Improving Storm Surge Forecasting in the North Sea using Data Assimilation

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Assimilate tide gauge observations into an operational storm surge forecasting model (CS3x) and investigate improvement to forecasts.
3DVar Assimilation

\[ J(x_a) = \partial x^T B^{-1} \partial x + d^T R^{-1} d \]

- **Analysis**
- Background error covariance matrix
- Observation error covariance matrix

**Increment**
\[ \partial x = x_a - x_b \]
\[ x_b = \text{background field} \]

**Innovation**
\[ d = y - H(x_b) \]
\[ y = \text{vector of observations} \]
3DVar Assimilation

$$\min_{x_a} \ J(x_a) = \partial x^T B^{-1} \partial x + d^T R^{-1} d$$

$$\nabla x_a J(x_a) = 0$$

J is quadratic => can use Conjugate Gradient Method for minimization.

$x_a$ 11918 variables

B 11918 x 11918 matrix

R n_obs x n_obs matrix
Estimating B

Use **Innovation Statistics**:

\[
\text{innovations} = \text{observations} - \text{background (model)}
\]

1. Obs spatially uncorrelated
2. Obs & Background uncorrelated

=> Innovation covariance at \( r > 0 \) is approximately background error covariance.

Reconstructed altimetry SSH
[Hoyer et al.] [Madsen et al.]
Estimating B

Parameterize correlations/covariance assuming

• Homogeneity (unchanging in space)

• Isotropic (correlation independent of direction)

• Time-independent.
Estimating B - Correlations

Function Criteria:

1. Generate positive definite correlation matrix.
2. Must equal 1 at zero distance.
3. Tends to 0 as distance goes to infinity.

Powered Exponential:

\[ e^{-bx^t} \]
Estimating B - Variance

Powered Exponential:

\[ ae^{-bx^t} \]

Background error variance estimate:

0.016
Estimating $R$

- White noise observation errors. No spatial correlation ($R$ is diagonal).
- Use high pass filter on 1 year of observations.
- Use this to estimate variance of observation errors:

  \[
  \text{Var} = 0.0001 \\
  \text{S.D} = 0.01\text{m}
  \]
1. Subtract mean sea level (19 years of data from PSMSL) from tide gauge observations.

2. Tide gauges assumed located at nearest model grid cell.

3. Assimilate once an hour for 6 hours.
Model Experiments

Two stormy periods during January 2005

CS3X: Storm surge model used operationally for the UK.
13/01/2005
TWL difference from control

Modelled Residuals
T T+6 T+4 T+2
13/01/2005

Modelled Residuals

North Shields

Lowestoft

Cuxhaven

Assimilation period
20/01/2005
TWL difference from control

T
T+2
T+4
T+6
20/01/2005

Modelled Residuals

Assimilation period

Lowestoft

West Terschelling

Cuxhaven
Conclusions & Future Work

• Changes due to assimilation don’t last long, therefore limited utility for forecasting.

• Model SSH is strongly influenced by atmospheric surface forcing and tidal boundary forcing.

• No real benefits seen due to this assimilation setup.

• Control model (CS3x) performed well anyway for chosen time periods.

• Look at better estimation of covariance matrices (anisotropy, inhomogeneity).

• Run more significant surge events (e.g. Winter 2013).

• Find events where model performed less well.
Summary

• Used 3DVar to assimilate tide gauge SSH observations into North Sea of CS3 Model.

• Generated correlations using homogeneous, isotropic 2D function.

• Performed assimilation experiments for two events in January 2005.

• Assimilated time series converge back to control time series within approximately 8 hours.

• Little benefit to TWL forecasting at the locations studied.

References


K. Madsen et al., Blending of satellite and tide gauge sea level observations and its assimilation in a storm surge model of the North Sea and Baltic Sea, *J. Geophys. Res*, 120, 2015