

Demonstration and Comparison of Sequential Approaches for Altimeter Data Assimilation in HYCOM

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Outline:

Assimilation Schemes

Twin Experiments

Results/Diagnostics





- 1. Optimal Interpolation
- 2. Multivariate Optimal Interpolation
 - (J. Cummings, O.M. Smedstad –NRL)
- 3. Ensemble Optimal Interpolation & Kalman Filter
 - (F. Counillon, L. Bertino NERSC)
- 4. Ensemble Reduced Order Information Filter

(T. M. Chin, Univ of Miami/JPL)

- 5. Singular Evolutive Extended Kalman Filter
 - (P. Brasseur LEGI, Grenoble)





- Oceanographic version of MVOI method used in NWP systems (Daley, 1991)
- Simultaneous analysis of five ocean variables: temperature, salinity, geopotential, and u-v velocity components (T, S, Φ , u, v) $x_a = x_b + P_b H^T (HP_b H^T + R)^{-1} [y - H(x_b)]$

Observation Space Formulation

where \mathbf{x}_{a} is the analysis

 $\mathbf{x}_{\mathbf{b}}$ is the background

 $\mathbf{P}_{\mathbf{b}}$ is the background error covariance

R is the observation error covariance

H is the forward operator (spatial interpolation)

 $(x_a - x_b)$ is the analyzed increment

[y-H(x_b)] is the innovation vector (synoptic T, S, u, v observations





Ensemble Optimal Interpolation (ENOI)

- Covariance are based on an historical ensemble composed of 3 year 10 day model output (106 members) without assimilation
- Covariance are 3D multivariate
- Conservation of the dynamical balance of the model since the update is a linear combination of model state
- Temporal invariance of the covariance matrix, computationally cheap

 $\begin{aligned} X^{a} &= X^{f} + \alpha A'A'^{T}H^{T} \left(\alpha HA'A'^{T} H^{T} + \varepsilon^{o} \varepsilon^{o} \right)^{-1} \left(Y - HX^{f} \right) \\ & \text{Kalman Gain} \qquad \text{obs-model} \end{aligned}$

- X : model state (η , t, s, u, v, thk); (a: analysis; f: forecast)
- A': centered collection of model states (A'=A-A)
- Y : observations
- H : interpolates from model grid to observation
- ε° : Observation error
- α : rebalance ensemble variability to realistic level





- The ROIF assimilation scheme parameterizes the covariance matrix using a second-order Gaussian Markov Random Field (GMRF) model
- A sparse auto-regression operator operates on the error in the MRF neighborhood

 $\mathbf{e}_{\mathbf{j}} = \Sigma_{\mathbf{i} \in \mathbb{Z}} \ \alpha_{\mathbf{i}\mathbf{j}} \mathbf{e}_{\mathbf{j}-\mathbf{i}} + \mathbf{v}_{\mathbf{j}}$

 The square of the regression operator is the Information Matrix which is the inverse of the covariance Matrix



MRF order 2 Neighborhood

- Recently replaced the extended KF with ensemble methods to propagate the information matrix.
- Uses a static Information matrix generated using 55 members in all experiments shown here





Gulf of Mexico Model Configuration

Configuration:

- 89° to 98°W Longitude and 8° to 31°N Latitude
- •1/12° horizontal grid (258x175 pts; 6.5km average spacing)
- 20 vertical layers
- Forcing from NOGAPS/FNMOC
 1999-2000
- Monthly River Runoff
- Nested within 1/12 N. Atlantic domain
- HYCOM V. 2.1.36







Synthetic Data Used in the Experimants

HYCOM Identical Twin SSH and SST Data

Ocean model sampled along observed tracks

Ocean model sampled at observed MCSST locations





Communication via restart files





Truth and Initial State of Assimilative Runs

98W

sea surf. height Aug 29, 1999



temperature zonal sec. 25.08n Aug 29, 1999



sea surf. height Aug 29,1999 RE ci 2.0 cm 14.1 to 8



30N





TRUTH

25

mosphil









RMS Error in SSH Forecasts











Temperature Zonal sec. 25.08n Oct 18,1999 (Day 50)



TRUTH





MVOI







OAPS Salinity Vertical Section Forecast Day 50







Mean & RMS Error Temperature day 2 Mean & RMS Error Temperature day 50



Mean and RMS Error Profiles (u & v)





Basin Averaged Layer Thickness





Transports across a closed section







Transports across a closed section



