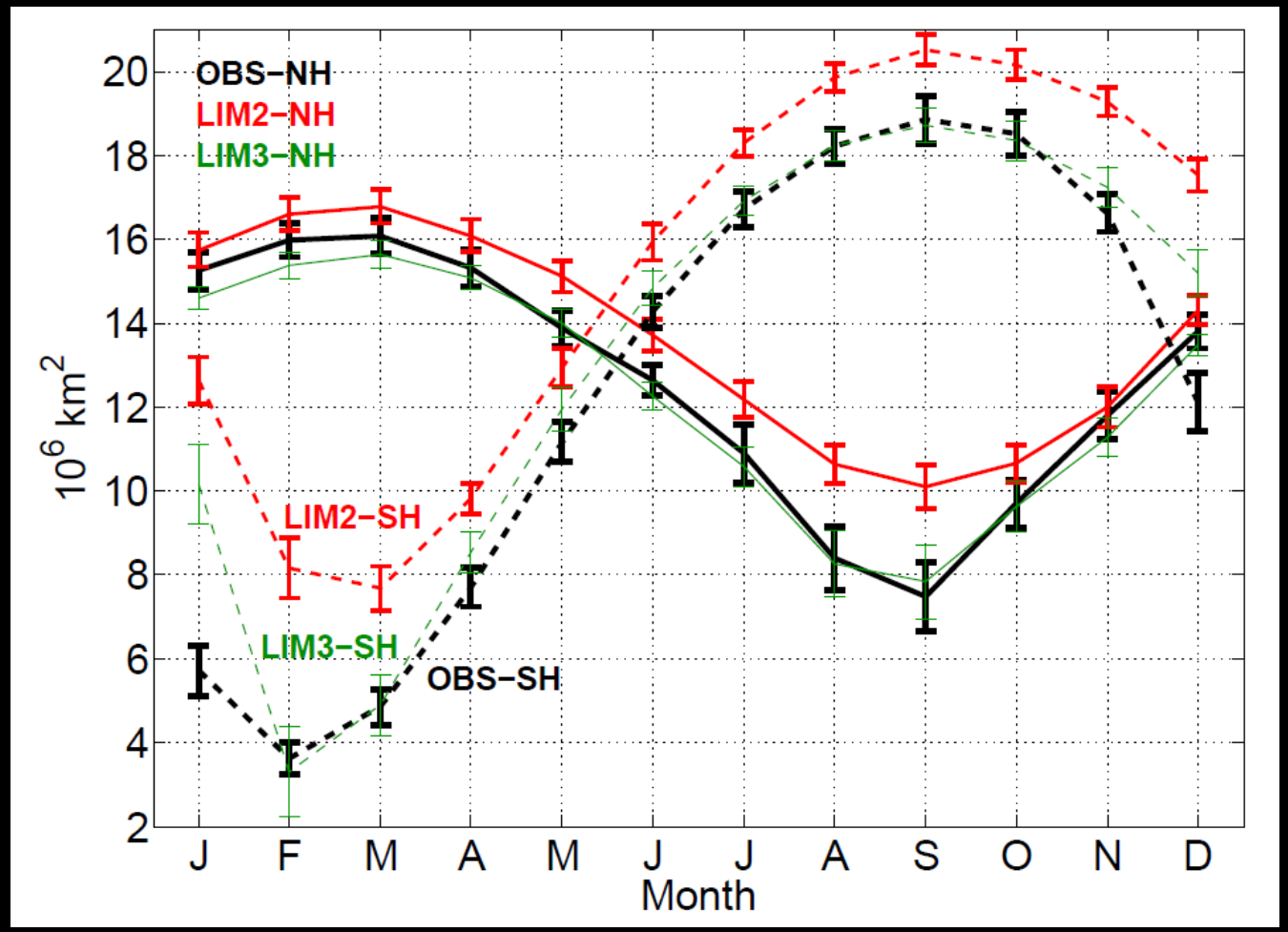

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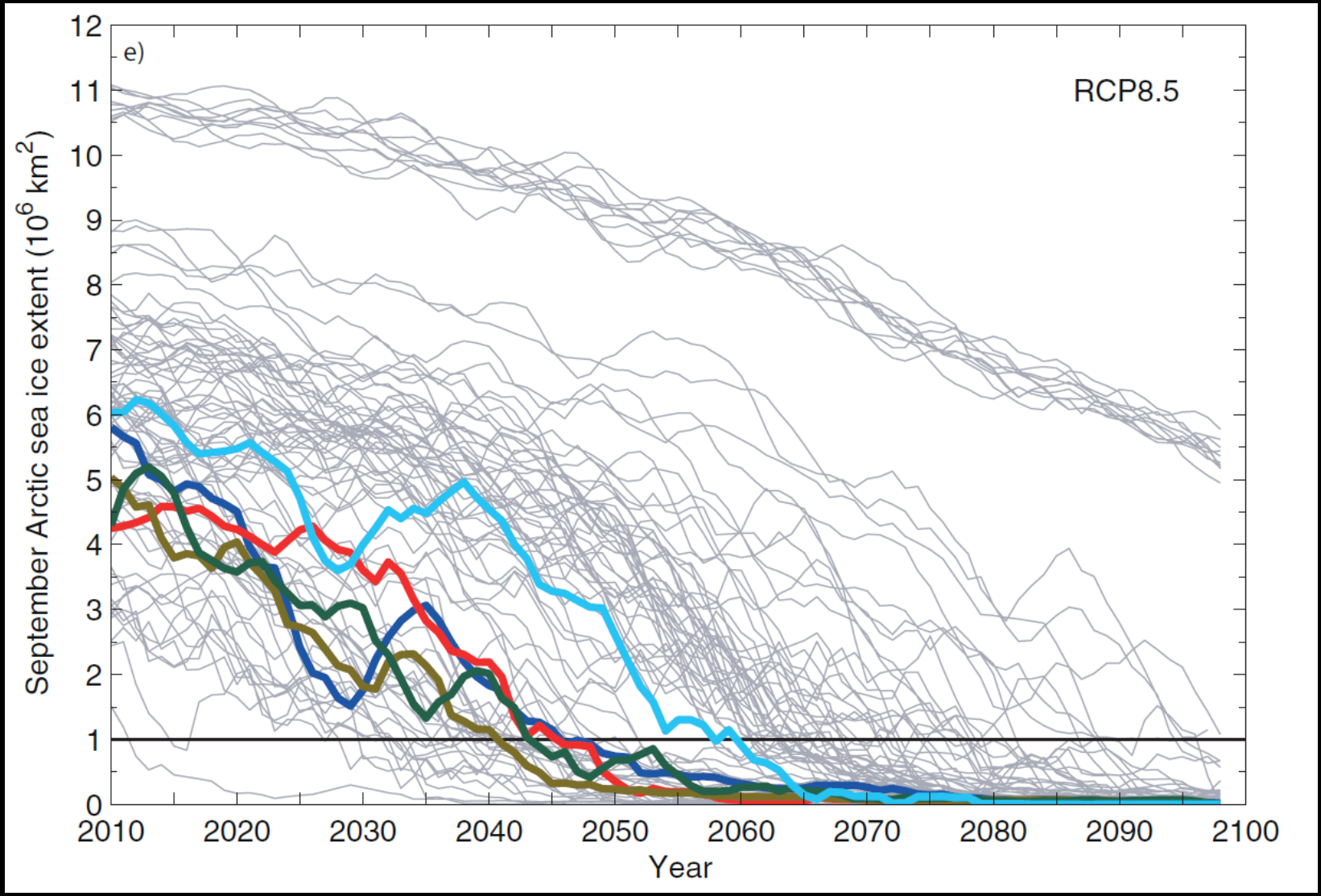
This study was conducted all other things being equal (only epistemic uncertainty was estimated)

Massonnet et al., *The Cryosphere*, 2011

CMIP5 projections of September Arctic sea ice extent



IPCC AR5 Chapter 12, 2013; Massonnet et al., *The Cryosphere*, 2012

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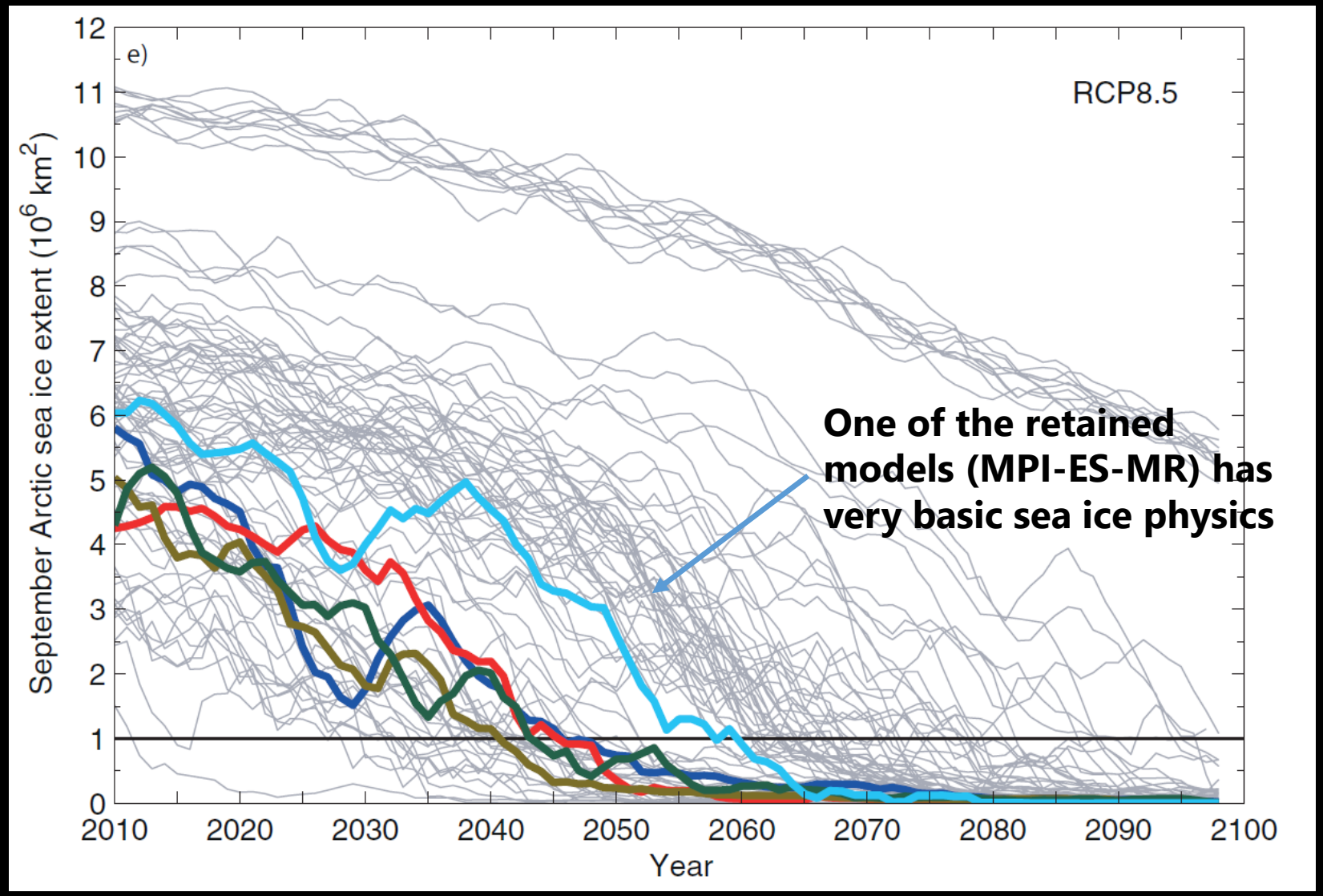
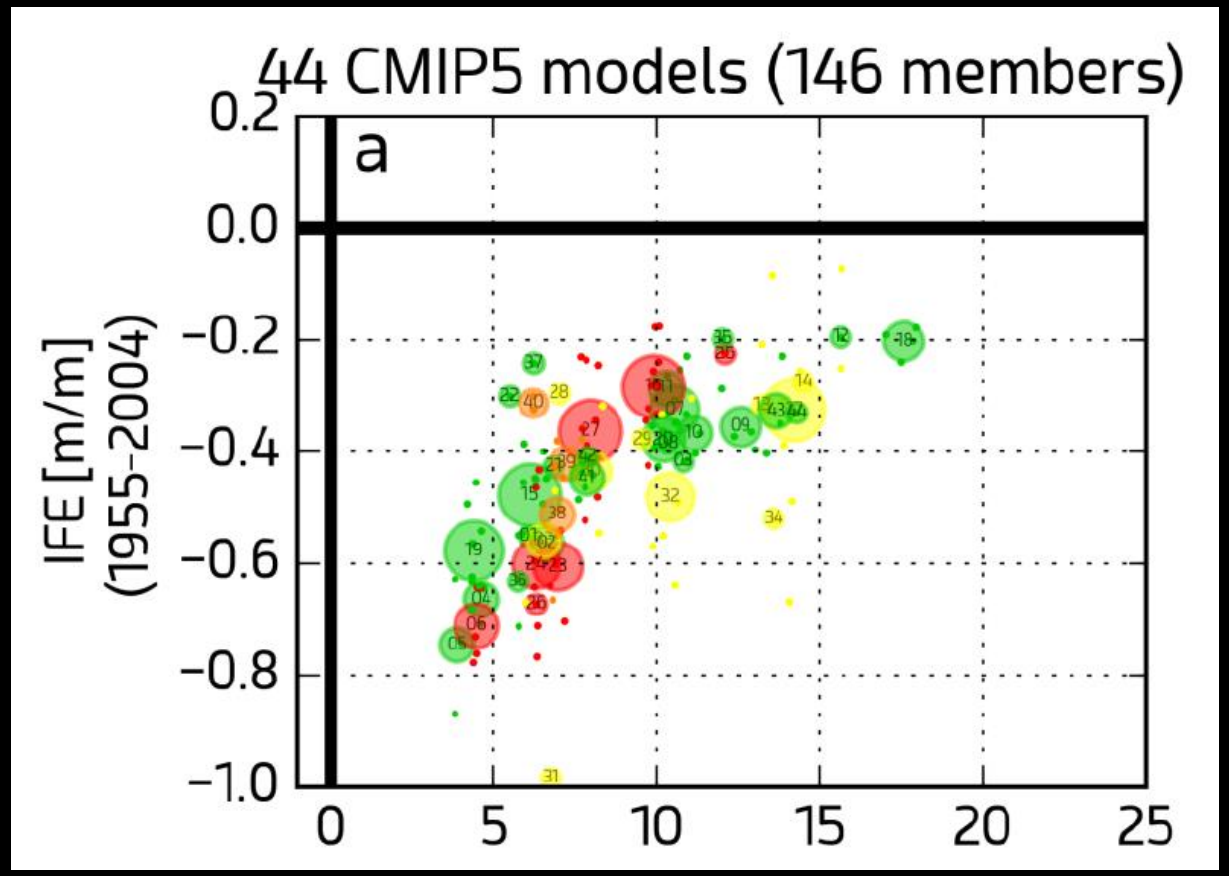


IPCC AR5 Chapter 12, 2013; Massonnet et al., *The Cryosphere*, 2012

In CMIP5 models, sea ice model physics is not a good predictor for the sea ice mean state and feedbacks



Central Arctic annual mean sea ice volume [10^3 km^3]

No ITD 0-layer

virtual ITD 0-layer

ITD or multi-layer

ITD and multi-layer

Massonnet et al., *Nature Clim. Change*, 2018

Do we need more complex sea ice models for climate change studies?

In principle, yes:

- Adding knowledge reduces epistemic uncertainty
- Model development is essential for process understanding

In practice, not until:

- internal variability is properly quantified
- parameter tuning is documented
- the source of biases is identified

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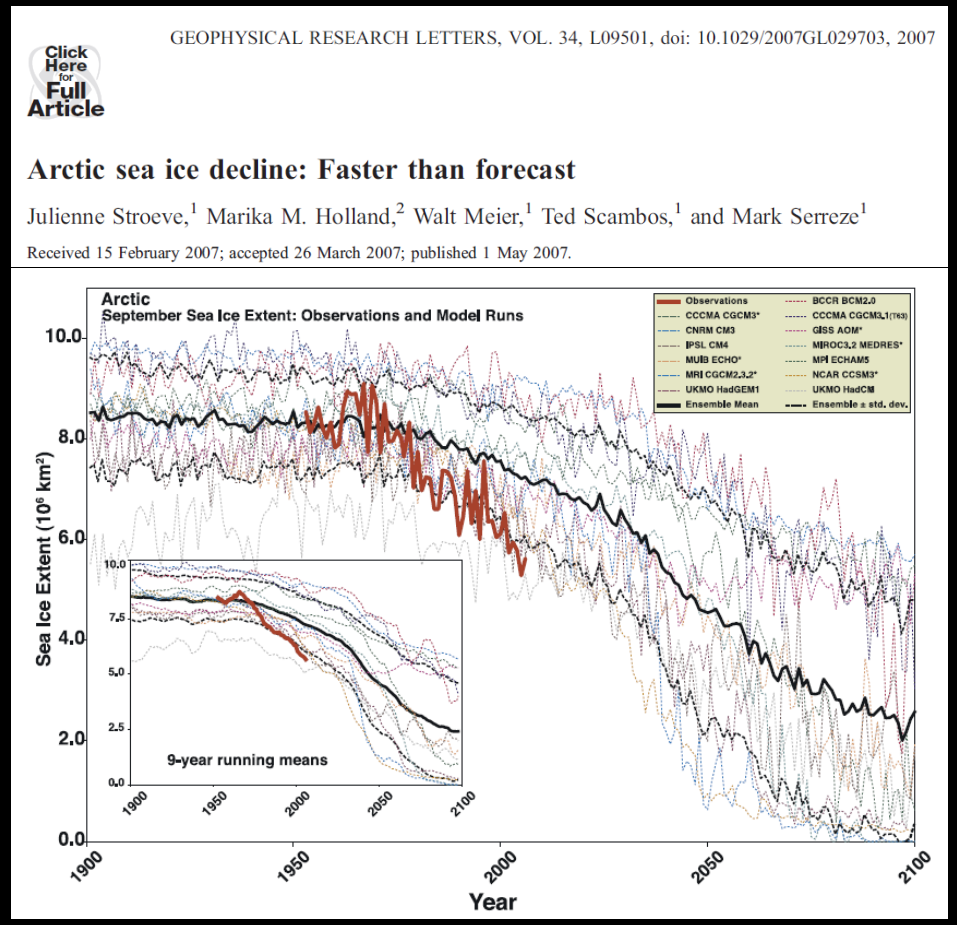

GEOPHYSICAL RESEARCH LETTERS, VOL. 34, L09501, doi: 10.1029/2007GL029703, 2007

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Arctic sea ice decline: Faster than forecast

Julienne Stroeve,[1] Marika M. Holland,[2] Walt Meier,[1] Ted Scambos,[1] and Mark Serreze[1]

Received 15 February 2007; accepted 26 March 2007; published 1 May 2007.

Stroeve et al., *Geophys. Res. Lett.*, 2007

Do we need more complex sea ice models for climate change studies?

15 DECEMBER 2016 ROSENBLUM AND EISENMAN 9179

Faster Arctic Sea Ice Retreat in CMIP5 than in CMIP3 due to Volcanoes

ERICA ROSENBLUM AND IAN EISENMAN

Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California

(Manuscript received 24 May 2016, in final form 4 October 2016)

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Sea Ice Trends in Climate Models Only Accurate in Runs with Biased Global Warming

Erica Rosenblum *and* Ian Eisenman
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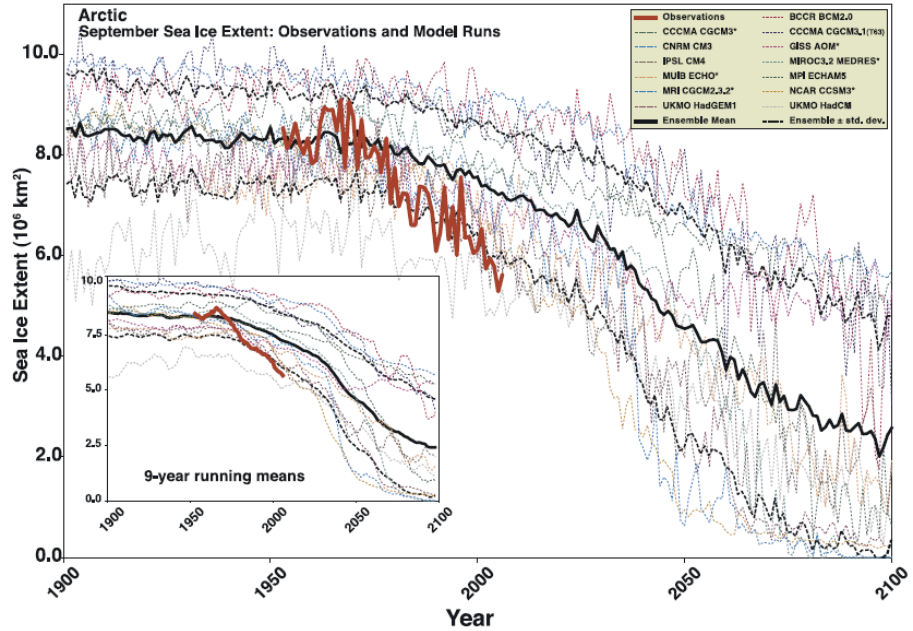

Rosenblum and Eisenman, *J. Climate,* 2016, 2017; Stroeve et al., *Geophys. Res. Lett.*, 2007

1. **How should we design a climate model to obtain better predictions of polar climates on timescales of decades?**

- The problem is that we have too many too similar sea ice models around for IPCC-like assessments
- For climate change studies, sea ice model complexity is perhaps less important than thought: mean state matters a lot for projected mass balance
- Keep developing models, but make them modular
- The NEMO4 will have a unified yet modular sea ice model

1. How should we design a climate model to obtain better predictions of polar climates on timescales of decades?
2. **How can we integrate observations better with models?**
3. What additional observations would help improving models?

Model evaluation

Data assimilation

1. How should we design a climate model to obtain better predictions of polar climates on timescales of decades?
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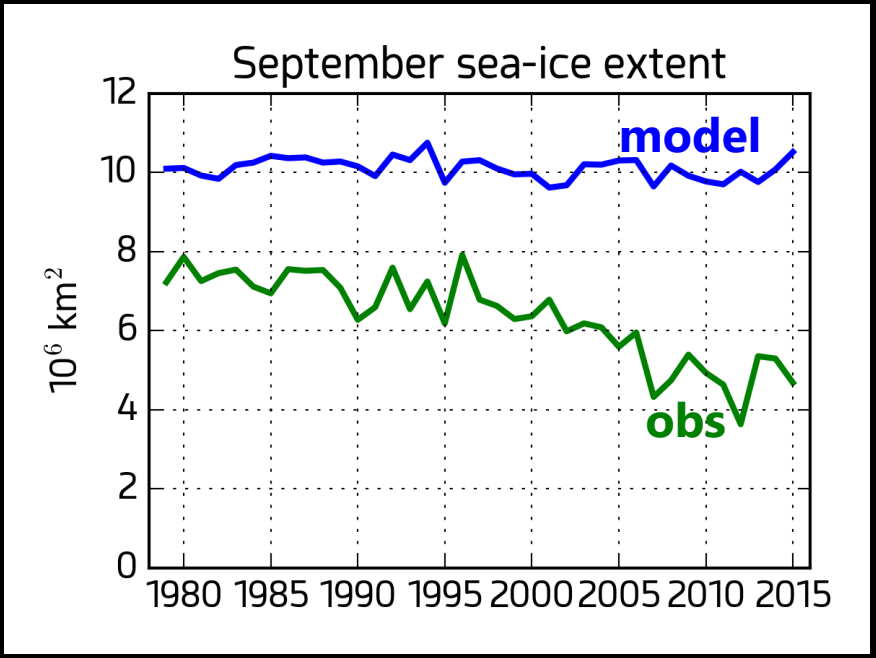
Model evaluation

Data assimilation

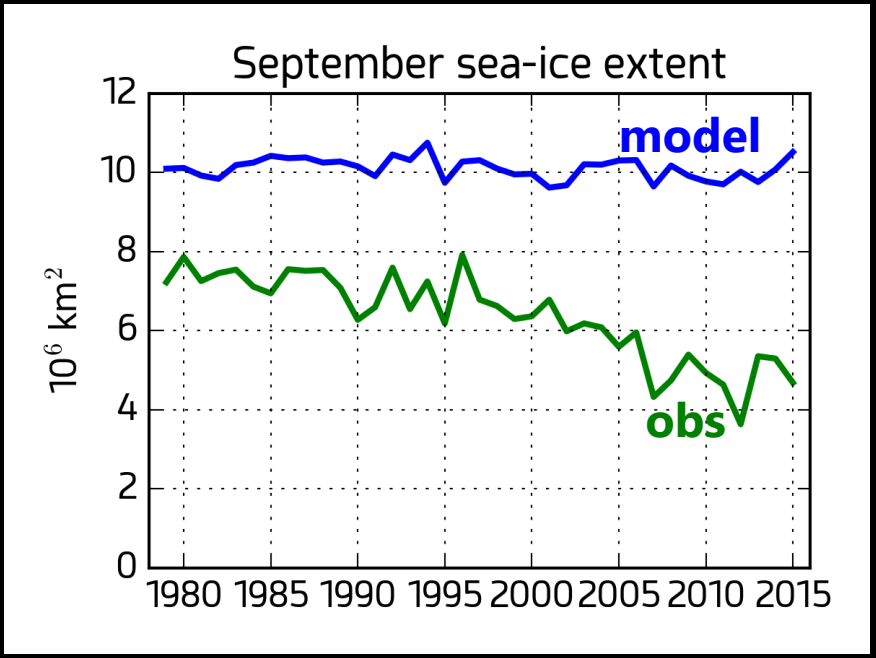
Why don’t models and observations match each other?



Why don't models and observations match each other?

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., *Nonlin. Proc. Geophys.*, 2001

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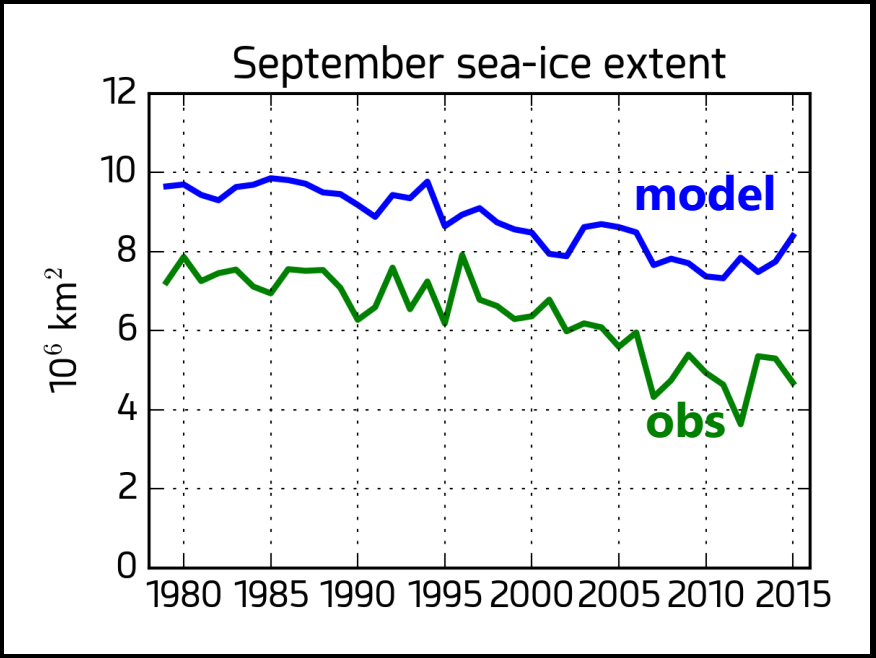

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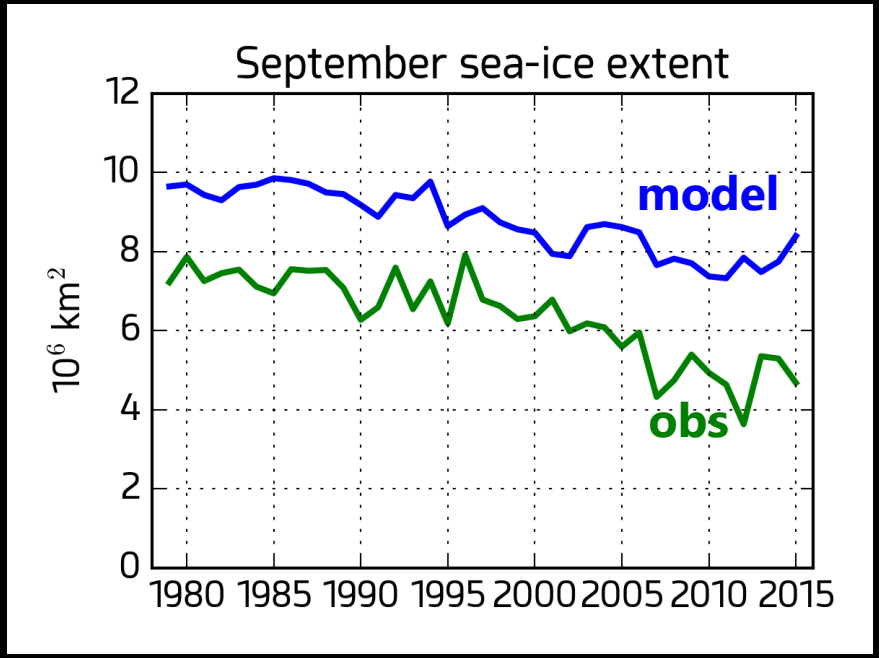
Why don't models and observations match each other?

It's the modellers fault

It's the observers fault

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



Ivanova et al., *Cryosphere*, 2014; Zygmuntowska et al., *Cryosphere*, 2014; Worby et al., *J. Geophys. Res.*, 2008

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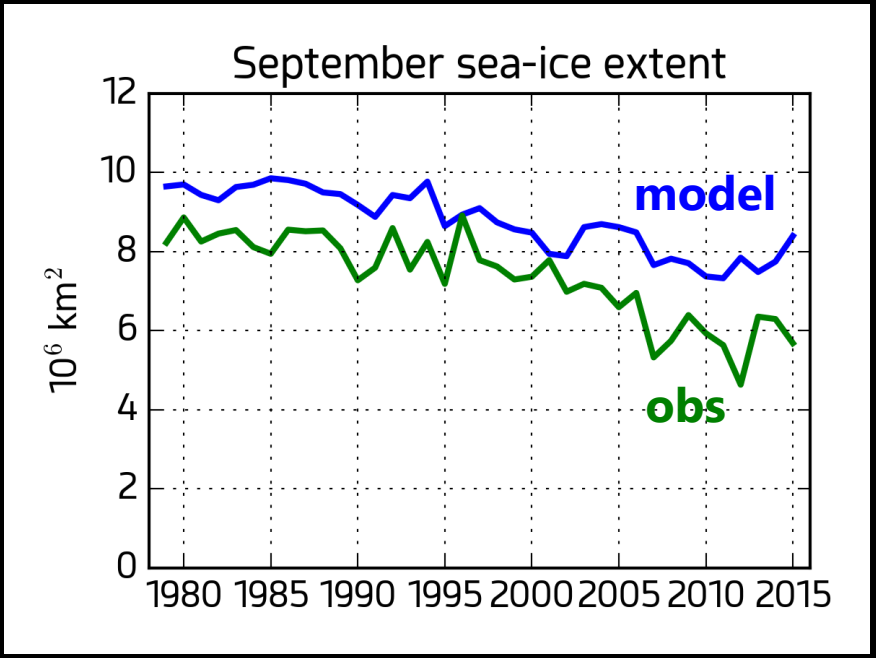

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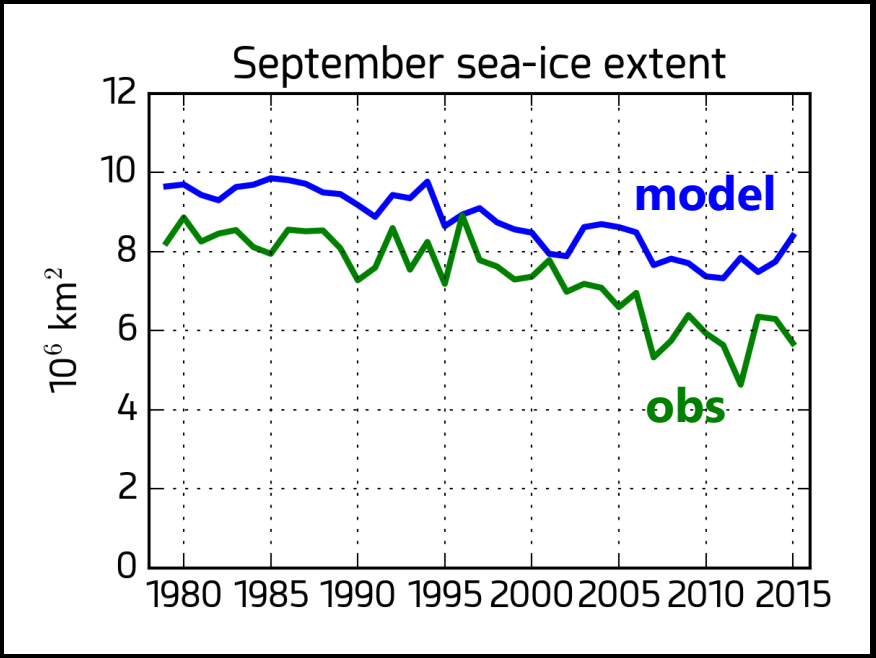

It's my fault

No scale-awareness

No definition-awareness

Kay et al., *J. Geophys. Res.*, 2016

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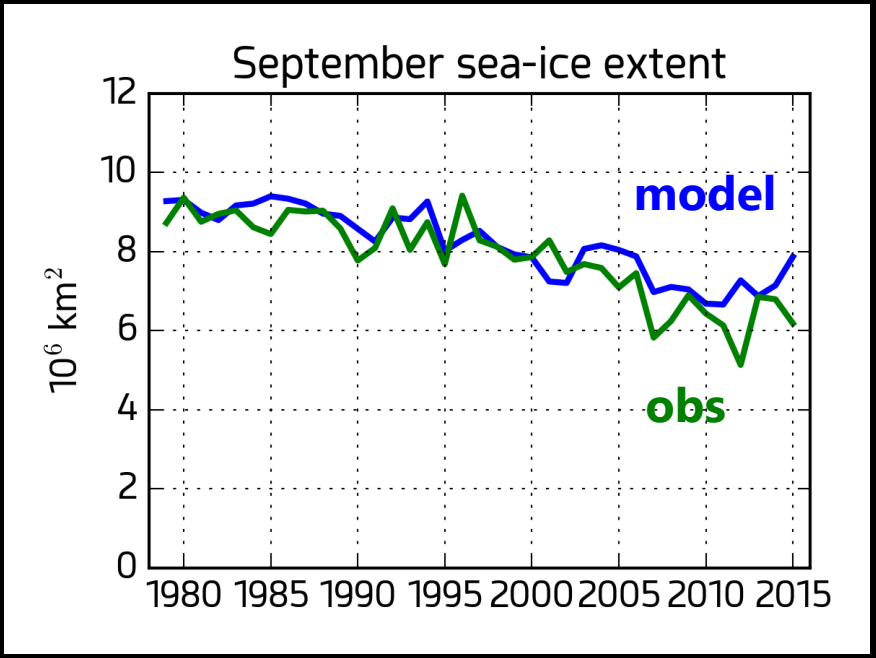

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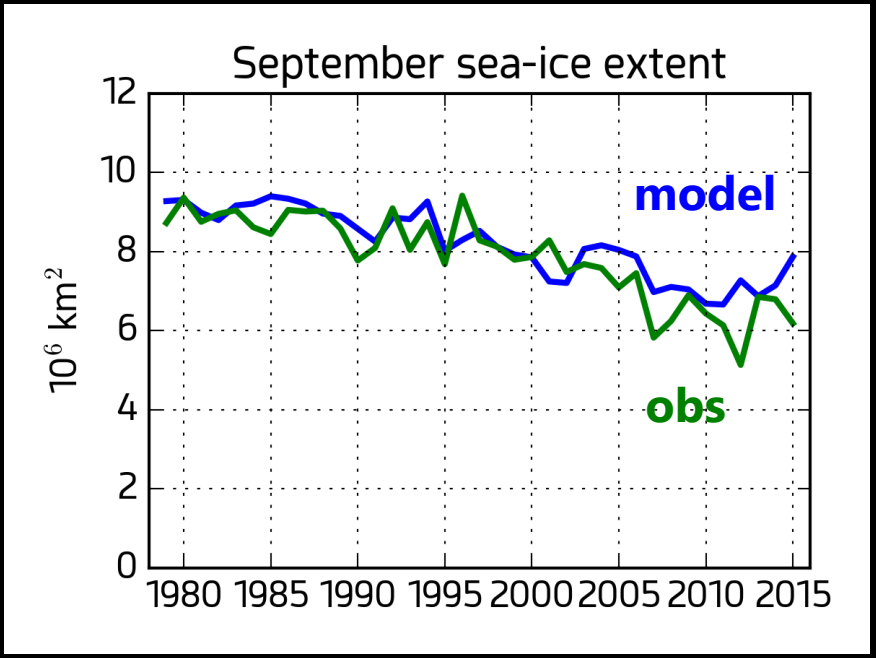


It's my fault

No scale-awareness

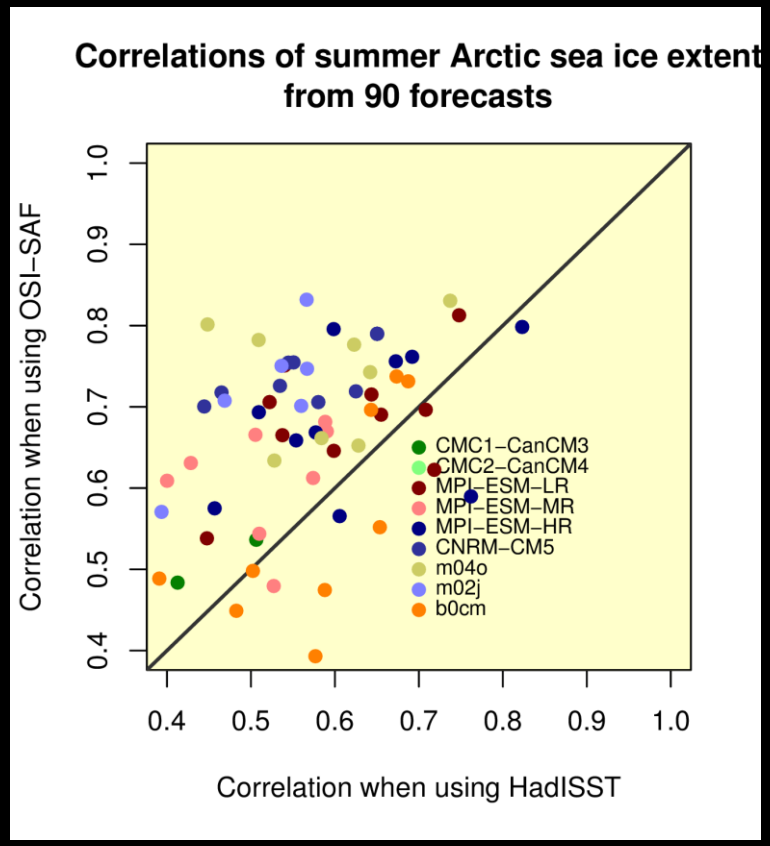
No definition-awareness

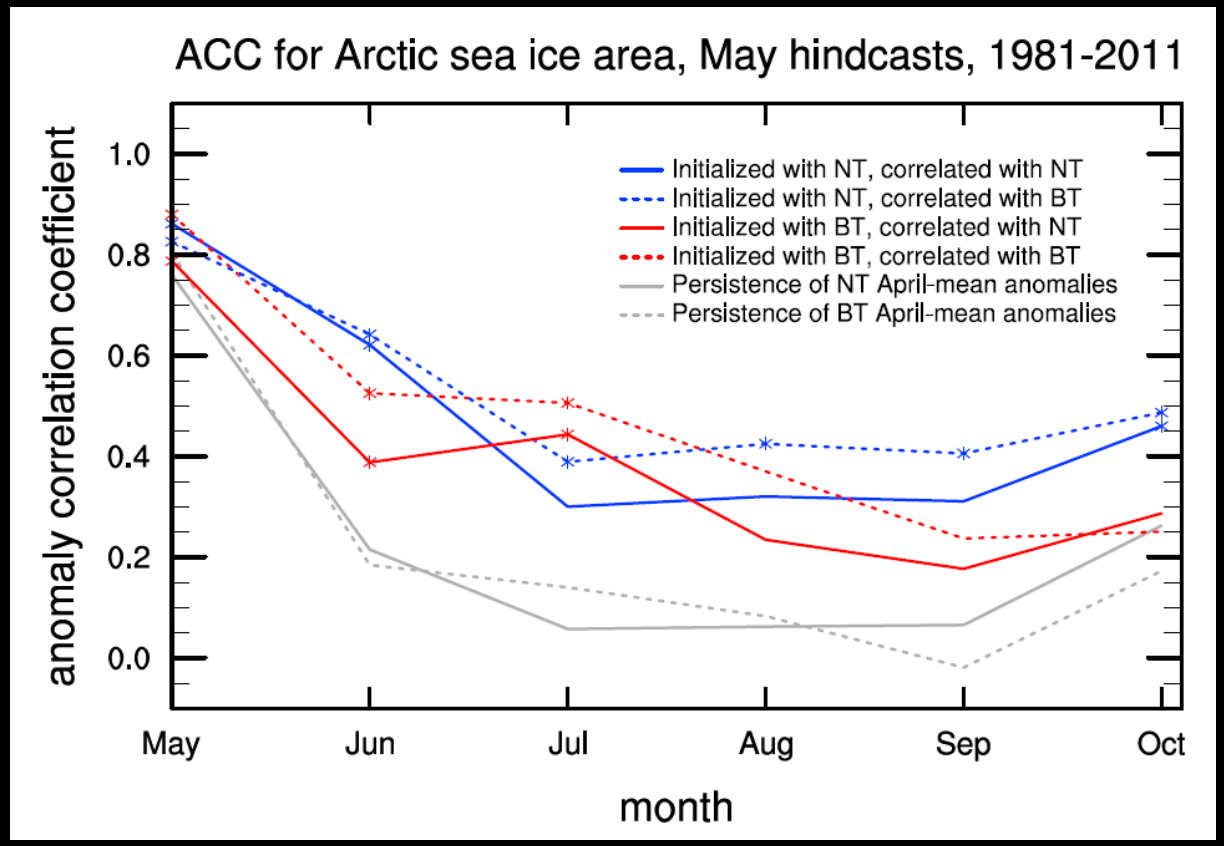
It's no one's fault

Internal variability

Notz, *Phil. Trans. Roy. Soc.*, 2015

Seasonal sea ice prediction skill is significantly affected by the choice of the verification product





Massonnet et al., *Science*, 2016

Bunzel et al., *Geophys. Res. Lett.*, 2016

Any statement on model quality cannot be formulated before of uncertainty in verification observational data is properly quantified

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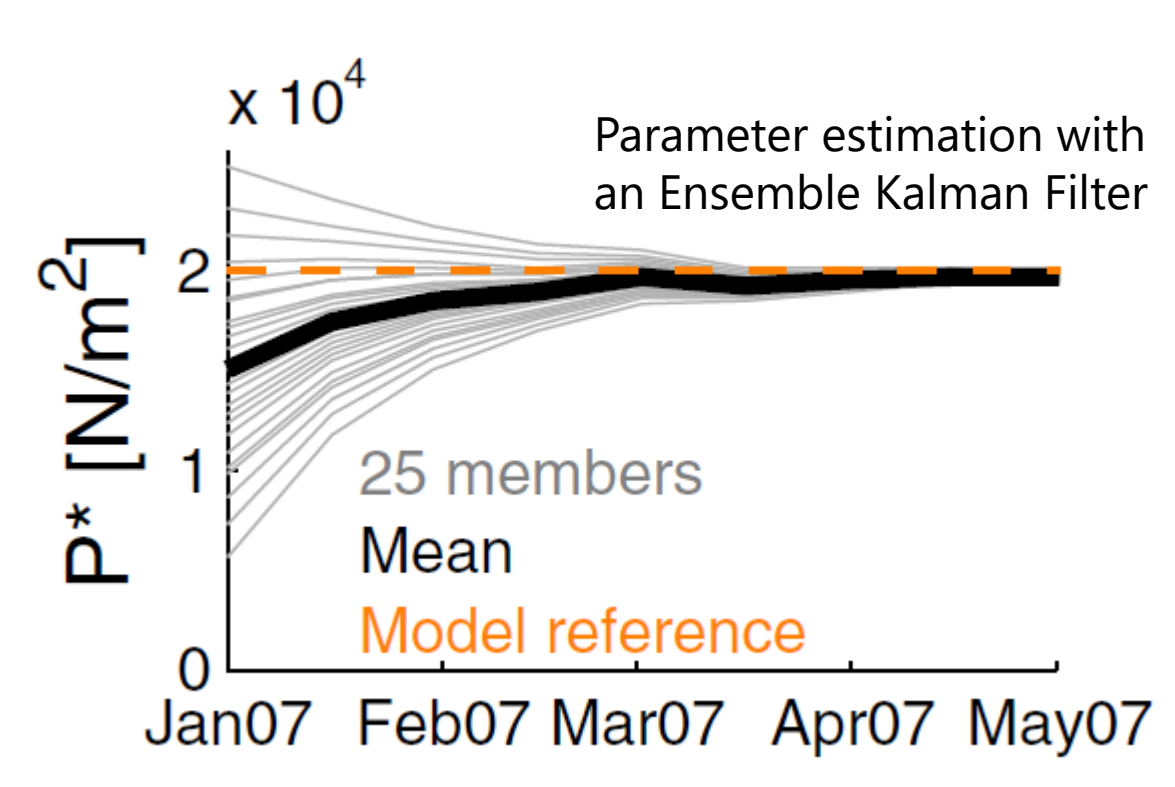
Which data assimilation approach for sea ice models?

	Nudging	**Variational (3D/4D Var)**	**Sequential methods (EnKF)**	**Particle filtering**
Ease of implementation	Fair	Hard (coding adjoint)	Medium-Hard	Medium
CPU consumption	Low	Low-Medium	High (~20-50 members)	Very high (~100 members to avoid degenerate solution)
Needs changes in model code?	Yes (restoring term added to tendencies)	Yes (adjoint)	No	No
Physical consistency	Little (univariate)	Up to linear approximation	Up to linear approximation	Full consistency
Estimation of prior uncertainty	None	Static	Dynamic	Dynamic
Assumptions to reach optimality	Not defined as an optimization problem	Gaussian centered errors	Gaussian centered errors	None
Produces ensembles?	No	No	Yes (hence available as IC)	Yes (hence available as IC)

Data assimilation as an elegant way for tuning large-scale sea ice models

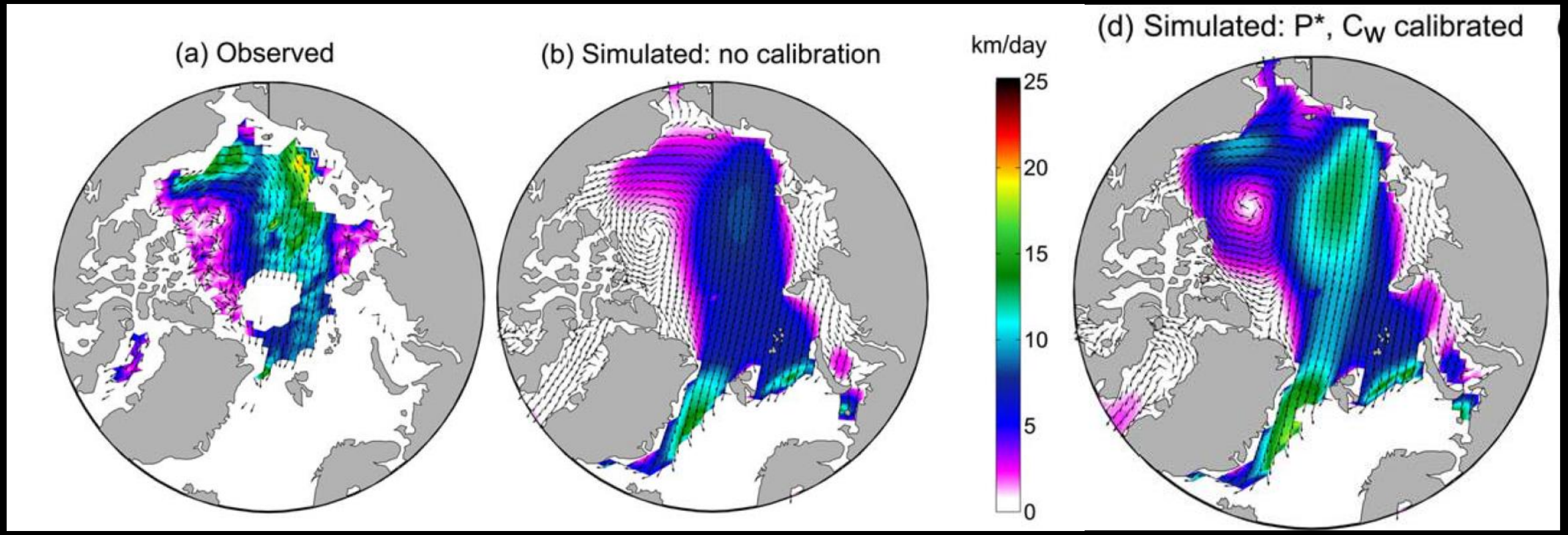
Perfect model tuning exercise: retrieving the reference value



Massonnet et al., *J. Geophys. Res.*, 2014

Data assimilation as an elegant way for tuning large-scale sea ice models

Snapshot of 12-14 april 2012 sea ice drift



Massonnet et al., *J. Geophys. Res.*, 2014

2. How can we integrate observations better with models?

- Account for (epistemic) observational uncertainty by using multiple products
- Work on quantifying aleatoric observational uncertainty is making its way
- « Ensembles » of observations (e.g., HadISST2)
- Data assimilation offers a mathematically robust framework for integrating observations in models for many purposes (state estimation, initialization, parameter calibration)

1. How should we design a climate model to obtain better predictions of polar climates on timescales of decades?
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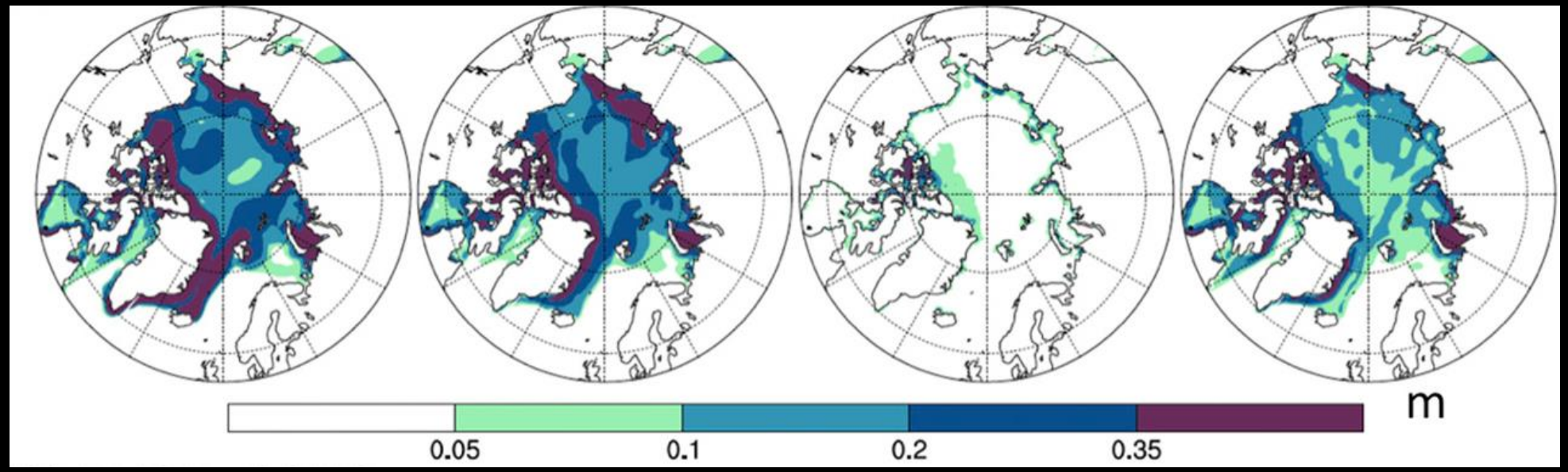
Observing System Experiments inform on what observations make the most impact

Root mean square error of 2001-2003 sea ice thickness
(CICE5 sea ice model + slab ocean + atmospheric forcing)
Reference: one model realization.

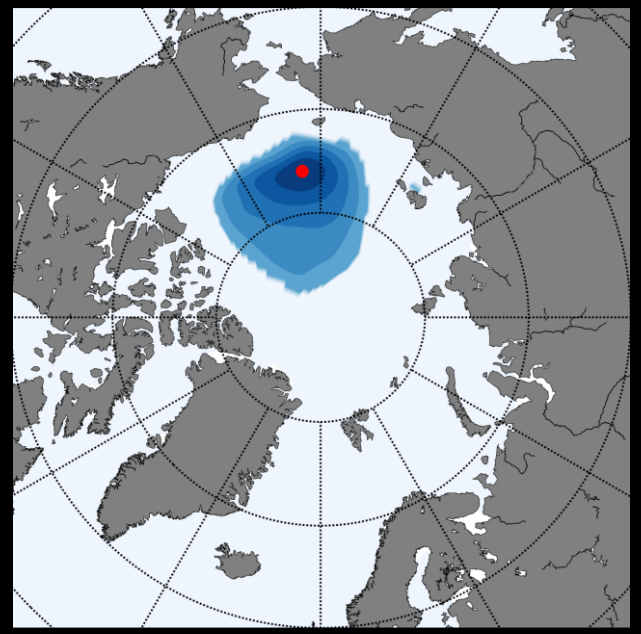
No assimilation | Concentration assimilated | Concentration & thickness assimilated | Concentration & multi-year ice conc. assimilated

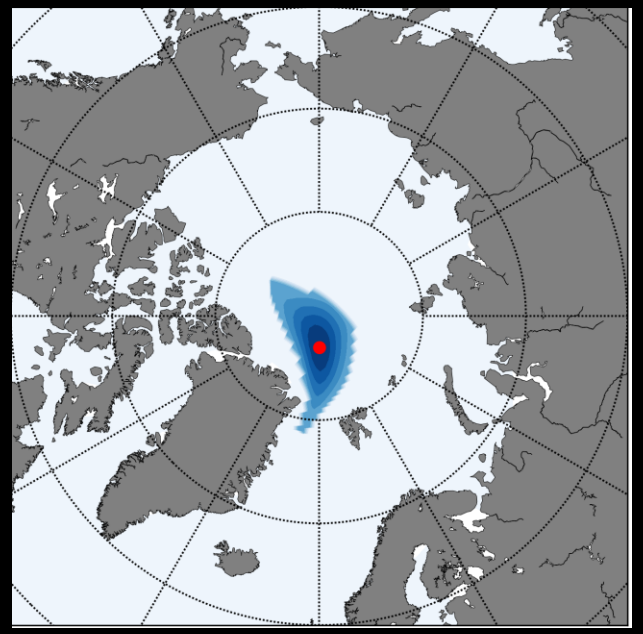


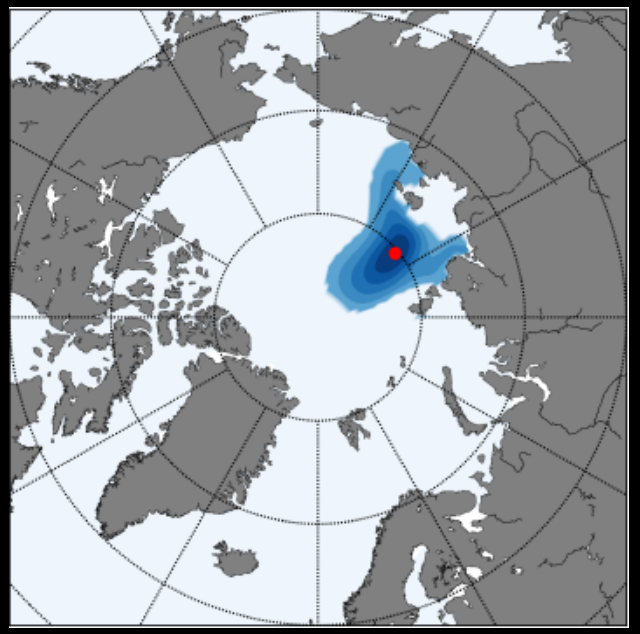
Zhang et al., *J. Clim.*, 2018

Optimal design of a sea ice thickness monitoring system

Area of influence of three given points for sea ice thickness (CESM-LE output)

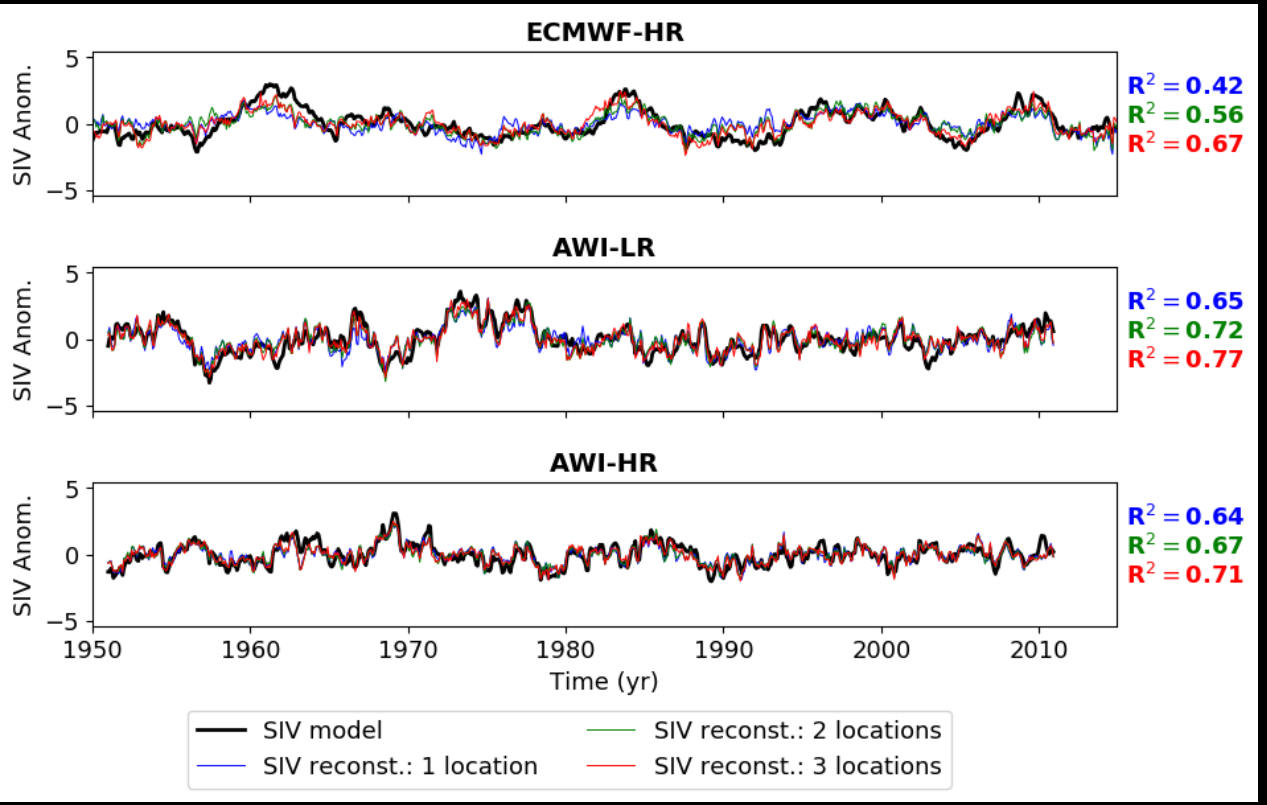


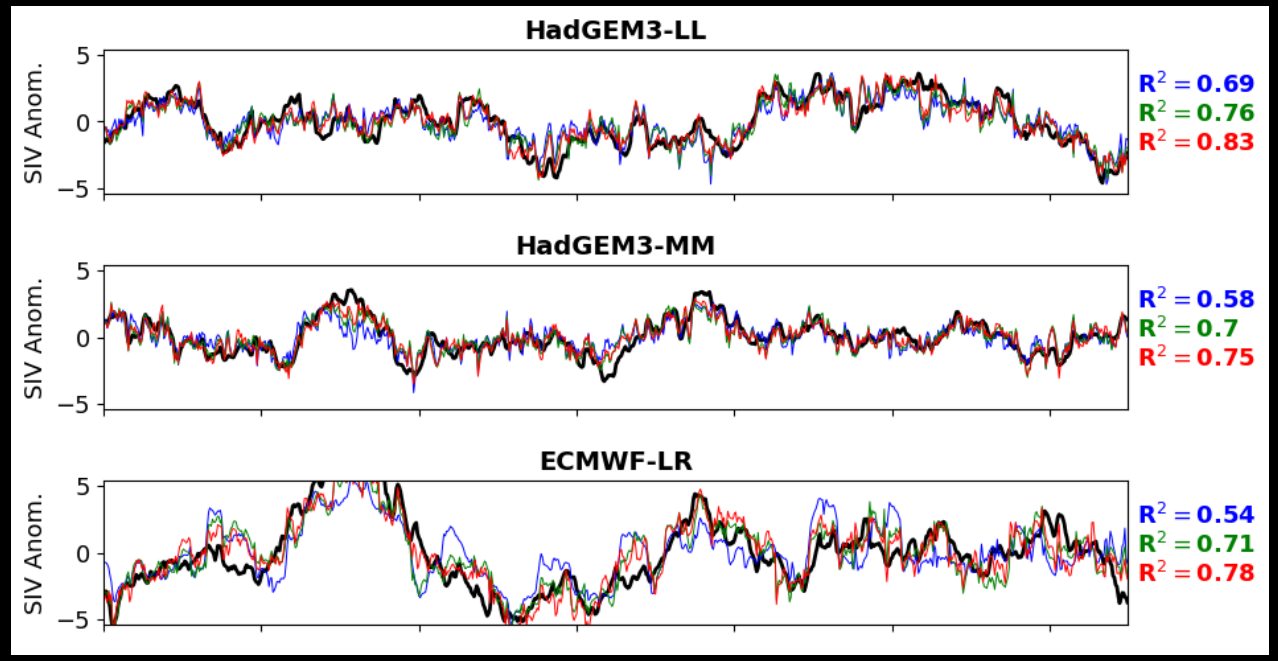




Courtesy Guillian van Achter

Retrieving Arctic sea ice volume from a selected set of thickness measurements



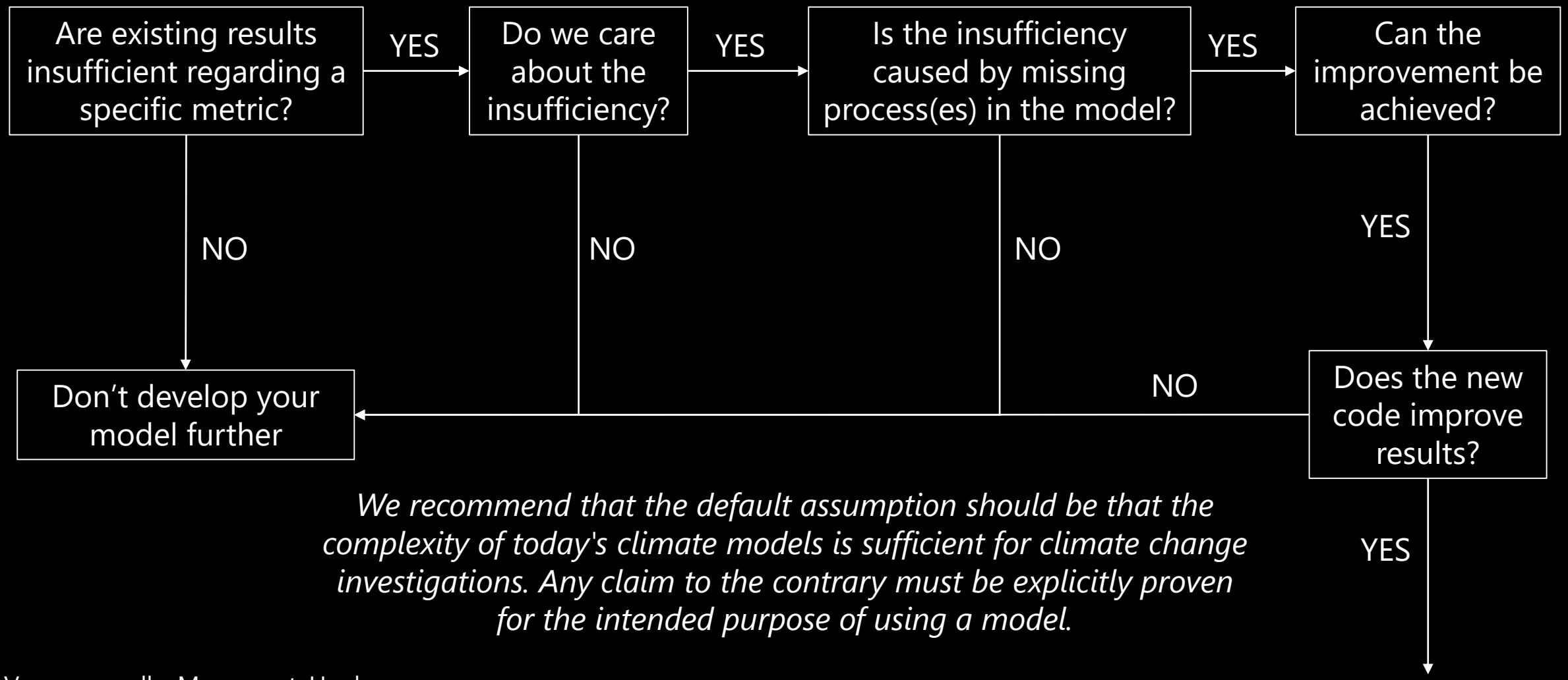


Courtesy Leandro Ponsoni

Conclusions

- We climate scientists all attempt to reduce epistemic (structural) uncertainty in the presence of aleatoric (irreducible) uncertainty
- Model development has value, but in a finite world with limited resources, priorities must be set depending on the underlying scientific question
- Model shortcomings are (by far) not the sole reason for model-observation mismatch
- Models can be used to find out which observation(s) are most valuable for prediction or climate change studies

A decision tree to guide model development (and to consider the need thereof)

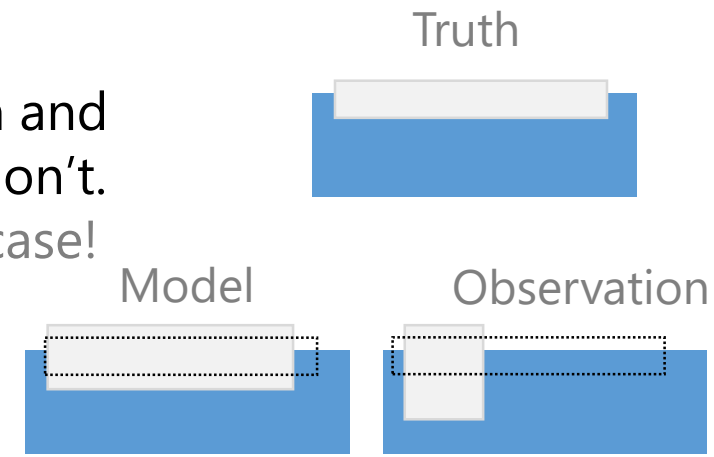


We recommend that the default assumption should be that the complexity of today's climate models is sufficient for climate change investigations. Any claim to the contrary must be explicitly proven for the intended purpose of using a model.

Notz, Vancoppenolle, Massonnet, Hunke

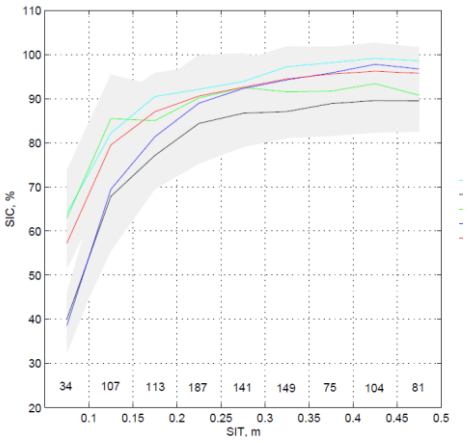
Why do models score better for the two most advanced and recent products?

Models simulate directly sea ice concentration and output it as a physical variable; observations don't. Models can be really good references in that case!

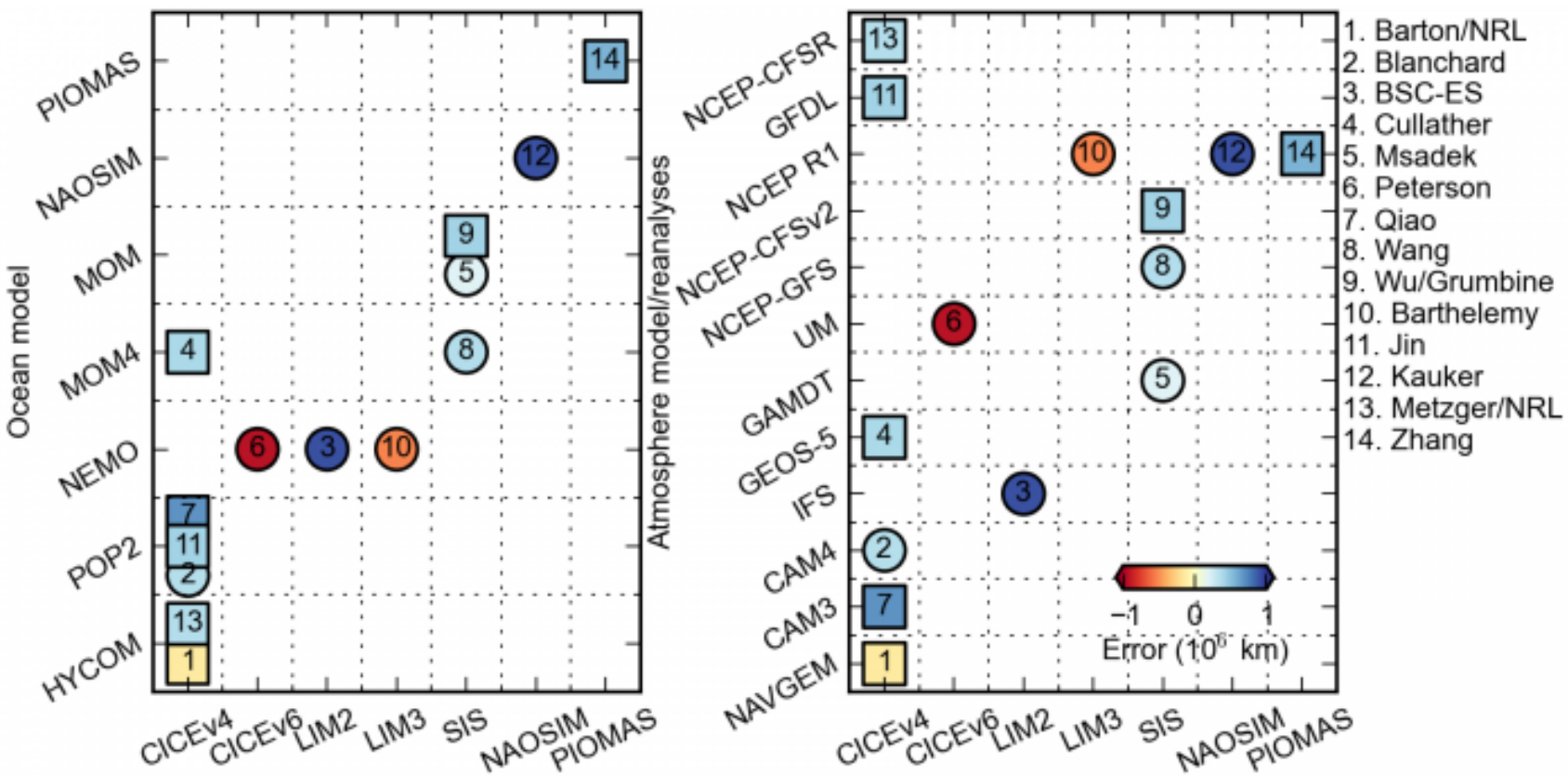


Observations have deficiencies that models don't have e.g. concentration of thin ice

According to the toy model results, ESA-CCI and OSI-SAF should have lower errors (but only these two provide errors)



Note: remarkably, the models are also the most independent w.r.t. OSI-SAF and ESA-CCI



A. Petty and F. Massonnet, SIPN report 2015
https://www.arcus.org/sipn/sea-ice-outlook/2015/post-season