



Empirical anisotropic multivariate localisation in the ensemble Kalman filter for Earth System models

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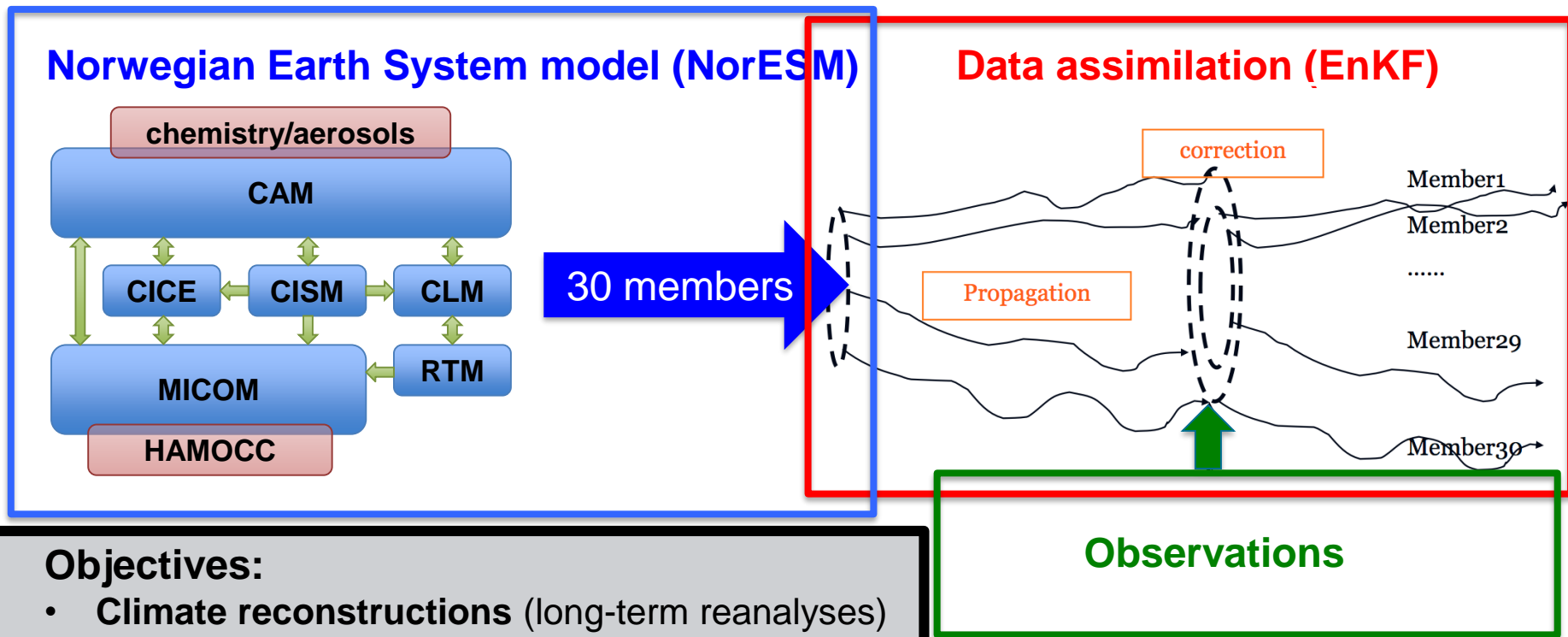
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Outline

1. Norwegian Climate Prediction Model (NorCPM)
2. Empirical localisation in NorCPM

Norwegian Climate Prediction Model (NorCPM)



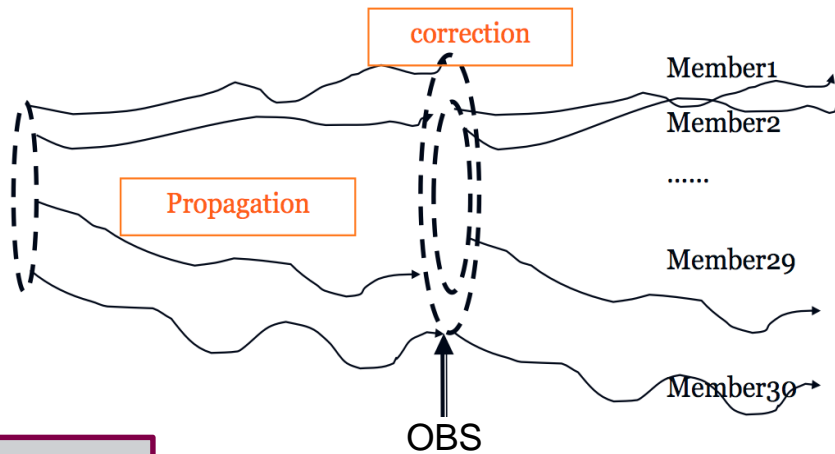
Objectives:

- **Climate reconstructions** (long-term reanalyses)
- **Skilful and reliable climate predictions**
 - CMIP6 decadal climate prediction project (DCPP)
 - Climate services

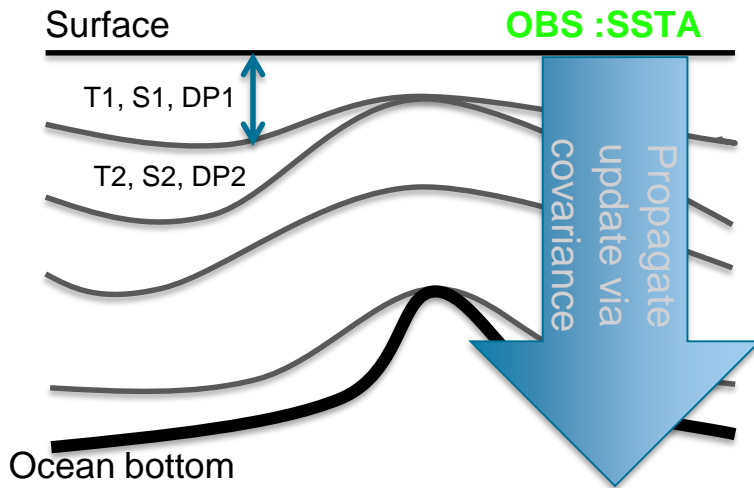
BCCR	GFDL	Met Office	MOHC	NRL
BSC	Institut Pierre Simon Laplace	MIP	MPI	Reading
CCMA	LASG	MRI	SMHI	SMHI
CERFACS	MIROC	NCAR UCAR	NCAR	

Key assets in NorCPM

1. We use dynamical covariance



2. Covariance are constructed in isopycnic coordinate

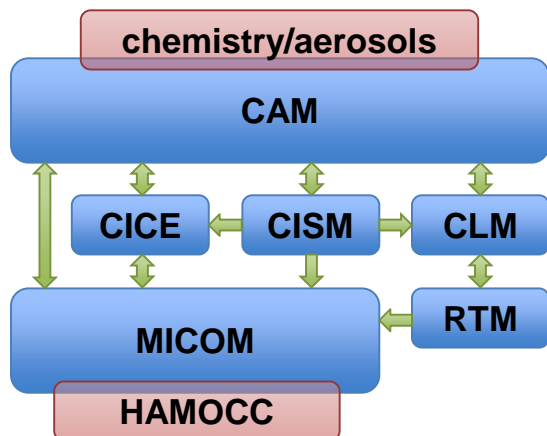


(Counillon et al., 2016)

- 3. Preservation of climate quantities (e.g. ocean heat and salt content, Wang et al., 2016).
- 4. Joint update of the ocean and sea ice components in the assimilation of oceanic data (strongly coupled DA)
- 5. Anomaly assimilation (Carrassi et al., 2018)

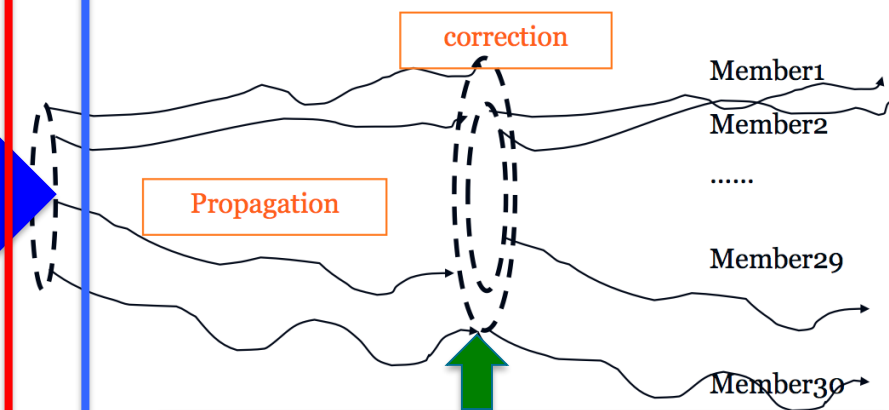
Norwegian Climate Prediction Model (NorCPM)

Norwegian Earth System model (NorESM)



30 members

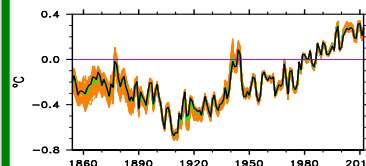
Data assimilation (EnKF)



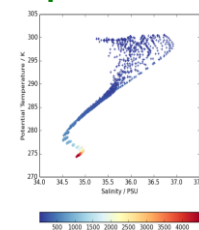
- NorCPM V0: SST (WCDA, ocean only)
- NorCPM V1: SST+TS (SCDA, ocean+sea ice)
- NorCPM V2: SST+TS+ICEC (SCDA ocean+sea ice)
- NorCPM V3: with atmosphere (in development)

Observations

SST & ice-conc SSH

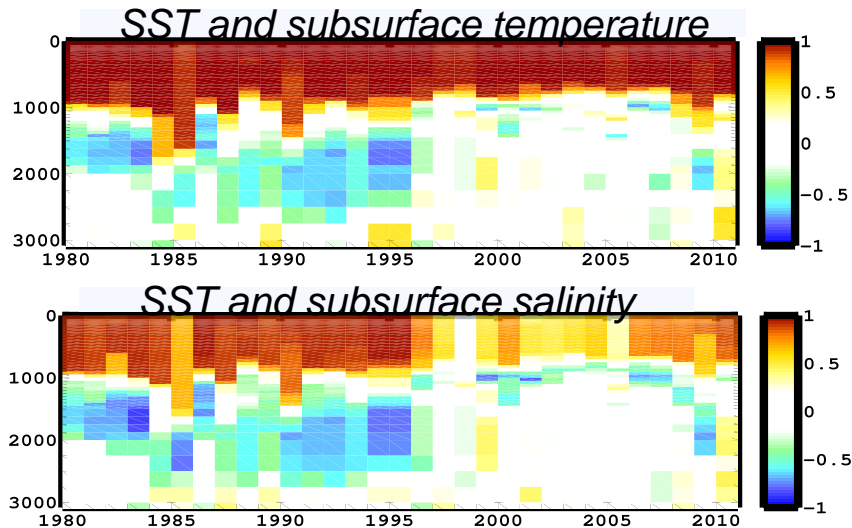


T-S profiles



Dynamical covariance in the Labrador Sea

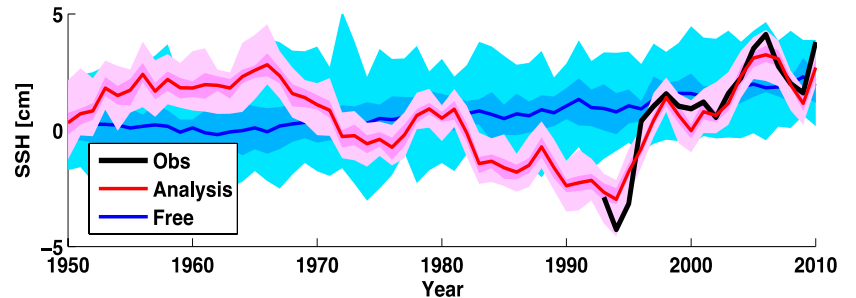
Correlation across the ensemble in April



Covariance are changing after the 1995 shift

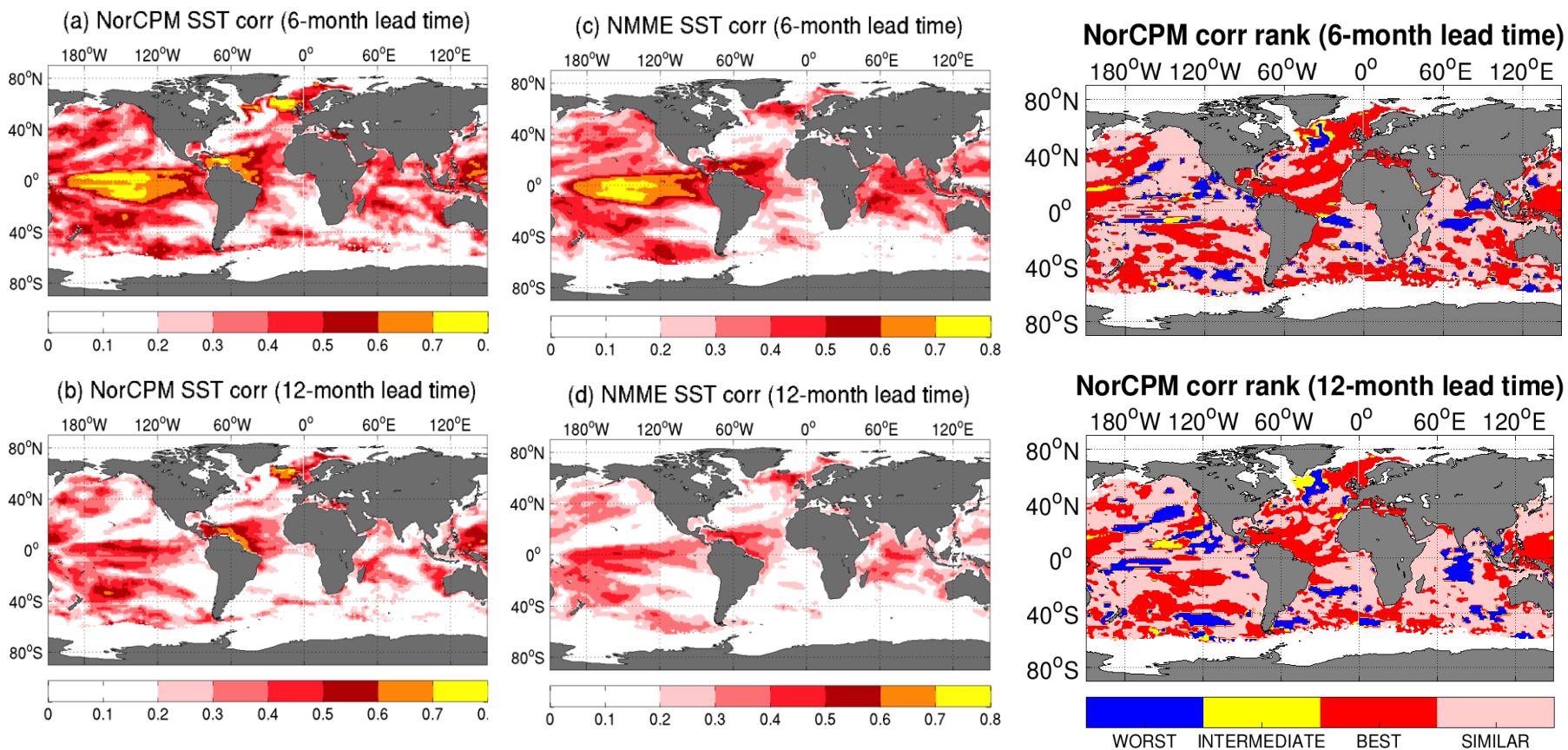
Just using SST observation we can control well the Subpolar Gyre strength

North Atlantic Subpolar Gyre



(Counillon et al. 2016)

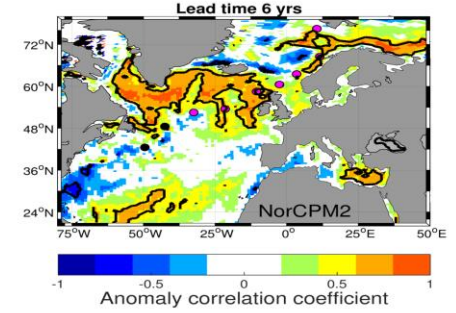
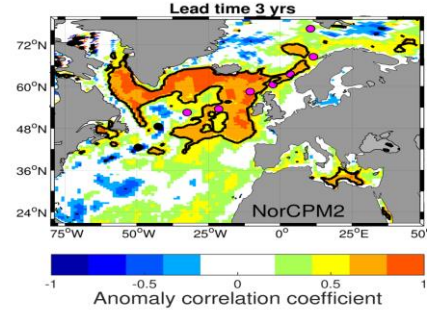
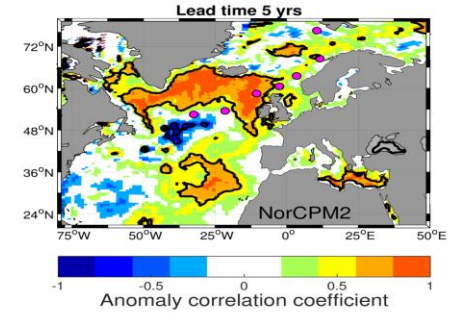
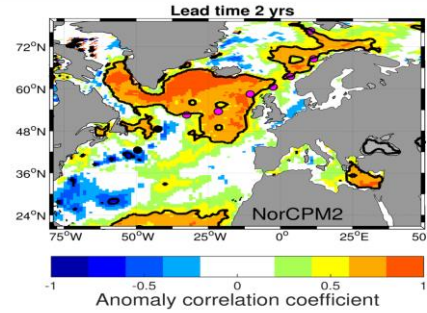
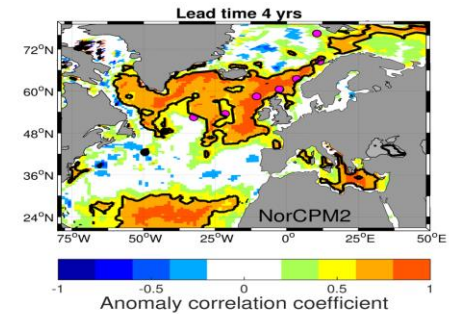
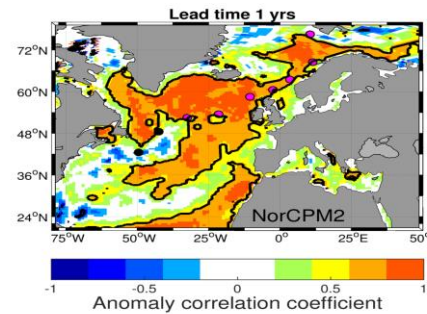
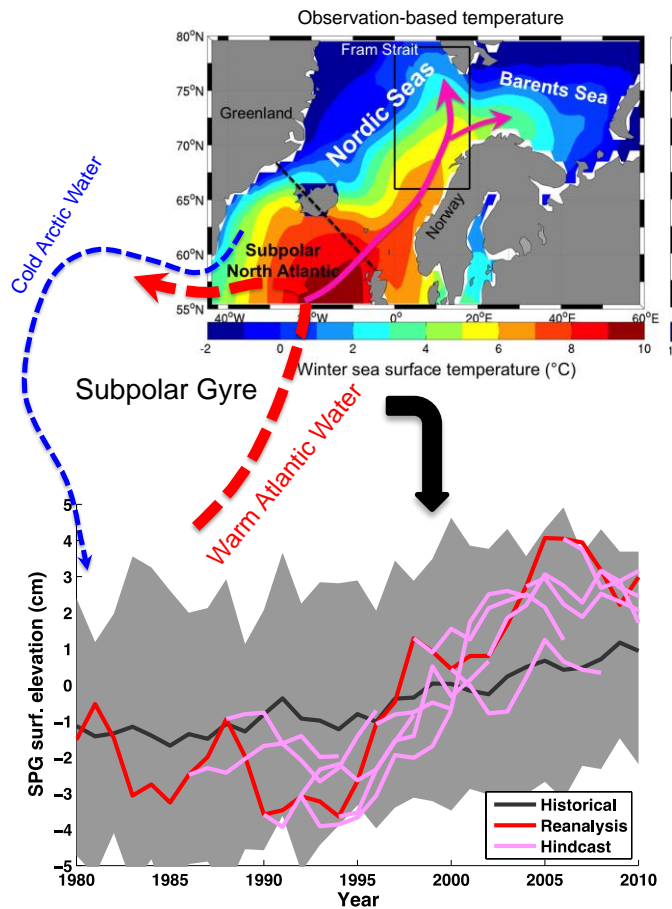
Seasonal prediction of SST tested by retrospective forecast from 1985-2010



NorCPM is competitive with NNME just using SST observations

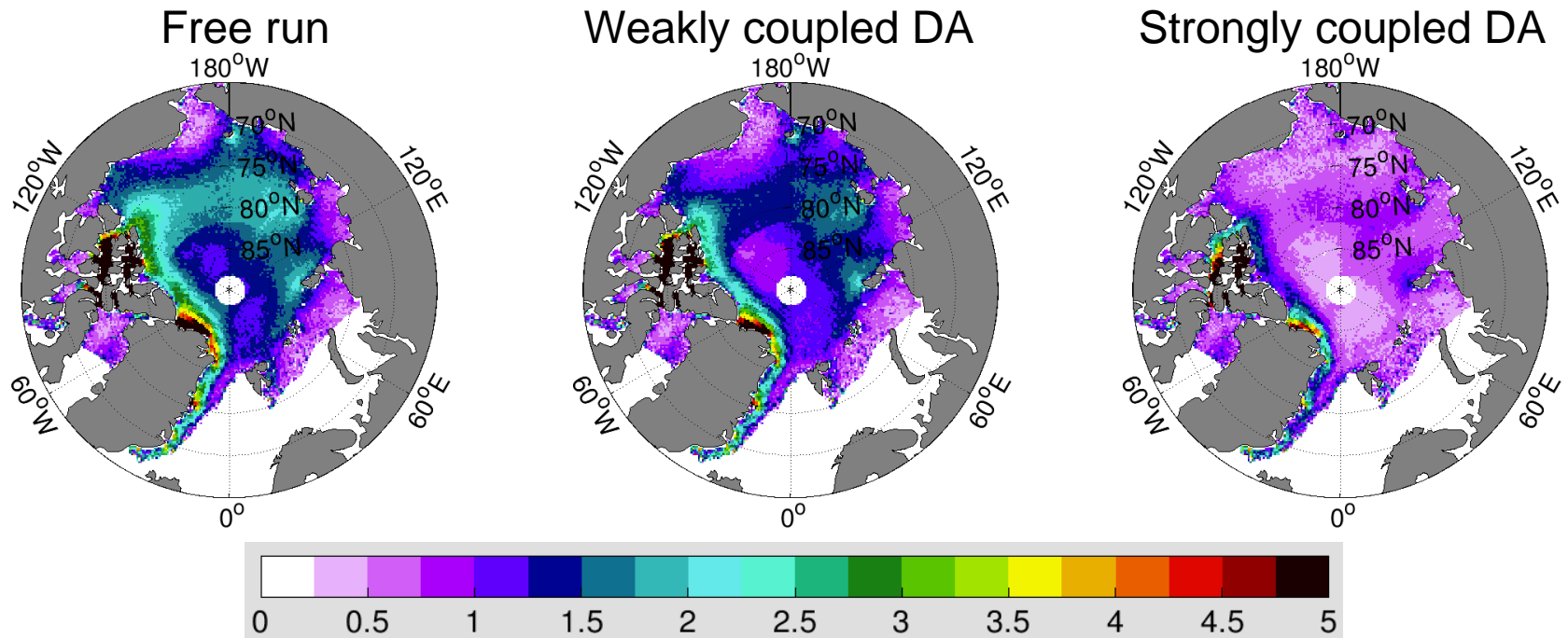
(Wang et al, under review)

Seasonal-to-decadal prediction skill with SST+TS



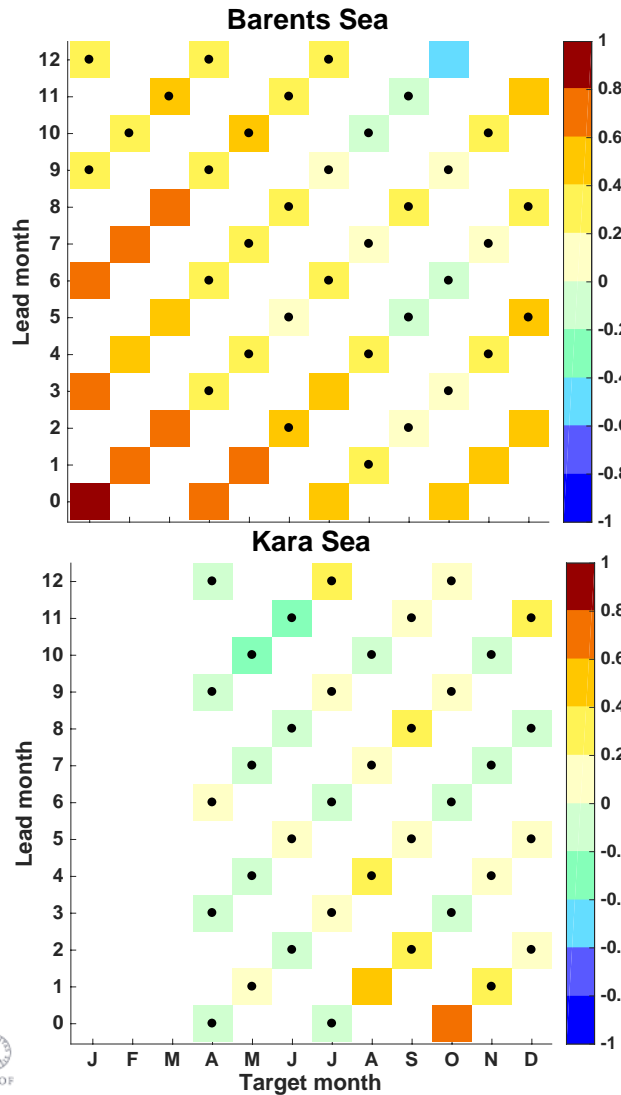
What happen if we allow oceanic data assimilation to update sea ice?

RMSE of sea ice thickness (2002-2017)

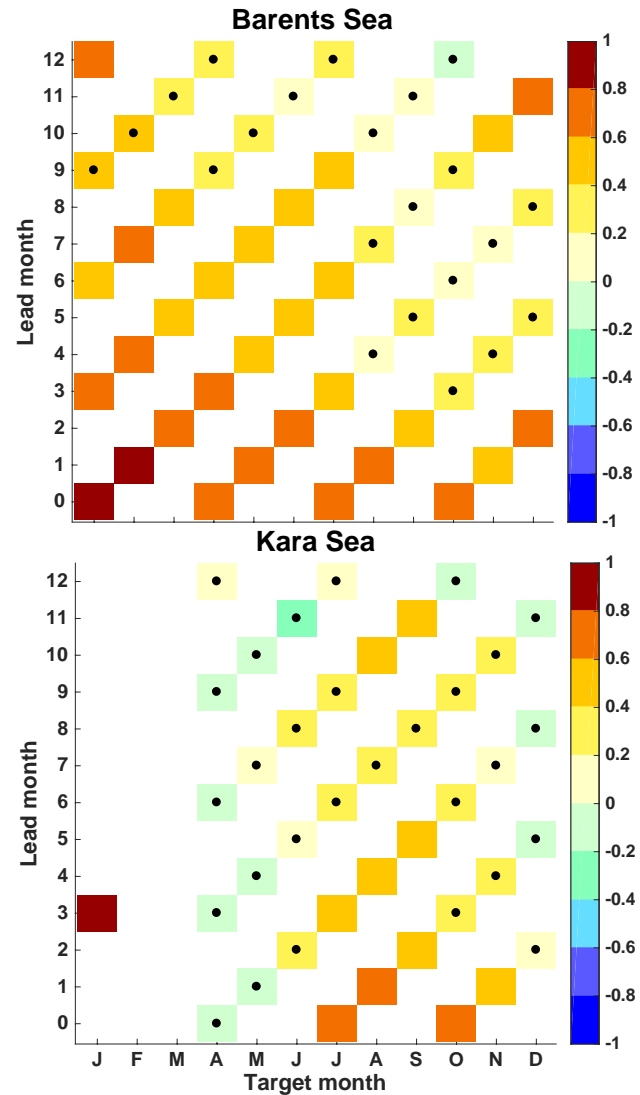


Seasonal prediction of sea ice concentration

Weakly coupled DA

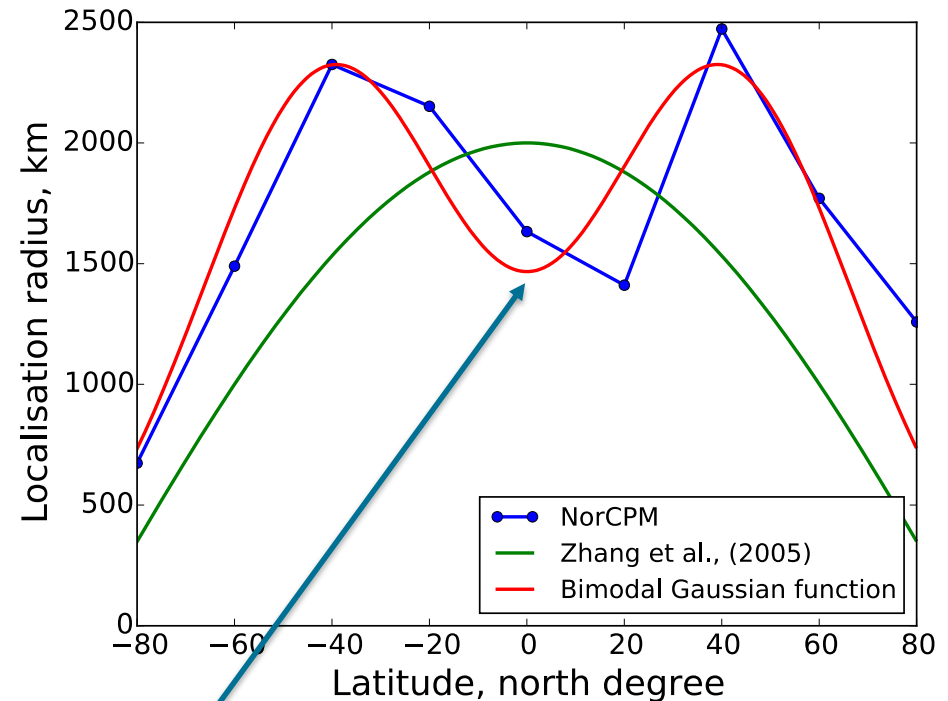
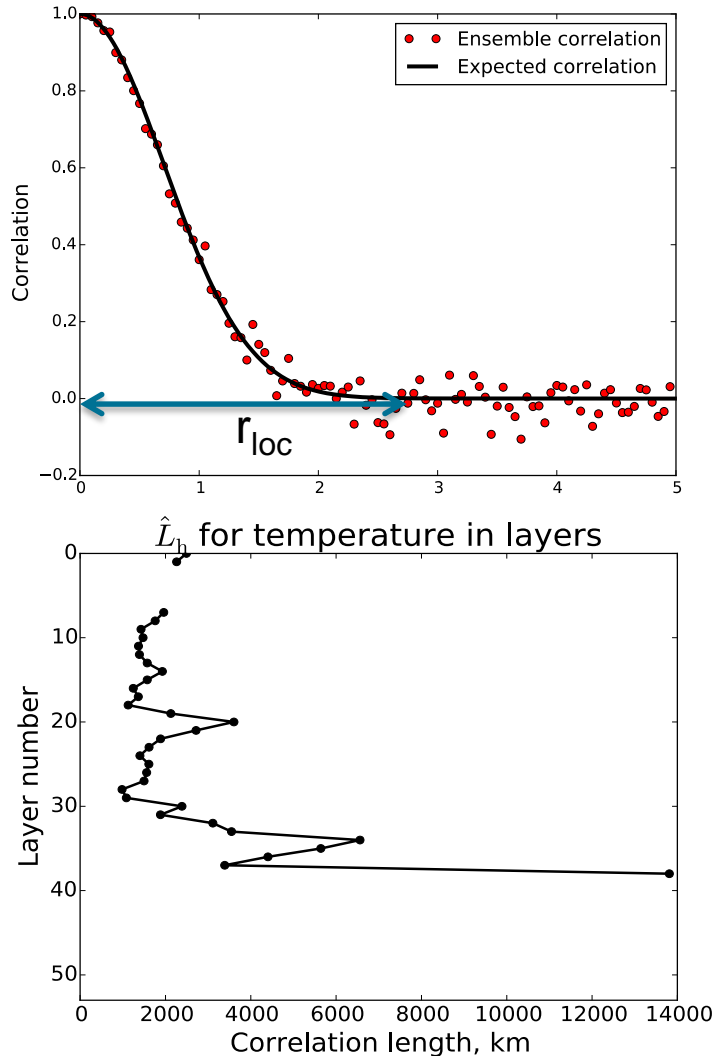


Strongly coupled DA



Empirical localisation in NorCPM

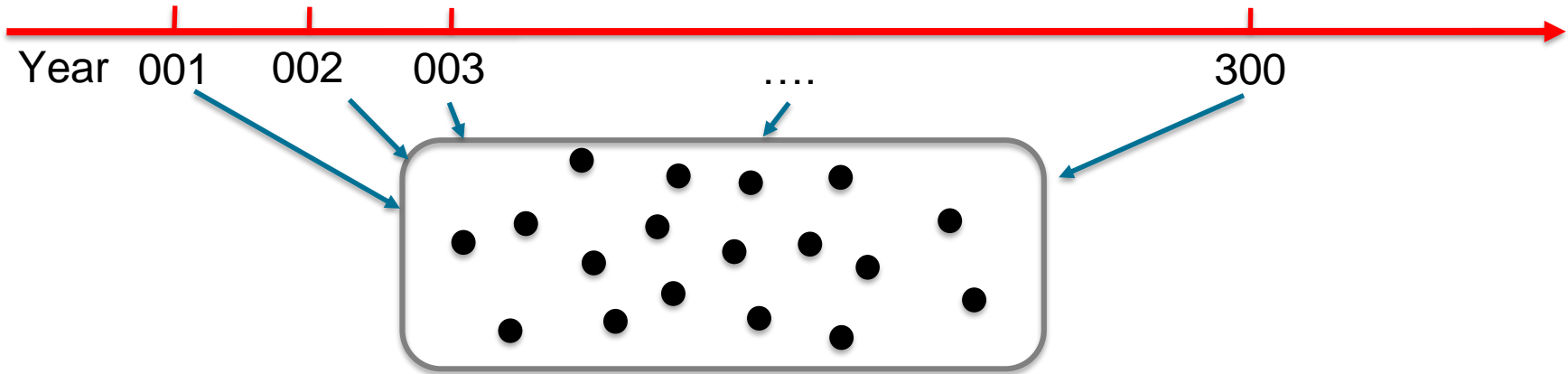
- Ensemble size is too small to span the whole model space (spurious correlations).
- We approximate the horizontal localisation radius by the auto-correlation length scale that best fits the Gaspari and Cohn function (Wang et al., 2017).



Auto-correlation is anisotropic at Equator due to the influence of Coriolis force.

Experimental design

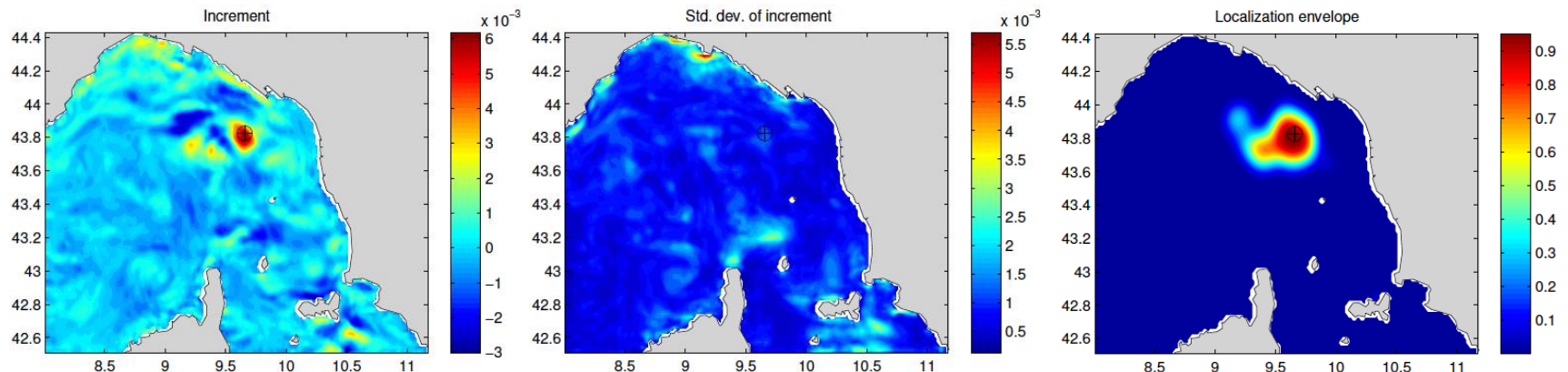
Pre-industrial run, save monthly restart files



- Big ensemble with 300 members for each calendar month (i.e., 3600 static members in total).
- We would like to test two approaches:
 1. Bootstrapping (Barth et al., personnel communication)
 2. Linear filtering of sample covariances (Menetrier et al., 2015)

Bootstrapping

- $x^a = x^f + Kd$, $P^a = P^f - KHP^f$
- K is treated as a random variable
- Create an ensemble of K from bootstrapping (sub-ensembles of 300 members with ensemble size of L , the size of dynamical ensemble)
- Obtain an ensemble of innovation vector
- Compute the localisation based on the variance of innovation vector and KHP^f (e.g. ad-hoc approach)



(Barth et al., personnel communication)

Linear Filtering of Sample Covariances

- Filtered matrix

$$\hat{\mathbf{B}} = \mathbf{L} \circ \mathbf{B}, \text{ where } \hat{B}_{ij} = L_{ij} B_{ij}$$

- Localization coefficient:

$$L_{ij} = \frac{(N-1)^2}{N(N-3)} - \frac{N}{(N-2)(N-3)} \frac{\mathbb{E}(A_{ijij})}{\mathbb{E}(B_{ij}^2)} + \frac{N-1}{N(N-2)(N-3)} \frac{\mathbb{E}(B_{ii}B_{jj})}{\mathbb{E}(B_{ij}^2)} \quad (1)$$

- In Gaussian case,

$$L_{ij} = \frac{N-1}{(N+1)(N-2)} \left\{ (N-1) - \frac{\mathbb{E}(B_{ii}B_{jj})}{\mathbb{E}(B_{ij}^2)} \right\} \quad (2)$$

- Using sample correlations,

$$L_{ij} = \frac{N-1}{(N+1)(N-2)} \left\{ (N-1) - \frac{1}{\mathbb{E}(C_{ij}^2)} \right\} \quad (3)$$

Menetrier et al.: Linear Filtering of Sample Covariances for Ensemble-Based Data Assimilation. Part I: Optimality Criteria and Application to Variance Filtering and Covariance Localization, MWR, 2015.

Linear Filtering of Sample Covariances

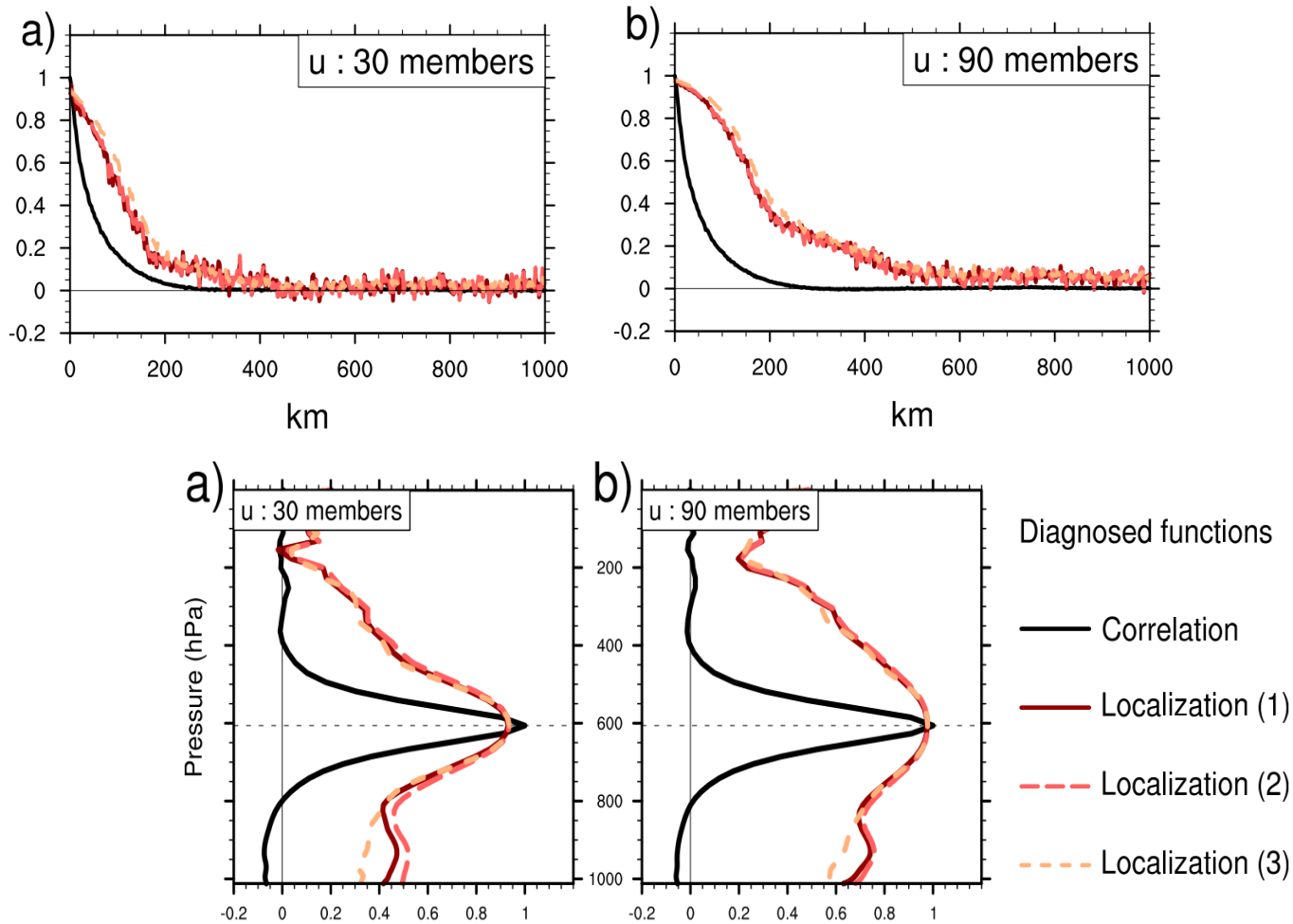


FIG. 14. Diagnosed vertical correlation (solid black) and localization functions (other colored curves) for zonal wind around 600 hPa, computed with Eq. (19) (“1”), Eq. (20) (“2”), and Eq. (21) (“3”) for ensembles of (a) 30 or (b) 90 members. Results are obtained from forecasts issued at 1800 UTC 3 Nov 2011.

Summary

- NorCPM is one of the state-of-art coupled climate prediction system:
 - Well reproduces the climate variability in the north Atlantic
 - Competitive seasonal prediction skill.
 - Successfully predict the winter SST in the NA SPG region several years ahead (up to 6 years in northern part of SPG).
- Localisation in NorCPM:
 - Bimodal Gaussian varying with latitude (isotropic and Gaspari-Cohn)
 - *Bootstrapping and linear filtering (anisotropic and non-Gaspari-Cohn)*