Lecture 4: Observing System Simulation Experiments (OSSEs)
OSSE experiments to explore effects of:

- number of outer-loops
- assimilation window length
- horizontal & vertical correlation lengths
- error models (incl innovation statistics)
- starting point
- errors in surface boundary conditions
- errors in open boundary conditions
- innovation pdfs
- independent obs
Model Configuration

4D-Var
- Dual
- B-preconditioned, Lanczos, RPCG
- Adjust i.c. only in most expts
- BGQC: $\pm 3\sigma$

Nature run:
- 1999-2010 COAMPS
- Jan-Apr 2003

Observations:
- Satellite SST – daily (AVHRR, AMSR, MODIS)
- Aviso gridded SSH - daily
- In situ T & S profiles
- 4 Jan – 18 April 2003
  First-guess:
- 1980-2010 ERA+CCMP
- Reanalysis

- 10km resolution. 42 $\sigma$-levels
- NRL COAMPS forcing
- SODA open boundary cons
Impact of Outer-Loops

Climatological stds, $\Sigma_c$
25 km horizontal decorrelation
90 m vertical decorrelation
Impact of Assimilation Window Length

Temperature – all depths

Salinity – all depths

V – all depths

ζ

2 outer-, 7 inner-loops
Modeled stds, $\Sigma_m$
25 km horizontal decorrelation
90 m vertical decorrelation

Analysis equation:

$$x_a = x_b + BH^T \left( HBH^T + R \right)^{-1} d$$

Implicit flow-dependent covariance
Impact of Horizontal Decorrelation Length

- a: Temperature – all depths
- b: Salinity – all depths
- c: V – all depths
- d: \( \zeta \)

Climatological stds, \( \Sigma_c \)
- 2 outer-loops
- 7 inner-loops
- 8 day window
- 90 m vertical decorrelation
Impact of Vertical Decorrelation Length

Climatological stds, $\Sigma_c$
2 outer-, 7 inner-loops
8 day window
25 km horizontal decorrelation
A Background Error Model

**Assumption:** The true value of $T_t$ can be found in the vertical profile of the background $T_b$ (Cooper and Haines, 1996; Mogensen et al, 2012).

$$T_t(z) = T_b(z + \delta z) \approx T_b(z) + \left( \frac{\partial T_b}{\partial z} \right) \delta z$$

The error in the background is therefore given by:

$$\left| T_t(z) - T_b(z) \right| \approx \left| \left( \frac{\partial T_b}{\partial z} \right) \delta z \right|$$

Choose:

$$\sigma \sim \left| \left( \frac{\partial T_b}{\partial z} \right) \delta z \right|$$
Suppose we apply this to every state-variable, $\varphi$, then using the formulation of Mogensen et al. (2012):

$$
\sigma_\varphi = \begin{cases} 
\max(\sigma_\varphi, \sigma_{\varphi}^{ml}) & \text{if } z \geq -D_{ml} \\
\max(\sigma_\varphi, \sigma_{\varphi}^{do}) & \text{if } z < -D_{ml} 
\end{cases}
$$

$$
\tilde{\sigma}_\varphi = \min(|(\partial \varphi / \partial z) \delta z|, \sigma_{\varphi}^{max})
$$

The parameter $\sigma_{\varphi}^{max}$ is the maximum value of $\sigma_\varphi$, while $\sigma_\varphi^{ml}$ and $\sigma_\varphi^{do}$ are the minimum values allowed in the mixed layer and deep ocean respectively. In ROMS, the mixed layer depth $D_{ml}$ is computed using the method described by Kara et al. (2000).
A Background Error Model

- Temperature - all depths
- Salinity - all depths
- V - all depths
- ζ - all depths

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_{\text{max}}$</th>
<th>$\sigma_{\text{m}}$</th>
<th>$\sigma_{\text{do}}$</th>
<th>$\delta z$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>0.66 C</td>
<td>0.1 C</td>
<td>0.04 C</td>
<td>40 m</td>
</tr>
<tr>
<td>Salinity</td>
<td>0.05</td>
<td>0.1</td>
<td>0.056</td>
<td>40 m</td>
</tr>
<tr>
<td>Velocity</td>
<td>0.12 ms$^{-1}$</td>
<td>0.1 ms$^{-1}$</td>
<td>0.04 ms$^{-1}$</td>
<td>500 m</td>
</tr>
<tr>
<td>SSH</td>
<td>0.05 m</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

$\alpha =$ scaling factor for all error model parameters (except $\delta z$)

- No assim
- $\alpha=0.25$
- $\alpha=0.5$
- $\alpha=1$
- $\alpha=1.5$
A Background Error Model

Temperature – all depths

Salinity – all depths

V – all depths

ζ

- No assim
- Climatological std
- Error model
Innovation Statistics

Statistics of the innovation vectors following Desroziers et al (2005):

\[
\begin{align*}
    \mathbf{d} &= (\mathbf{y} - H(\mathbf{x}_b)) \\
    \mathbf{d}_a^0 &= (\mathbf{y} - H(\mathbf{x}_a)) \\
    \mathbf{d}_b^a &= (H(\mathbf{x}_a) - H(\mathbf{x}_b)) \\
    \tilde{\sigma}_b^2 &= (\mathbf{d}_b^a)^T \mathbf{d} / p \\
    \tilde{\sigma}_o^2 &= (\mathbf{d}_a^0)^T \mathbf{d} / p
    \end{align*}
\]

Compare $\tilde{\sigma}_o$ with $\sigma_o$ & $\tilde{\sigma}_b$ with $\sigma_b$
25km, 90m
(clim stds)

25km, 90m, $\alpha=1$
(error model)

REPLOT USING NEW RUN DATA
Errors in Boundary Conditions

- Errors in surface forcing
  - No assim
  - FRC ADJUST
  - IC only

- Errors in open boundary conditions
  - No assim
  - OBC ADJUST
  - IC only
Starting Point

- We are solving a non-linear minimization problem using a truncated Gauss-Newton method.
- There is no guarantee that the problem will converge to a unique solution if multiple minima exist in the cost function.
- We can test this by solving the same minimization problem using different starting points.
Innovation PDFs

![Graphs showing distribution of SST, SSH, T, and S with mean and standard deviation marked.](image)
Verification Against Independent Obs

8-day hindcasts from 4D-Var analyses
References


