Observability and Predictability of Volcanic Ash Transports

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Objectives

- **Impact**: Empower simulations of unexpected events with uncertainty measures, to provide a **stronger basis for decision making**
- Project contribution: Earth System Knowledge Platform (**ESKP**) – development of a forecast system to predict atmospheric natural hazard processes
- Solve algorithmic challenge: for inversion, no useful a priories available (parameters like emission rates and injection heights are poorly known)
- Identify area of observation constraints in the analyses (by adapted 4D-var data assimilation)
- Provide uncertainties of the forecasts (by particle smoother)

bringing together

Observability – Which simulated temporal and spatial concen-tration patterns are controlled by observations?

Predictability – How skillful is the forecast? What is the forecast error?

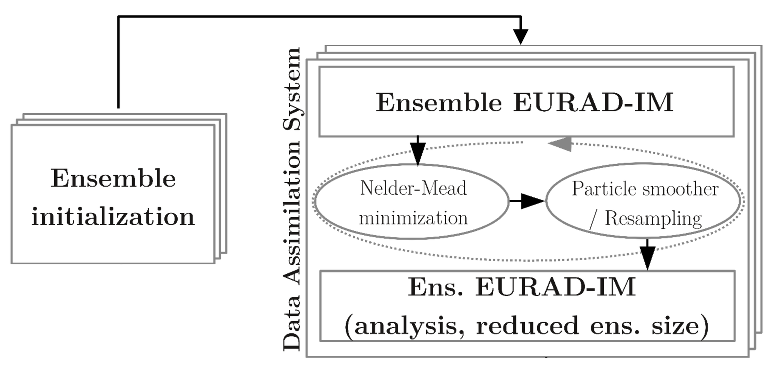
- This work also serves educationally as part of PhD theses of Philipp Franke (predictability) and Anne Caroline Lange (observability)

New hyper-ensemble system **ESIAS**-Chem

The atmospheric chemistry part of the new **Ensemble for Stochastic Integration of Atmospheric Simulations** (ESIAS-Chem, up to > 1000 members) comprises a particle smoother in combination with a Nelder-Mead simplex minimization method (best of a test suit). The system is able to retrieve the vertical distribution of the volcanic ash emissions by assimilating volcanic ash column mass loadings. The cost function J needs to be modified to

$$J(a) = (aHx - y)^T \mathrm{R}^{-1}(aHx - y) + \sum_{i=1}^{N_{emis}} a^T \mathrm{K}^{-1} a.$$

The weights a are applied to discrete emission packages for the generation of an analysis. For the stochastic analysis presented here, the emissions are of one hour reso-lution in one vertical model layer. The analysis ensemble size is 60.

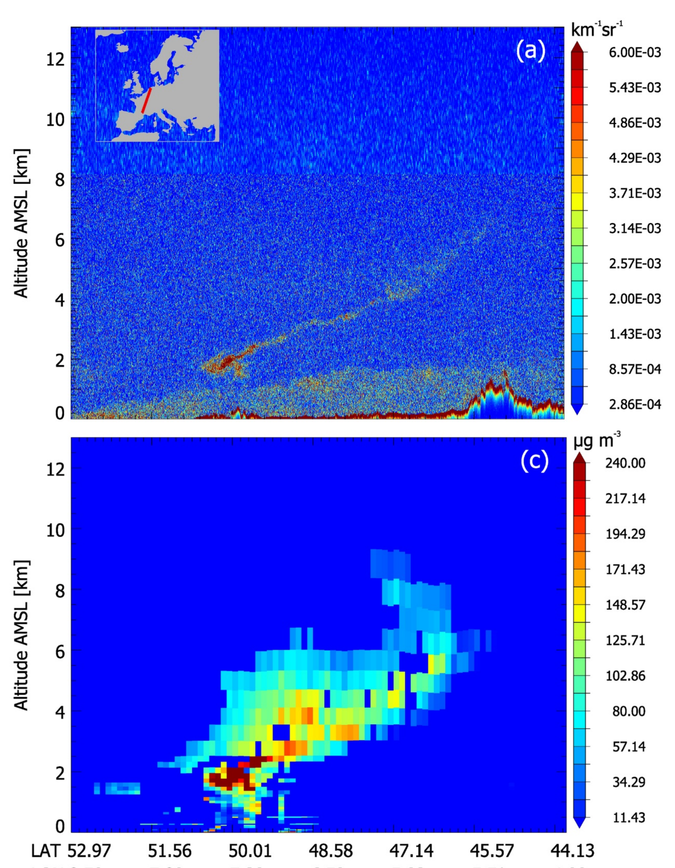


Schematic of ESIAS-Chem: Workflow of the ESIAS-Chem model. Staggered boxes indicate ensemble representations. The ESIAS-Chem model is a particle smoother extension, thus, the assimilation is restarted from the beginning if new observations become available.

Assimilation of remote sensing data

In 4 dim. variational data assimilation, the model trajectory, which best combines the background state x_b and the observations y is determined by minimizing the **cost function** J:

$$J(\mathrm{x}) = \frac{1}{2}\left((\mathrm{x} - \mathrm{x}_b)^T \mathrm{B}^{-1}(\mathrm{x} - \mathrm{x}_b) + \int (HM(\mathrm{x}(t)) - \mathrm{y}(t))^T \mathrm{R}^{-1}(HM(\mathrm{x}(t)) - \mathrm{y}(t))dt\right)$$



Comparison: CALIOP attenuated backscatter signal (top) and EURAD-IM analysis of volcanic ash concentrations during the Eyjafjallajökull eruption on 17 April 2010.

Observation operators H:

The application of vertically resolved **CALIOP lidar backscatter signals** are one of the most valuable methods to compare observational data with model simulations.

Lidar equation

$$P(r) = c_{sys}\frac{\beta(r)}{r^2}\exp(-2\int_0^r \alpha(r')dr')$$

To investigate the horizontal dispersion of the volcanic ash plume above Europe, retrieved **volcanic ash column mass loadings from SEVIRI** onboard the Meteosat satellite are additionally assimilated.

SEVIRI H-operator

$$H(x_{ij})\left[\frac{\mathrm{g}}{\mathrm{m}^2}\right] = 10^6 \sum_k c_{ij,k}^{ash} dz_{ij,k}$$

Main challenges: cloud coverage attenuates satellite signals, CALIOP data does not discriminate volcanic ash from clouds and aerosols, SEVIRI data is a vertically integrated value, SEVIRI data does not include zero values to remove volcanic ash from the background

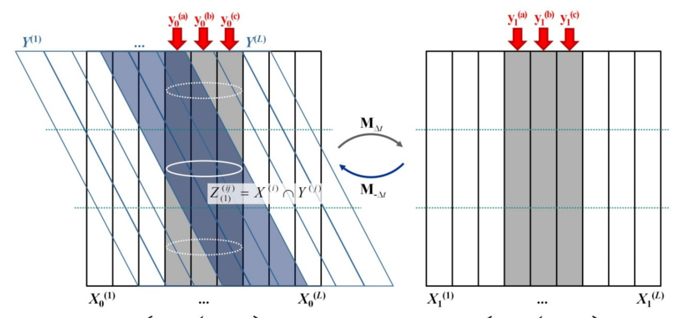
Observability analysis

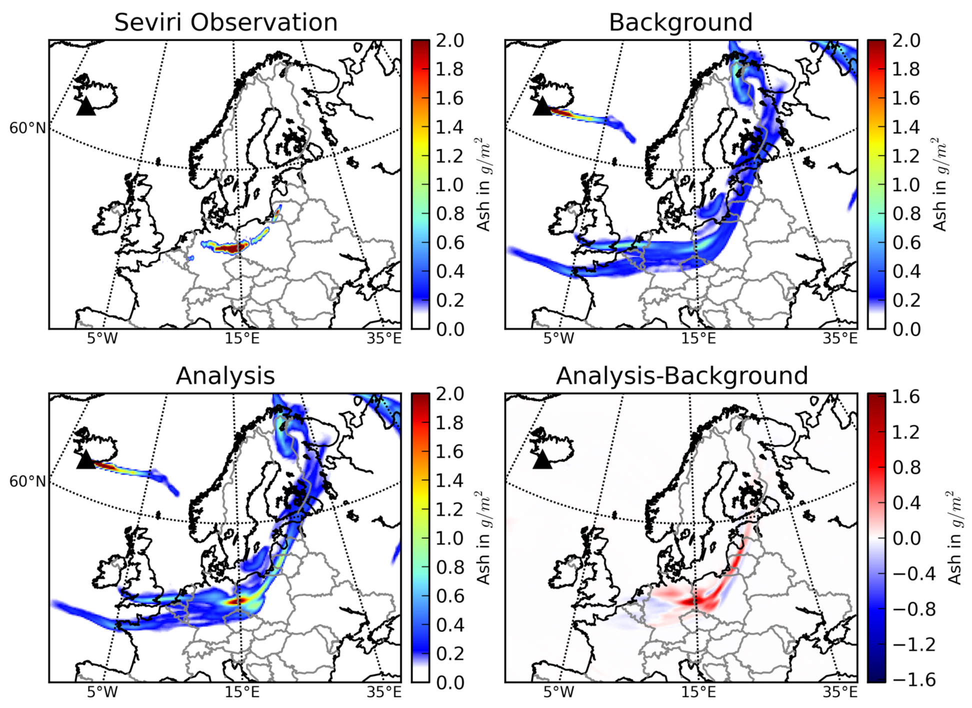
Can ash cloud heights been inferred from satellite column loads?

A height dependent wind shear is essential for sequential height analysis. Information flux/time is described by the **Kolmogorov-Sinai entropy** h:

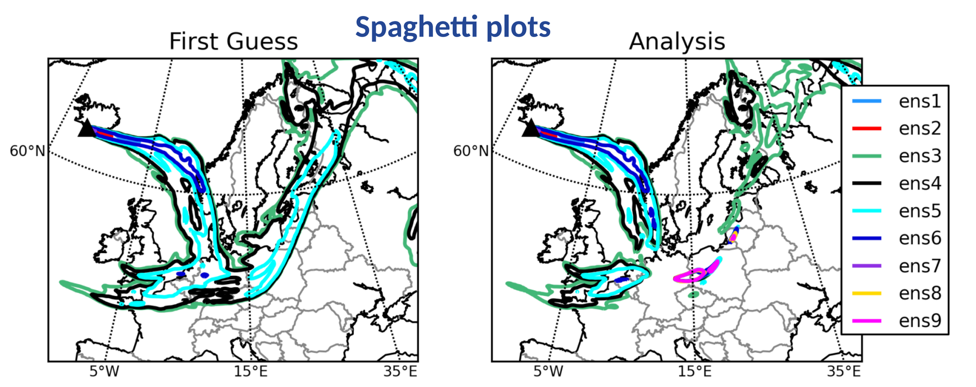
$$h(\mu) = \sup_{X,\Delta t}\left(\lim_{k\to\infty}\frac{I(Z_{(k)})}{k\Delta t}\right)$$

$$I(Z) = -\sum_{i,j} p(Z_{ij})\ln(p(Z_{ij}))$$





An **ensemble 4D-var** analysis is performed with 9 ensemble members, initialized with differ-ing volcanic emission heights and strengths, for the Eyjafjallajökull eruption in April 2010. The SEVIRI observations con-strain the model evolution such that profound advices on air traffic safety can be assessed.



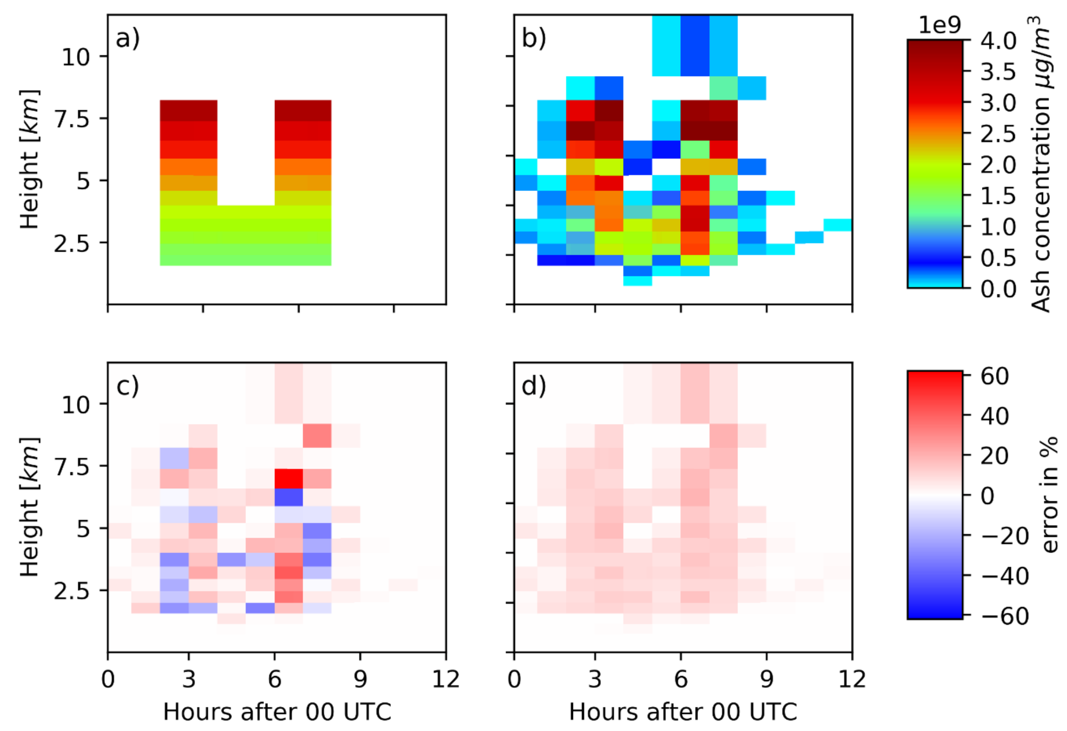
Analysis of volcanic ash dispersion during the Eyjafjallajökull eruption on 16 April 2010, 12 UTC:

Background generated considering emission profiles according to Keflavik radar observations. SEVIRI volcanic ash column mass loadings are assimilated within an assimilation window of 24 hours.

First guess and analysis of air traffic threshold contours at 1.0 gm^{-2} of the 9 ensemble members.

Stochastic analysis

The ESIAS-Chem system is validated by **identical twin experiments**. The performance of the system depends strongly on the sufficiently large vertical wind shear (see Kolmogorov-Sinai entropy above). If so, the ESIAS-Chem model predicts the vertical distribution of the volcanic ash emission well. The ensemble standard deviation is of the order of the error of the ensemble mean, which complies with a necessary con-dition for a probabilistic forecast system.



Comparison of the analysed emission profiles for the strong winds identical twin experiment on April 15th, 2010:

(a) Nature run emission profile; (b) Ensemble mean emission profile of the analysis; (c) Difference between (b) and (a); (d) Ensemble standard deviation of the analysis. The total mass emitted in this eruption is 4.25e8 tons for the nature run and 4.62e8 tons for the ensemble mean of the analysis.

An identical twin experiment over a longer lasting hypothetical volcanic eruption proves the ESIAS-Chem system successful (See Table). The statistics summarized for the error corrected column mass loading (CML) and maximum volcanic ash concentrations (MAX) at 33 simulated lidar stations show a good agreement of the forecast with the observation.

	RME	RMSE	ME	CC	BS	BSS	ROC-A
CML	1.7 %	0.14 gm^{-2}	0.0 gm^{-2}	0.98	0.10	0.48	0.93
MAX	-0.1 %	80.8 µgm^{-3}	-14.9 µgm^{-3}	0.96	0.14	0.23	0.89

Statistical evaluation: Relative mean error (RME), root mean square error (RMSE), mean error (ME), correlation coefficient (CC), Brier Score (BS), Brier Skill Score (BSS), and area under the relative operating characteristics curve (ROC-A).

Conclusion and outlook

- Volcanic ash emission and dispersion can be successfully evaluated by column data assimilation with ESIAS-Chem with increasing shear
- Forecast uncertainties and more reliable areas including observation-driven patterns can be identified
- Results are likely transferable to other special aerosol events

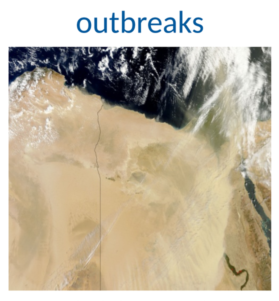
Volcanic eruptions

Eyjafjalla eruption, Iceland April 2010

Accidental releases of harmful compounds

Fukushima explosion, Japan March 2011

Mineral dust outbreaks



Dust storm, Egypt April 2012

Wild fires

Wild fires, Canada Aug. 2003