

# Representer-Based Variational Data Assimilation in a Nonlinear Model of Nearshore Circulation

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## INTRODUCTION

### Variational data assimilation (DA):

- finds the ocean state estimate by fitting dynamical models to observations in a least squares sense, in a finite time interval
- adjusts model inputs (initial and boundary conditions, forcing, parameters)
- interpolates between observations (sparse in space and time) utilizing a dynamically consistent state-dependent model solution error covariance

### Challenges with nonlinear models:

- Tangent linear (TL) and adjoint (ADJ) models are required; optimization algorithms are complicated and computationally intense
- Growing instabilities in the TL model may pose a threat to convergence
- Variability associated with nonlinear eddy interactions is not necessarily present in the model inputs (forcing). However, variational DA finds the optimal solution by adjusting model inputs.

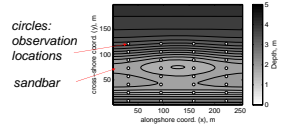
Can we correctly estimate the ocean state dominated by these interactions?

## SHALLOW-WATER NEARSHORE CIRCULATION MODEL

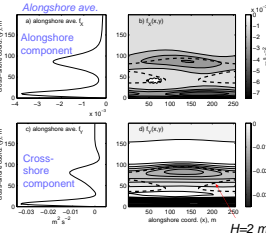
(after Slimi, Allen & Holtman, JGR 2000)

- Forcing: steady, represents the effect of breaking waves
- Linear bottom drag, bi-harmonic horizontal dissipation
- Alongshore periodic boundary conditions

### Computational domain

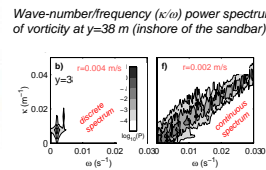
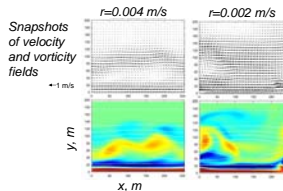
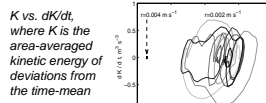


Forcing: peaks over the bar and near coast



### Model response to steady forcing depends on the magnitude of bottom friction coefficient (r):

- r=0.004 m/s: equilibrated waves
- r=0.002 m/s: more strongly nonlinear, irregular eddy flow



## DATA ASSIMILATION METHOD (ref: Chua and Bennett, Oc. Mod. 2001)

Nonlinear model:  $\frac{\partial \mathbf{u}}{\partial t} = N(\mathbf{u}) + \mathbf{f}(t) + \boldsymbol{\varepsilon}_r(t)$

Initial condition:  $\mathbf{u}(x, 0) = \mathbf{i}(x) + \boldsymbol{\varepsilon}_0$

Data:  $\mathbf{g}_k = \mathbf{u}_k + \boldsymbol{\varepsilon}_k$  ( $k = 1, \dots, K$ ), or  $L(\mathbf{u}) = \mathbf{d} + \boldsymbol{\varepsilon}$

Penalty functional:  $J(\mathbf{u}) = \boldsymbol{\varepsilon}_0^T \boldsymbol{\varepsilon}_0 + \sum_{k=1}^K \boldsymbol{\varepsilon}_k^T \boldsymbol{\varepsilon}_k + \boldsymbol{\varepsilon}_r^T \boldsymbol{\varepsilon}_r + \boldsymbol{\varepsilon}_c^T \boldsymbol{\varepsilon}_c$

The n-th inverse solution:  $\mathbf{u}_{inv}^n = \mathbf{u}_{inv}^{n-1} + \boldsymbol{\psi}^n$

Prior (fwd) model (full state TL model):

$$\frac{\partial \mathbf{u}_{TL}}{\partial t} = N(\mathbf{u}_{TL}^n) + \mathbf{A}(\mathbf{u}_{TL}^n) (\mathbf{u}_{TL}^n - \mathbf{u}_{inv}^{n-1}) + \mathbf{f}$$

$$\mathbf{u}_{TL}^n(x, 0) = \mathbf{i}$$

TL operator, dependent on previous iteration solution

The representer method: nonlinear Euler-Lagrange equations (necessary conditions for min J(u)) are solved iteratively, as a series of linearized optimization problems ("outer loop iterations",  $\{\mathbf{u}_{inv}^n\}$ )

To compute the n-th correction field ( $\boldsymbol{\psi}^n$ ), utilize the ADJ and "perturbation" TL models repeatedly, searching for optimal  $\mathbf{b}_k$  in the data subspace ("inner loop iterations"):

ADJ model:

$$-\frac{\partial \boldsymbol{\lambda}^n}{\partial t} = \mathbf{A}(\mathbf{u}_{TL}^n) \boldsymbol{\lambda}^n + \sum_{k=1}^K \mathbf{b}_k \mathbf{g}_k$$

$$\boldsymbol{\lambda}^n(x, T) = 0$$

Perturbation TL model:

$$\frac{\partial \boldsymbol{\psi}^n}{\partial t} = \mathbf{A}(\mathbf{u}_{TL}^n) \boldsymbol{\psi}^n + \mathbf{C}_T \boldsymbol{\lambda}^n$$

$$\boldsymbol{\psi}^n(x, 0) = \mathbf{C}_T \boldsymbol{\lambda}^n(x, 0)$$

The convergence of the nonlinear optimization algorithm over long integration times and the accuracy of the forcing estimate may depend on the choice of the assumed forcing error covariance  $\mathbf{C}_T(x_1, t_1, x_2, t_2) = \mathbf{C}_T(x_1, x_2) \mathbf{C}_T(t_1, t_2)$  (particularly, the choice of  $\mathbf{C}_T$ )

## THE VALIDITY LIMIT OF THE TL MODEL

### Dataless Iterations:

- Use the full state TL model (linearized w/ respect to previous iter TL solution or 0 on the 1st iteration)
- Run with true forcing and IC

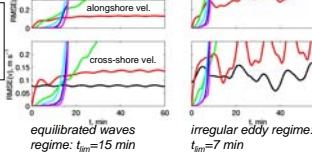
TL solutions converge to the truth only in a limited time interval  $t_{lim}$

Can DA be approached in a time interval  $T \gg t_{lim}$ ?

Area-averaged RMS error, prior and TL solutions

r=0.004 m/s

r=0.002 m/s



## DA EXPERIMENT SET-UP (WITH SYNTHETIC DATA):

- True solution: fully developed eddy flow
- Observations: true surf. elevation and velocities sampled at the 32 locations (see map on the left), every min; random noise added (0.02 m, 0.02 m/s)
- Prior=0 (deliberately, the prior is chosen to be substantially different from the truth, to explore the nonlinear part of the algorithm)

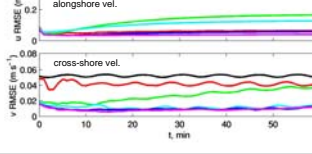
## ASSIMILATION IN THE WEAKLY NONLINEAR (EQUILIBRATED WAVES) REGIME (r=0.004 m/s):

Outer loop iterations converge to the true solution in the 1 h interval with the steady  $\mathbf{C}_T$  ( $\mathbf{C}_T = \text{const}$ )

In this regime, initial conditions and steady forcing provide effective means of control of the time-variable flow. Forcing provides a correct steady energy input and initial conditions define the initial phase of the shear wave

Area-averaged RMS error, prior and TL solutions

(legend as above)

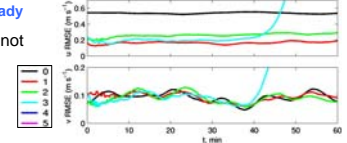


## ASSIMILATION IN THE STRONGLY NONLINEAR (IRREGULAR FLOW) REGIME (r=0.002 m/s):

Case 1. Try  $\mathbf{C}_T = \text{const}$ , since true forcing is steady

Then, scales of observed flow variability are not represented in the forcing correction.

Outer loop iterations do not converge

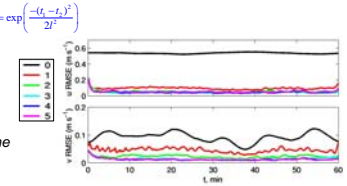


Case 2. Standard bell-shaped  $\mathbf{C}_T$ :  $\mathbf{C}_T(t_1 - t_2) = \mathbf{C}_T^{bell} \exp\left(-\frac{(t_1 - t_2)^2}{2}\right)$

l=5 min: no convergence

l=1 min: convergence (TL solution is close to the true NL solution)

In this regime, it is important to allow variability in forcing associated with rapid changes inshore of the sand bar

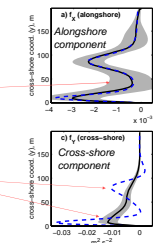


Forcing estimate: not quite accurate with  $\mathbf{C}_T = \mathbf{C}^{bell}$

Alongshore and time ave. forcing  $\pm$  temporal StD (blue line is true forc)

Temporal variations comparable to the time mean

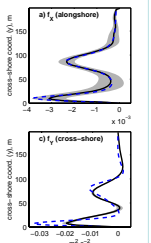
Underestimated peak forcing



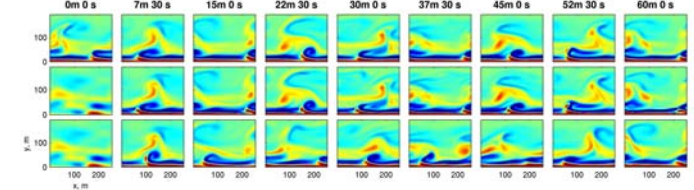
Case 3: composite  $\mathbf{C}_T$  ( $\mathbf{C}_T = 1 + a \mathbf{C}^{bell}$ , where  $a < 1$ )

Accurate and convergent TL solution

Better, than in case 2, forcing estimate



Vorticity snapshots (in case 3): (top) truth, (middle) iteration 7 TL inverse solution, and (bottom) NL solution obtained using inverse initial conditions and forcing estimates



## CONCLUSIONS:

In a strongly nonlinear flow regime, the representer method converges to an accurate solution over a time interval that is substantially longer than the validity limit of the TL model or the eddy time scale

To stabilize inversion, time variability in the forcing (on eddy time scale) is allowed by a choice of the forcing error covariance