

More than gradients:

Dynamical attribution in ocean science using adjoint models



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- 1. Short recap: the global ocean circulation inverse problem
- 2. The adjoint (or Lagrange multiplier) method
 - Getting the adjoint of a GCM
- 3. Causal / dynamical attribution based on the dual ocean state
 - Application to the North Atlantic circulation



1.

Short recap:

The ocean circulation inverse problem



The ocean circulation inverse problem – historical

Drawn by Carl Wunsch on the occasion of Walter Munk's 65th Birthday, 1982



Munk & Wunsch: Observing the Ocean in the 1990s. Phil. Trans. R. Soc. Lon. A (1982)

The ocean circulation inverse problem – today Estimating the Circulation and Climate of the Ocean (ECCO)



The ocean circulation inverse problem

Consider model L, and observation y with noise ϵ :

$$x_{k+1} = L x_k$$
, and $y_{k+1} = E x_{k+1} + \epsilon_{k+1}$

Variational form of least-squares estimation problem:

$$\begin{aligned} \mathcal{J}(x) &= \sum_{0 \leq k \leq N} \left[E \, x_k \, - \, y_k \right]^T \mathbf{R}^{-1} \left[E \, x_k \, - \, y_k \right] \\ &+ \left[x_k \, - \, x^b \right]^T \mathbf{B}^{-1} \left[x_k \, - \, x^b \right] \,, \quad t = k \Delta t \end{aligned}$$

Extend to Lagrange function \mathcal{L} , Lagrange multipliers μ_k :

$$\mathcal{L}(x,\mu) = J(x) + \sum_{0 \le k \le N} \mu_k^T [x_{k+1} - Lx_k]$$

Wunsch & Heimbach Physica D (2007)

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The ocean circulation inverse problem

Lagrange multiplier method:

Stationary point of \mathcal{L} leads to set of normal equations:

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \boldsymbol{\mu}(t)} &= \mathbf{x}(t) - \mathcal{L}[\mathbf{x}(t-1)] = 0 & 1 \le t \le t_f \\ \frac{\partial \mathcal{L}}{\partial \mathbf{x}(t)} &= \frac{\partial J_0}{\partial \mathbf{x}(t)} - \boldsymbol{\mu}(t) \\ &+ \left[\frac{\partial \mathcal{L}[\mathbf{x}(t)]}{\partial \mathbf{x}(t)} \right]^T \boldsymbol{\mu}(t+1) = 0 & 0 < t < t_f \\ \frac{\partial \mathcal{L}}{\partial \mathbf{x}(t_f)} &= \frac{\partial J}{\partial \mathbf{x}(t_f)} - \boldsymbol{\mu}(t_f) = 0 & t = t_f \\ \frac{\partial \mathcal{L}}{\partial \mathbf{x}(0)} &= \frac{\partial J}{\partial \mathbf{x}(0)} - \left[\frac{\partial \mathcal{L}[\mathbf{x}(0)]}{\partial \mathbf{x}(0)} \right]^T \boldsymbol{\mu}(1) & t_0 = 0 \end{aligned}$$

Wunsch & Heimbach Physica D (2007)

The ocean circulation inverse problem

$$\mu_{0} = \frac{\partial J}{\partial x_{0}} = \sum_{1 \le k \le N} \frac{\partial x_{k}}{\partial x_{0}} \left(\frac{\partial J}{\partial x_{k}} \right)$$

$$= \frac{\partial x_{1}}{\partial x_{0}} \left(\frac{\partial J}{\partial x_{1}} \right) + \frac{\partial x_{1}}{\partial x_{0}} \frac{\partial x_{2}}{\partial x_{1}} \left(\frac{\partial J}{\partial x_{2}} \right)$$

$$+ \dots + \frac{\partial x_{1}}{\partial x_{0}} \cdots \frac{\partial x_{N}}{\partial x_{N-1}} \left(\frac{\partial J}{\partial x_{N}} \right)$$

$$= \mathbf{L}^{T} \frac{\partial J}{\partial x_{1}} + \mathbf{L}^{T} \mathbf{L}^{T} \frac{\partial J}{\partial x_{2}} + \dots + \mathbf{L}^{T} \cdots \mathbf{L}^{T} \frac{\partial J}{\partial x_{N}}$$

$$\mathbf{L}^{T}: \text{ is the adjoint model (and L is the tangent linear model)}$$

$$\mu_{k} = \left(\frac{\partial J}{\partial x_{k}} \right): \text{ Lagrange multipliers or gradients}$$

Wunsch & Heimbach Physica D (2007)

2.

Getting the adjoint of an ocean general circulation model



THE UNIVERSITY OF TEXAS AT AUSTIN

Some of the challenges:

Generating & maintaining the adjoint of a state-of-the-art ocean circulation model

$$\frac{D\vec{\mathbf{v}}_{h}}{Dt} + f\hat{\mathbf{k}} \times \vec{\mathbf{v}}_{h} + \frac{1}{\rho_{c}} \nabla_{z} p = \vec{\mathcal{F}}$$

$$\epsilon_{nh} \frac{Dw}{Dt} + \frac{g\rho}{\rho_{c}} + \frac{1}{\rho_{c}} \frac{\partial p}{\partial z} = \epsilon_{nh} \mathcal{F}_{w}$$

$$\nabla_{z} \cdot \vec{\mathbf{v}}_{h} + \frac{\partial w}{\partial z} = 0$$

$$\rho = \rho(\theta, S)$$

$$\frac{D\theta}{Dt} = \mathcal{Q}_{\theta}$$

$$\frac{DS}{Dt} = \mathcal{Q}_{s}$$

VASA

Approx. form of Navier-Stokes equations for incompressible fluid:
momentum equation (including Coriolis term)

~10 000km

http://mitgcm.org

~1 000km

conservation of mass – NLFS & real water flux

~100km

- conservation of tracers (heat, salt)
- nonlinear equation of state for sea water
- subgrid-scale parameterizations
- scalable (domain decomposition)
- general curvilinear grid

~10km

~1km

~100m

• adjoint capability

Some of the challenges:

Generating & maintaining the adjoint of a state-of-the-art ocean circulation model

Global ocean simulation on a "cubed-sphere" grid topology





Some of the challenges:

Generating & maintaining the adjoint of a state-of-the-art ocean circulation model



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- domain decomposition (tiles) & overlaps (halos)
- split into extensive on-processor and global phase



Global communication/arithmetic op.'s supported by MITgcm's intermediate layer (WRAPPER) which need hand-written adjoint forms

	operation/primitive	forward		reverse
•	communication (MPI,):	send	\longleftrightarrow	receive
٠	arithmetic (global sum,):	gather	\longleftrightarrow	scatter
•	active parallel I/O:	read	\longleftrightarrow	write

The inverse problem

Α input/control variables $\mathbf{x} = (x_1, \ldots, x_N)$ initial conditions boundary conditions model parameters input x_1 \mathbf{B} grid cell #1 grid cell #1grid cell #1 Т S T)S T)S w u [v][w V grid cell #2grid cell #2grid cell #2simulated TS TS T S GCM GCM GCM ocean state uvw uvw uvw grid cell #K grid cell #K grid cell #K Т T)[S] S Т S (u) (v) (w (v)(w u at t_0 at t_1 at t_T simulated $f_1(\mathbf{x})$ $f_M(\mathbf{x})$. . . observations $\mathbf{C.I}$ model-data misfit output function $J_{\text{misfit}}(\mathbf{x})$ y_M observations y_1 . . . (I) State estimation

Courtesy Nora Loose

The sensitivity analysis problem



Courtesy Nora Loose

3. Dynamical attribution via the dual (adjoint) state



Dynamical attribution:

The Atlantic Meridional Overturning Circulation







(North) Atlantic Meridional Overturning Circulation (AMOC) variability

Quantity of interest:



 $\delta \mathcal{J}(u(x, y, t)) \equiv Monthly AMOC Anomaly$

"controlled" by:

 $\delta u(x, y, t) \equiv$ Surface Atm. Forcing Perturbations

through (assumed) linear dynamics described by:

$$\frac{\partial \mathcal{J}}{\partial u}(x, y, t) \equiv \text{Sensitivity}$$



Pillar et al., J. Clim. (2016)



Recall:

$$\frac{\partial J}{\partial x_0} = \sum_{1 \le k \le N} \frac{\partial x_k}{\partial x_0} \left(\frac{\partial J}{\partial x_k} \right)$$
$$= \frac{\partial x_1}{\partial x_0} \left(\frac{\partial J}{\partial x_1} \right) + \frac{\partial x_1}{\partial x_0} \frac{\partial x_2}{\partial x_1} \left(\frac{\partial J}{\partial x_2} \right)$$
$$+ \dots + \frac{\partial x_1}{\partial x_0} \cdots \frac{\partial x_N}{\partial x_{N-1}} \left(\frac{\partial J}{\partial x_N} \right)$$

Sensitivity of J with respect to zonal wind stress, 1, 3, and 12 months back in time,

... carried by the time-evolving dual/adjoint state

INSTITUTE FOR Pillar et al., J. Clim. (2016)

NEERING & SCIFNCES



Recall:

$$\frac{\partial J}{x_0} = \sum_{1 \le k \le N} \frac{\partial x_k}{\partial x_0} \left(\frac{\partial J}{\partial x_k} \right)$$
$$= \frac{\partial x_1}{\partial x_0} \left(\frac{\partial J}{\partial x_1} \right) + \frac{\partial x_1}{\partial x_0} \frac{\partial x_2}{\partial x_1} \left(\frac{\partial J}{\partial x_2} \right)$$
$$+ \dots + \frac{\partial x_1}{\partial x_0} \cdots \frac{\partial x_N}{\partial x_{N-1}} \left(\frac{\partial J}{\partial x_N} \right)$$

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Sensitivity of J with respect to (from left to right):

- zonal wind stress
- merid. wind stress
- heat flux

JEERING

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• freshwater flux

Pillar et al., J. Clim. (2016)

& SCIENCES



(Where) are uncertainties in externally forced AMOC uncertainties determined by ...

- 1. regions most sensitive to forcings?
- 2. regions exhibiting largest forcing uncertainties?







Fractional contribution of uncertainty in reanalysis air-sea flux forcing fields to the total uncertainty in the modelled AMOC



Pillar et al., J. Clim. (2018)



4.

Uncertainty Quantification & Optimal Observing System Design



Recall: The inverse problem



Courtesy Nora Loose



Uncertainty propagation via the time-evolving dual/adjoint state

More on this on Thursday AM



Nora Loose (Uni Bergen & Oden Institute), Ph.D. thesis (2019)



Conclusions

Looking beyond optimization...

- Adjoints are powerful tool for gaining dynamical and quantitative insight into processes governing ocean variability
 - (linear) sensitivity analysis
 - dynamical (as opposed to statistical) attribution
 - non-normal transient amplification (not shown)
 - uncertainty quantification
 - optimal observing system design
- Plenty of reasons for exploring adjoint models



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