The GMAO Ocean EnKF and Application to the Assimilation of Altimetry Data

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GMAO Ocean Data Assimilation System (ODAS-1)

Algorithms:
- Univariate optimal interpolation (UOI): functional error covariances
- Multivariate OI (MvOI): steady-state ensemble based error representation
- Multivariate EnKF

Model:
- Poseidon v4 OGCM (Schopf and Loughe, 1995):
  - Quasi-isopycnal vertical coordinate
  - Prognostic variables are $h$, $t$, $s$, $u$ and $v$
  - Sea surface height (SSH) is diagnostic: \( \eta = \sum_i \text{buoyancy}(t_i, s_i)h_i/g \)
  - 538 x 572 x L27 ((1/3° x 5/8° x L27): About 30 million prognostic variables

Observations:
- UOI: T, S
- MvOI: T, S, SSH
- EnKF: T, S, SSH

ODAS-2

Algorithms:
- UOI: tested
- MvOI: tested
- EnKF: upcoming

Models:
- Poseidon v5: tested
- MOM v4: development
- MITGCM: upcoming

Why a new system?:
- Adherence to ESMF gridded component paradigm
- Model independent & enhanced portability
- Main new features:
  - Faster analysis
  - Analysis conducted at any arbitrary resolution
  - Supports multi-model, multi-resolution ensembles
  - OMF calculation at observation time
  - 4-D (x, y, z, 1/t) error-covariance specification
  - No code changes required to include new data types
**Ocean EnKF** *(MWR 130, 2951-2965, 2002; JMS 40-41, 363-380, 2003; NPG 12, 491-503, 2005)*

- Multivariate compactly supported background covariances: updates T, S, u & v
- Massively parallel
- System noise representation:
  - Random linear combinations of model-state EOFs to simulate model errors
  - Forcing perturbations to simulate forcing errors (colored spectrum in space and time)
- Online bias correction (used in SSH assimilation)

**Challenge**: Transit EnKF from R&D status to a production application

- Match the performance/outperform production ODAS
- Good performance with very small ensembles

**EnKF validation experiments**

- Assimilate T/P SSH anomalies + TAO & XBT temperature profiles 1/1/2001-12/31/2001
- Online bias estimation in SSH assimilation
- 4 runs: 9, 17, 33 & 65 member EnKF
- Compare with
  - no-assimilation control
  - Production ODAS (temperature OI + S(T) correction)
T/P altimetry data are anomalies. Hence bias must be accounted for when assimilating SSH.

**b) Assimilation with online bias estimation (OBE)**

Side by side estimation of:
- Unbiased error
- Climatological error (bias)
Compactly supported EnKF (bias estimation omitted)

\[
x_{i,k}^\Phi = (1 - \beta)x_{i,k-1}^\Phi + \beta x_{i,k}^f, \quad i = 1, \ldots, n,
\]

\[
x_{i,k}^f = M(x_{i,k-1}^n, f_{k-1}) + N_{i,k-1}, \quad \text{E}(N_{i,k-1}N_{i,k-1}^T) \approx Q_{k-1}, \quad i = 1, \ldots, n, \quad (1a)
\]

\[
S = \{s_1, s_2, \ldots, s_n\} = \{H(\Phi(x_1^f - \bar{x}^f)), H(\Phi(x_2^f - \bar{x}^f)), \ldots, H(\Phi(x_n^f - \bar{x}^f))\}, \quad (1b)
\]

Spatial filtering operator \( HP^f H^T = \frac{1}{n-1} SS^T \), \( (1c) \)

\[
a_i = [C \cdot (HP^f H^T + R)]^{-1}(y + e_i - H(x_i^f)), \quad \text{E}(e_i e_i^T) \approx R, \quad i = 1, \ldots, n, \quad (1d)
\]

\[
x_{i,1}^q = x_{i,1}^f + \frac{1}{n-1} \sum_{j=1}^{n} (\Phi(x_{j,1}^f - \bar{x}^f)) s_j^T (c_i \cdot a_i), \quad i = 1, \ldots, n. \quad (1e)
\]

Improving the performance for small ensembles

Spatio-temporal filtering of background-error covariances
- Temporal filter applied to \( X^f \) integration (exponential moving average)
- Spatial filter applied to \( (X^f - \langle X \rangle) \) deviations (Gaussian filter)

Effect of time filtering

<table>
<thead>
<tr>
<th>( \beta )</th>
<th>1 (no time filter)</th>
<th>0.01</th>
<th>0.005</th>
<th>0.0025</th>
<th>0.00125</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMS OMF (K)</td>
<td>1.174</td>
<td>1.165</td>
<td>1.161</td>
<td>1.164</td>
<td>1.177</td>
</tr>
</tbody>
</table>

Table 1. RMS OMF difference for \( T \) as a function of the time-filtering parameter \( \beta \) in 30 day 17-member EnKF runs assimilating TAO and XBT observations (model timestep: 1200s).
Effect of spatial filtering
Example of marginal Kalman gain: $T_{\text{obs}}(0n,156\,E,150\,m)$ on 12/31/01
horizontal section through $\langle T', T' \rangle$ covariances

EnKF-9

EnKF-17

EnKF-33

EnKF-65

Unfiltered, not compactly supported
Unfiltered, compactly supported
Filtered, compactly supported
Effect of spatial filtering
Example of marginal Kalman gain: $T \text{obs @} (O\text{n}, 156E, 150m)$ on 12/31/01
horizontal section through $<T', T'>$ covariances

<table>
<thead>
<tr>
<th></th>
<th>EnKF-9</th>
<th>EnKF-17</th>
<th>EnKF-33</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unfiltered, globally supported (UGS)</td>
<td>0.36</td>
<td>0.46</td>
<td>0.67</td>
</tr>
<tr>
<td>Unfiltered, compactly supported (UCS)</td>
<td>0.51</td>
<td>0.58</td>
<td>0.75</td>
</tr>
<tr>
<td>Filtered, compactly supported (FCS)</td>
<td>0.63</td>
<td>0.70</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Table 2. Correlation of the horizontal section through the unfiltered globally supported (UGS) marginal gain for $T$ in the EnKF-65 run with the corresponding UGS, unfiltered compactly supported (UCS) and filtered compactly supported (FCS) horizontal sections through the corresponding marginal gain in the EnKF-9, EnKF-17 and EnKF-33 runs.

- Filtering increases correlation of Kalman gain with corresponding raw (no filter, globally supported) gain from EnKF-65 run
- Especially for very small ensembles, the filter “simulates” the covariances one would get from a larger ensemble
Temporal evolution of Kalman gain for T obs.

EnKF-33: filter
Schur(C,P) @(ON,156E,150m)
Temporal evolution of Kalman gain for SSH obs.

EnKF-33: filter
Schur(C,P) @(0N,156E,150m)
H-section z=150m V-section x=156E

Corr(SSH,S)
Corr(SSH,T)

-1  -0.8  -0.6  -0.4  -0.2   0   0.2   0.4   0.6   0.8   1.0
SSH OMF and OMA statistics

- **Control**
  - Mean OMF
  - RMS OMF
  - Mean OMA
  - RMS OMA

- **OI+S(T)**

- **EnKF-9**

- **EnKF-17**

- **EnKF-33**

- **EnKF-65**

- Control is most biased
- OI partly corrects SSH bias but worsens RMS OMF
- EnKF runs have no noticeable SSH bias
Validation with December 2001 ADCP zonal currents

- **Validation with December 2001 ADCP zonal currents**

(a) ADCP

(b) 0.4 contour extends too far West

(c) 0.4 contour too deep, amplitude underestimated

(d) 0.4 contour too deep, better amplitude

(e) better amplitude, better 0.4 contour
Impact of assimilation on CGCM hindcast skill

- 17-member EnKF
- Assimilate T + SSH for February-April of each year from 1993 to 2002
- Couple OGCM to AGCM & LSM after running ODAS
- 12-month May start CGCM hindcasts initialized with ocean from EnKF runs (to save CPU time, EnKF-initialized CGCM hindcasts have only 5 ensemble member)

- Assess impact of assimilation on SST hindcast skill
- Compare to history of production May-start hindcasts
May start Niño-3.4 SST hindcasts

Applications:
- EnKF-17 initialization
- False LN alert
- Missed EN

Technique:
- OI + S(T) initialization
  - Missed EN
  - False EN alert
  - Missed EN
  - False LN alert
Niño-3 SSH

EnKF T+SSH, OBE
GMAO CGCMv1

hindcast correlations with TOPEX

EnKF T+SSH, no OBE
CGCMv1

May start SSH hindcasts
**Conclusions**

- Analysis speed up makes it practically feasible to use the EnKF in the production forecast initialization.
- Small ensemble EnKF can outperform production system provided background covariances are appropriately preconditioned.

**Ongoing work**

- More hindcast experiments with EnKF and Poseidon v4 (Robin Kovach).
- ODAS-2 testing and development: towards multi-model multi-resolution EnKF.
- Investigating use of bred vectors (Shu-Chih Yang):
  - in lieu of model EOFs in MvOI
  - in EnKF system noise model and initialization.