Ensemble analysis and forecast of ecosystem indicators in the North Atlantic using ocean colour observations and prior statistics from a stochastic NEMO/PISCES simulator

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Context: H2020 **SEAMLESS** project (2021-2023) (www.seamlessproject.org)

- Tier-3 project, to sustain the evolution of the « green » component of the CMEMS, targetting impact at a 3-5 year horizon
- WP3: « Ensemble generation and assimilation methods »
- Partners: PML, NERSC, AWI, OGS, IGE

The model configuration is based on **NEMO/PISCES**, as provided by **Mercator Ocean**

- \rightarrow global coupled configuration, at 1/4° resolution
- → with explicit simulation of model uncertainties (in link with the Odessa tier-2 project, lead by the University of Liège)







Towards a **simplified** analysis and forecasting system based on a prior ensemble model simulation

Approach:

- → Perform a **prior ensemble simulation**, with a state-of-the-art coupled circulation/ecosystem model
- → Condition this 4D ensemble on ocean colour observations to obtain the ensemble analysis and forecast

Features:

- → **Decouple** the complex models **simulations and** the **inversion** problem \rightarrow more flexibility in the system
- \rightarrow Focus the 4D inversion on specific variables on a specific region and time window
- \rightarrow Directly estimate **ecosystem indicators**

Shortcomings:

- → The complex model is not used as a direct constraint in the inverse problem, but only indirectly through the prior ensemble
- → Prior uncertainty may be larger as compared to sequential systems

Inverse problem

We focus on a small 4D subregion in the North-East Atlantic (31°-21°W, 44°-50.5°N):

- 40 X 40 grid points (10° x 7°, at 1/4° resolution)
 - X 32 levels (down to 220 m)
 - X 93 days (March 15 to June 15, 2019)
 - X 6 tracers (+ two 2D indicators) = \sim 30 x 10⁶ variables



L3 chlorophyll product

between March 15 and June 15, 2019

Obs. error std: 30%

~ 2×10^5 observations



The prior ensemble simulation

A sample from the global NEMO/PISCES stochastic simulator:

- \rightarrow 40 ensemble members
- \rightarrow daily outputs for our region of interest
- → embedding location uncertainties, parameter uncertainties, and uncertainties emerging from the unresolved scales

Probabilistic scores have been applied to evaluate this ensemble simulation using L3 ocean colour observations.

- → Example of rank histogram for the subregion used as an example below
- → In the North Atlantic Drift: 31°W-21°W, 44°N-50.5°N, April 21 to June 19, 2019



The reliability of the prior ensemble is essential to obtain a reliable solution to the inverse problem

Methods : a brief summary		
	LETKF analysis	MCMC sampler
Assumptions	Gaussian background errors	Gaussian background errors
	Linear and local observation operator H	Nonlinear/nonlocal observation operator H
	Gaussian observation error with prescribed covariance R	Non-Gaussian observation error conditioned on x: p(y° x).
	\rightarrow Gaussian analysis errors	\rightarrow non-Gaussian analysis errors
Features	domain localization	covariance localization
	anamorphosis must be applied to x, y° and R	anamorphosis must be applied to x only
In practice	Linear algebra formula to compute Kalman gain	Iterative method (MH algorithm), with fast random draws from the proposal distribution
	Loop and parallelization on local subdomains	Direct parallelization, with distributed x and y°

Results from the LETKF and MCMC sampler: ensemble analysis and forecast



Results from the LETKF and MCMC sampler: <u>members</u> of ensemble analysis for May 26, 2019 (using past and future observations)



Results from the LETKF and MCMC sampler: **<u>quantiles</u> of ensemble analysis for May 26, 2019** (using past and future observations)



Results from the LETKF and MCMC sampler: **1-day ensemble forecast for May 26, 2019** (i.e. using observations until May 25 only)



Results from the LETKF and MCMC sampler: **4-day ensemble forecast for May 26, 2019** (i.e. using observations until May 22 only)



Summary of the probabilistic scores



Cross-validation is used to keep the observations independent in the computation of the analysis scores

Ecosystem indicator: phenology for chlorophyll concentration



<u>A simple definition:</u> first day at which the chlorophyll concentration reaches half of its maximum

The prior uncertainty is quite large

Strongly reduced by the observations

Quite consistently in the two methods

Phenology for chlorophyll and zooplankton



Three possible time windows in the prior ensemble. Reduced to one in the posterior ensembles.

Vertical profiles of chlorophyll and zooplankton



Ecosystem indicator: trophic efficiency



Time series of vertically integrated trophic efficiency at the center of the region of interest 36°W 47.25°N

Conclusions

In this example, the two methods produce **similar results**, thus somehow validating each other.

- In both cases, they produce an **ensemble analysis** that is continuous in time, with a reliable description of posterior uncertainty, at least for the observed variable.
- The statistical **ensemble forecast** can contain valuable information for a few days after the last observation.
- For the **ecosystem indicators** (and any non-observed variable), the reliability of the ensemble analysis and forecast depends on the **reliability of the prior ensemble**.

A practical method to perform **4D ensemble analyses and forecasts.**

→ No need for full controllability of the complex model (with so many state variables, when so few are observed). No model restart from the analysis.

The focus is on **sampling possibilities** consistent with the observations.

In terms of operational application, this approach is more flexible and provides several advantages:

- \rightarrow it can focus on a specific region of interest,
- \rightarrow it can produce targetted products to meet users' requirements,
- \rightarrow it may serve as a baseline to compare with the dynamical system.

In terms of method, the MCMC sampler opens also new possibilities:

- \rightarrow it provides an efficient way to **solve the problem globally** in space and time, with covariance localization,
- → it can cope with fully **general observation constraint** $p(y^{\circ}|x)$ (nonlinear, non-Gaussian, nonlocal),
- \rightarrow it can be used in 3D as a **possible substitute** to the analysis step in ensemble Kalman filters.

Difficulties may come from:

- → the size of the problem and the cost to evaluate the observation constraint,
- \rightarrow the number of iterations required to reach convergence.

Complements



Iterative method in 2 steps:

1. **Propose** pseudo-random perturbation of x' (with cost linear in n) \rightarrow by modulation of an ensemble member with large-scale signals (~10¹¹ pseudo-random directions of perturbations)

- \rightarrow equivalent to a localization of the prior ensemble covariance
- 2. Accept/reject according to cost function: $J^{\circ} = -\log p[\mathbf{y}^{\circ} | A^{-1}(\mathbf{x'})]$

Brankart J;-M., 2019 : Implicitly Localized MCMC Sampler to Cope With Non-local/Nonlinear Data Constraints in Large-Size Inverse Problems. Front. Appl. Math. Stat. 5:58.

Downward flux of POC at 100 m depth



Scatterplot between observed quantity and indicator at the center of the region of interest 36°W 47.25°N on May 26 In black: prior ensemble simulations from NEMO/PISCES In blue: ensemble analysis using all L3 observations In red: ensemble forecast using L3 observations until May 22