WP4: Benchmarks

CNRS-LGGE, Grenoble, France

SANGOMA progress meeting – April 1-2, 2014

WP4: Benchmarks

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1. Introduction

Introduction: objectives of WP4

General objective:

Comparison and assessment of data assimilation methods on systems of different complexity from small-scale to realistic large-scale close to operational configuration.

Three benchmarks:

1) small scale: portable Lorenz-40 model

2) medium scale: portable ocean case of the NEMO model (double gyre configuration)

3) large scale: realistic configuration of the NEMO model (North Atlantic at 1/4° resolution)

Introduction: content of deliverables

Three deliverables:

1) DL4.1: Definition of the three benchmarks:

model configurations, specification of the assimilation problem, definition of metrics.

2) DL4.2: Benchmark implementation:

table with implementation of the benchmarks performed by every SANGOMA partners.

3) DL4.3: How to use the probabilistic metrics on small and medium benchmarks:

Manual to perform probabilistic verification in practical case for the small and medium benchmarks.

2. Implementation of benchmarks (DL4.2)

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Benchmarks

Comparison and assessment of impacts of assimilation methods on systems of different complexity:

- Small case benchmark: Lorenz-40 model
- Medium case benchmark: double-gyre NEMO configuration
- Large case benchmark: North-Atlantic 1/4° NEMO/LOBSTER configuration

The benchmarks include (i) the detailed specification of the model configurations and assimilation alogrithm, (ii) the definition of a set of metrics to assess the performance of the assimilation systems, and (iii) the eveluation of the results of the experiments:

- Detailed specification of benchmarks
- Definition of metrics
- Evaluation of the results

2.1 Small case benchmark

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Small case benchmark: Lorenz-40 model

The small case benchmark is based on the portable Lorenz-40 model (Lorenz and Emmanuel, 1998). The model is available:

- in Fortran, in the PDAF software,
- in Java, in the openDA software, or
- in Matlab, in the EnKF Matlab code.

References

- Lorenz, E. N. and K. A. Emanuel, 1998: Optimal sites for supplementary weather observations: Simulation with a small model. J. Atmos. Sci., 55, 399-414.

Small case benchmark: implementation

Three registered implementations:

1) Partner AWI (P. Kirchgessner/ L. Nerger):
- -methods: (L)ESTKF, (L)ETKF, EWPF
- -ensemble size: between 8 and 40

2) Partner GHER (F. Laenen):
- -methods: square root analysis in EnKF, anamorphosis
- -ensemble size: between 25 and 80

3) Partner MEOM-LGGE (S. Metref/E. Cosme):
- -methods: EnKF, MRHF, RHF, PF
- -ensemble size: between 20 and 100

2.2 Medium case benchmark

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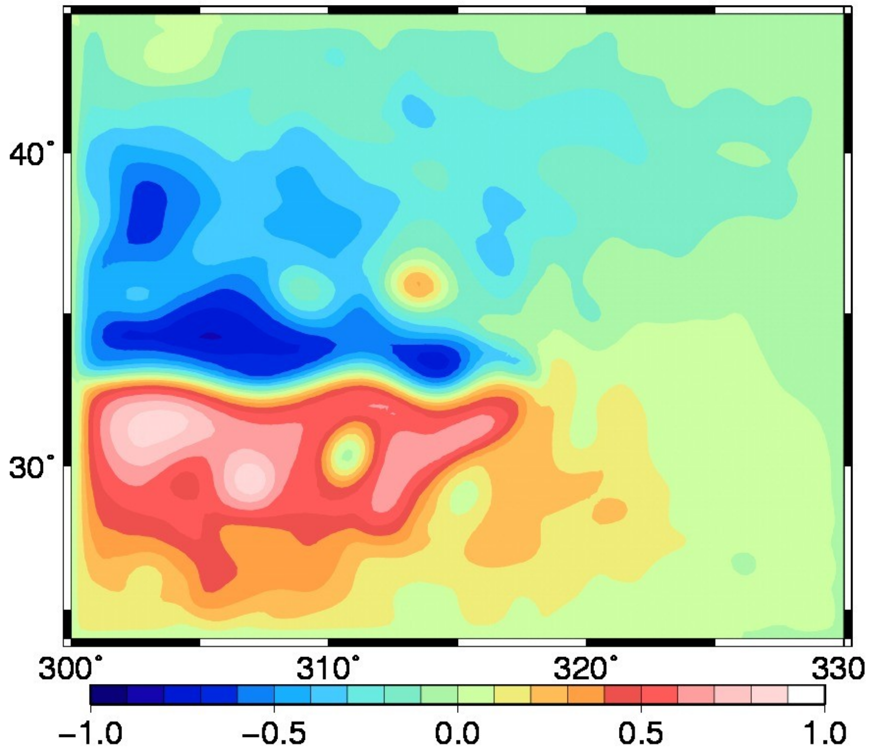
Medium case benchmark: Double-gyre NEMO configuration

The medium case benchmark is based on an idealized configuration of the NEMO ocean model: a square and 5000-meter deep flat bottom ocean at mid latitudes (the so called square-box or SQB configuration).



Medium case benchmark: implementation

Five registered implementations:

1) Partner AWI (P. Kirchgessner/ L. Nerger):

-methods: (L)ESTKF, EWPF

-ensemble: generated through a SVD decomposition of a sample from the background run

2) Partner GHER (Y. Yan):

-methods: square root analysis in EnKF

-ensemble size: 40 and 100

3) Partner MEOM-LGGE (G. Ruggiero/E. Cosme):

-methods: SEEK, backward smoother, back and forth KF

-ensemble size: between 20 and 100

Medium case benchmark: implementation

4) Partner MEOM-LGGE (P.-A Bouttier):

-methods: incremental 4DVAR, 3DFGAT

-ensemble: none, **B** is parameterized

5) Partner TUDelft:

-methods: EnKF, DenKF, with OpenDA toolbox

-ensemble size: between 20 and 100

2.3 Large case benchmark

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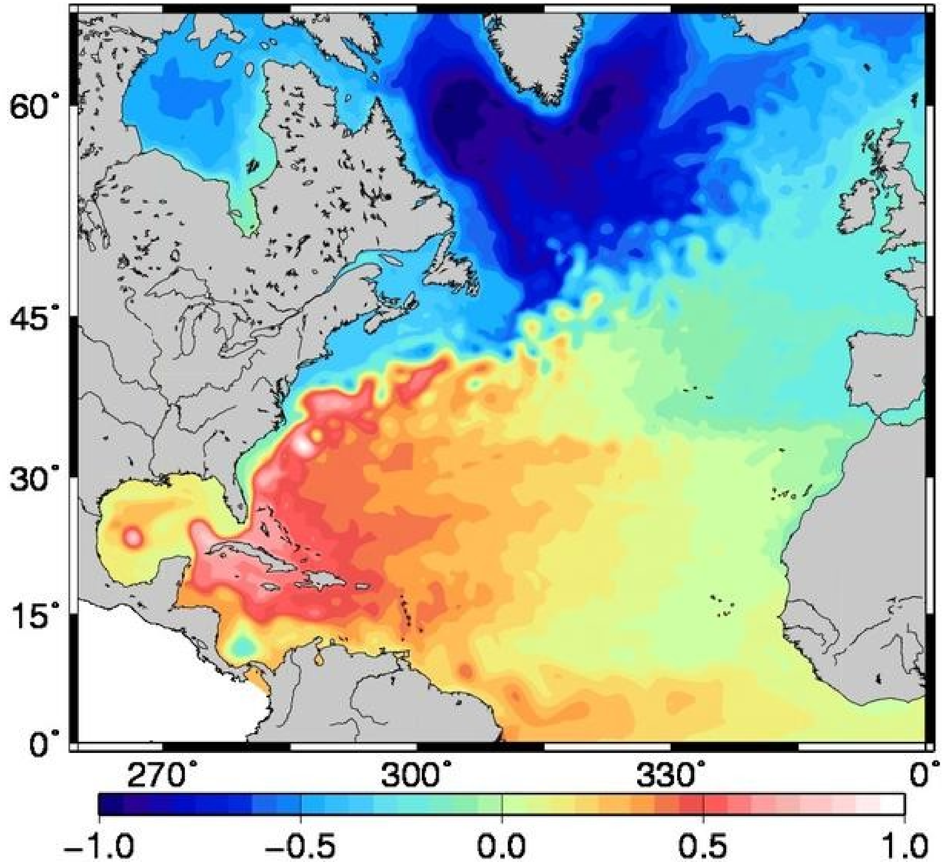
Large case benchmarks: North-Atlantic 1/4° NEMO/LOBSTER configuration



Large case benchmark: implementation

Two registered implementations:

1) Partner GHER (Y. Yan):

-method: square root analysis in EnKF, with OAK
-specificities: localization (~300km), IAU
-ensemble size: 60
-perturbations: in the atmospheric forcing
-assimilated data: Jason-1, SST, ARGO profiles

2) Partner MEOM-LGGE (G. Candille):

-methods: ensemble update with SEEK algorithm (~LETKF)
-specificities: localization (~433km), IAU, observation equivalent of ensemble at appropriate time
-ensemble size: 96
-perturbation: in the equation of state
-assimilated data: Jason-1, Envisat

3. Implementation of metrics (DL4.3)

Implementation of metrics (DL4.3)

<u>List of probabilistic metrics in DL4.3:</u>

1) Rank Histogram

2) Reduced Centered Random Variable (RCRV)

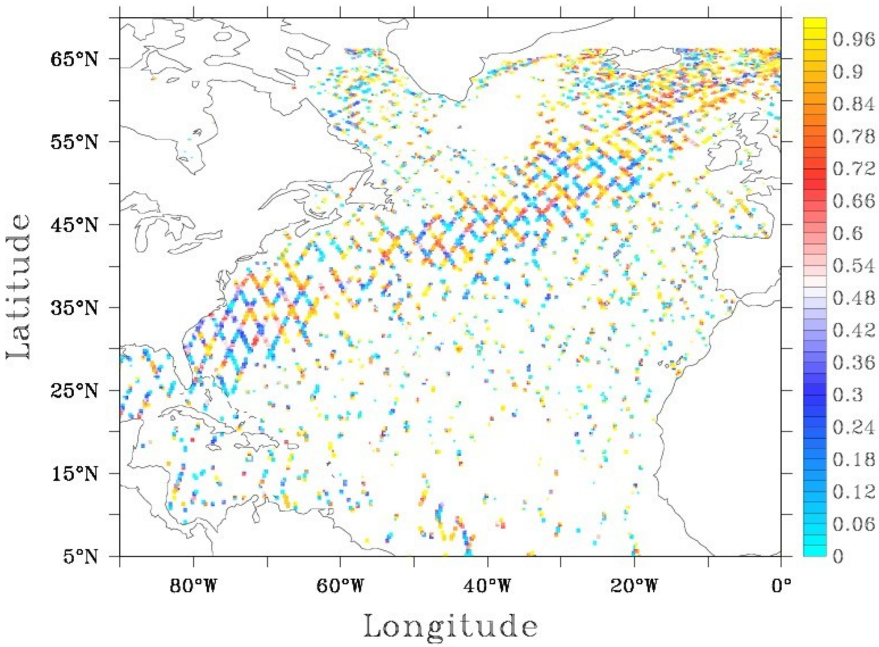
3) Continuous Ranked Probability Scores (CRPS)

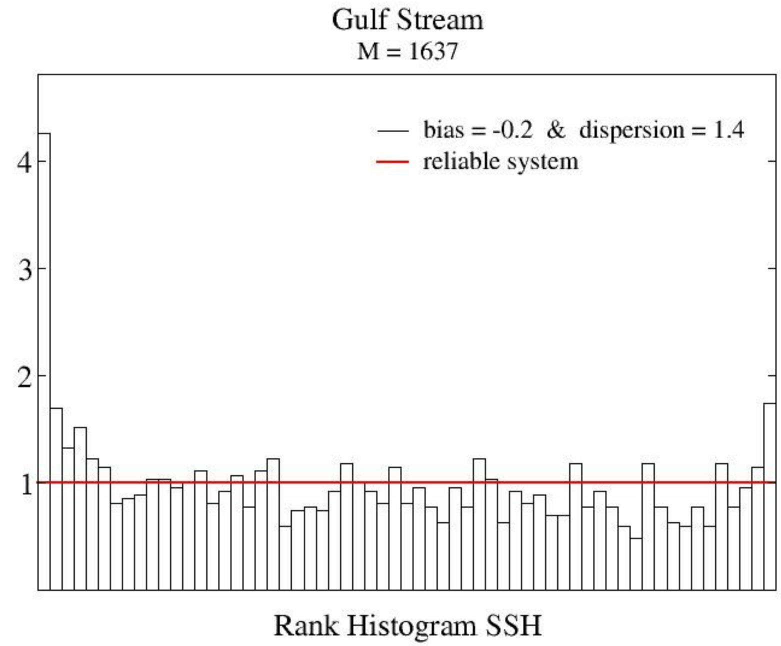
4) Brier score & Entropy

<u>Implementation of the metrics in the benchmarks:</u>

→ manual to use the programs implementing the metrics
in the small-scale and medium-scale benchmarks

Example: rank histogram, with JASON-1 observations





Rank of JASON-1 altimetric observations in the ensemble simulation

Histogram of ranks in the Gulf Stream region

4. Focus on the large scale benchmark:

stochastic perturbations

Two different perturbation strategies

1) Partner GHER (Y. Yan):

- add realistic noise in the atmospheric forcing
(wind, air temperature, long and short wave radiation flux)
- growing perturbation during 6 months (1/1 → 29/6/2005)

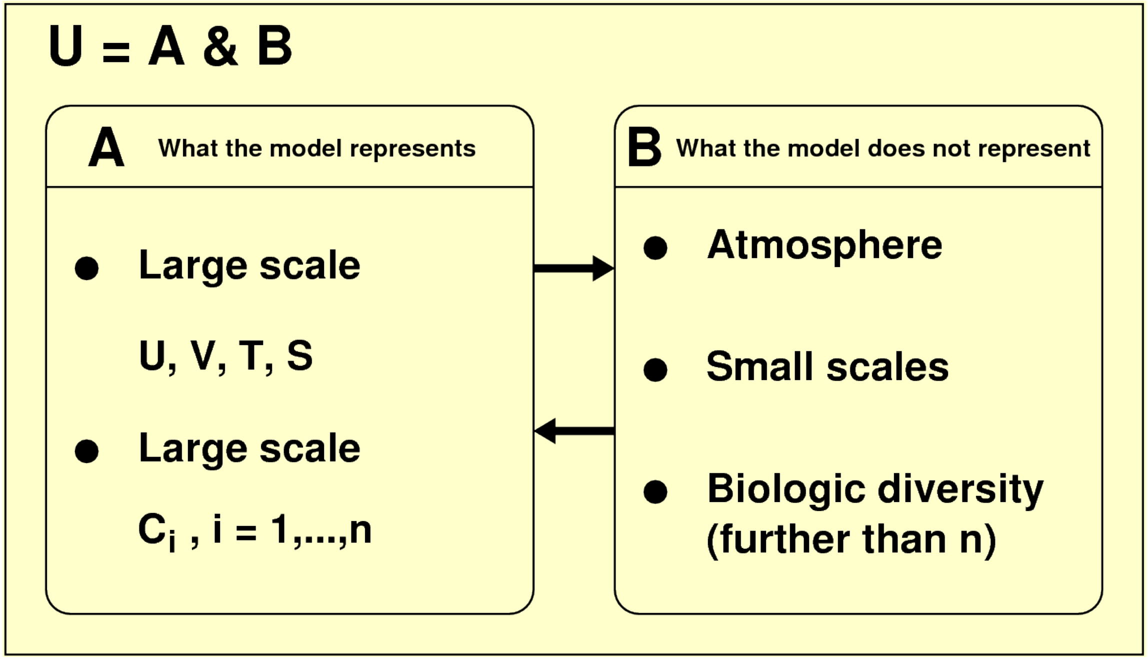
→ see presentation by Yajing Yan

2) Partner MEOM-LGGE (G. Candille):

- simulate the effect of unresolved scales in the seawater equation of state
- growing perturbation during 6 months (1/1 → 29/6/2005)

→ based on stochastic parameterization of uncertainties in NEMO

4.1 Basic ideas: définition of the system



•Even if the dynamics of **U** can be assumed deterministic,
the system **A** alone **cannot be assumed deterministic**.

•To obtain a deterministic model for **A**, one must assumed, either
that **B** is known (→ atmospheric forcing), or
that the effect of **B** can be parameterized (→ paramétrisation of unresolved scales or unresolved biologic diversity).

→ B is the main source of uncertainty in the model.

4.2 Stochastic formulation of NEMO

<u>Objective</u>: transform the *deterministic* model into a *probabilistic* model

Describe the non-deterministic nature of the system

Allow objective comparison with observation

Introduce a weak model constraint in data assimilation systems

<u>Method</u>: explicitly simulate model uncertainties using *random numbers*

Propose a generic and flexible technical approach

Develop a first simple implementation

- **atmospheric forcing**
- **unresolved scales**
- **unresolved diversity**

Order *n* autoregressive processes (1)

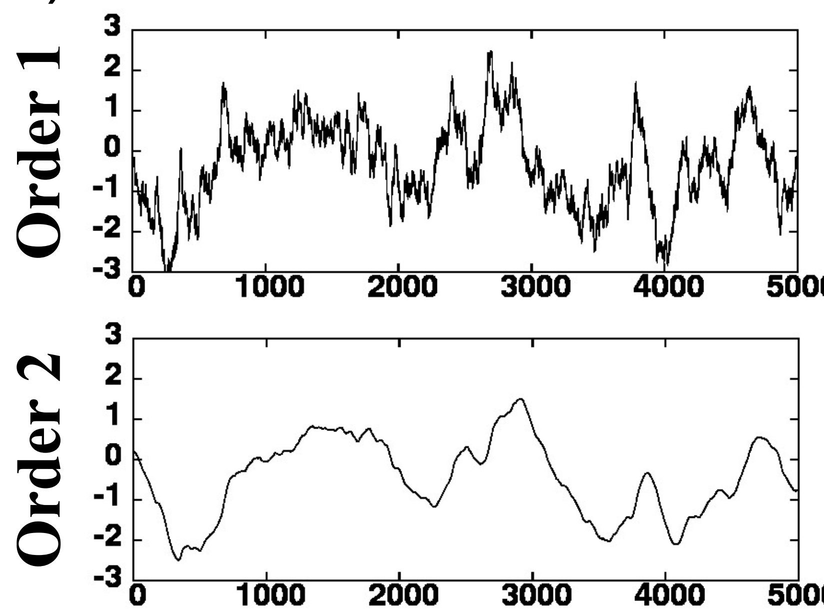
At every model grid point (in 2D or 3D), generate a set of **independent Gaussian autoregressive processes:**

$$\xi(t_k) = a\,\xi(t_{k-1}) + b\,w + c$$

where ***w*** is a Gaussian white noise (→ order 1 process) or an autoregressive process of order n-1 (→ order n process)

Parameters ***a, b, c*** to specify:

mean, standard deviation and correlation timescale



Order *n* autoregressive processes (2)

Introduce a spatial correlation structure	**Modify the marginal probability distributions**

by applying a spatial filter to the map of autoregressive processes:

$\tilde{\xi} = \mathcal{F}[\xi]$ (filtering operator)

$\mathcal{L}[\tilde{\xi}] = \xi$ (elliptic equation)

which can easily be made flow dependent if needed

by applying anamorphosis transformation to every individual Gaussian variable:

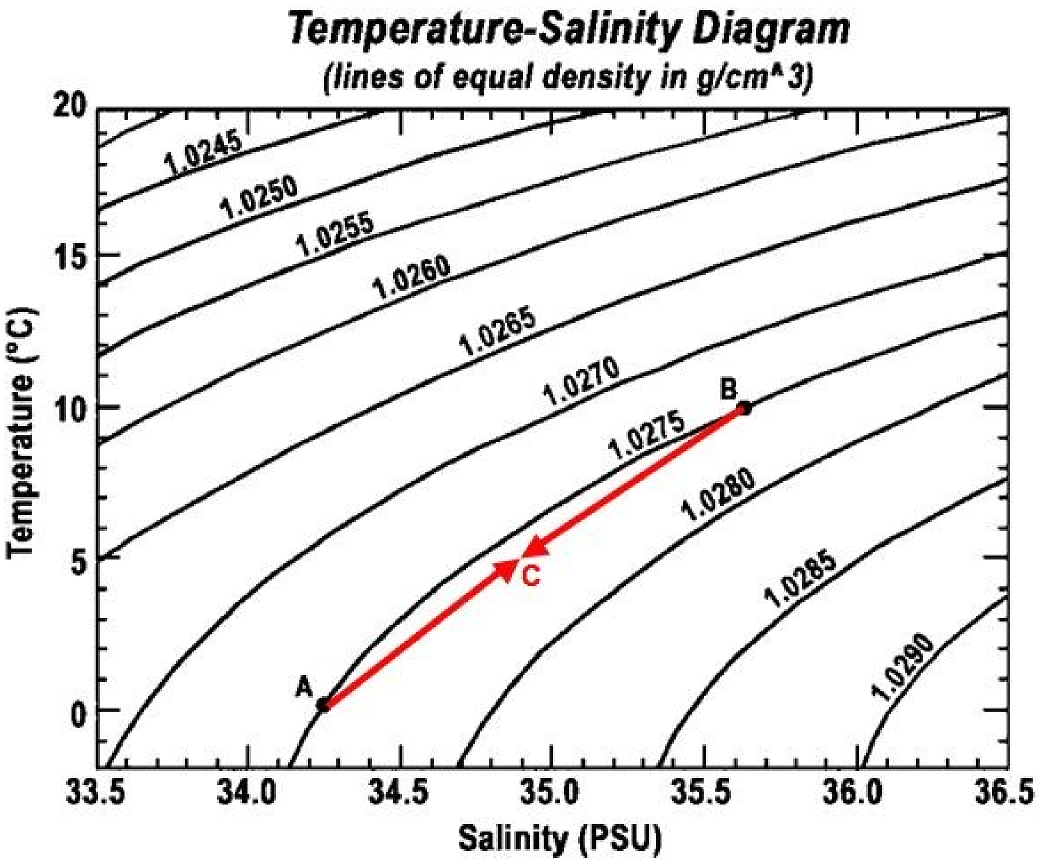
$\tilde{\xi} = \mathcal{T}[\xi]$ (nonlinear function)

for instance to transform the Gaussian variables into lognormal or gamma variables if positive noise is needed

→ **This provides a generic technical way of implementing a wide range of stochastic parameterizations**

4.3 Uncertainties in the computation of density (1)

In the model, the large-scale density is computed form large-scale temperature and salinity, using the sea-water equation of state.



(a)
Mixing waters of equal density but different T&S systematically increases density (cabbeling)

(b)
Averaging T&S equations systematically overestimates density (in a fluctuating, non-deterministic way)

However, because of the nonlinearity of the equation of state, unresolved scales produce an average effect on density.

Stochastic equation of state
for the large scales

Stochastic parameterization

using a set of random T&S fluctuations
ΔT_i et ΔS_i , i=1,...,p
to simulate unresolved T&S fluctuations

$$\rho = \frac{1}{2p}\sum_{i=1}^{p}\left\{\rho\left[T+\Delta T_i, S+\Delta S_i, p_0(z)\right]+\rho\left[T-\Delta T_i, S-\Delta S_i, p_0(z)\right]\right\}$$

Leading behaviour of $\Delta\rho$:

$$\Delta\rho = \frac{\partial^2\rho}{\partial T^2}\left(\frac{1}{2p}\sum_{i=1}^{p}\Delta T_i^2\right)+2\frac{\partial^2\rho}{\partial T\partial S}\left(\frac{1}{2p}\sum_{i=1}^{p}\Delta T_i\Delta S_i\right)+\frac{\partial^2\rho}{\partial S^2}\left(\frac{1}{2p}\sum_{i=1}^{p}\Delta S_i^2\right)$$

No effect if the equation of state is linear.
Proportional to the square of unresolved fluctuations.

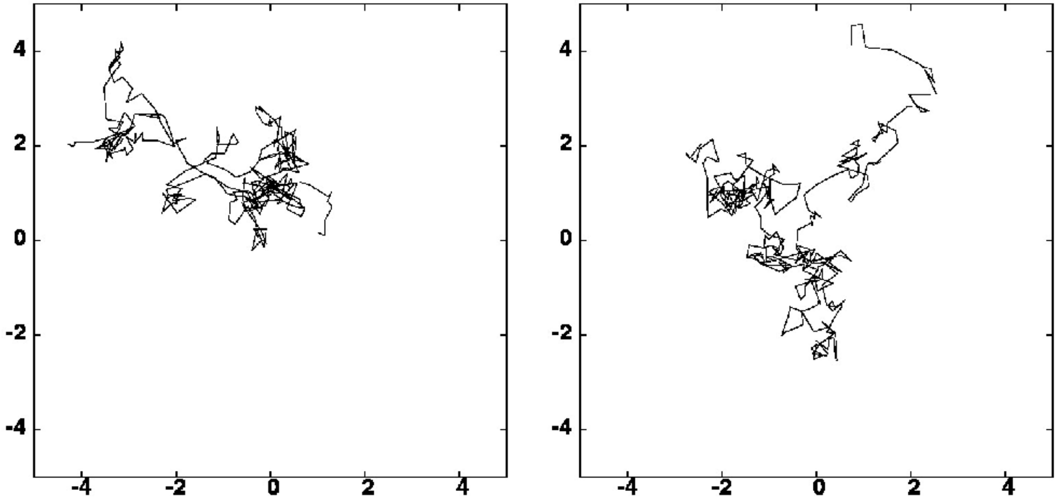
Random walks to simulate unresolved temperature and salinity fluctuations

Computation of the random fluctuations ΔT_i et ΔS_i

as a scalar product of the local gradient with random walks ξ_i

$$\Delta T_i = \boldsymbol{\xi}_i \cdot \nabla T \quad \text{and} \quad \Delta S_i = \boldsymbol{\xi}_i \cdot \nabla S$$

Random walks



Assumptions

AR1 random processes

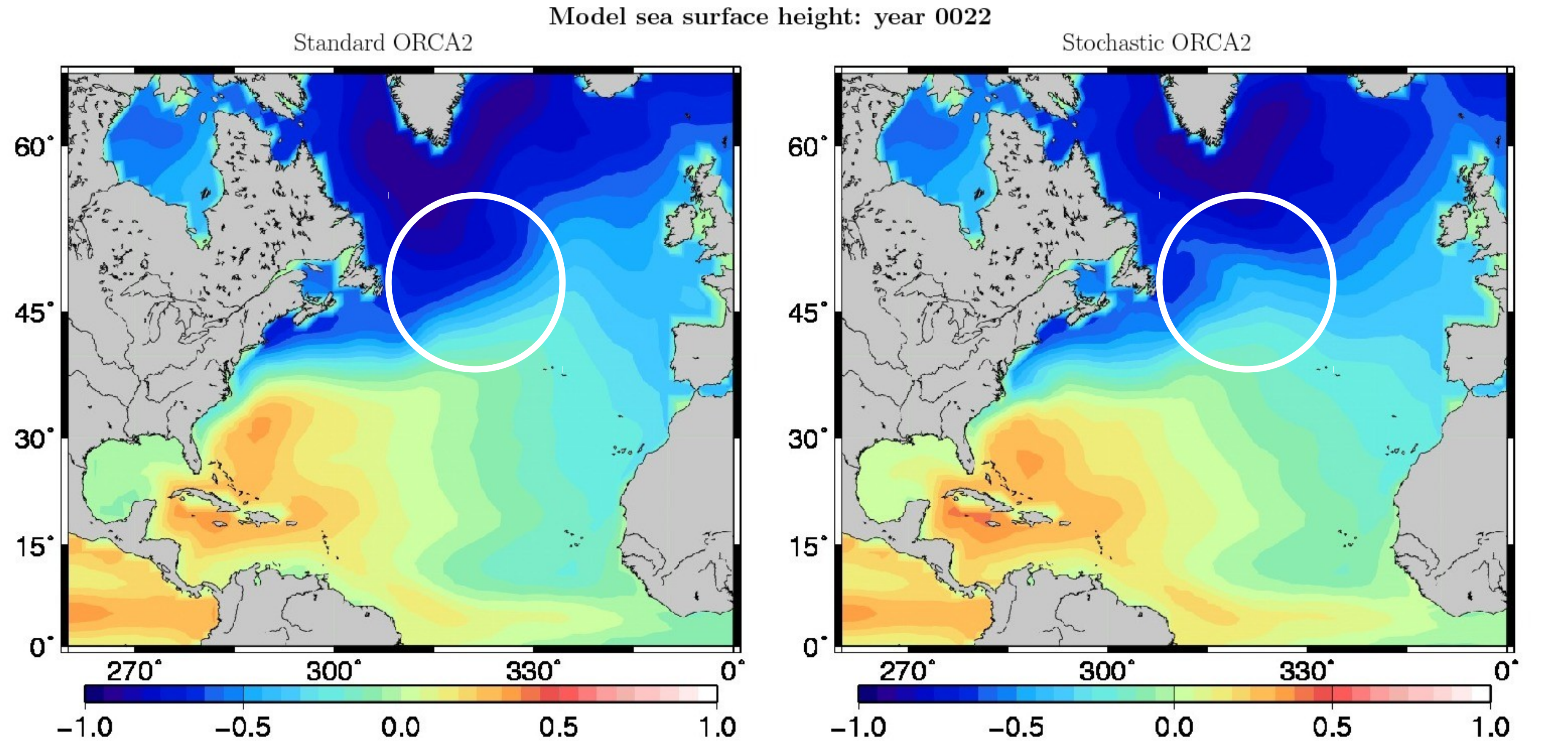
uncorrelated on the horizontal

fully correlated
along the vertical

5-day time correlation

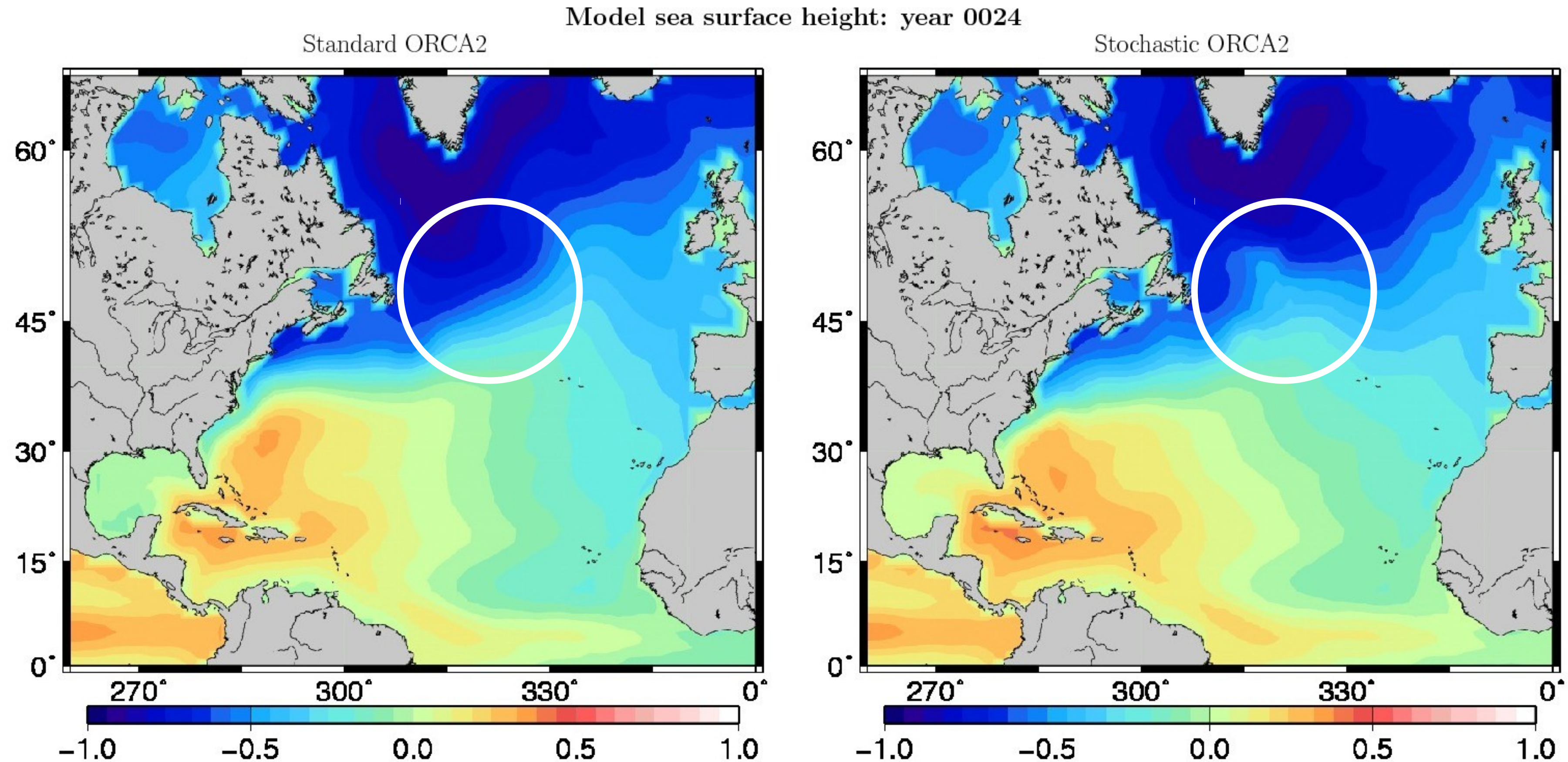
horizontal std: 2-3 grid points
vertical std: <1 grid point

Sea surface elevation in the North Atlantic



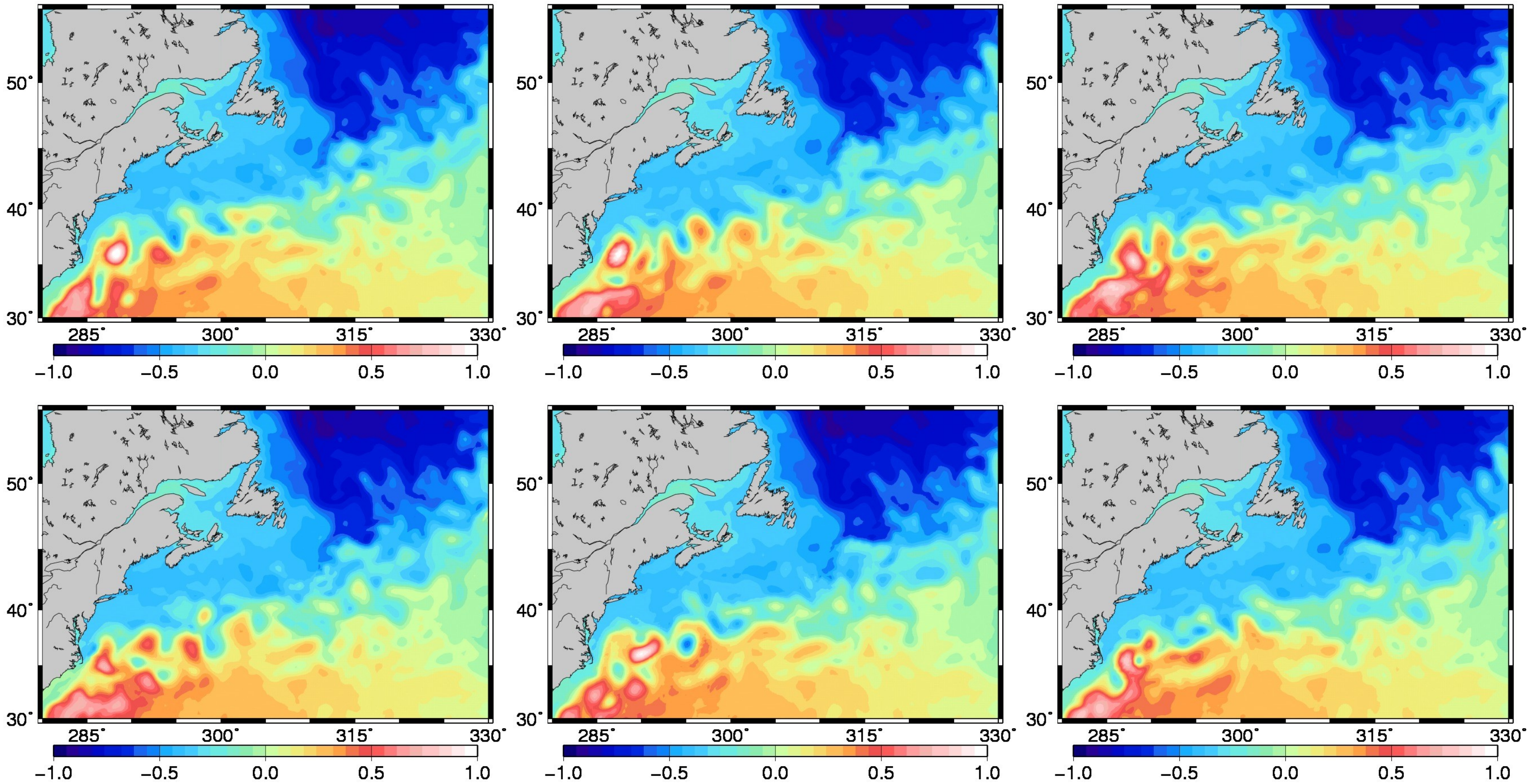
Standard simulation: (almost) no intrinsic interannual variability
Stochastic simulation: significant intrinsic interannual variability

Sea surface elevation in the North Atlantic



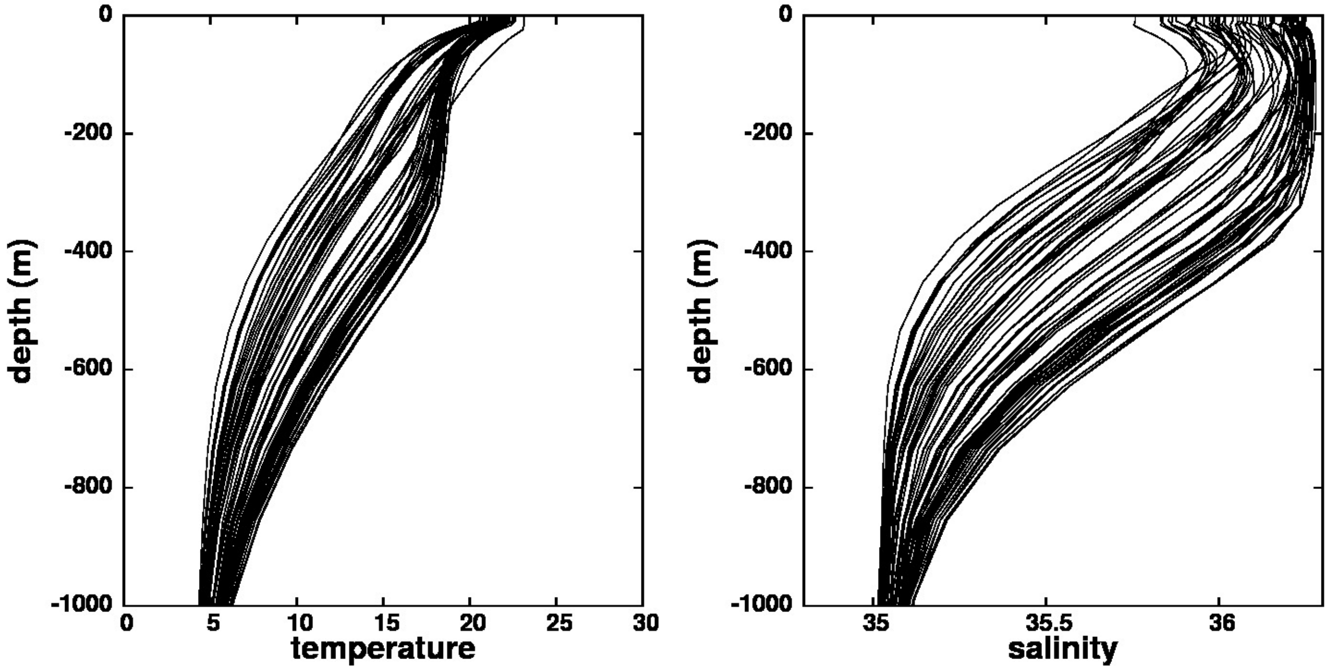
Standard simulation: (almost) no intrinsic interannual variability
Stochastic simulation: significant intrinsic interannual variability

Application to the large-case SANGOMA benchmark



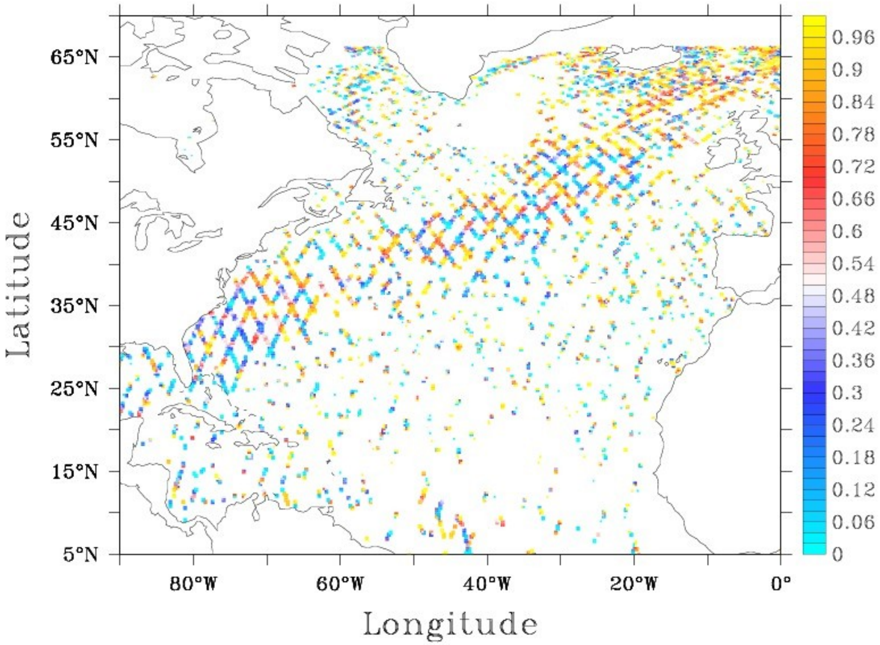
Ensemble spread in the Gulf Stream region after 6 months (6 members among 96)

Spread on the TS vertical structure

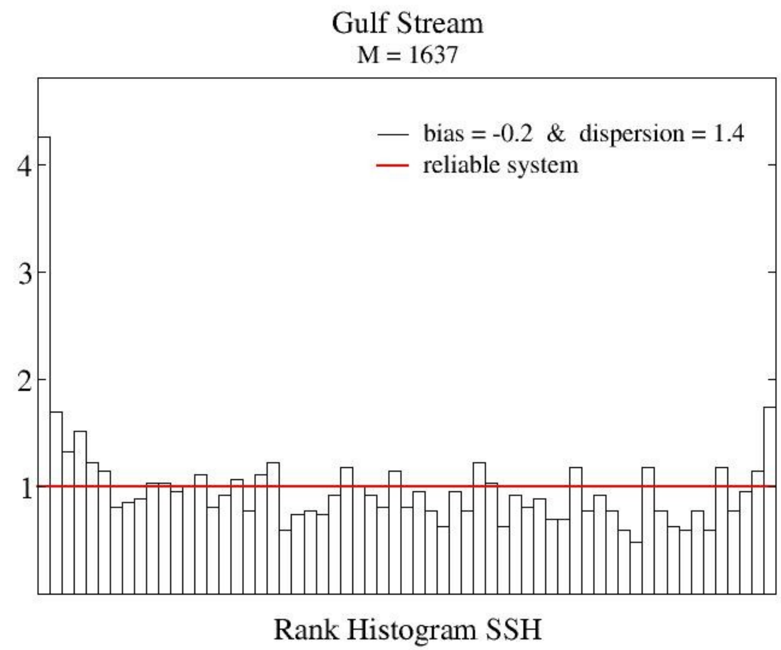


Ensemble spread in the Gulf Stream region after 6 months

Rank histogram, after 6 months



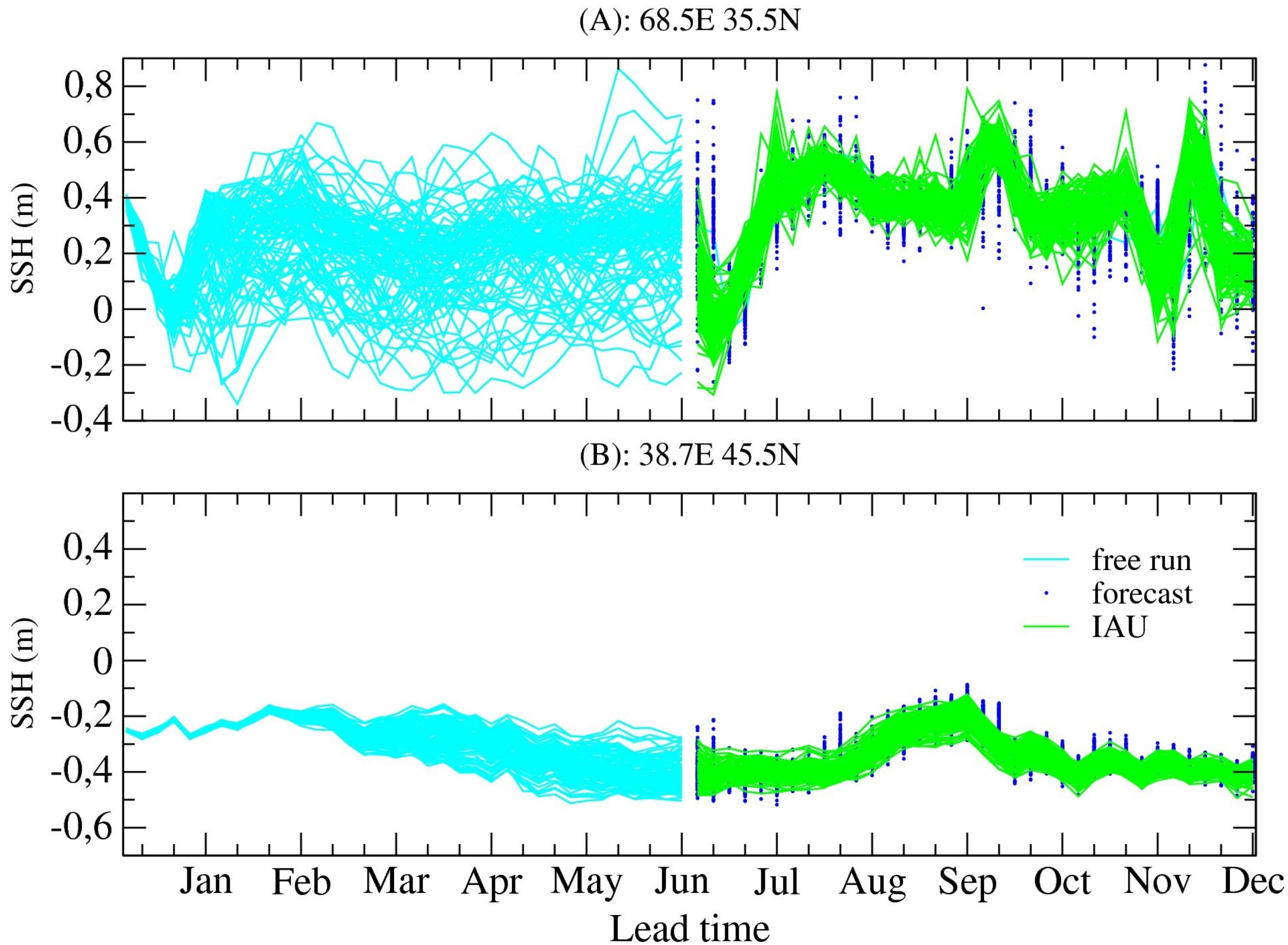
Rank of JASON-1 altimetric observations in the ensemble simulation



Histogram of ranks in the Gulf Stream region

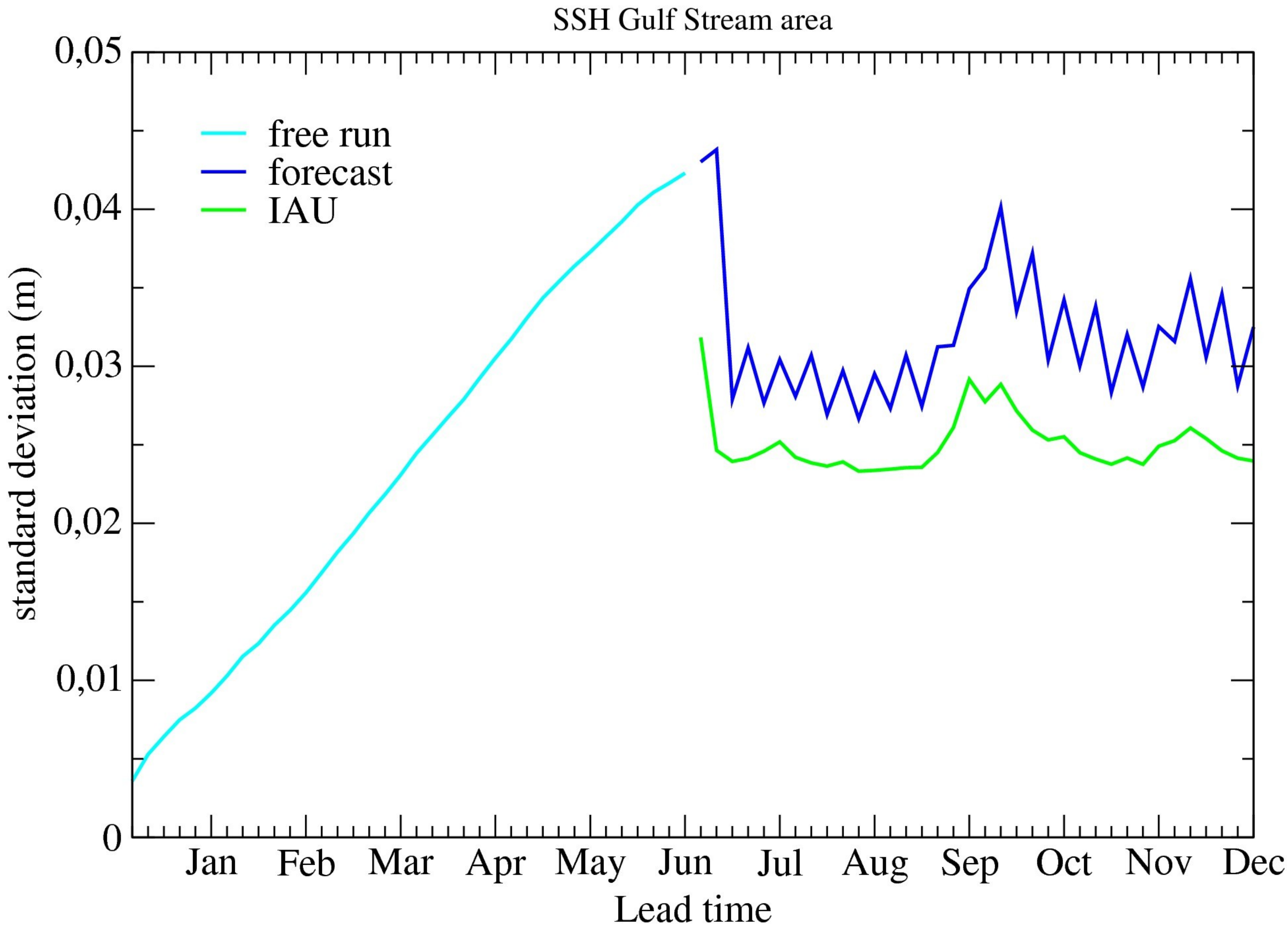
→ We can start assimilating altimetric observations

Evolution of SSH ensemble spread



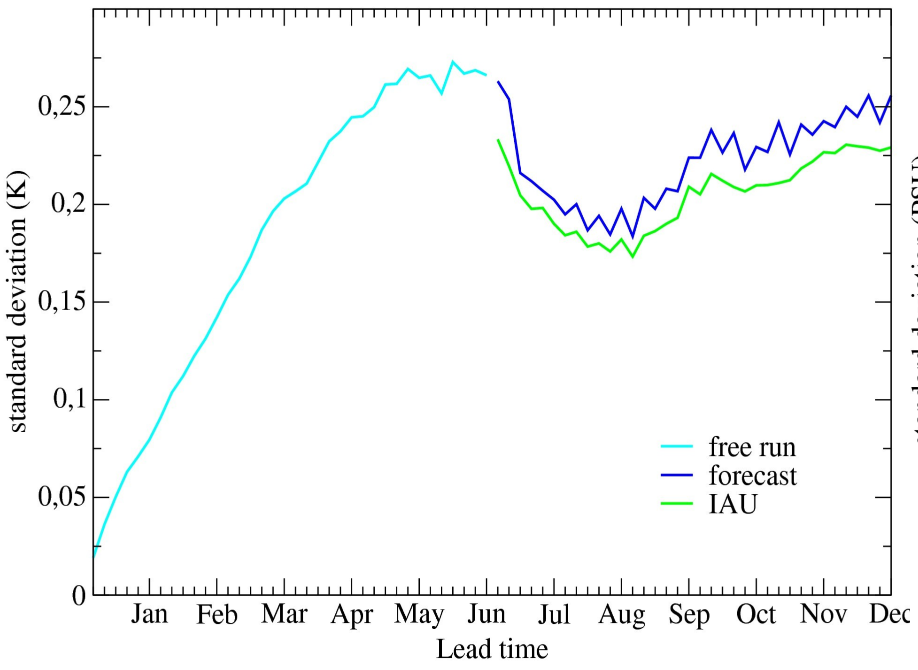
Before assimilation	With assimilation

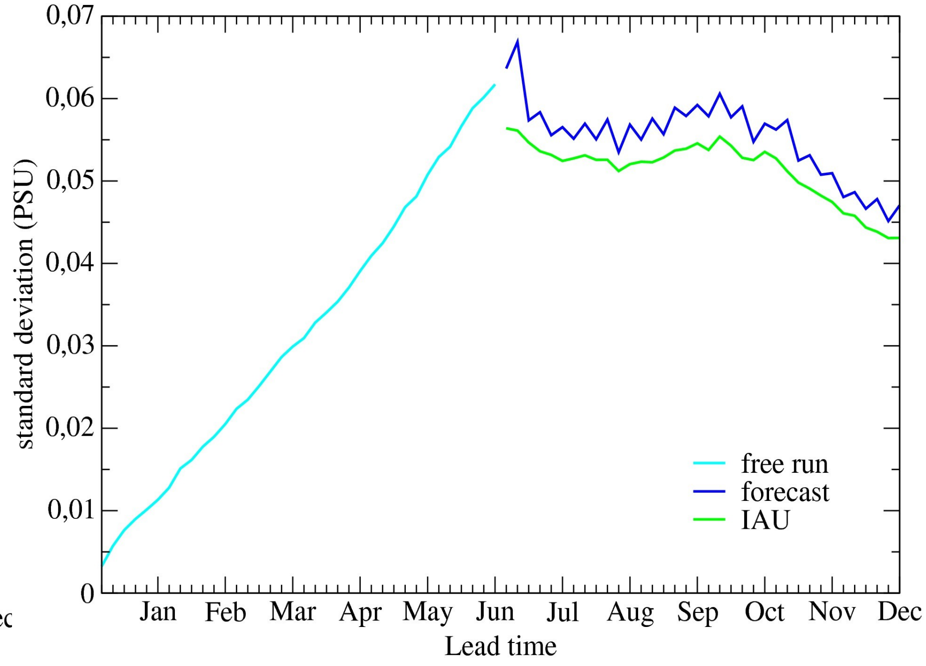
Ensemble standard deviation (SSH)



Before assimilation	With assimilation

Ensemble standard deviation (SST and SSS)

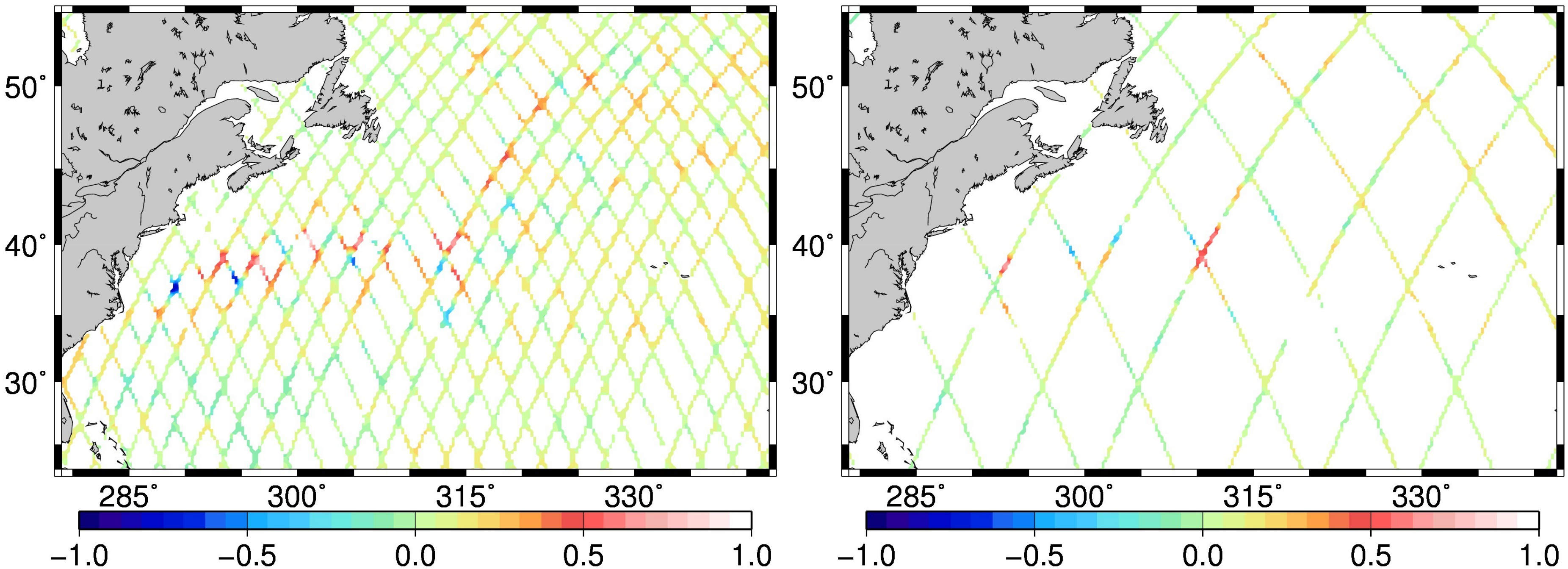




Sea surface temperature

Sea surface salinity

Jason-1 observations: September 2005

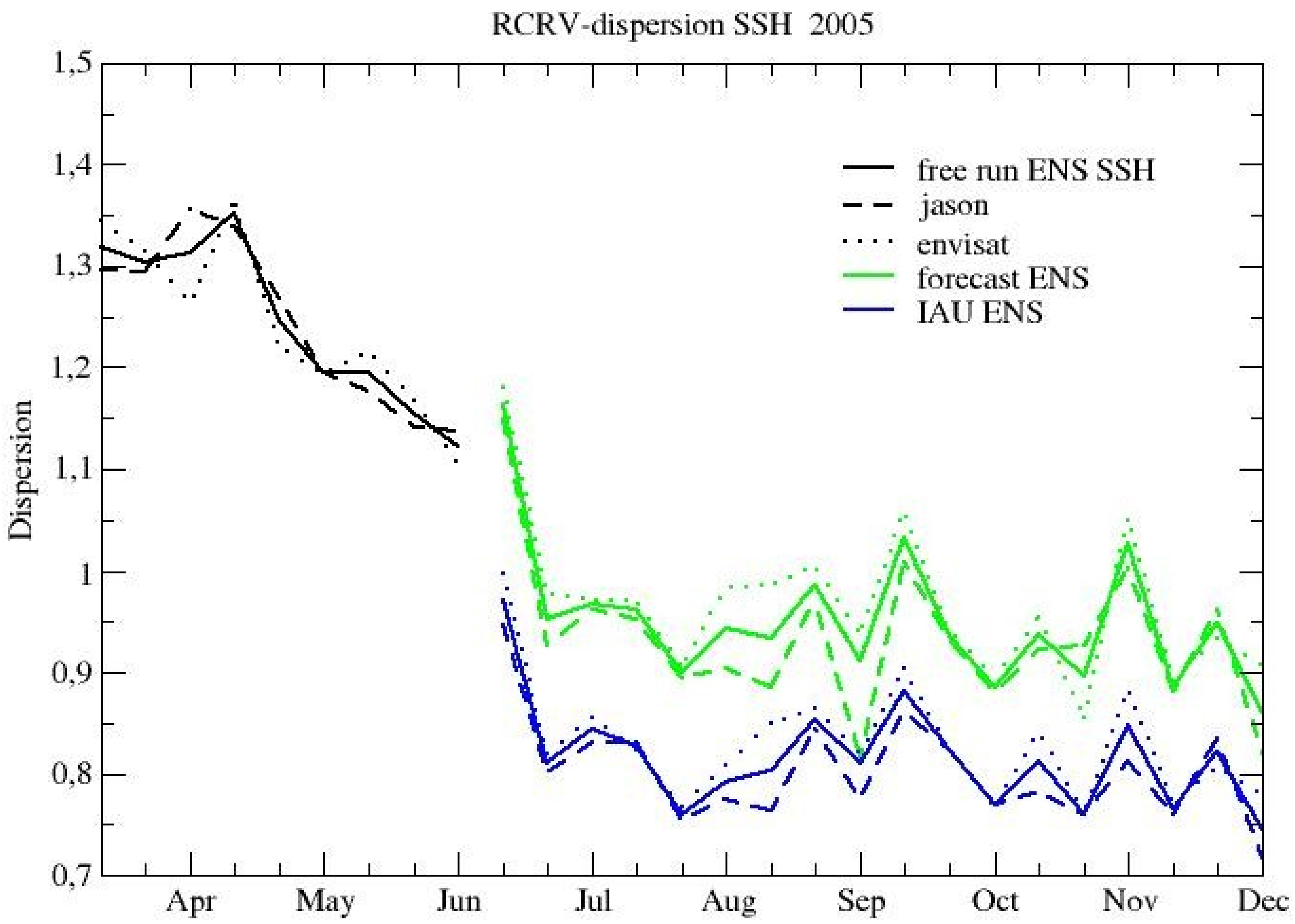


Normal coverage

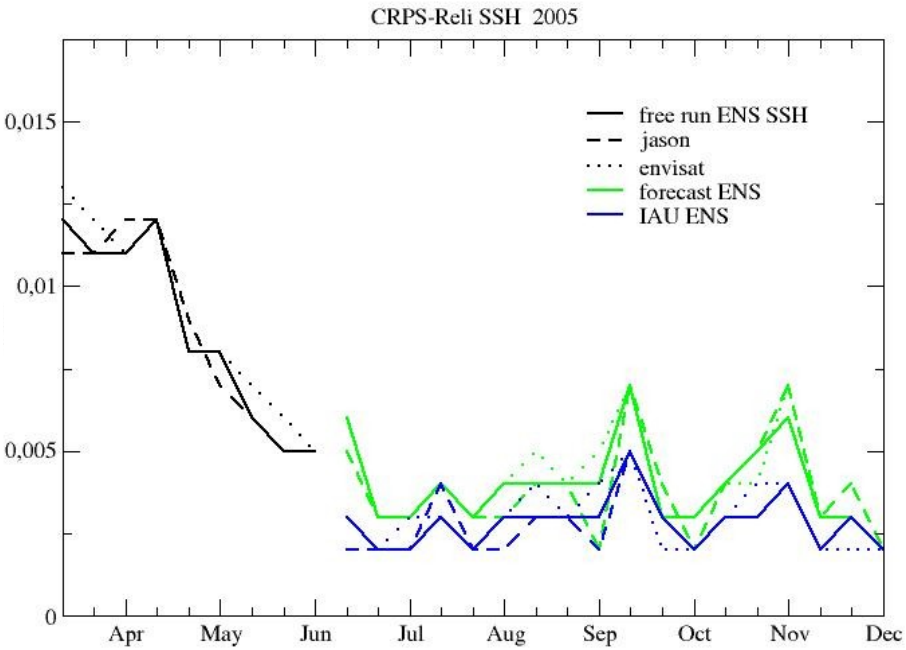
Missing tracks around 27/9/2005

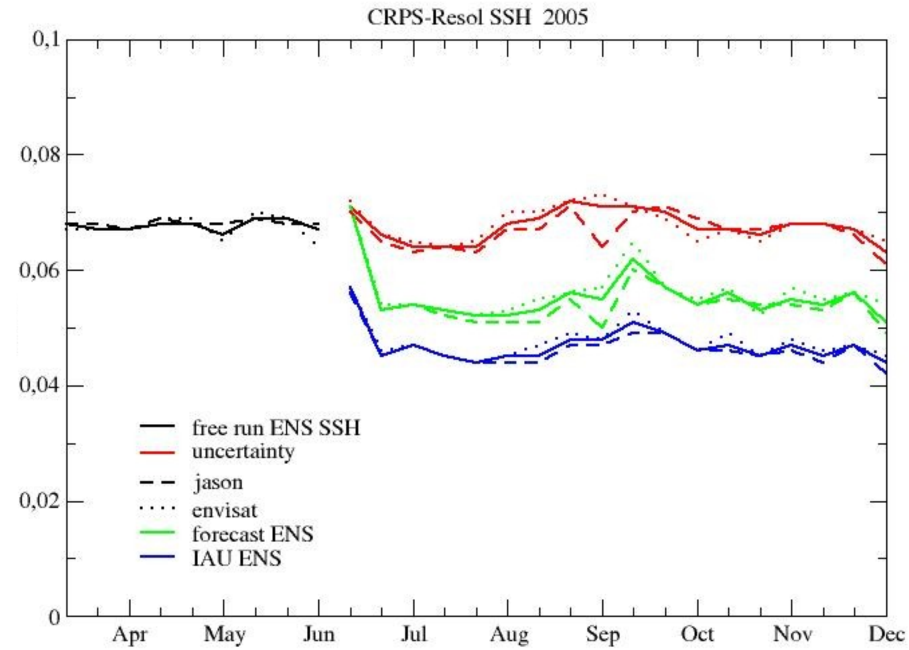
→ Missing JASON-1 observations explaining the larger spread in September 2005

RCRV metrics



CRPS metrics





RELIABILITY **RESOLUTION**

→ We improve resolution, without losing reliability with respect to free ensemble

Conclusions

Main characteristics of the method:

1) Stochastic parameterization of model uncertainties
(→ no inflation factor in the assimilation system)
2) Observation equivalent of all ensemble members at appropriate time (→ 4D observational update)
3) Ensemble incremental analysis update (IAU)
(→ no time discontinuities in the updated ensemble)

Main outcomes of the experiment:

1) The ensemble spread is sufficient to account for altimetric observations in the Gulf Stream region (↔ RH)
2) After assimilation has started, both forecast and IAU ensembles remain reliable (↔ CRPS reliability score)
3) Assimilation substantially improves the resolution of the ensemble (↔ CRPS resolution score)