



Assimilation of Data Into Ocean Models:

On-Line Estimation of Background Error Covariance Parameters

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State and Parameter Estimation

Let x and y be true ocean state and observation vectors, and θ a vector of uncertain parameters of covariance of x. The posterior pdf of state and parameters given observations is

 $p(x, \theta \mid y) \propto p(y \mid x)p(x \mid \theta)p(\theta)$

Under the Gaussian error assumption, maximizing the posterior pdf is the same as minimizing L wrt x and θ

$$J \equiv (y - Hx)^T R^{-1} (y - Hx) + (x_b - x)^T B^{-1} (x_b - x)$$
$$L(x, \theta) \propto \log |B(\theta)| + J(x, \theta) - 2\log p(\theta)$$

Online estimation of θ similar in principle to Dee (1995).

Features of the Scheme

- Extended version of 3DVar.
- Physical constraints used to give B matrix that is physically realistic, state dependent, and easier to deal with computationally.
- Second minimization gives state dependent parameters of B.
- Parameters estimated by maximizing the joint rather than marginal pdf (as in Dee, 1995).

Observed Sea Level and Dynamic Height From Argo



Argo Temperature and Salinity



- Scatterplots of T and S at different depths
- ~55.2W, 38.4N
- Complex, depth dependent structure
- Lines show Yashayaev climatology
- Shows importance of vertical advection in at depth

Modelling Uncertainty in the Background State

Motivated by these physical balances, assume

$$T = T_{b} - \partial T_{b} / \partial z \xi_{D} + \xi_{T}$$

$$S = S_{b} - \partial S_{b} / \partial z \xi_{D} + \xi_{S}$$

$$\eta = \eta_{b} + \Delta_{\rho} \xi_{D} + \int (\alpha_{T} \xi_{T} + \alpha_{S} \xi_{S}) dz$$

Builds on: Cooper and Haines (1996), Troccoli and Haines (1999), Haines et al. (2006), Ricci et al. (2005), Weaver et al. (2006)

Parameterization of B

Physical constraints give state dependent transformation from original to auxiliary variables. Thus B can be written as function of covariance matrix of auxiliary variables.

Assume

$$B_{\zeta\zeta} = B_{DD} \oplus (B_{HH} \otimes B_{VV})_{\zeta_T,\zeta_S}$$
$$B_{VV} = \begin{bmatrix} B_{TT} & B_{TS} \\ B_{TS}^T & B_{SS} \end{bmatrix}$$
$$B_{DD} = \gamma_1 C^T \exp(-r^2 L_D^{-2}) C$$
$$B_{HH} = \gamma_2 C^T \exp(-r^2 L_H^{-2}) C$$

Constructing an Idealized B Matrix

Assume xi are uncorrelated with separable (x,z) covariance:



North Atlantic Example

- POP ocean model, 1/3 degree, 23 levels.
- Spectrally nudged to Yashayaev monthly climatology.
- > Daily atmospheric forcing from NCEP reanalysis.
- Assimilate Argo and altimeter data, 2003-5.
- Vertical gradient of background is linear combination of climatology and forecast.
- Uncertain covariance parameters (theta) are horizontal length scales and variance of the xi variables.

Time Variation of Parameters



Typical Snapshot of Sea Level





Forecast Skill For Sea Level

•Rms of obs-pred vs lead time

•Based on 24 monthly forecast runs (each 60d)

Forecast Skill for T and S



Summary

- ✓ New scheme is computationally efficient (adds 30% to run time and memory) and has useful skill.
- Second minimization allows background error covariance matrix (B) to change with state.
- Online estimation of B gives scheme robustness and flexibility. Computationally feasible because joint posterior pdf maximized rather than marginal.
- Reasonable parameters estimated every 2 days in the North Atlantic example.
- Forecasts improved in Gulf Stream region by allowing covariance parameters to change with time.
- ✓ Implemented in NEMO and evaluation underway.