Optimised assimilation of sea ice concentration and implications for climate prediction

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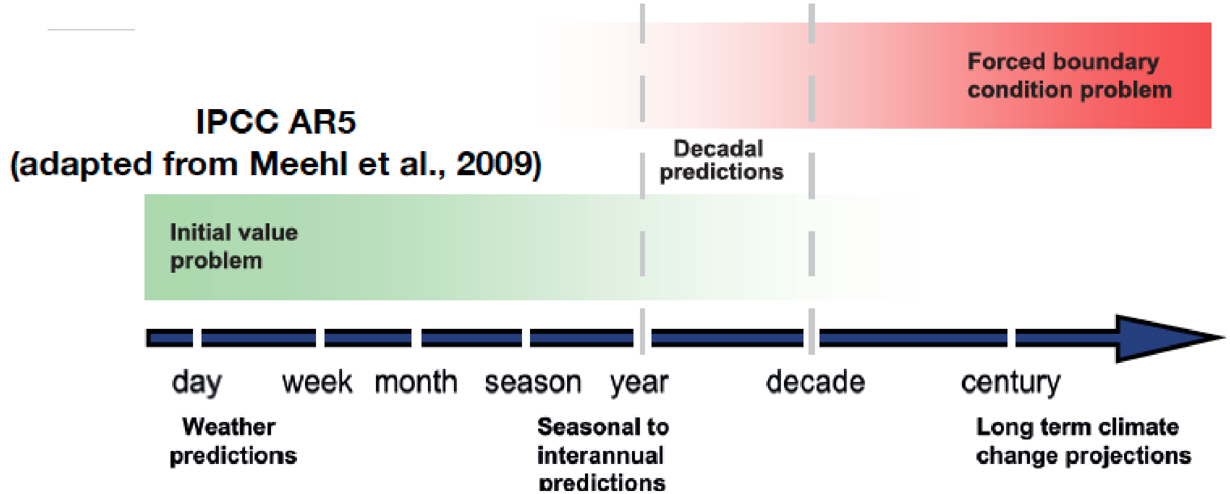
Workshop on observations and analysis of sea-surface temperature and sea ice for NWP and Climate Applications,
Reading, UK, *January 24th 2018*

Data assimilation of sea ice

Seasonal-decadal variability depends on initial condition & forcing



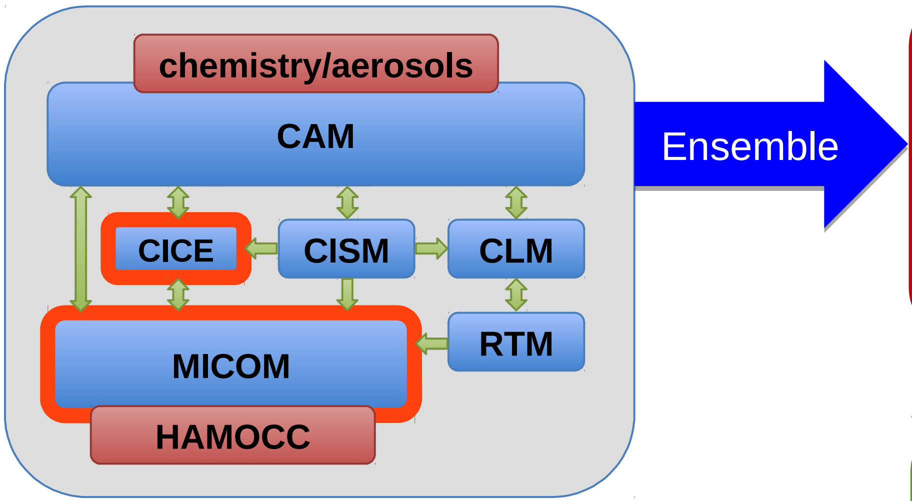
- Provides improved coupled reanalysis of the climate
- Enhances prediction skill on seasonal-to-decadal time scale
- Allows testing climate sensitivity to changes in sea ice

Bjerknes Centre for Climate Research

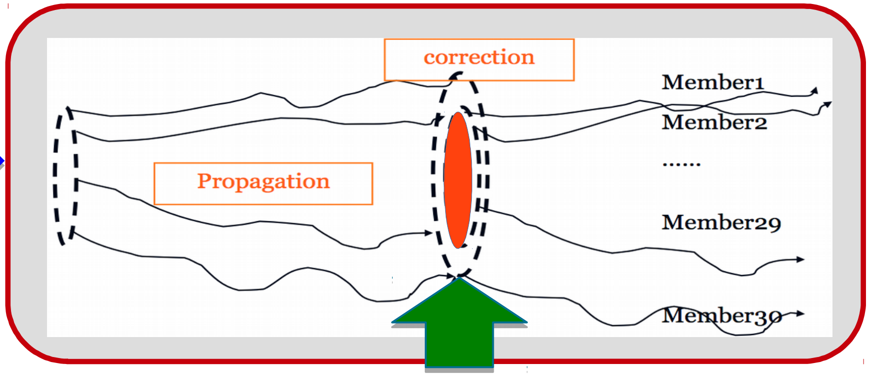
NERSC

Norwegian Climate Prediction Model NorCPM

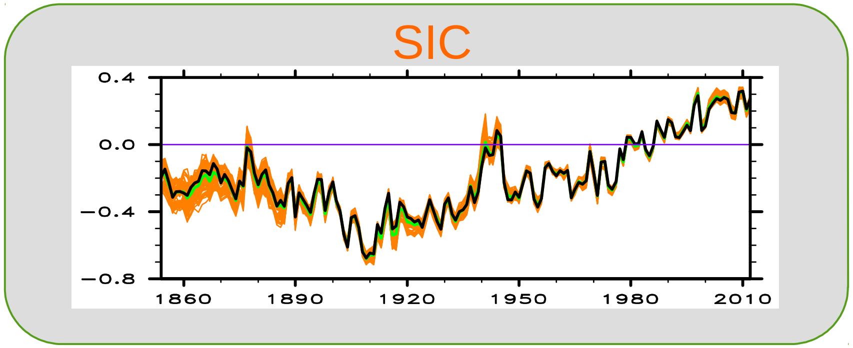
Norwegian Earth System model



Data assimilation (EnKF)



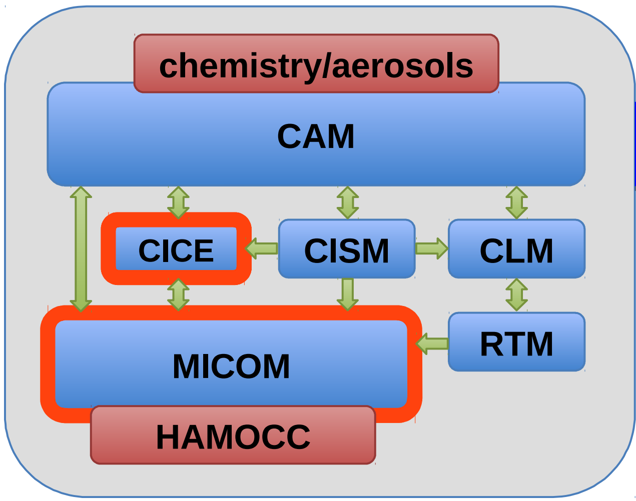
Observations

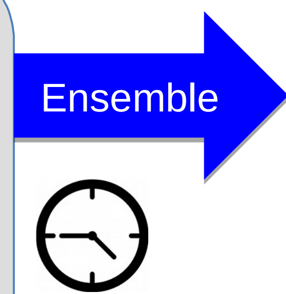


UNIVERSITY OF BERGEN uni Research Nansen Center, Bergen HAVFORSKNINGSINSTITUTTET INSTITUTE OF MARINE RESEARCH

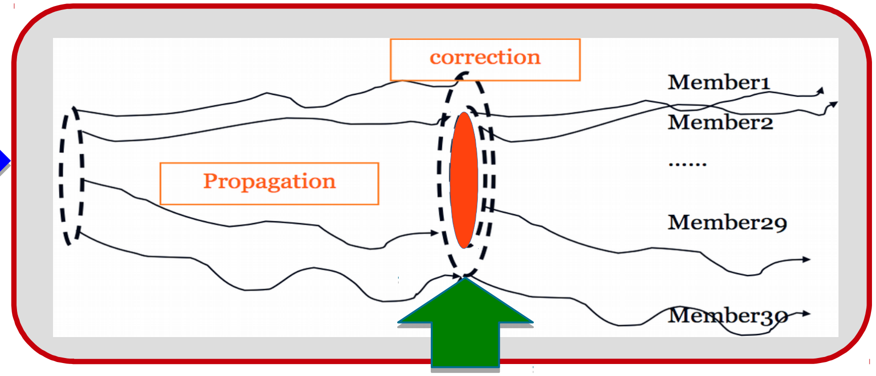
Norwegian Climate Prediction Model
NorCPM

Norwegian Earth System model



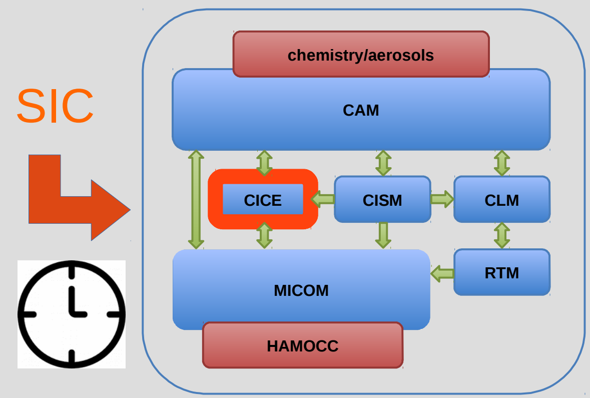


Data assimilation (EnKF)



Observations

Synthetic observations



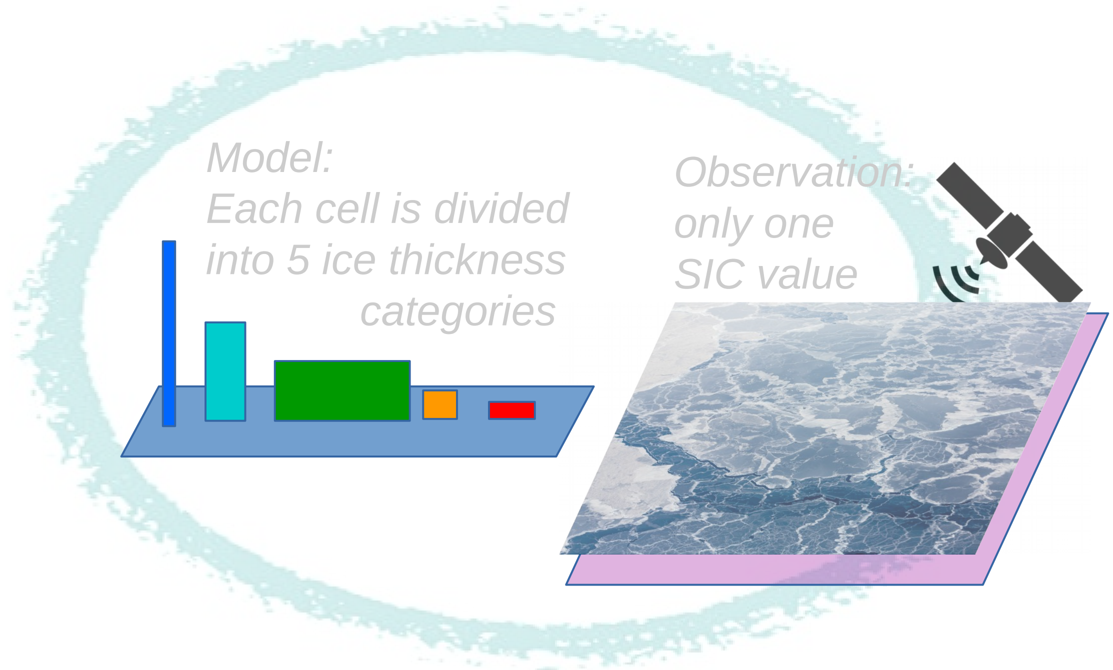
→ monthly assimilation
→ preindustrial

Twin experiment

→ **know the "truth" (ALL variables)**

→ **can study assimilation problem without model bias**

(Kimmritz et al. (in press))



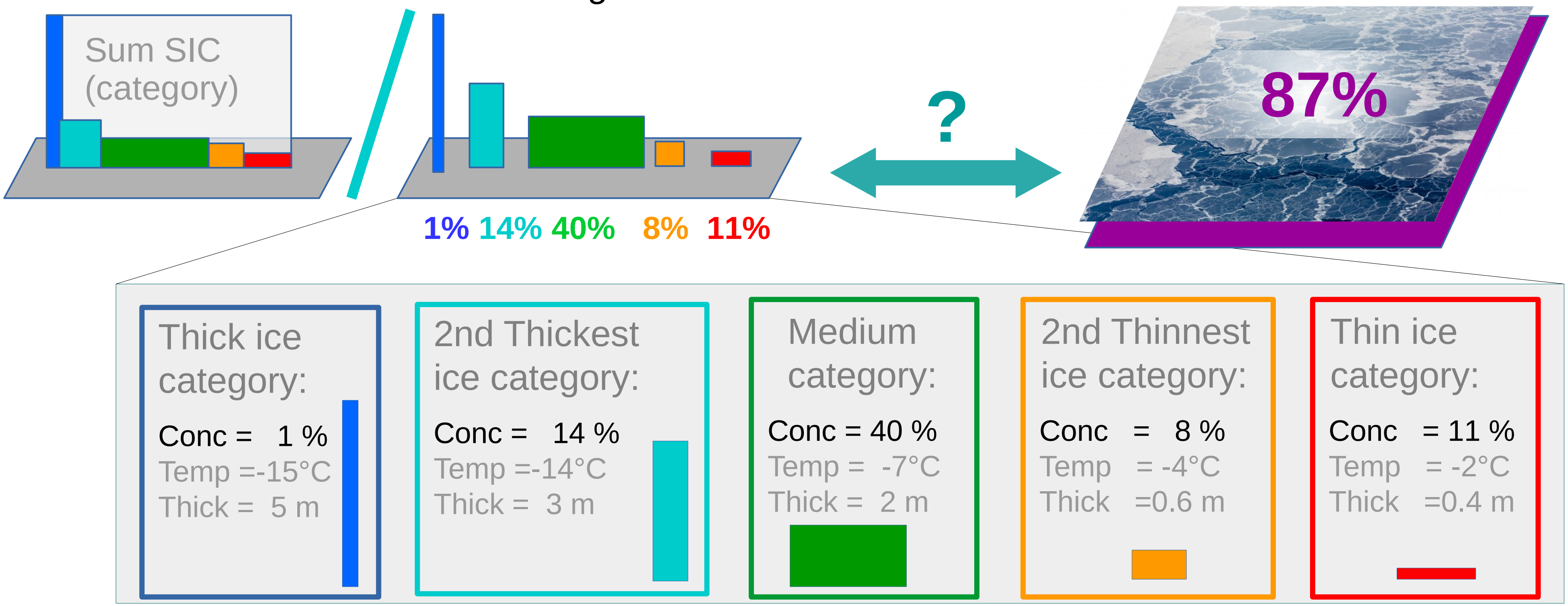
I. Key features regarding the sea ice model

Credit: National Snow and Ice Data Center

Multicategory sea ice model

Model:
Each cell is divided into
5 ice thickness categories

Observation:
only one SIC value



Total (model) concentration 74 % to be compared with observation (87%)

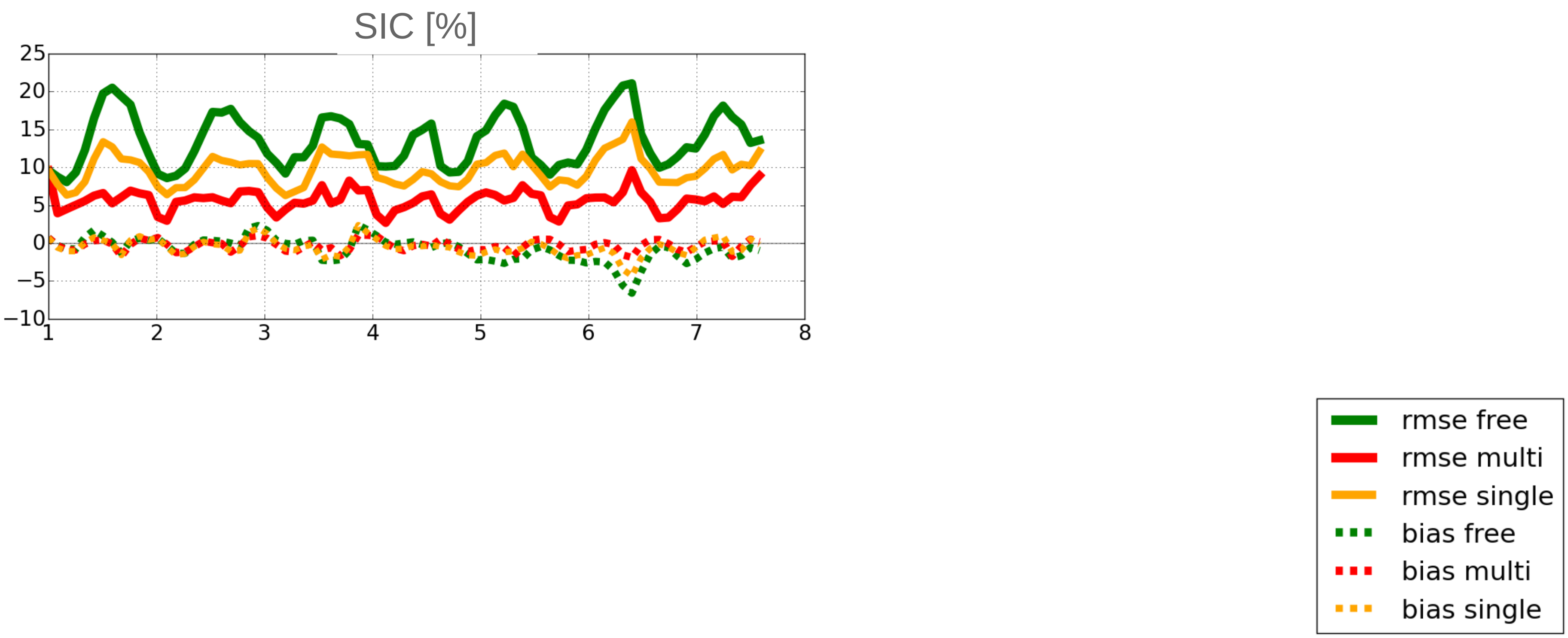
How should we update the individual category with DA?

A) the sum & uniformly stretch each individual category

B) each category individually from the innovation

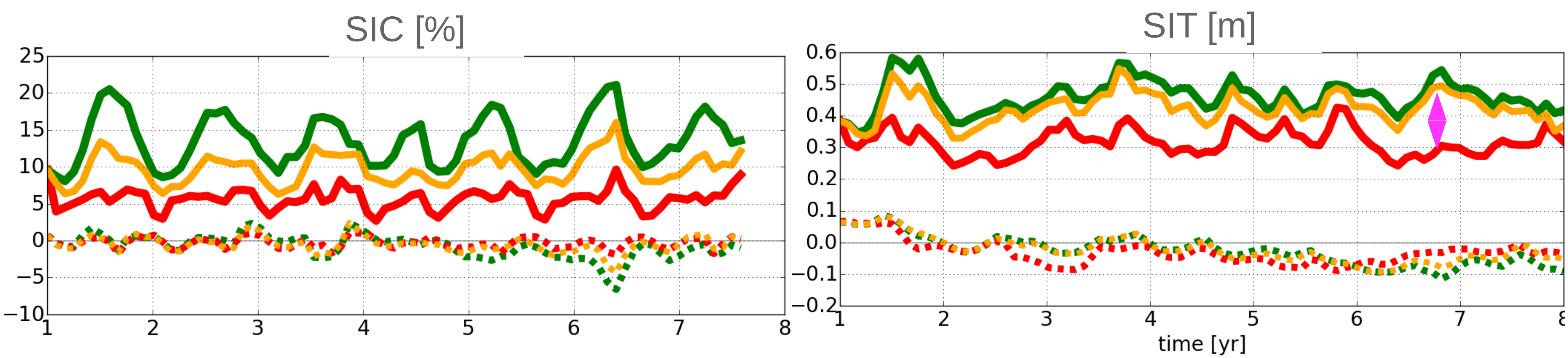
Multicategory sea ice model

Spatially averaged RMSEs, BIASes



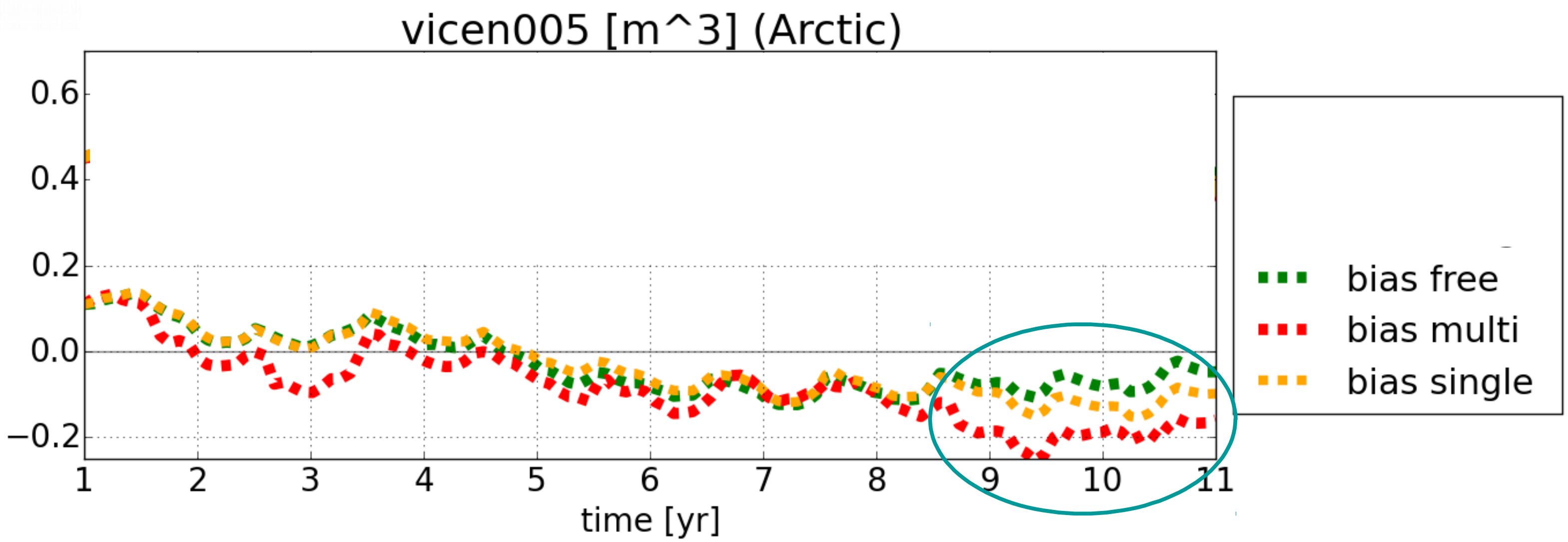
Multicategory sea ice model

Spatially averaged RMSEs, BIASes



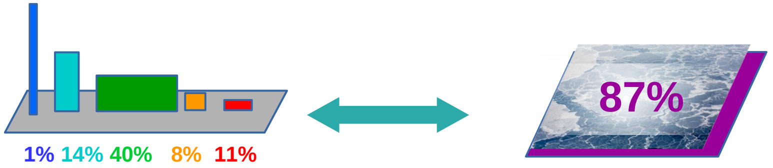
Assimilating in a **multicategory** sea ice model clearly **outperforms single category** with stretching

Degradation of the bias for thick ice

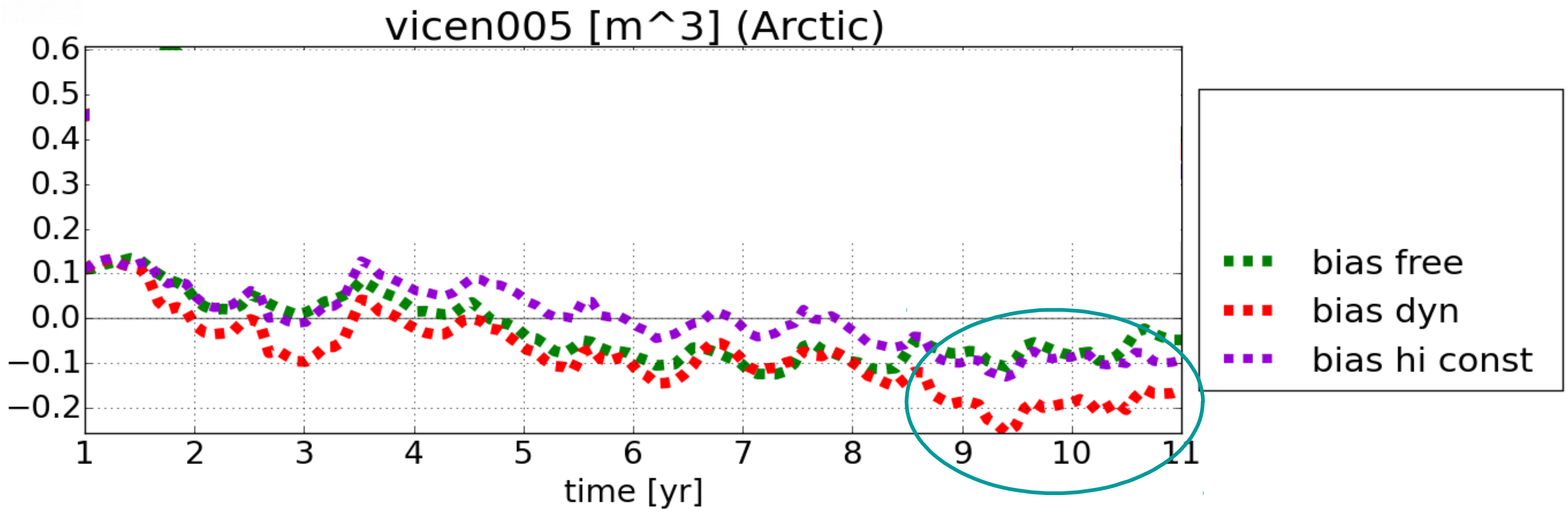


	dynamic
state vector (EnKF)	aicen(1:5), vicen(1:5)
postproc. vicen(1:5)	cut due to hicen(1:5)

We create unphysical values that need to be postprocessed!

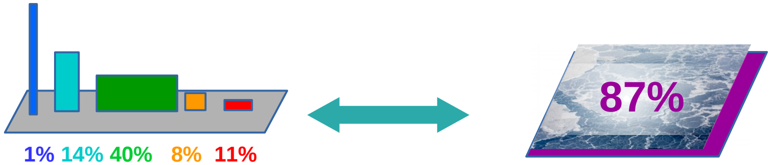


Degradation of the bias for thick ice



	dynamic	hi constant
state vector (EnKF)	aicen(1:5), vicen(1:5)	aicen(1:5)
postproc. vicen(1:5)	cut due to hicen(1:5)	scale s.th. hicen(1:5) preserved

- removes the bias degradation in thick ice
- no degradation of performance in total thickness

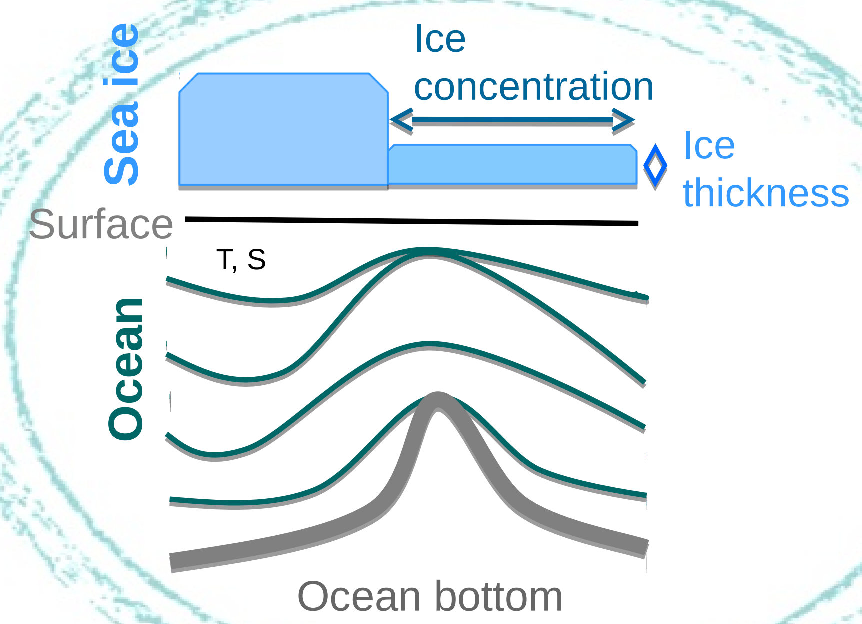


Take home msg: sea ice component

→ Update dynamically in *all* ice thickness classes
instead of the aggregated variables (+ stretching)!

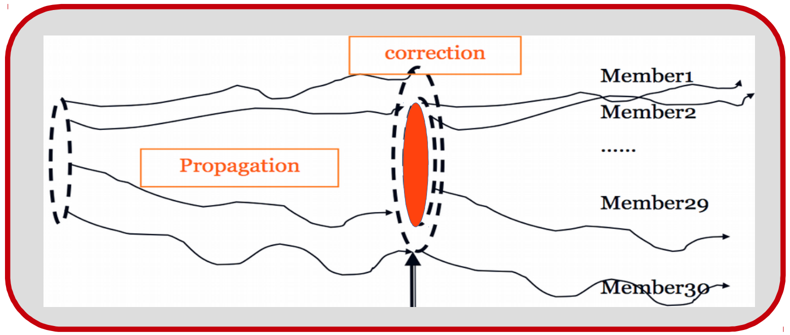
→ Limit postprocessing
Choose state vector and postprocessing wisely
to avoid a drift in the biases!

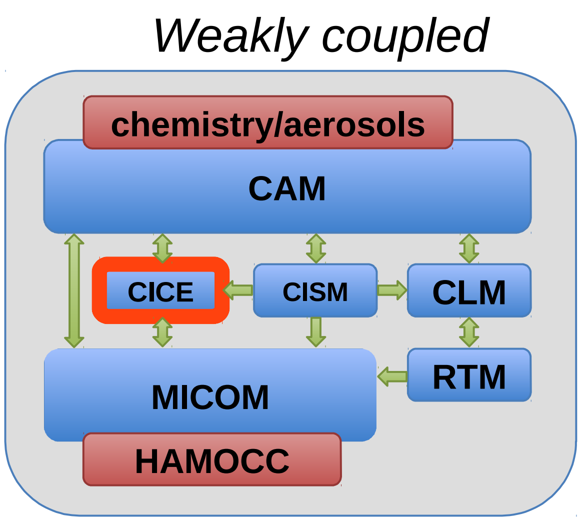
II. Key features regarding the coupling with other ESM components

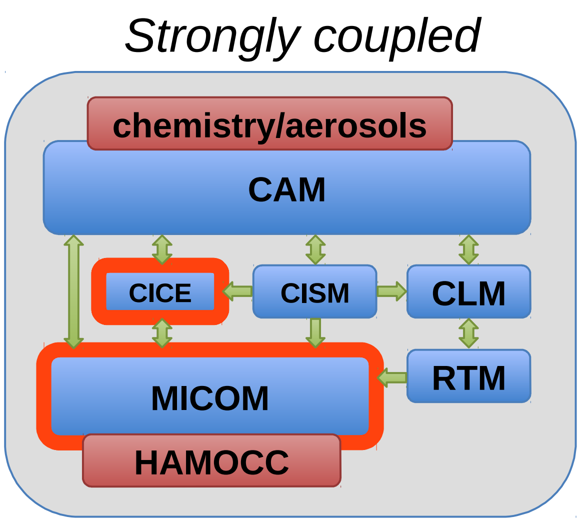


Credit: National Snow and Ice Data Center

Constraining sea ice: a coupled problem





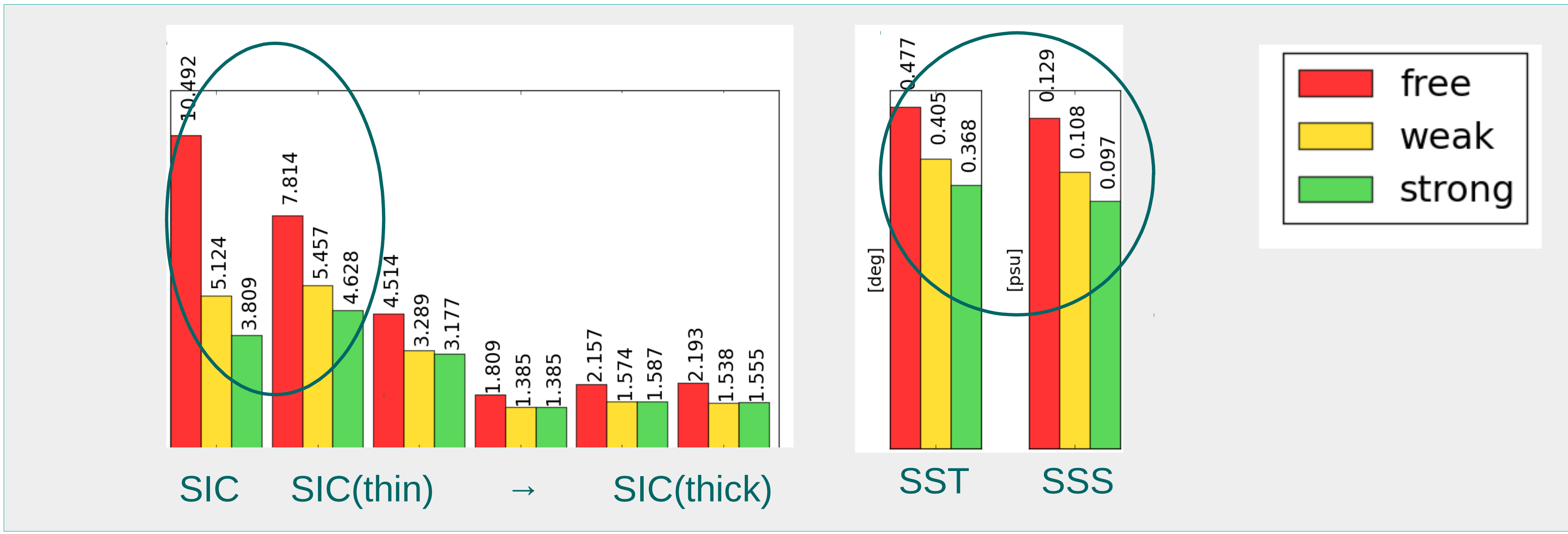


No update of ocean state during assimilation!

Dynamical update of ocean state in mixed layer (temperature,salinity) during assimilation!

Constraining sea ice: a coupled problem

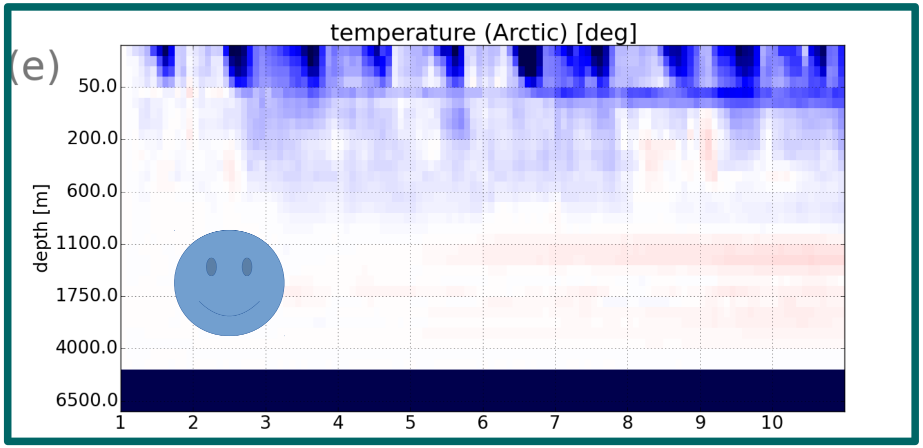
Space&time averaged rmse's in the Southern Ocean

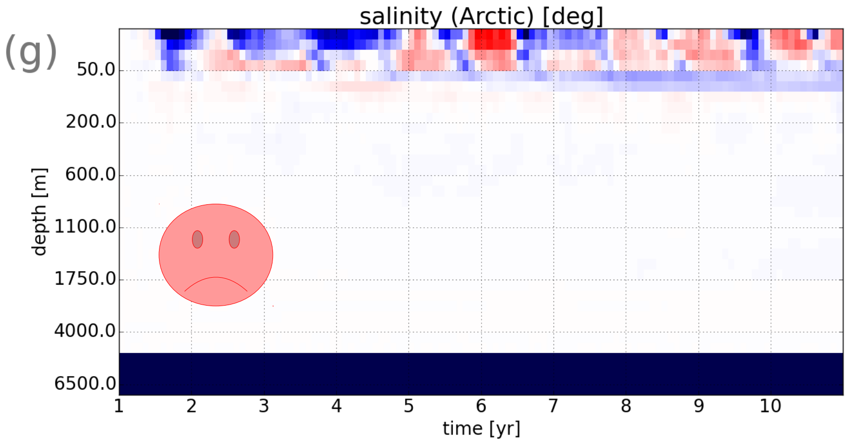


Strongly coupled gives remarkable improvements in thinnest category & in ocean surface states

Constraining sea ice: a coupled problem

Differences in RMSE between
weakly coupled & free



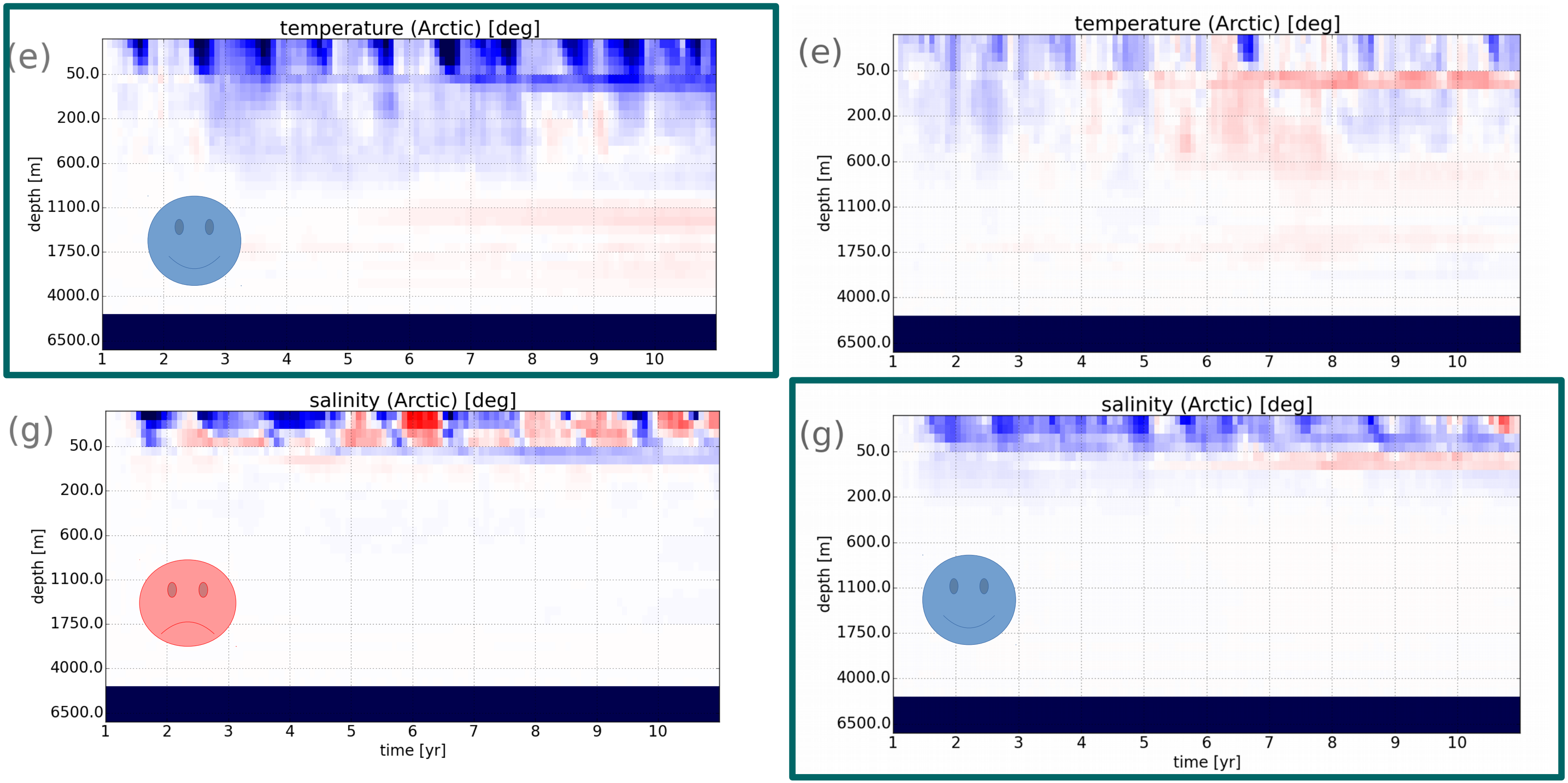


weakly coupled already beneficial for temperature,
but not for salinity

Constraining sea ice: a coupled problem

Differences in RMSE between
weakly coupled & free

Differences in RMSE between
strongly & weakly coupled



weakly coupled already beneficial for temperature,
but not for salinity

Take home msg: coupling with the ocean

→ only updating ice (ocean adjusts itself)

- beneficial – even for ocean temperature
- not well captured salinity in upper Arctic ocean

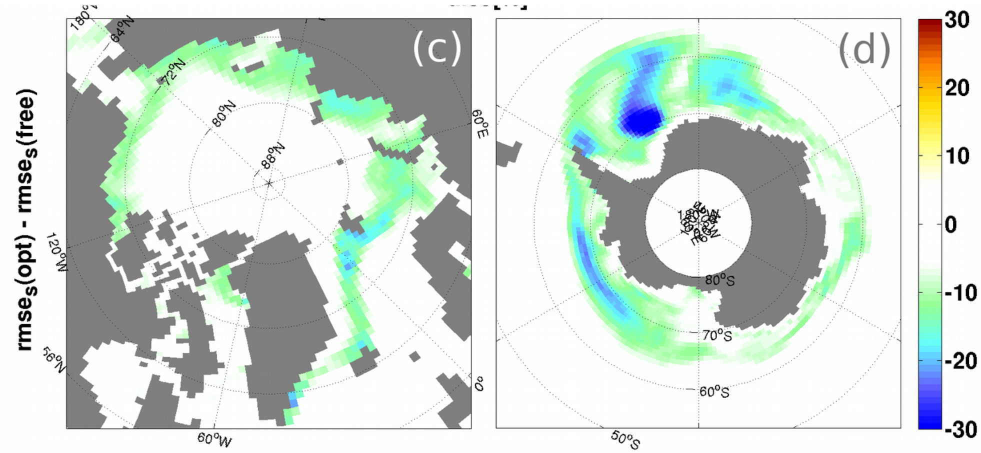
→ dynamically updating ice *and* ocean

- improved thin ice states & ocean state
  (partic. salinity in Arctic and temp. In Southern Ocean)

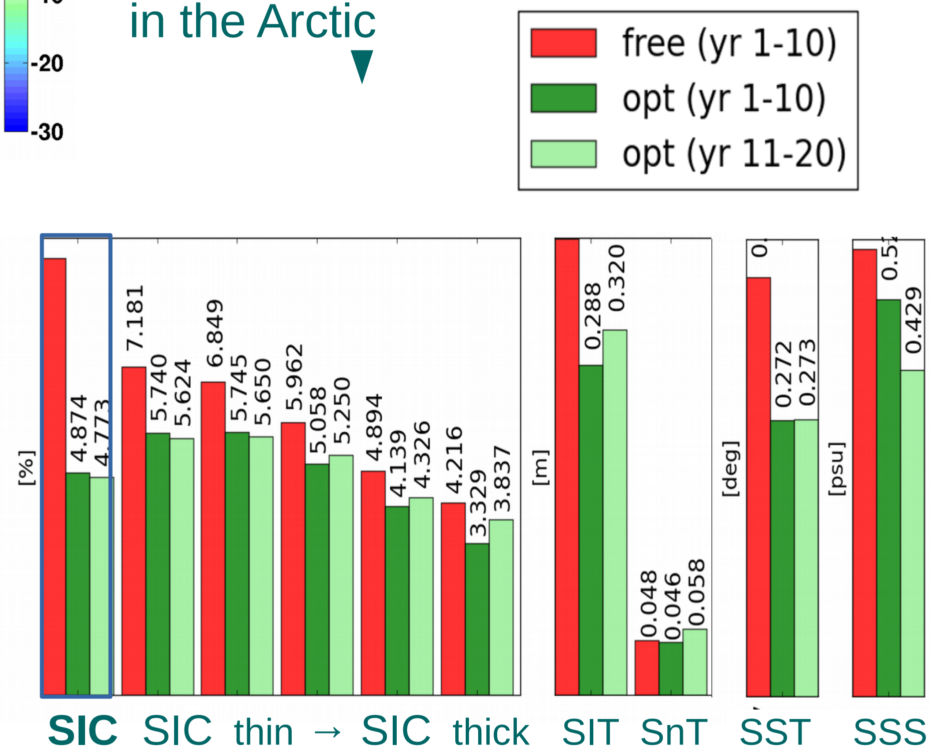
III. Gains of optimal assimilation strategy

Data assimilation of SIC in NorCPM
Optimal strategy

Time averaged RMSE of SIC



Time and space averaged RMSEs in the Arctic

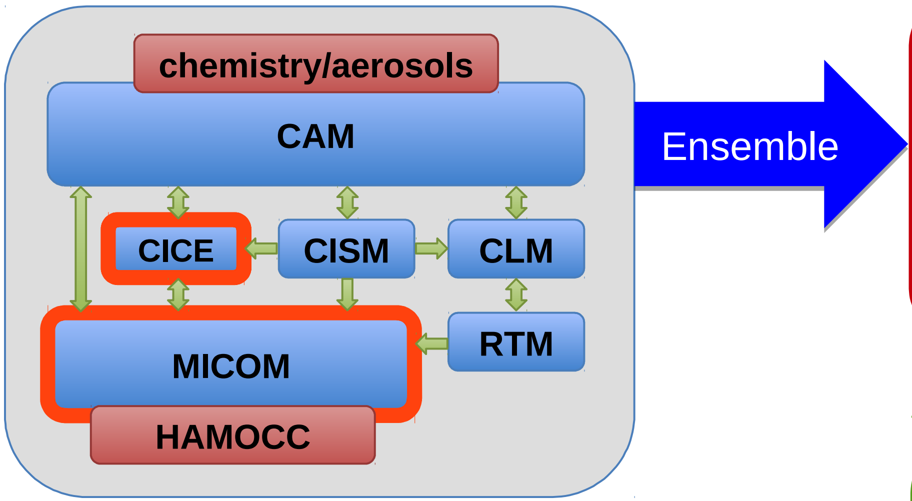


Much of sea ice and ocean variability can be constrained just with aggregated ice concentration in a reliable way!

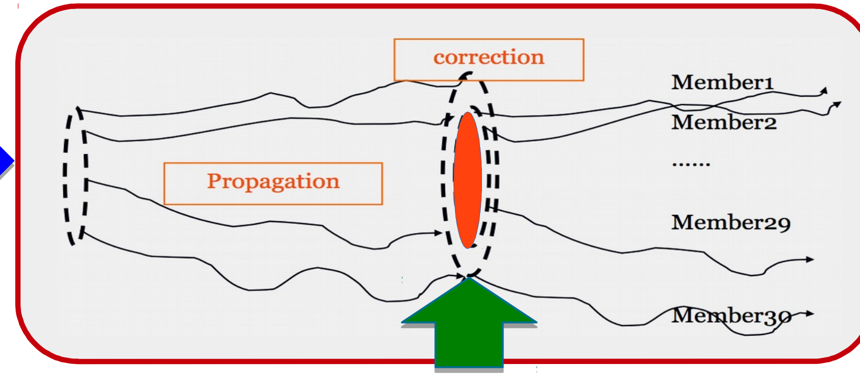
IV. Using realistic observations

Norwegian Climate Prediction Model NorCPM

Norwegian Earth System model

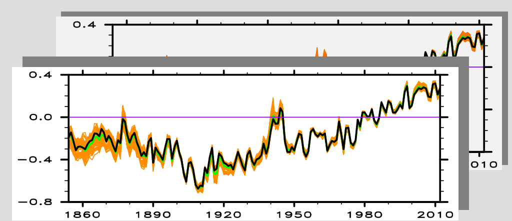


Fullfield *Data assimilation (EnKF)*

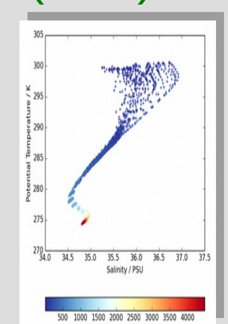


Observations

SST, SIC (HadISST2)

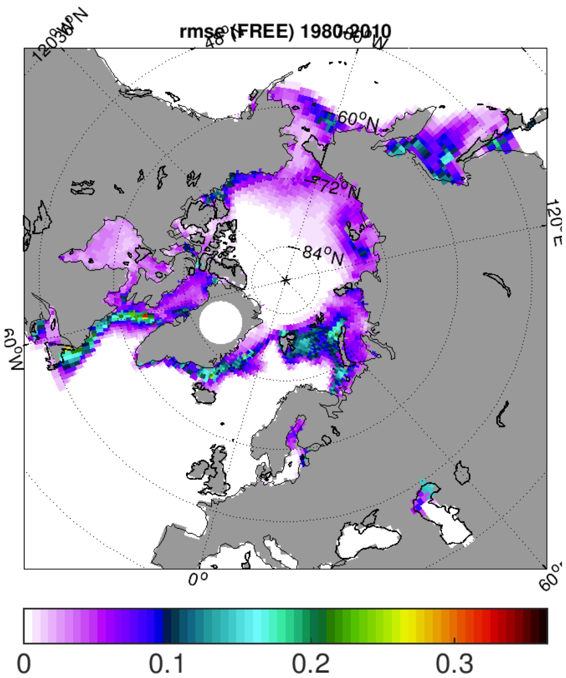


T,S profiles (EN4)

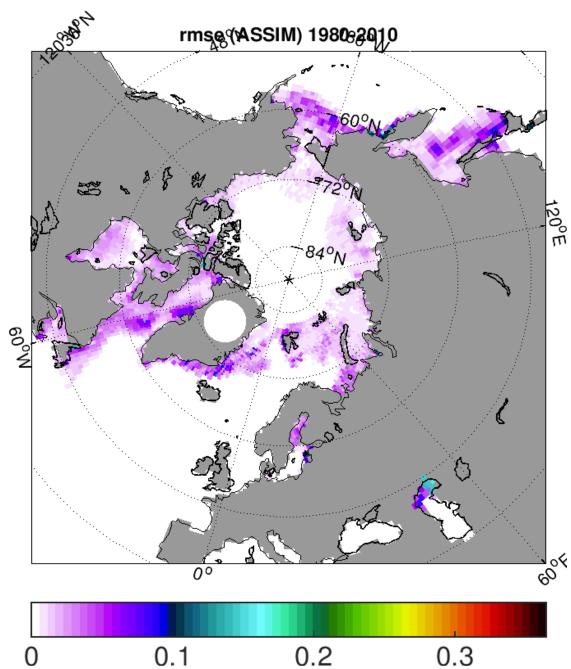


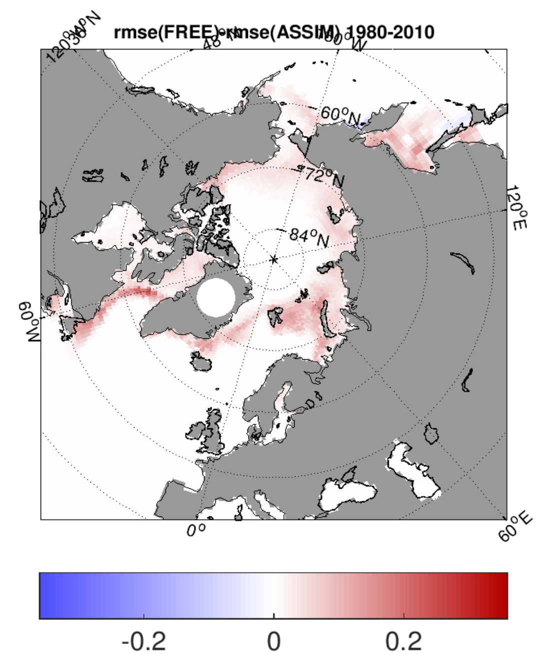
SIC(HadISST2)

rmse(FREE)



rmse(ASSIM)



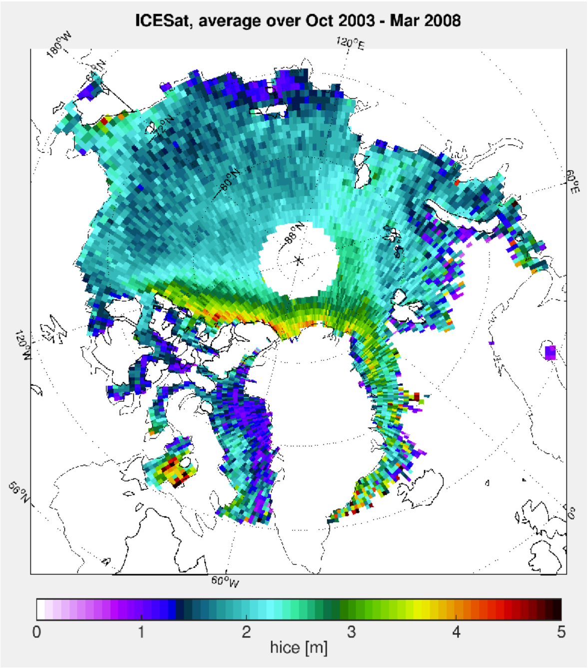


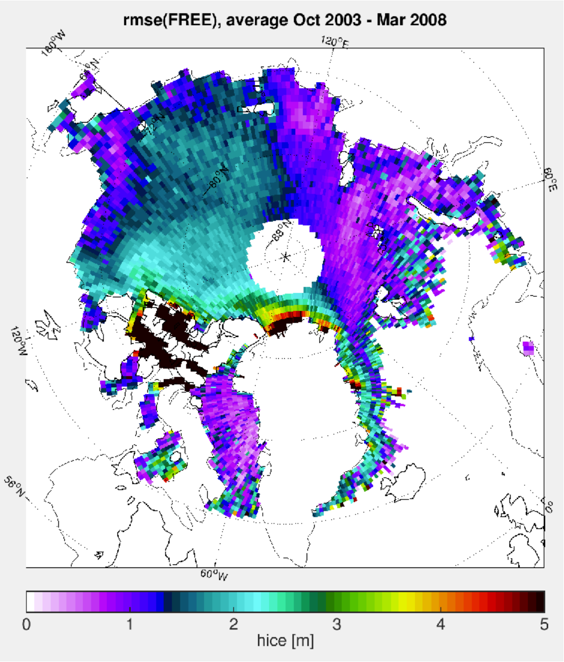
SIT (ICESat 2003 - 2008)

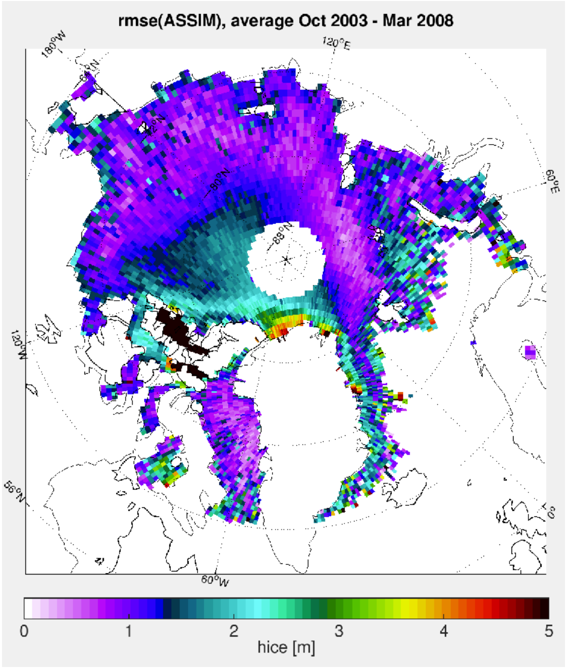
Observations: ICESat

mse(FREE)

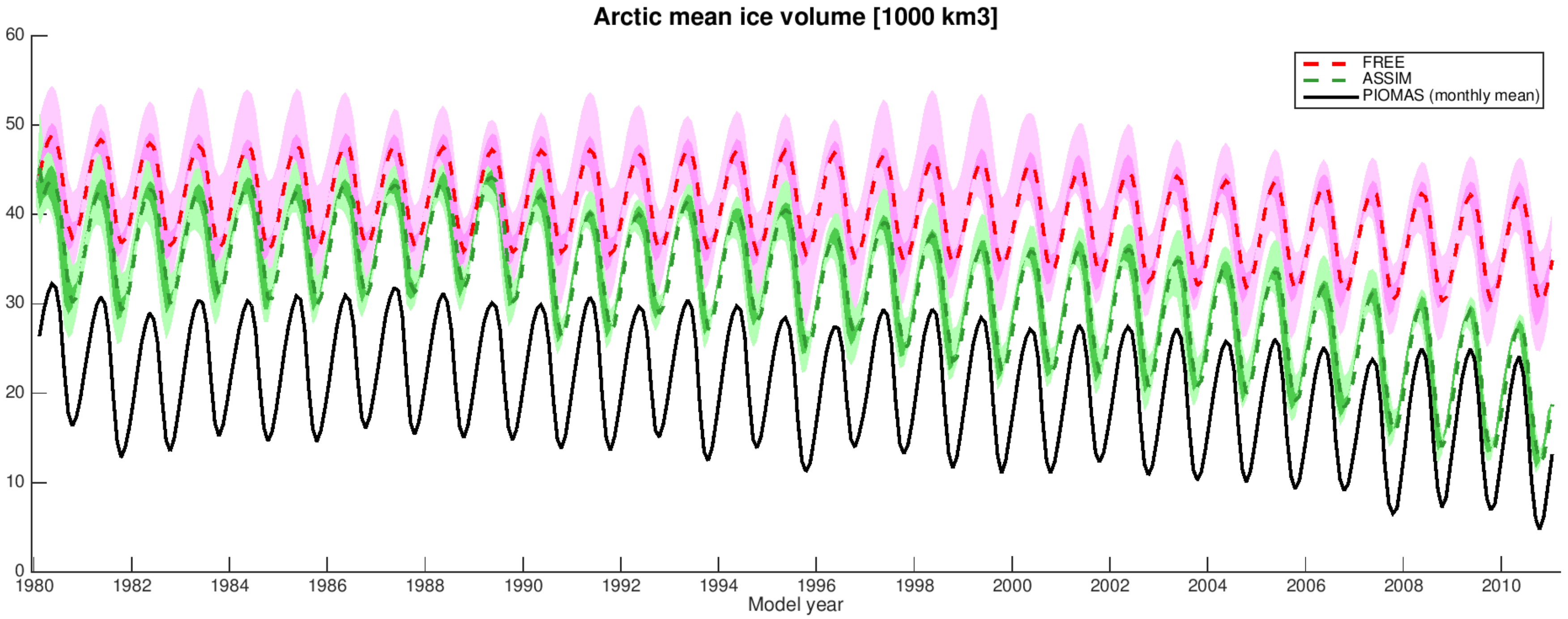
rmse(ASSIM)





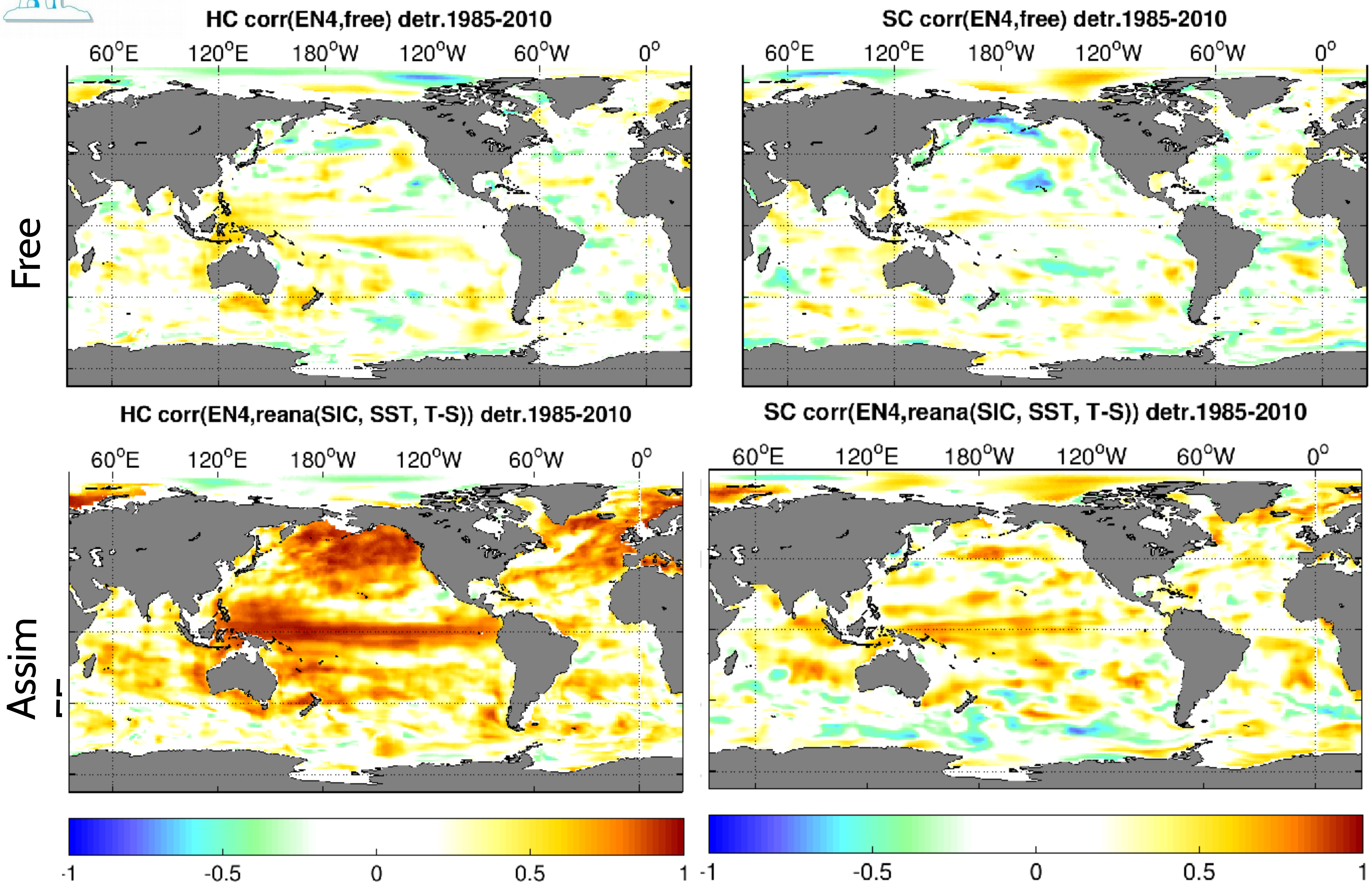


SIVol Piomas



Correlation of **Heat content, salt content** with observations EN4 (0-200m)

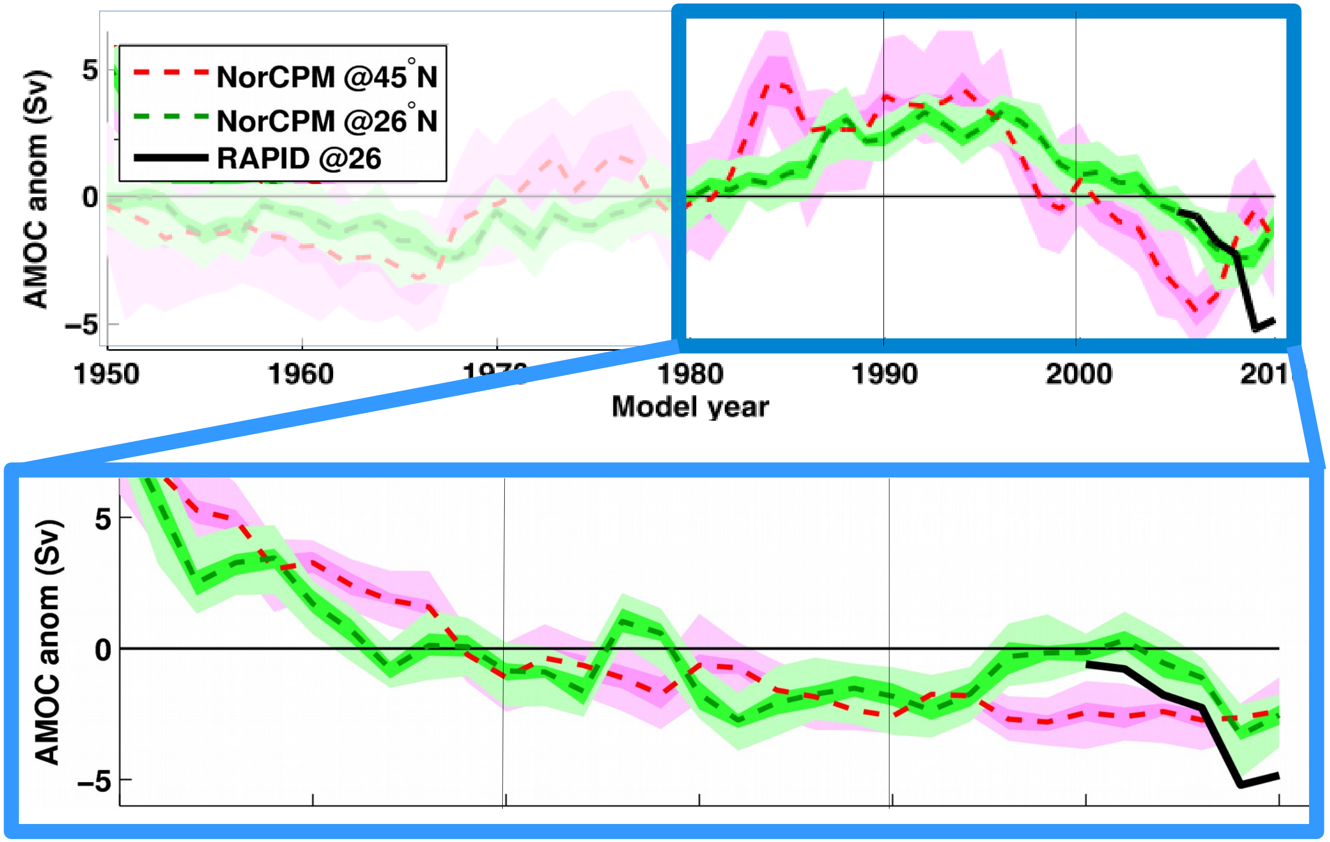
(1985-2010)



Heat Content

Salt Content

AMOC



AMOC anomaly
SST**A** assim
Counillon et al. 2016

AMOC anomaly,
CICE,SST,S,T
fullfield assim

V. Summary

Summary

Much of sea ice variability can be constrained just with aggregated ice concentration (reliable!)

→ Sea ice model

Multicategory is beneficial over single category assimilation

Limit/smart postprocessing to avoid drift in model bias

→ Coupling with the ocean component

Strongly coupled outperforms weakly coupled for thin ice

Assimilation into deep ocean only has a minor impact,
and is not suggestable for real observations

→ Assimilation **Fullfield SIC, SST, ST**

Reanalysis data: beneficial for sea ice state, heat+salt content, AMOC

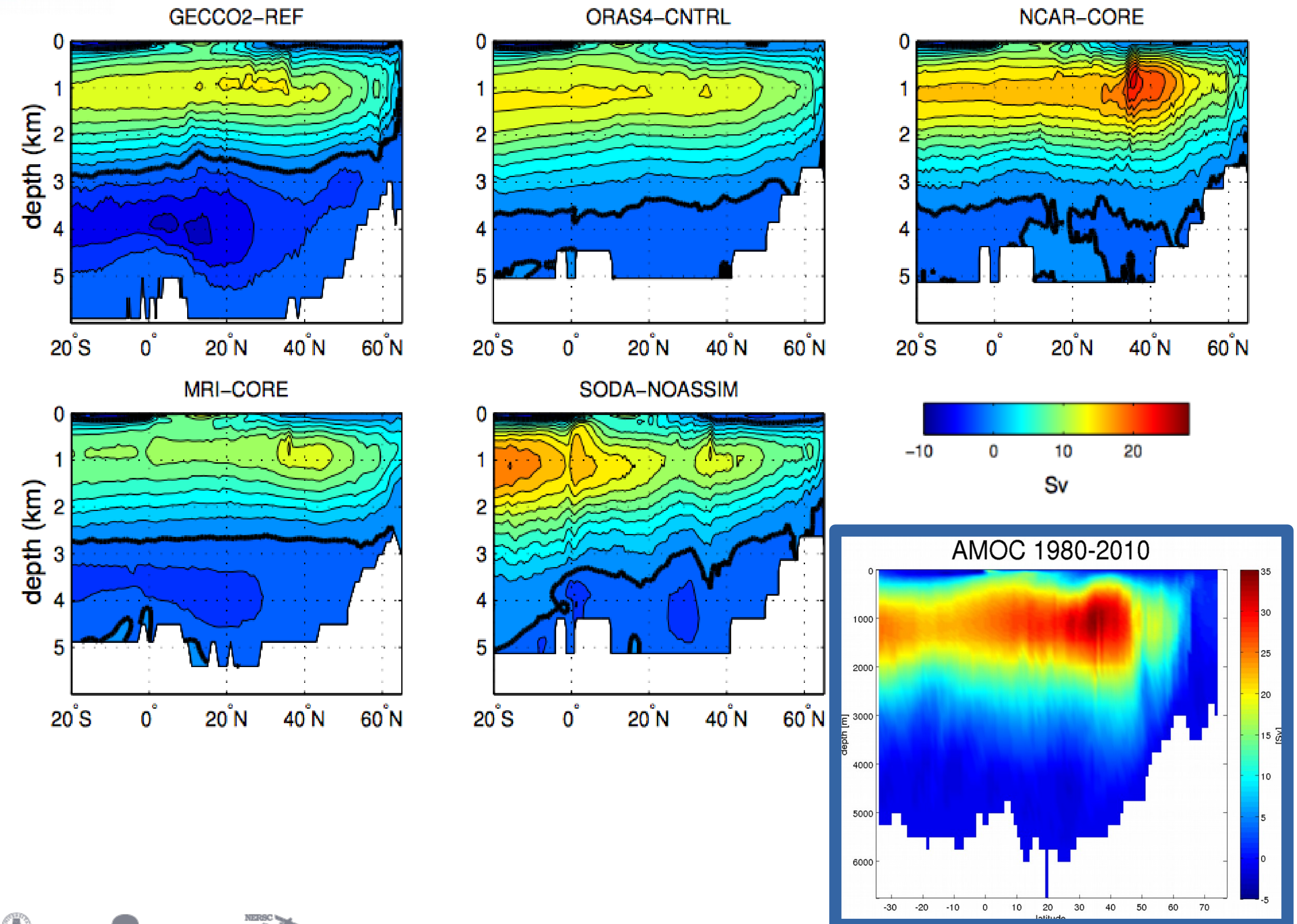
Seasonally not well represented

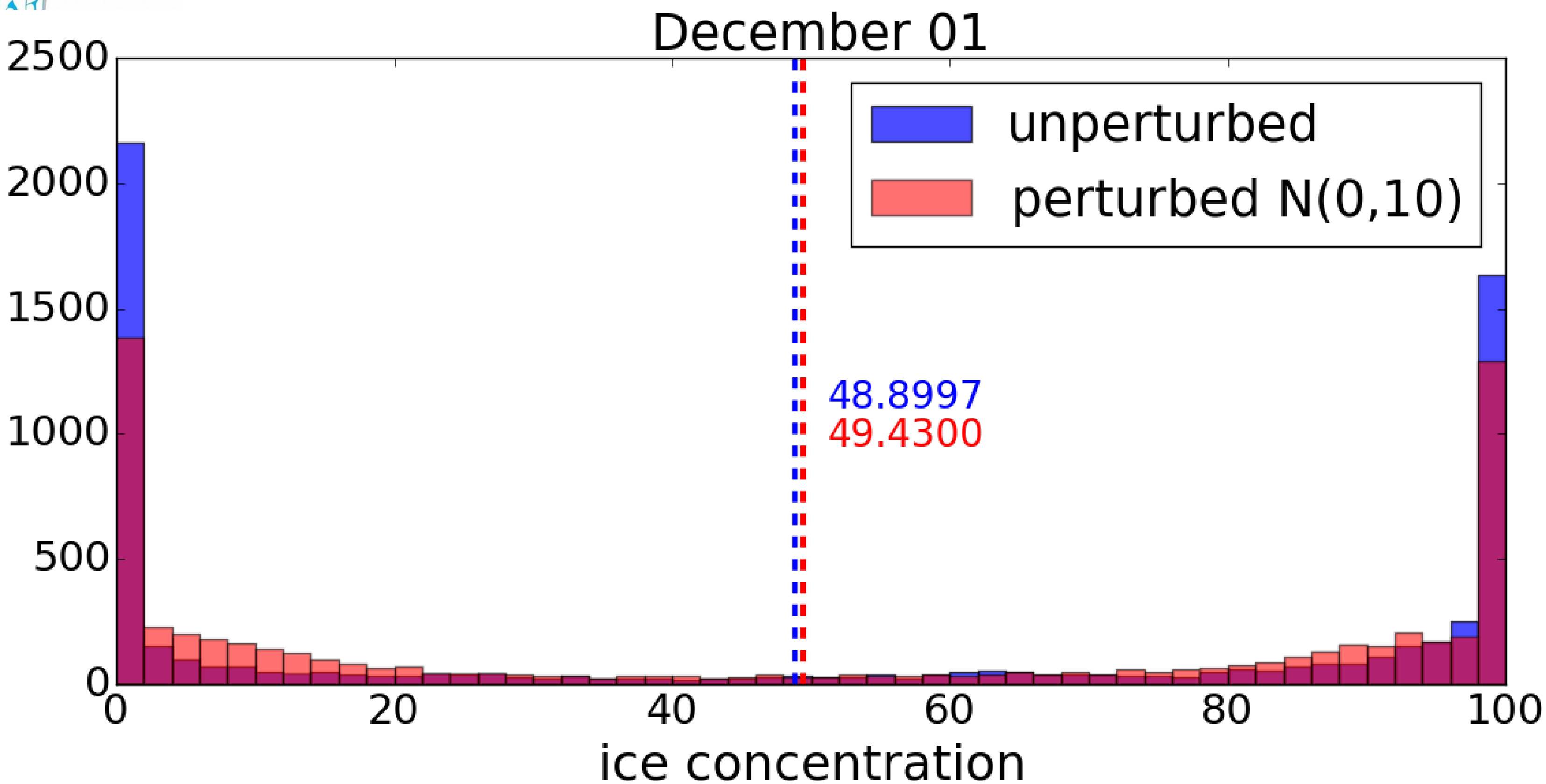
Thanks!

Appendix

AMOC : intermodel comparison

pointwise maximum over all considered years of ensemble mean





- → **sea ice concentration: nonGaussian distributed**
- → **perturbation of observations and postprocessing changes mean**
- → **introduction of bias**
- → **not clear assessment of assimilation techniques**

Multicategory sea ice model

	single-category	multi-category
aicen(1:5) vicen(1:5)	**sum** → EnKF **sum** → EnKF	EnKF EnKF

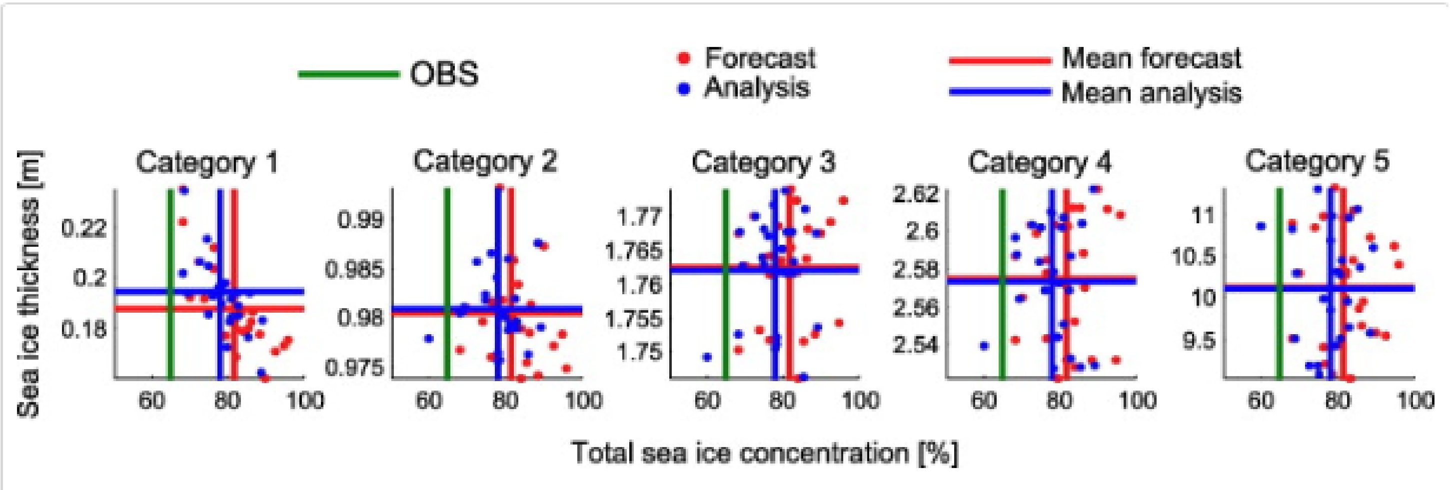
Temperature, salinity in mixed layer: EnKF

Post processing for ice:

- Basic adjustment (dependent on aice>0, thickness categories)
- Scaling of ice/snow energy and snow thickness
- due to changes in vicen(1:5) and aicen(1:5)

- Sea ice state

Using LIM3

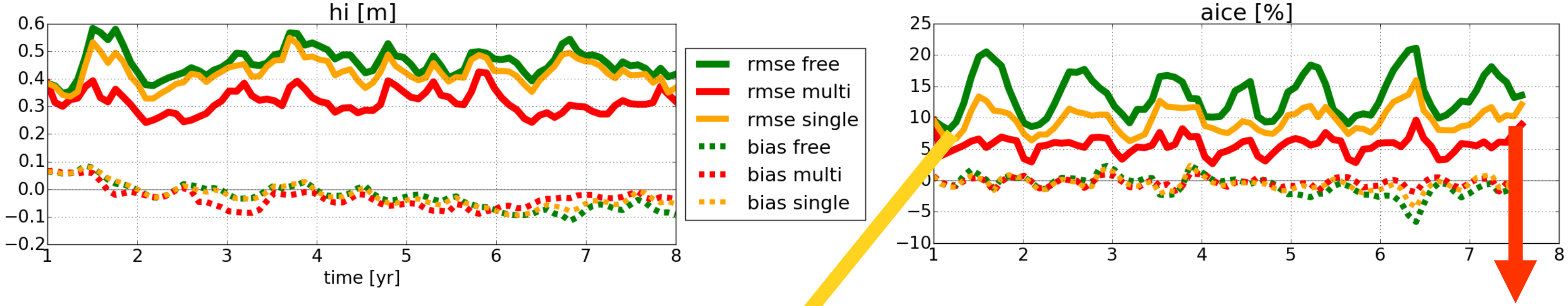


Massonnet et al. 2015

Beneficial: use correlations for each category

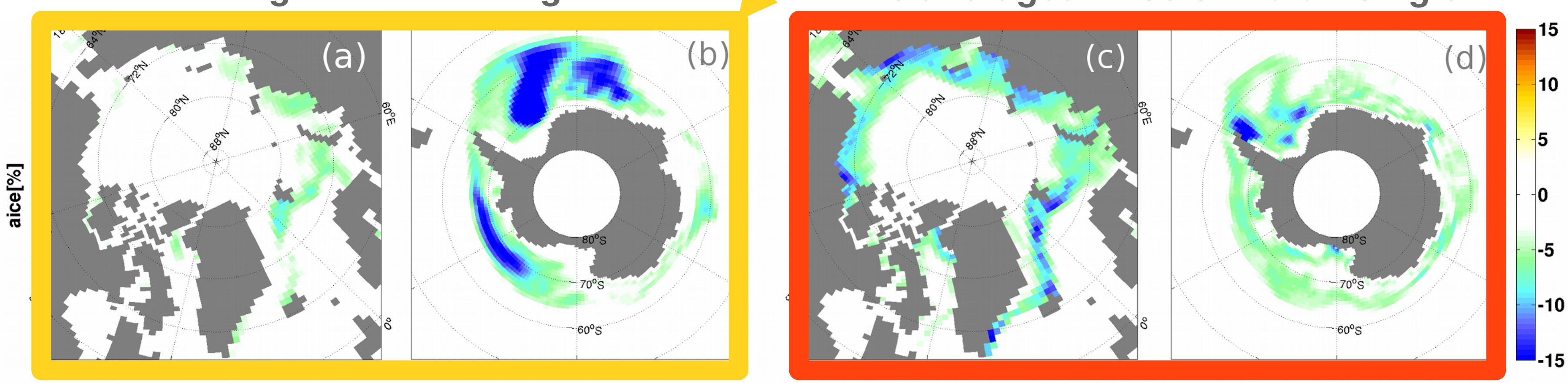
Multicategory sea ice model

Space averaged rmse's and biases
For free (green), single category (yellow) and multi category (red)



Time averaged rmse's: single - free

Time averaged rmse's: multi - single



singlecategory states in EnKF
→ improvement mostly in thin ice

multicategory states in EnKF
→ improvement in every single category
→ *largest for thick ice categories*

Twin experiment

coupled covariance

	• weak	prescribed	strong
aicen(1:5) vicen(1:5)	EnKF	EnKF	EnKF
temp in mixed layer saln in mixed layer	no update	diagnosed Temp = -1.8, if ice Temp > -1.8+eps, if no ice	EnKF

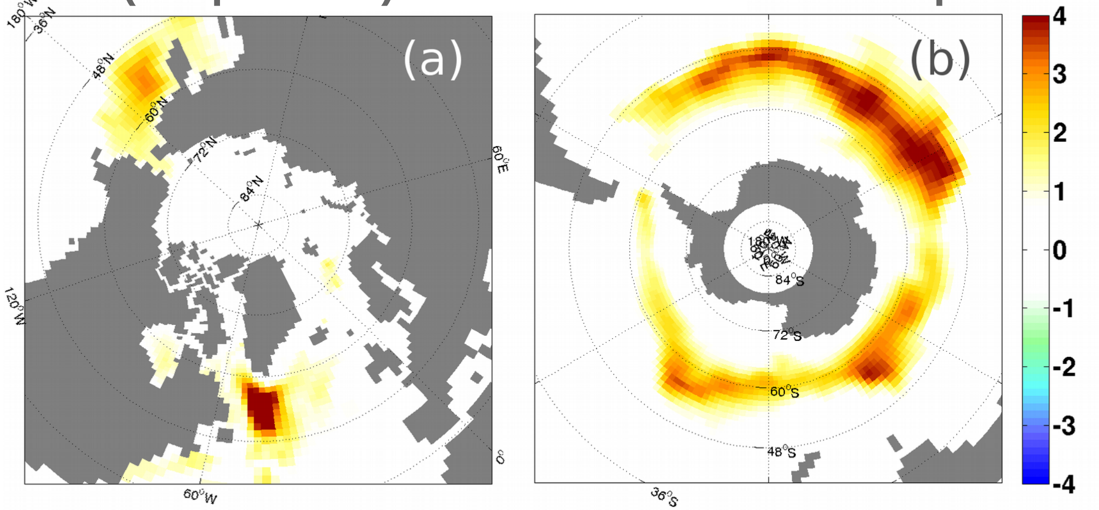
Constraining sea ice: a coupled problem
Is it sufficient to *crudely* adapt the ocean?

Time averaged RMSE(temperature): Differences between coupled and free

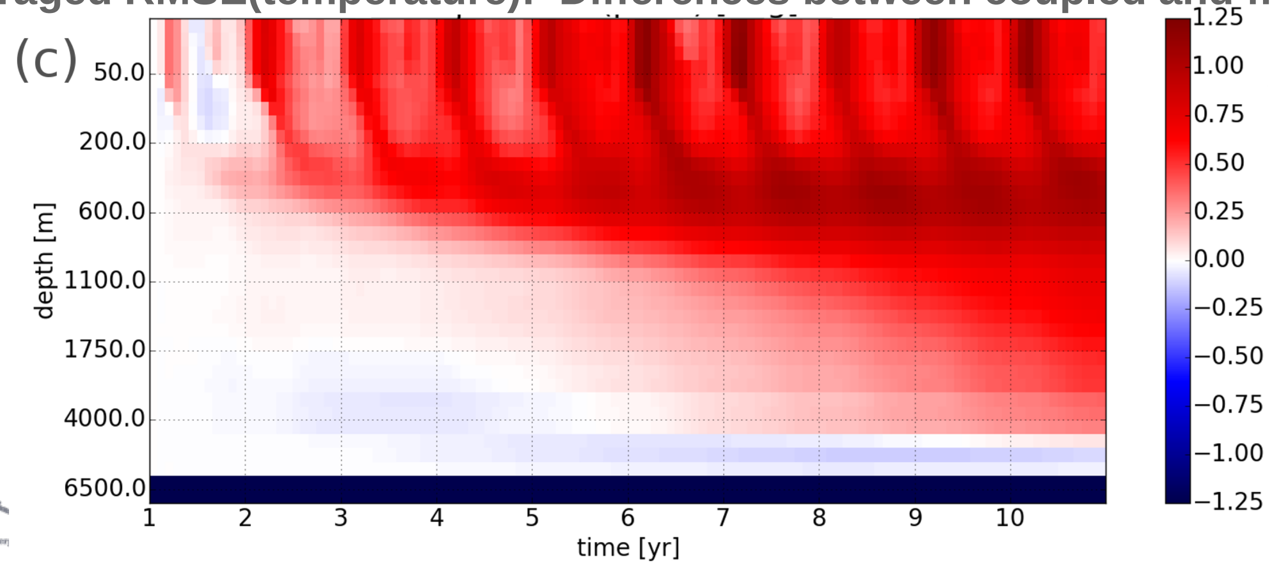
Where is ice,
assure T=-1.8degC

Where is no ice,
assure T > -1.8degC

Keep salinity untouched

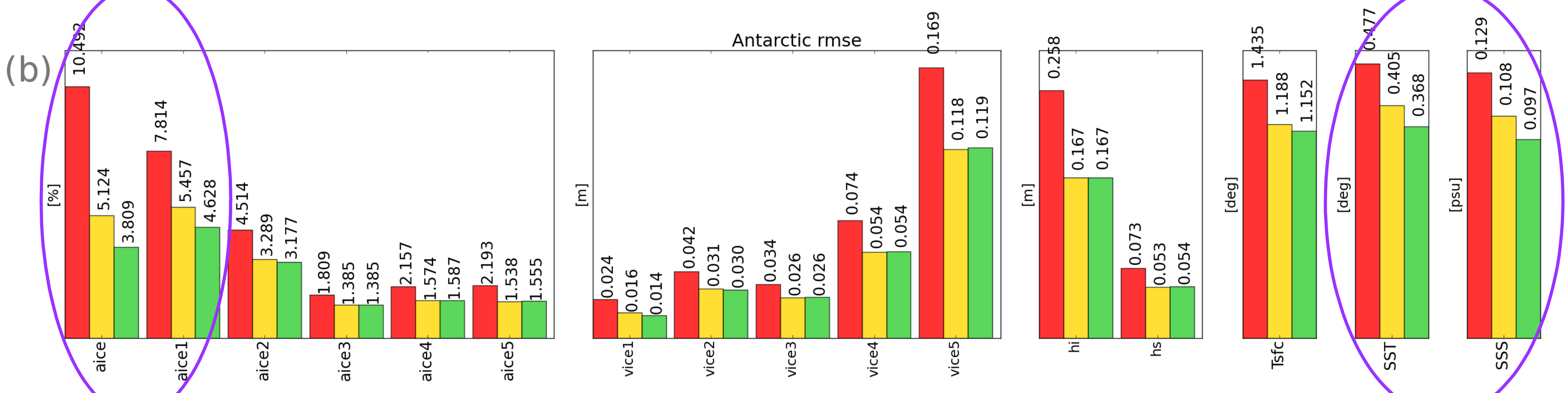


Spatially averaged RMSE(temperature): Differences between coupled and free



Constraining sea ice: a coupled problem

Space&time averaged rmse‘s in the Southern Ocean
for free, weakly coupled and strongly coupled (mixed layer)

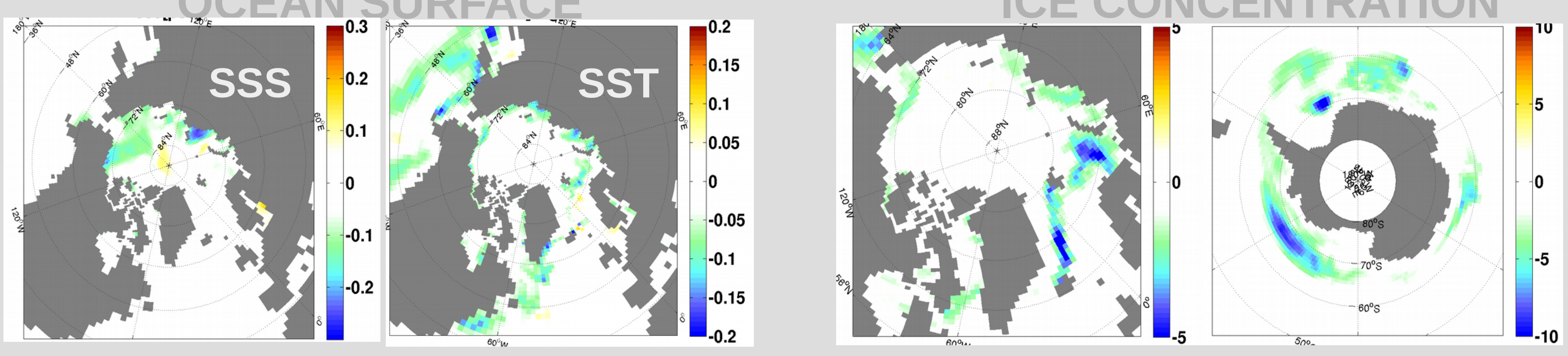


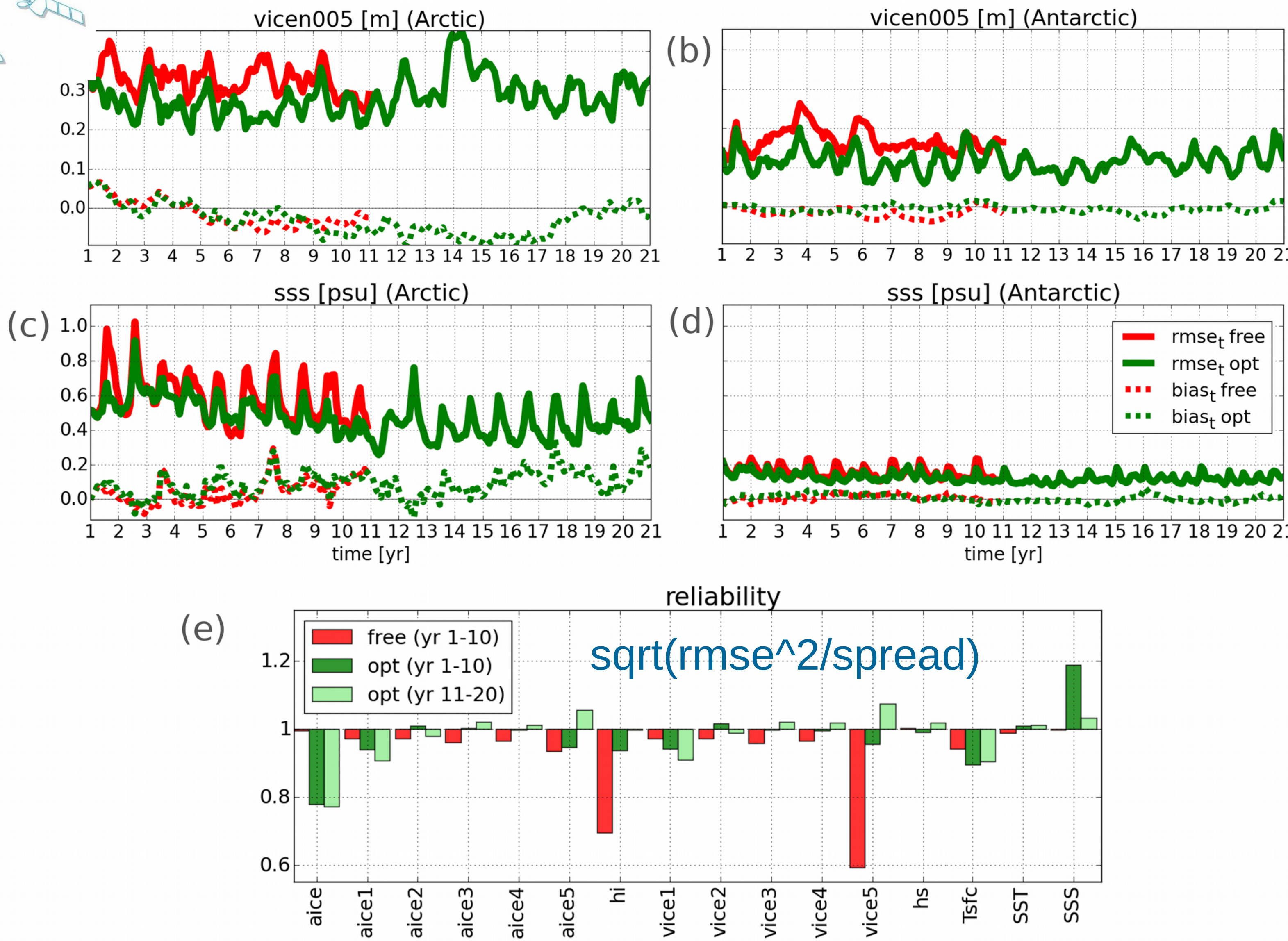
improvement of strong in thinnest ice category and in ocean surface states

Time averaged rmse‘s: differences between strongly and weakly coupled

OCEAN SURFACE

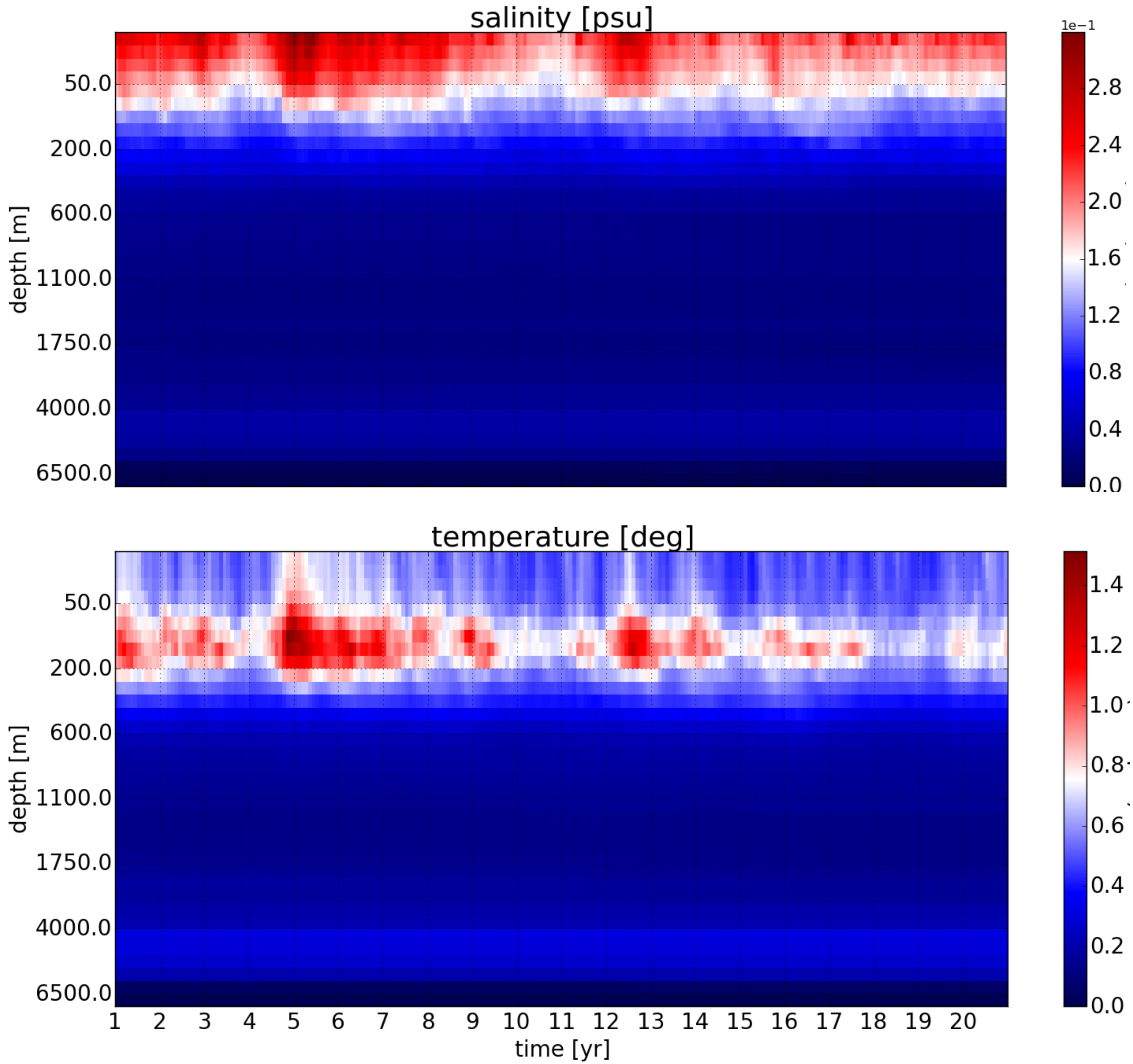
ICE CONCENTRATION





vicen005 [m] (Arctic)
vicen005 [m] (Antarctic)
(b)
sss [psu] (Arctic)
sss [psu] (Antarctic)
(c)
(d)
time [yr]
rmse$_t$ free
rmse$_t$ opt
bias$_t$ free
bias$_t$ opt
reliability
(e)
free (yr 1-10)
opt (yr 1-10)
opt (yr 11-20)
sqrt(rmse^2/spread)
aice
aice1
aice2
aice3
aice4
aice5
hi
vice1
vice2
vice3
vice4
vice5
hs
Tsfc
SST
SSS

RMSE



salinity [psu]
depth [m]
50.0
200.0
600.0
1100.0
1750.0
4000.0
6500.0
1e−1
2.8
2.4
2.0
1.6
1.2
0.8
0.4
0.0
temperature [deg]
depth [m]
50.0
200.0
600.0
1100.0
1750.0
4000.0
6500.0
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
time [yr]