Long coupled Earth System reanalysis with a focus on ocean and sea ice

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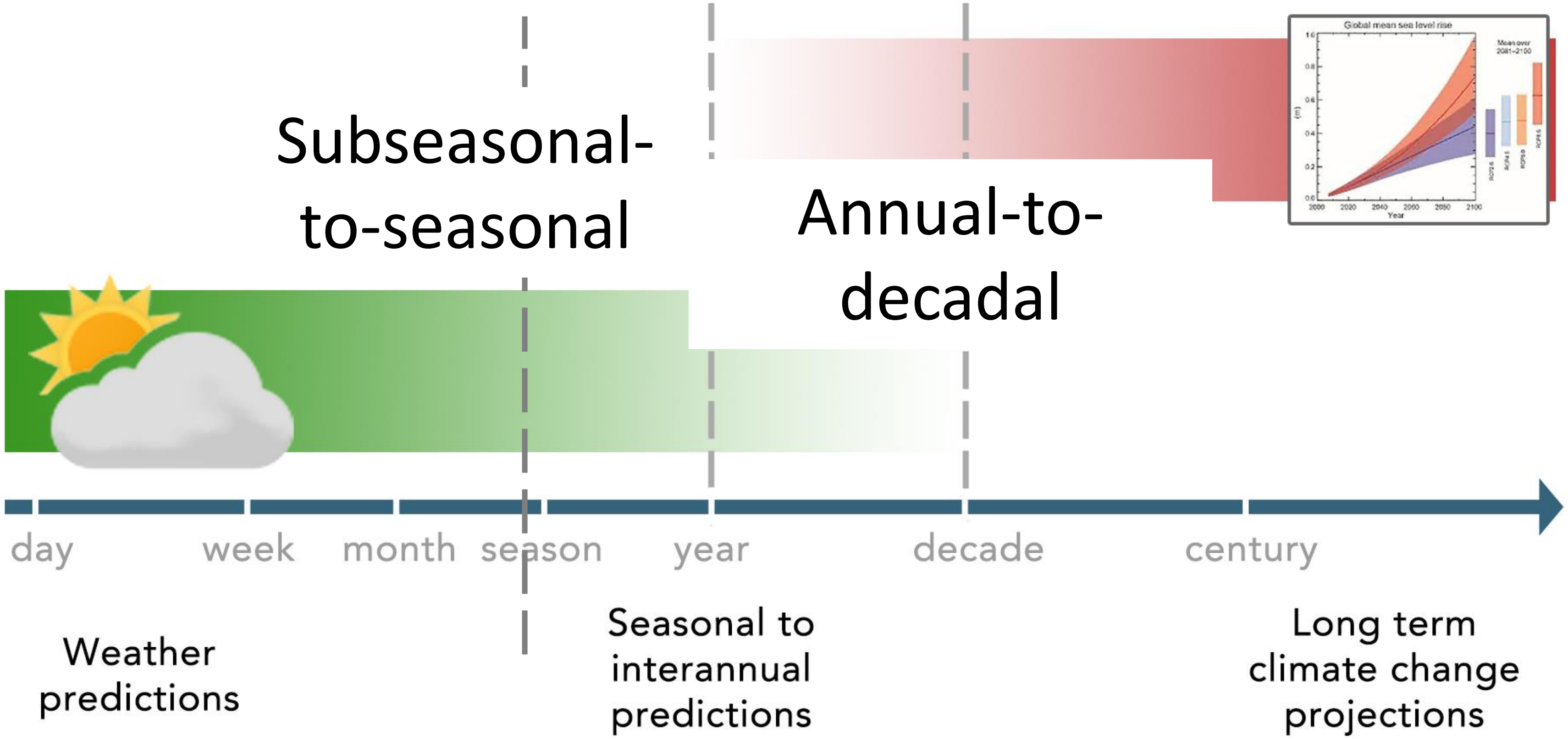
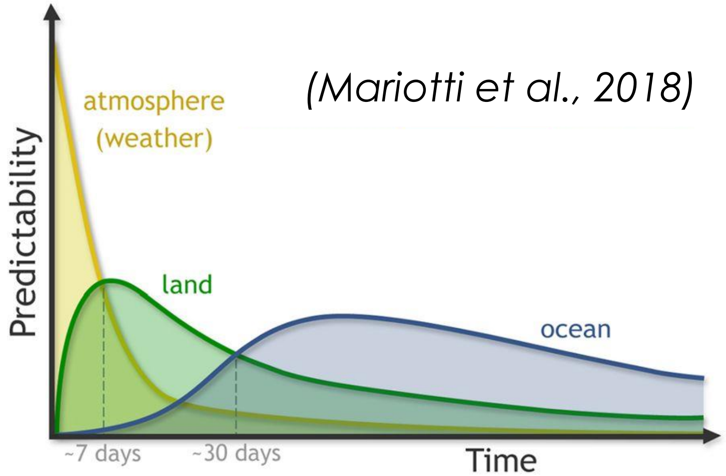
Seamless prediction to help societal transformation



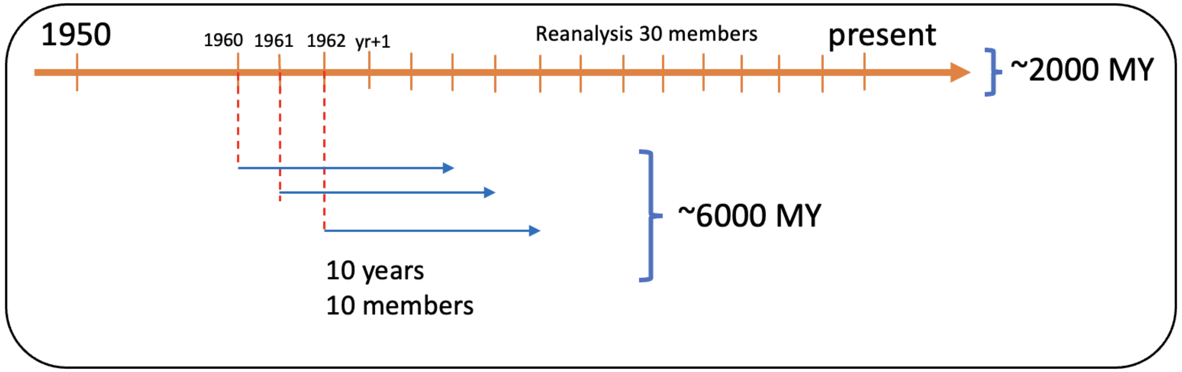
Adapted from Meehl et al. 2009



(Mariotti et al., 2018)

Annual-to-decadal prediction

CMIP6 Decadal Prediction Project (DCPP)



WMO Lead Centre for Annual-to-Decadal Climate Prediction

The Lead Centre for Annual-to-Decadal Climate Prediction collects and provides hindcasts, forecasts and verification data from a number of contributing centres worldwide.

New! WMO Global Annual to Decadal Climate Update for 2023–2027: PDF

Past reports: 2020-2024 | 2021-2025 | 2022-2026

A long coupled reanalysis with ocean DA from 1850 to present

Why is the used of that :

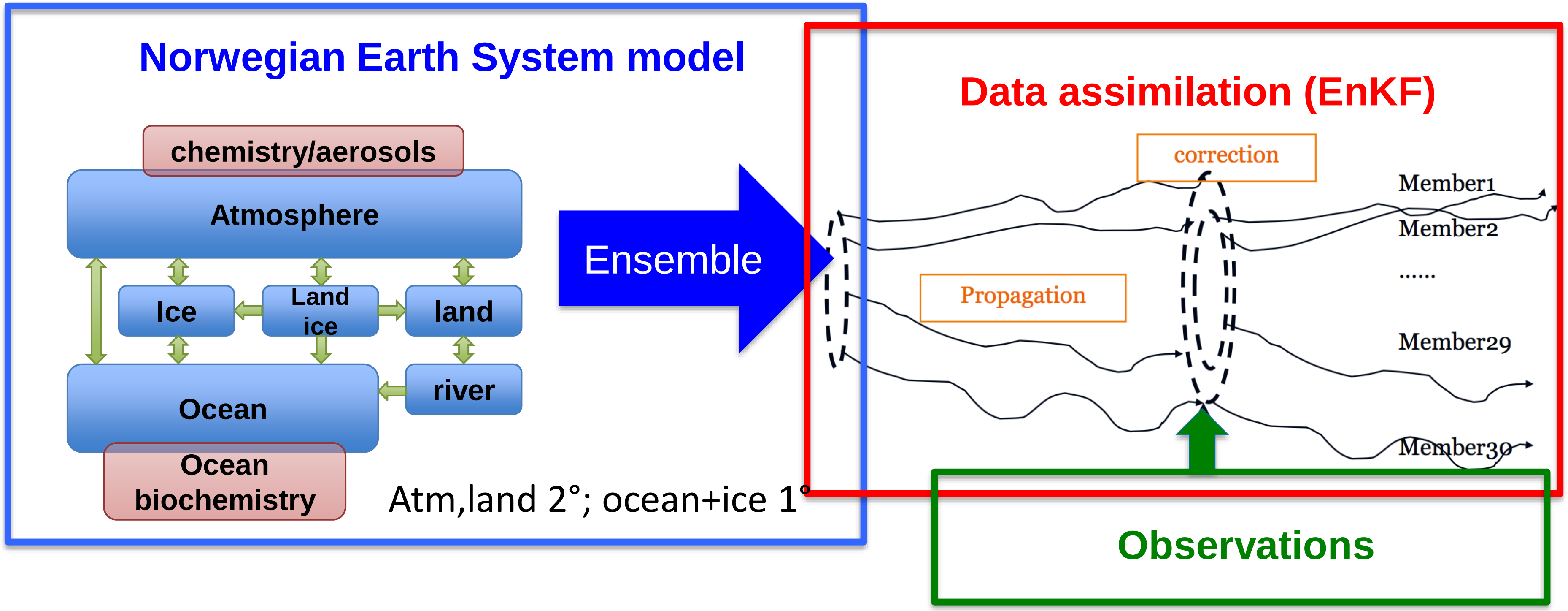
- Predictions initialised from a reanalysis produced with the same ESMs reduce model drift (imbalance takes a very long to dissipate in the ocean)
- The CMIP6 Decadal Prediction Project period (1950:2010) is too short to assess decadal prediction skill
- A coupled reanalysis with sole ocean initialisation can enhance our understanding of the slow climate variability

Bias is a key challenge

- Ocean in ESMs have very large bias but constraining its bias has many challenges :
  - Ocean observations are sparse and heterogeneously and a changes in the observation network cause spurious signal
  - Covariance during DA will transfer biases where there are no observations

➔We focus on anomaly assimilation and only assimilate data available for the entire period (sparse input reanalysis)

Norwegian Climate Prediction Model (NorCPM)

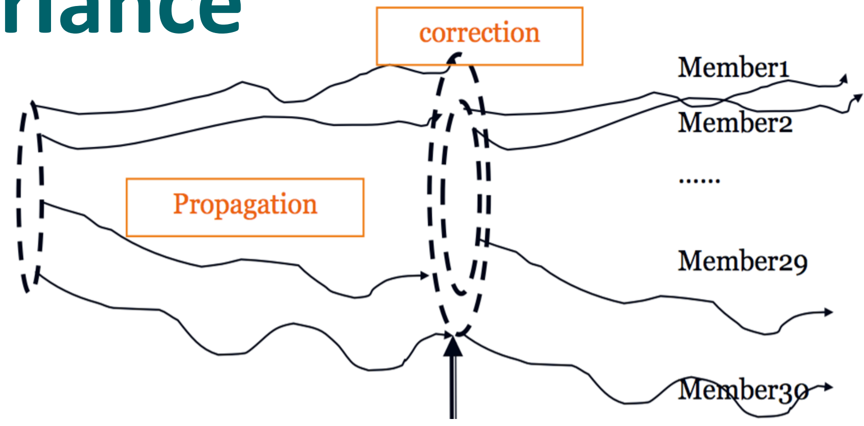


Objectives:

- **Long climate reanalysis**
  - Instrumental (from 1950; ongoing from 1850)
- **Climate prediction**
  - Annual-to-decadal time scale (CMIP6 DCPP, WMO-ADCP)
  - Seasonal time scale (Climate Services, SFI climate futures)

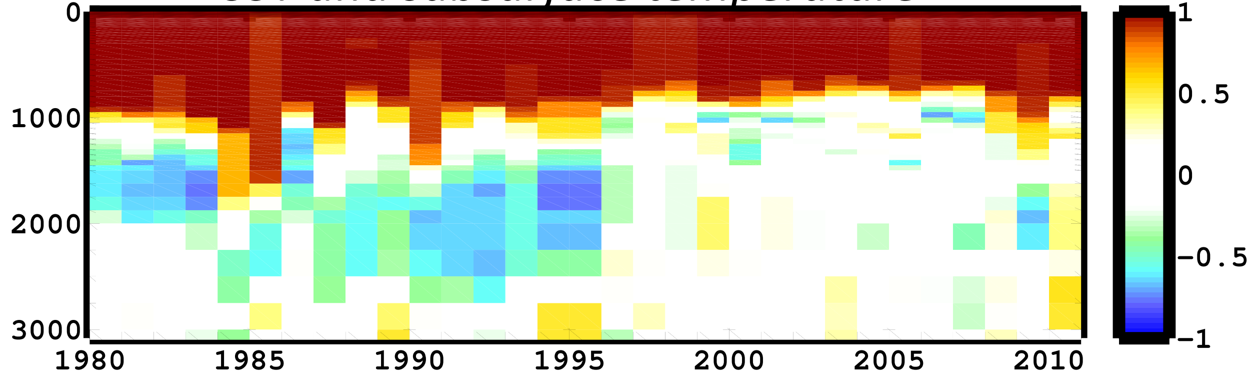
(Bethke et al. 2021)

Importance of flow dependent covariance

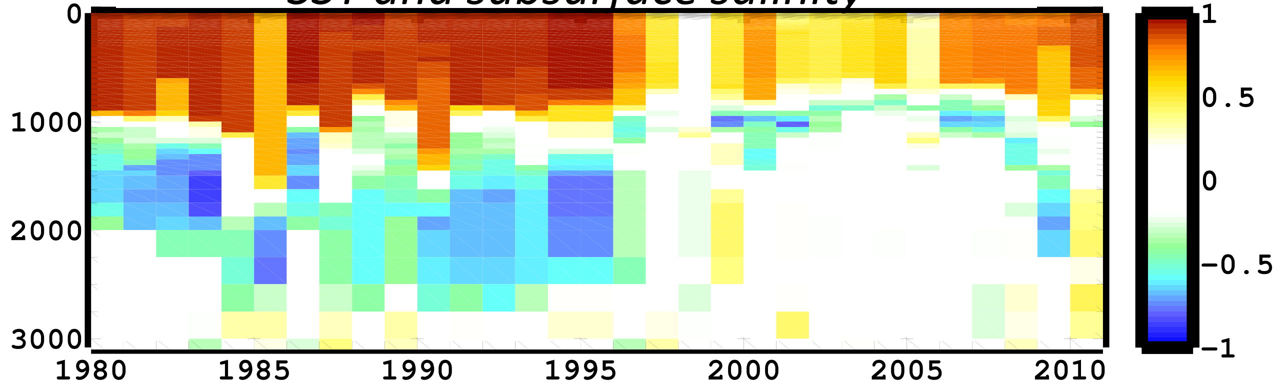


Correlation across the ensemble in April in the Labrador Sea

SST and subsurface temperature



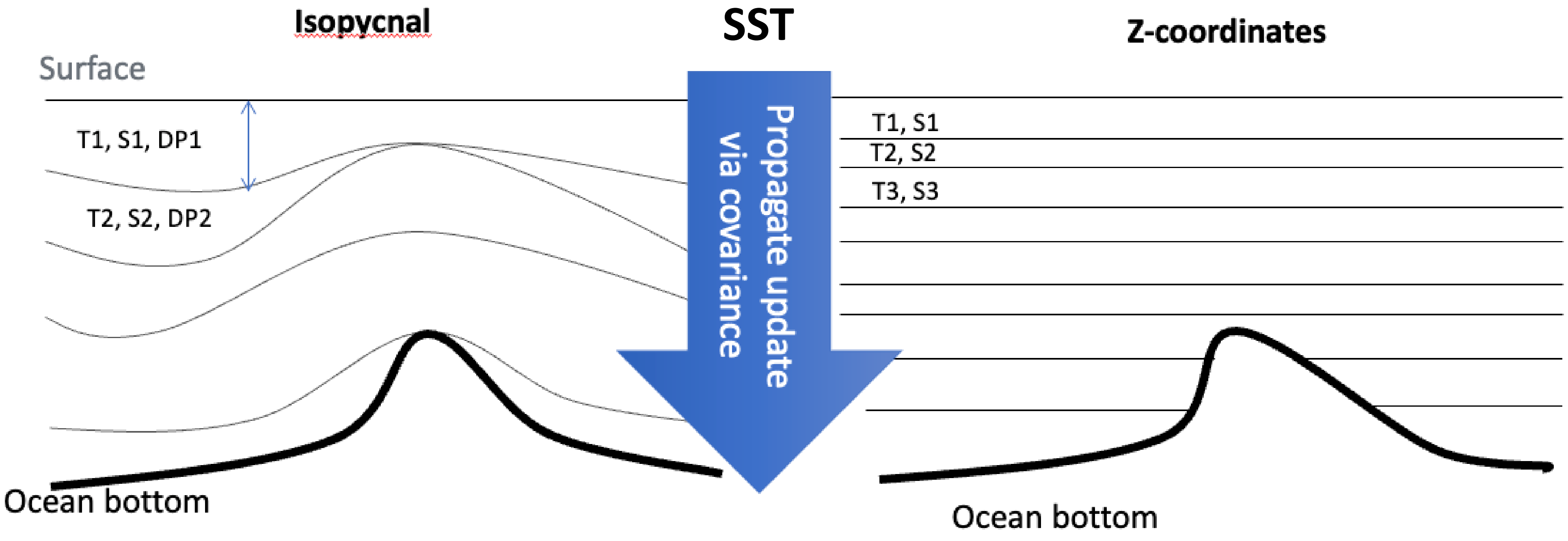
SST and subsurface salinity



Corrections changes with climate regime shift

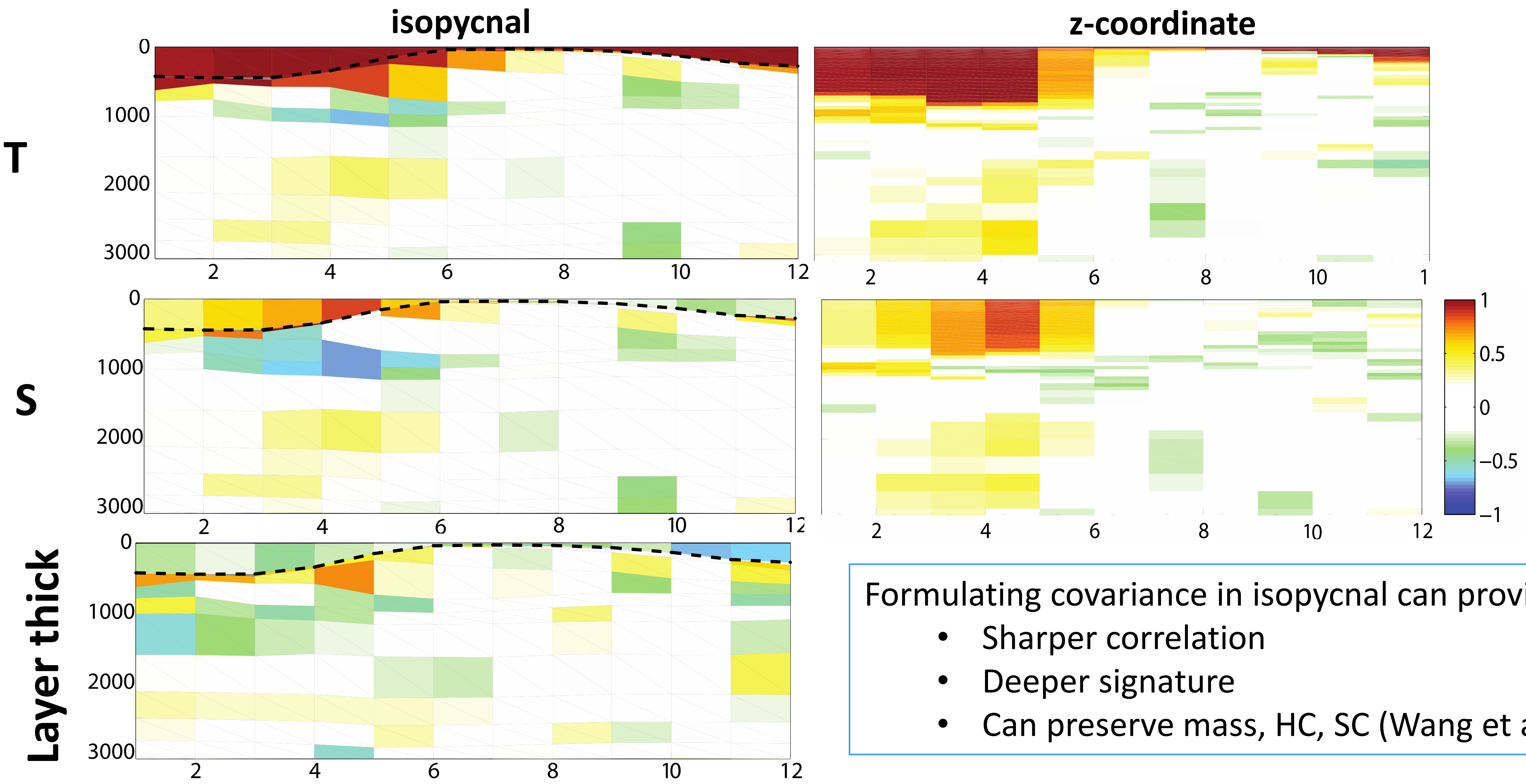
(Counillon et al. 2016)

Importance of the vertical structure of the covariance



Vertical structure of ocean covariance

Seasonal correlation of SST with the water column in the Labrador Sea

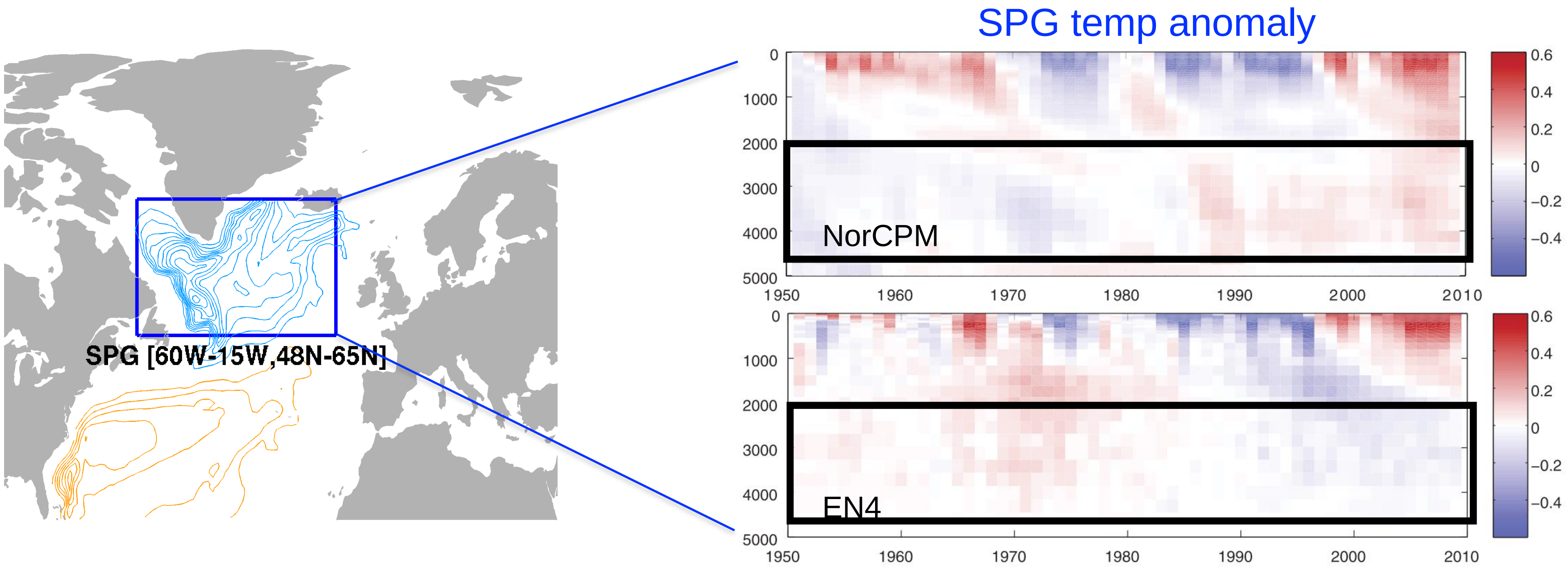


Formulating covariance in isopycnal can provides :

- Sharper correlation
- Deeper signature
- Can preserve mass, HC, SC (Wang et al. 2017)

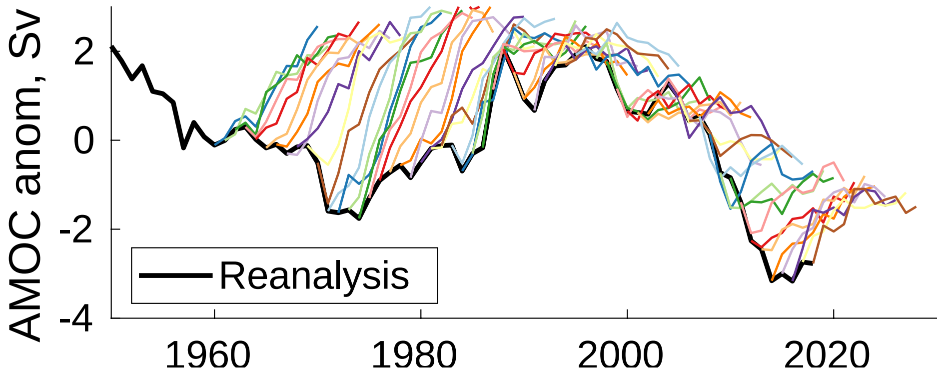
(Counillon et al. 2016)

Still some degradation noticed in the deep ocean…

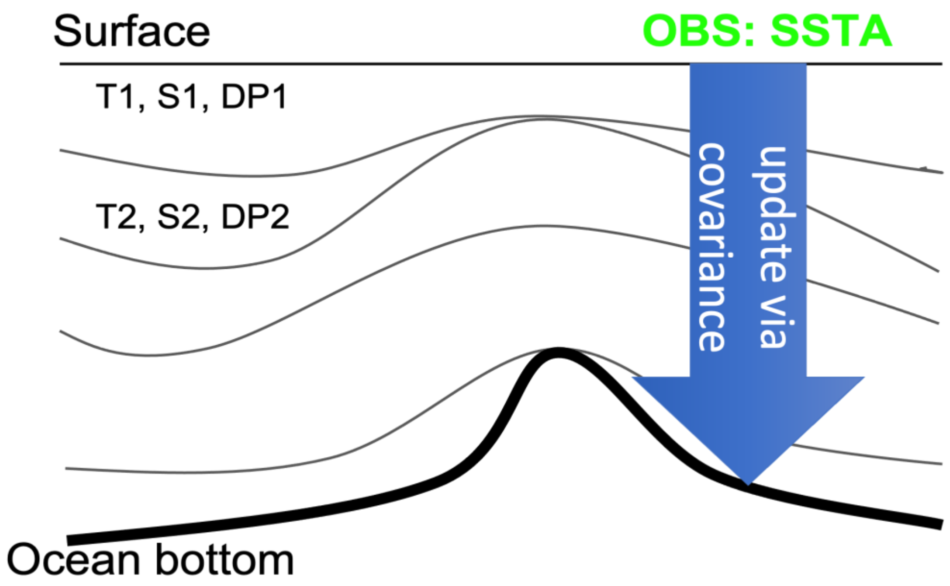


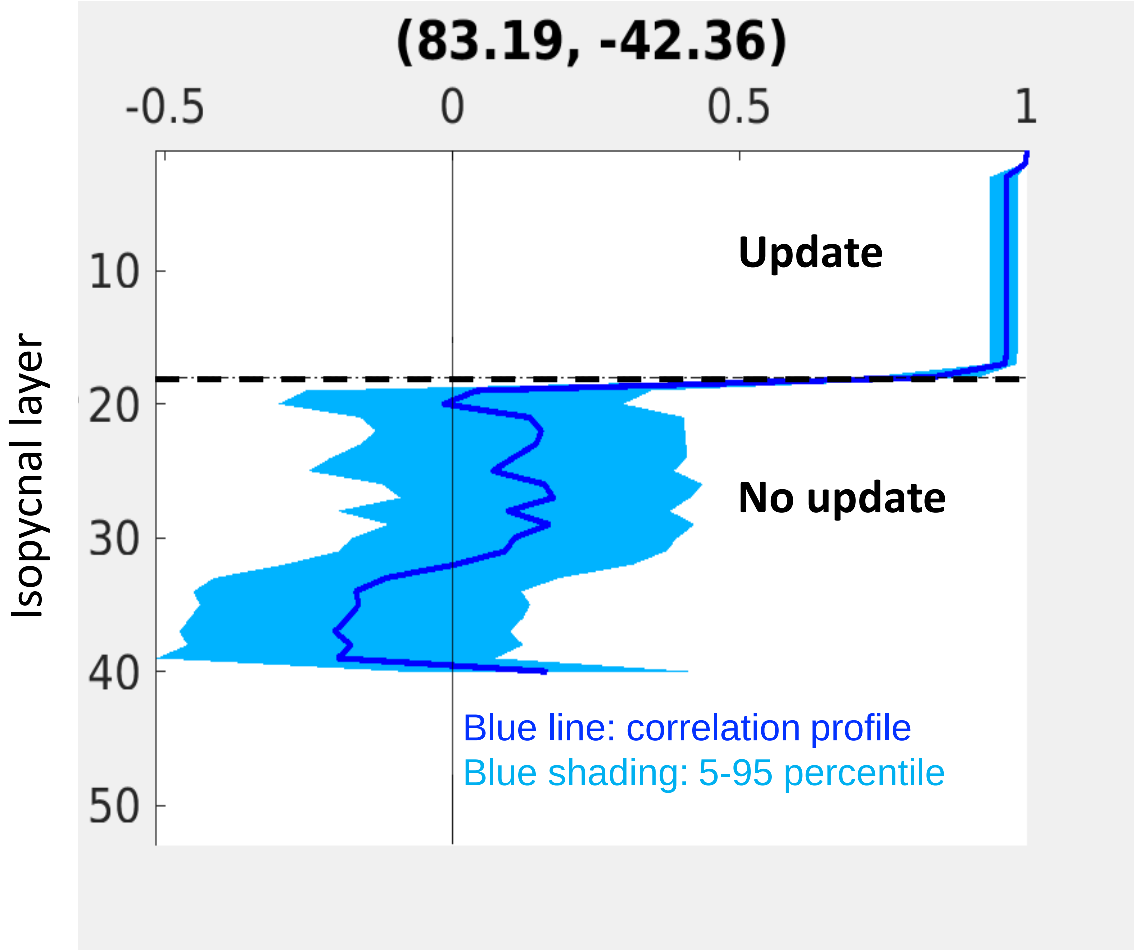
(Counillon et al., 2016)

- Deep water anomalies introduce a drift in climate predictions!



Isopycnal coordinate vertical localisation

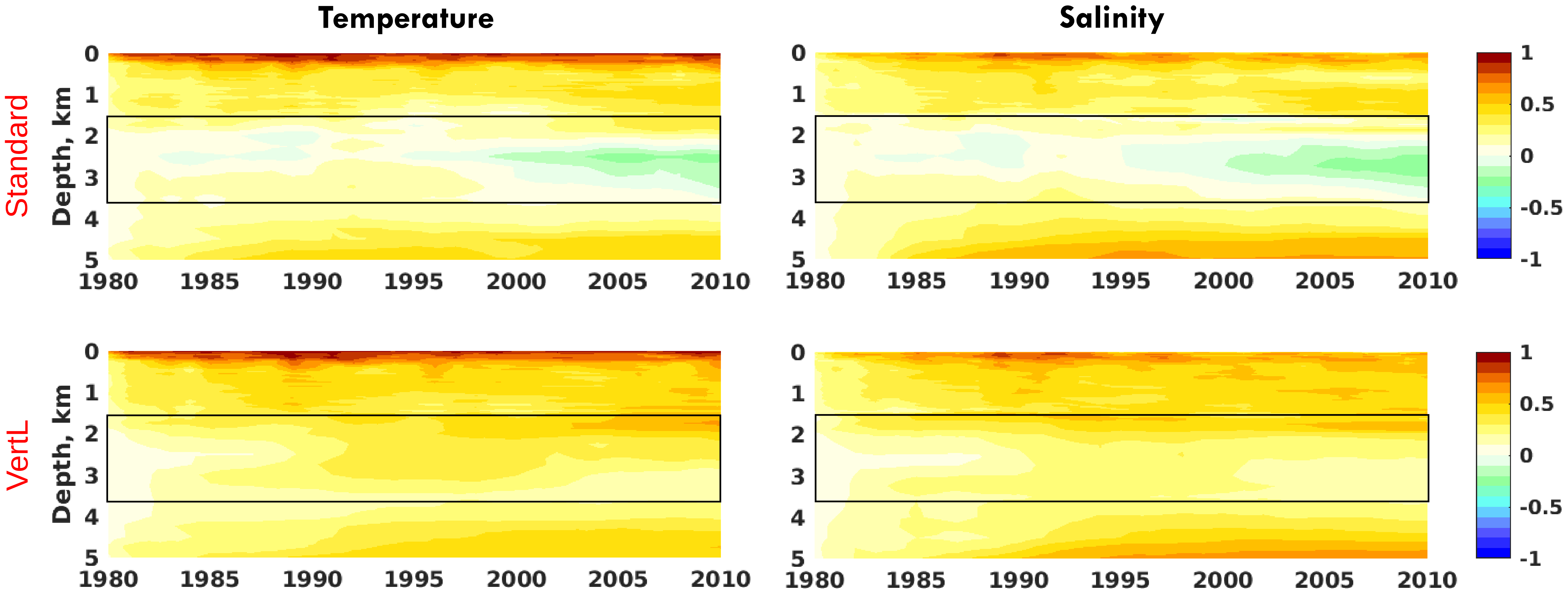




(Wang et al. 2022)

Error reduction wrt the non-assimilated run

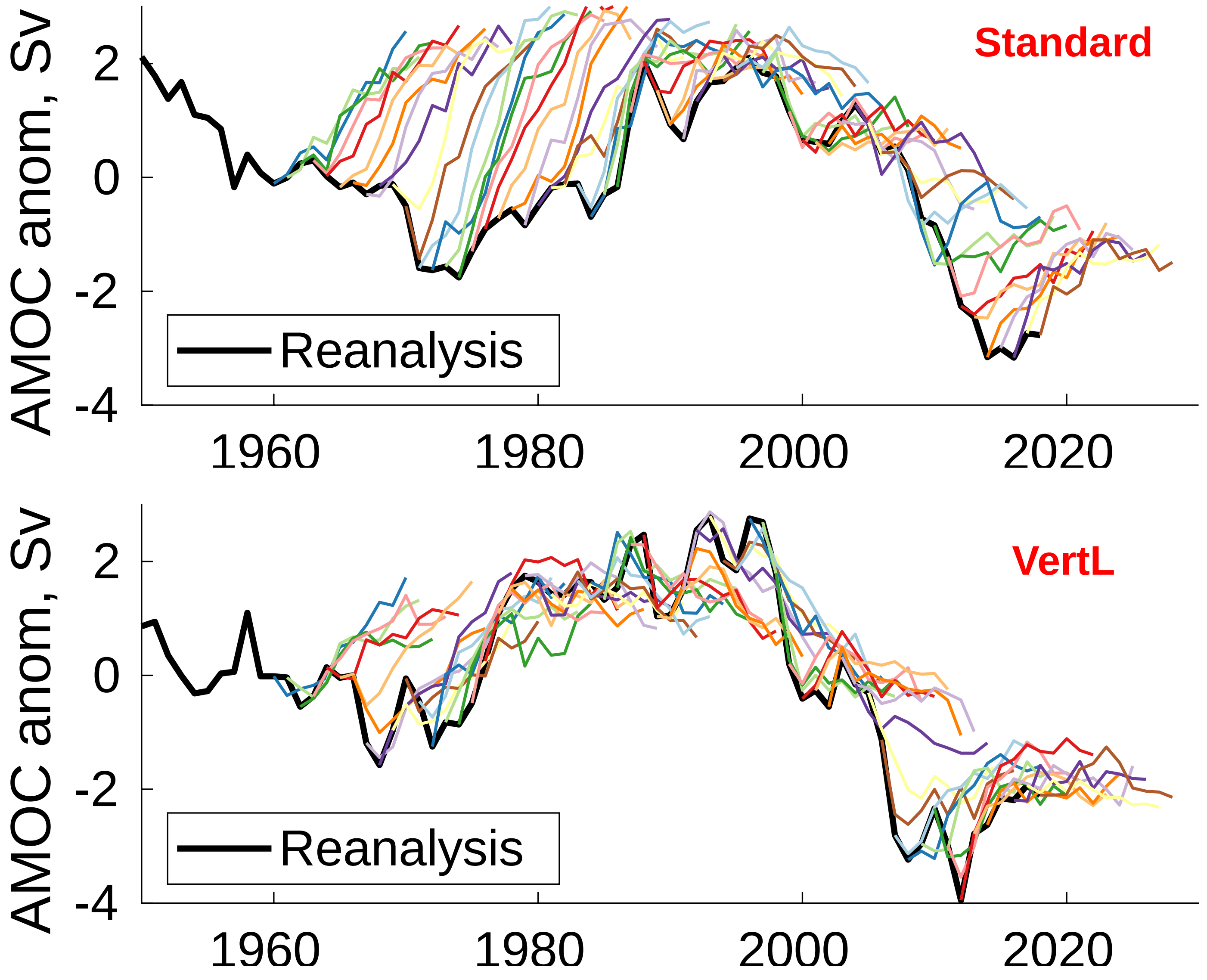
idealised twin experiment



Warm colours: improvement **Cold colours: degradation**

(Wang et al., 2022)

CMIP6 DCPP experiment

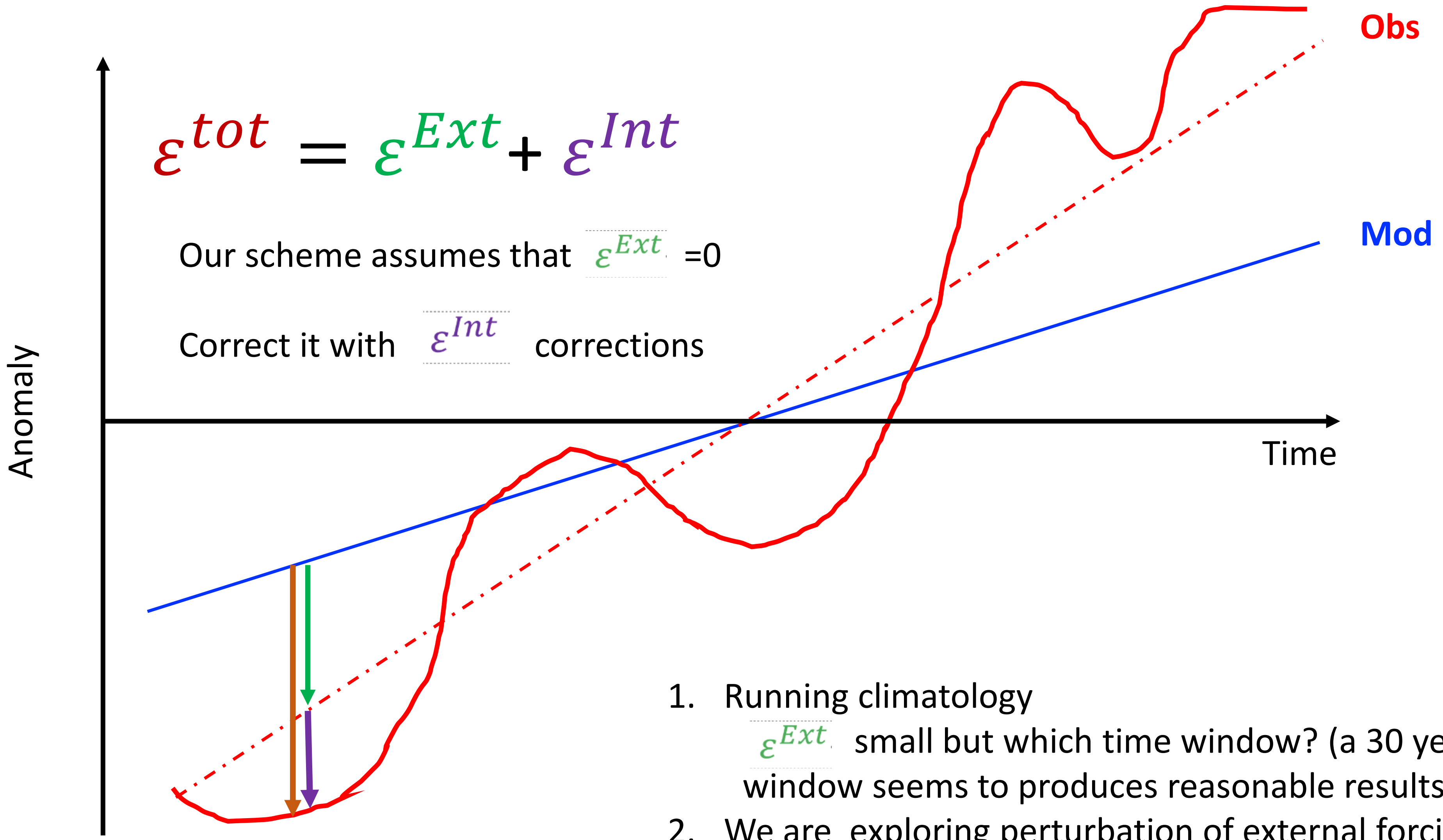


Errors in the trend and internal variability

$$\varepsilon^{tot} = \varepsilon^{Ext} + \varepsilon^{Int}$$

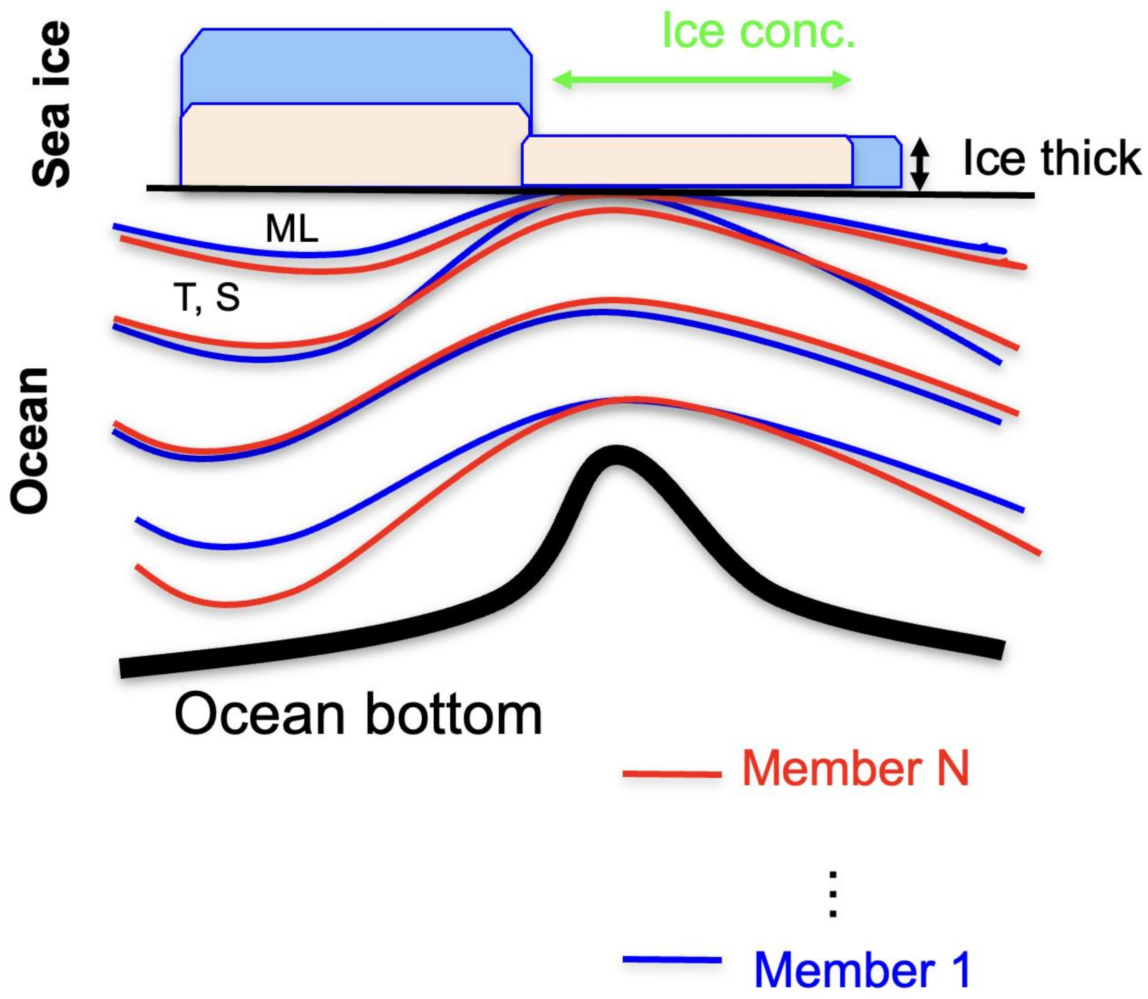
Our scheme assumes that ε^{Ext} =0

Correct it with ε^{Int} corrections



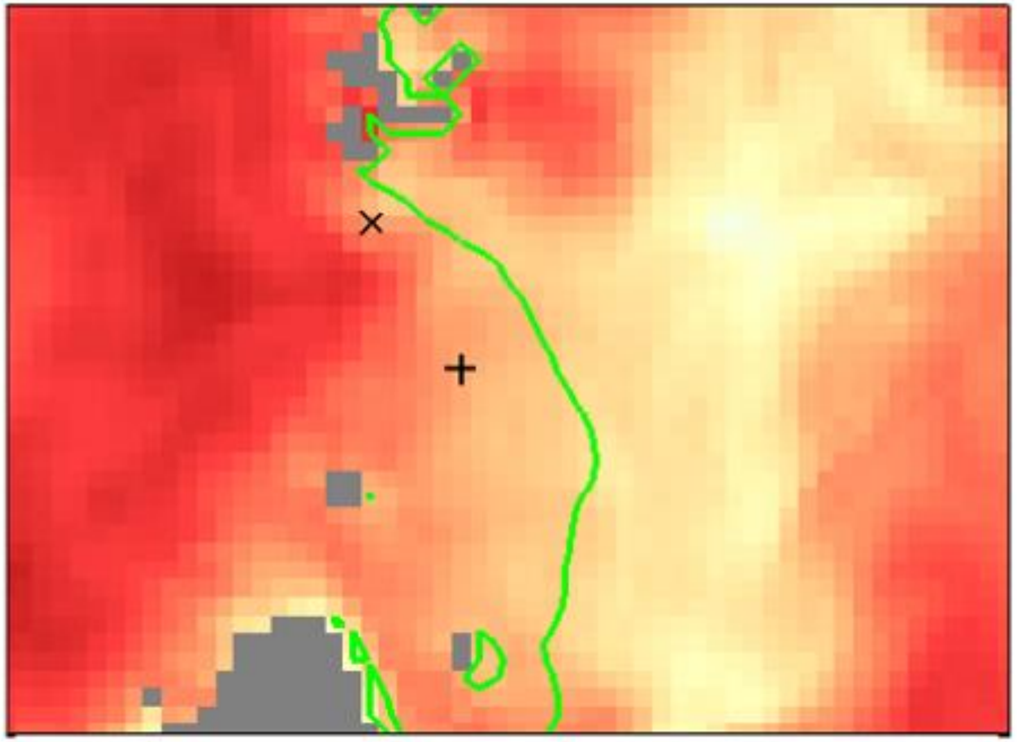
1. Running climatology
   ε^{Ext} small but which time window? (a 30 year window seems to produces reasonable results)
2. We are exploring perturbation of external forcing or online bias estimation and parameters estimation

How to update the ocean and sea ice consistently



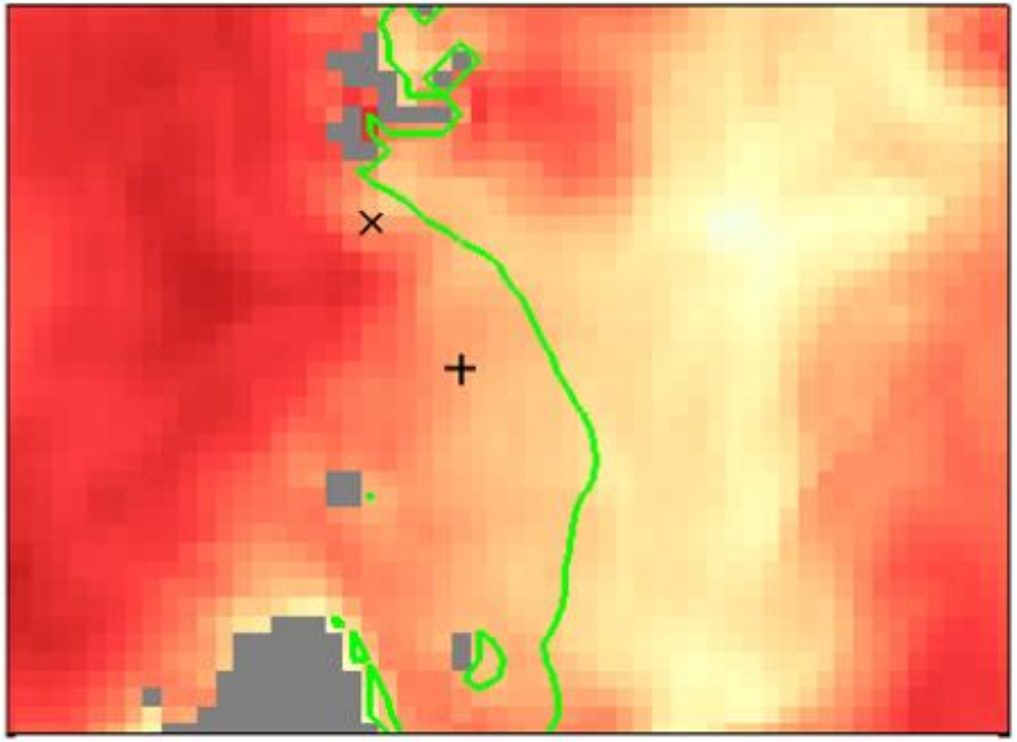
Coupled covariance between salinity and sea ice concentration

Static covariance

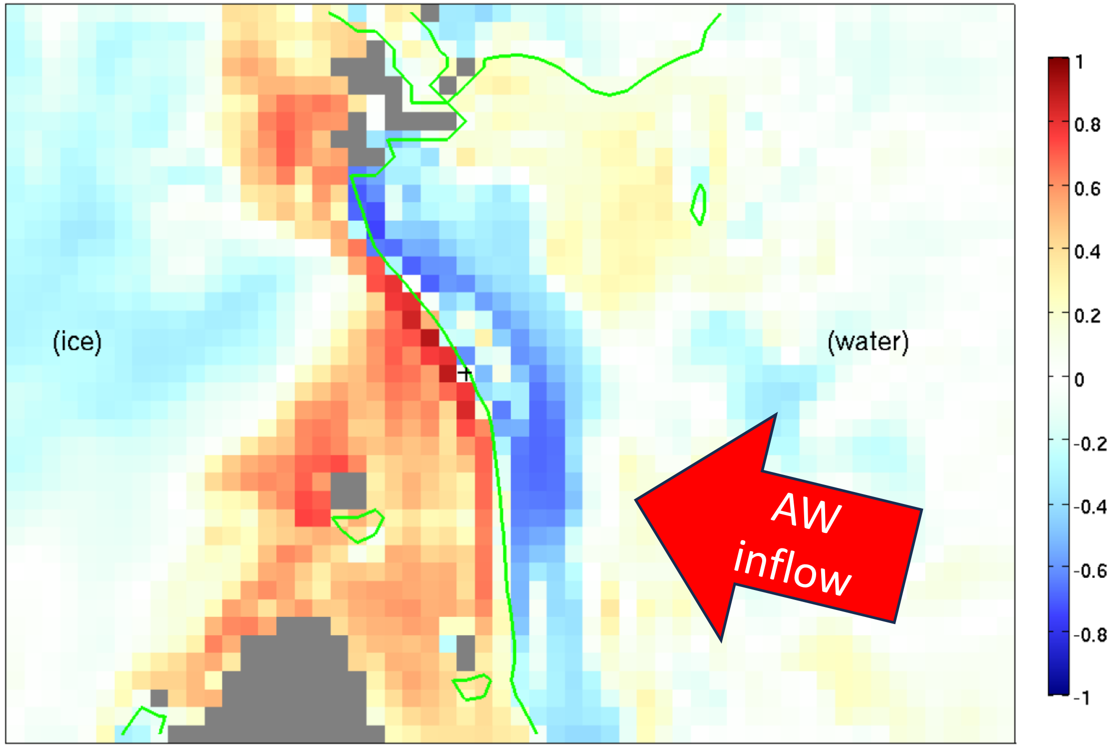


Coupled covariance between salinity and sea ice

Static covariance



dynamic covariance

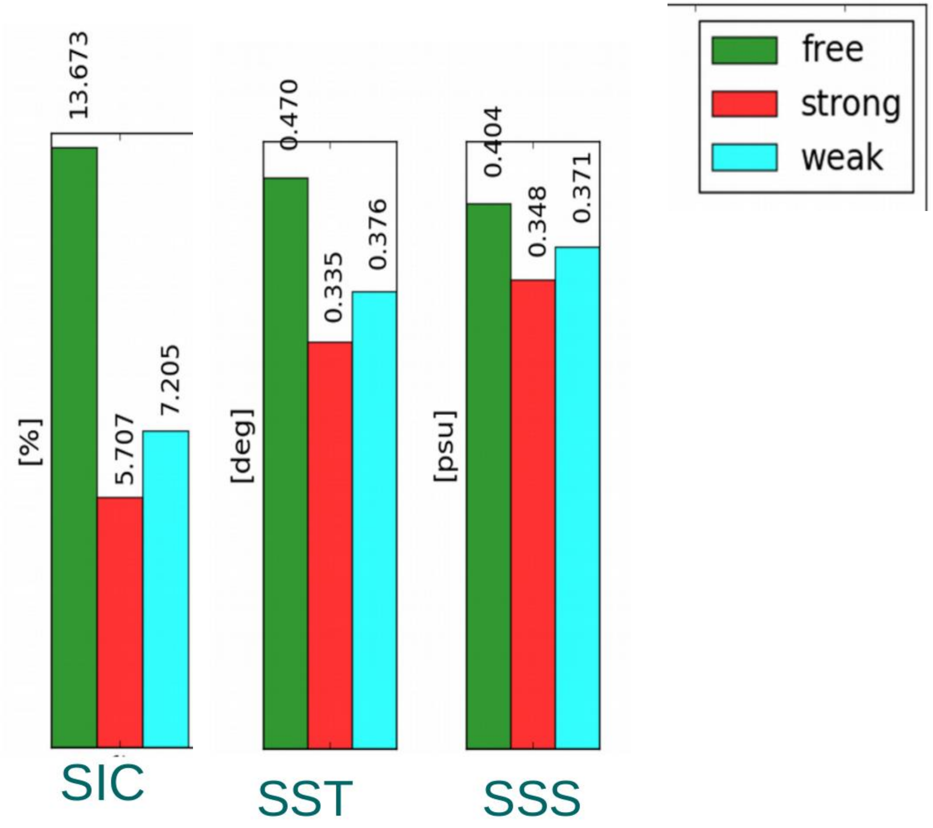


Ensemble Kalman Filter can handle the flow dependent and strongly anisotropic cross covariance between salinity and sea ice

(Lisæter et al. 03, Sakov et al.12)

Strongly coupled data assimilation between ocean and sea ice

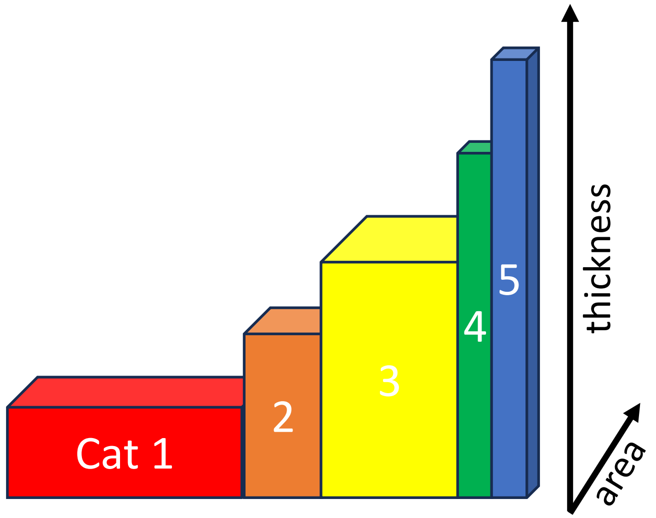
We compare performance of 10-year reanalysis in twin experiment



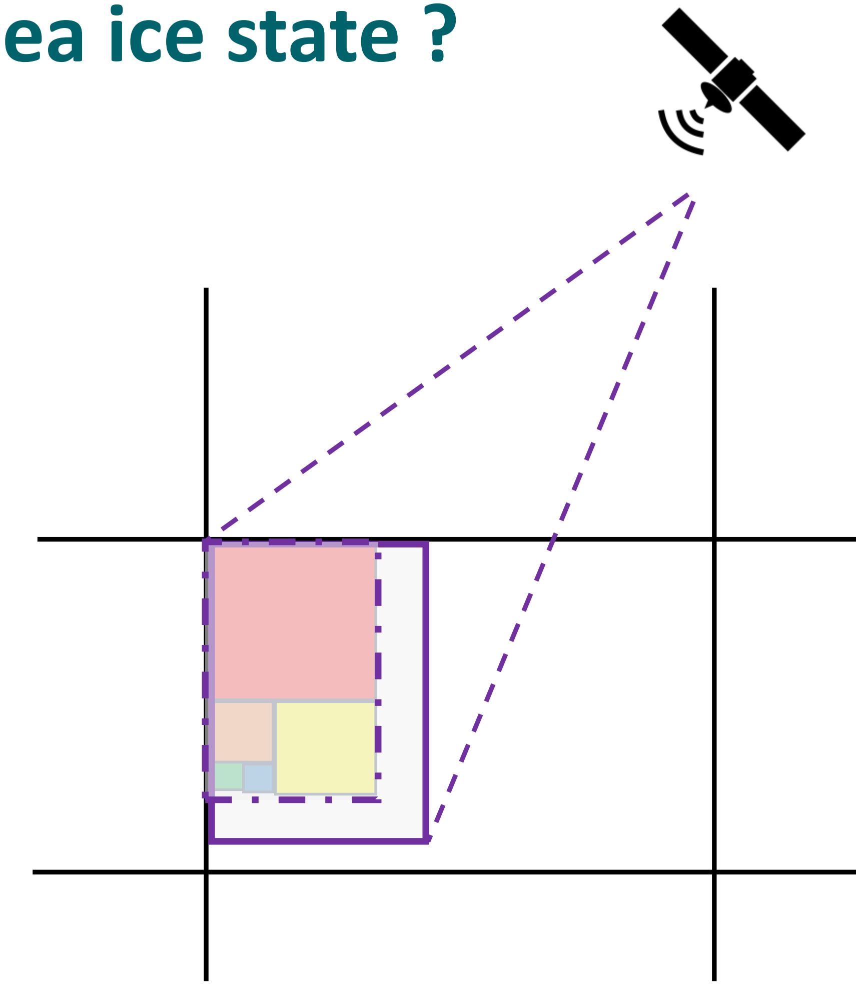
With flow dependent DA, strongly coupled DA (SCDA) of ocean and sea ice yields improvements over weakly CDA.

(Kimmritz et al. 2018)

How can we update the multicategory sea ice state ?



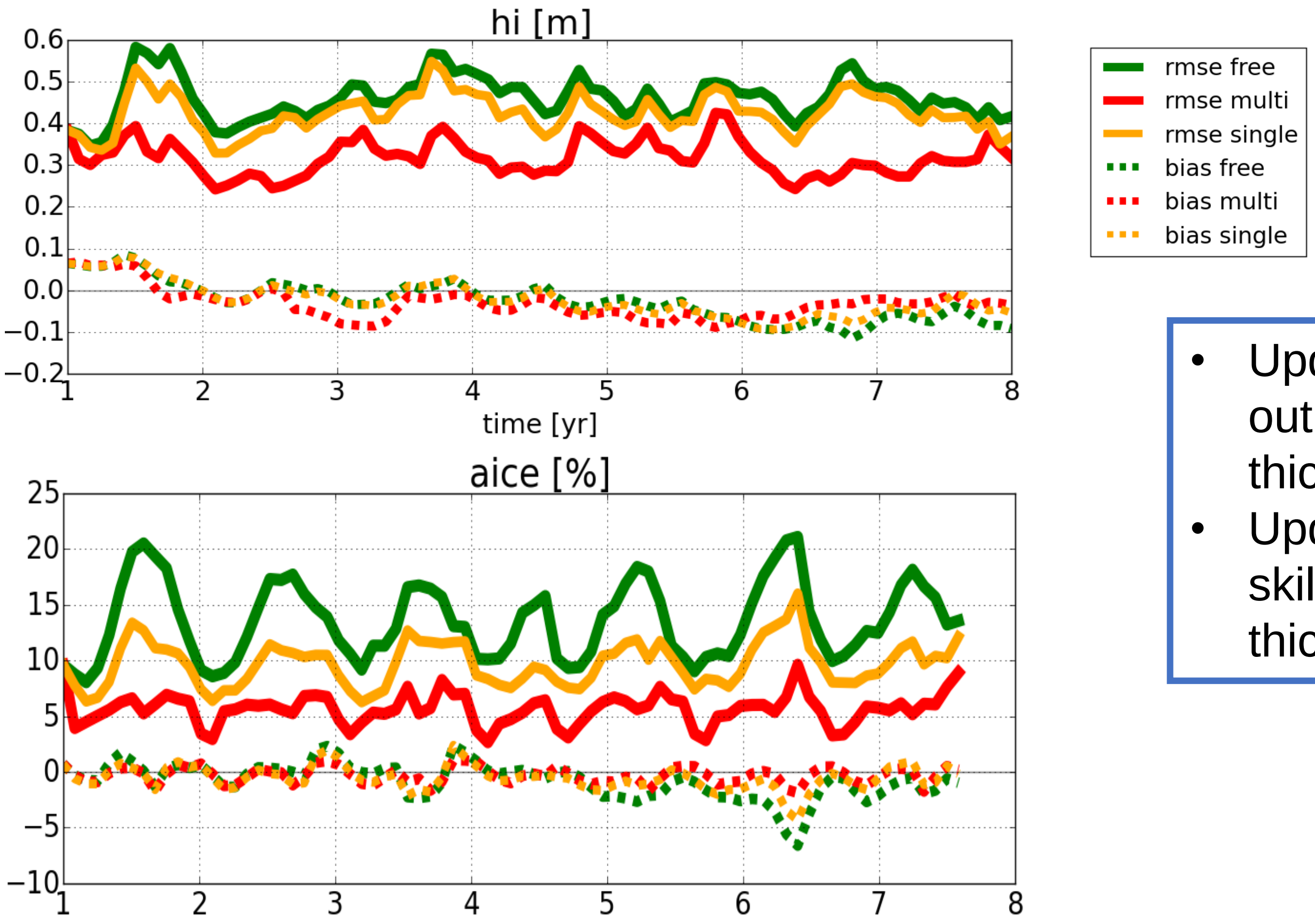
- The thickness of each category is bounded (transferred if out of bound)
- Total thickness depends on individual thickness and concentration



How updating the multicategory sea ice state from ice concentration ?

- Update the agregated properties and stretch each category uniformly (e.g. Allard et al. 2018)
- Update each category concentration via ensemble covariance (e.g. Massonnet et al. 2015)
- Only update concentration of each thickness category ? (Kimmritz. 2018)

Assimilation of sea ice concentration in twin experiments



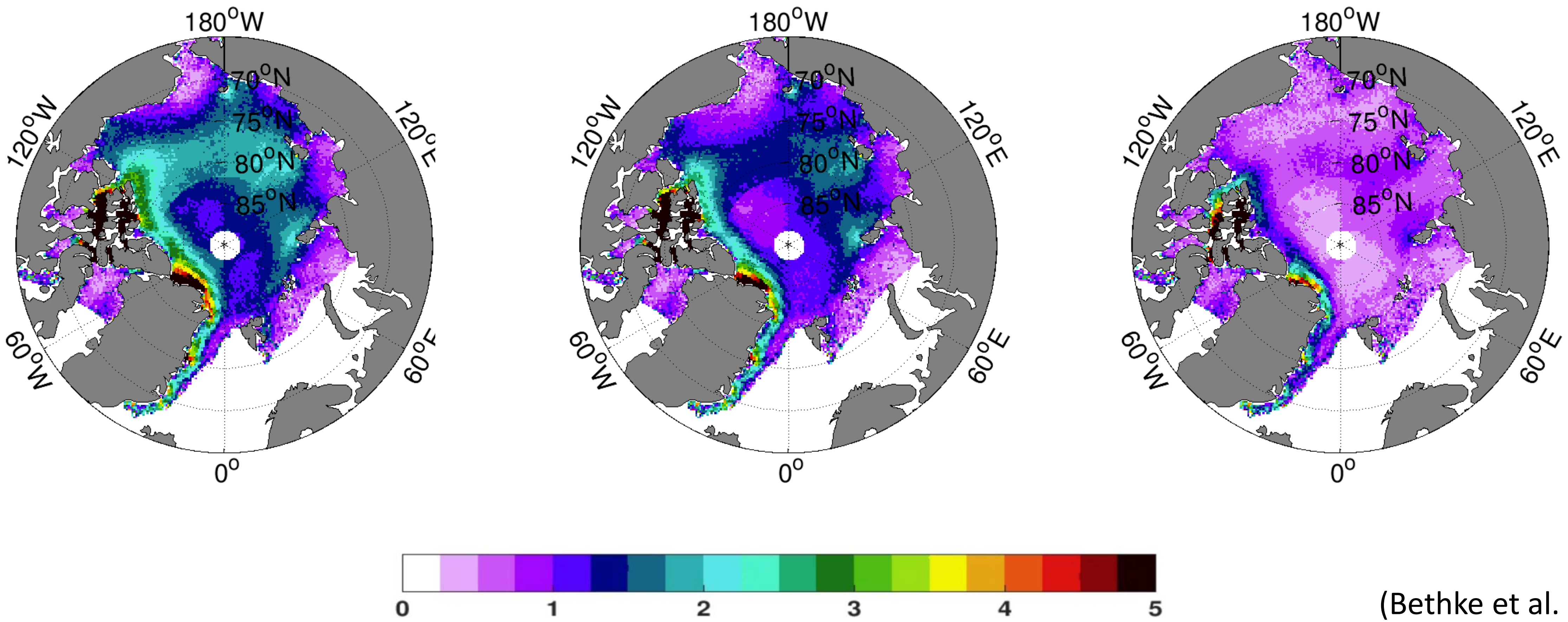
- Updating the multicategory sea ice state outperforms assimilation of aggregated thickness and concentration
- Updating individual thickness do not improve skill but introduce a drift when redistributing thickness in their characteristic thickness

(Kimmritz et al. 2018)

Can we update sea ice state from ocean data only ?

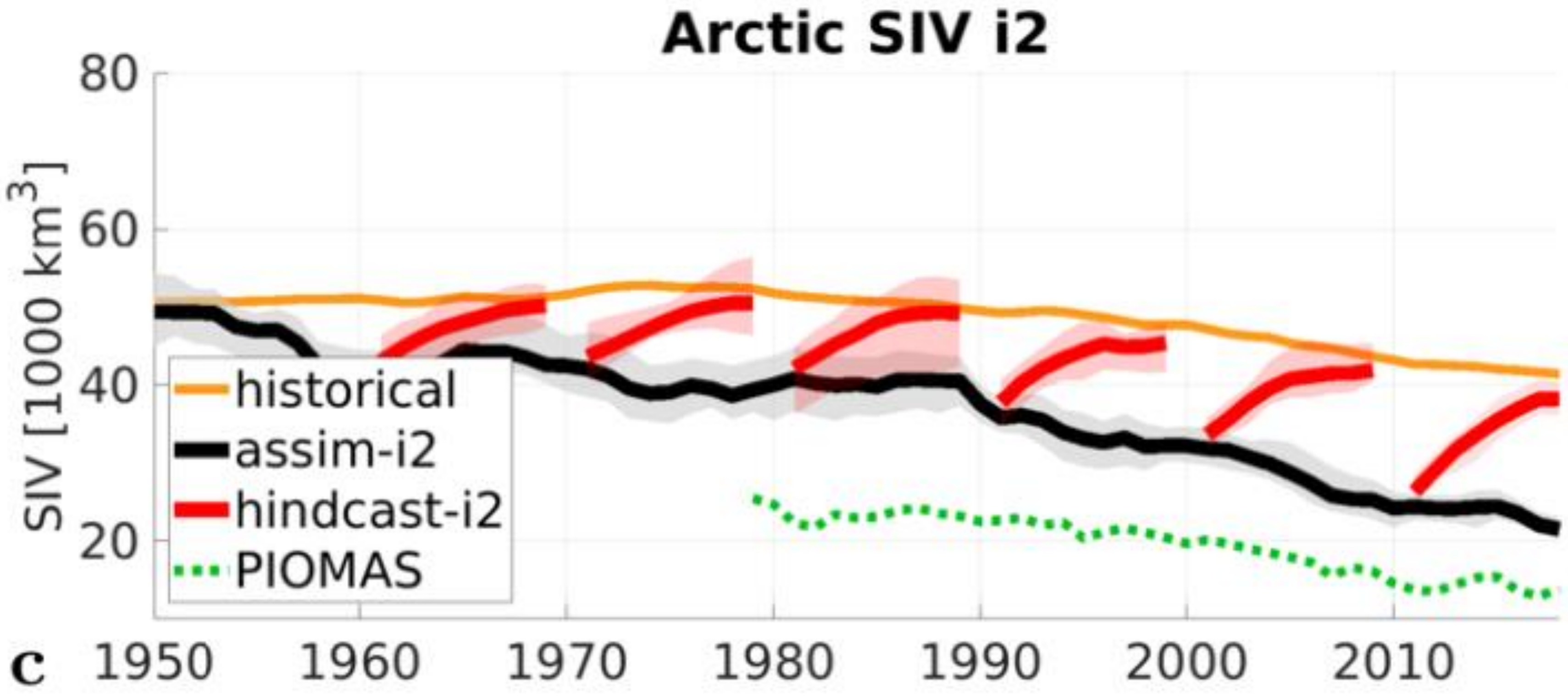
RMSE of sea ice thickness vs CRYOSAT-2 (November-March)

Free run | Weakly coupled DA | Strongly coupled DA



(Bethke et al. 2021)

How is the error reduction sustained during predictions ?



Bias recover after 10 years.

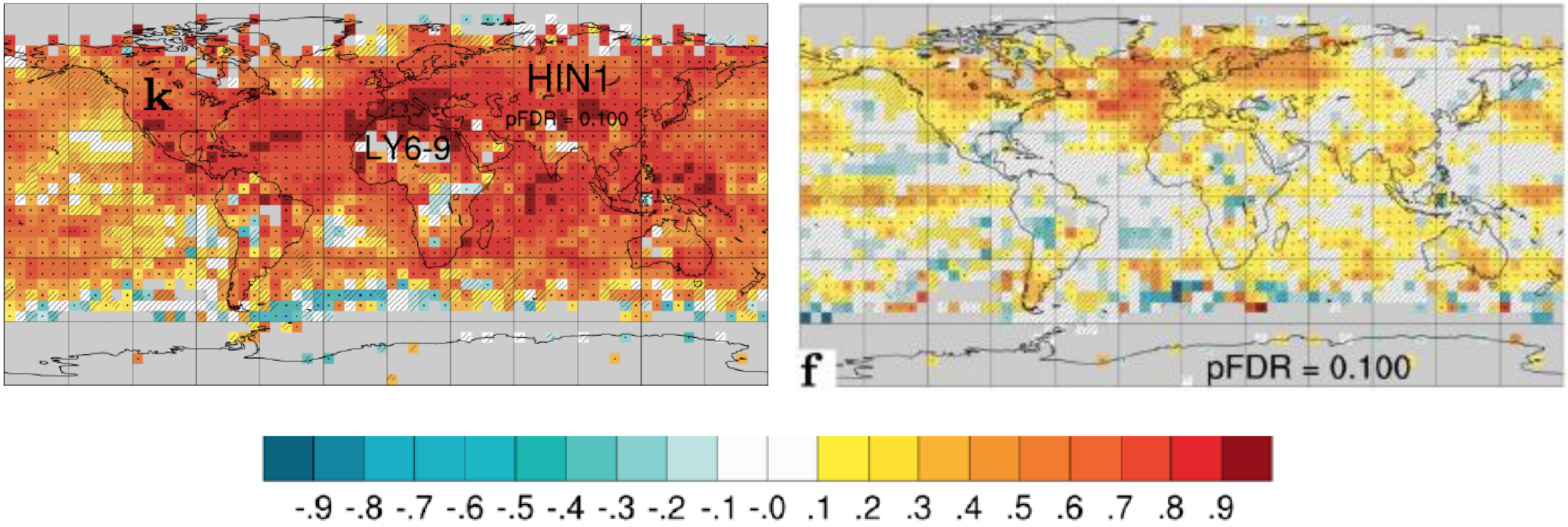
[Bethke et al. 2021]

External forcing versus internal climate dynamics?

NorCPM, yearly hindcasts 1960-2010, 10 members, assimilation of ocean hydrography

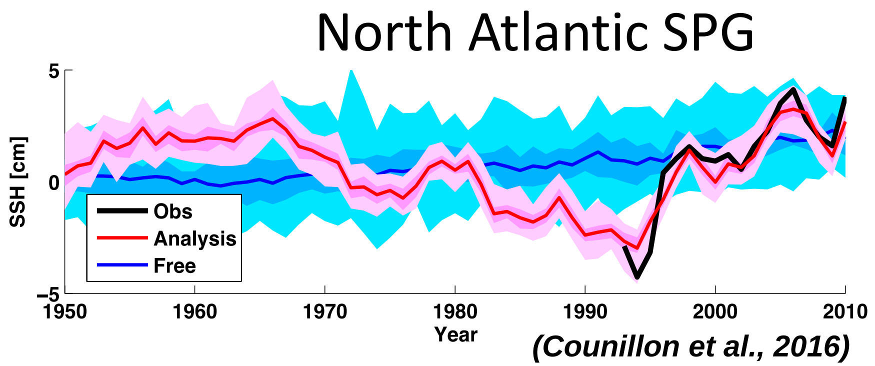
Total skill (greenhouse gas + ocean)

Skill added by ocean data
Prediction of deviations from external forced change



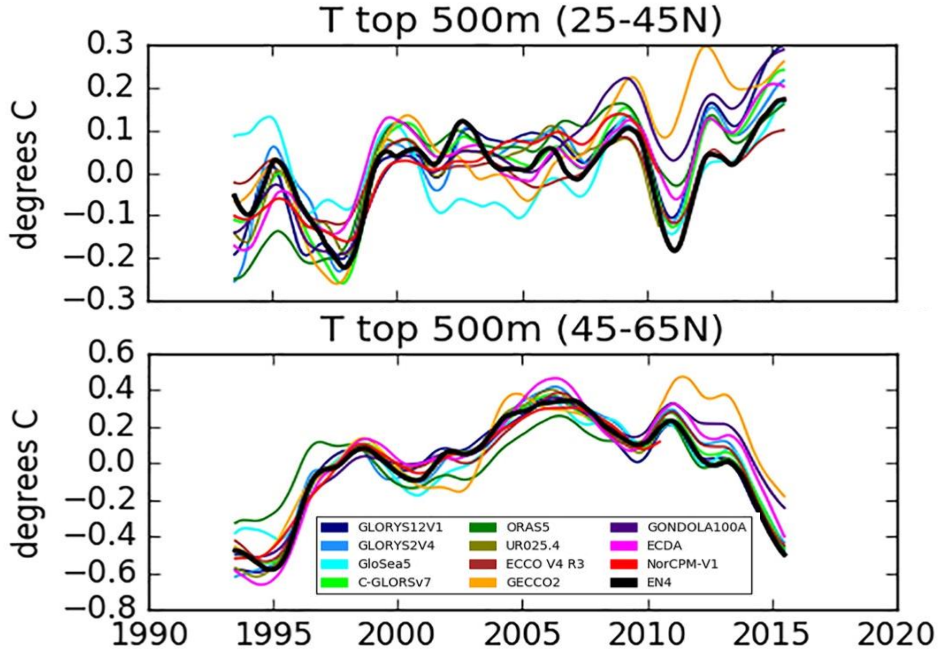
Bethke et al. 2021

Coupled reanalysis from 1950 how does it performs ?



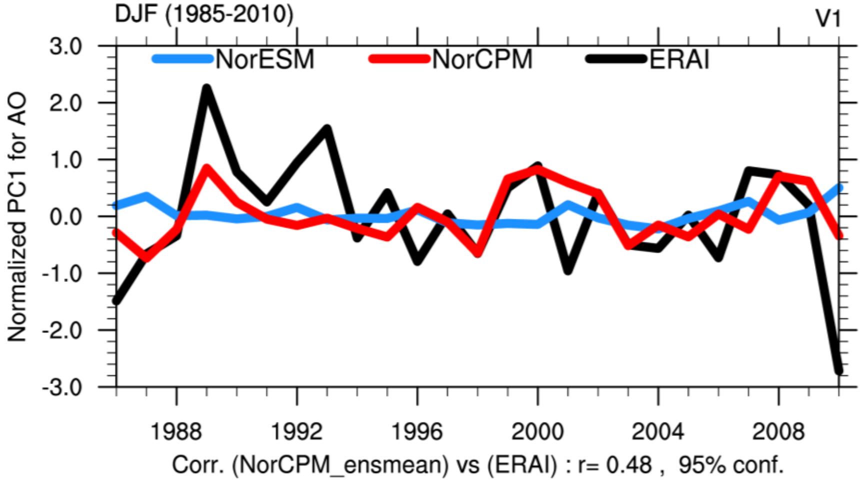
(Counillon et al., 2016)

Comparable behaviour to other product for the slow variability



(Jackson et al., 2019)

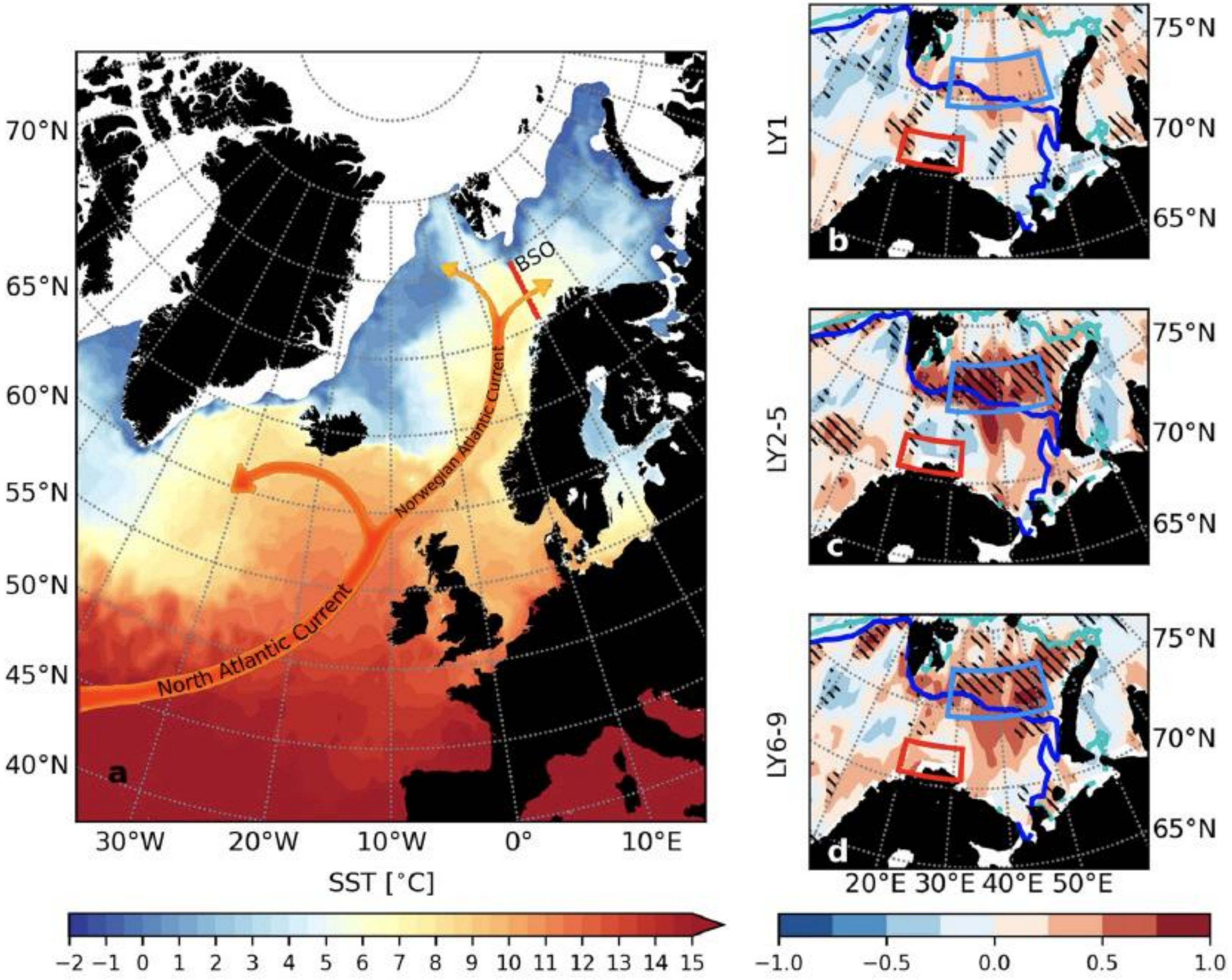
Can partly constrain atmospheric variability



Predictability of BGC demonstrated in high-latitudes

Predictability pathway from North Atlantic to Arctic

Snapshot of ocean temperature



Correlation skill in predicting phytoplankton at different lead times from NorCPM

[Fransner et al. 2023]

How ocean DA compared to nudging atmospheric variability ?

Compare reanalysis and prediction skill with a large span of methods with NorESM

Case	Ocean DA	Atmo Nudging (6h) ERA-I	Vars ( )atm [ ] ocean	Atm energy fix (EF)
NudF-UVT	-	FF	(U, V, T)	-
NudA-UVT	-	Anom	(U, V, T)	-
ODA + NudA-UV	Anom	Anom	(U, V), [SST+ T, S]	yes
ODA	Anom	-	[SST+T, S]	-

Reanalysis:

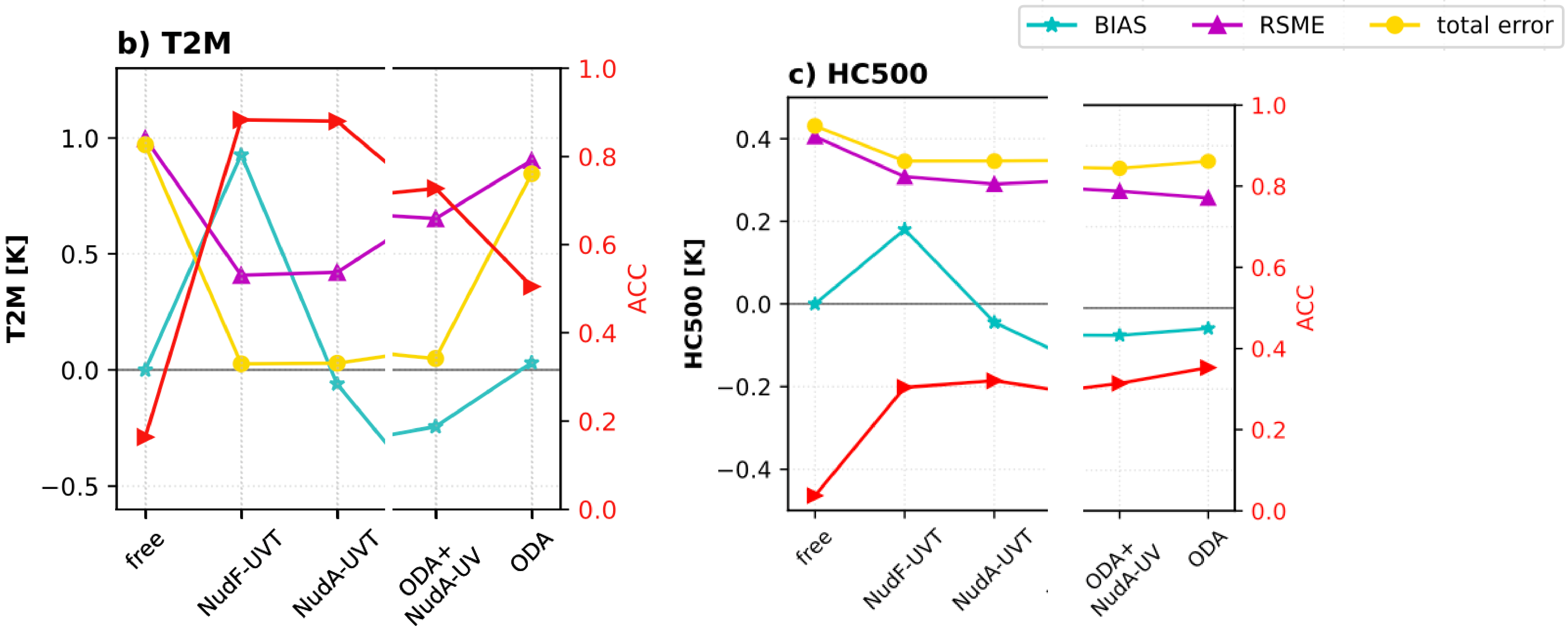
- Ensemble size: 30.
- Reanalysis for 1980-2010

Hindcasts:

- Seasonal: Started each Feb, Mar, Aug and Nov (1985-2010
- Decadal: Started each November every other year (1985-2010).

Garcia et al. subm

Reanalysis verification

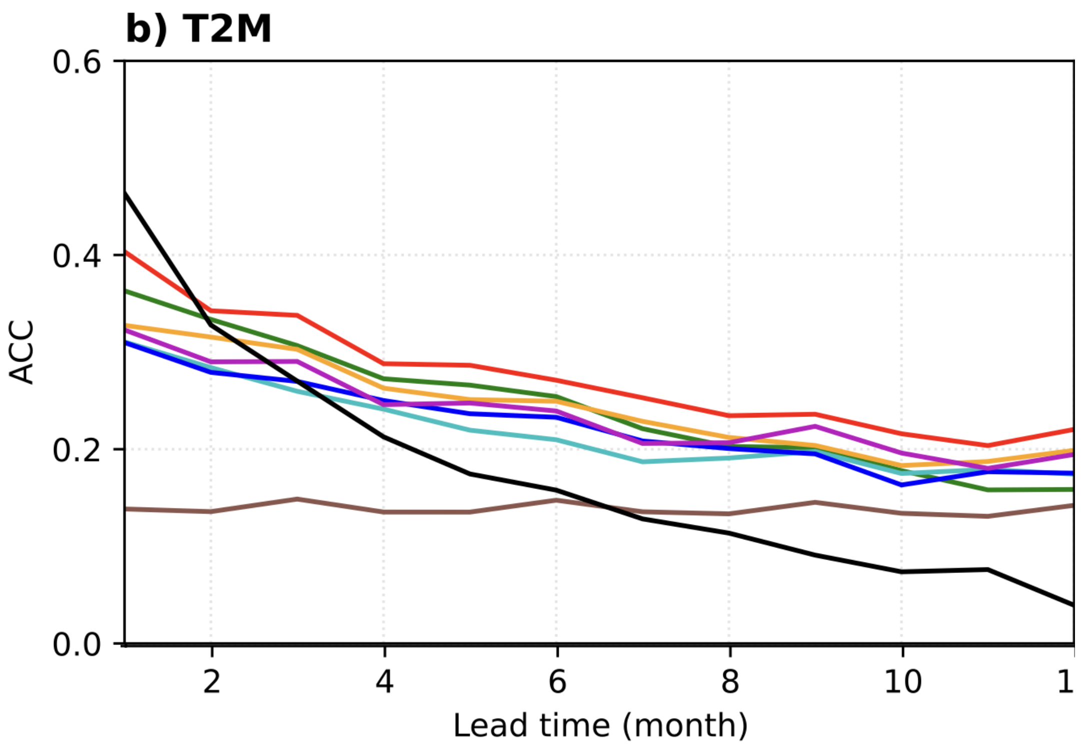


- Atmospheric nudging constrains well atmospheric variability while ODA is poor
- ODA performs best in the ocean (SST, HC, SC).
- Unlike anomaly nudging, Full-field nudging introduces a large climatological change (cyan lines).
- Atmospheric nudging collapses the ensemble spread at the ocean surface and degrade ODA impact.

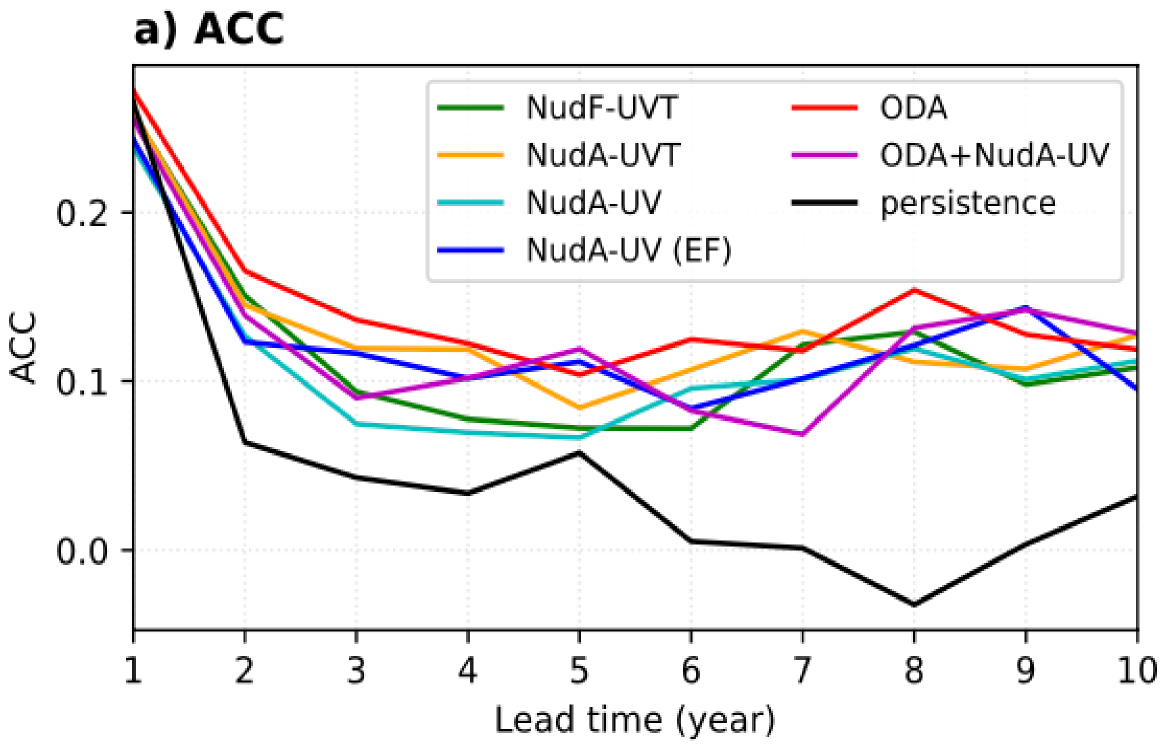
Garcia et al. subm

Impact on prediction skill

Seasonal time scale



Decadal time scale

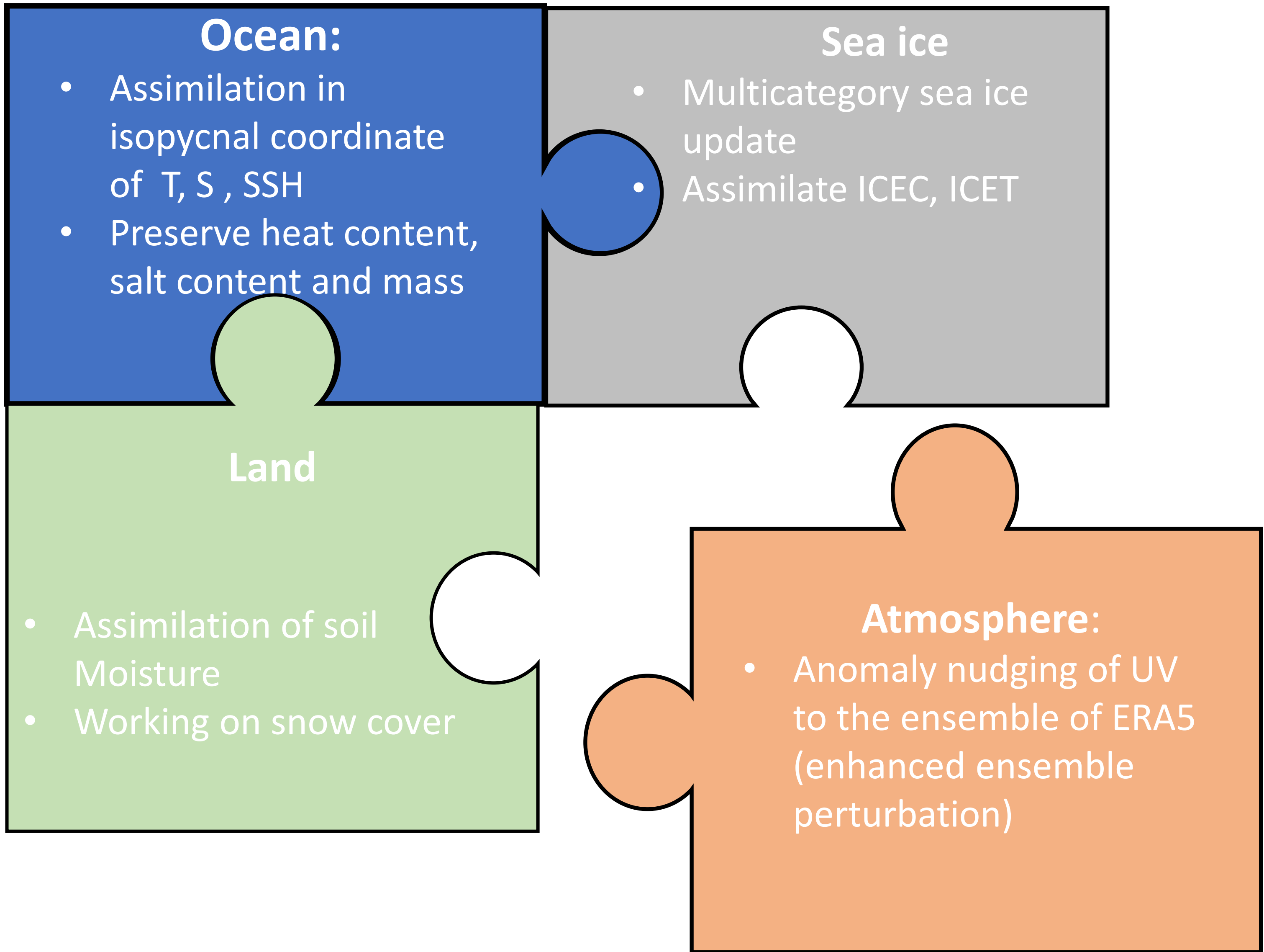


- ODA works overall best but on specific event nudging perform best
- Combination of ODA perform poorly because nudging to single atmosphere collapse spread at the surface

From a sparse to a full input coupled reanalysis

Overall characteristics

- Ensemble data assimilation
- Coupled reanalyses and S2D predictions
- Anomaly assimilation
- All components are constrained within the coupled framework and with the same system as for prediction



Conclusions

- A stochastic coupled ESM reanalysis with assimilation of SST in the ocean and sea ice components can control major indices of climate variability (a reanalysis from 1850 is under production)
- Flow dependent assimilation and the way to organise covariance (isopycnal, sea ice multi category) are impactful; Ad-hoc methods are needed to address sampling error
- A new version of NorCPM with full input data (ocean, land, sea ice and atm) for recent period is under development
- Bias is a key challenge for ocean data assimilation. We keep anomaly assimilation and investigate other way to mitigate those biases:
    - Improved models
    - Parameter estimation
    - Super-resolution DA (emulation of the model at increased resolution)