

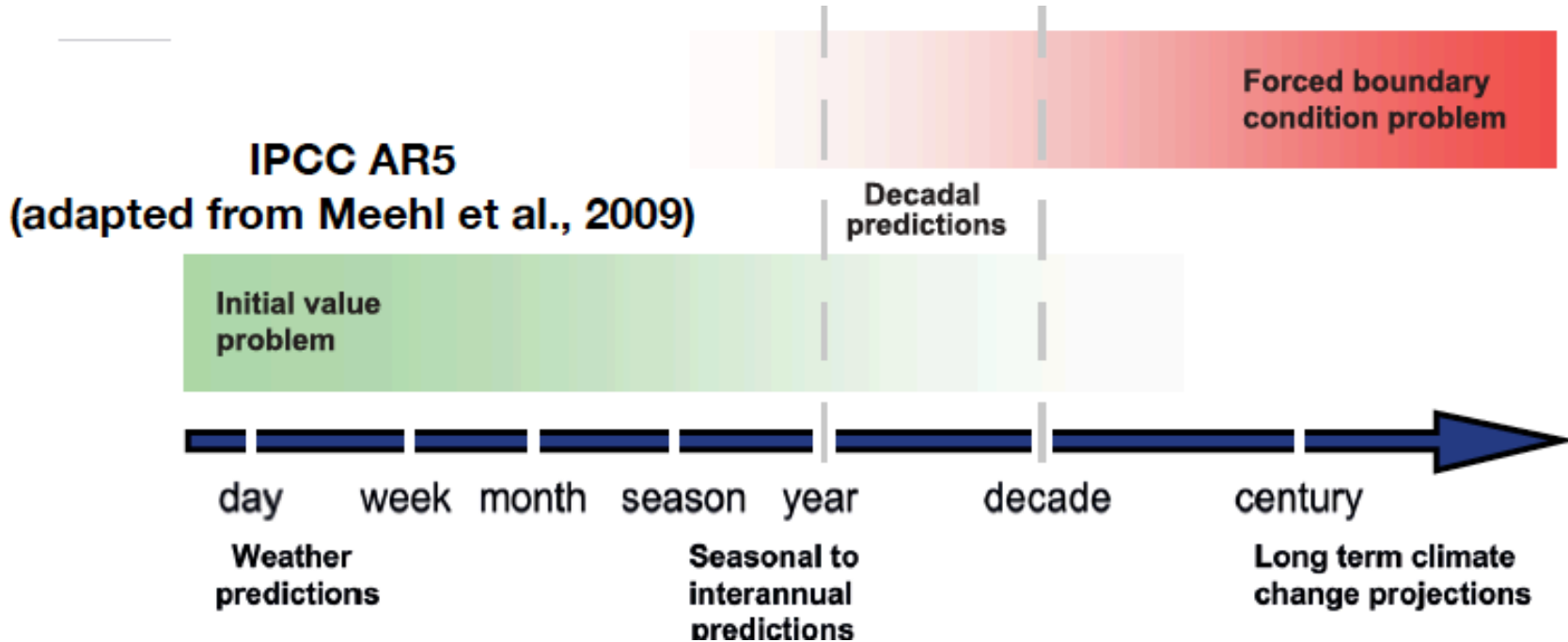
Seasonal-decadal prediction with the Norwegian Climate Prediction Model

“getting ready for CMIP6 DCPP”

F. COUNILLON, Y. WANG, I. BETHKE, N. KEENLYSIDE, M-L SHEN



Seasonal-decadal prediction



- Seasonal-decadal prediction depends on initialization & Forcing
- Most of the predictability is in the ocean (larger inertia and heat capacity)
- Prior attempt showed potential using simple initialisation method (Keenlyside 08, Smith 08, Pohlman 09)

Can advanced data assimilation method improve predictability ?

NorCPM

Norwegian Climate Prediction Model

NorCPM = NorESM + data assimilation (EnKF)

Objectives:

- Long term reanalysis
- Seasonal-to-decadal prediction
 - Regional focus into the Nordic Seas & Scandinavia

Only SST available for a sufficiently long period of time (1850-present) to demonstrate skill for decadal time scale

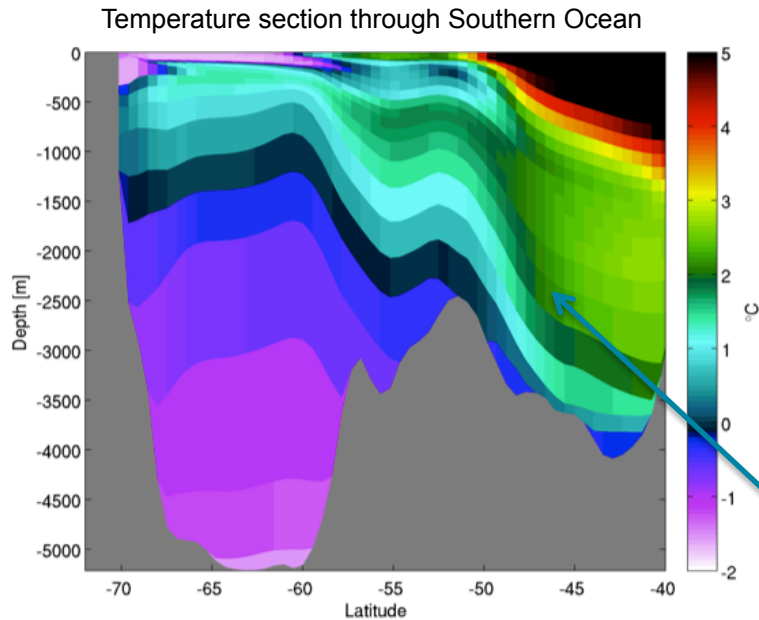
Outlines:

- Twin-experiment (Counillon et al. 2014)
- First test with real observation 1980-2005
- How to avoid assimilation drift in isopycnal model (*Wang et al.*)

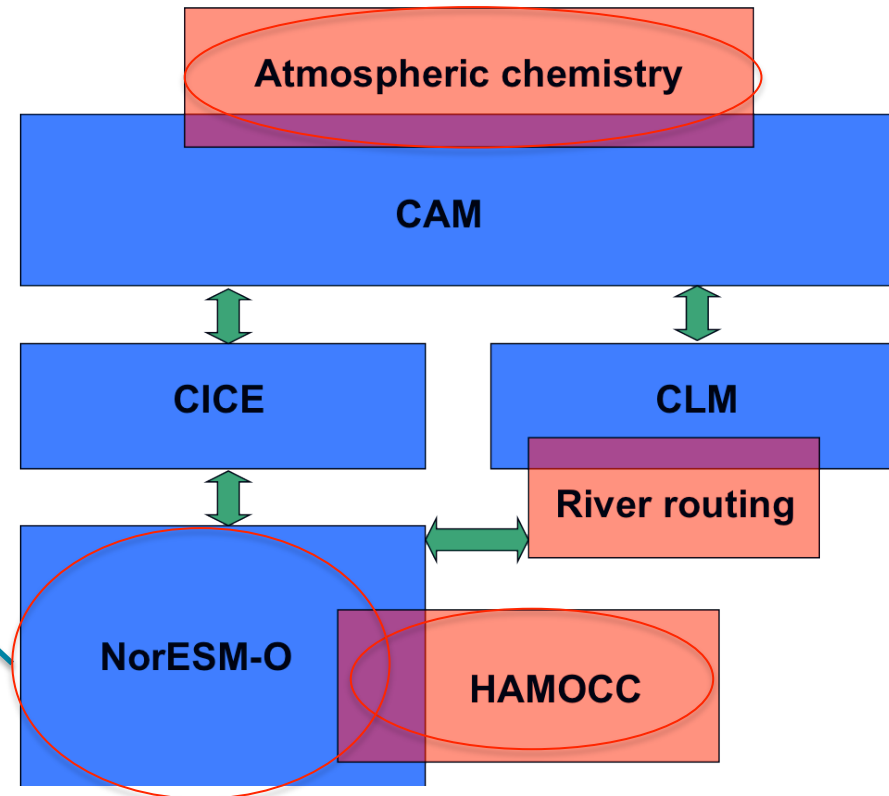


Norwegian Earth System Model (NorESM)

Based on NCAR's Community Earth System Model version 1 (CESM1)



Isopycnic coordinate ocean model with a bulk mixed layer on top



Bentsen et al. 2012

CMIP5 version:

NorESM1-ME (Tjiputra et al 2013, GMD)

atmosphere: CAM4-OSLO on $1.9^\circ \times 2.5^\circ$, 26 levels

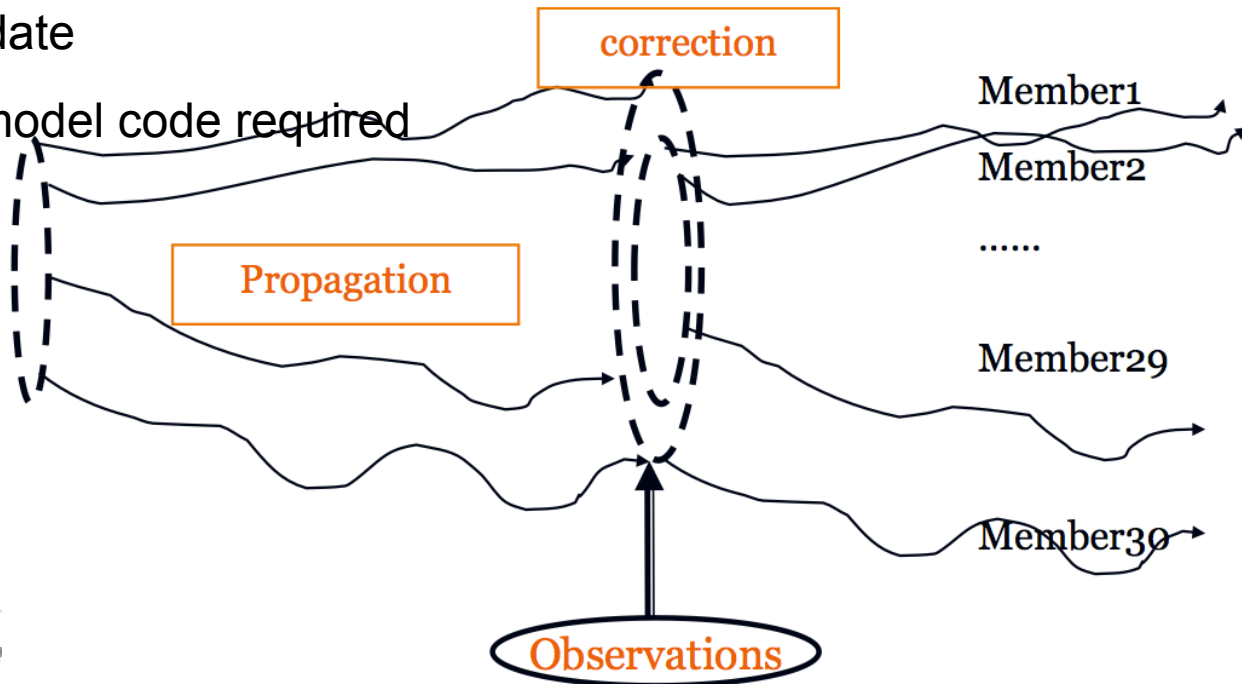
ocean: MICOM on 1° , 53 levels

Ensemble Kalman Filter (EnKF)

Sequential Monte-Carlo method with **propagation** and **correction** step

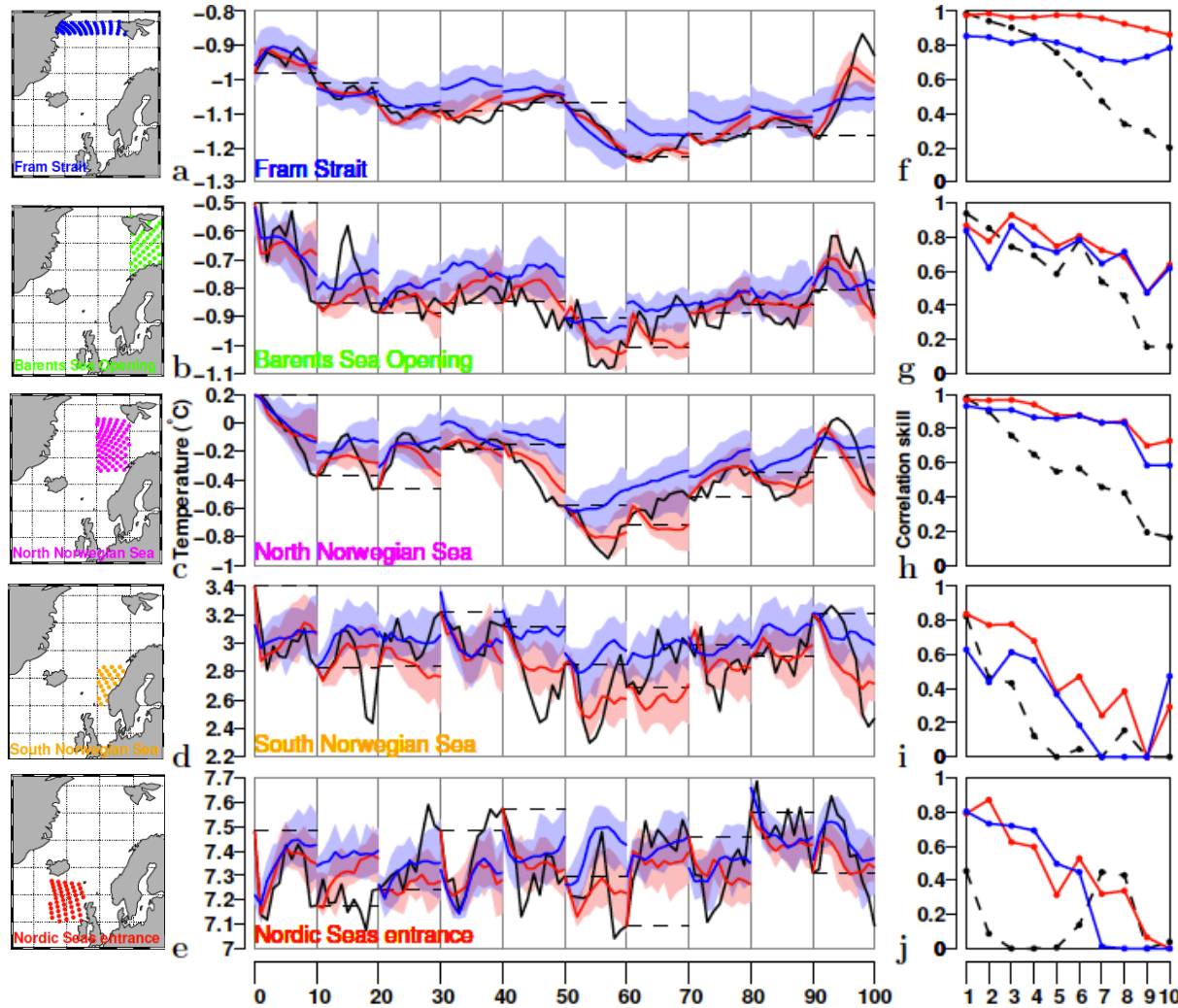
- Forecast = Ensemble mean, Forecast uncertainty = ensemble std deviation
- Ensemble covariance used to update the **full water column** from the obs (e.g., SST)

- **More information extracted** from sparse observations
- Consistency in the update
- No knowledge of the model code required





Nordic Seas heat content (0—300m) Predictability 1—10 lead-year



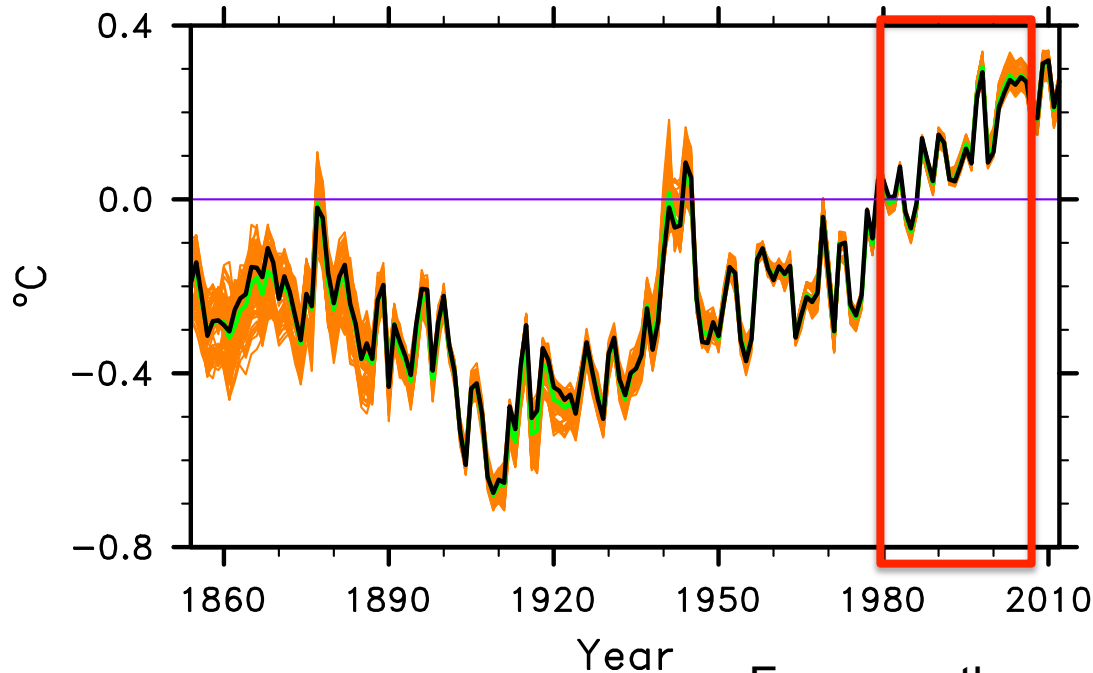
In twin-experiment, EnKF-SST shows skills for AMOC Nordic Sea heat content and SPG index comparable to the limit of predictability

Counillon et al. 2014



Assimilation of real observation

(b) SSTA (60S–60N)



- HadISST2 1850-2007
- 1° resolution, monthly
- Obs error varies space & time

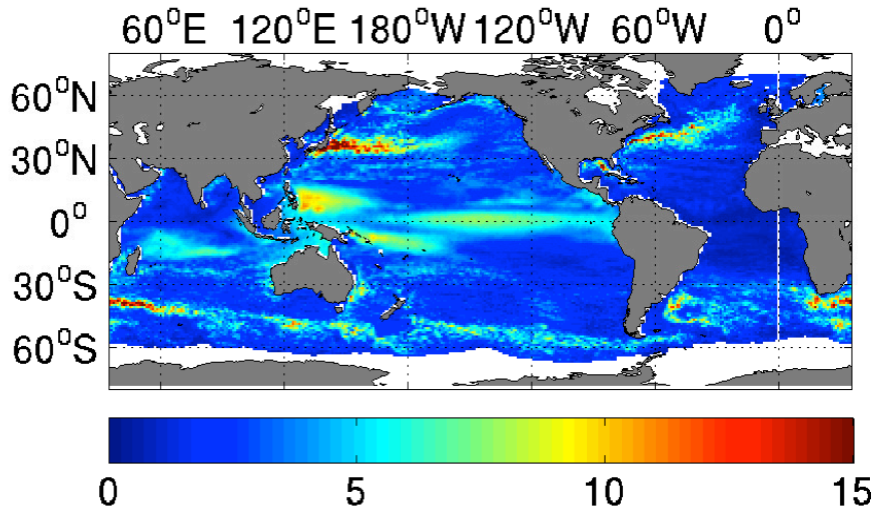
Assimilate anomaly w.r.t. 1980-2000

Focus on the period 1980-2005 first:

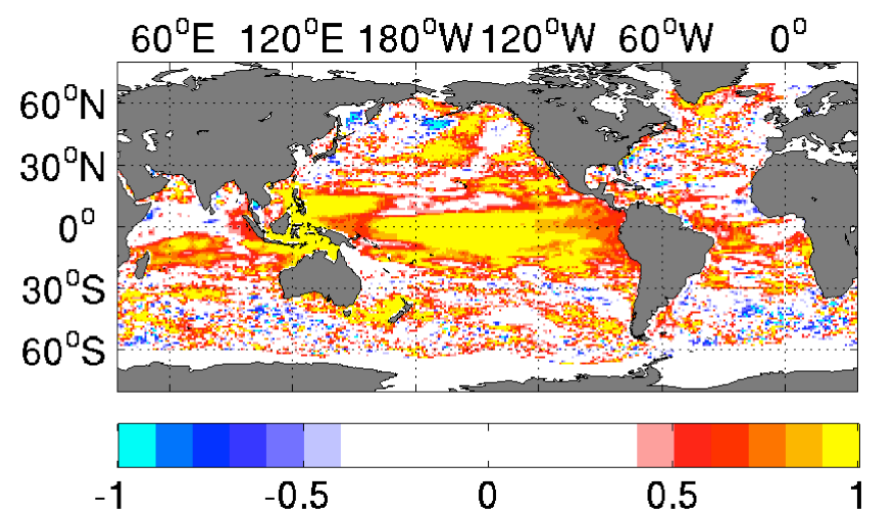
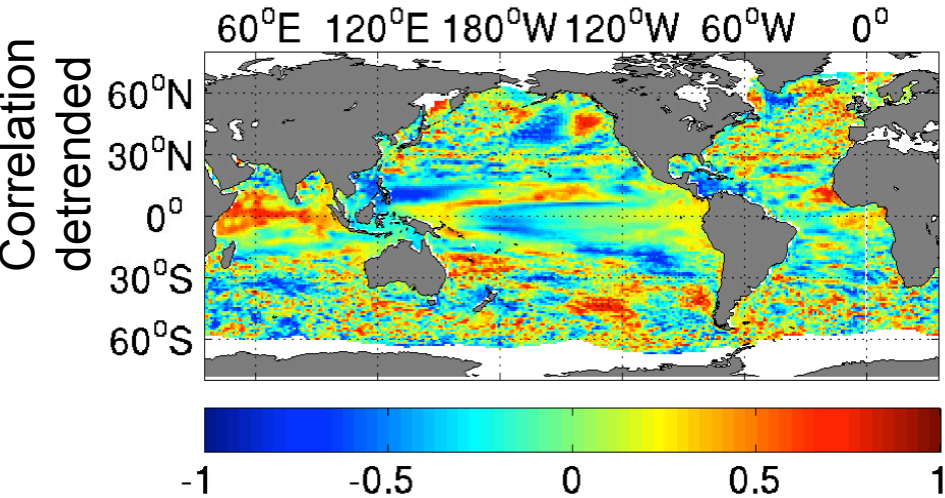
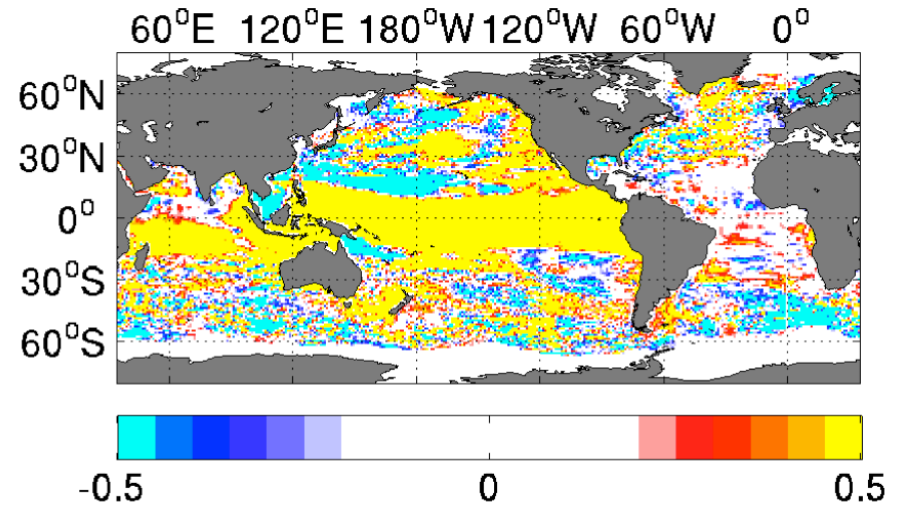
→ plenty of independent obs for validation

Validation with SSH data

Free run

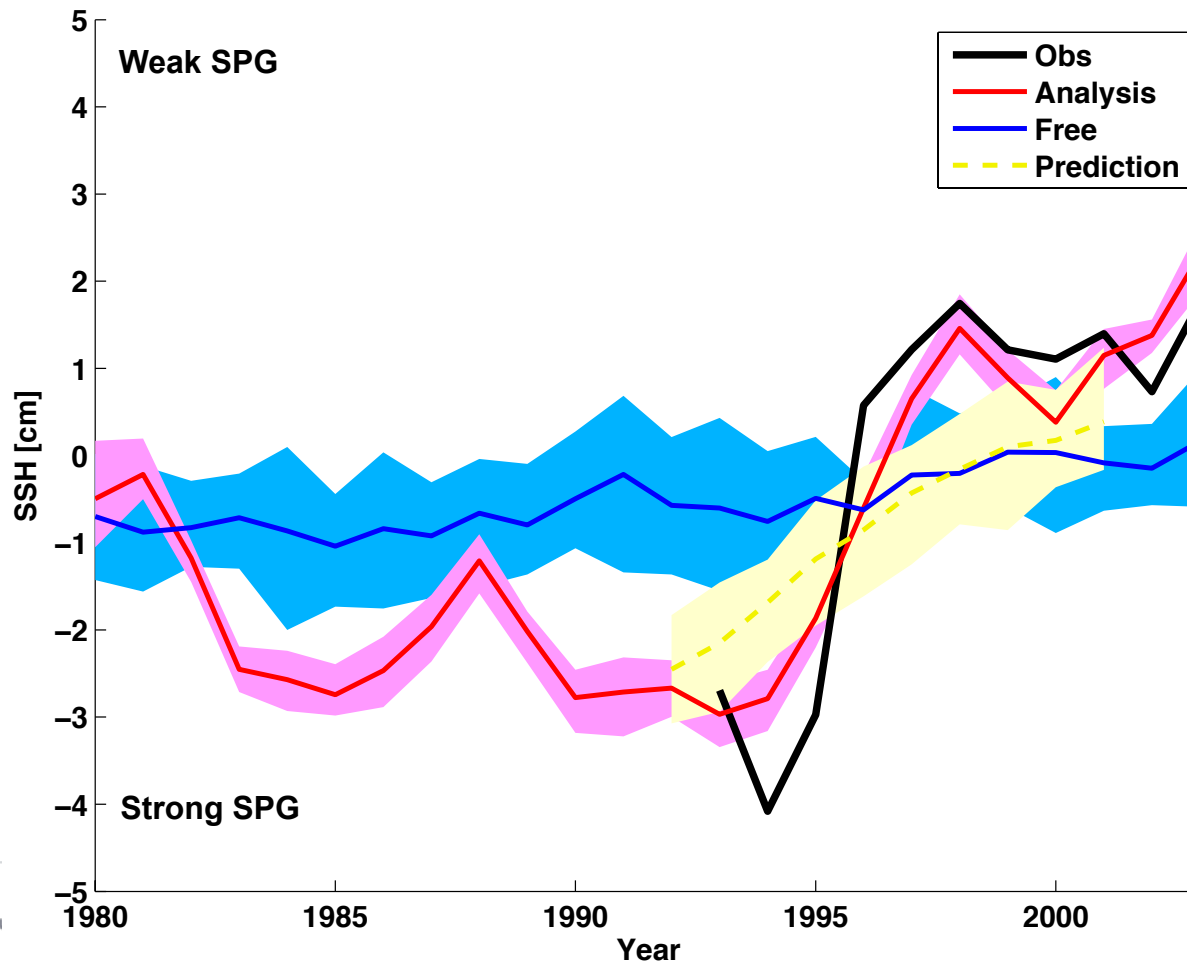


Free run – EnKF



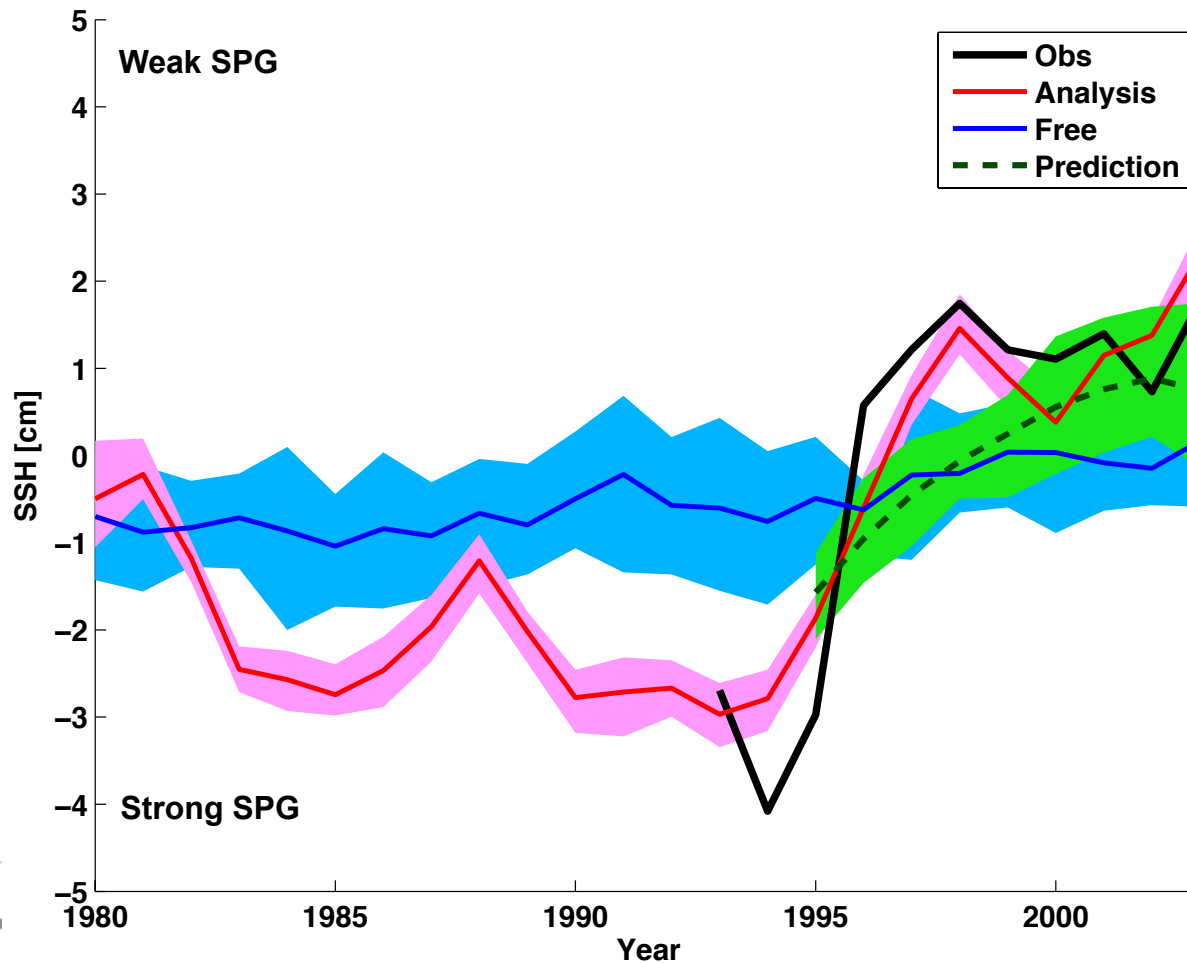
SPG index

- SPG index is box-averaged SSH [60W-15W,48N-65N]



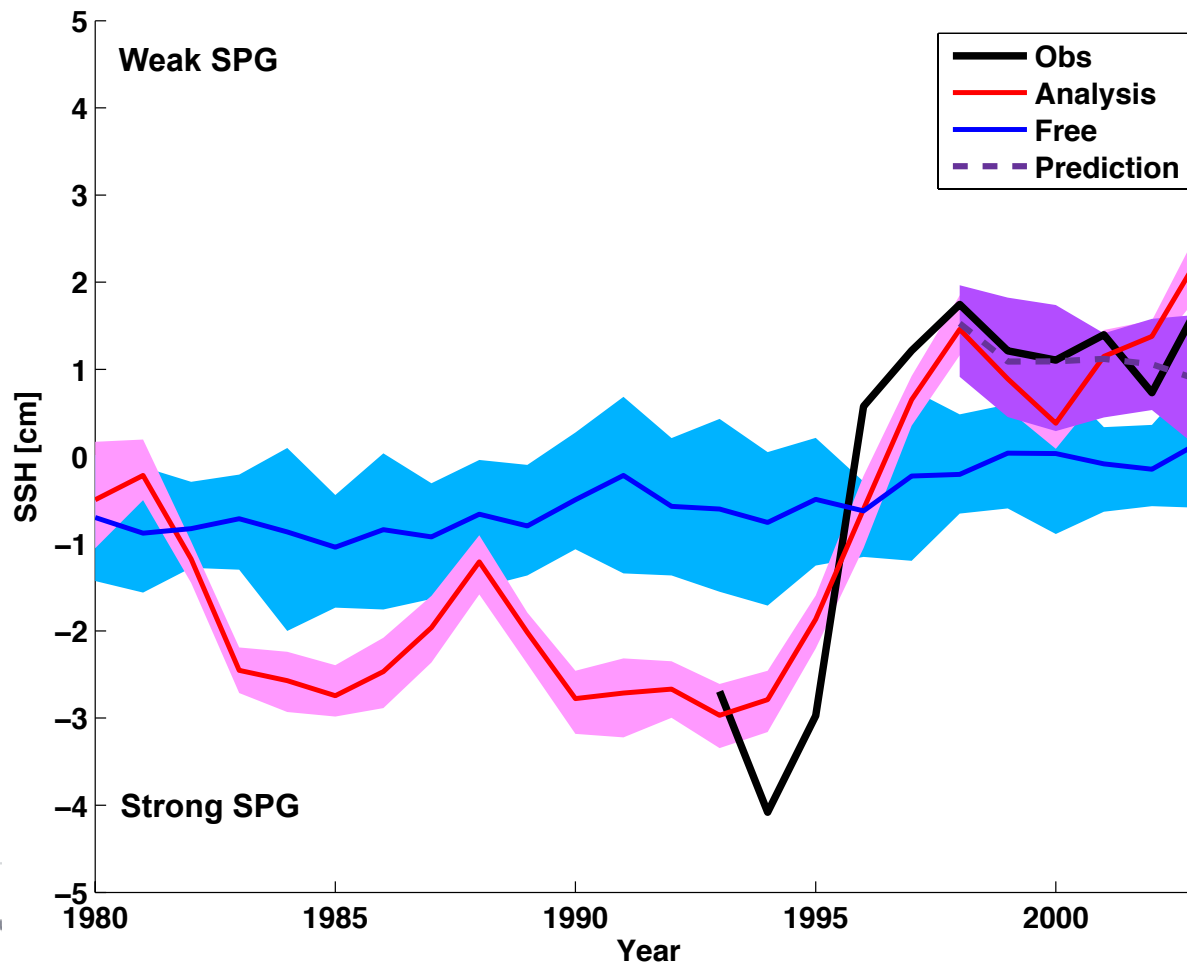
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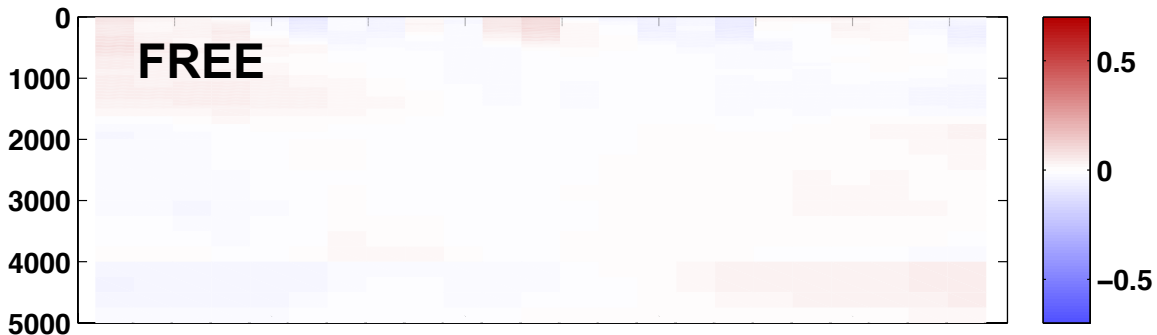
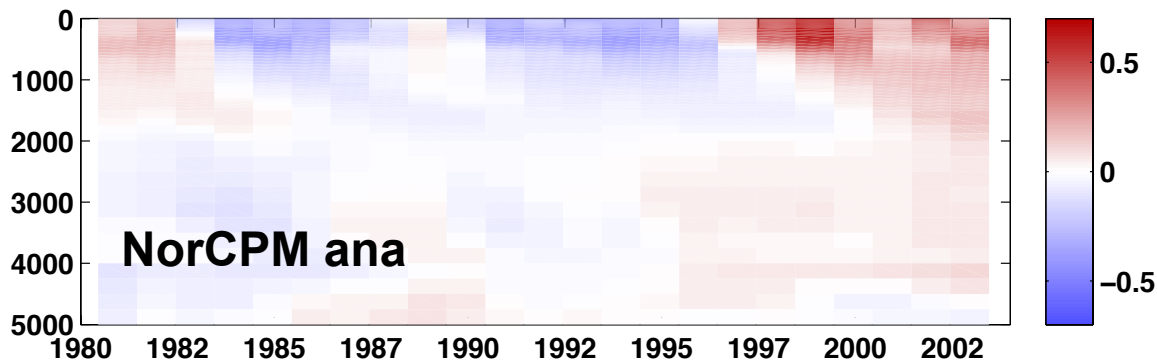
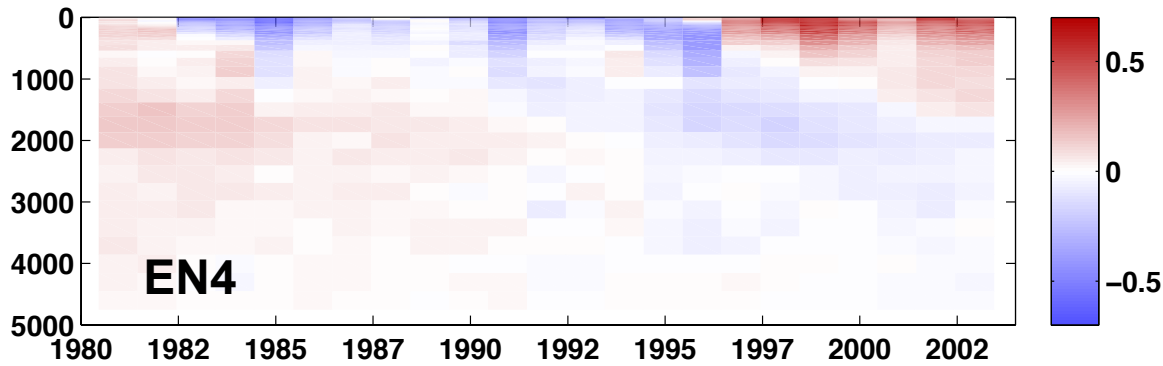
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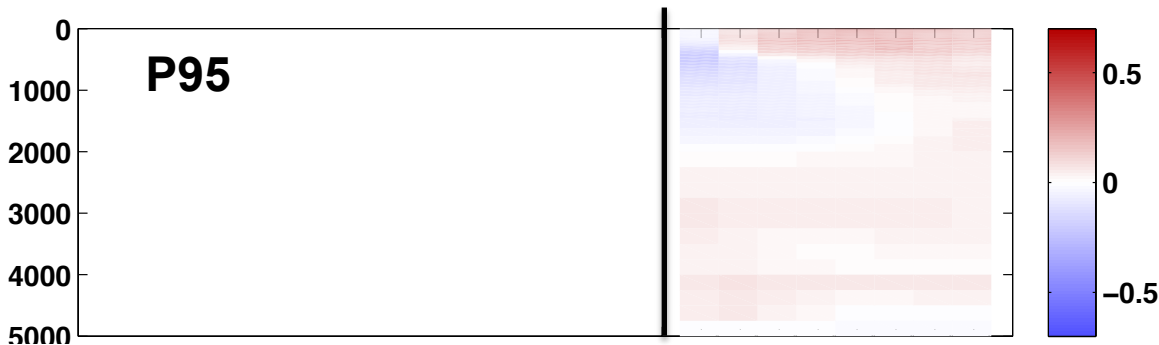
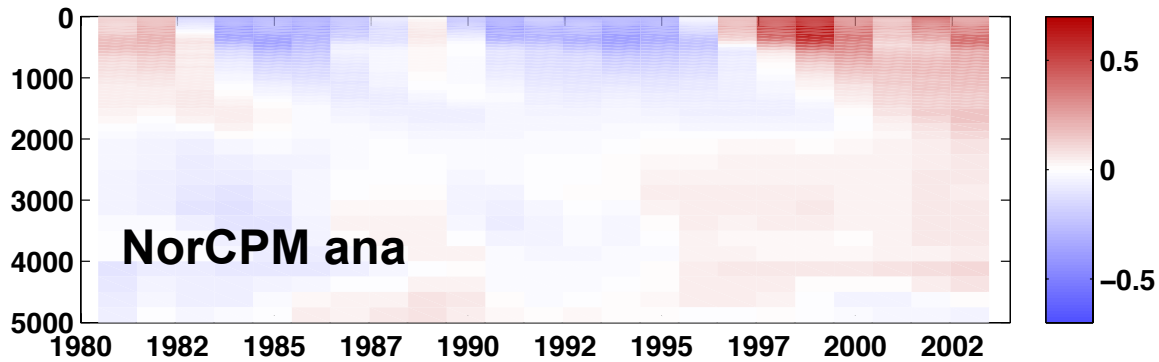
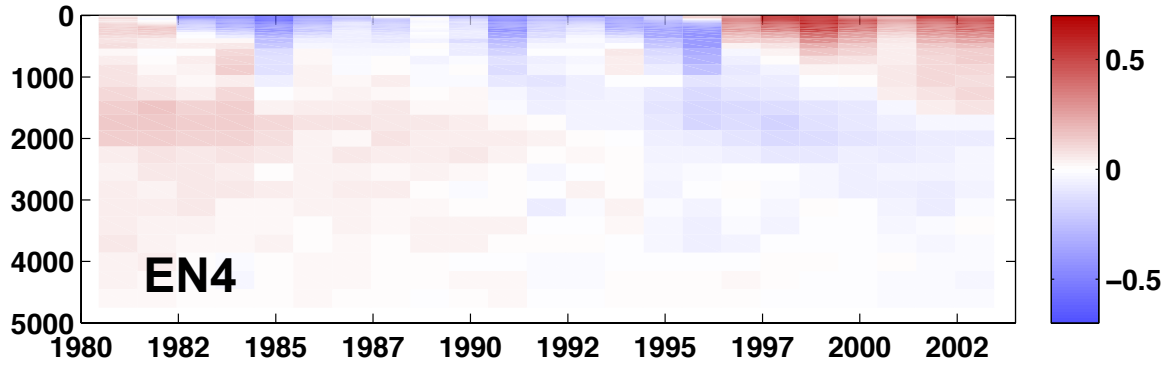


SPG temperature anomaly 1980-1995





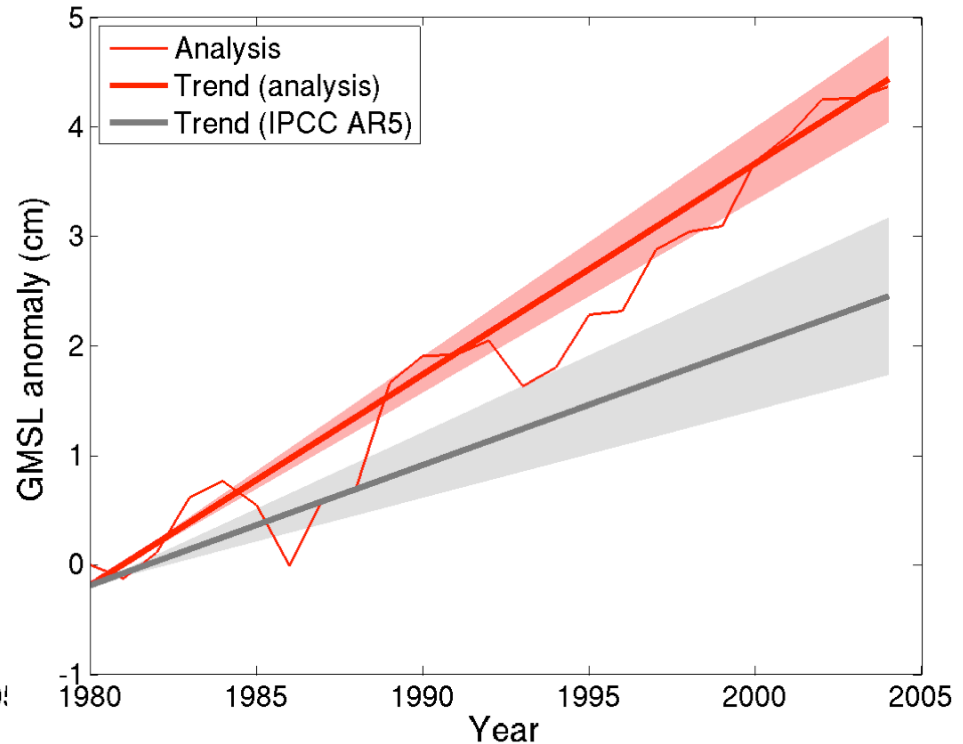
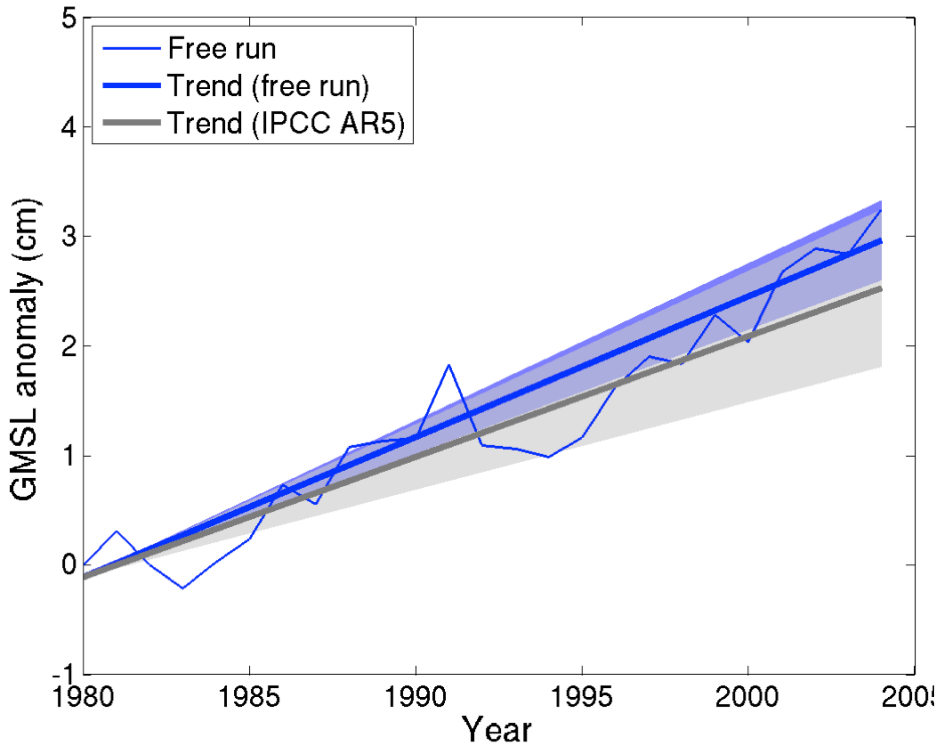
SPG temperature anomaly 1980-1995



Data assimilation introduces a drift

Assimilation of layer thickness is :
profitable but introduces a drift

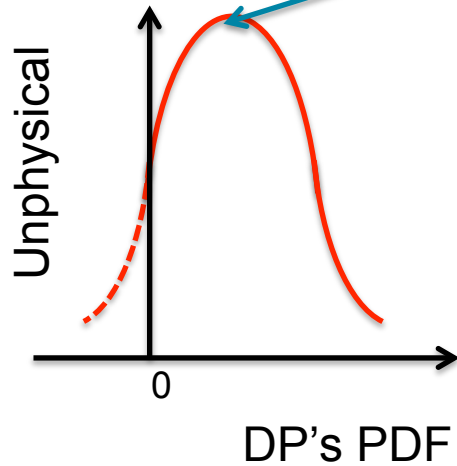
Degradation of the water masses at intermediate depth induces an artificial drift in the steric mean sea Level



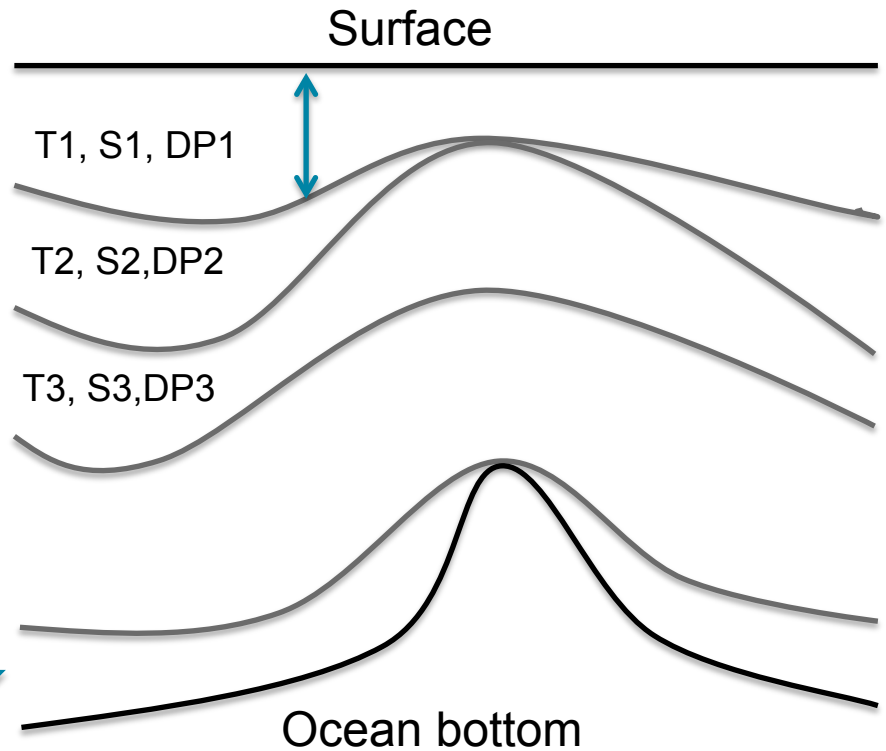
The Norwegian Climate Prediction model

OBS :SSTA

Linear analysis update in EnKF produces unphysical values ($DP < 0$)



Propagate update via covariance



Correcting for those unphysical value inevitably introduces a drift

Physical constraints in NorCPM

–Non-negative layer:

$$\forall 1 \leq i \leq m, 1 \leq j \leq l \quad DP_a^{i,j} \geq 0,$$

–unbiased estimator of mass in each layer:

$$\forall 1 \leq j \leq l \quad E(a\rho^j \overline{DP}_a^j) = E(a\rho^j DP_t^j),$$

–unbiased estimator of heat in each layer:

$$\forall 1 \leq j \leq l \quad E(ac_p \rho^j \overline{DP}_a^j \overline{T}_a^j) = E(ac_p \rho^j DP_t^j T_t^j),$$

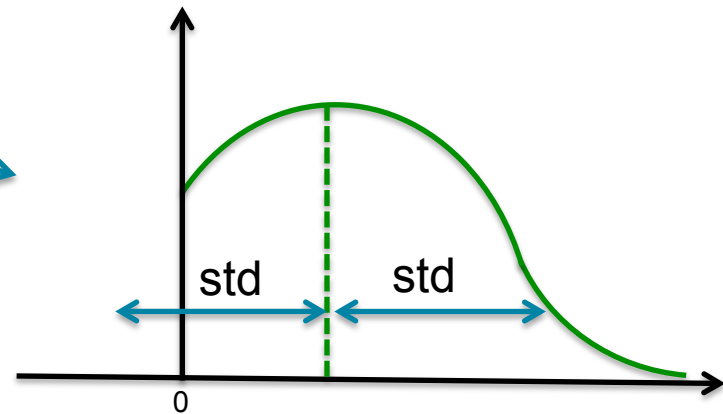
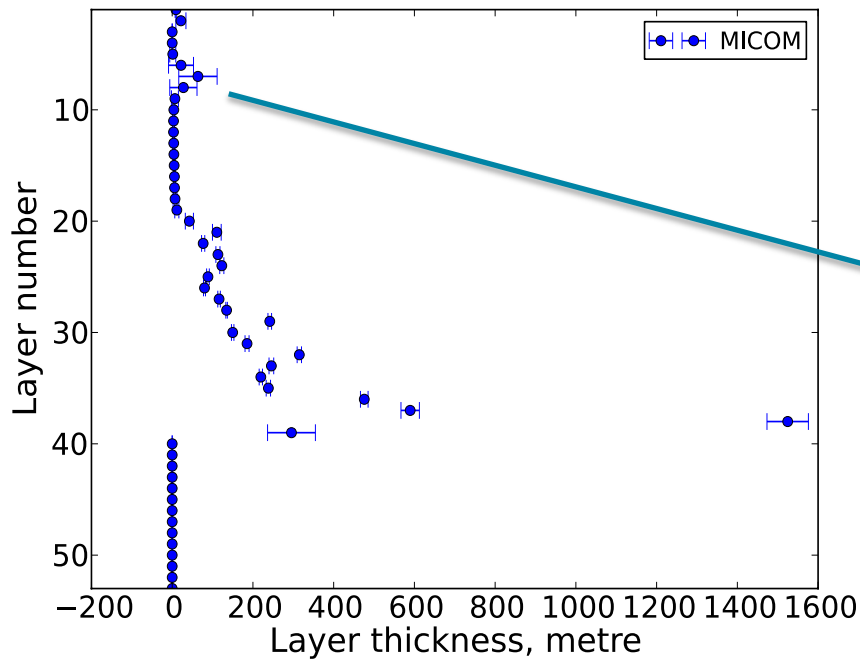
–unbiased estimator of salt in each layer:

$$\forall 1 \leq j \leq l \quad E(a \overline{DP}_a^j \overline{S}_a^j) = E(a DP_t^j S_t^j),$$

t denote 'truth', *m* ensemble size; *l* nb of vertical layers; $E(\bullet)$ expected value of a infinite number of assimilation
a: grid cell area (m^2); ρ water density ($kg\ m^{-3}$), c_p : sea water specific heat capacity ($J\ kg^{-1}K^{-1}$)

Upscaling (aggregating) method:

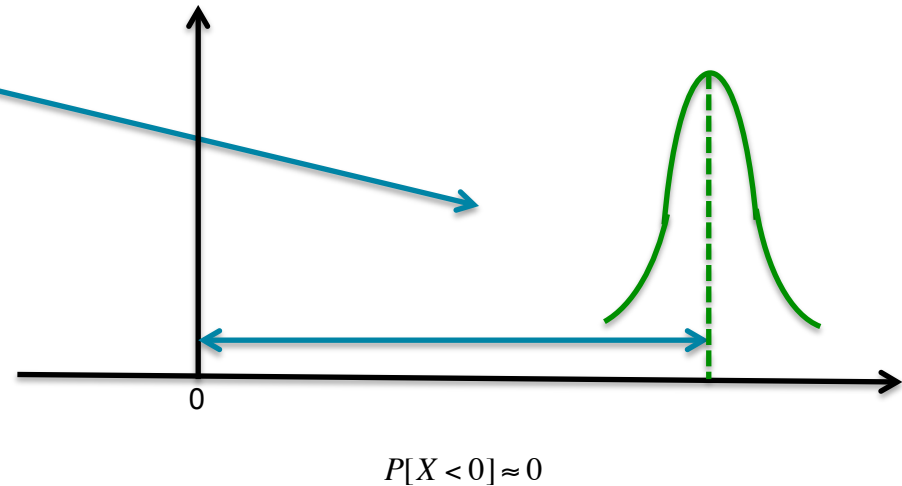
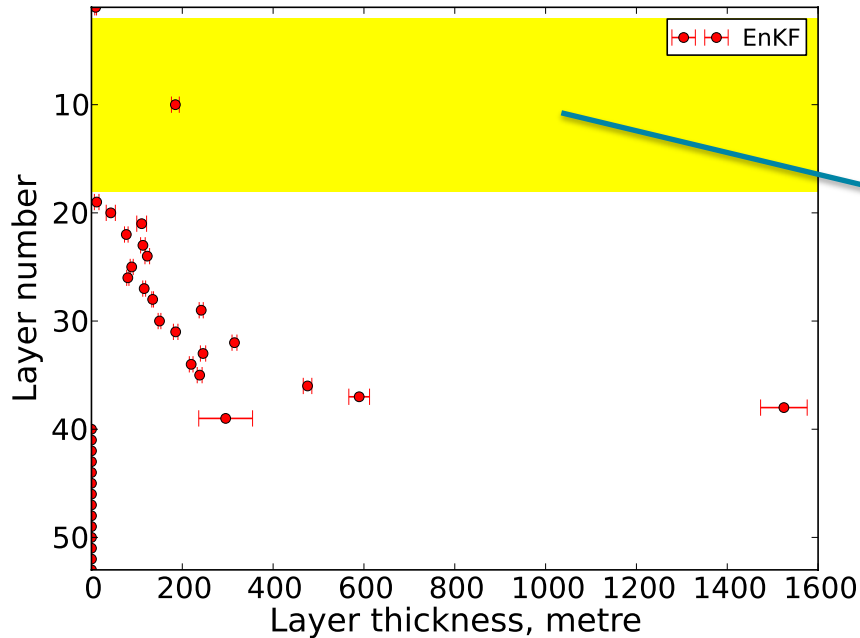
Main idea



Upscaling (aggregating) method:

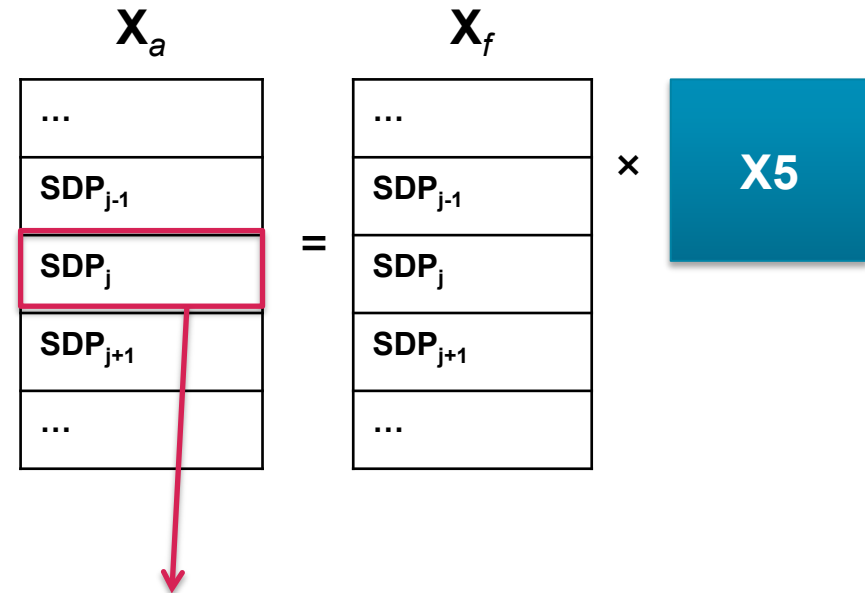
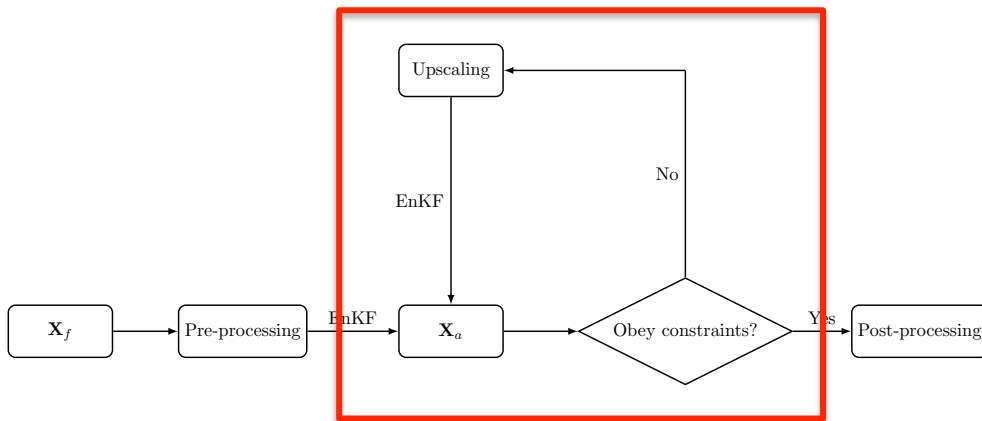
Main idea

By upscaling (or aggregating) we are moving the pdf away from the constraint and shrinking the spread → risk of getting a unphysical value reduced



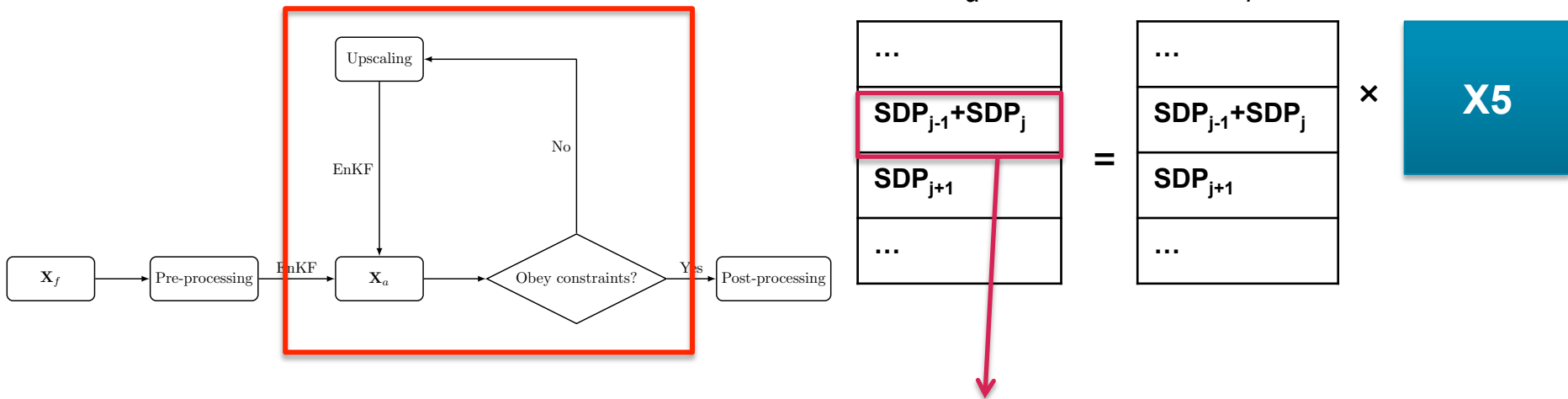
Upscaling (aggregating) method: *iterative method*

Processing: updating of **T**, **S** and **SDP**



Upscaling (aggregating) method: *iterative method*

Processing: updating of **T**, **S** and **SDP**



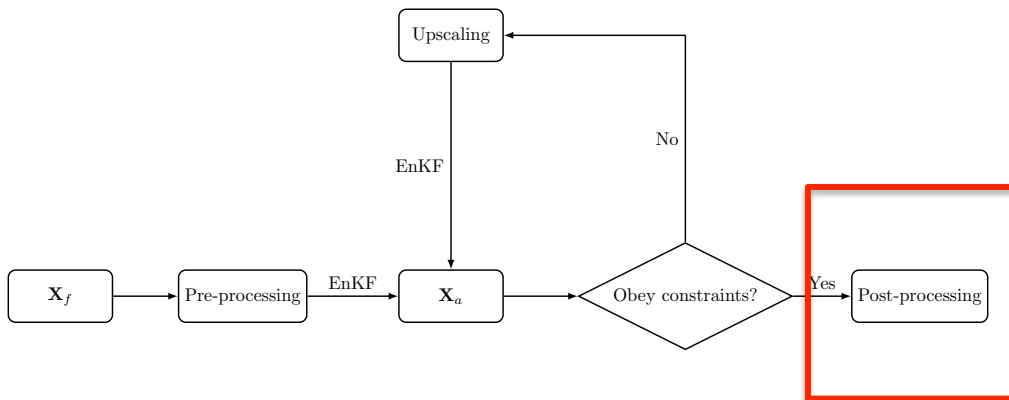
If not negative we redistribute the update

Upscaling (aggregating) method: *Post-processing*

Post-processing: Distribution of SDP_a

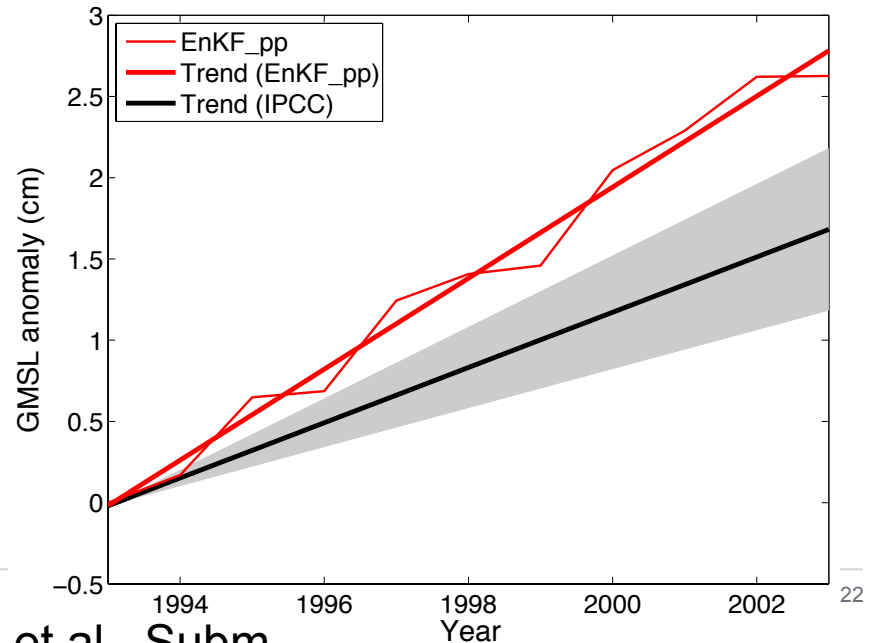
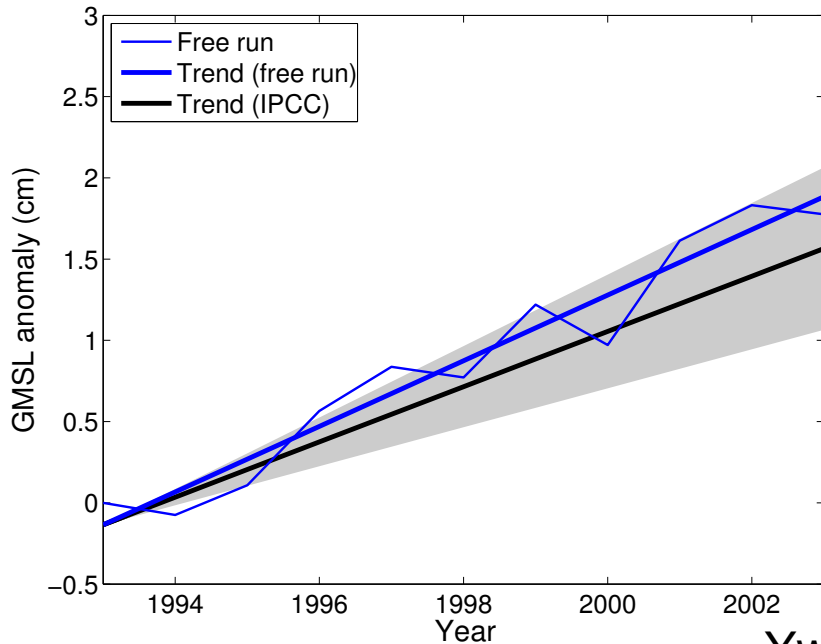
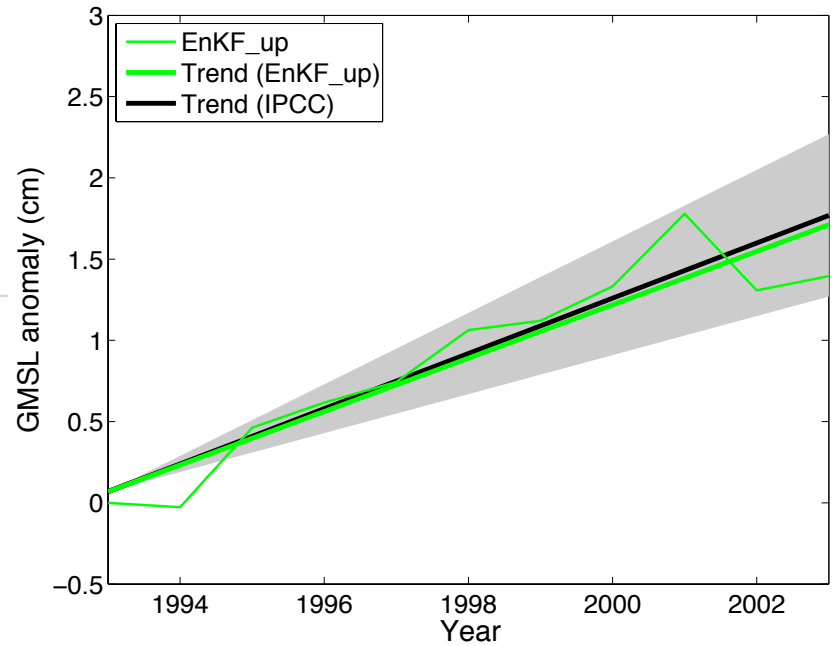
$$\forall 1 \leq i \leq m, j_0 \leq j \leq j_1,$$

$$DP_a^{i,j} = \frac{DP_f^{i,j}}{SDP_f^i} \times SDP_a^i,$$

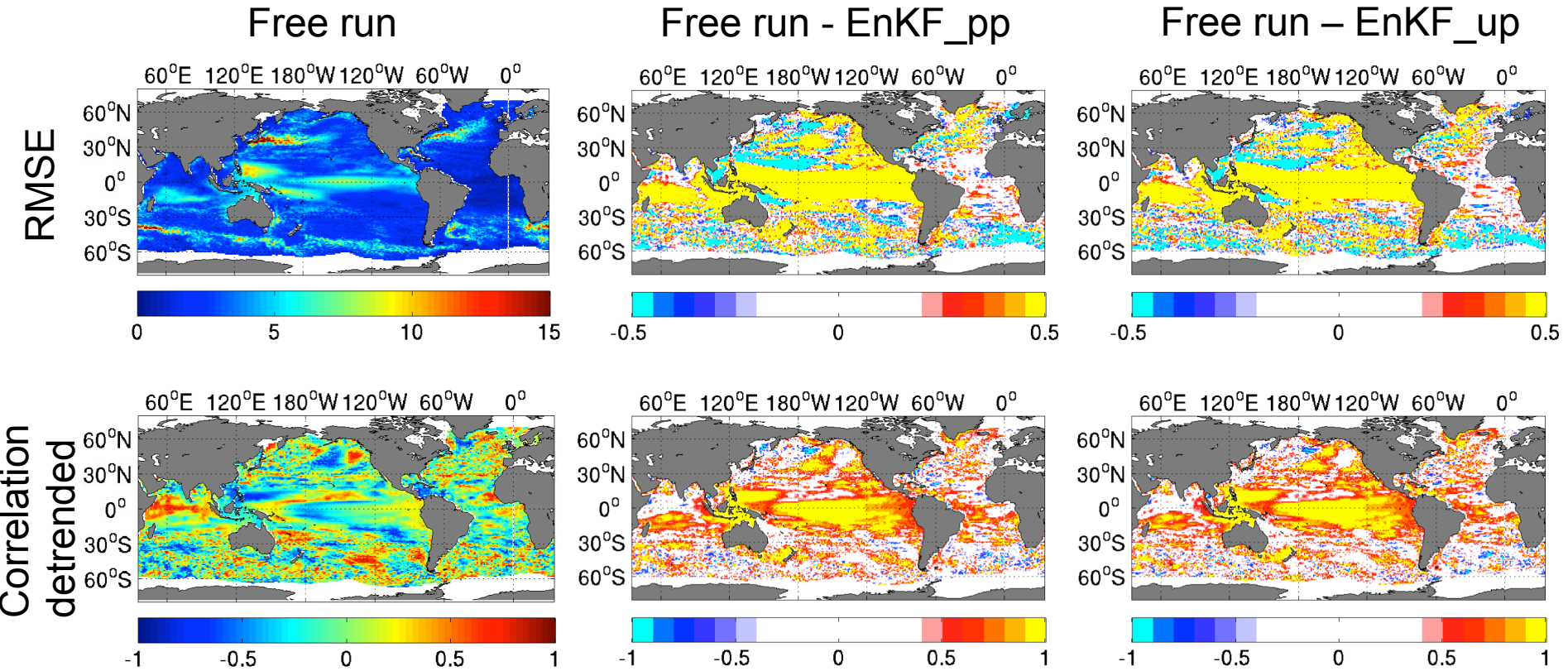


Demonstration in real framework

Method demonstrated in real framework and reduces drift down by a factor 10



Validation with SSH data



Conclusion

- Assimilation of SST in twin experiment shows:
 - Decadal prediction skill (AMOC, SPG, Nordic HC)
 - Assimilation in isopycnal coordinate introduce drift

Counillon et al. 2014

- Assimilation of SST in real framework (1980-2005):
 - Shows skill against independent data (SSH, T-S profile)
 - Predictability reduced compare to twin exp
 - No skill for prediction in the Nordic Sea

Counillon et al. in prep

- The aggregation method handle drift caused by data assimilation for variable with a constrain:
 - Annihilates drift for DA with single member (3D-var, 4D var, EnOI)
some drift remains for ensemble method (reduce by factor 10)
 - Methods does not impair predictive skill

Wang et al. subm.