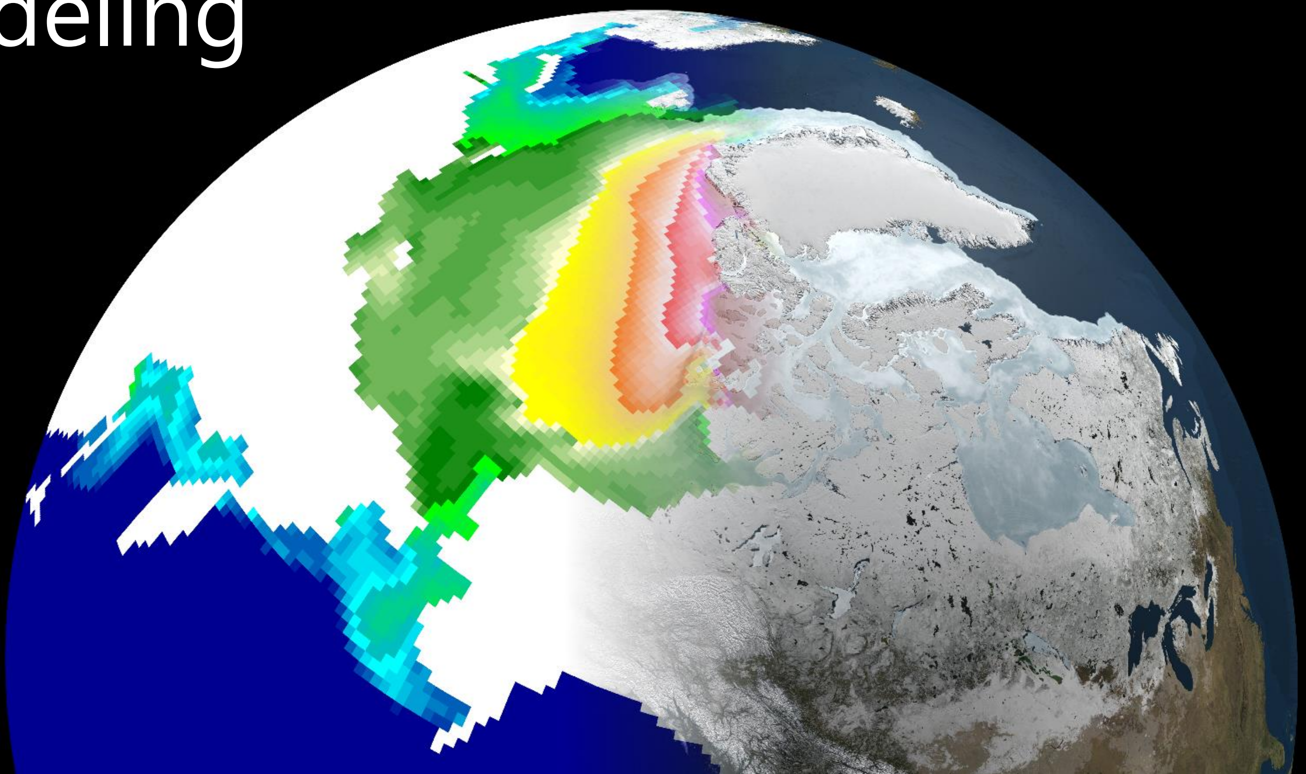
LGGE, Grenoble
9th of July, 2014

Data assimilation in sea ice modeling

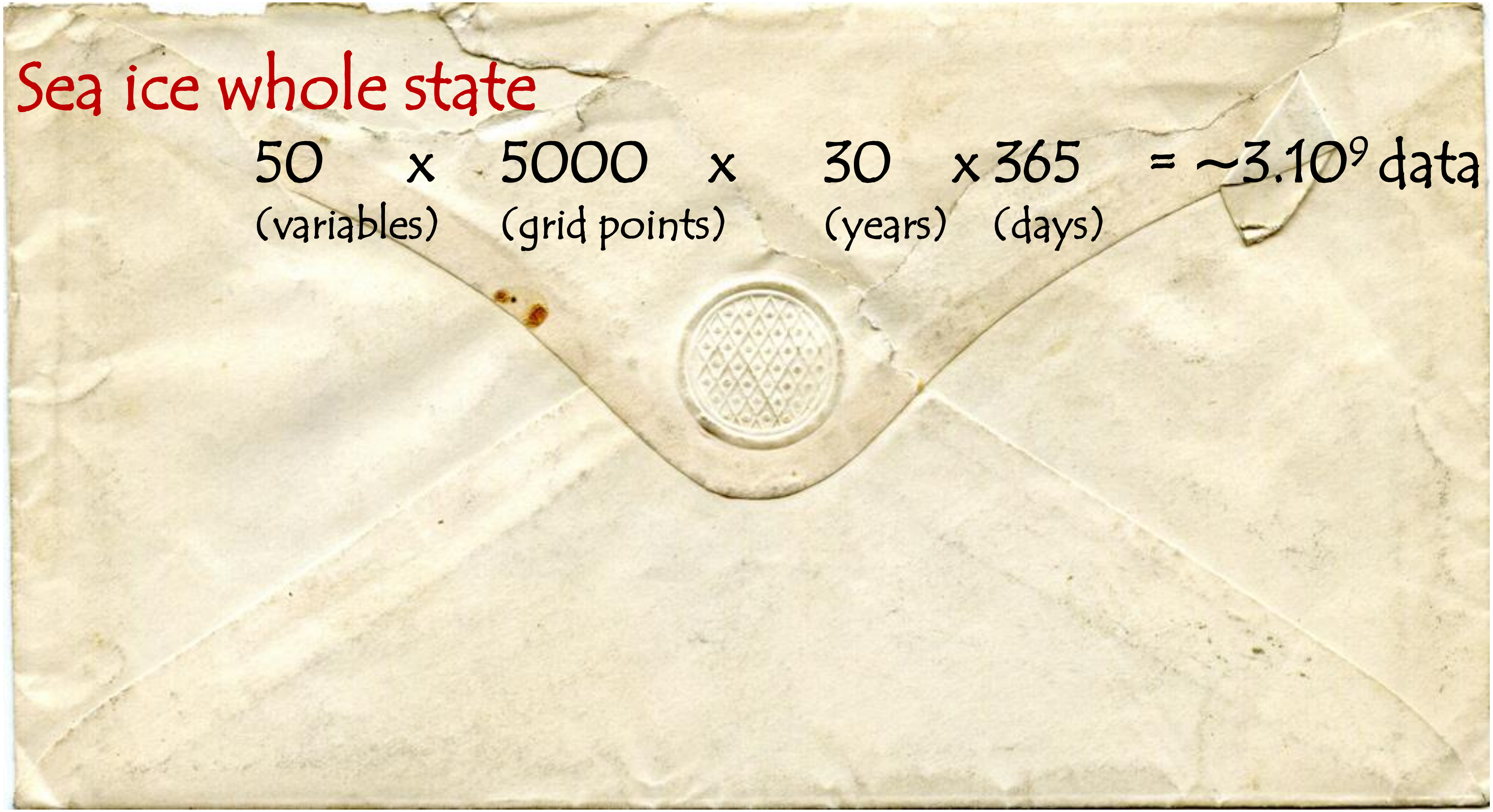


François Massonnet

FNRS Research Fellow

Université catholique de Louvain, Belgium

« Back-of-the-envelope » calculation



« Back-of-the-envelope » calculation

Sea ice whole state

50 (variables) x 5000 (grid points) x 30 (years) x 365 (days) = ~3.10^{9} data

Sea ice observations

Concentration
Drift

2 (variables) x 5000 (grid points) 30 (years) x 365 (days) = ~1.10^{8} data

« Back-of-the-envelope » calculation

Sea ice whole state

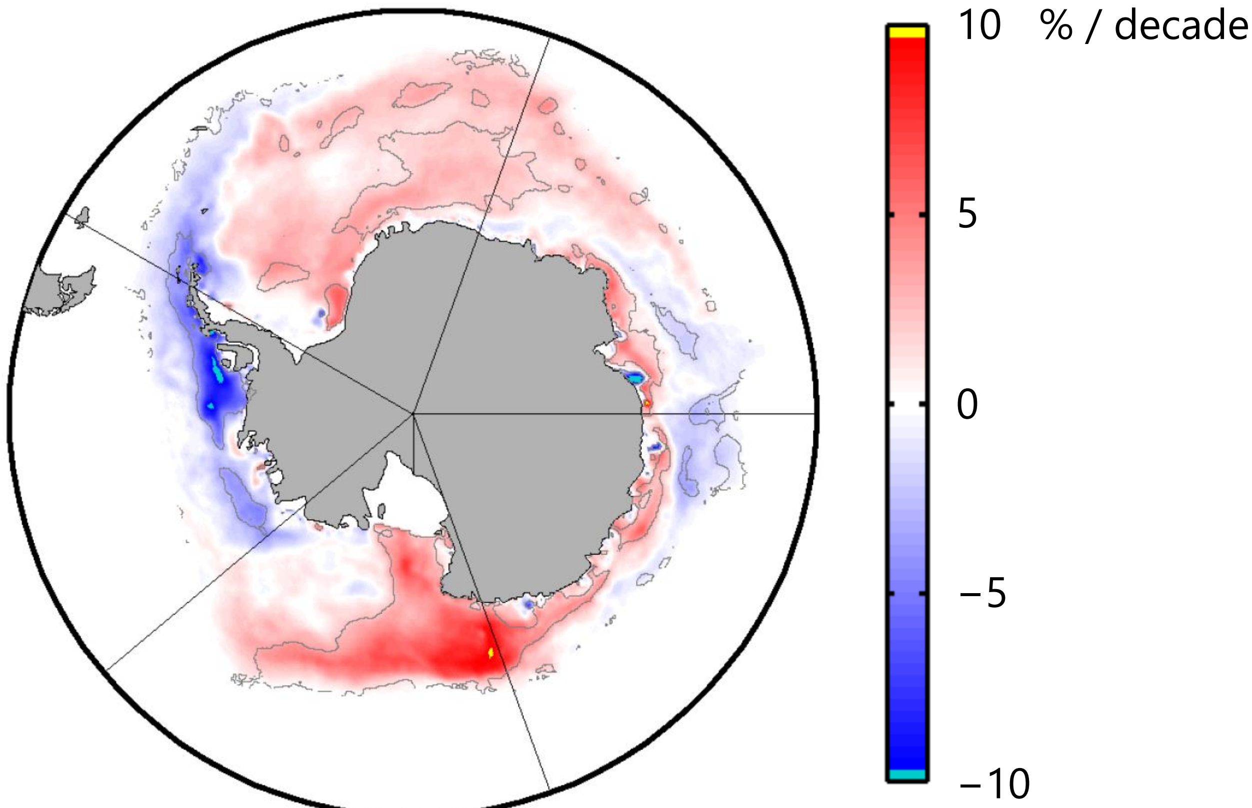
	50 (variables)	x 5000 (grid points)	x 30 (years)	x 365 (days)	= ~3.10⁹ data

Sea ice observations

Concentration Drift	2 (variables)	x 5000 (grid points)	30 (years)	x 365 (days)	= ~1.10⁸ data
Thickness	1 (variable)	x 500 (grid points)	10 (years)	x 60 (days)	= ~3.10⁵ data

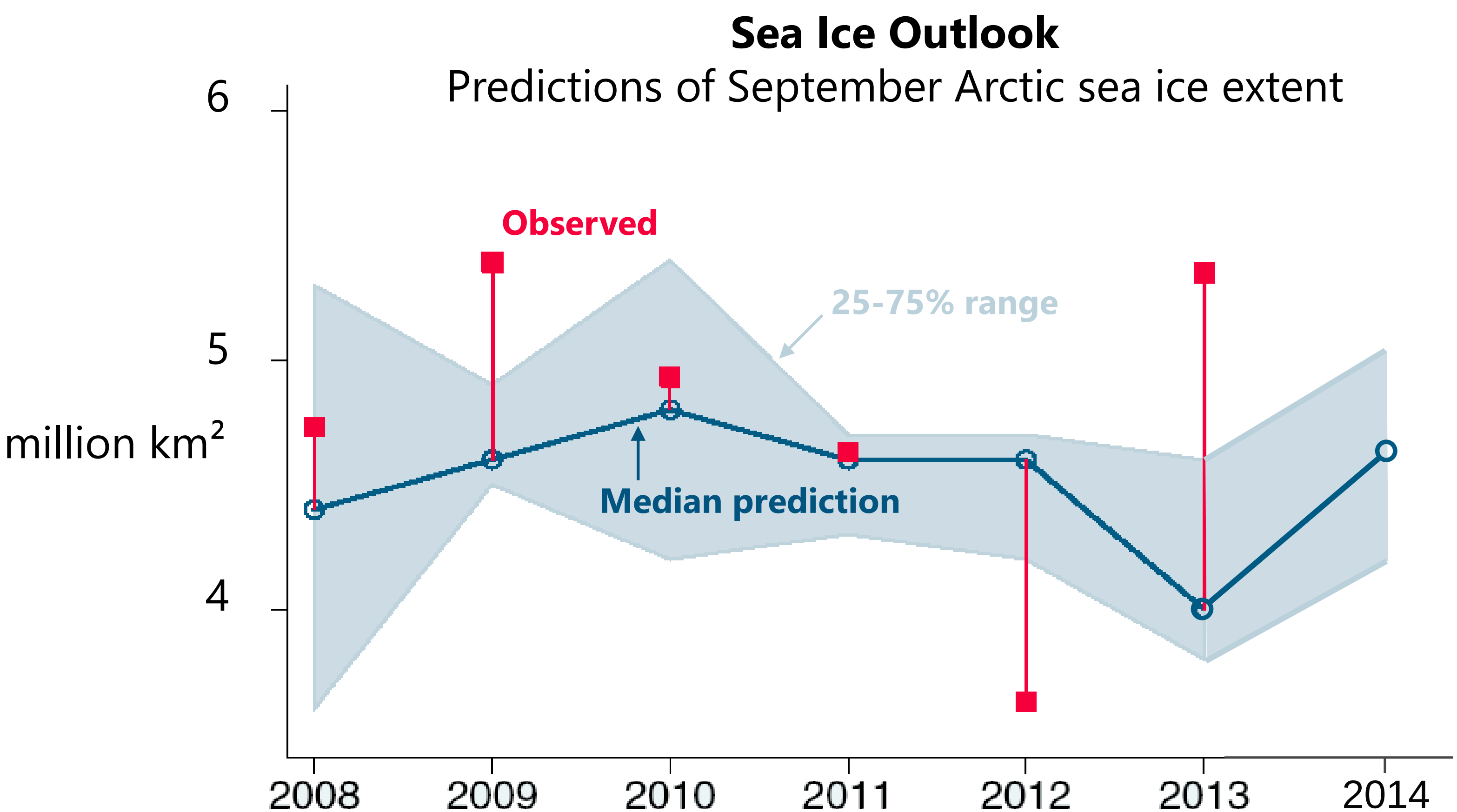
Puzzle 1: Antarctic sea ice area is increasing (in a warming world)

Observed changes (1980-2008) in
Antarctic sea ice concentration



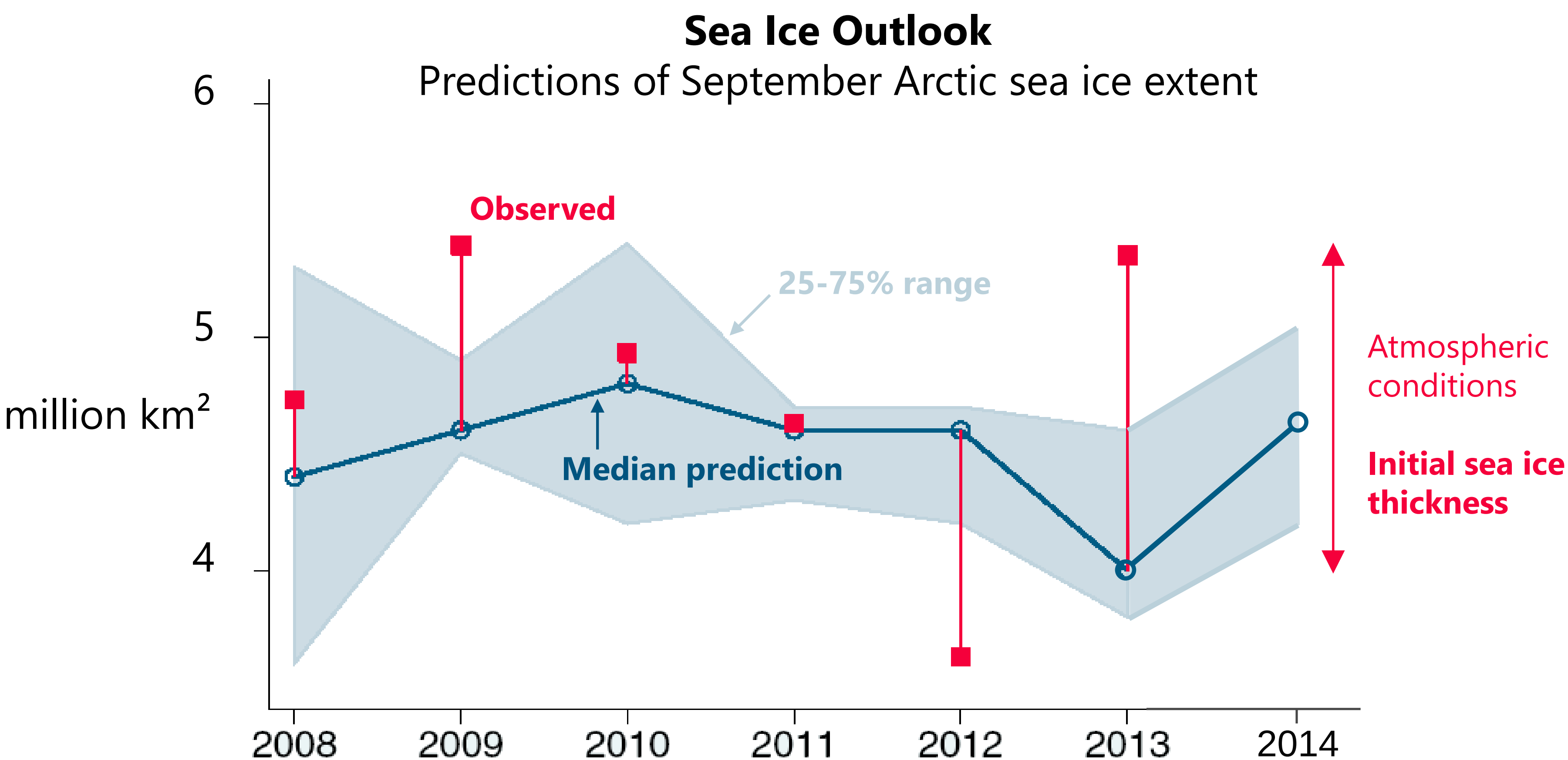
[data: Comiso et Nishio, JGR, 2008]

Puzzle 2: Seasonal sea ice prediction has random pattern of success



[adapted from Stroeve et al., GRL, 2014]

Puzzle 2: Seasonal sea ice prediction has random pattern of success



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Sea ice observations and models are complementary

Observations	Models
Incomplete coverage	Complete coverage
No predictive skill	Predictive skill
Proxies for reality	Approximations of reality
Uncertainties	Uncertainties, systematic biases

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data assimilation

Data assimilation in sea ice modeling

1. The problem: estimation of the whole sea ice state

2. The limitations: importance of hypotheses

3. The applications: three examples in sea ice modeling

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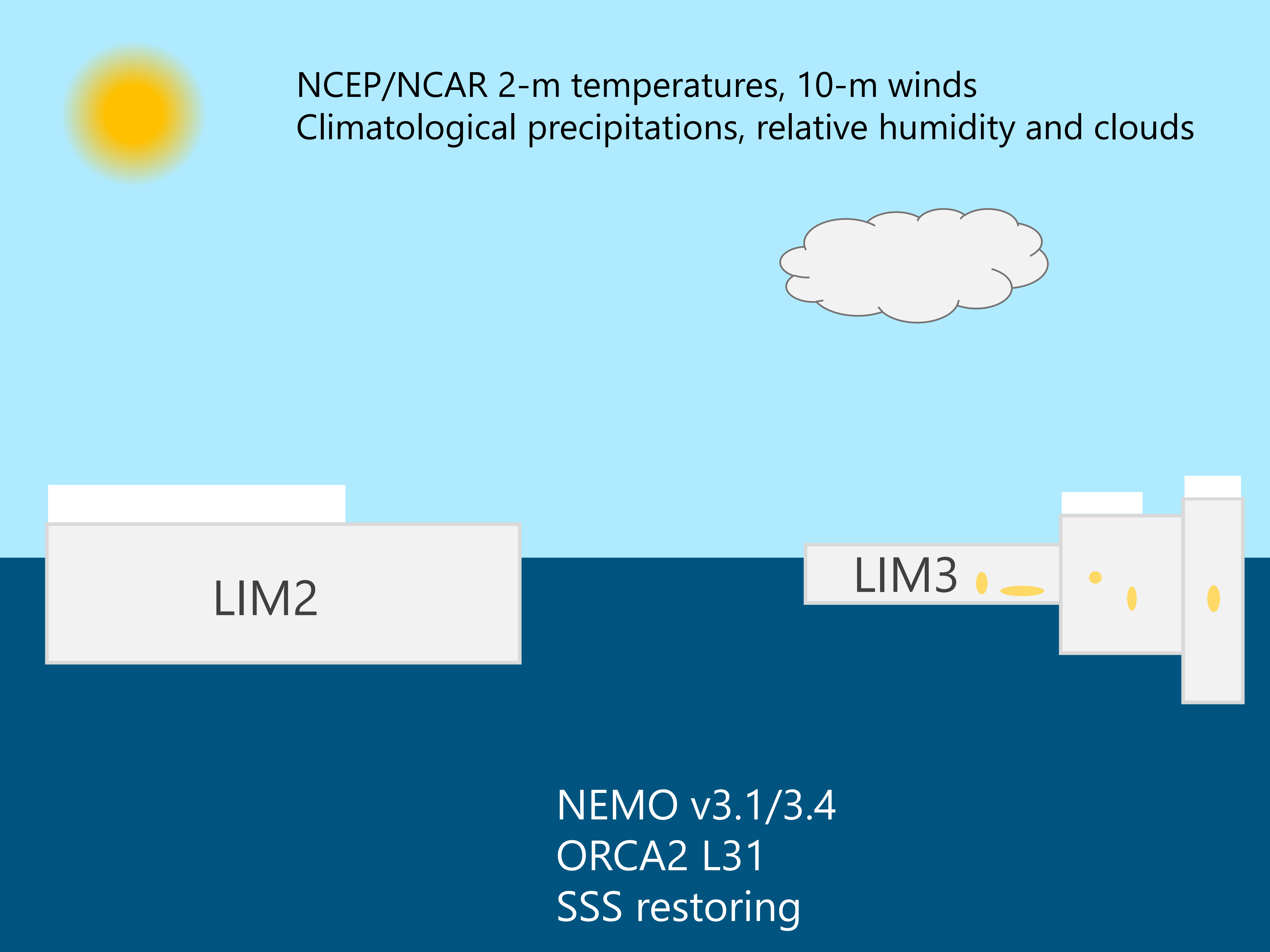

NCEP/NCAR 2-m temperatures, 10-m winds
Climatological precipitations, relative humidity and clouds
LIM2
LIM3
NEMO v3.1/3.4
ORCA2 L31
SSS restoring

Just as any model,
NEMO-LIM exhibits biases

The model physics can be improved
Rheology, ocean—sea ice interactions, snow are subject of intense research

Atmospheric reanalyses are not perfect, either
Antarctic sea ice concentration trends suspicious in the western seas

All model parameters were tuned by « trial-and-error »
Parameter space may have been underexplored

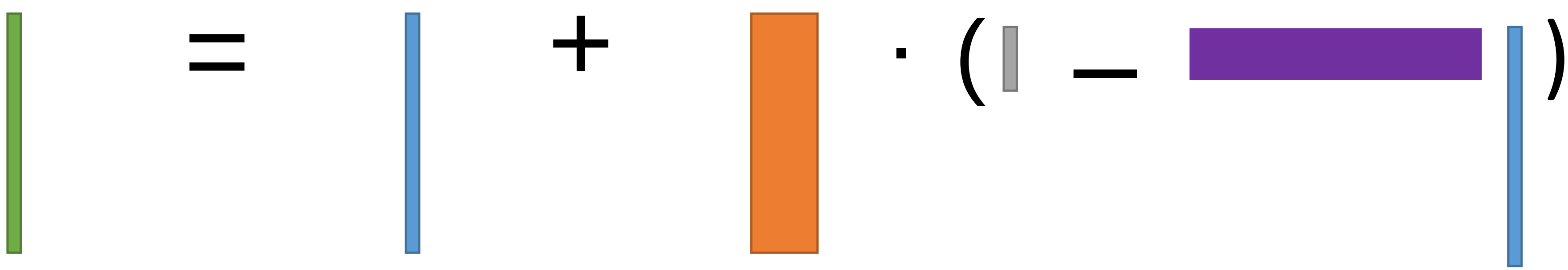
Observations alone are not sufficient to estimate the whole sea ice state

	Spatial sampling	Temporal sampling
Concentration	~25 km, everywhere	~daily, 1979-2014
Thickness	~25 km (tracks, more in Arctic)	~daily (seasonal, intermittent, 2004-2014)
Drift (large-scale)	~25 km, central Arctic	~daily, 2007-2014
Deformation	~10 km, central Arctic	~daily (winter, since 1995)
Snow, melt ponds	very limited	very limited

The ensemble Kalman filter is a data assimilation method

Analysis **Model forecast** **Kalman gain** **Observations**

$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K} \cdot (\mathbf{d} - \mathbf{H}\,\mathbf{x}^f)$$



[Evensen, 2003]

The ensemble Kalman filter is a multivariate data assimilation method

Analysis **Model forecast** **Kalman gain** **Observations**

$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K} \cdot (\mathbf{d} - \mathbf{H}\,\mathbf{x}^f)$$

$$\mathbf{K} = \mathbf{P}\,\mathbf{H}^T \left(\mathbf{H}\,\mathbf{P}\,\mathbf{H}^T + \mathbf{R}\right)^{-1}$$

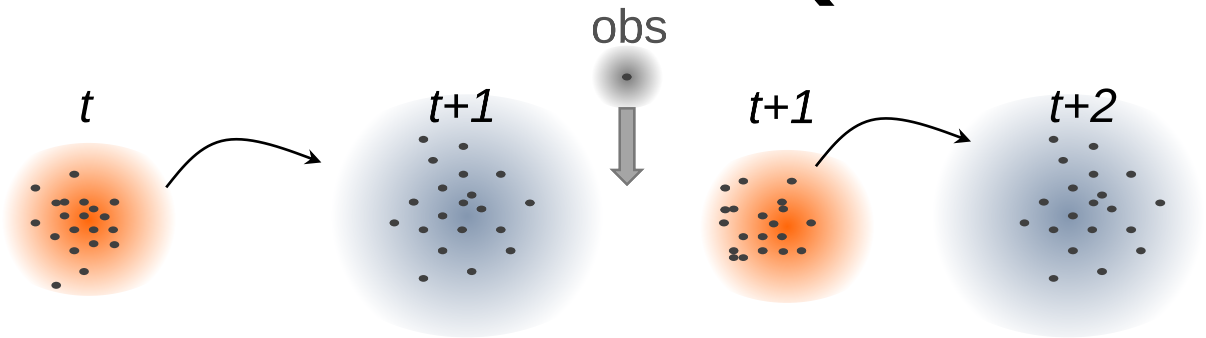
[Evensen, 2003]

The ensemble Kalman filter is a sequential ensemble multivariate data assimilation method

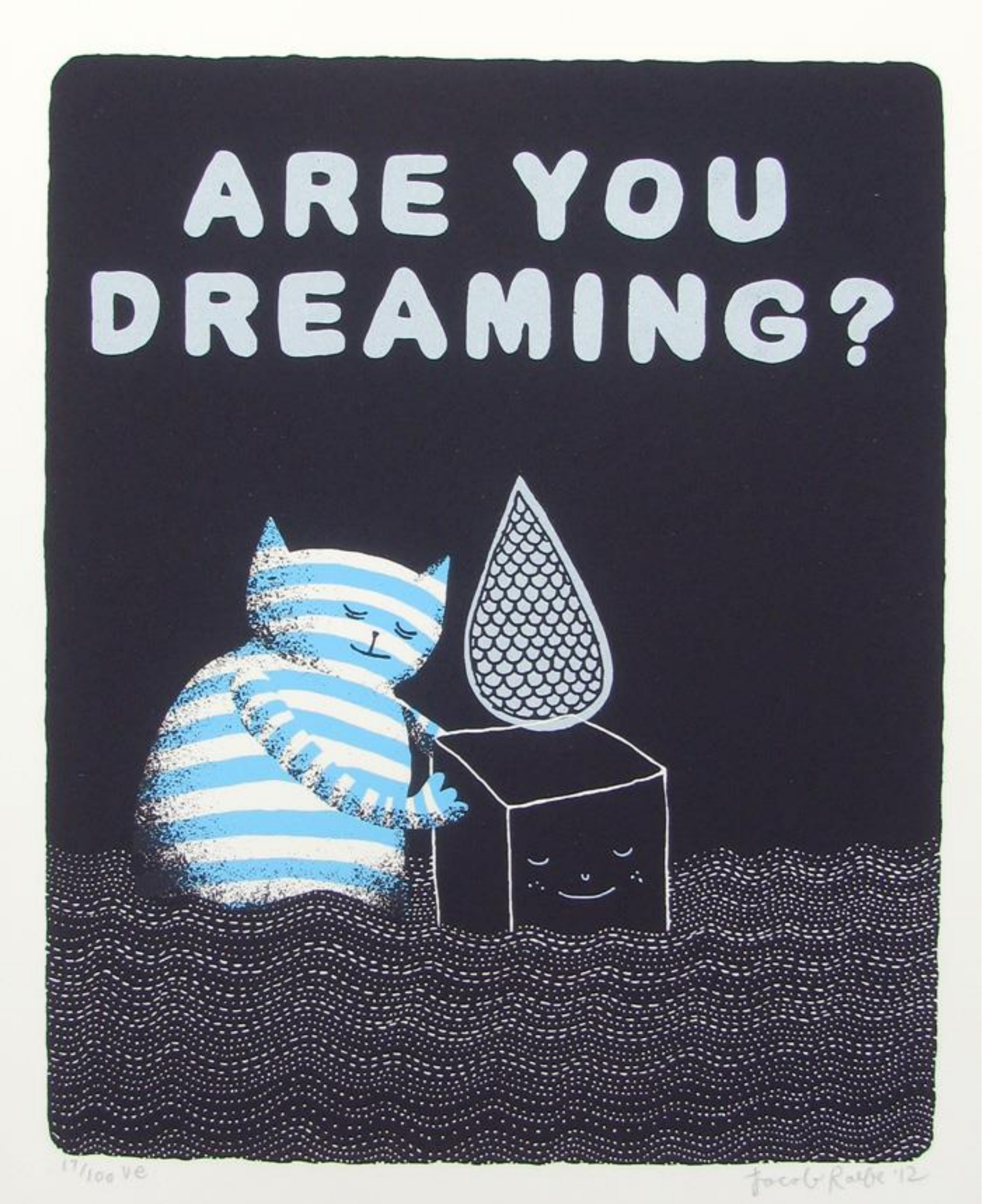
Analysis | Model forecast | Kalman gain | Observations

$$\mathbf{x}^a = \mathbf{x}^f + \mathbf{K} \cdot (\mathbf{d} - \mathbf{H}\,\mathbf{x}^f)$$

$$\mathbf{K} = \mathbf{P}\,\mathbf{H}^T \left(\mathbf{H}\,\mathbf{P}\,\mathbf{H}^T + \mathbf{R}\right)^{-1}$$



[Evensen, 2003]


ARE YOU
DREAMING?
17/100 VE

Data assimilation in sea ice modeling

1. The problem: estimation of the whole sea ice state

   The EnKF is a sequential, ensemble, multivariate data assimilation method

2. The limitations: importance of hypotheses

3. The applications: three examples in sea ice modeling

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Not all the hypotheses to reach optimal analysis are fulfilled

1. « The forward model is linear »
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3. « Model and obs. errors are centered around zero »
   → certainly not the case (model has biases)

4. « The sample model error covariance matrix is a good proxy for model error structure »
   → certainly not the case (25 members, only the atmosphere is perturbed)

Can data assimilation provide a consistent and optimal estimation of the whole sea ice state?

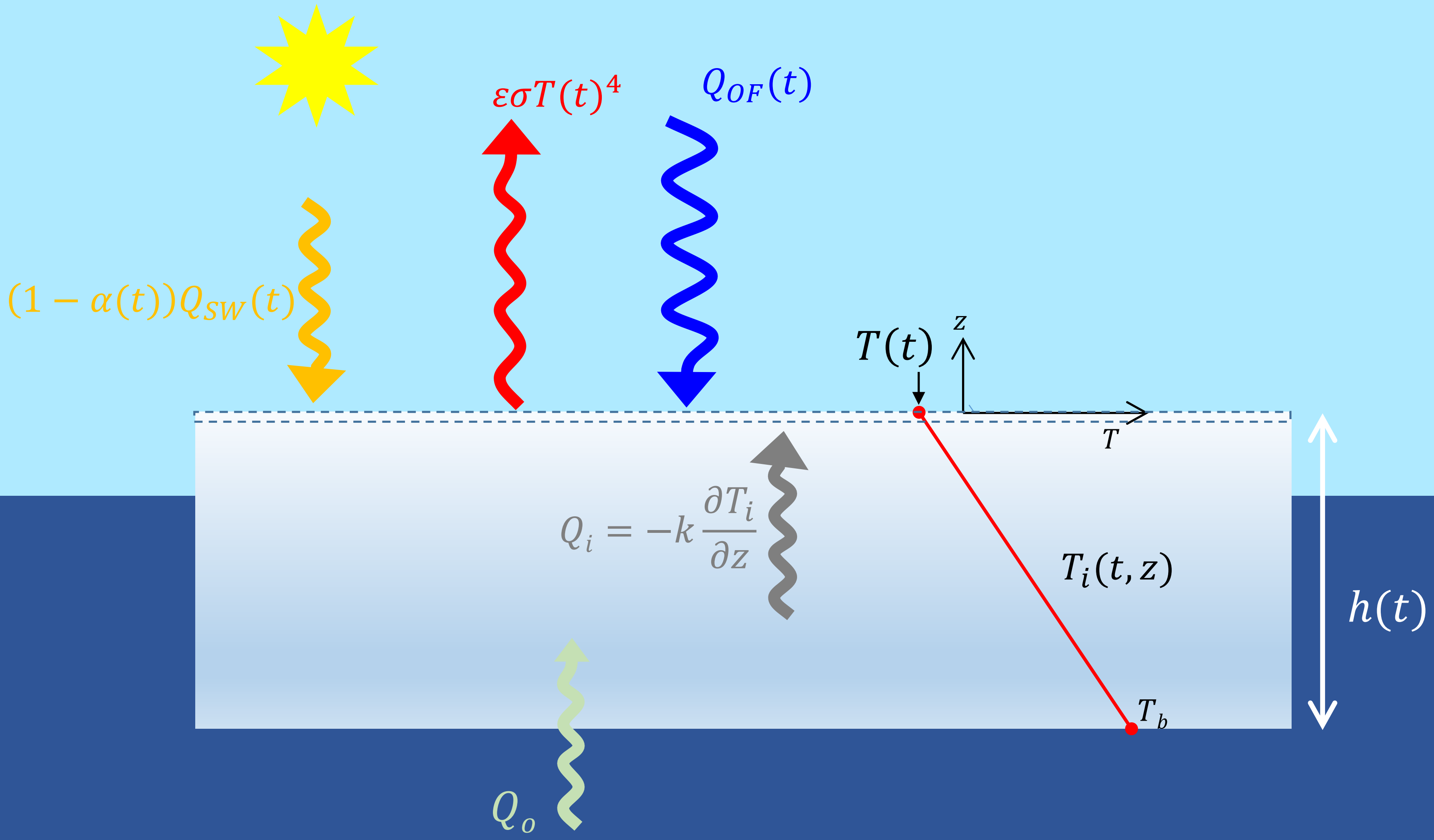
Can data assimilation provide a consistent and optimal estimation of the whole sea ice state?

↓

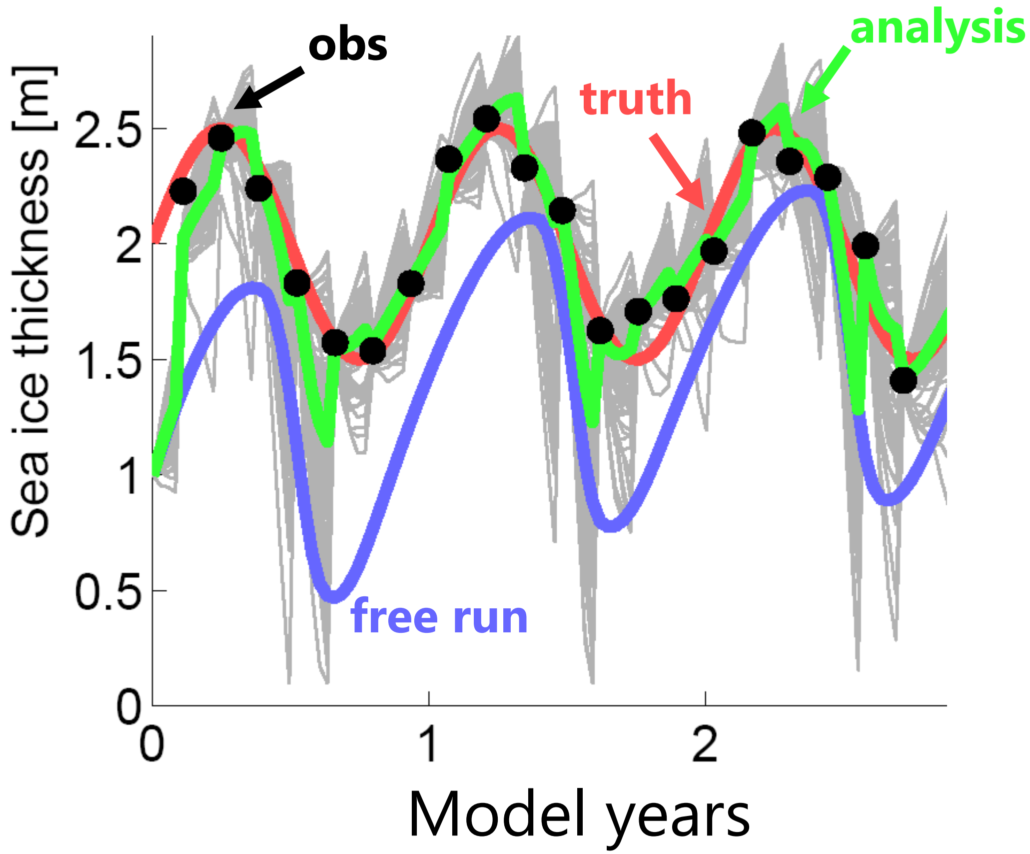
Even if the approximate solution is known to be sub-optimal, can data assimilation help us out to estimate the whole sea ice state?

2-variable sea ice model

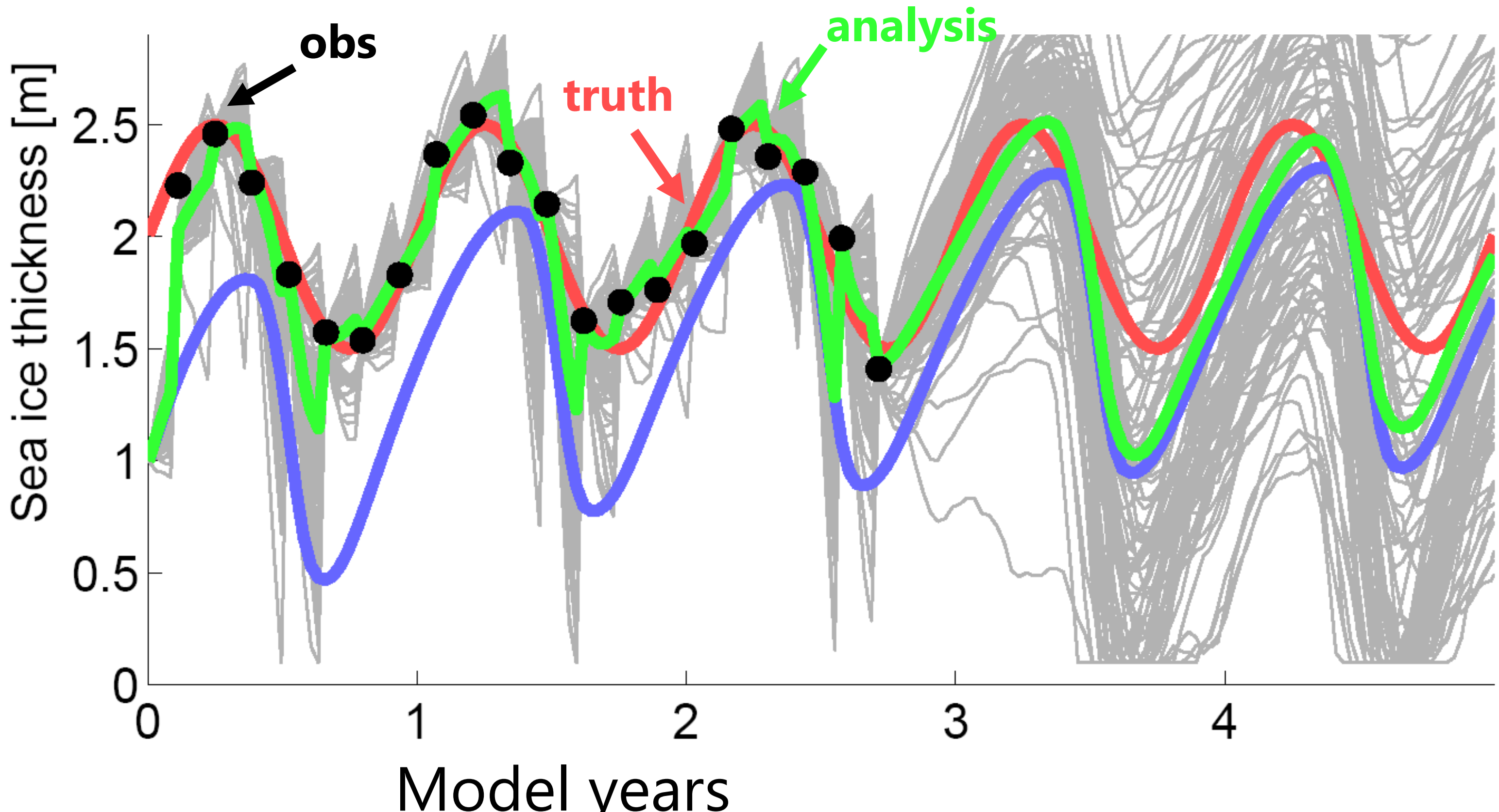
[Semtner, 1976; Notz, 2005]

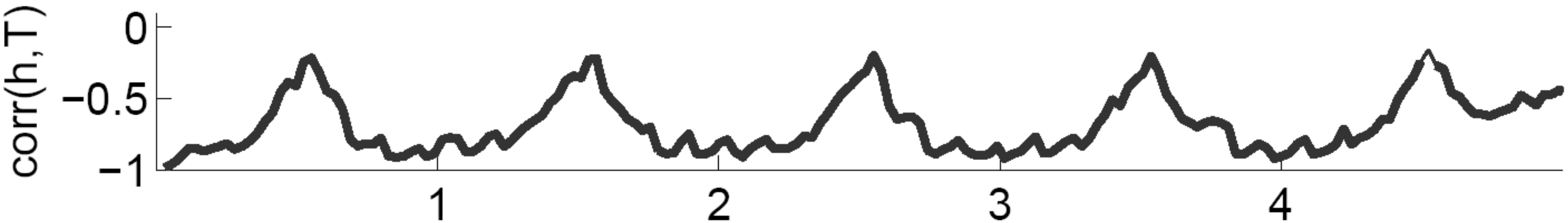


Model bias is not a major issue for estimating the observed variable



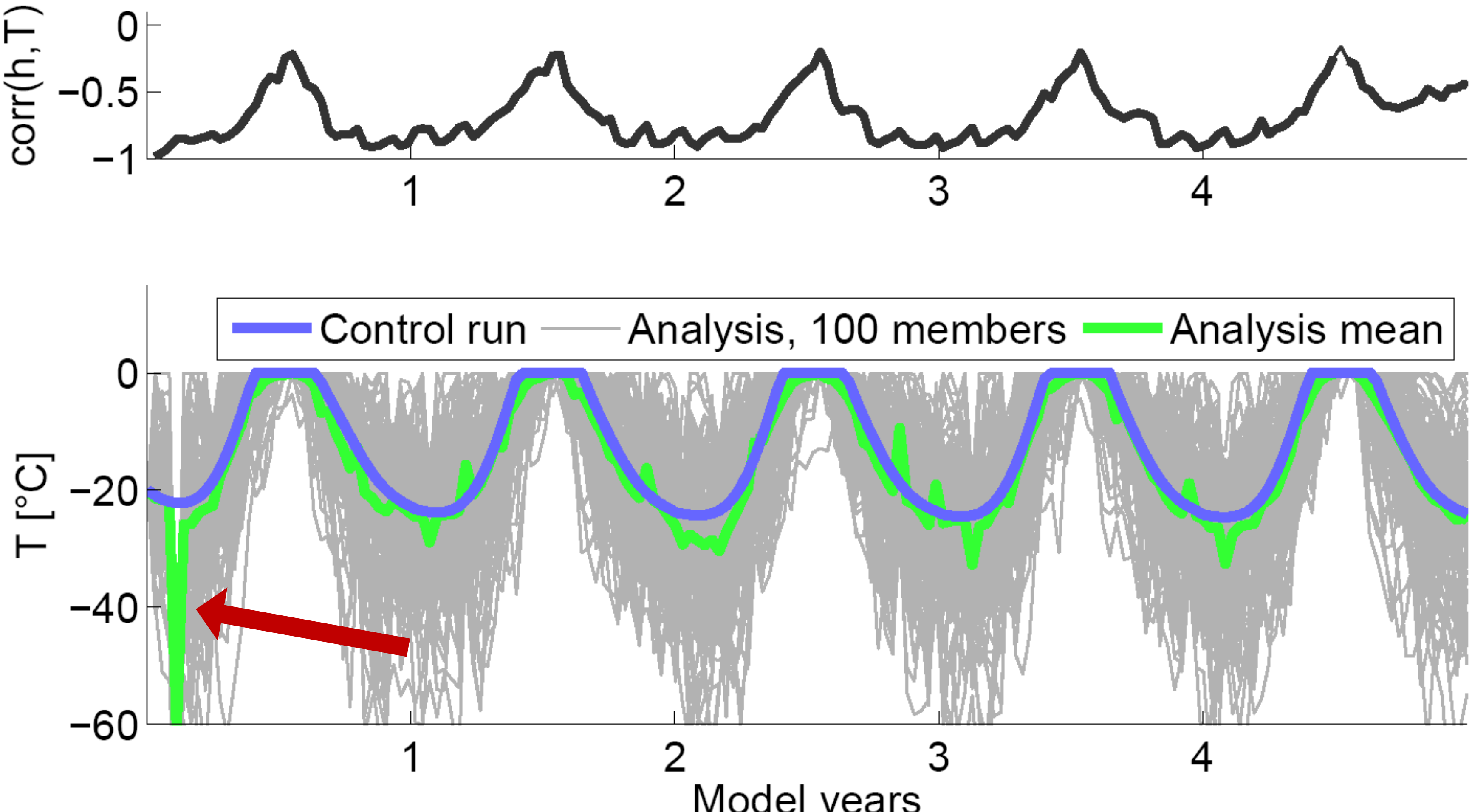
Model bias is more problematic for initialization of predictions



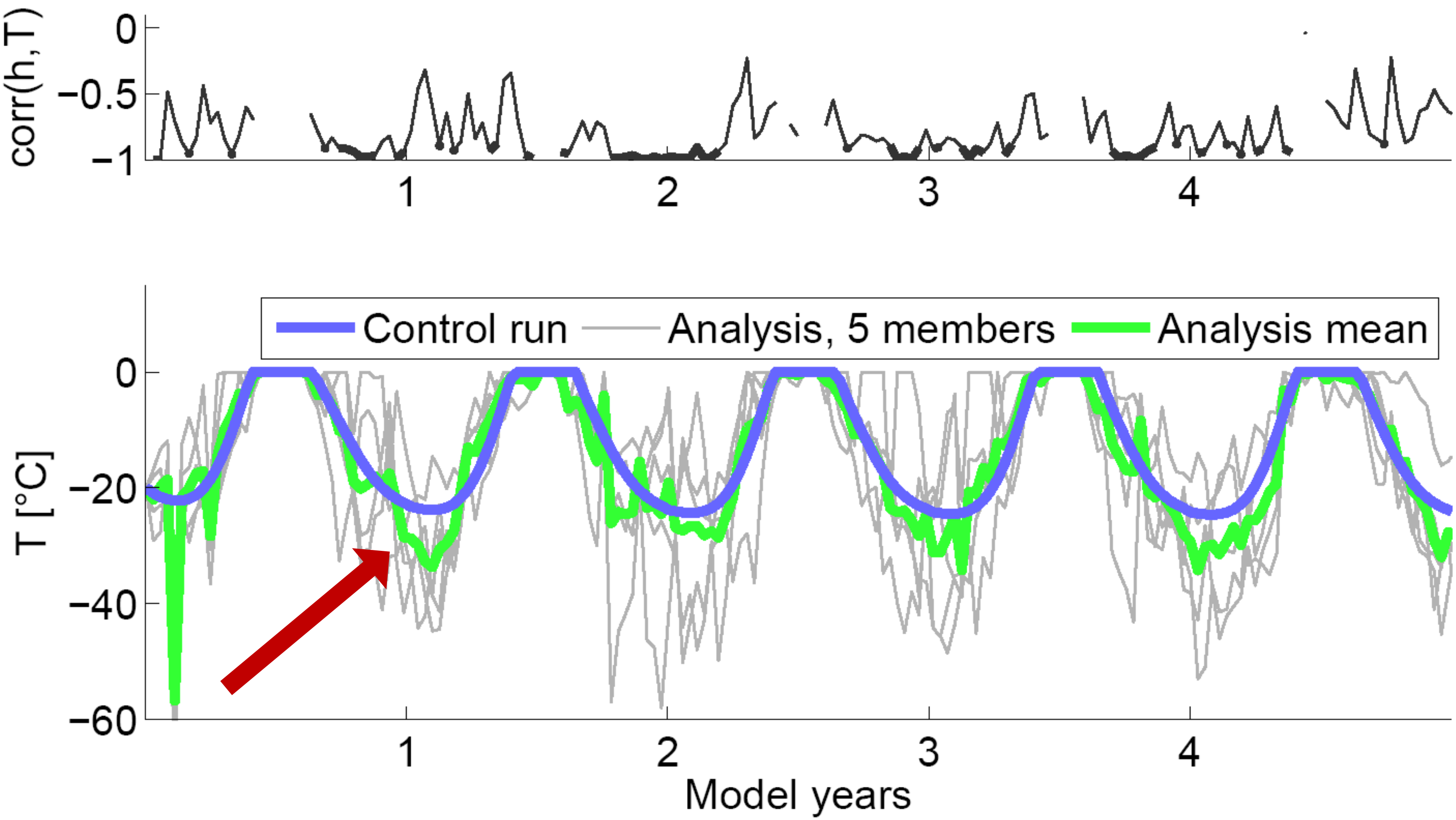


corr(h,T)
0
−0.5
−1
1
2
3
4

Model bias may lead to physical instabilities in the first time steps

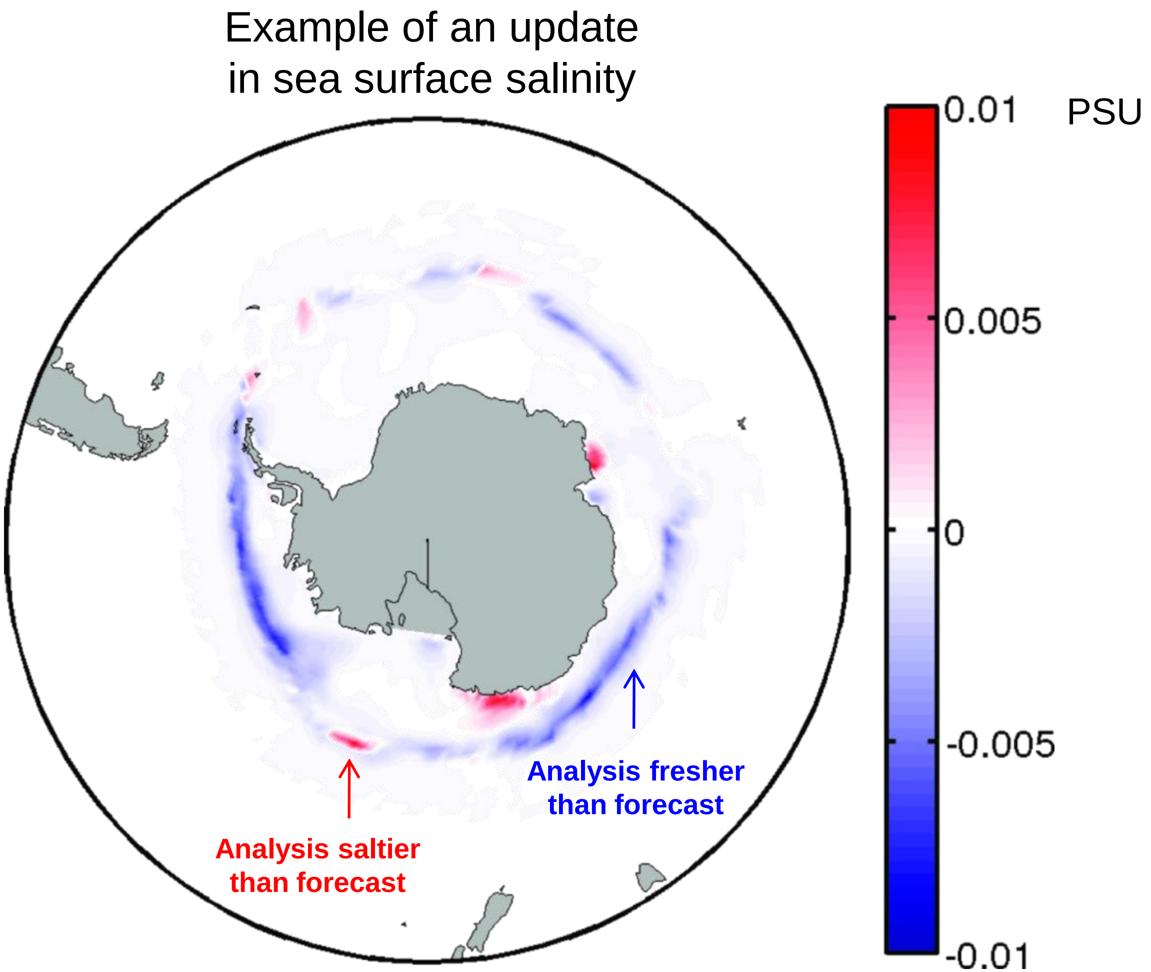


Statistical under-sampling may lead to weak constraints on the non-observed variables



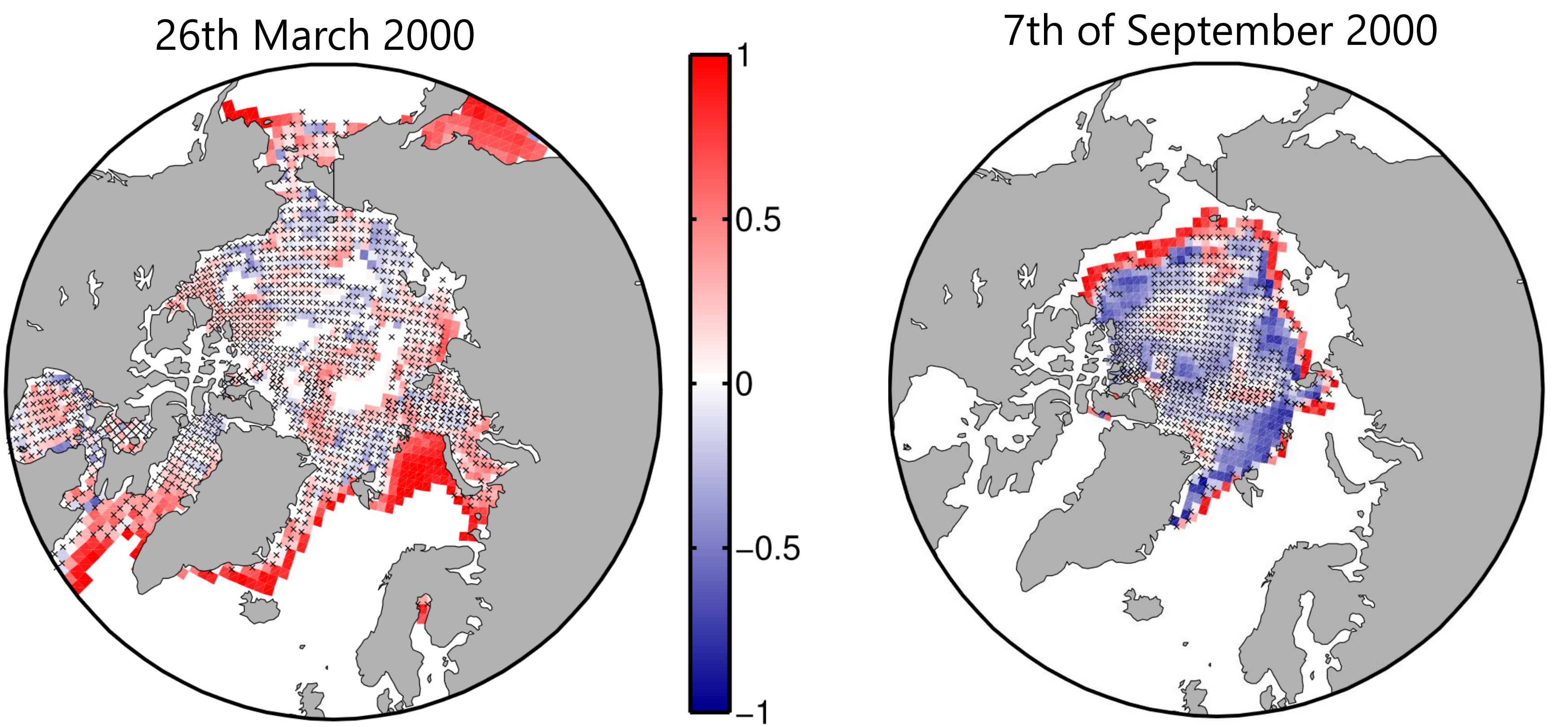
How are these approximations reflected in the large-scale setup?

The ensemble Kalman filter is a multivariate data assimilation method



In a large-scale setup, the covariances are space- and time-dependent!

Correlation between ice concentration and thickness,
in an ensemble of 25 members



x = p-value > 5% (2-sided test)

Data assimilation in sea ice modeling

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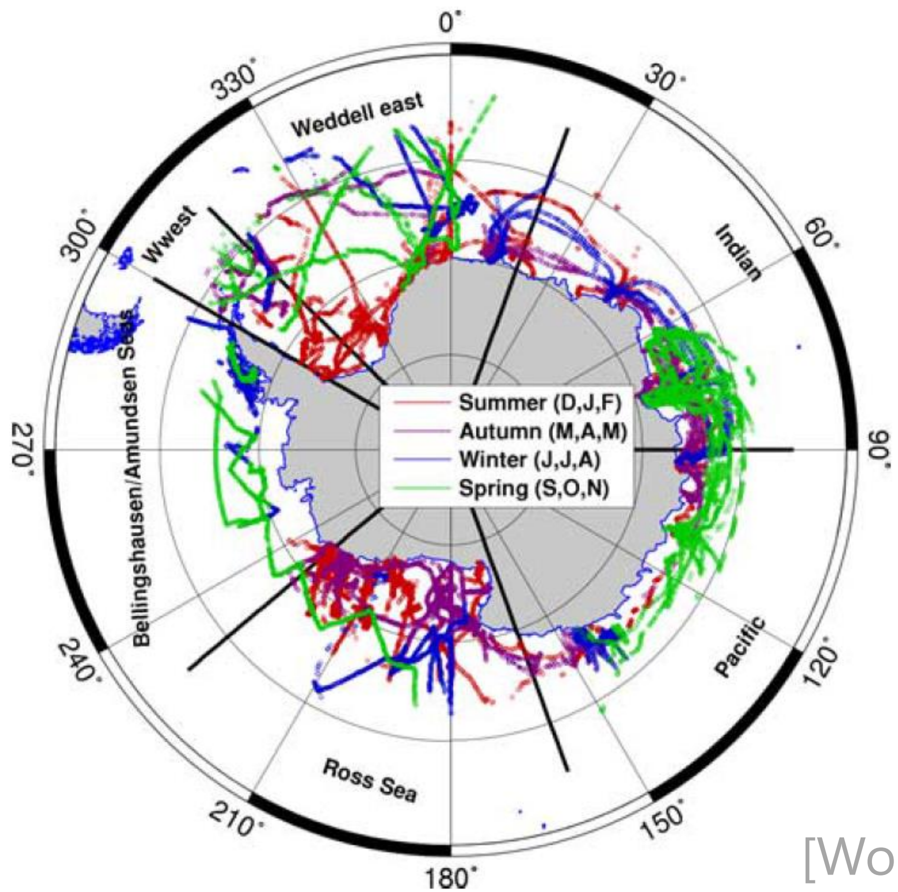
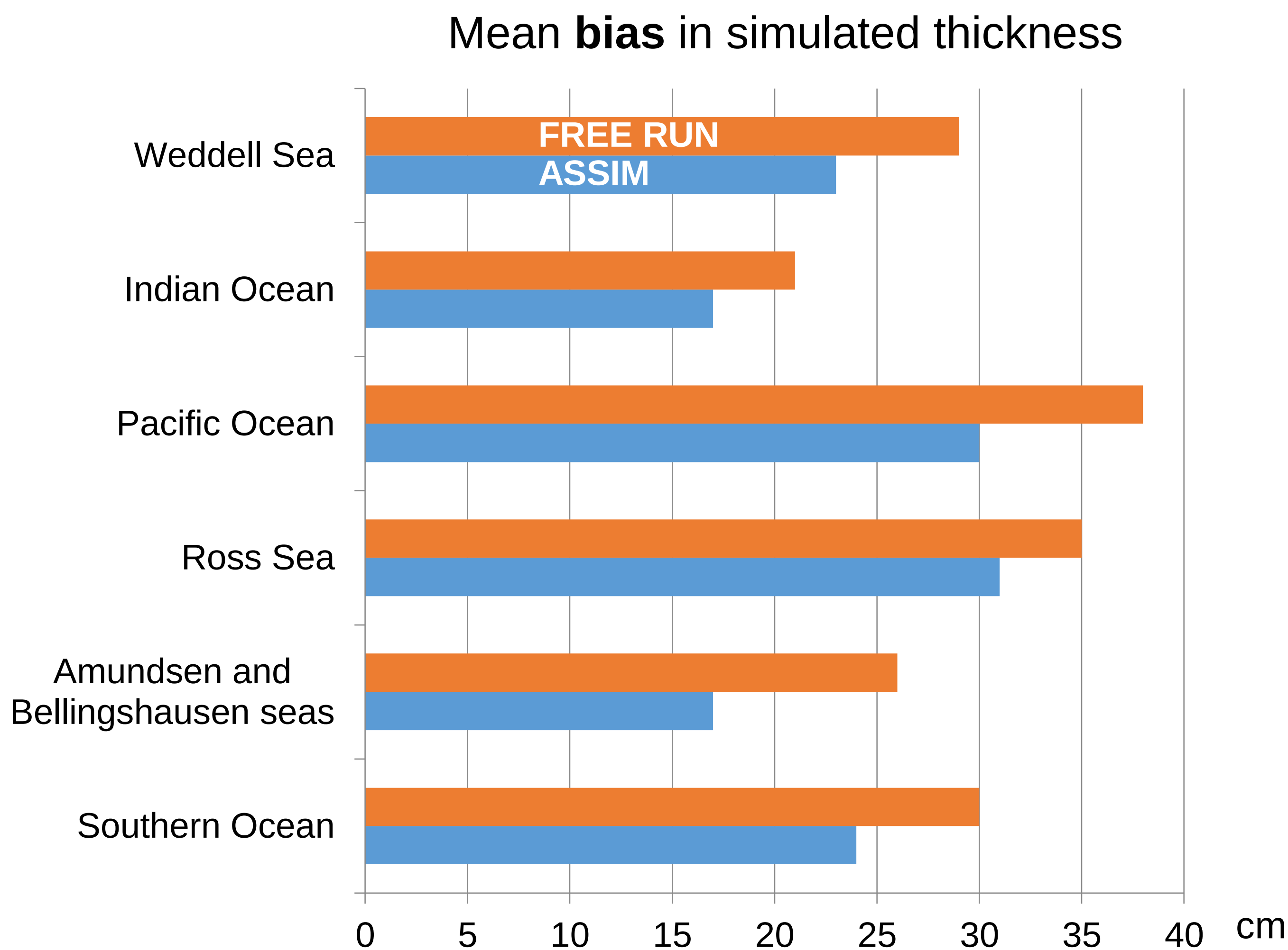
Observations of Antarctic thickness are too sparse to understand past variability

Distribution of 81 ship cruises between 1981 and 2005



[Worby et al., JGR, 2008]

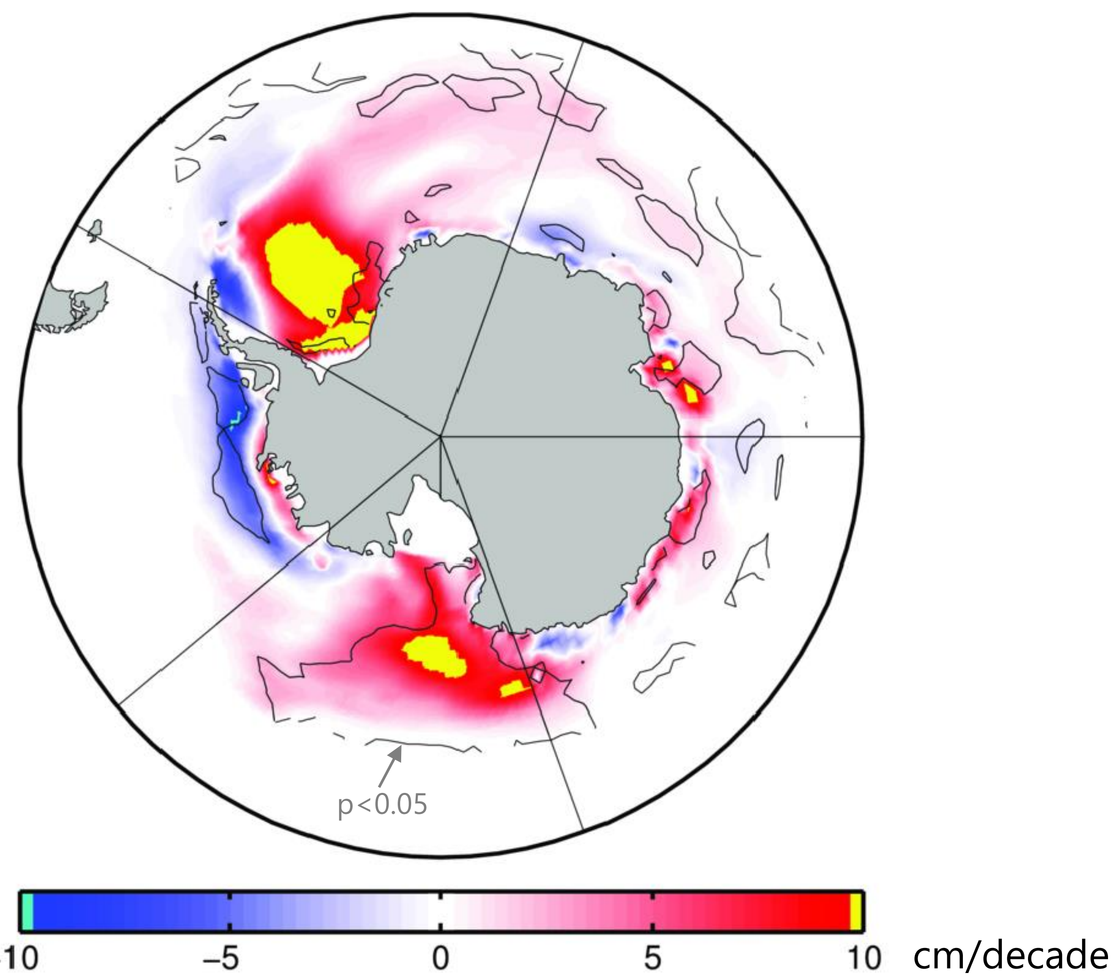
Antarctic sea ice thickness has lower bias after assimilation of ice concentration



[Antarctic thickness data: Worby et al., JGR, 2008]

State estimation: reconstruction of Antarctic sea ice thickness

Sea ice thickness trends (1980-2008)

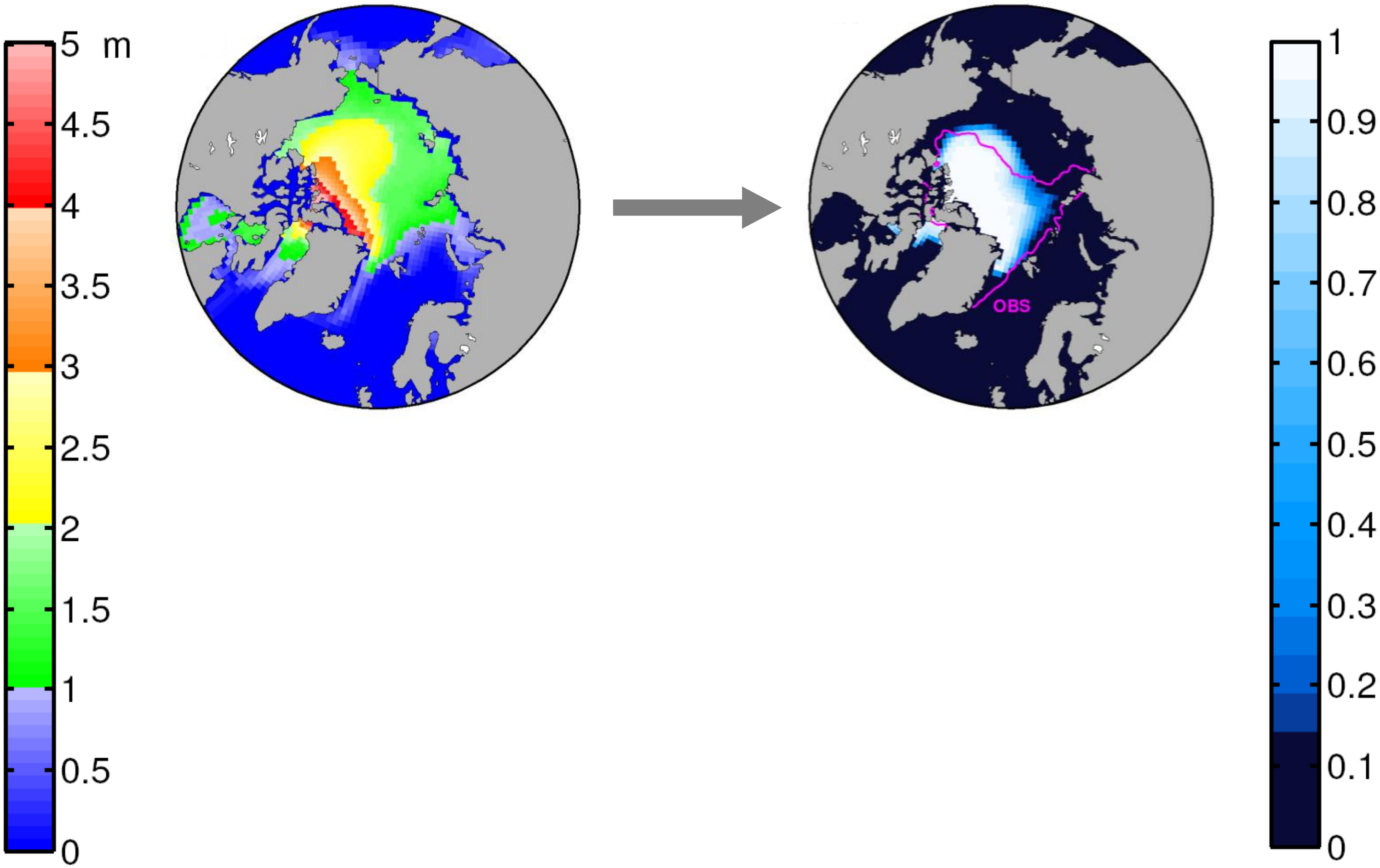


[Massonnet et al., Ocean Modell., 2013]

Seasonal « prediction » for 2007 (atmosphere known)

March ice thickness

September ice concentration



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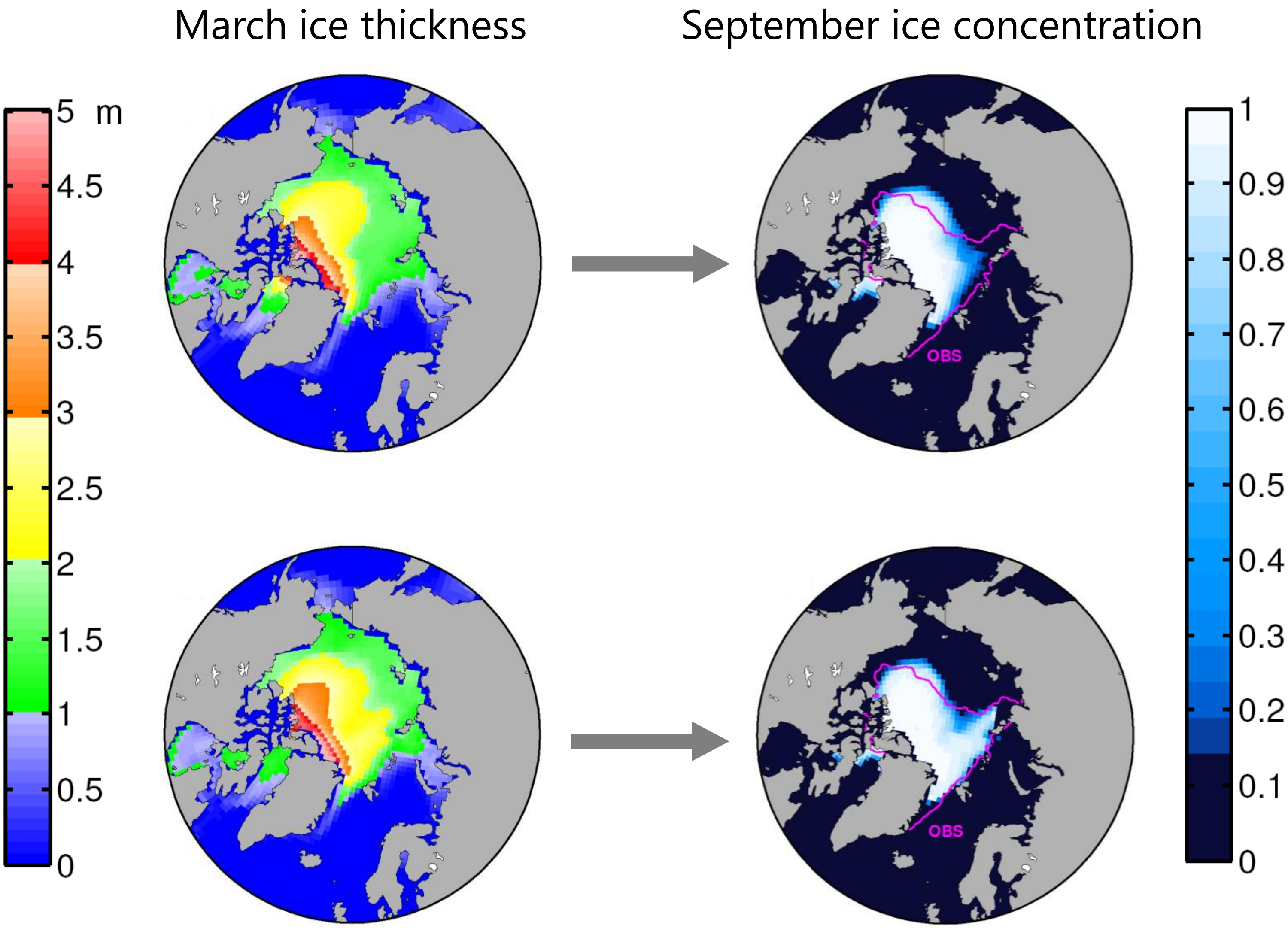
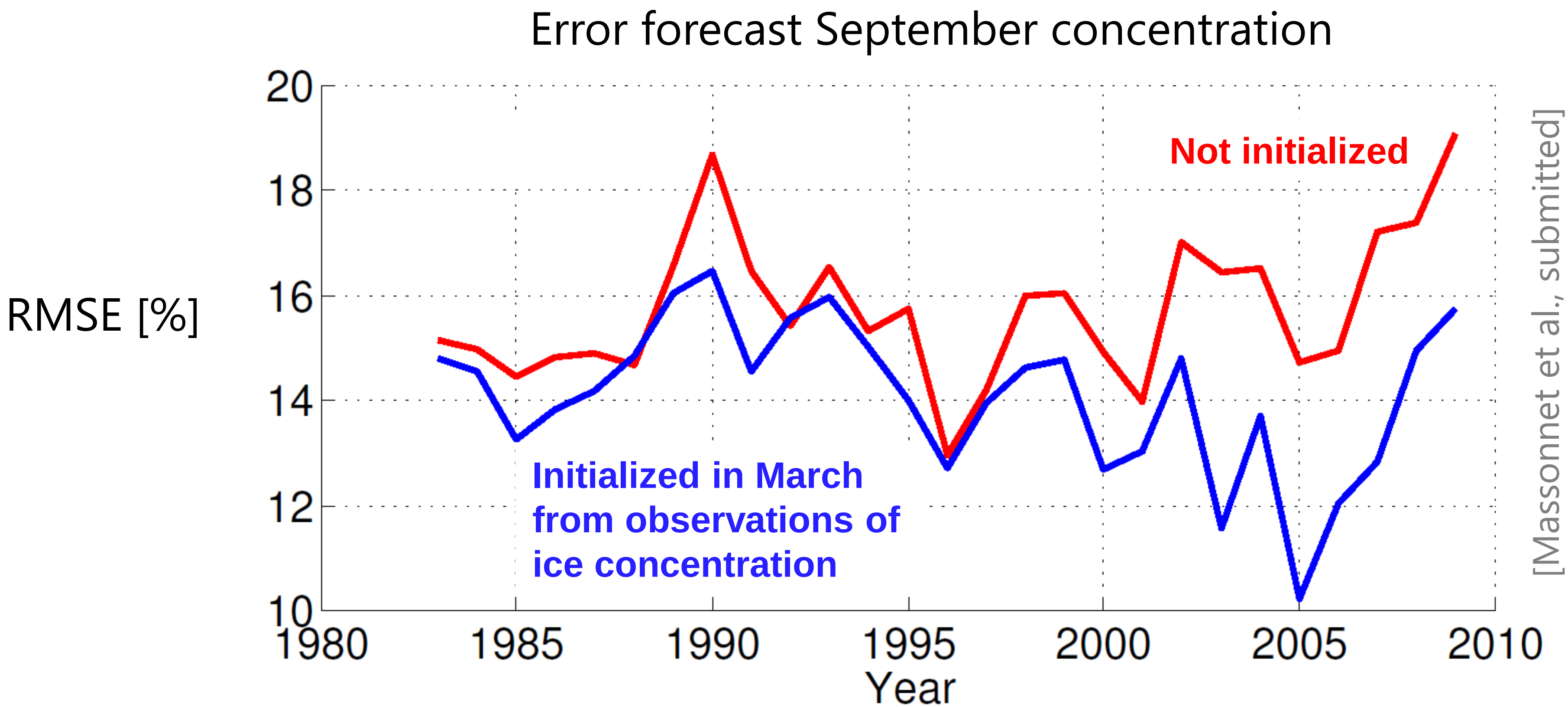
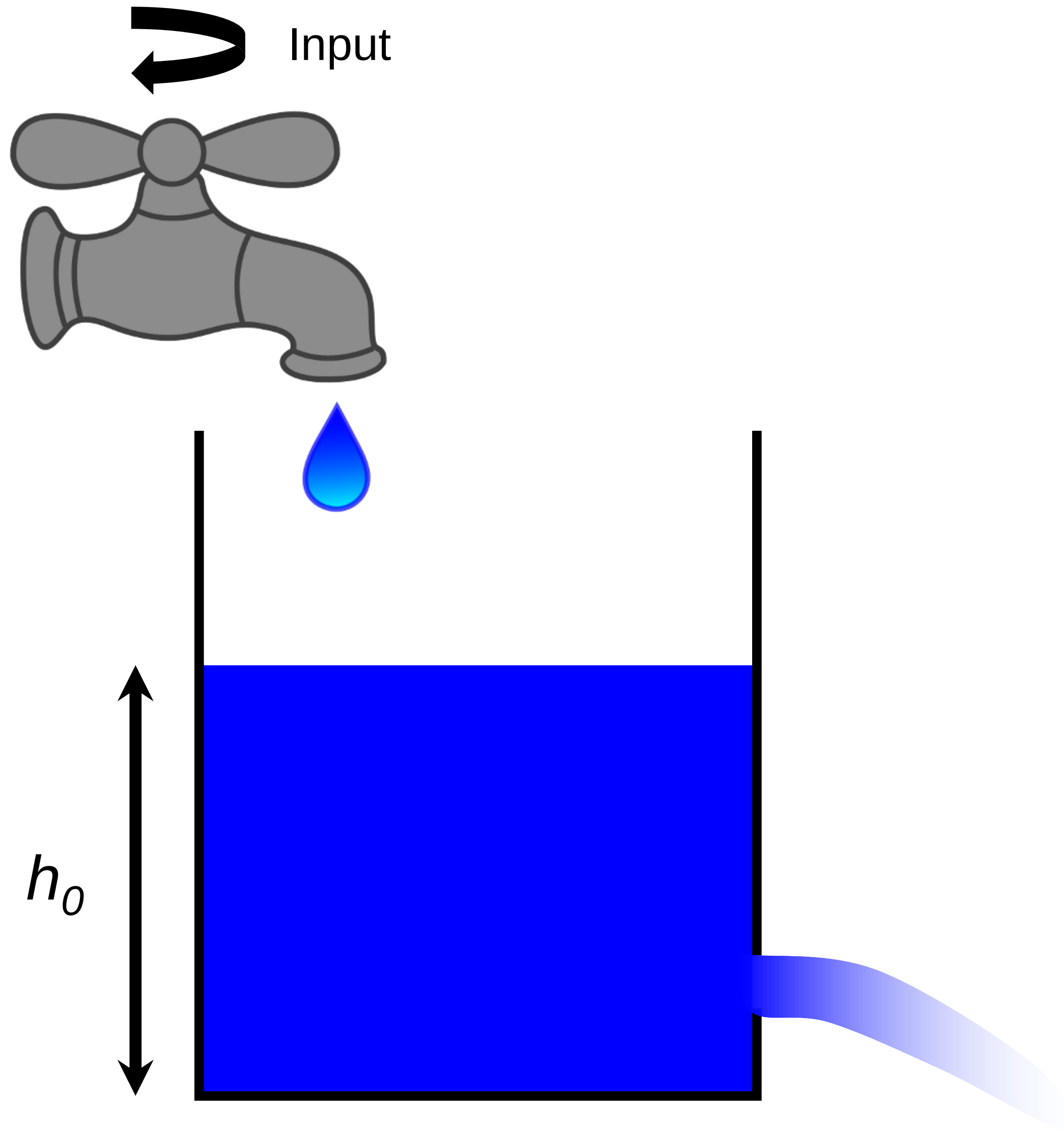


Initialization from sea ice concentration improves seasonal Arctic predictions




Input
h_0

```
clc; clear all; close all

g=9.81;                                  % accélération de la
                                         gravité
h0=0.34;                                 % hauteur initiale du
                                         niveau d'eau
dt=0.1;                                  % pas de temps
tf=30;                                   % durée de la
                                         simulation
h=zeros(length(0:dt:tf),1)               % h(t), à trouver

                                  ...

alpha=1.34                               % Coefficient de
                                         % bidouillage

                                  ...
for t=1:dt:tf
       [a,b,c]=compute_gain(h(t-1))
       ...
```

```
clc; clear all; close all

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```
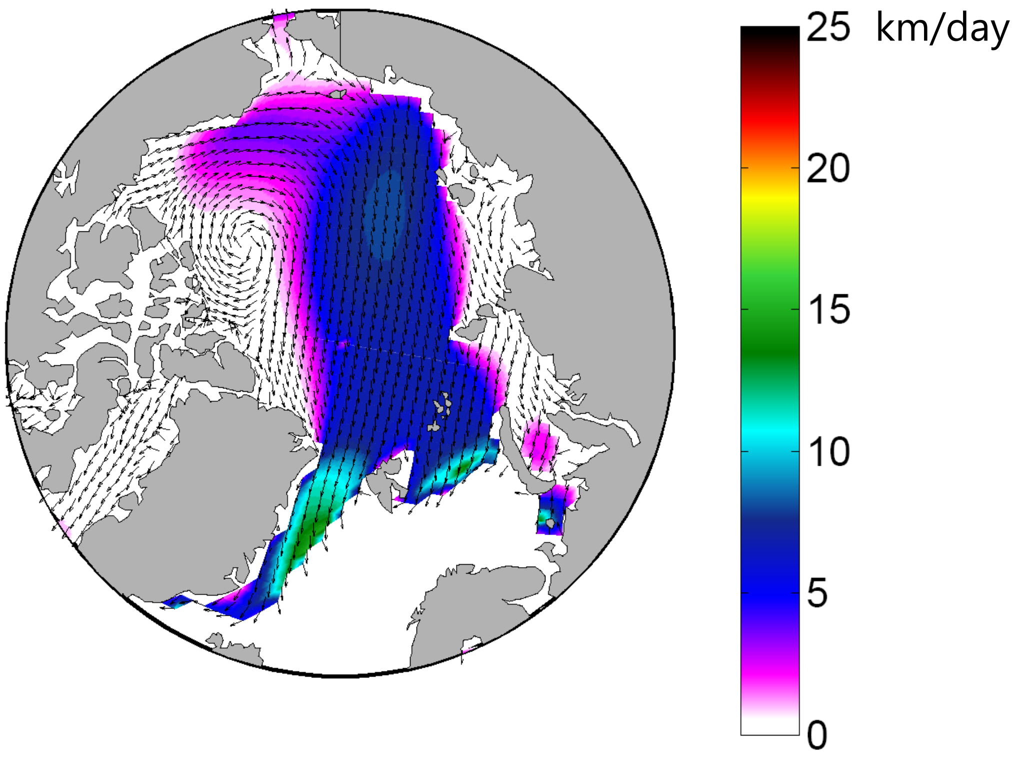

$$\vec{F}_{air/ice} + \vec{F}_{ocean/ice} + \vec{F}_{ice/ice} \approx 0$$

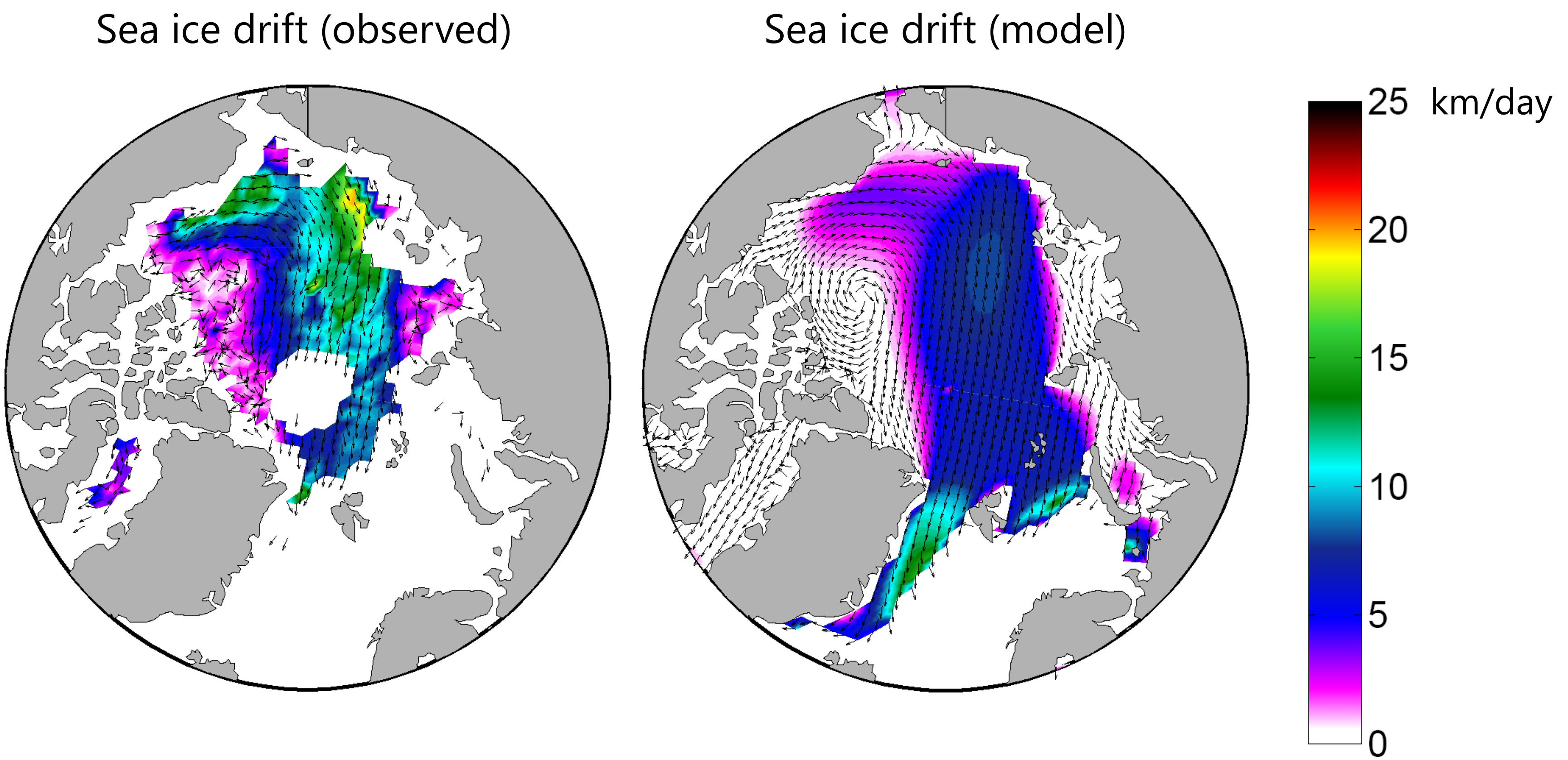
$$\begin{array}{ccc} \downarrow & \downarrow & \downarrow \\ C_a & C_w & P^* \end{array}$$

Sea ice drift (model)



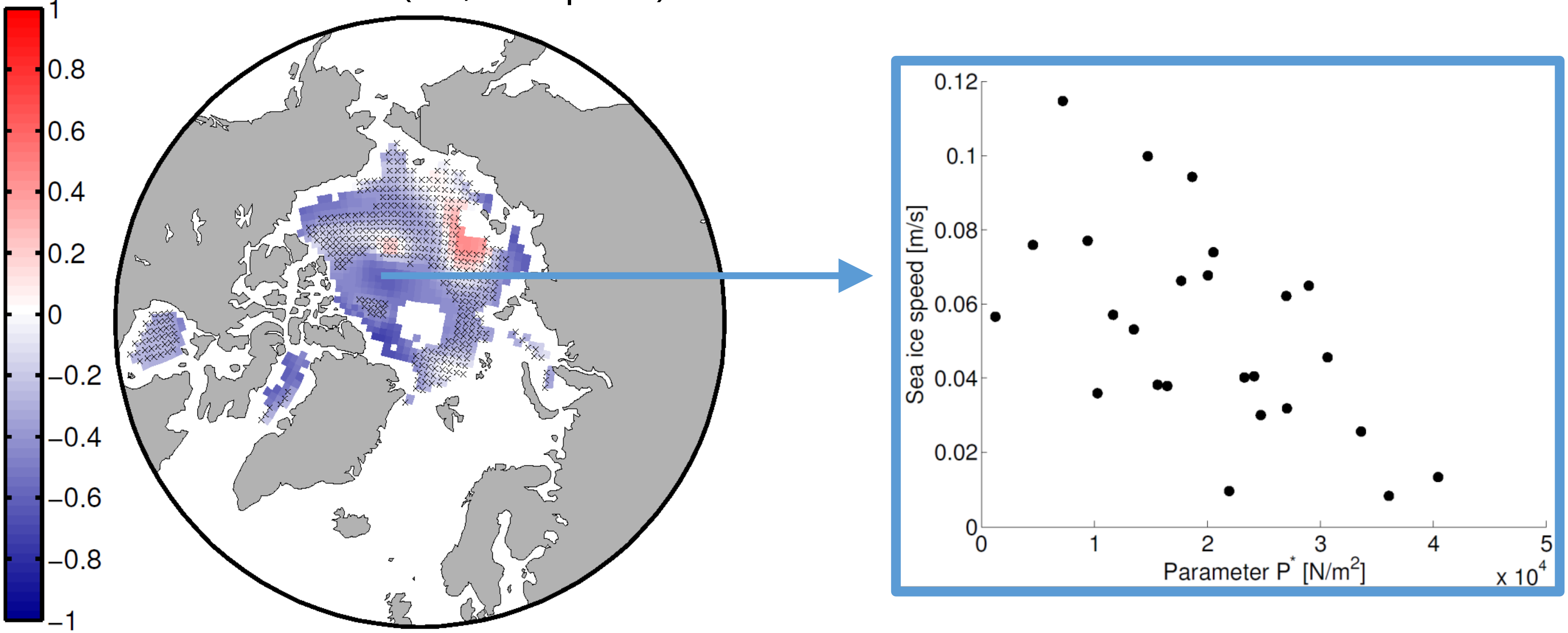
$$\vec{F}_{air/ice} + \vec{F}_{ocean/ice} + \vec{F}_{ice/ice} \approx 0$$

$$C_a \qquad C_w \qquad P^*$$



Parameter estimation is a state-augmented data assimilation problem

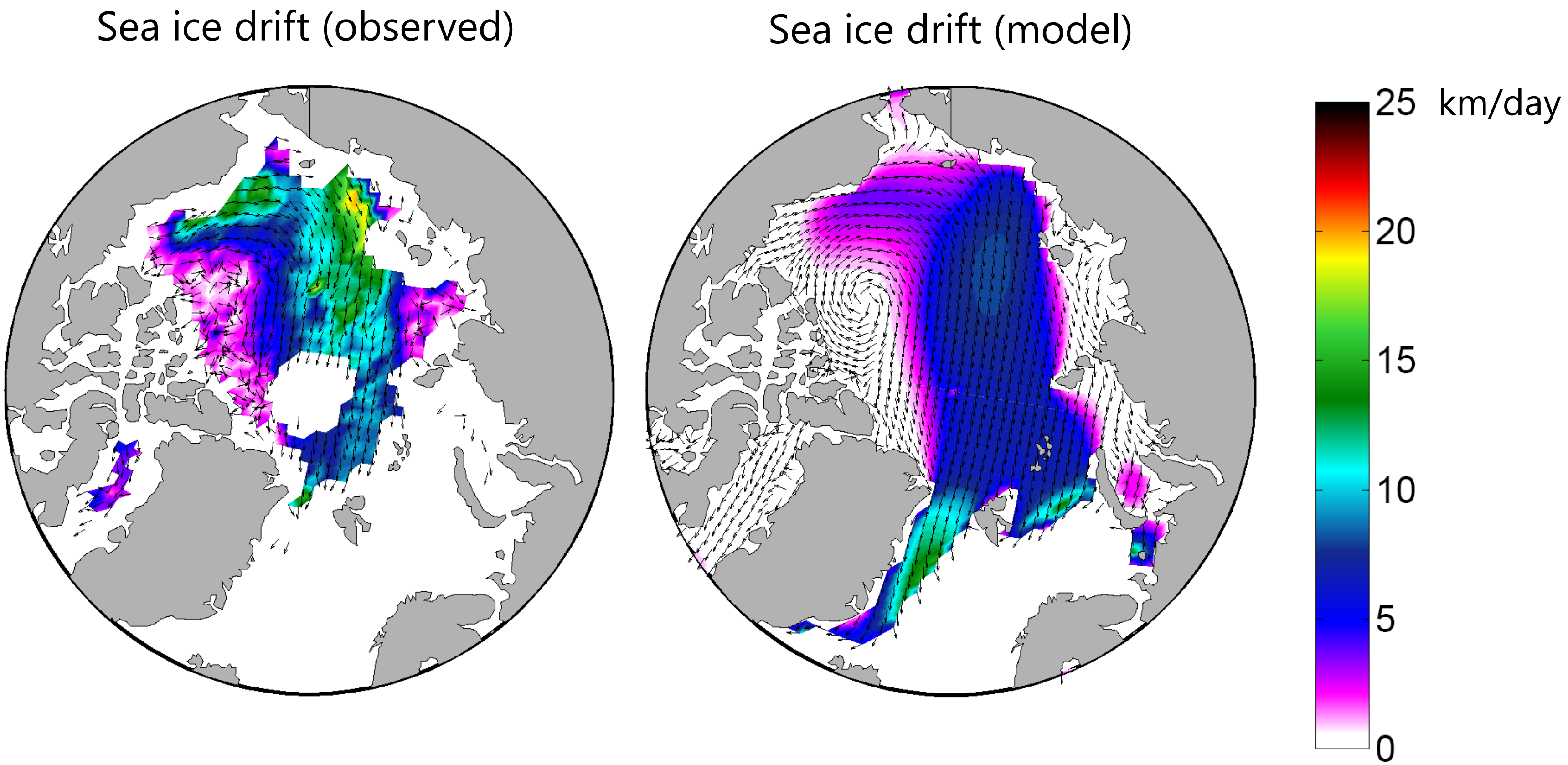
Correlation ($P*$, ice speed)



x= p-value > 5% (2-sided test)

$$\vec{F}_{air/ice} + \vec{F}_{ocean/ice} + \vec{F}_{ice/ice} \approx 0$$

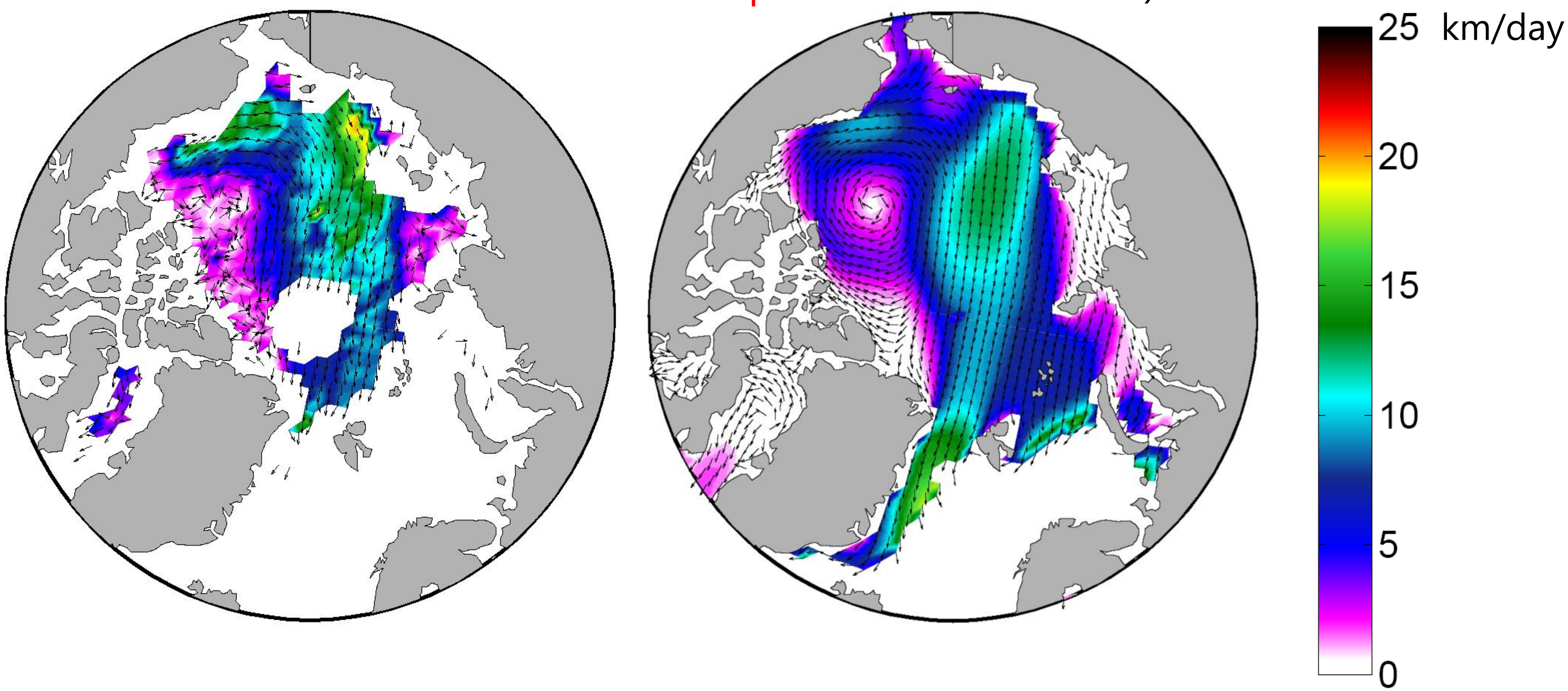
C_a ↓ C_w ↓ P^*



$$\underset{\substack{\downarrow \\ C_a}}{\vec{F}_{air/ice}} + \underset{\substack{\downarrow \\ C_w}}{\vec{F}_{ocean/ice}} + \underset{\substack{\downarrow \\ P^*}}{\vec{F}_{ice/ice}} \approx 0$$

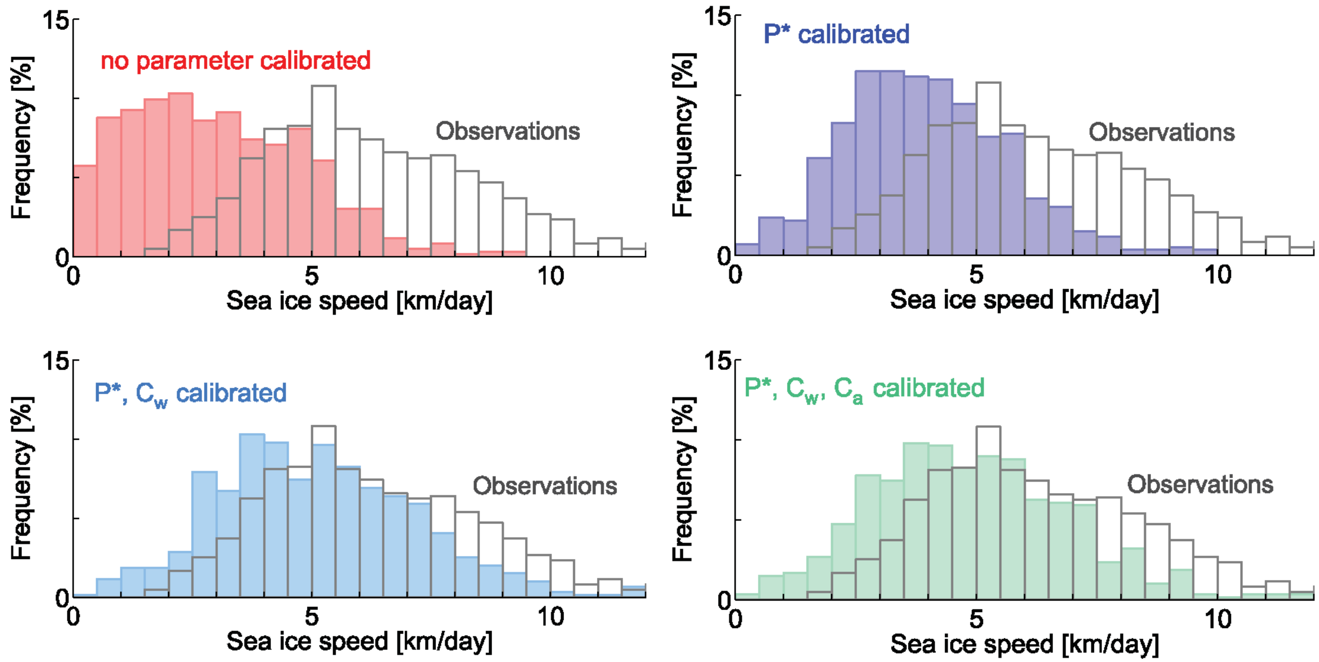
Sea ice drift (observed)

Sea ice drift (model, parameters calibrated)



Estimating *more* parameters is not a guarantee for better solution

Distribution of Arctic sea ice speeds (fall-winter, 2007-2012)



[Massonnet et al., JGR, 2014]

Estimating *more* parameters is not a guarantee for better solution

$$
\begin{cases}
\boldsymbol{\tau}_a + \mathbf{F}_{int} = 0 & \text{(regime 1, compact ice)} \\
(C_a) \qquad (P^*) & \\
\boldsymbol{\tau}_a + \boldsymbol{\tau}_w = 0 & \text{(regime 2, free drift)} \\
(C_a) \qquad (C_w) &
\end{cases}
$$

[budget analysis based on Steele et al., JGR, 1997]

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3. The applications: three examples in sea ice modeling
   Sea ice data assimilation helps understand past variability, improve short term predictions and calibrate model parameters

Lessons learned

Models or observations alone are not sufficient
to address key questions in the polar regions

Even if it is suboptimal, the solution returned by the
ensemble Kalman filter has generally an added value

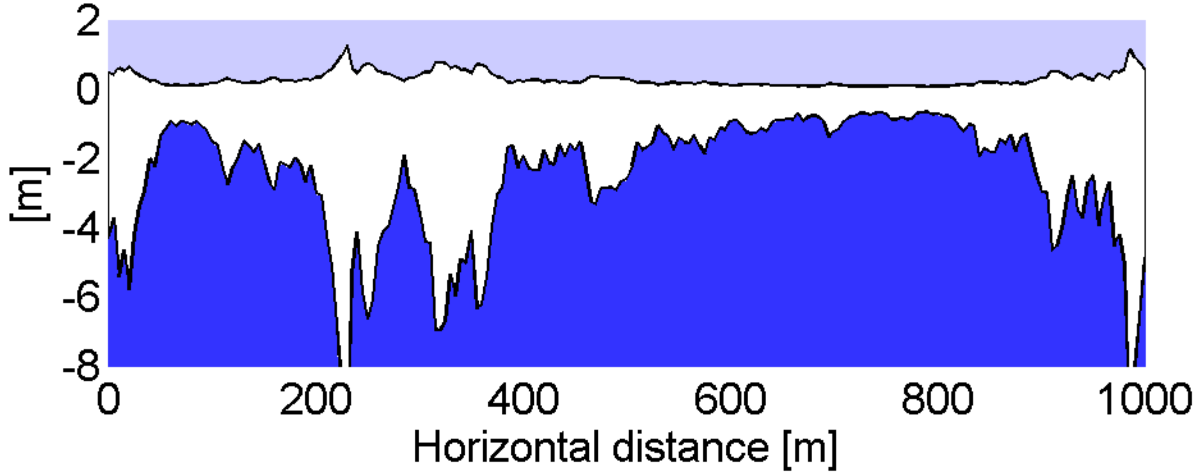
It’s never too late to start
playing with very simple models

Thank you!

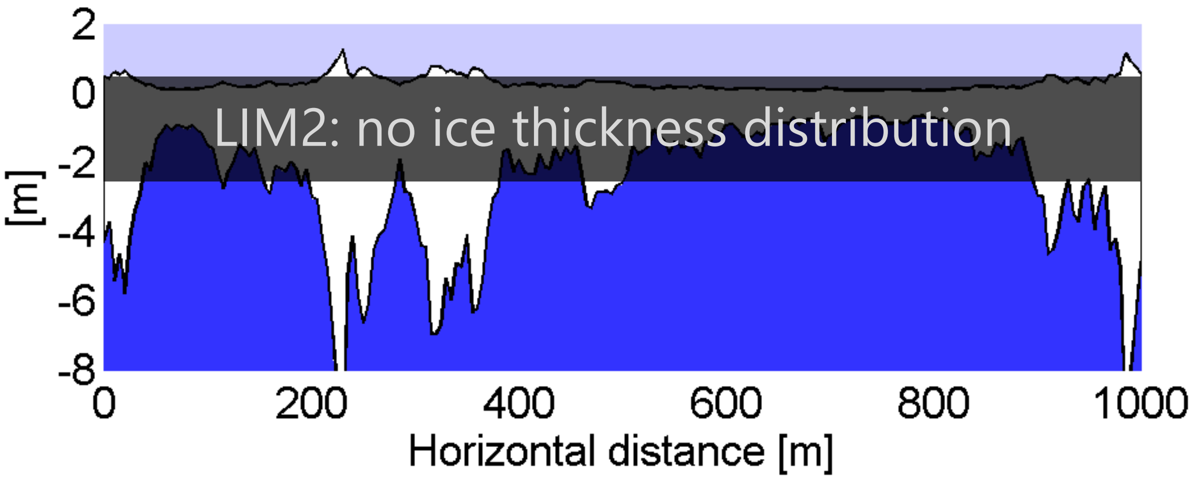
francois.massonnet@uclouvain.be

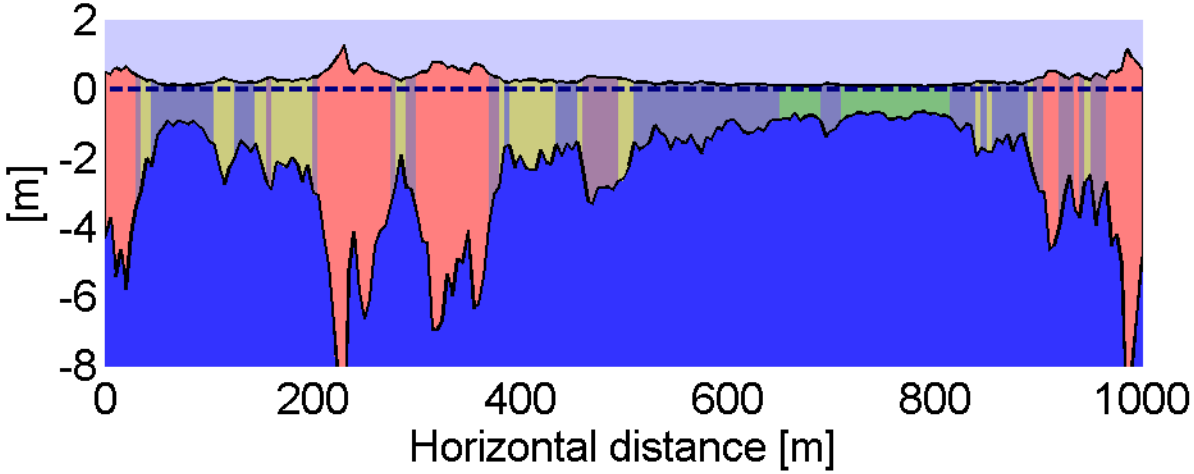
www.climate.be/u/fmasson

@FMassonnet

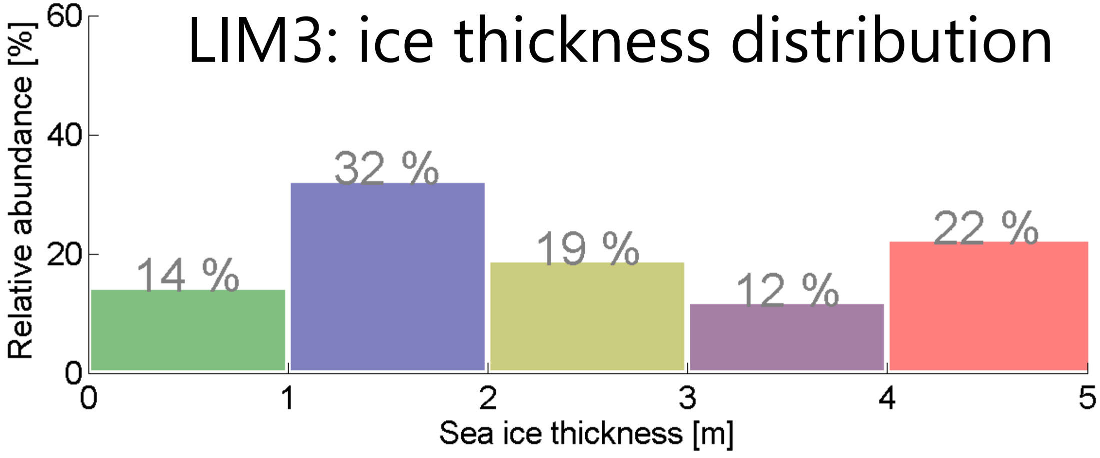


2
0
-2
-4
-6
-8
[m]
0
200
400
600
800
1000
Horizontal distance [m]


2
0
-2
-4
-6
-8
[m]
0
200
400
600
800
1000
Horizontal distance [m]
LIM2: no ice thickness distribution



LIM3: ice thickness distribution

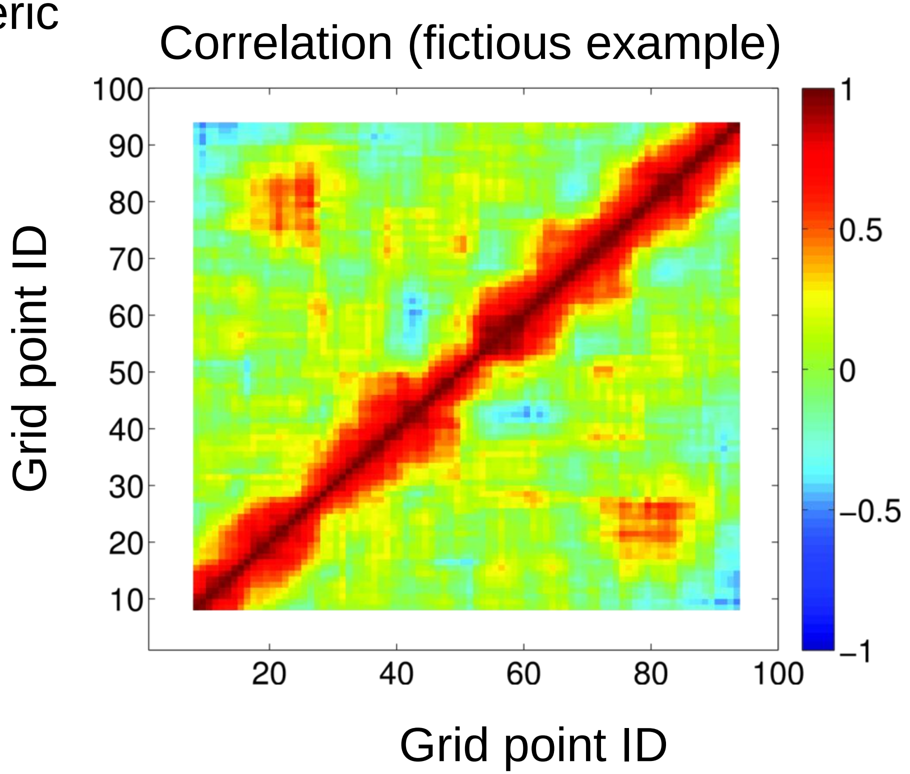


Ensemble spread, restartability and limitations

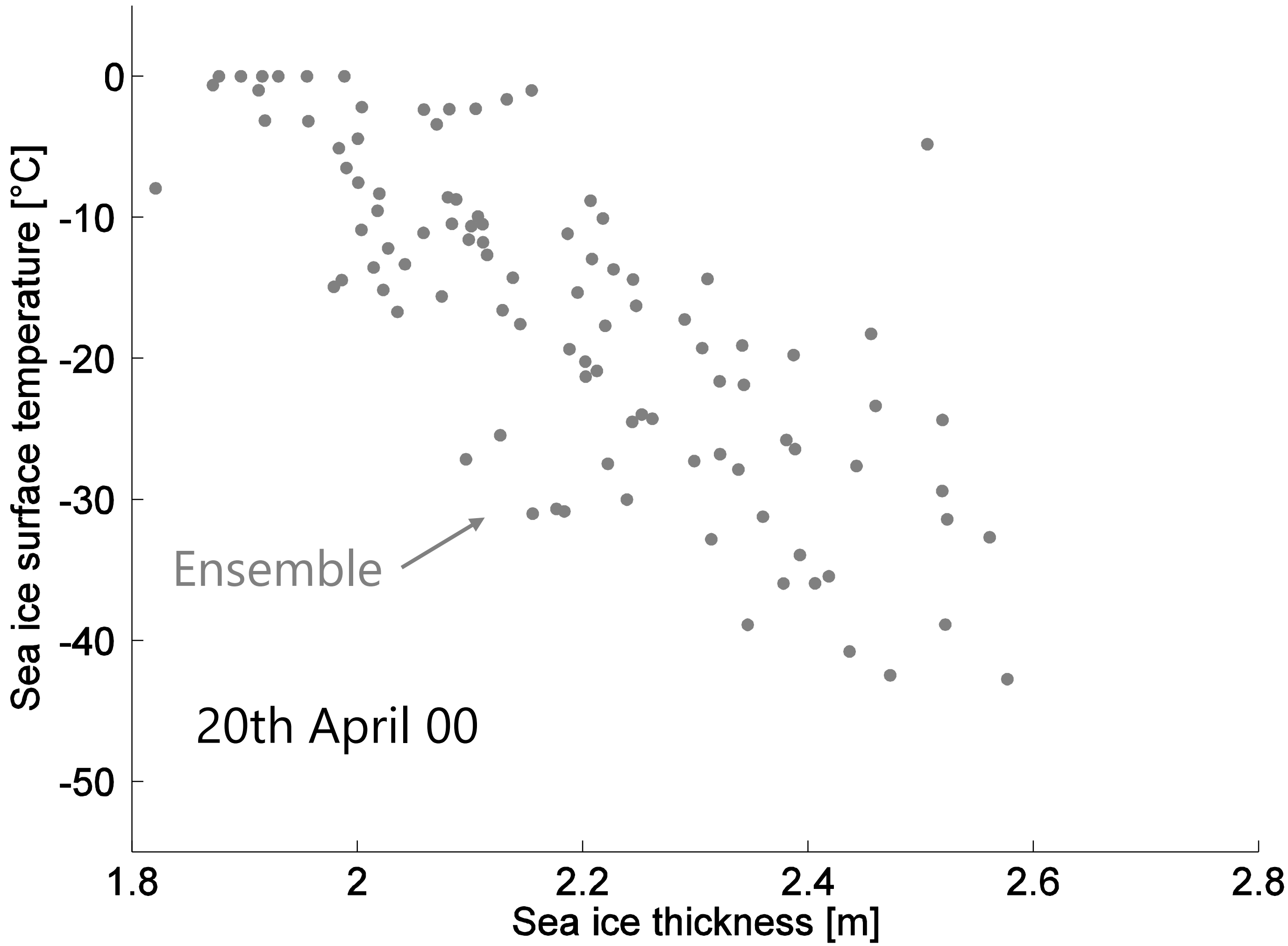
The distribution of ensemble members should reflect the full model uncertainty

* 25 members with perturbed atmospheric forcing (winds/2m-air temperature)

* Localization [Sakov and Bertino, 2010]



The tricky part: updating the other variable



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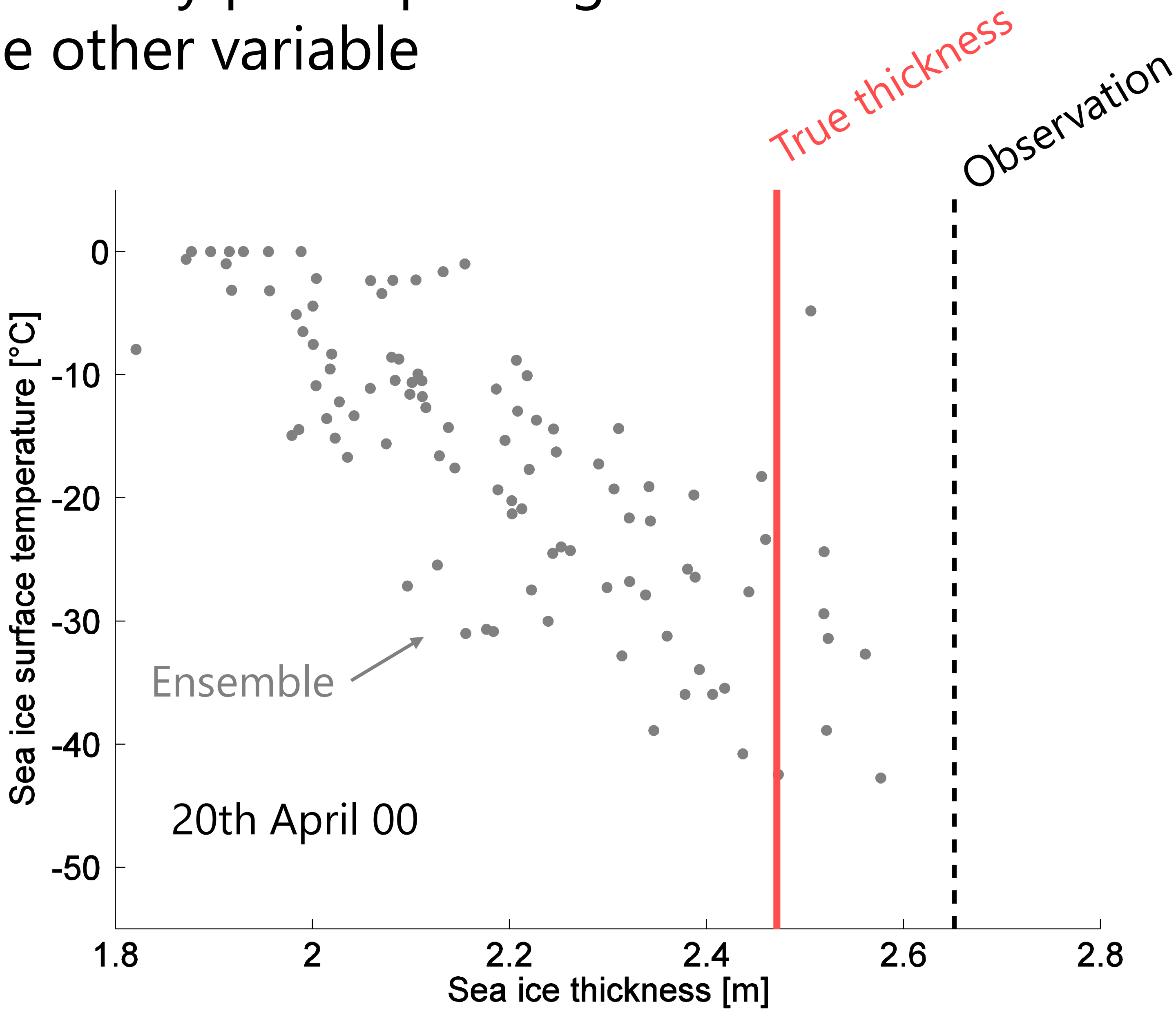
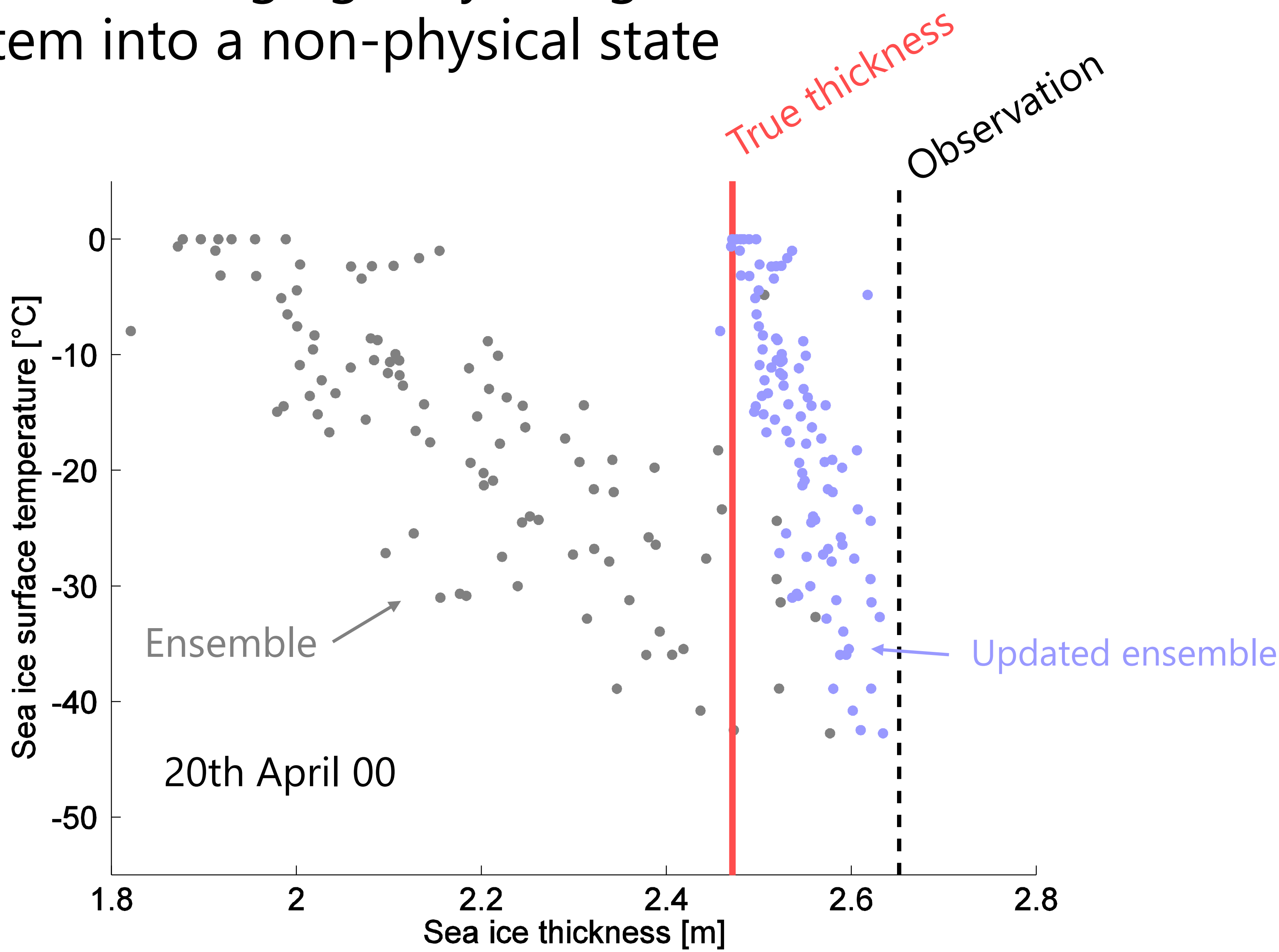
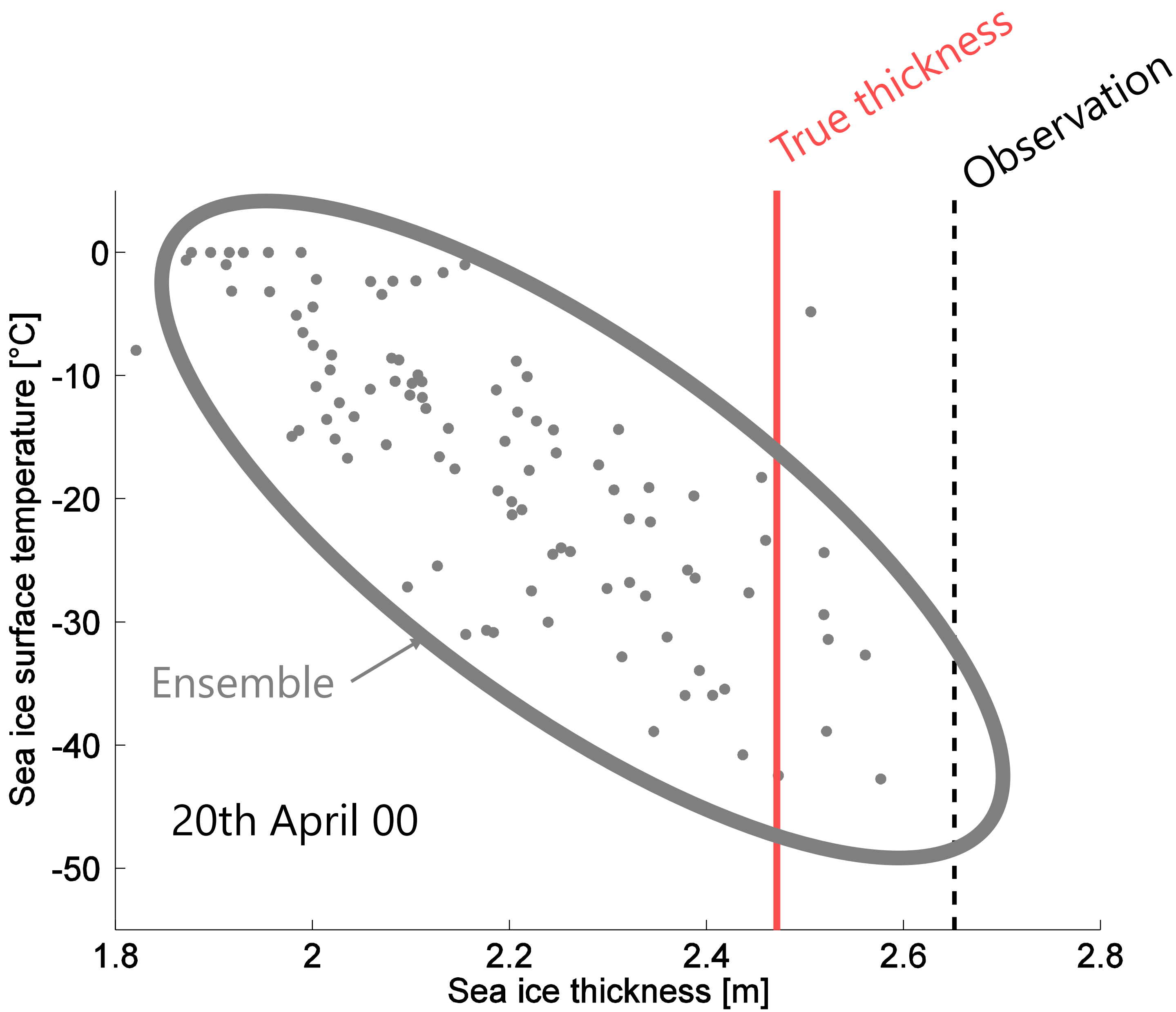


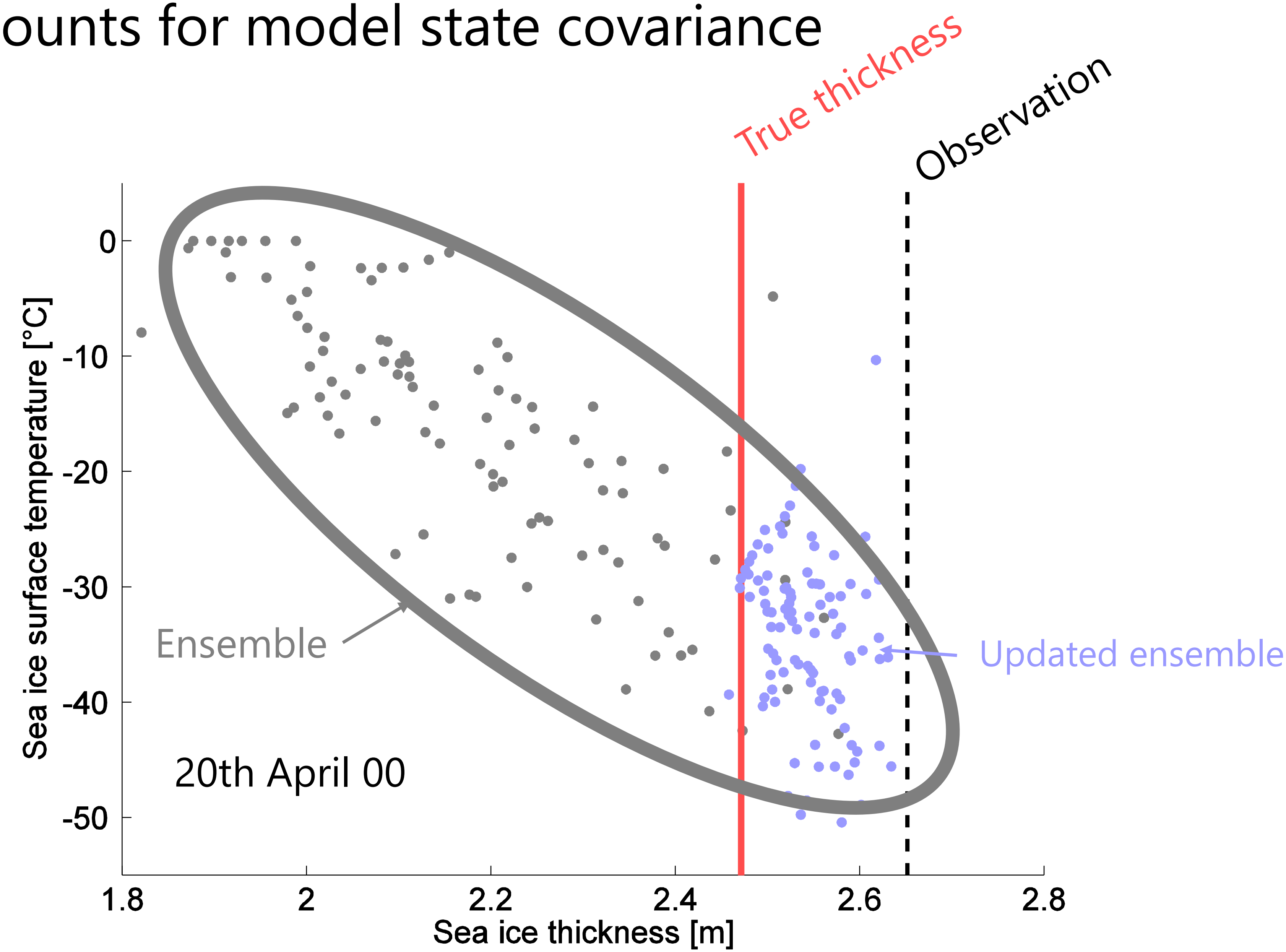
Primitive nudging may bring the system into a non-physical state





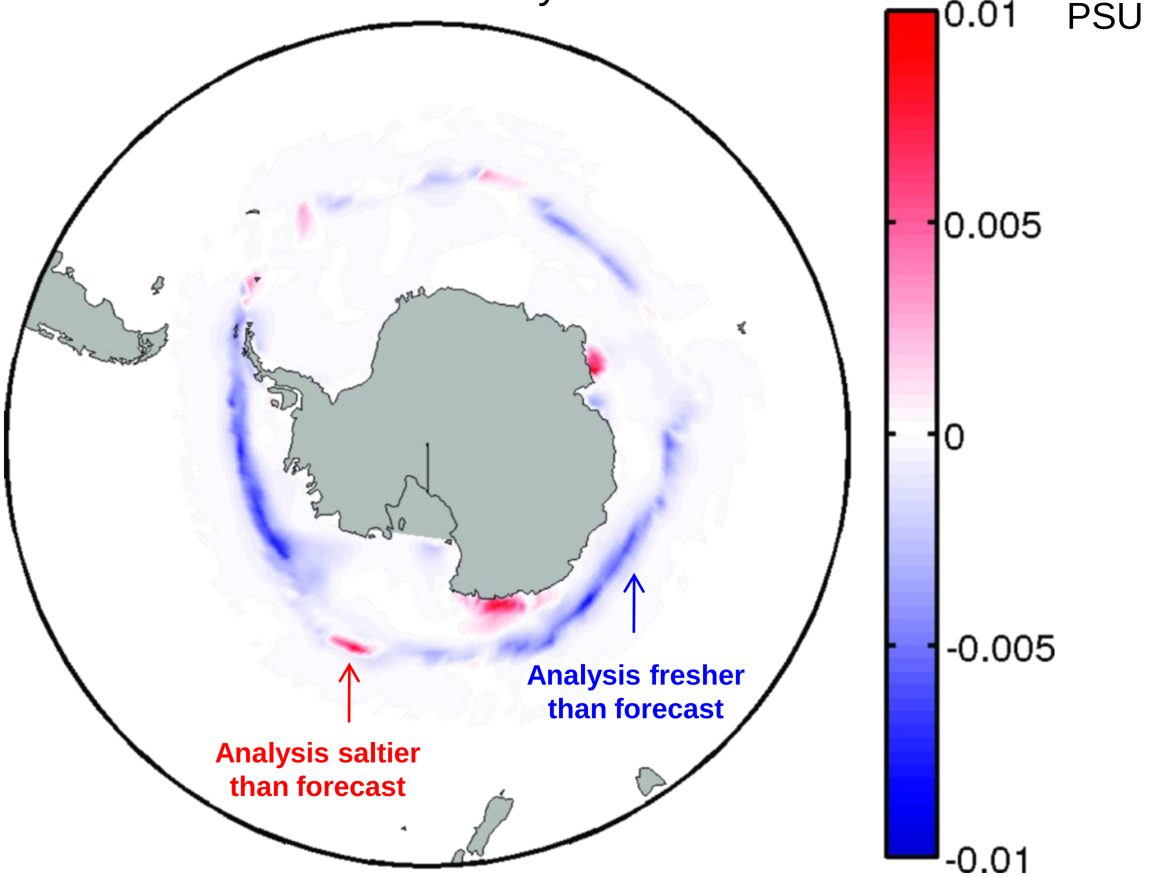
True thickness
Observation
Sea ice surface temperature [°C]
0
-10
-20
-30
-40
-50
Ensemble
20th April 00
1.8
2
2.2
2.4
2.6
2.8
Sea ice thickness [m]

Multivariate data assimilation accounts for model state covariance

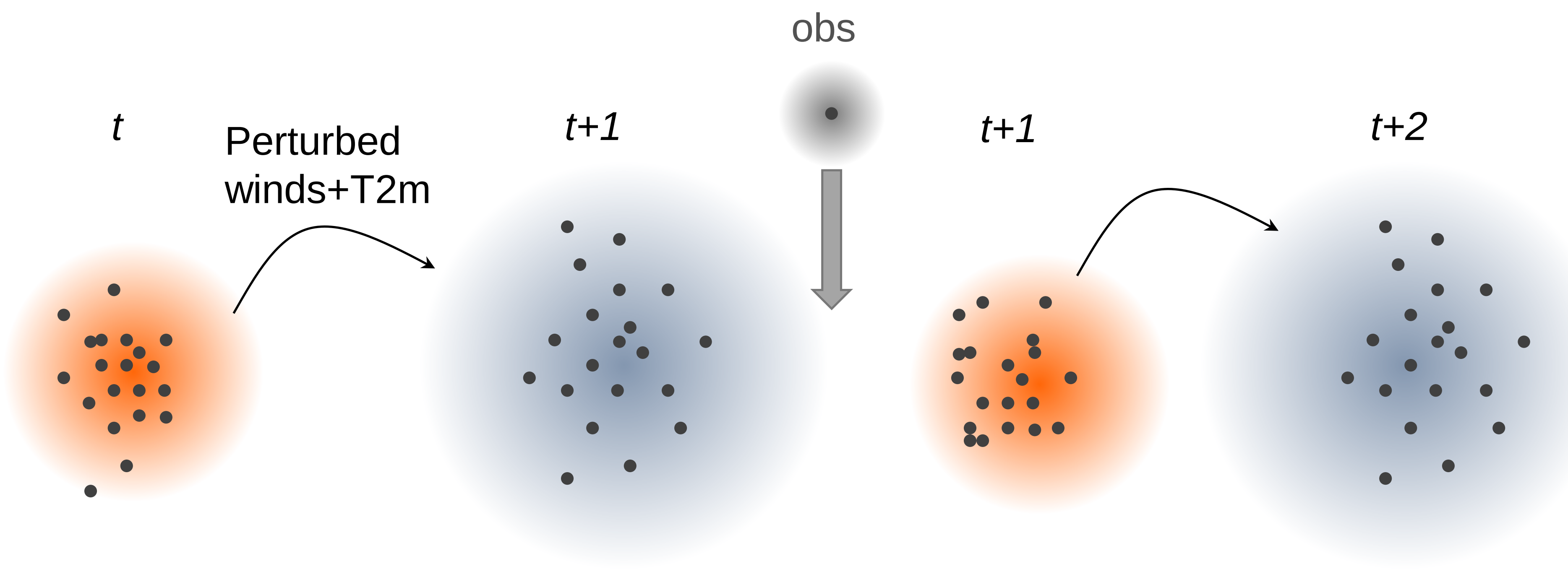


The ensemble Kalman filter is a multivariate data assimilation method

Example of an update in sea surface salinity



The ensemble Kalman filter is a forecast-analysis method



Ensemble spread, restartability and limitations

A « sanity check » for the model is necessary because gaussianity assumption is rarely fulfilled

> Reset negative ice concentrations/thickness to zero

> Bound total ice concentration by 1

> Ice thickness stays within category bounds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7 September 2000

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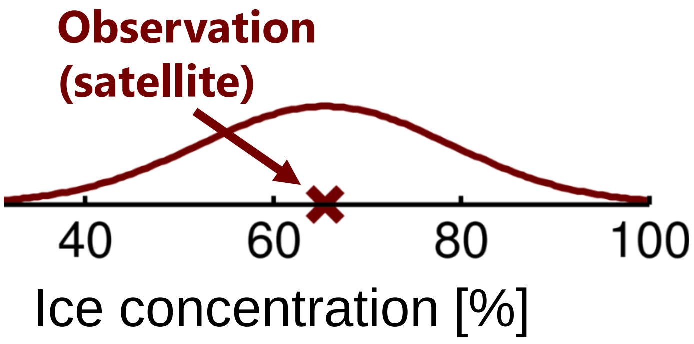

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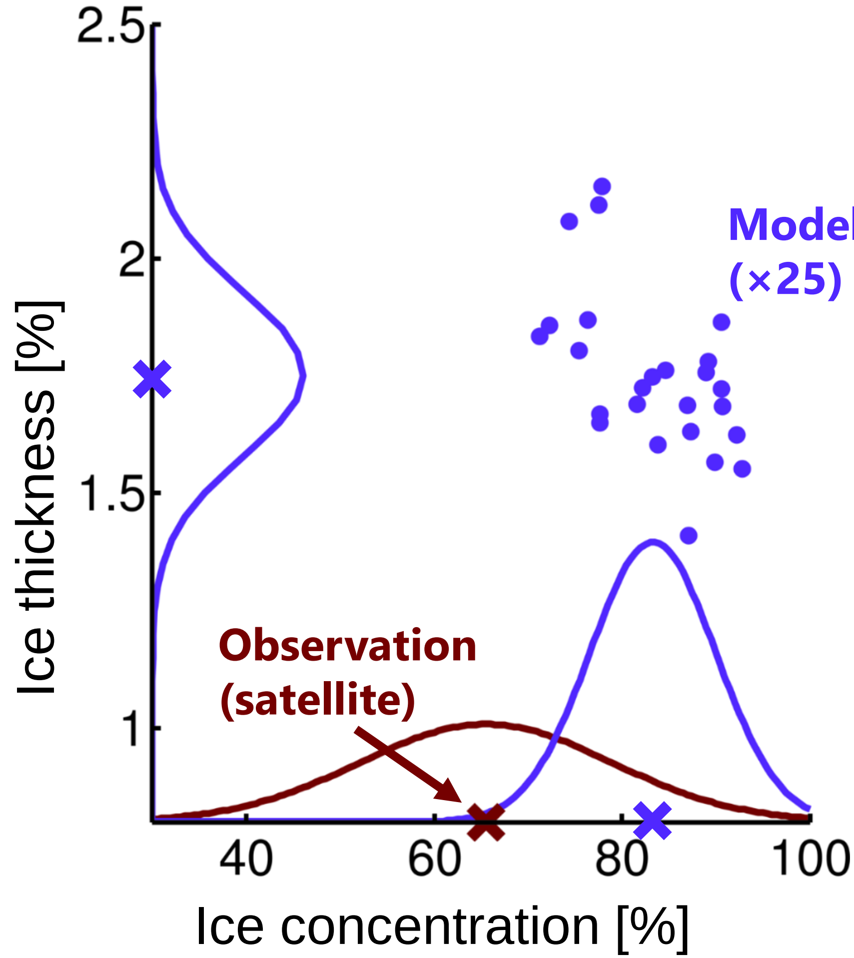
7 septembre 2000



The ensemble Kalman filter approximates the model error covariance matric with a finite number of particles

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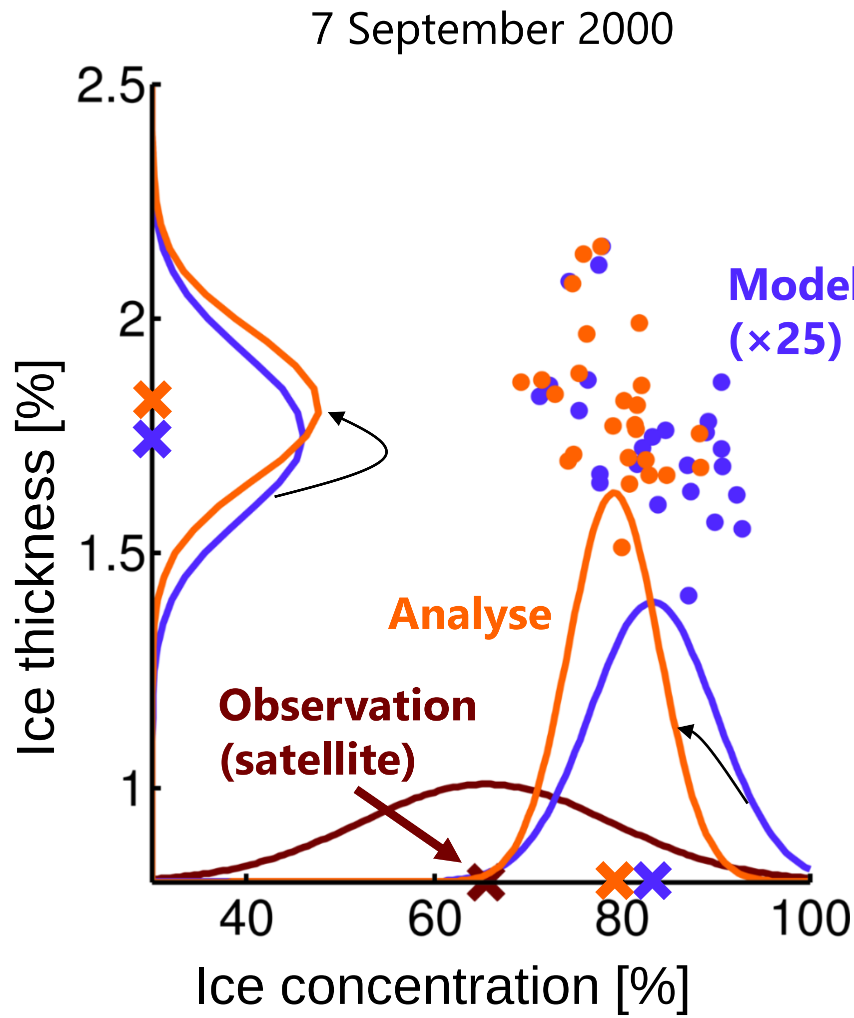
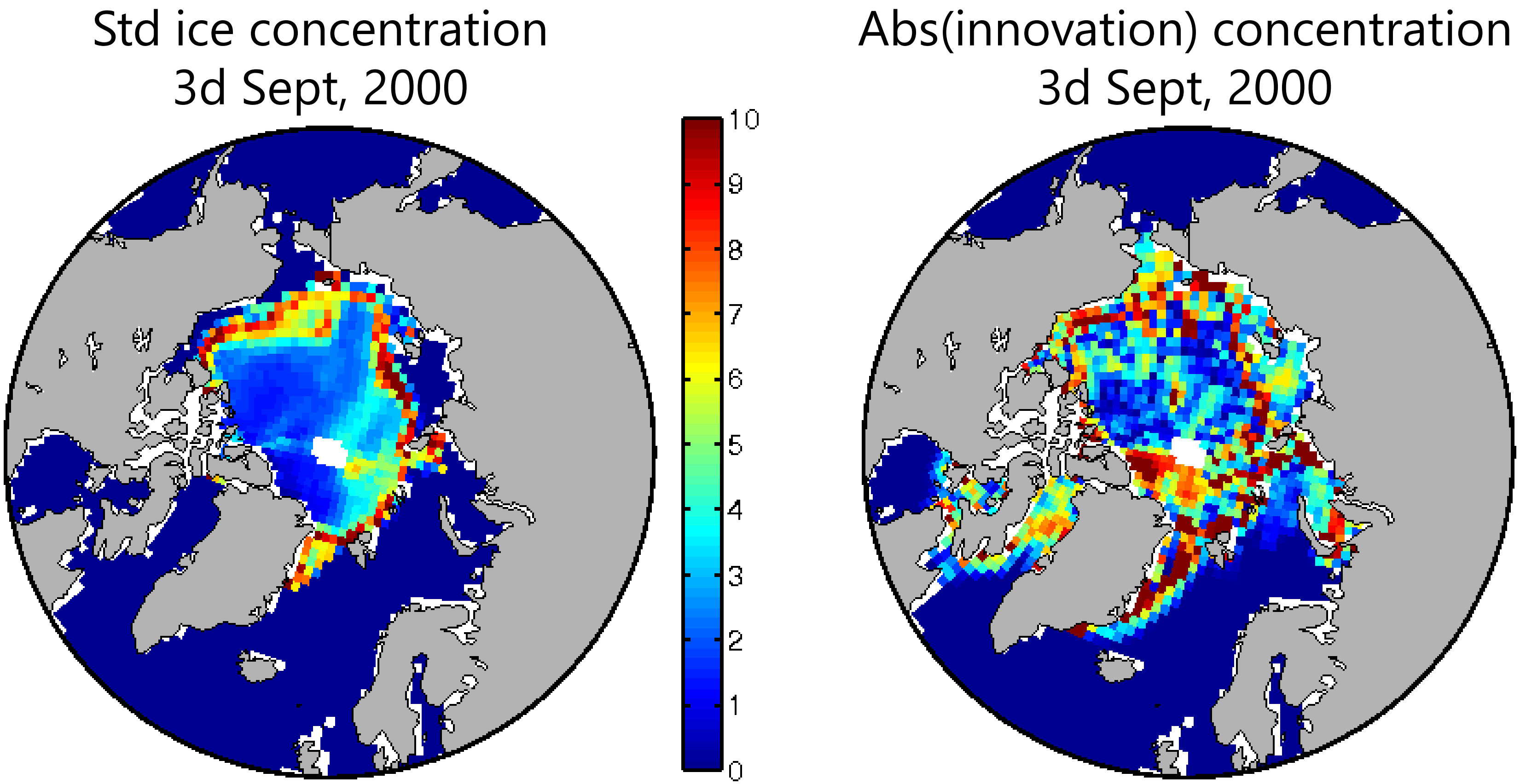
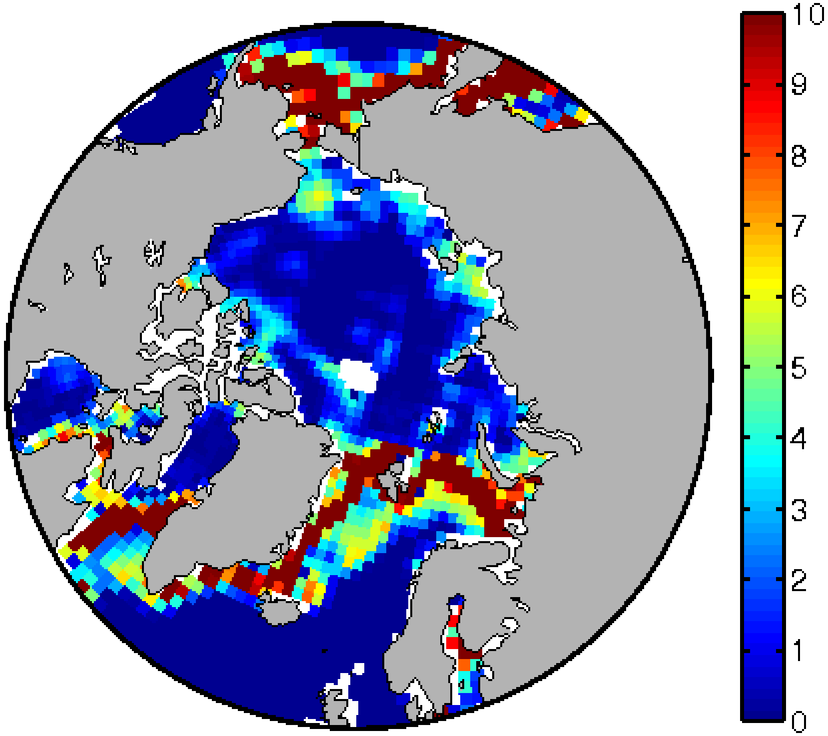


Simulating the right spread in the marginal ice zone is challenging



Simulating the right spread in the marginal ice zone is challenging

Std ice concentration
22nd March 1999



Abs(innovation) concentration
22nd March 1999