





Tako Janelidze (Phd student at TSU, IEK-8)

Novel adjoint advection schemes for Atmospheric Chemistry

Supervisors: Ramaz Botchorishvili (TSU) Hendrik Elbern (FZJ, Uni Köln),

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Outline

- Motivation
 - atmospheric chemistry & 4D-var data assimilation

• Adjoint developments

• Numerical results



Atmospheric chemistry transport modeling

General atmospheric processes

- emission
- transport
- chemistry
- deposition

Transport continuity equation

$$\frac{\partial(\rho q)}{\partial t} + \nabla \cdot (\rho q v) = 0$$

 $\begin{array}{lll} \rho & - \ density \\ q & - \ mass & concretration \\ v & - \ wind & velocity & vector \end{array}$



Numerical models are used to simulate atmospheric motion and provide better understanding of the processes determining the dynamical and chemical state







Benefit from satellite observation data for improved

atmospheric chemistry and Climate Model performance





Combining models with observations: a complex mathematical optimisation task

ScienceBRIDGE

CONNECTING PEOPLE AND KNOWLEDGE

Result: the accuracy of the forecast is greatly improved

ICON Model

Joint project of German Weather Service (DWD) and Max-Plank Institute of Meteorology (MPI-M)

ICON model icosahedral grid, Zängl et. al, 2014

4D-var data assimilation (II)

Cost function

$$J(q_0) = f^b(q_0, q^b) + \int_0^T \int_\Omega f^o(q, q^o, t, \lambda, \theta) d\lambda d\theta dt$$

 Ω - surface of the sphere (λ, θ) - longitude-latitude coordinates \vec{q}_0 - initial concentation (eg. greenhouse gases) \vec{q}^{o} - observational data (satellite or ground-based measurements) \vec{q}^{b} - background information

Data assimilation problem: find the initial state q_0 that minimizes the cost function subject to the constraints:

$$\frac{\partial(\rho q)}{\partial t} + \nabla \cdot (\rho q \vec{v}) = 0 \quad q(0, \lambda, \theta) = q_0(\lambda, \theta)$$

Source: ICON Database- Reference Manual

Solution approach Gradient

$\nabla_{q_0} J(q_0) = \nabla_{q_0} f^b(q_0, q^b) - \rho(0, \lambda, \theta) q^*(0, \lambda, \theta)$

 $q^*(0,\lambda,\theta)$ -solution at t=0 of the adjoint equation

Adjoint equation

$$\rho(\frac{\partial q^*}{\partial t} + v \cdot \nabla q^*) = \nabla_q f^o(q, q^o, t, \lambda, \theta), \quad q^*(T, \lambda, \theta) = 0$$

Numerical challenge for adjoint development

- Delta-peak like transport during backward transport of $\nabla_q f^o(q, q^o, t, \lambda, \theta)$ requires **non-linear schemes**
- MPI based parallel computations
- Long time needed on adjoint development and verification

Paths to build the adjoint code

Standard method

Paths to build the adjoint code

Adjoint operators for ICON advection schemes

Splitted 3D continuity equation

ICON Schemes

- Miura's scheme with third order least square reconstruction
 Adjoint for horizontal scheme
- Third order Piecewise Parabolic Method (PPM)

Adjoint for vertical scheme

FCT Zalesak limiter (1979)

ICON-FFSL and its adjoint: standard method

Numerical scheme

• Forward scheme

$$\frac{\rho_j^{n+1}q_j^{n+1} - \rho_j^n q_j^n}{\Delta t} + \frac{1}{|\Omega_j|} \sum_{i \in S_j} \alpha_{ji} (\{\bar{\rho}_k^n, \bar{v}_k^n\}_{k \in K_{ji}}) q_i^n = 0, \quad S_j = \bigcup_{i \in I_j} K_{ji}$$

Adjoint scheme

$$\bar{\rho}_{j}^{n} \frac{q_{j}^{*,n+1} - q_{j}^{*,n}}{\Delta t} + \frac{1}{|\Omega_{j}|} \sum_{i \in S_{j}^{*}} \alpha_{ij} (\{\bar{\rho}_{k}^{n}, \bar{v}_{k}^{n}\}_{k \in K_{ij}}) q_{i}^{*,n} = 0$$

 $\begin{array}{l} K_{ji} & \text{-reference number of cells for flux } F_{ji} \\ S_j & \text{-reference number of cells on the stencil} \\ I_j = \{1,2,3\} \end{array}$

New method: artificial source term adjoint (I)

New method: artificial source term adjoint (II)

Theory:

- If forward scheme is stable adjoint scheme is also stable
- If accuracy of forward scheme is O(h^k) then accuracy of adjoint scheme is O(h^k)
- If forward scheme is convergent then adjoint scheme is also convergent for smooth solution

ICON-FFSL and its adjoint: art. source term method

$$\rho \frac{\partial q^*}{\partial t} + \nabla \cdot (\rho q^* \vec{v}) = q^* \nabla \cdot (\rho \vec{v})$$

$$\bar{\rho}_{j}^{n} \frac{q_{j}^{*,n+1} - q_{j}^{*,n}}{\Delta t} + \frac{1}{|\Omega_{j}|} \sum_{i \in I_{j}} F_{ji}(\{\bar{\rho}_{j}^{n}, \bar{v}_{k}^{n}, q_{k}^{*,n}\}_{k \in K_{ji}}, \vec{n}_{ji}, l_{ji}) = \frac{1}{|\Omega_{j}|} \sum_{i \in I_{j}} F_{ji}(\{\bar{\rho}_{j}^{n}, \bar{v}_{k}^{n}, q_{j}^{*,n}\}_{k \in K_{ji}}, \vec{n}_{ji}, l_{ji})$$

Using new method, limiters are directly inherited in adjoint equation, while for standard adjoint numerical scheme development extra procedure is necessary to include limiters.

Numerical experiments - do the methods work ?Linear horizontal advection

- Divergent velocity
- Non-divergent velocity
- FCT Zalesak Flux limiter (1979)
- One full rotation-12 days

Error norms

$$l_{1,rel} = \frac{\sum_{i=1}^{n_c} |\Omega_i| |q_i - q_i^{true}|}{\sum_{i=1}^{n_c} |\Omega_i| |q_i^{true}|}$$

$$l_{2,rel} = \frac{\sqrt{\sum_{i=1}^{n_c} |\Omega_i| (q_i - q_i^{true})^2}}{\sqrt{\sum_{i=1}^{n_c} |\Omega_i| |q_i^{true}|}}$$

$$l_{\infty,rel} = \frac{\max_{i=\overline{1,n_c}} |q_i - q_i^{true}|}{\max_{i=\overline{1,n_c}} |q_i^{true}|}$$

$$l_{1,abs} = \sum_{i=1}^{n_c} |q_i - q_i^{true}|$$

$$l_{2,abs} = \sqrt{\sum_{i=1}^{n_c} (q_i - q_i^{true})^2}$$

$$l_{\infty,abs} = \max_{i=\overline{1,n_c}} |q_i - q_i^{true}|$$

Results: linear advection (I)

• Standard adjoint method introduces oscillations and might leads to

negative concentration

Results: linear advection (II)

Artificial source term method has better shape precervance, smaller

error norms

Numerical experiments

Data assimilation

- Convergence
- Impact of observation points
- Mesh refinement
- Manipulating with weights
- Deformational flow with non-divergent velocity vector
- Moving vortex
- Identical twin experiment
- > 12 hr assimilation window
- ➤ Grids: R2B4, R2B5, R2B6, R2B7
- > Observations: 12.5%, 25%, 50%, 100%
- ➤ Initial error: 10%, or 1% if concentration=0
- Observation at each time-step

Results: data assimilation (I)

• Convergence

Both methods ensure convergence with increasing number of iterations

• Number of observations

The choice of adjoint solver influences ⁸⁰⁰ the minimisation process ⁷⁰⁰

Impact of number of observations

Artificial source term method offers more reliable behavior in most cases

Cast

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course adjoint

Results: data assimilation (II)

Mesh refinement

as adjoint

• Mesh refinement

Art. source term method yelds smaller final cost function

	Griu	COSt	Art. source aujoint	Art. source aujoint
			without limiter	with limiter
Deformational flow	R2B4	Final	5.43400710	1.568333807
	R2B5	Final	7.25133893	7.422831065
	R2B6	Final	$6.07498723 \mathrm{E}{+}04$	6.838604955 ± 01
	R2B7	Final	$1.38570810\mathrm{E}{+}05$	$2.653808533E{+}02$
	R2B4	Final	7.42488109E + 04	1.24677839E + 02
	R2B5	Final	2.89551111E + 04	2.49163938E+02
	R2B6	Final	$4.64099399E{+}05$	$6.98240016 \text{E}{+}02$
	R2B7	Final	1.12492223E + 06	1.38281501E + 03

Manipulating with weights
 The choice of adjoint solver influences
 the minimisation process

Manipulating with weights

Artificial source term method gives good results when standard approach fails

3D pure tracer advection test (Jablonowski, 2008)

Horizontal velocity vector

 $u(\lambda, \theta, \eta) = u_0 \cos(\theta \cos \alpha + \sin \theta \cos \lambda \sin \alpha),$ $v(\lambda, \theta, \eta) = -u_0 \sin \lambda \sin \alpha$

• Vertical velocity vector

$$\dot{\eta}(\lambda,\theta,\eta) = \frac{\omega_0}{p_0}\cos(\frac{2\pi}{\tau}t)\sin(s(\eta)\frac{\pi}{2})$$

- Solid body rotation in horizontal direction with a period of 12 days
- Wave-like trajectory in the vertical direction with a period of 4 days
- > 60 vertical layers up to ≈12 km.

Initial Art. source term adjoint scheme gives the same result as forward scheme horizontal grid projected on (λ, 0) line

Data assimilation results

 Initial error: 10%, or 1% if concentration=0, on the layers 34-42
 Observation at each time-step

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Thank you !