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Cesa

Regional Data assimilation

in atmospheric chemistry and air quality

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Introduction: Setting the scene



Contents

1. Introductory remarks

- 2. Where is atmospheric chemistry a challenge for data assimilation ? (focal topics)
 - 1. strongly anisotropic covariances
 - 2. diversity of chemical regimes: validation
 - 3. varying value of observations
 - 4. more than initial values to be optimised
- 3. Aerosol data assimilation

Chemistry-transport model EURAD-IM (Reaction-advevtions-diffusion equation) and further simulated processies

 Optionale Chemiemechanismen, ca. 60 gas phase constituents aqueous phase chemistry **Mexico City** $(0 \sim 5 \text{ species})$ aerosols (+ > 50 parameters - inorganic – secondary organic - mineral dust - sea salt Canary islands – wild fires

Objectives of air quality data assimilation

- bring together air quality measurements and CTMs to provide optimal spatio-temporal reconstructions of air quality parameters,
- estimate variability, sources, sinks, and trends
- provide better air quality predictions
- reconstruct past changes,
- act as a decision support system for protection measures (which emissions are most critical?)

Which constituents/complexity really matters?

- <u>Human health</u>:
 - **PM**₁₀, PM_{2.5}, PM₁ (= Particulate Matter)
 - POPs (*Persistent Organic Pollutants*):
 - PAHs (Polycyclic Aromatic Hydrocarbons),
 - PCBs (PolyClorinated Biphenyls),
 - HCHs (HexaCloroHexanes),
 - benzene,
 - benzopyrene,
 - Trace metals: Cd, Be, Co, Hg, Mo, Ni, Se, Sn, V, As, Cr, Cu, Mn, Zn, Pb
 - Ozone, PAN, NO, NO₂, SO₂, CO
 - Pollen
- <u>Crops</u>:
 - Ozone
- Forests, lakes, other vulnerable ecosystems
 - "Acid rain"
 - ozone



Special challenges of tropospheric chemistry data assimilation

The following problems prevail:

- 1. strong influence of manifold processes including *emissions* and *deposition*
- 2. temporarily highly variable "chemical regimes"
- 3. chemical state observability (= "analyseability") hampered by *manifold* **hydrocarbon** species
- 4. consistency with *heterogeneous* data sources: satellite data and in situ observations

State of the Art Examples How are today's services designed?

- 1. solvers of a **deterministic** transport-diffusionreaction equation, mostly operator-split-wise (except probably reaction-vert. diffusion)
- 2. continental, or regional nest (1 km < Δx < 250 km horizontal resolution)
- tropospheric gas phase chemistry, 40-100 species,
 < 200 reactions
- 4. basic aerosol treatment of at least NH_3 , HNO_3 , H_2SO_4

2. How can we model atmospheric chemistry? Processes in a complex chemistry-transport model



Special challenge: which is the appropriate scale for air quality modelling?

- intercontinental / long range transport of pollutants
- many processes are local: point and line source emissions
- surface patterns/tesselation affects simulation skills
- boundary layer and convection simulation at least of like importance as in meteorology

Contents

- 1. What does atmospheric chemistry research expect from data assimilation?
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- 3. What is the state of the art in the troposphere?

Some advanced auxiliary calculations (1) singular value analysis ϵ (scalar product): $(\epsilon, C\epsilon) = 1$

unit constraint (scalar product): maximise Raleigh quotient:

⇔maximise ⇒generalised EV problem

$$\max_{i} \left(\frac{(\mathbf{PM}(t_1, t_0)\epsilon_i, \mathbf{EPM}(t_1, t_0)\epsilon_i)}{(\epsilon_i, \mathbf{C}\epsilon_i)} \right)$$

$$V(\epsilon) = (\mathbf{PM}(t_1, t_0)\epsilon_i, \mathbf{EPM}(t_1, t_0)\epsilon_i) - \lambda(\epsilon^T \mathbf{C}\epsilon - 1)$$

$$\nabla_{\epsilon} J(\epsilon) = 0 \equiv \mathbf{M}^{T}(t_{1}, t_{0}) \mathbf{P}^{T} \mathbf{EPM}(t_{1}, t_{0}) \epsilon = \lambda \mathbf{C} \epsilon$$

- ε_i perturbation vector of potential optimisation parameters: initial values boundary values, emission rates, deposition velocities
 C norm inducing pos. def., sym. operator at initial time t₀ (Mahalanobis)
 M tangent linear model
- **E** norm inducing pos. def., sym. operator at optimisation time t_1
- (**P** projection operator, extinguishing areas or species outside focus)
- λ Lagrange parameter and generalised eigenvalues

3. Focus: varying value of observations



BERLIOZ NO_x-VOC emissions variation ensemble (20.7.1998, 15:00 UTC)

Note: not C-orthogonal, not max. sensitivities aligned

VOCs

3. Focus: varying value of observations



BLUE-based assimilation algorithms

 $J(\mathbf{x}) = \frac{1}{2} [\mathbf{x}^b - \mathbf{x}]^T \mathbf{B}_0^{-1} [\mathbf{x}^b - \mathbf{x}] + \frac{1}{2} \left\{ \mathbf{y}^0 - H[\mathbf{x}(t)] \right\}^T \mathbf{R}^{-1} \left\{ \mathbf{y}^0 - H[\mathbf{x}] \right\}$ The gradient then reads

$$\nabla J(\mathbf{x}) = \mathbf{B}_0^{-1}[\mathbf{x}^b - \mathbf{x}] + H^T \mathbf{R}^{-1} \left\{ \mathbf{y}^0 - H[\mathbf{x} + (\mathbf{x}^b - \mathbf{x}^b)] \right\}$$

where a trivial expansion is introduced for later manipulation. At the minimum (=optimum, = analysis, $\mathbf{x} = \mathbf{x}_a$) $\nabla J(\mathbf{x}_a) = 0$ $\nabla J(\mathbf{x}) = 0 = \mathbf{B}_0^{-1} [\mathbf{x}^b - \mathbf{x}_a] + H^T \mathbf{R}^{-1} \{ \mathbf{y}^0 - H[\mathbf{x}^b] \} - H^T \mathbf{R}^{-1} H[\mathbf{x}_a - \mathbf{x}^b],$

from which follows:

$$\mathbf{x}_a - \mathbf{x}_b = (\mathbf{B}_0^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \left\{ \mathbf{y}^0 - H[\mathbf{x}^b] \right\}$$

$$= \mathbf{B}\mathbf{H}^{T}(\mathbf{R} + \mathbf{H}^{T}\mathbf{B}\mathbf{H})^{-1}\left\{\mathbf{y}^{0} - H[\mathbf{x}^{b}]\right\}$$

with the latter result obtained after some manipulation.

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Components of a chemistry 4D-var system



2 level forward and backward integration scheme time direction





<u>Advanced spatio-temporal methods used in</u> <u>tropospheric chemistry data assimilation</u>

Spacio-temporal BLUEs applied in tropospheric chemistry data assimilation:

- 4D var:
 - with EURAD (Elbern and Schmidt, 1999, 2001),
 - with POLAIR (Issartel and Baverel, 2003)
- Kalman Filter
 - with LOTOS model (van Loon et al, 2000), (RRSQR)
 - with EUROS model (Hanea et al. 2004) (En+RRSQRKF)

Question: Which parameter to be optimized? Hypothesis:

initial state and emission rates are least known



In the troposphere, for **emission rates,** the product (*paucity of knowledge*importance*) is high

Emission Rate Optimization

minimize cost function

$$J(\mathbf{x}(t_0), \mathbf{e}) = \frac{1}{2} (\mathbf{x}^b(t_0) - \mathbf{x}(t_0))^T \mathbf{B}_0^{-1} (\mathbf{x}^b(t_0) - \mathbf{x}(t_0)) + \frac{1}{2} \int_{t_0}^{t_N} (\mathbf{e}_b(t) - \mathbf{e}(t))^T \mathbf{K}^{-1} (\mathbf{e}_b(t) - \mathbf{e}(t)) dt + \frac{1}{2} \int_{t_0}^{t_N} (\mathbf{y}^0(t) - H[\mathbf{x}(t)])^T \mathbf{R}^{-1} (\mathbf{y}^0(t) - H[\mathbf{x}(t)])$$

deviations from background initial state deviations from a priori emission rates

model deviations from observations

- $\mathbf{x}^{b}(t_{0})$ background state at t = 0
- $\mathbf{x}(t)$ model state at time t
- $\mathbf{e}_b(t_0)$ background emission rate at t = 0
- $\mathbf{e}(t)$ emission rate field at time t
- **K** emission rate error covariance matrix
- H[] forward interpolator
- $\mathbf{y}^0(t)$ observation at time t
- \mathbf{B}_0 background error covariance matrix

Incremental Formulation

- Analysis State: $egin{array}{ccc} {m x}^a = {m x}^b + \delta {m x}^a \ {m u}^a = {m u}^b + \delta {m u}^a \end{array}$
- New "State" Variables: $v = \mathbf{B}^{-1/2} \delta x$ $w = \mathbf{K}^{-1/2} \delta u$
- Cost Function: $J(\boldsymbol{v}, \boldsymbol{w}) = \frac{1}{2} \boldsymbol{v}^T \boldsymbol{v} + \frac{1}{2} \boldsymbol{w}^T \boldsymbol{w} + \frac{1}{2} \left[\mathbf{H} \delta \boldsymbol{x}_i - \boldsymbol{d}_i \right]^T \mathbf{R}^{-1} \left[\mathbf{H} \delta \boldsymbol{x}_i - \boldsymbol{d}_i \right]$
- Gradient: $\nabla_{\boldsymbol{v}} J = \nabla_{\boldsymbol{v}} J_{IV} + \nabla_{\boldsymbol{v}} J_O = \boldsymbol{v} + \mathbf{B}^{T/2} \nabla_{\delta \boldsymbol{v}} J_O$ $\nabla_{\boldsymbol{w}} J = \nabla_{\boldsymbol{w}} J_{EF} + \nabla_{\boldsymbol{w}} J_O = \boldsymbol{w} + \mathbf{K}^{T/2} \nabla_{\delta \boldsymbol{w}} J_O.$

Background Error Covariance Matrix B

- must be provided as an operator (size is of order 10¹³)
- we would like to have an operator which can easily be factorised by $B=B^{1/2}B^{T/2}$
- Weaver and Courtier (2001):
 - –general diffusion equation serves for a valid operator generating a positive definite covariance operator
 - -diffusion equation is self adjoint
 - -B^{1/2} and B^{T/2} by applying the diffusion operator half the diffusion time

Transport-diffusion-reaction equation and its adjoint

Tendency Equations

direct chemistry transport equation

$$\frac{\partial c_i}{\partial t} + \nabla \cdot (\mathbf{v}c_i) - \nabla \cdot (\rho \mathbf{K} \nabla \frac{c_i}{\rho}) - \sum_{r=1}^R \left(k(r) \left(s_i(r_+) - s_i(r_-) \right) \prod_{j=1}^U c_j^{s_j(r_-)} \right) = E_i + D_i$$

- c_i concentration of species i
- **v** wind velocity
- k(r) reaction rate of reaction r
- U number of species in the mechanism
- E_i emission rate of species *i* (source)

- c_i^* adjoint of concentration of species *i*
- s stoichiometric coefficient
- **K** diffusion coefficient
- R number of reactions in the mechanism
- D_i deposition rate of species i (sink)

adjoint chemistry transport equation

 $-\frac{\partial \delta c_i^*}{\partial t} - \mathbf{v} \nabla \delta c_i^* - \frac{1}{\rho} \nabla \cdot \left(\rho \mathbf{K} \nabla \delta c_i^*\right) + \sum_{r=1}^R \left(k(r) \frac{s_i(r_-)}{c_i} \prod_{j=1}^U \bar{c_j}^{s_j(r_-)} \sum_{n=1}^U \left(s_n(r_+) - s_n(r_-)\right) \delta c_n^*\right) = 0$

Adjoint integration "backward in time"

direct model

Find minimum of $J(\mathbf{x}(t_0), \mathbf{e})$ with $\nabla_{[\mathbf{x}(t_0), \mathbf{e}]} J$ by use of a minimization routine

How to make the parameters of resolvents i $\mathbf{M}(t_{i-1},t_i)$ available in *reverse* order??

back

s.tex p. 2

The 4D variational method: Key development: construction of the adjoint code

CONTRACE Convective Transport of Trace Gases into the upper Troposphere over Europe: Budget and Impact of Chemistry Coord.: *H. Huntrieser, DLR*

flight path Nov. 14, 2001

CONTRACE Nov. 14, 2001 north (= home) bound

Kalman filter, basic equations

forecast

$$\mathbf{x}^{f}(t_{i}) = \mathbf{M}(t_{i}, t_{i-1})\mathbf{x}^{a}(t_{i-1}) + \eta$$
(1)

background error covariance matrix

$$\mathbf{P}_i^b = \mathbf{M}(t_i, t_{i-1}) \mathbf{P}_i^a \mathbf{M}^T(t_i, t_{i-1}) + \mathbf{Q}$$

optimally estimated state

$$\mathbf{x}^{a}(t_{i}) = \mathbf{x}^{b}(t_{i}) + \mathbf{K}_{i}\mathbf{d}_{i}, \qquad (1)$$

Kalman gain matrix

$$\mathbf{K}_{i} := \mathbf{P}_{i}^{b} \mathbf{H}_{i}^{T} (\mathbf{H}_{i} \mathbf{P}_{i}^{b} \mathbf{H}_{i}^{T} + \mathbf{R}_{i})^{-1} \quad \in \mathcal{R}^{n \times p_{i}}$$
(2)

and analysis error covariance matrix

$$\mathbf{P}_i^a = (\mathbf{I} - \mathbf{K}_i \mathbf{H}) \mathbf{P}_i^b. \tag{3}$$

Treatment of the inverse problem for emission rate inference

emission_treatmentid

Normalised diurnal cycle of anthropogenic surface emissions *f(t)*

Optimisation of emission rates

amplitude optimisation for each emitted species and grid cell

Background emission rate covariance matrix D

Reduction of the partial cost functions relative to observation type (coarse grid, 54 km)

<u>2. Analyses</u>, Example (i): Analysis of emissions by 4D-var (VERTIKO)

Observed and analysed ozone evolution at St. Poelten Vertical bars: ozone observations with error estimates.

- ---- Control run without data assimilation.
 - initial value optimisation.
- ----- emission factor optimisation.
 - joint initial value and emission factor optimisation (Strunk et al., 2011)



Rhine-Main area box: (Frankfurt-Mainz) 9.-10. August 1997







Some BERLIOZ examples of NOx assimilation (20. \rightarrow 21. 07.1998)



Emission source estimates by inverse modelling Optimised emission factors for Nest 3



surface

Nest 2: (surface ozone) (20.→21.07.1998)

without assimilation

O₃; level=1; it=01; hr=06 160.0 60 150.0 140.0 50 130.0 120.0 110.0 40 100.0 90.0 80.0 30 70.0 60.0 20 50.0 40.0 30.0 10 20.0 10.0 0.0 0 0 10 20 30 40 50 60



with assimilation

Satellite information:

ESA UV-VIS satellite footprints Ruhr area comparison



Error variances applied for period 1.-10.7.2006 over model domain

NO2 columns from KNMI data files: R (diagonal)			
molecules/ cm ²	E(y)	Ε(Δ y)	
OMI	1.4*10 ¹⁵	0.8*10 ¹⁵	
SCIAMACHY	1.2*10 ¹⁵	0.9*10 ¹⁵	

Forecast error covariances **B** schematic formula

 \mathbf{B}_{ii} (spec,lev)= max{1 ppb,0.8*var(spec,lev), 0.5 max(spec,lev)}





model domain mean averaging kernel.

Exploitation of NO2 column averaging kernel information

- AK profile mostly dependent on optical properties of the atmosphere (cloud cover), rather than NO2
- typical maximal sensitivity above the boundary layer
- does not allow a clear distinction between PBL or lower free troposphere pollution burden

How to proceed to obtain benefit from trop. column integral information?

(A typical problem of Inverse Modelling by Integral Equations)

Two more specific questions:

- When is it justified to project averaging kernel information to the surface?
- Can this be done without heuristics, destroying the BLUE property of the assimilation algorithm?

$\begin{array}{c} Observation \ operator \ H \\ {\rm Formally \ an \ integral \ equation \ to \ be \ solved \ for \ vertical \ NO_2 \ molecule \ density \end{array}$

Formally an integral equation to be solved for vertical NO₂ molecule density function x (σ vertical coordinate)

$$y=\int_{1}^{0}w(\sigma)x(\sigma)d\sigma$$

Discretisation

$$y = \sum^{K} h_k x_k$$

At the minimum $\mathbf{x} =: \mathbf{x}_a$

$$d\mathbf{x}_a := \mathbf{x}_a - \mathbf{x}_b = (\mathbf{B}_0^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \left\{ \mathbf{y}^0 - H[\mathbf{x}_b] \right\}$$
$$= \mathbf{B} \mathbf{H}^T (\mathbf{R} + \mathbf{H} \mathbf{B} \mathbf{H}^T)^{-1} \left\{ \mathbf{y}^0 - H[\mathbf{x}_b] \right\}$$

For scalar column retrieval:

$$d\mathbf{x}_{a}^{c} = \underbrace{\mathbf{B}\mathbf{h}^{T}(r+b)^{-1}}_{\mathbf{x}_{b}}\left\{y^{0} - H[\mathbf{x}_{b}]\right\}$$

adjoint representer

 \rightarrow vertical structure function in B essential!

4. Focus: ioint emission rate initial value optimisation Vertical structure function:

Extending the information from observation location by vertical exchange of polutants and information



4. Focus: ioint emission rate initial value optimisation Comparison of NO2 tropospheric columns in

molecules/cm2 for July 6th, 2006, 09-12 UTC.





:EURAD forecasted (Hx_h) ;



column analyses (Hx_a) .





model column [molec/cm²] ; it=01

o 15 30 column measurements [molec/cm²]

1.0E+14

Data assimilation result in terms of tropospheric columns for July 6th, 2006. NO2 model columns based on OMI and SCIAMACHY

assimilation within interval, 09-12 UTC.



Difference field giving implied changes for tropospheric columns by assimilation (middle), and induced surface concentration changes by NO2 ppb (right)

Data assimilation result in terms of tropospheric columns for July 7th, 2006. NO2 model columns based on OMI and SCIAMACHY assimilation within the assimilation interval, 09-12 UTC.



Emission rate optimisation factors for NO2 after assimilation of

OMI retrieved NO2 tropospheric columns



2 x 4 days assimilation sequence. Left panel shows results after assimilation procedures from July 1.-4. 2006, right panel for July 7.-11., 2006. OMI data from KNMI

MOPITT tropospheric CO assimilation

CO 01.07.03 11.00 UTC [ppbV]





retrieved 850 h P a concentrations in ppbV.

first guess at 11:00 UTC;.

850 hPa, 1 July. 2003

Note: Colour codes are not fully consistent!



4D-Var analysis for the same time;

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Example: Aerosol Chemistry in **MADE**

Modal Aerosol Dynamics for EURAD/Europe (Ackerman et al., 1998, Schell 2000)

dM_i^k/dt=nuk_i^k+coag_{ii}^k+coag_{ij}^k +cond_i^k+emi_i^k

M_i^k:=kth Moment of ith Mode

assimilation of aerosol By satelite retrievals: e.g. Bridge from optical to chemical properties

MERIS MODIS AATSR+SCIAMACHY....



Secondary ORGanic Aerosol Model (SORGAM) Biogenic and anthropogenichydrocarbons to particles



Modal representation of particles

Particulate Matter (PM_x) and Particle Number Density (PND_{0.005-3.0})



Assimilation of Aerosol observations

• In situ:

EEA Airbase: Database of groundstations of EU member countries & states:

- 450 stations for PM₁₀ (2003)
- No PM_{2.5}. (4 stations in UK only)
- Satellite measurements:

SYNAER (SYNergetic AErosol Retrieval, DLR-DFD, [Holzer-Popp, 2001])*

- combines GOME&ATSR-2, SCIAMACHY&AATSR measurements aboard ERS-2/ENVISAT
- ATSR-2/AATSR: dark field detection, BLAOT (Boundary Layer Aerosol Optical Thickness) and albedo are calculated

 GOME/SCIAMACHY: Provides PM_{0.5}, PM_{2.5} and PM₁₀ columns and its composition (6 intrinsic species)

SYNAER retrieval algorithm

SYNergetic AErosol Retrieval (Holzer-Popp, 2001)

SYNAER makes combined use of two instruments (Radiometer and Spectrometer) on ERS-2, Envisat, and MetOp:

- ATSR-2/AATSR/AVHRR Dark field detection, BLAOT (Boundary Layer AOT), Albedo
- GOME/Sciamachy/GOME-2

Measured spectra taken to identify aerosol mixture of highest

probability out of 40 predefined mixtures via a Least Squares

Method

SYNAER retrieval algorithm

Species Mapping

EURAD-IM [µg/m³]		SYNAER - AOT	
SO ₄ , NH ₃ , NO ₃ , H ₂ O, SOA		WASO (WAter SOluble)	
Unidentified PM		INSO (water INSOluble)	
Elemental Carbon		SOOT	
Sea Salt		SEAS	
Mineral Dust		DUST	
radiative transfer model 🛛 🔶			
🗲 🛛 adjoint radiative transfer model			

Case study I: Summer 2003

- Episode July 1 July 14, 2003
- Purpose Validation of aerosol assimilation scheme & SYNAER retrievals
- Assimilation
- Data assimilated in 3 sub-cases:
 - 1. SYNAER-AOT only
 - 2. SYNAER-AOT & EEA in-situ

8 – 16(14) UTC

- 3. EEA in-situ only
- Grid 107 x 97 x 23 Cells, 45km spacing
- Timestep 600 s

Model Domain and Observations



Aerosol observations (14.7.2003, ~10:00 UTC)



Analysis and increments for acc. SO₄²⁻ July 1, 8 UTC







Do aerosol data assimilation effects accumulate? (14. July 2003)



Developement of forecast performance



First Guess Costs / Reference Run Costs for measurements with a minimum relative change of 0.005. SYNAER+EEA affects ~ 3% more observations than EEA

Developement of forecast performance


Case study II: ZEPTER-2 Campaign 2008 • Episode Oct 17 - Nov 8, 2008

- Assimilation acc. to flight schedule or 8 16/14/12 UTC
- Data assimilated
 - PND (Particle Number Densities) from
 - Zepter2 CPC
 - SYNAER-AOT
 - EEA in-situ PM_x
- Focus
- Validate aerosol 4Dvar on nested grids
- Assimilate PND as a new species



Model domains

EUR

- 107 x 97 x 23
- Resolution: 45 km
- Timestep: 600 s

CEN

- 70 x 76 x 23
- Resolution: 15 km
- Timestep: 240 s

ZP2

- 97 x 88 x 23
- Resolution: 5 km
- Timestep: 60 s





2. Analyses, Example (ii):

Zepter 2: 4D-var assimilation of particle number densities

Flight 14 assimilation of PND (0.005-3.0 µm) 02.11.2008 (11-15 UTC)





<u>2. Analyses</u>, Example (ii cntd.): Flight 14 assimilation of PND (0.005-3.0 μm), Nov. 2nd 2008



from Lars Nieradzik, PhD thesis 2011

Development of forecast performance



Airborne CPC Observations available

Assimilation statistics

Particle Number Density 0.005 - 3 µm



Development of forecast





Y. Hara, K. Yumimoto, I. Uno, A. Shimizu, N. Sugimoto, Z. Liu, and D. M.Winker, 2009

Asian Dust by 4D-var CALIOP DA





Y. Hara, K. Yumimoto, I. Uno, A. Shimizu, N. Sugimoto, Z. Liu, and D. M.Winker, 2009

Example CALIOP

Variational volcanic ash data Assimilation Module with selective background weakening for special events

km⁻¹sr⁻¹

2.29

3.32

LiDAR 4D-var data assimilation for improved analysis of unexpected aerosol eventS \rightarrow automated online adaptation of background error covariace matrix

5.0E-03 14 4.5E-03 CALIOP observation of the Eyjafjallajökull ash cloud 12 4.0E-03 10 3.6E-03 Altitude AMSL [km] 17 April 2010, 02:01:19 - 02:14:53 UTC (Winker et al., 2012) 3.1E-03 8 2.6E-03 2.1E-03 1.7E-03 km ¹sr ¹ 1.2E-03 5.0E-03 12.0 7.1E-04 4.7E-03 4.5E-03 2.4E-04 4.2E-03 46 20 44.07 3.9E-03 km⁻¹sr⁻¹ 9.0 3.6E-03 14 5.0E-03 3.4E-03 Analysis H(x) Altitude AMSL [km] 3.1E-03 4.5E-03 2.8E-03 12 2.6E-03 4.0E-03 6.0 2.3E-03 10 3.6E-03 2.0E-03 Altitude AMSL [km] 1.8E-03 3.1E-03 8 1.5E-03 2.6E-03 1.2E-03 3.0 9.5E-04 6 2.1E-03 6.8E-04 4.1E-04 1.7E-03 4 1.4E-04 1.2E-03 LAT 53.00 51.53 50.07 48.60 47.13 45.65 44.17 2 7.1E-04 6.09 5.42 4.78 3.59 3.04 2.51 LON 4.17 2.4E-04 A. Lange, master thesis LAT 52.69 51.00 49.70 48.00 46.29 44.97

LON 5.88 5.36

4.18

3.73

Summary

- chemical weather forecasts are a multiple scale problem
- chemical data assimilation rests on sparse and heterogeneous observations, with variable error characteristics (incl. error of representativity)
- initial value optimisation is insufficient, as at least emissions are less known and more important
- the ability for inversion is therefore required to optimize emission rates
- much is to be done for optimising multivariate covariance matrices