

# Variational assimilation – Building a 4D-Var system

Amos S. Lawless

Data Assimilation Research Centre

University of Reading

*a.s.lawless@reading.ac.uk*

*@amoslawless*

# 4D-Var problem

Minimize

$$\mathcal{J}(\mathbf{x}_0) = \frac{1}{2}(\mathbf{x}_0 - \mathbf{x}^b)^T \mathbf{B}^{-1}(\mathbf{x}_0 - \mathbf{x}^b) + \frac{1}{2} \sum_{i=0}^N (\mathcal{H}_i(\mathbf{x}_i) - \mathbf{y}_i)^T \mathbf{R}_i^{-1} (\mathcal{H}_i(\mathbf{x}_i) - \mathbf{y}_i)$$

with respect to  $\mathbf{x}_0$ , subject to

$$\mathbf{x}_{i+1} = \mathcal{M}_i(\mathbf{x}_i).$$

# Minimization using iterative methods

The minimization of the cost function in variational data assimilation usually requires an iterative *gradient method* such as conjugate gradient or quasi-Newton.

These methods need to be able to calculate the cost function and its first derivative with respect to the initial state on each iteration.

In general the user must supply a routine which calculates  $J(\mathbf{x}_0)$  and  $\nabla J(\mathbf{x}_0)$  for any value of  $\mathbf{x}_0$ .

# Calculating the gradient

The gradient is given by solving the adjoint equation backwards in time:

$$\lambda_i = \mathbf{M}_i^T \lambda_{i+1} - \mathbf{H}_i^T \mathbf{R}_i^{-1} (\mathcal{H}_i(\mathbf{x}_i) - \mathbf{y}_i)$$

Then

$$\nabla \mathcal{J}(\mathbf{x}_0) = -\lambda_0 + \mathbf{B}^{-1}(\mathbf{x}_0 - \mathbf{x}^b)$$

# Notes

- The words *adjoint* and *transpose* are often used interchangeably. In fact the transpose is an adjoint for a particular inner product.
- The use of other inner products is only important if we want to give a physical meaning to adjoint variables.

# Discrete method

Let us suppose we have the line of code

$$z = x*y + y*y$$

We can linearize these lines of code by putting

$$x = X + \delta x, \quad y = Y + \delta y, \quad z = Z + \delta z$$

$X, Y, Z$  are called linearization states.

Then we obtain

$$\delta z = X*\delta y + \delta x*Y + 2*Y*\delta y$$

TLM

To obtain the adjoint model we consider the TLM statement as a matrix system in which we also consider  $\delta x$  and  $\delta y$  to be unchanged inputs to the system.

We can write the TLM Fortran statement as a matrix system as follows:

$$\delta z = X*\delta y + \delta x*Y + 2*Y*\delta y$$

TLM

$$\begin{pmatrix} \delta x \\ \delta y \\ \delta z \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ Y & X + 2Y \end{pmatrix} \begin{pmatrix} \delta x \\ \delta y \end{pmatrix}$$

The adjoint model can then be found by transposing this system of equations



ADJ

$$\begin{pmatrix} \delta x'' \\ \delta y'' \end{pmatrix} = \begin{pmatrix} 1 & 0 & Y \\ 0 & 1 & X + 2Y \end{pmatrix} \begin{pmatrix} \delta x'' \\ \delta y'' \\ \delta z'' \end{pmatrix}$$

which implies the adjoint code

$$\delta x'' = \delta x'' + Y * \delta z''$$

$$\delta y'' = \delta y'' + (X + 2*Y) * \delta z''$$

We note that this adjoint code can be derived directly from the TLM code, without writing out the matrices

TLM

$$\delta z = X * \delta y + \delta x * Y + 2 * Y * \delta y$$

ADJ

$$\delta x^{//} = \delta x^{//} + Y * \delta z^{//}$$

$$\delta y^{//} = \delta y^{//} + (X + 2 * Y) * \delta z^{//}$$

We also need to set  $\delta z^{//} = 0$

Hence the adjoint code can be developed directly from the TLM code, following some simple rules.

- Set initial values of adjoint variables to zero.
- Work backwards through the TLM code, taking the transpose of each line of code and setting LHS variables to zero.
- Reverse also the order of any loops which depend on the loop order.
- For each line of adjoint code increment the adjoint variables.

# Automatic adjoint compilers

The procedure shown in the previous slides is so automatic that it is possible to for ‘adjoint compilers’ to do it automatically. Such packages will produce a TLM and adjoint model from a nonlinear model source code, *e.g.*

- TAF
- ODYSSEE
- ADIFOR
- Python modules

# Testing of a TLM - Correctness

*Is the TLM coded correctly?*

Consider a perturbation  $\gamma\delta\mathbf{x}$ , where  $\gamma$  is a scalar.

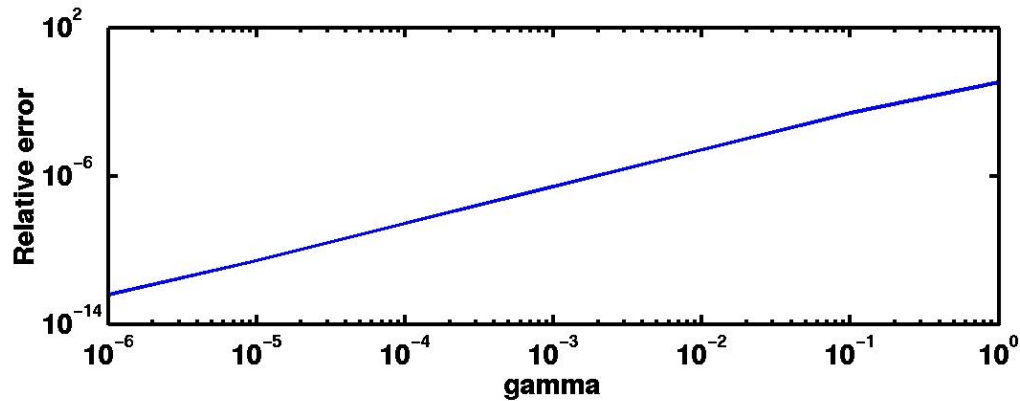
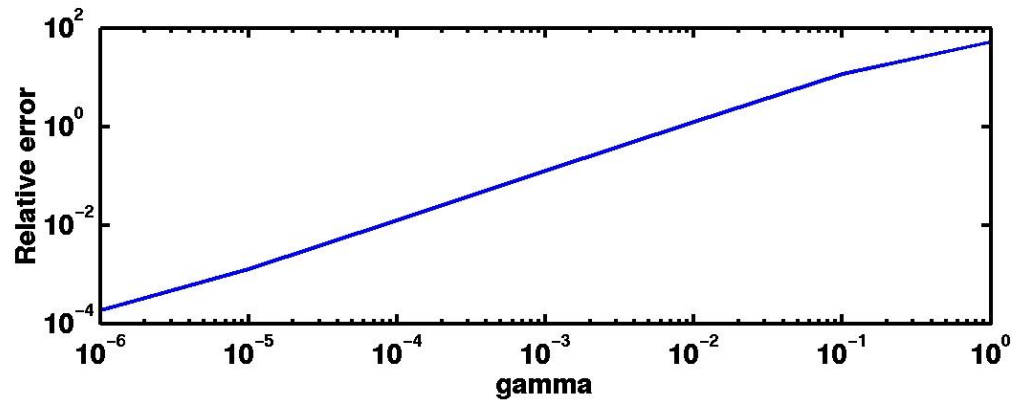
Then by a Taylor series expansion we have

$$M(\mathbf{x}_0 + \gamma\delta\mathbf{x}) = M(\mathbf{x}_0) + \mathbf{M}(\mathbf{x}_0) \gamma\delta\mathbf{x} + h.o.t.$$

Hence

$$\lim_{\gamma \rightarrow 0} \frac{\|M(\mathbf{x}_0 + \gamma\delta\mathbf{x}) - M(\mathbf{x}_0) - \mathbf{M}(\mathbf{x}_0)\gamma\delta\mathbf{x}\|}{\|\mathbf{M}(\mathbf{x}_0)\gamma\delta\mathbf{x}\|} = 0$$

# Testing of a TLM - Correctness



# Testing of a TLM - Validity

*Does the linear model provide a good approximation?*

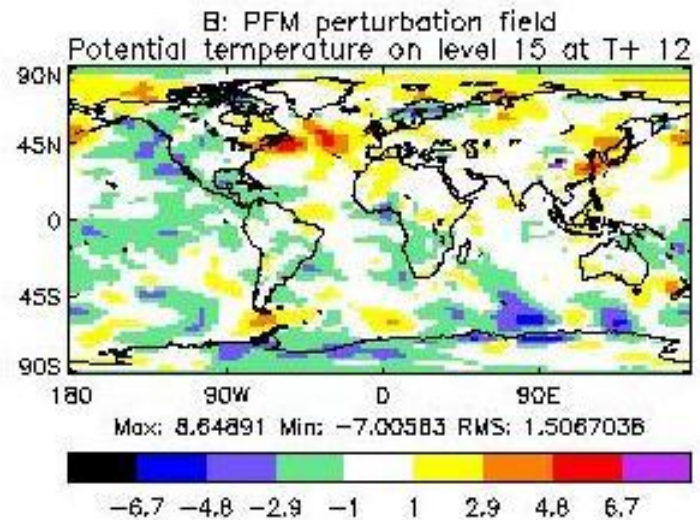
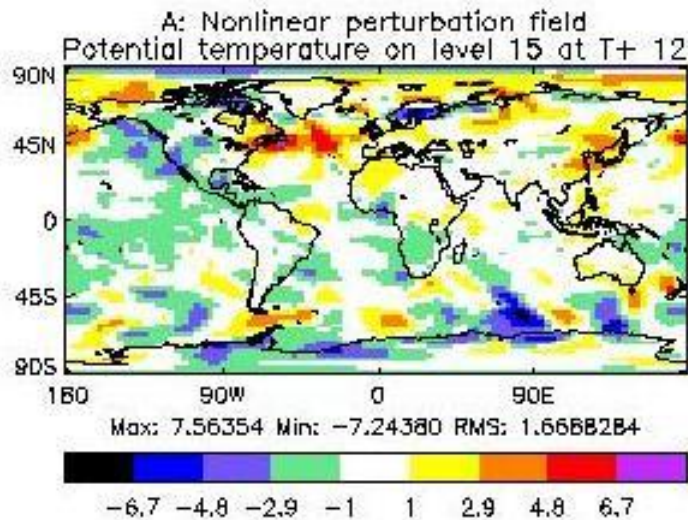
For a *realistic* perturbation  $\delta\mathbf{x}$ , compare the nonlinear evolution

$$M(\mathbf{x}_0 + \delta\mathbf{x}) - M(\mathbf{x}_0)$$

with the linear evolution  $\mathbf{M}(\mathbf{x}_0) \delta\mathbf{x}$

*Realistic* implies a size of the order of analysis error and not dominated by gravity waves.

# Testing of a TLM - Validity





Note that validity will depend on

- Size of perturbation
- Time of evolution
- Linearization state
- Application

# Test of adjoint model

For any operator  $\mathbf{M}$  and its adjoint  $\mathbf{M}^T$  we have

$$(\mathbf{M} \delta \mathbf{x}, \mathbf{M} \delta \mathbf{x}) = (\delta \mathbf{x}, \mathbf{M}^T \mathbf{M} \delta \mathbf{x})$$

*To test an adjoint model we*

1. Start with a random perturbation  $\delta \mathbf{x}$
2. Apply the TLM, which gives  $\mathbf{M} \delta \mathbf{x}$
3. Apply the adjoint model to the result of 3, to obtain  $\mathbf{M}^T \mathbf{M} \delta \mathbf{x}$
4. Verify that the above identity is satisfied to machine precision

# Summary so far

So far we have been able to

- Code the cost function using the nonlinear model.
- Calculate the tangent linear model from the nonlinear model & test the TLM.
- Calculate the adjoint model from the tangent linear model & test the adjoint.
- Code the gradient of the cost function using the adjoint model.

As a final step we want to test the gradient.

# Gradient test

$$J(\mathbf{x} + \alpha\mathbf{h}) = J(\mathbf{x}) + \alpha\mathbf{h}^T \nabla J(\mathbf{x}) + O(\alpha^2)$$

Define

$$\Phi(\alpha) = \frac{J(\mathbf{x} + \alpha\mathbf{h}) - J(\mathbf{x})}{\alpha\mathbf{h}^T \nabla J(\mathbf{x})} = 1 + O(\alpha)$$

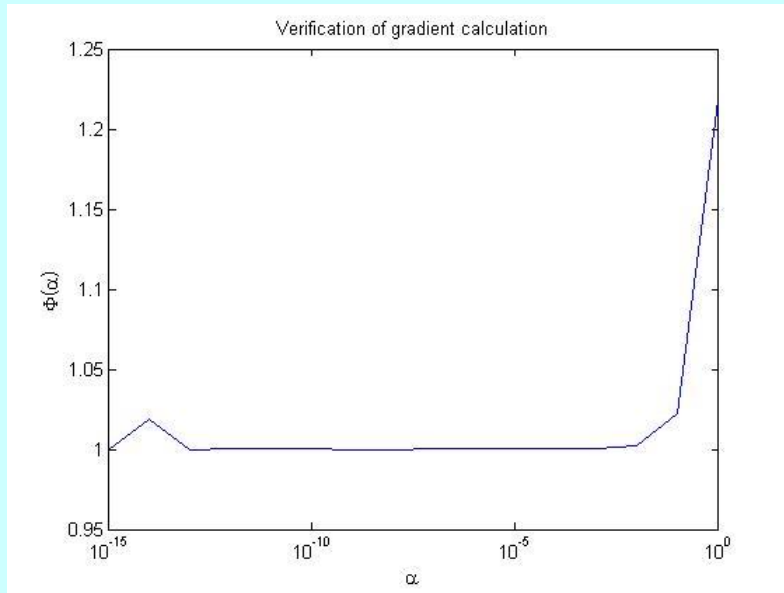
and plot  $\Phi(\alpha)$  as  $\alpha$  tends to zero.

Note that  $\mathbf{h}$  should be of unit length, *e.g.*

$$\mathbf{h} = \frac{\nabla J(\mathbf{x})}{\|\nabla J(\mathbf{x})\|}$$

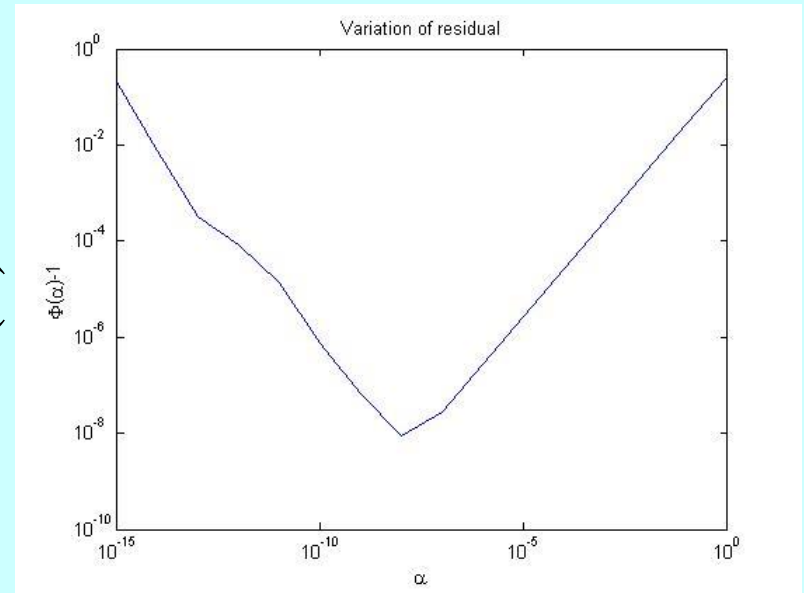
# Gradient test

$\Phi(\alpha)$



$\alpha$

$\Phi(\alpha)-1$



$\alpha$

# References

## *Coding a TLM and adjoint:*

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