QUANTITATIVE ESTIMATION OF VOLCANIC ASH EMISSIONS AND ITS UNCERTAINTY BY A COMBINED MINIMIZATION – PARTICLE SMOOTHER

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INTRODUCTION

Motivation

Influence of volcanic ash

- May cause severe impacts on humans, environment, economy, and aviation
- Eyjafjallajökull eruption (Iceland) in 2010:
  - 100,000 air planes stayed on ground with more than 7 million passengers stranded
  - 1.3 billion Euros direct damage

Need for uncertainty assessment

- Doubts that closure of European air space was necessary in 2010
- Observation network is weak
  - Lidar measurements resolve vertical ash distribution but are sparse in space
  - SEVIRI measurements have prinically good spatial coverage but deliver only column integrated ash mass loadings
  - Observations come with large uncertainties ($\sim 40\ \%$ for SEVIRI)
- Decision making must be based on best knowledge
  $\rightarrow$ includes errors to reduce costs and risks

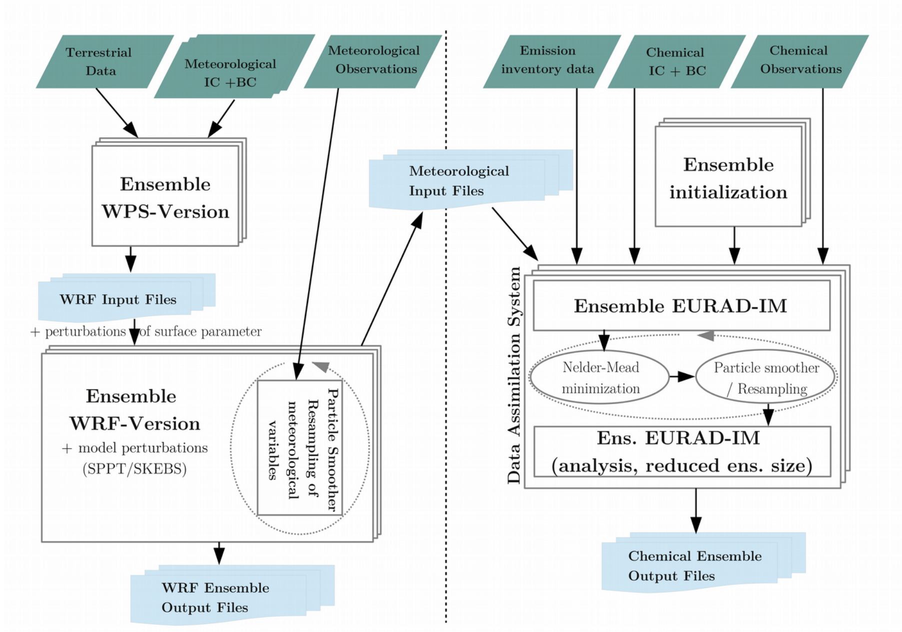
INTRODUCTION

Our approach: Stochastic Integration by a large ensemble

Uncertainty estimation of volcanic ash emissions by

- Use of column mass loadings observations as obtained from SEVIRI satellite
- Ensemble of distinct emission packages
- Ensemble-based Nelder-Mead minimization algorithm
- Particle smoother to optimize ensemble variance
- Ensemble is computationally demanding → IBM BlueGene/Q super computer by Jülich Supercomputing Center (JSC)

Ensemble for Stochastic Integration of Of Atmospheric Simulations (ESIAS)



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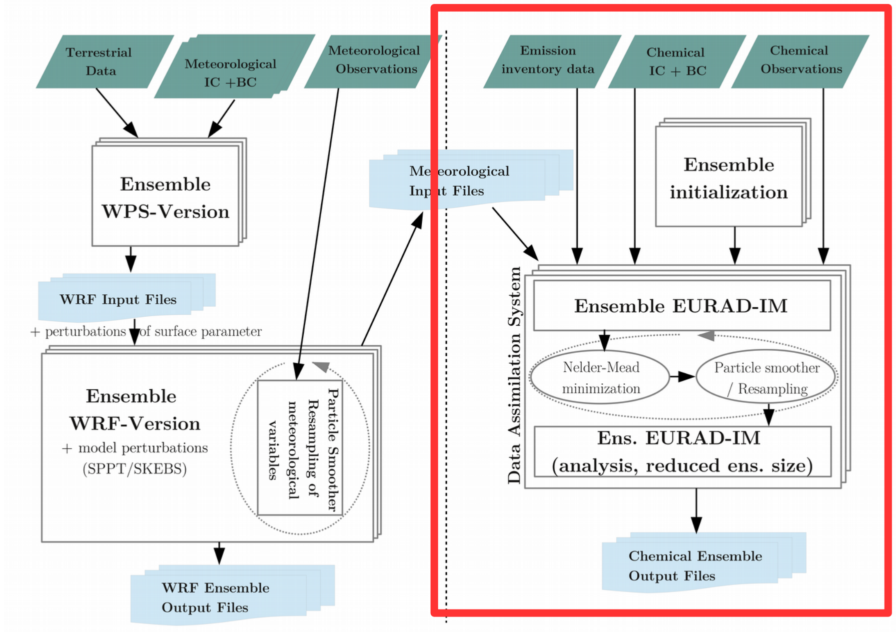

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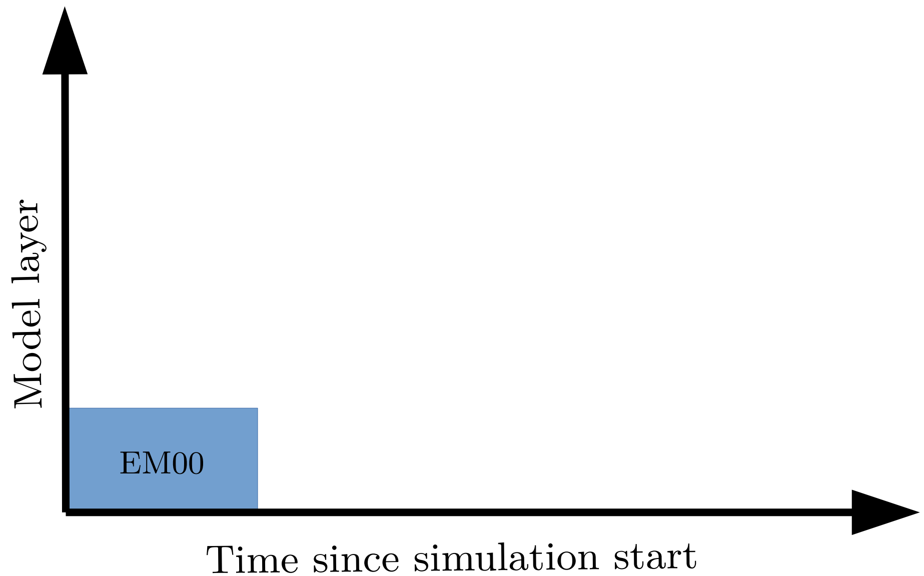
ESIAS-CHEM

ENSEMBLE OF EMISSION PACKAGES

Each ensemble member (EM) gets distinct emissions

- Emission packages are defined for a specific time and height instance
- Each emission package contains a unit mass
- Increasing the data assimilation length increases ensemble size or reduces resolution of emissions



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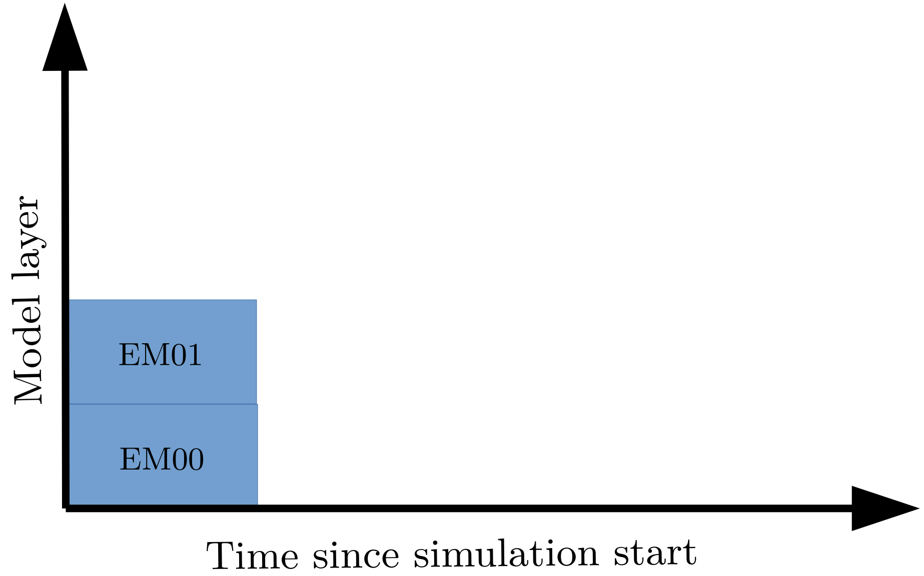

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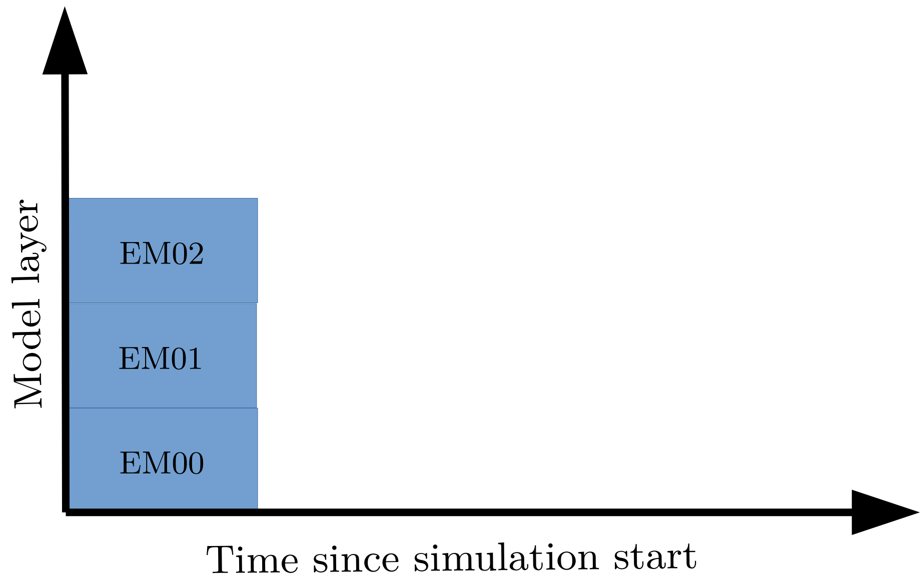

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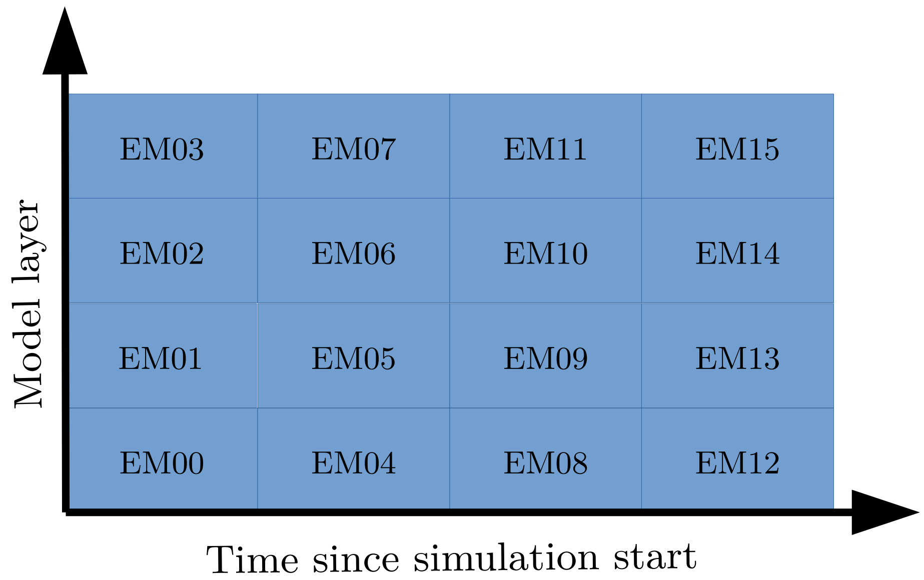

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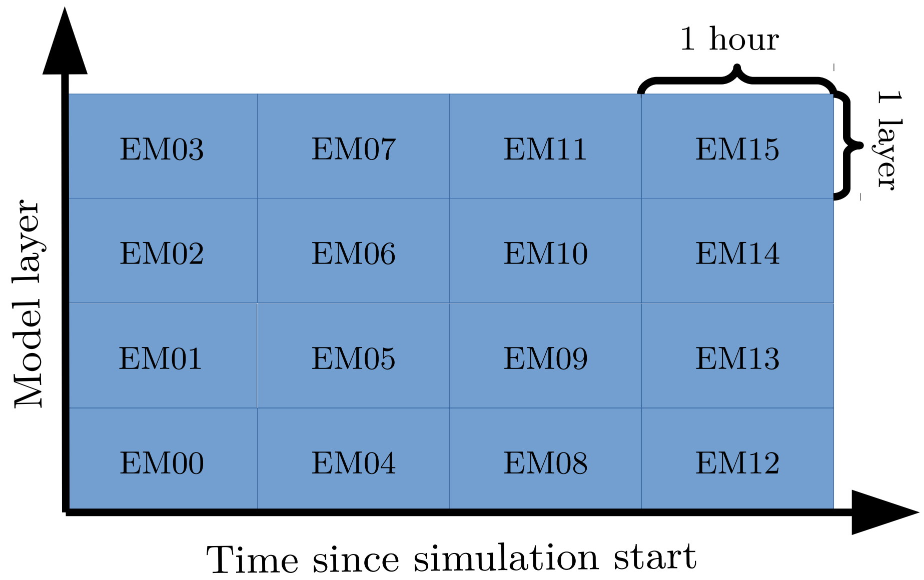

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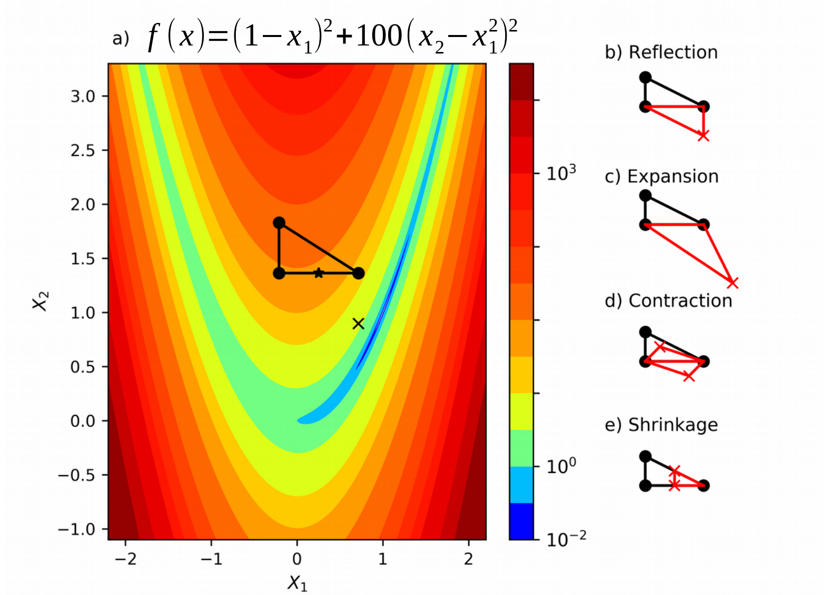
Nelder-Mead minimization algorithm

Objective

$$argmin\, J(a) = \sum_{t=1}^{L} \left(H\, M_t[a_t e_0] - y_t\right)^T R^{-1} \left(H\, M_t[a_t e_0] - y_t\right)$$

- a is n-dimensional vector (n degrees of freedom)
- start minimization at random point a^0 (initial vertex)
- create simplex around initial vertex

a: ensemble member factor
H: observation operator
M_t: source-receptor model from time t to assimilation time L
e_0: unit a priori emission strength



Extension

- Attach regular grid to solution space
- Improve minimization if first guess is far away (likely for volcanic eruptions)
- Perform minimization from N initial vertices

ESIAS-CHEM

Particle Smoother

Particle filter basics

- Ensemble based data assimilation
- Set of N (iid) model runs (particles)
- Prediction step: sample from $p(x_{t-1})$

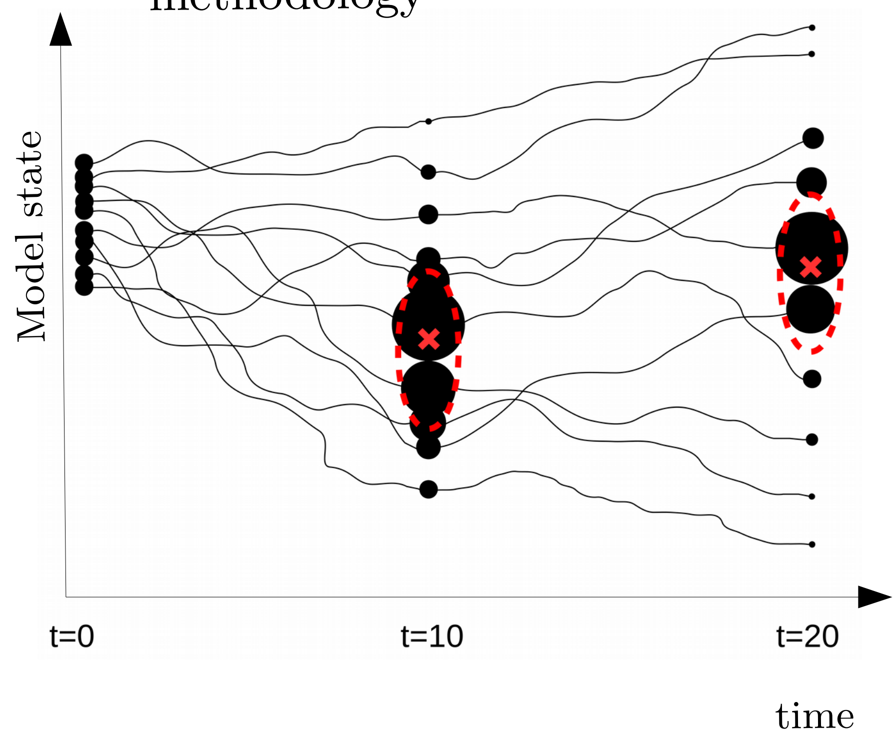
$$x_t^i = M(x_{t-1}^i + e_{t-1}^i) \quad p(x|y) = \frac{p(y|x)\,p(x)}{\int p(y|x)\,p(x)\,dx}$$

- Update step: weight each particle according to Bayes‘ Theorem

$$p(x_t|y_{1:t}) \sum_{i=1}^{N} w_t^i x_t^i \qquad p(x_t) \frac{1}{N} \sum_{i=1}^{N} \delta(x_t - x_t^i)$$

- For large N: $p(x|y) \lim_{N \to \infty} p(x_{true}|y)$

Schematic of particle filter methodology



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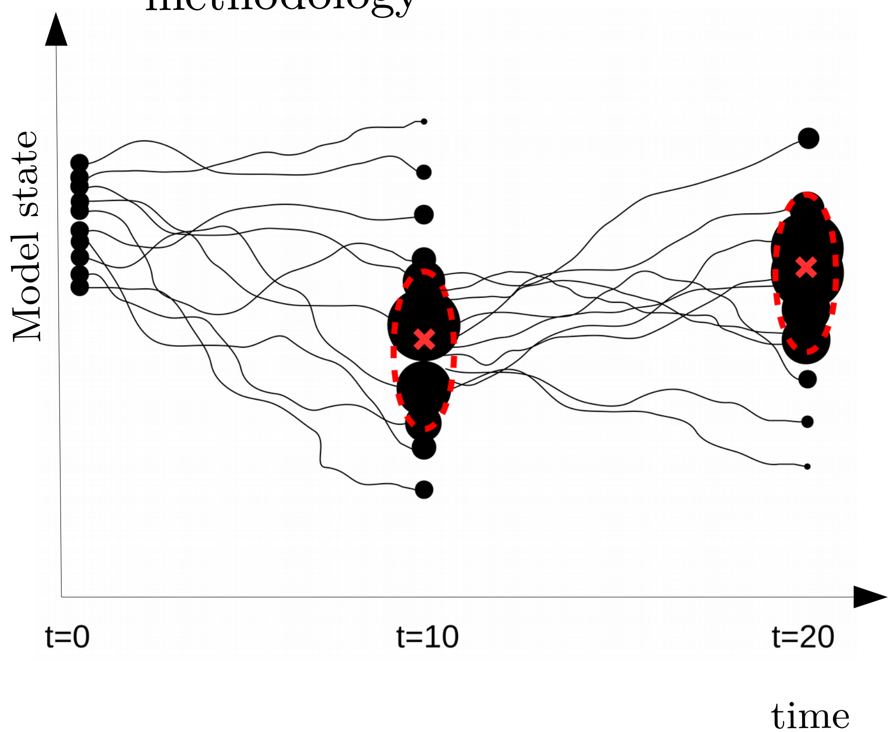
Particle Smoother

Sequential Importance Resampling

- Sample from new PDF $p(x|y)$
- Duplicate particles with high probability according to their weights
- Remove low probability particles
- Perturb particle position to get N particle again

Schematic of particle filter methodology



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Particle Smoother

Workflow

Occurence of a volcanic eruption

1. Wait for first observations to come
2. Start a priori ensemble
   (distinct emission pacakages)
3. Run Nelder-Mead minimization
4. Optimize analysis ensemble by weighting and resampling
5. Go to step 2 when new observations are available

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Particle Smoother

Observations of
column mass loadings

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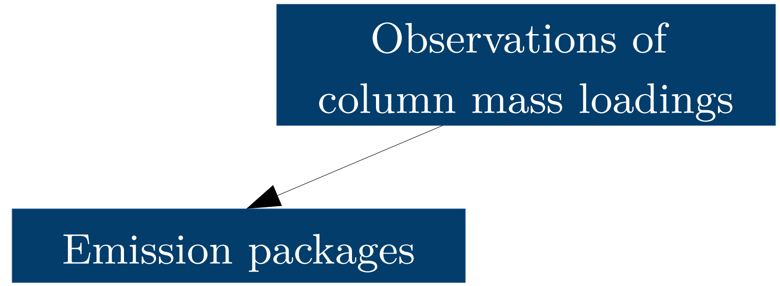

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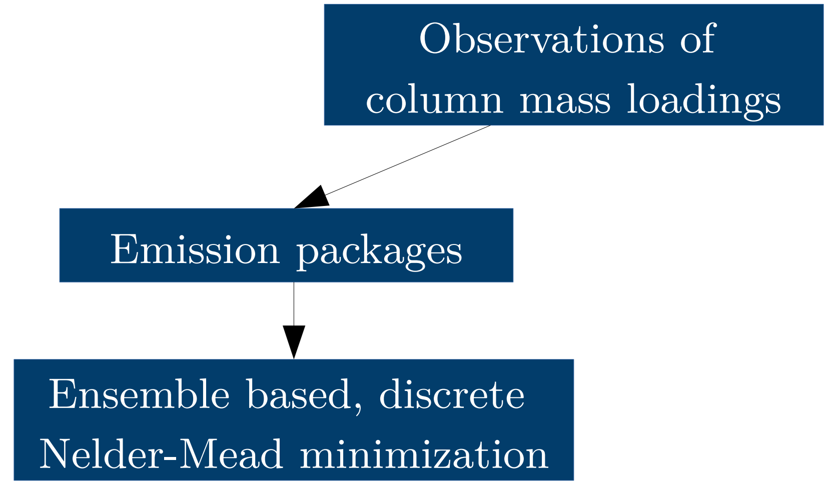

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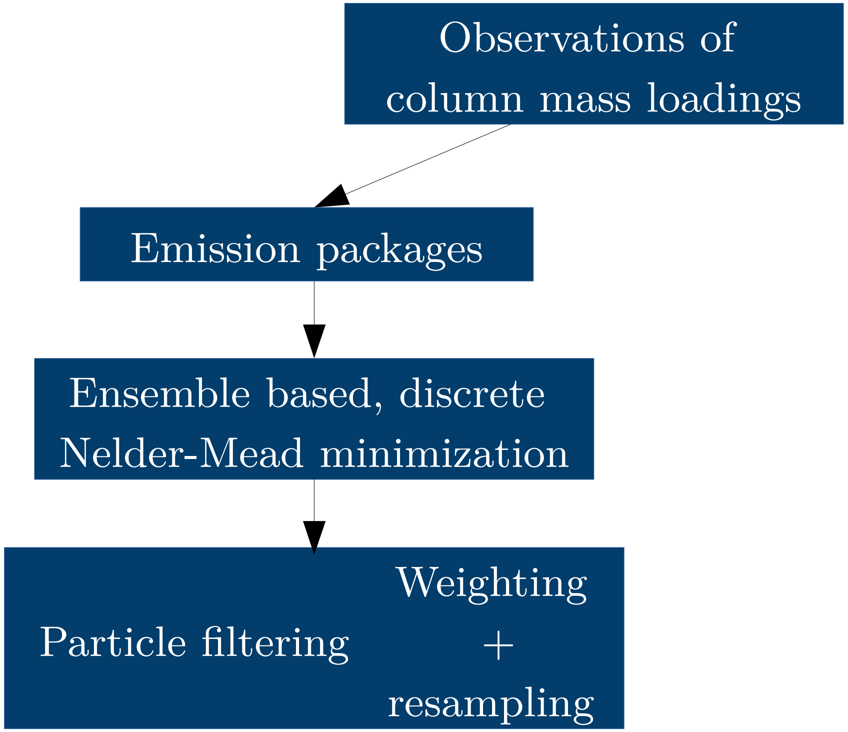

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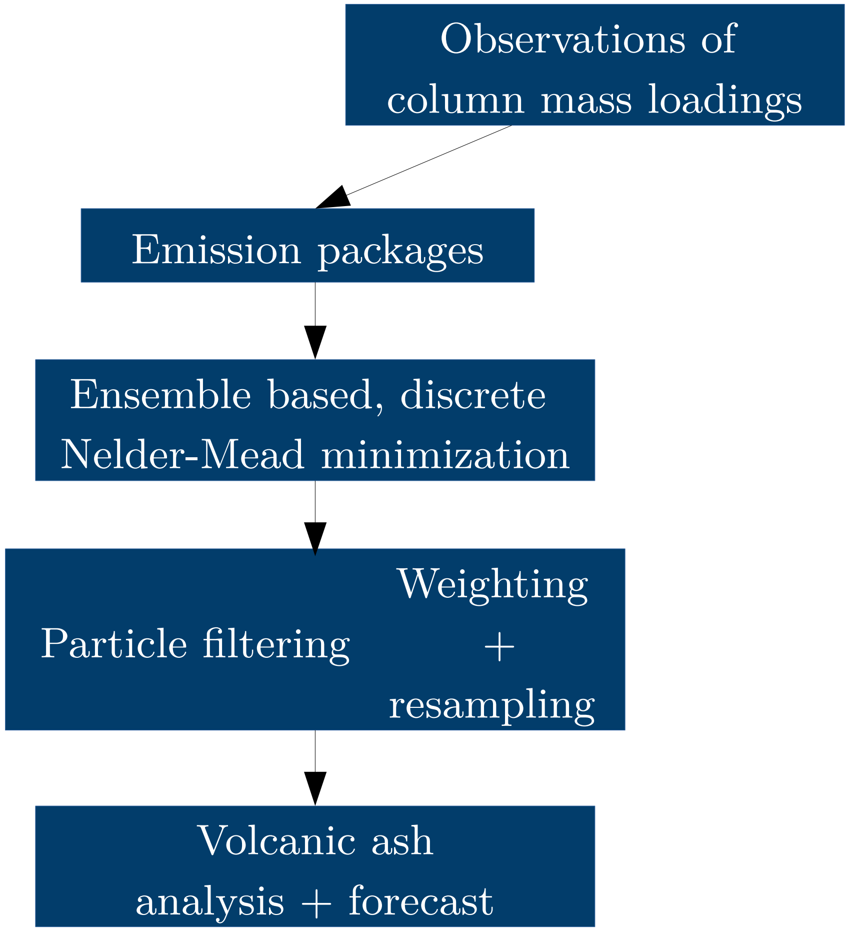

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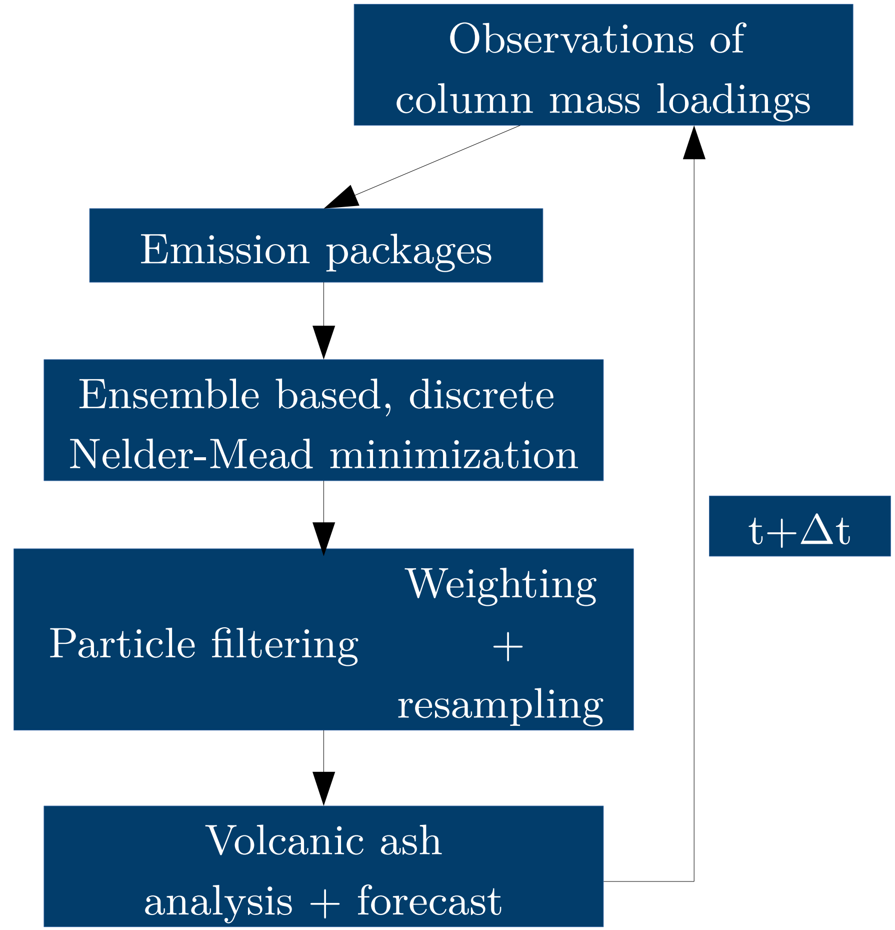
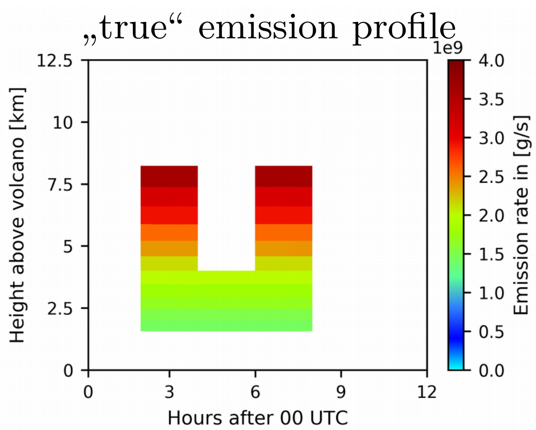
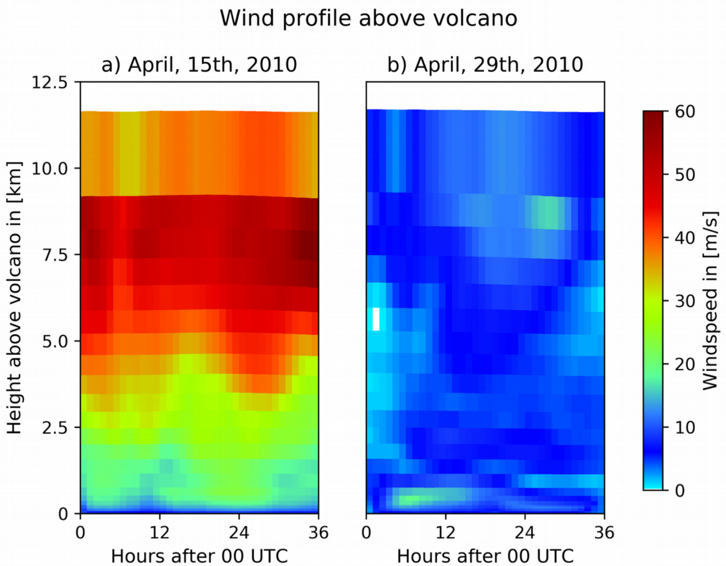


RESULTS

Sensitivity analysis





Setup of experiments

- Identical twin experiments on two days with strong (15/04/2010) and weak winds (29/04/2010) at the Eyjafjalla-jökull volcano (45km hor. resolution)
- SEVIRI-like observations of column mass loadings every 6 hours (incl. „zero“-values)
- Use perturbed observations

$$\sigma_y = max\left[\frac{(y_i * 0.4)^2}{max[y_i * 0.4]}, 0.1\right]$$

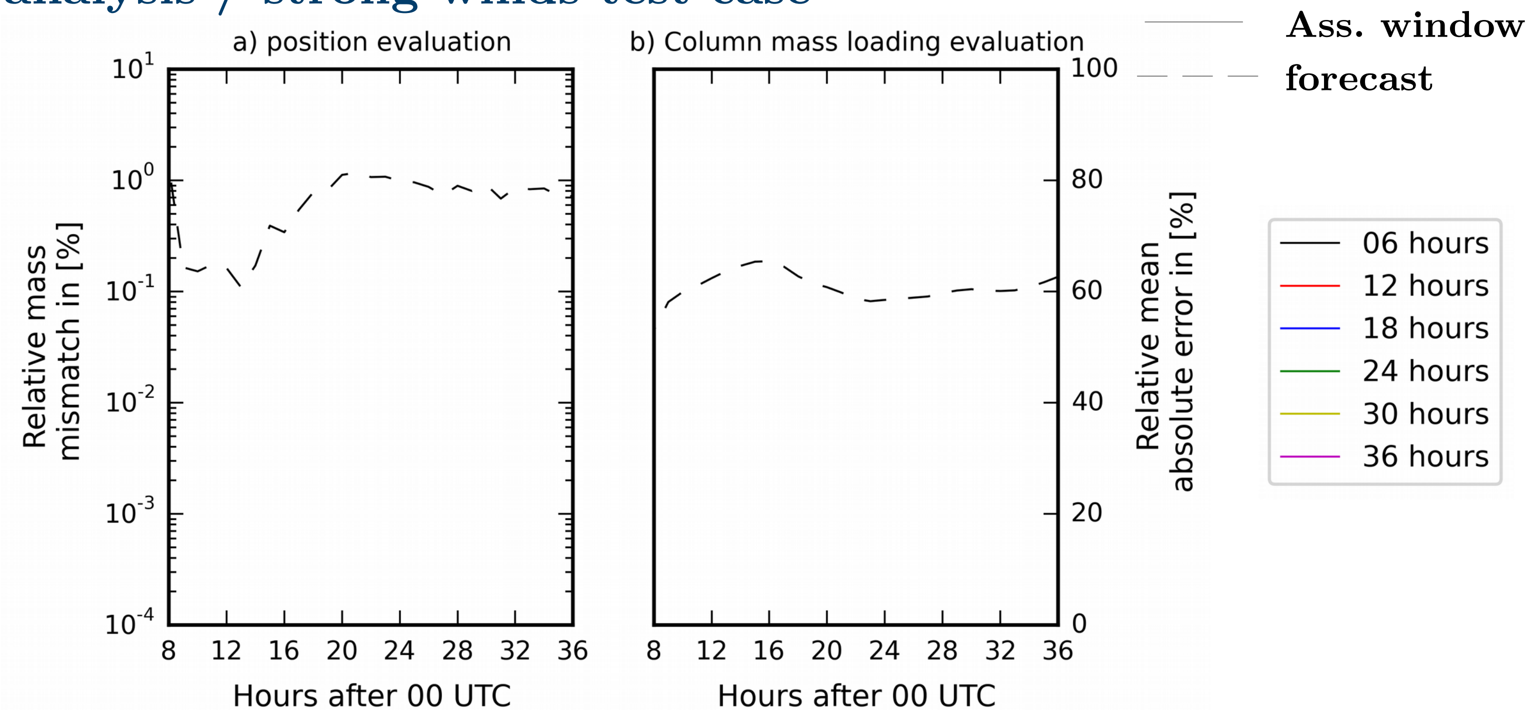
- Emission resolution: 1 hour;
  1 model layer
- Analysis ensemble size: N = 60

Objective

Extract vertically resolved emissions (t-z dimension) from column mass loadings observations (x-y dimension)

RESULTS

Sensitivity analysis / strong winds test case



Relative mass mismatch

$$m = 100 \frac{\bar{m}_{fp} + \acute{m}_{fn}}{(\bar{m}_{tp} + \acute{m}_{tp})/2}$$

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$$RMAE = 100 \frac{1}{N_y} \sum_{j=1}^{N_y} \left| \frac{\bar{m}_j - \acute{m}_j}{\sum_i \acute{m}_i} \right|$$

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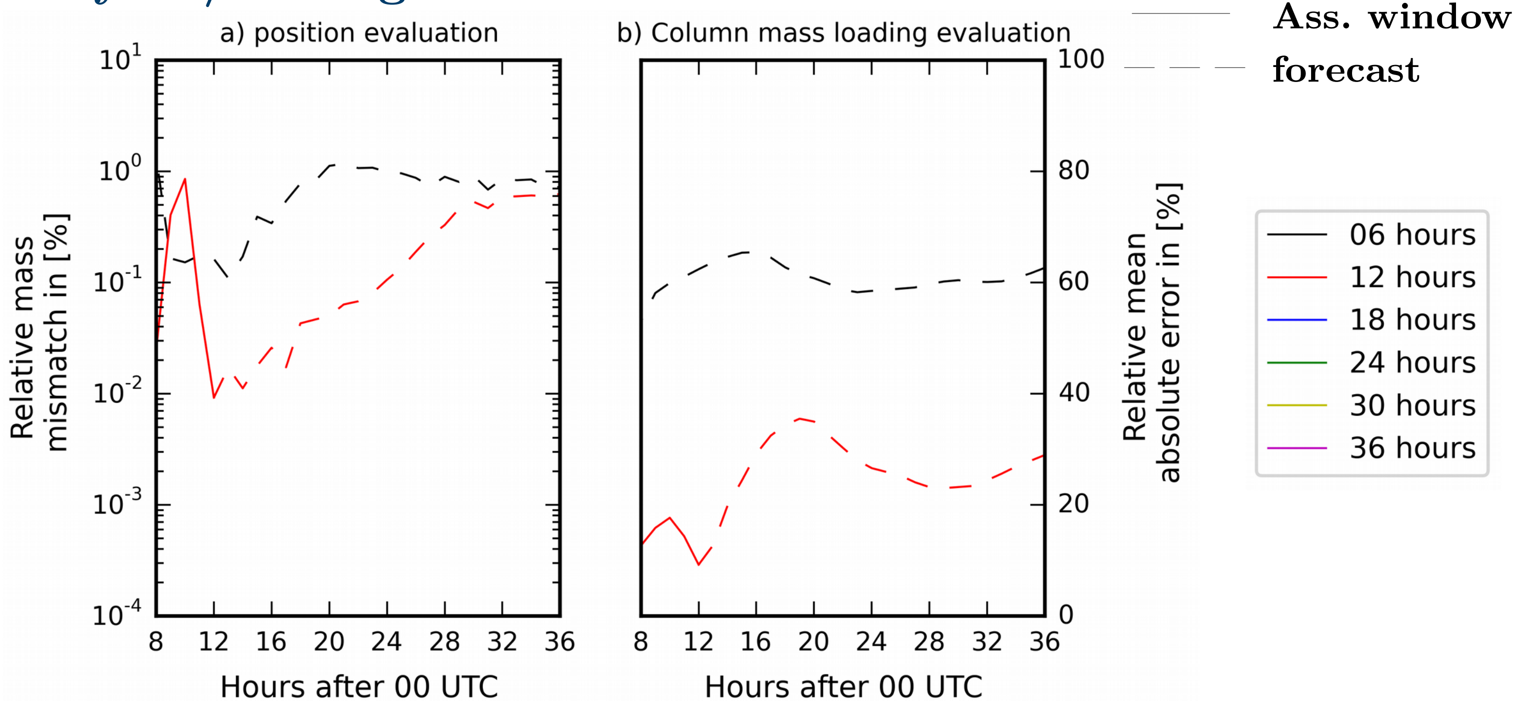

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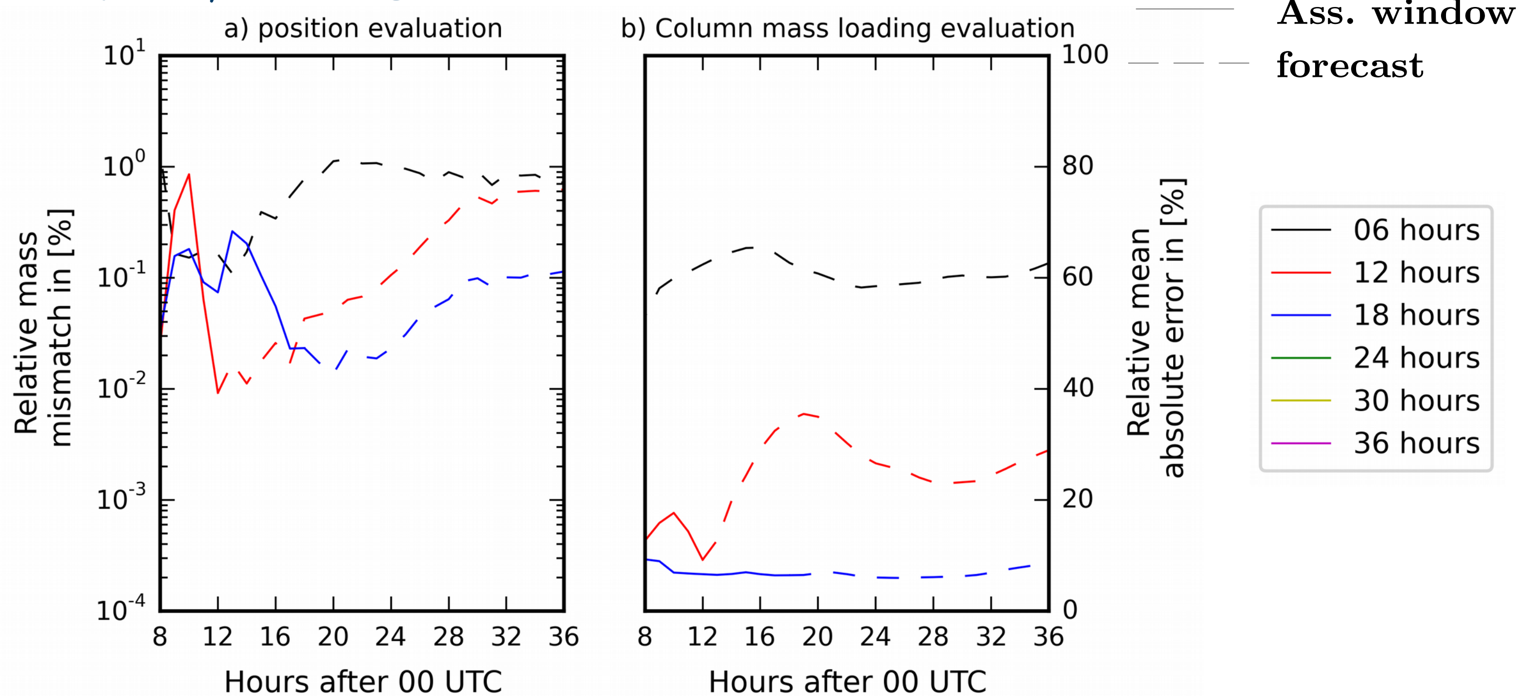

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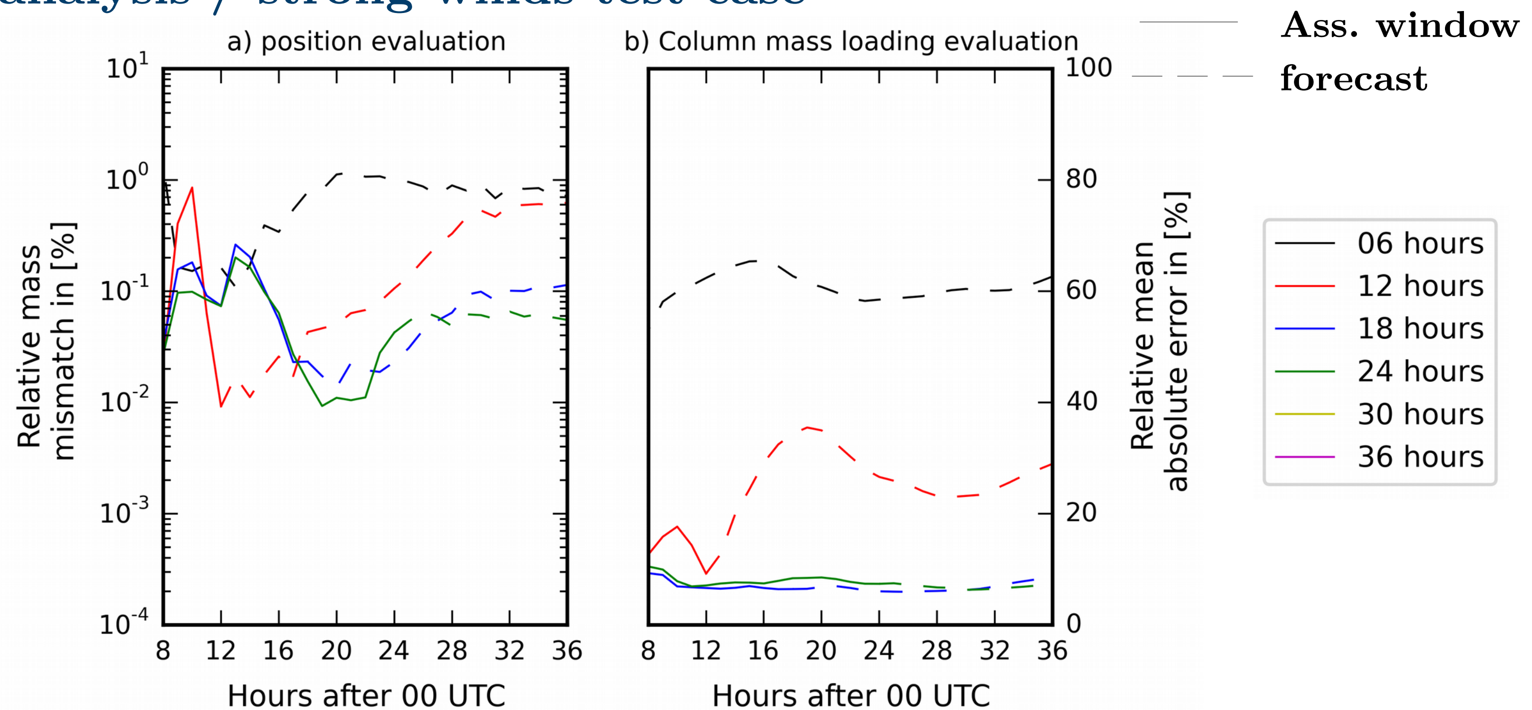

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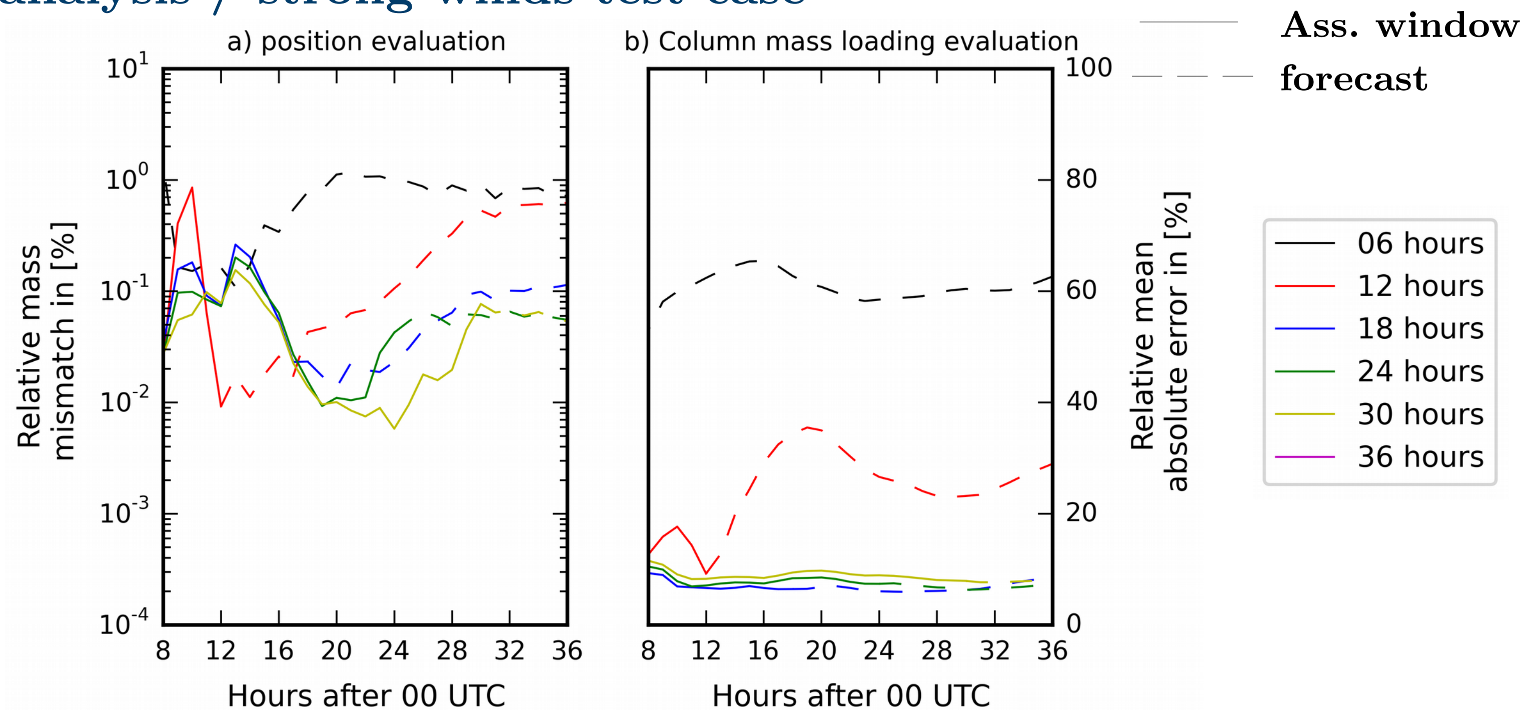

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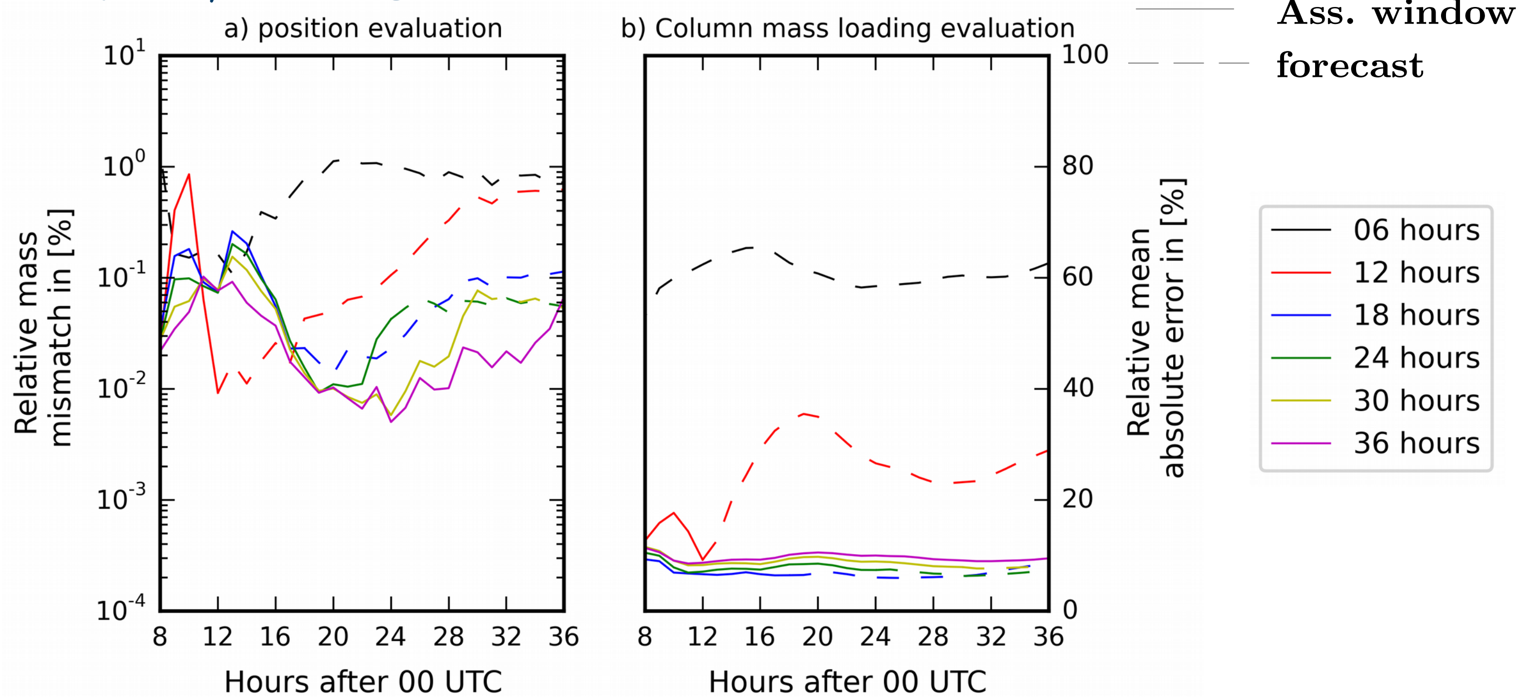

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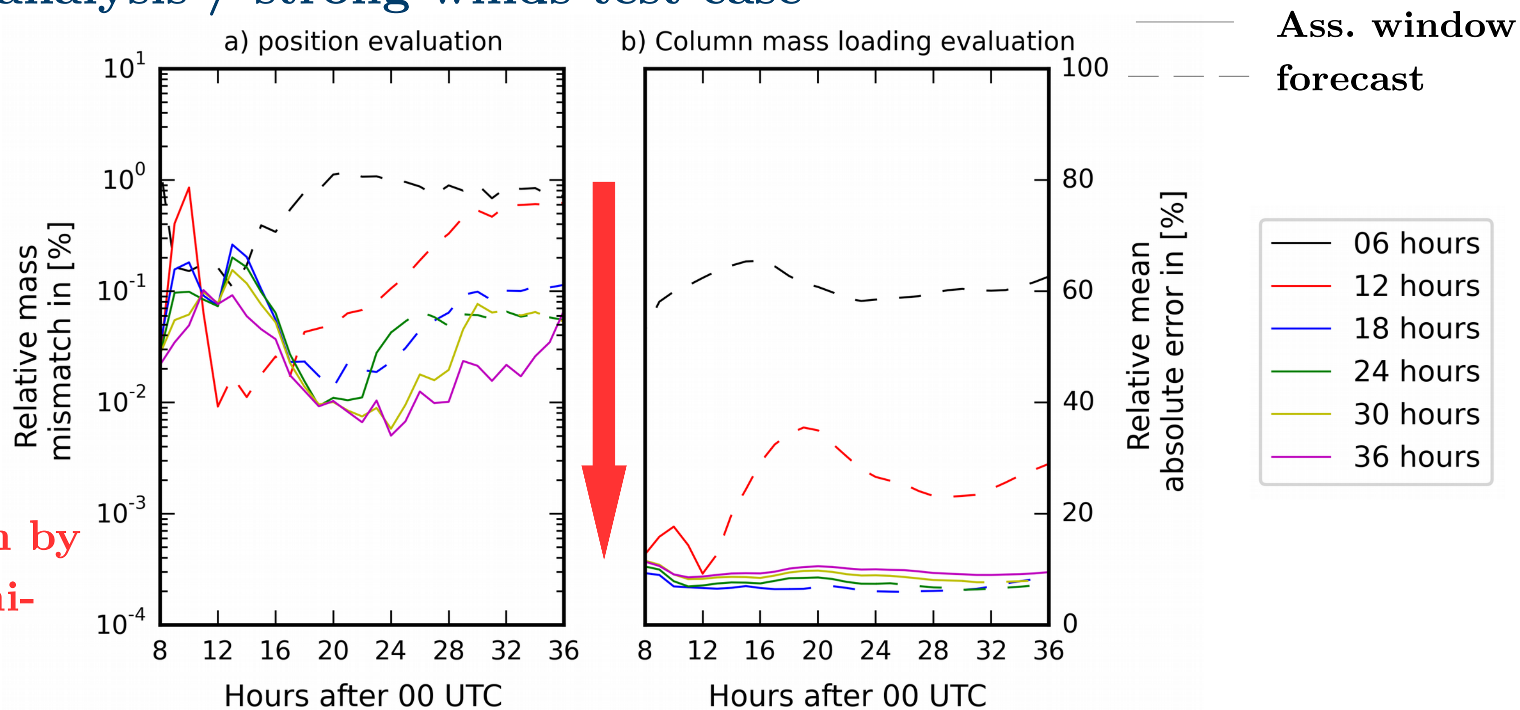

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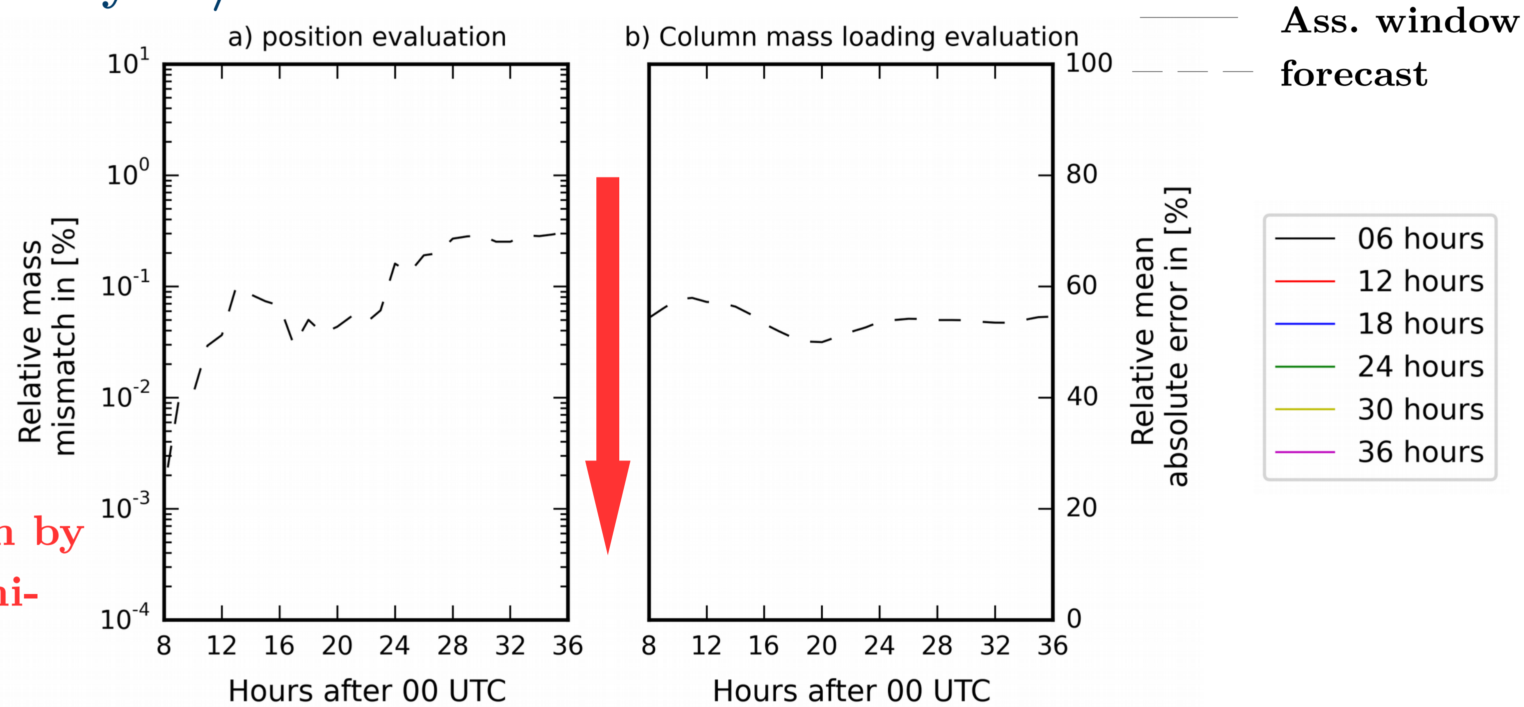

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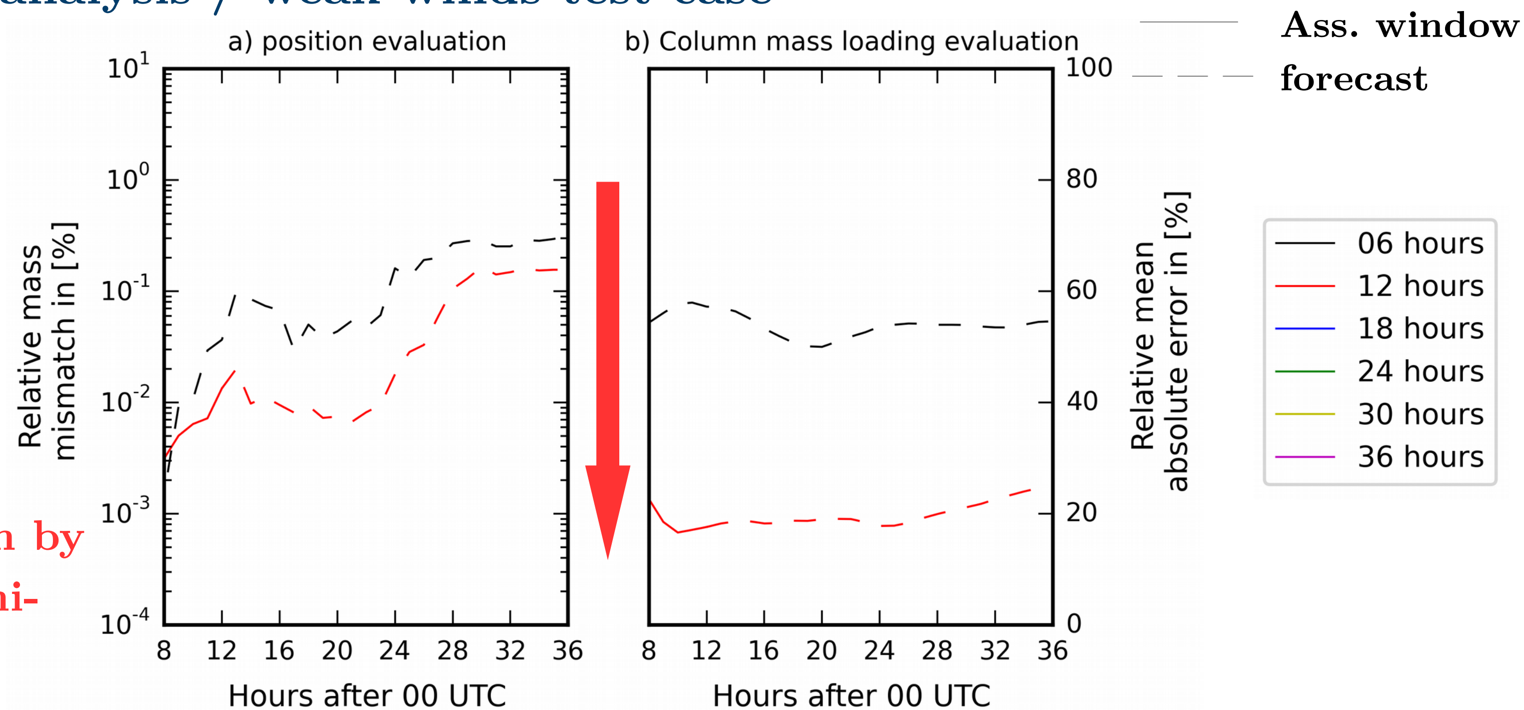

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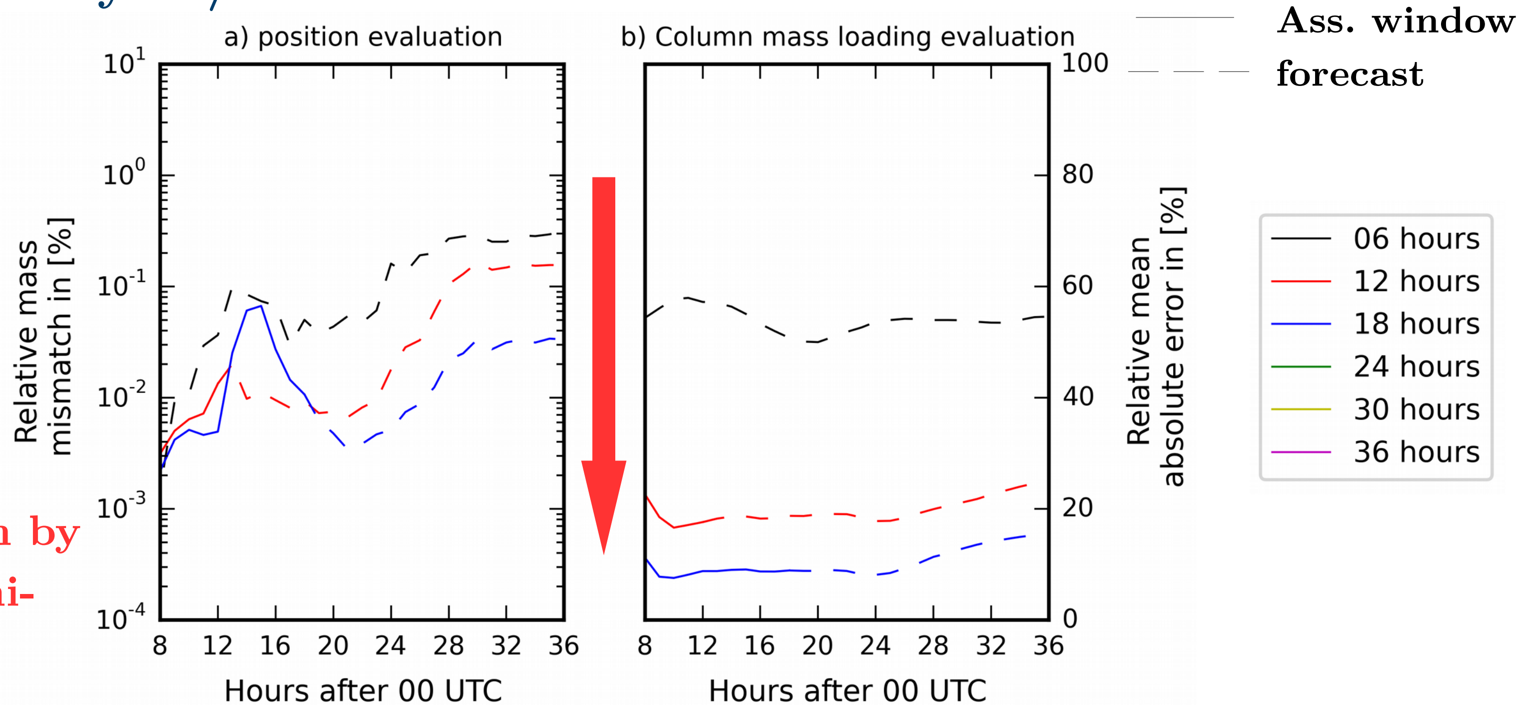

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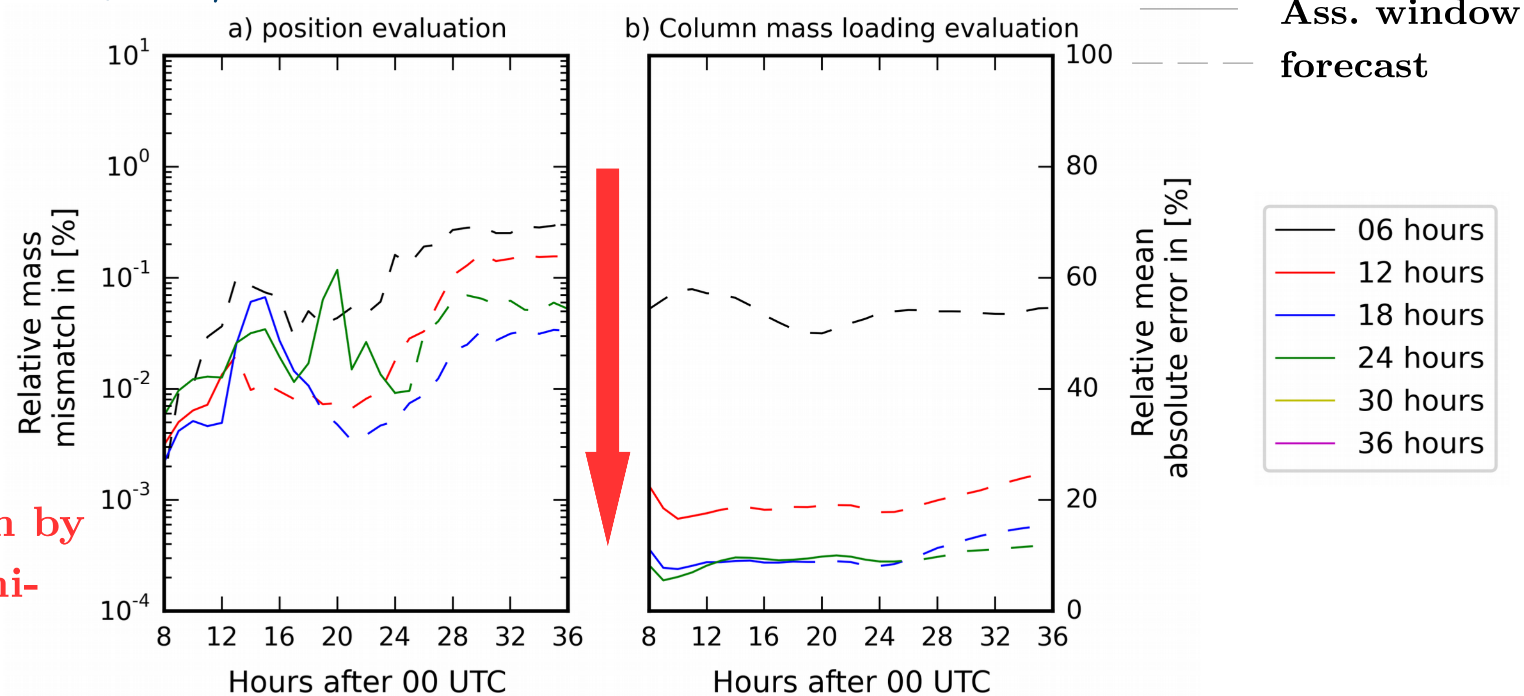

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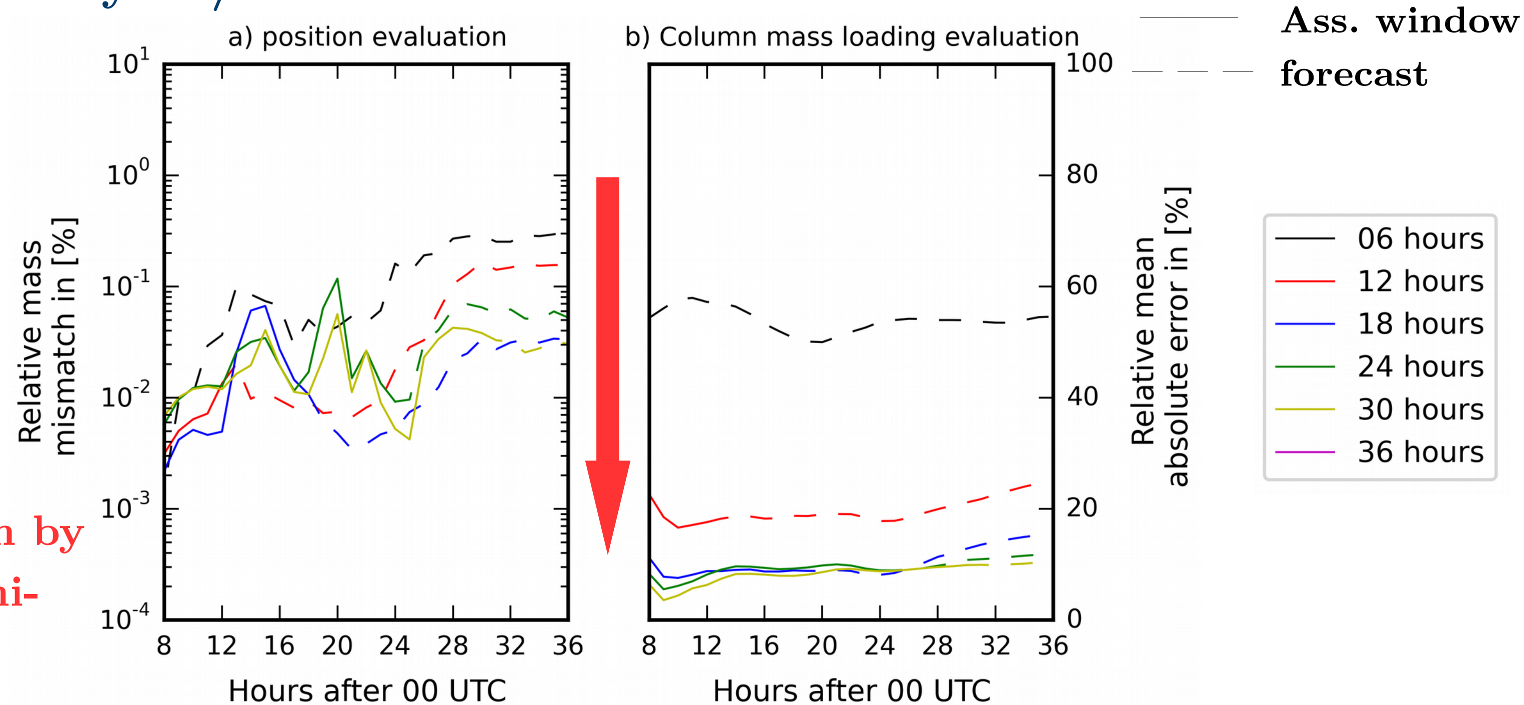

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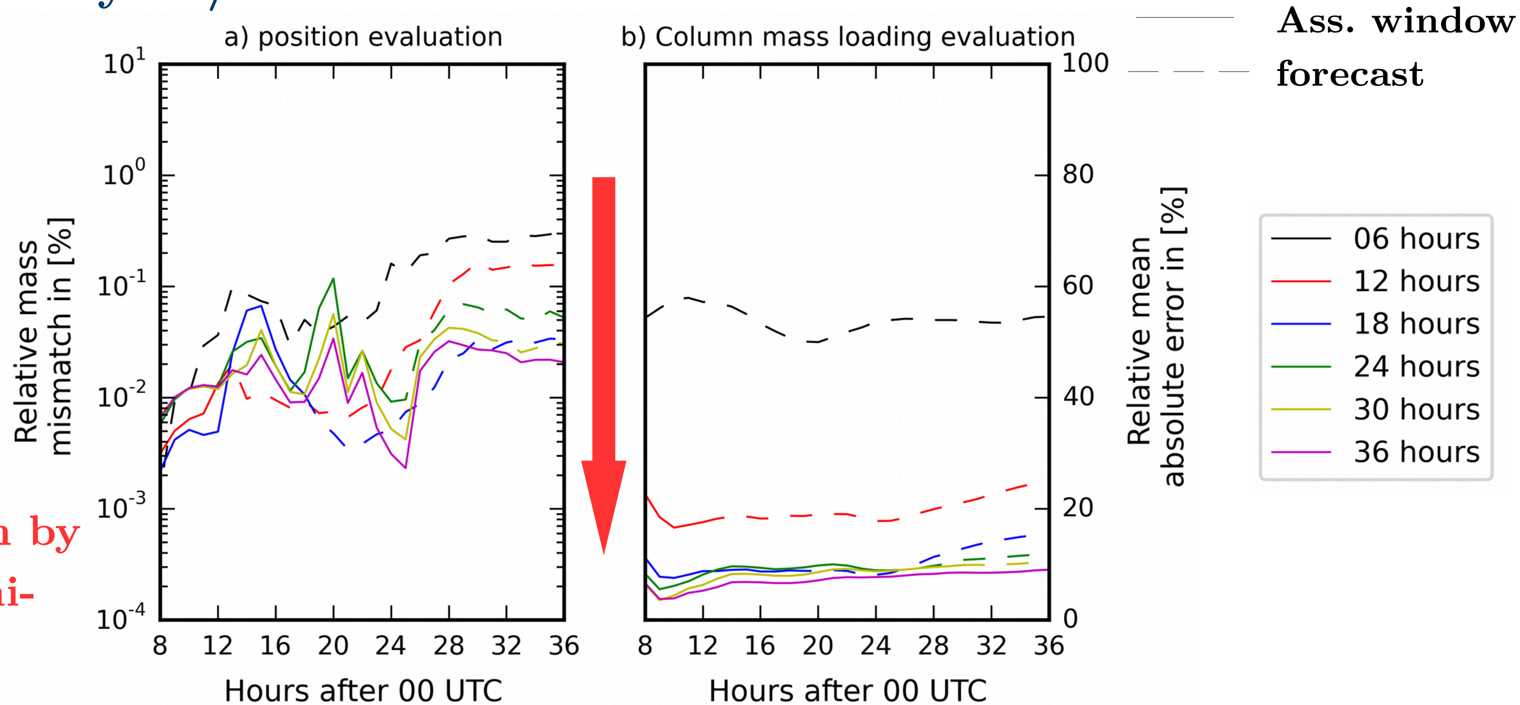

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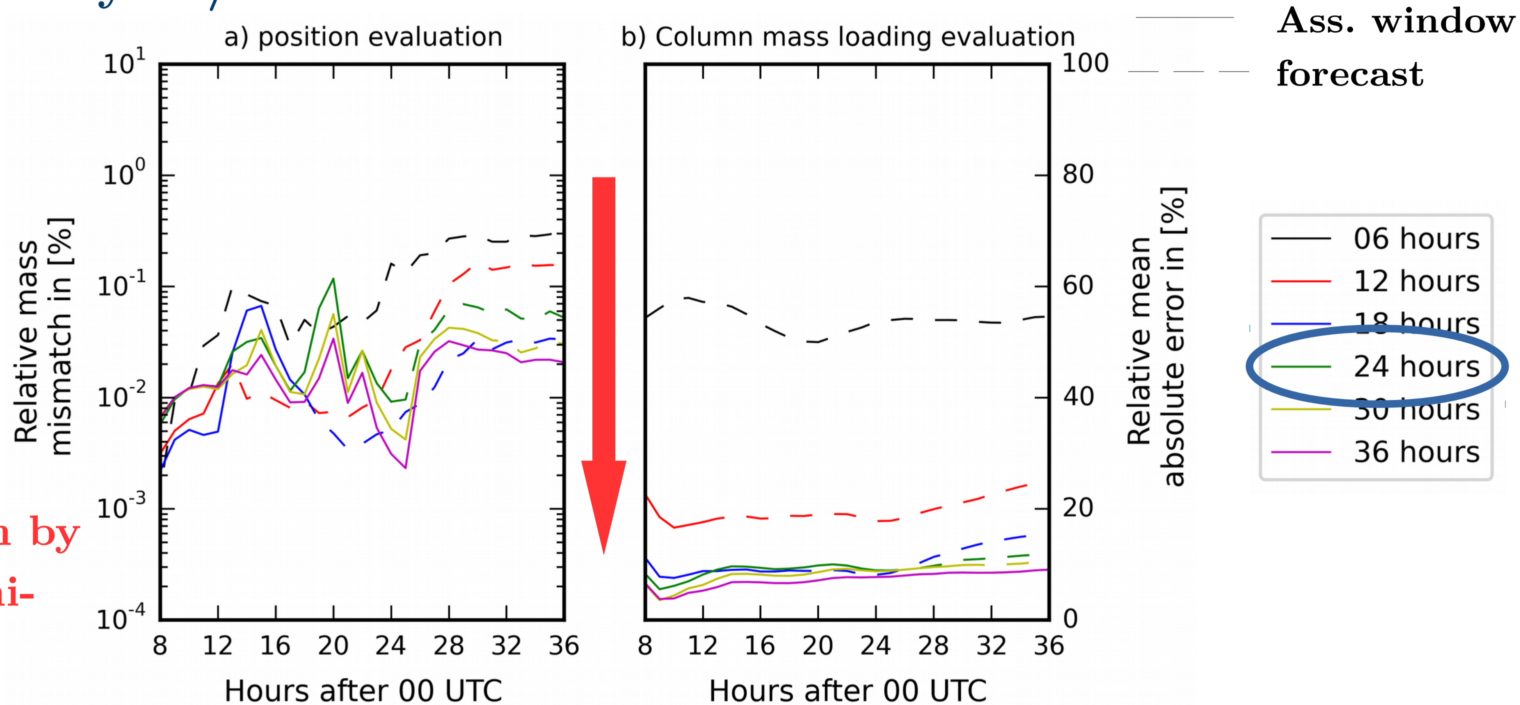

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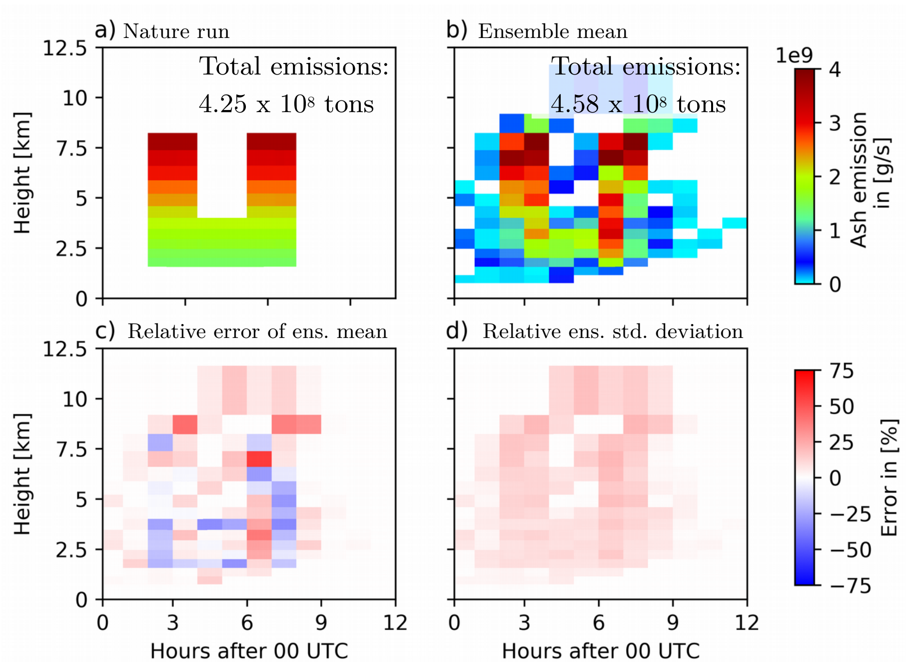
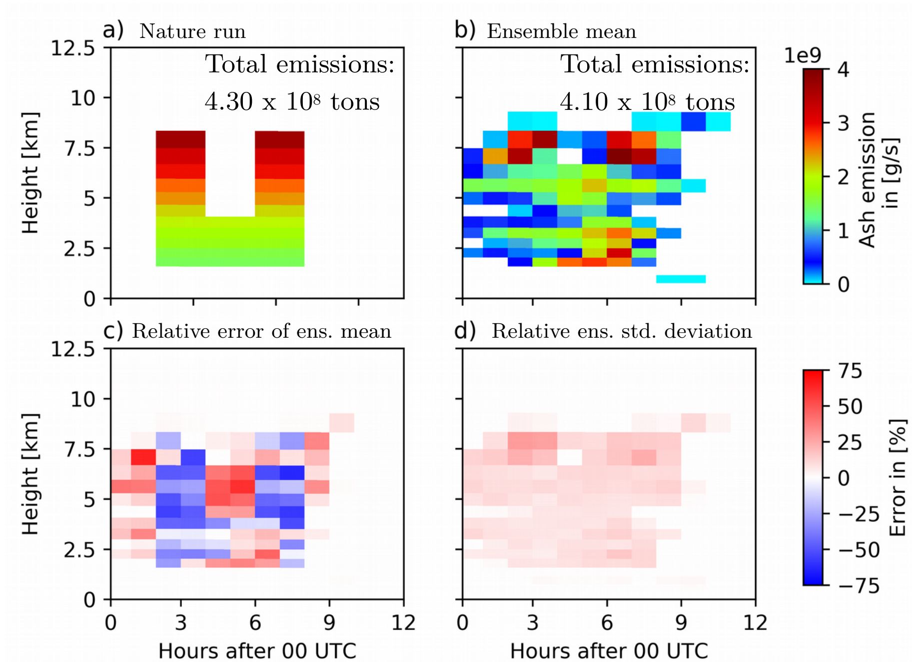
Sensitivity analysis / Potential and limitations





Strong wind case (15/04/2010)

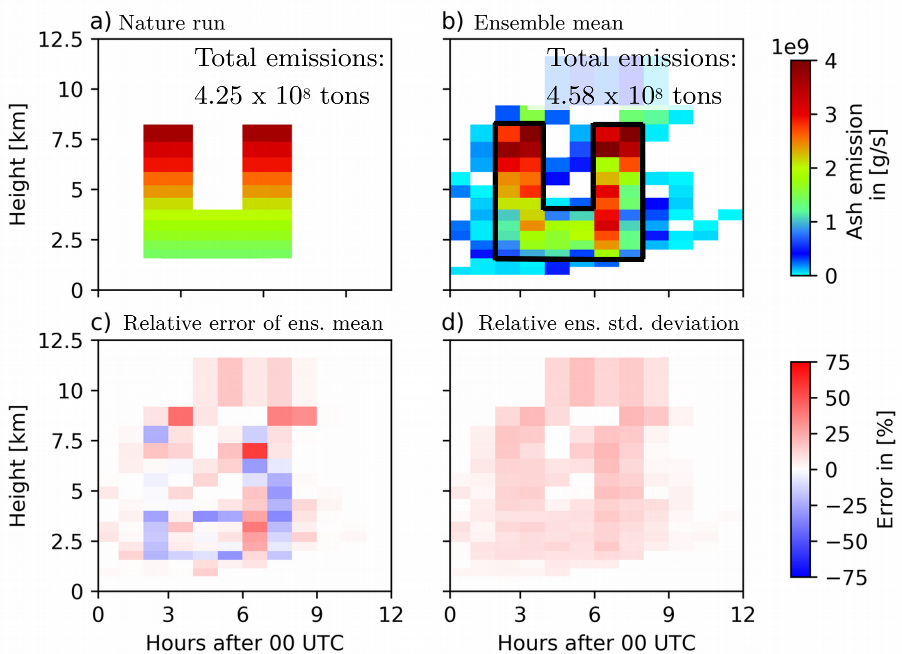
- Distinction of explosive eruptions
- Relative mean error of same size than relative ensemble standard deviation

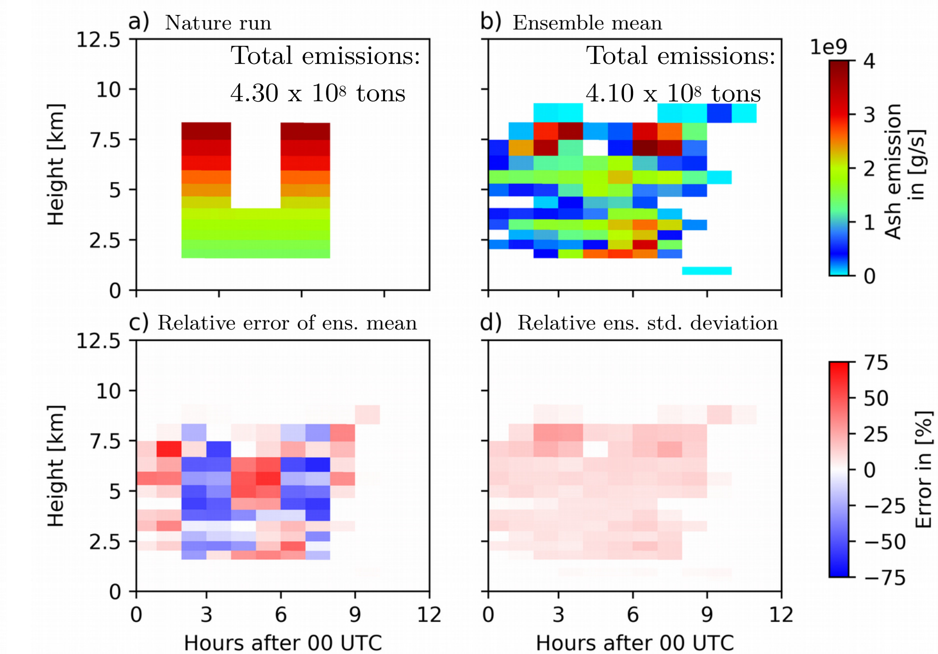
Weak wind case (29/04/2010)

- No distinction of explosive eruptions
- Relative ensemble standard deviation is smaller than relative mean error

RESULTS

Sensitivity analysis / Potential and limitations





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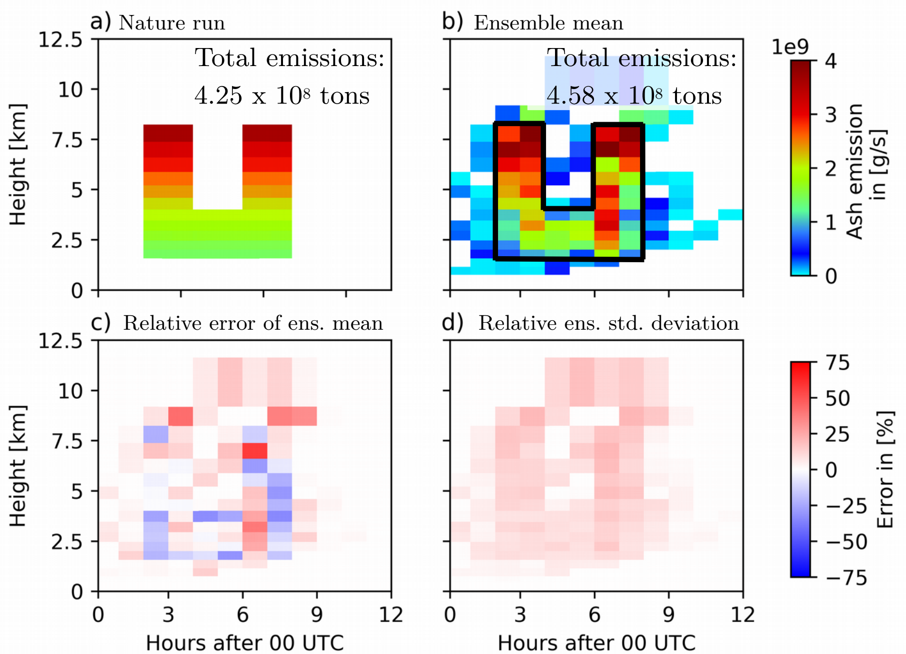

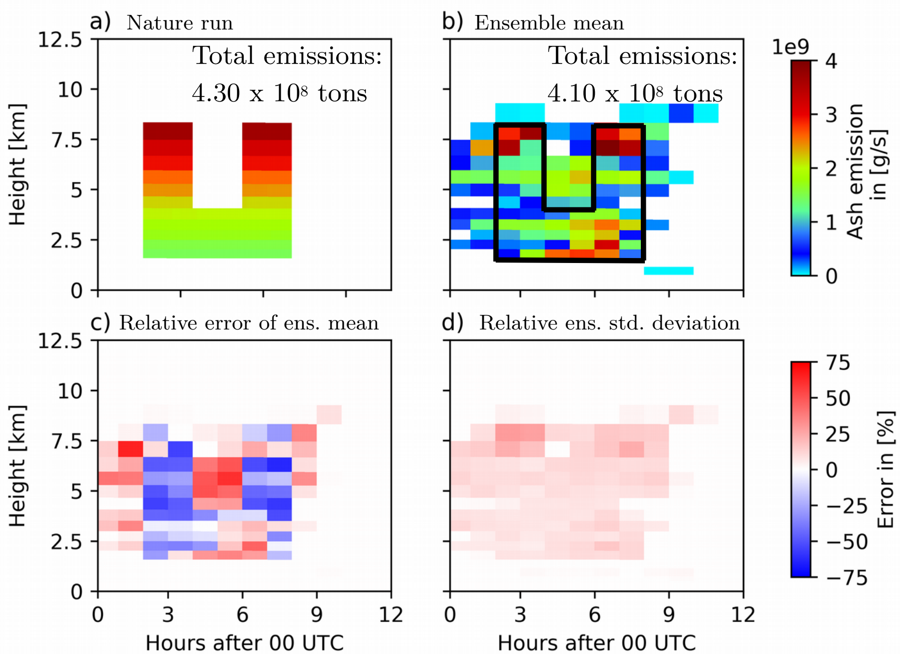

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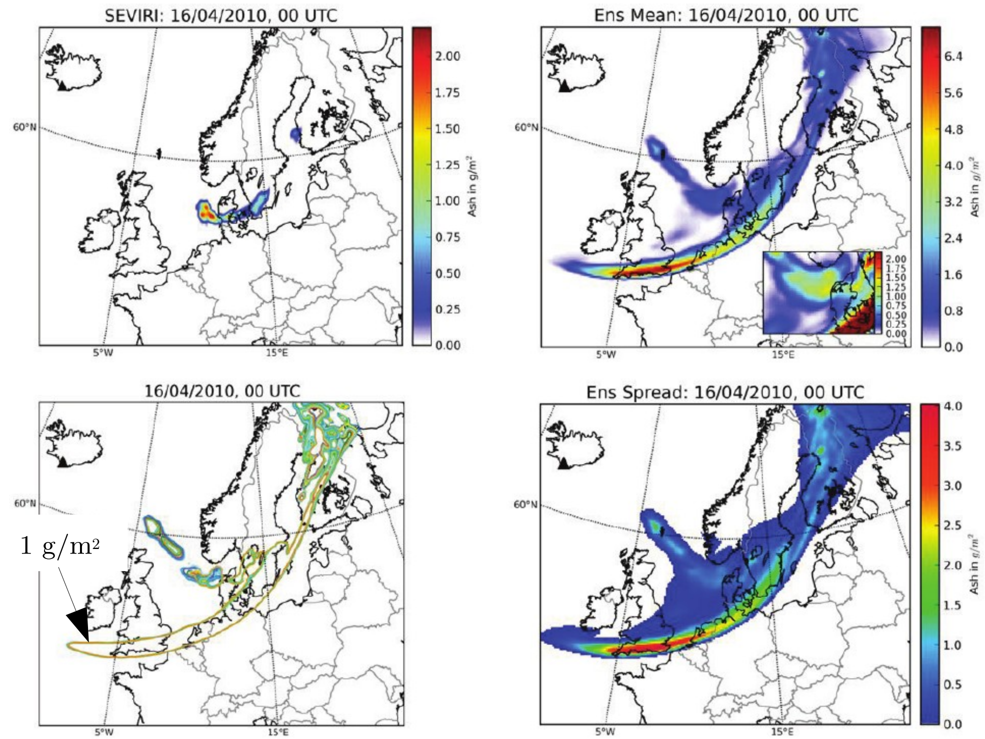
RESULTS

Application to Eyjafjallajökull eruption

Experimental setup

- Explosive initial phase of Eyjafjalla eruption at 14/04/2010–16/04/2010
- Emission optimization for the time 14/04/2010 06 UTC – 15/04/2010 12 UTC with 3h emission resolution (1 model layer in the vertical)
- 15 km horizontal model resolution
- 23 model layers up to 100 hPa
- SEVIRI observations > 0.45 g/m² (72h assimilation window)

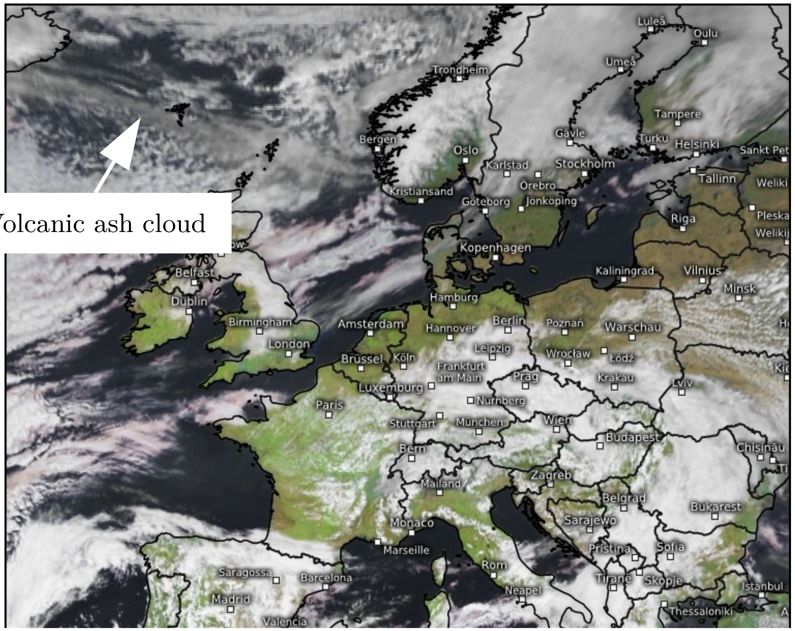


Results

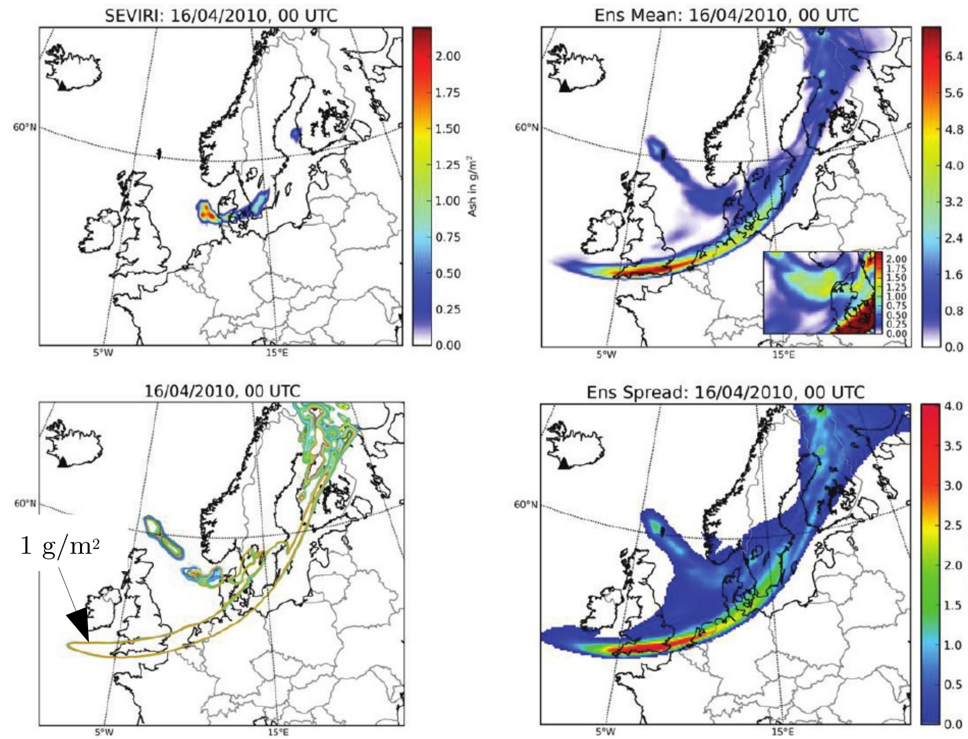
- Model show smoother volcanic ash distribution → higher emission resolution
- Meteorological model would increase diversity of analysis ensemble
- Meteorological clouds hinder better constraining of volcanic ash in the model

RESULTS

Application to Eyjafjallajökull eruption



15/04/2010 07am local time — Weather.us



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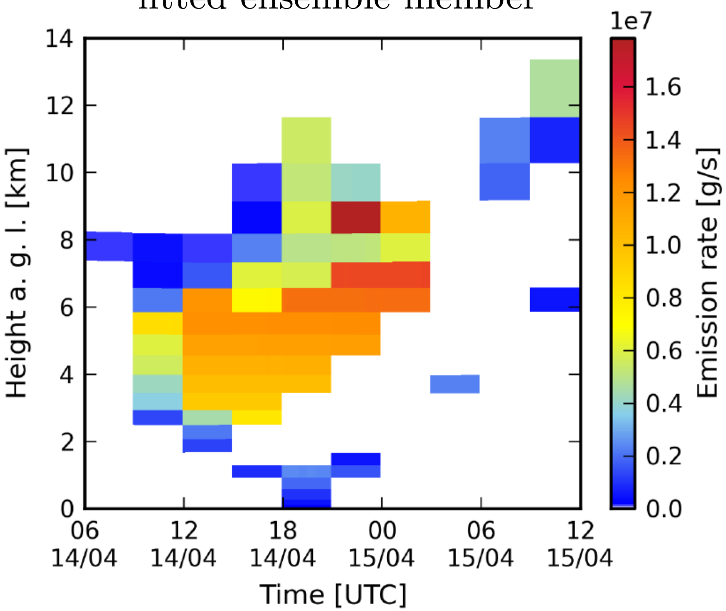
Observability application to Eyjafjallajökull eruption

Emission profile of the best fitted ensemble member



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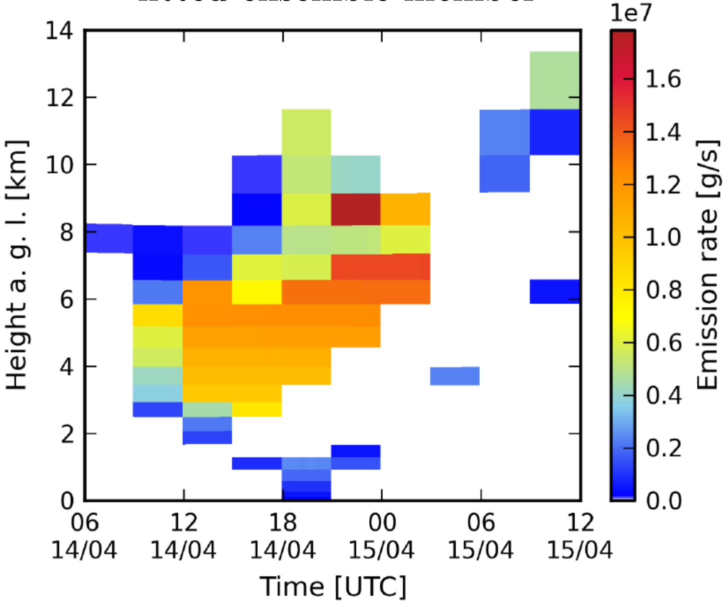

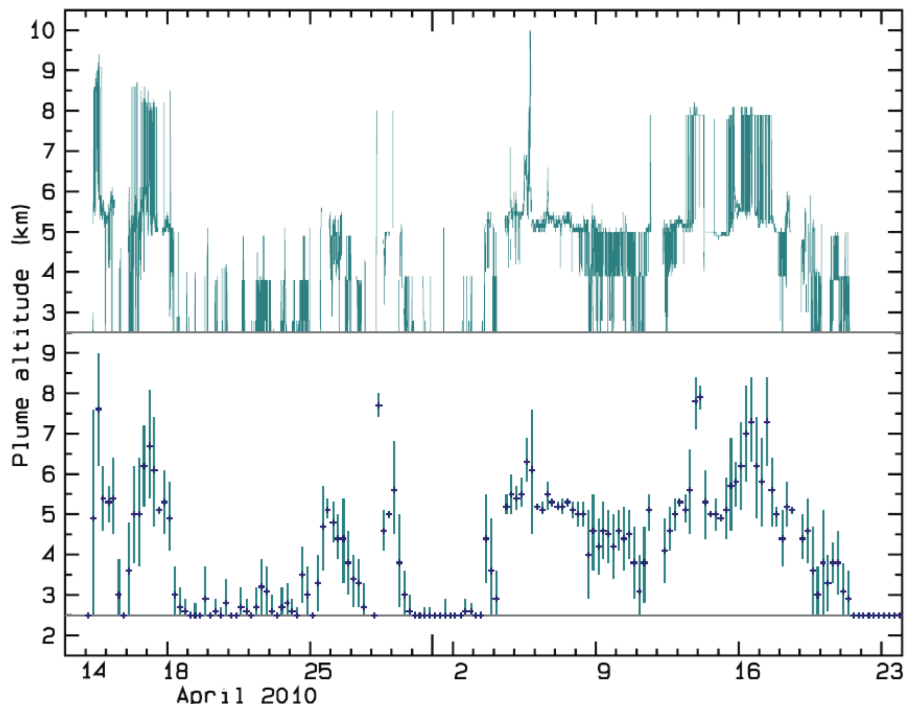

Radar observations at Keflavik (Arason et al. 2011)

JÜLICH Forschungszentrum

RESULTS

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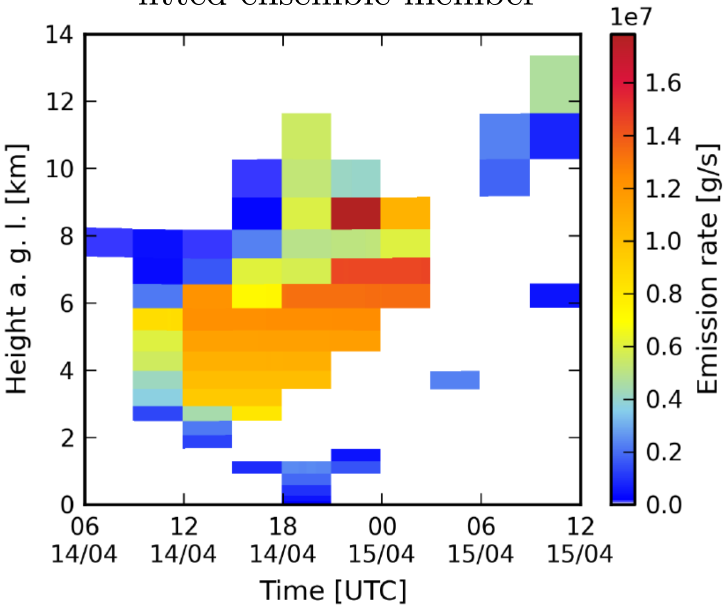

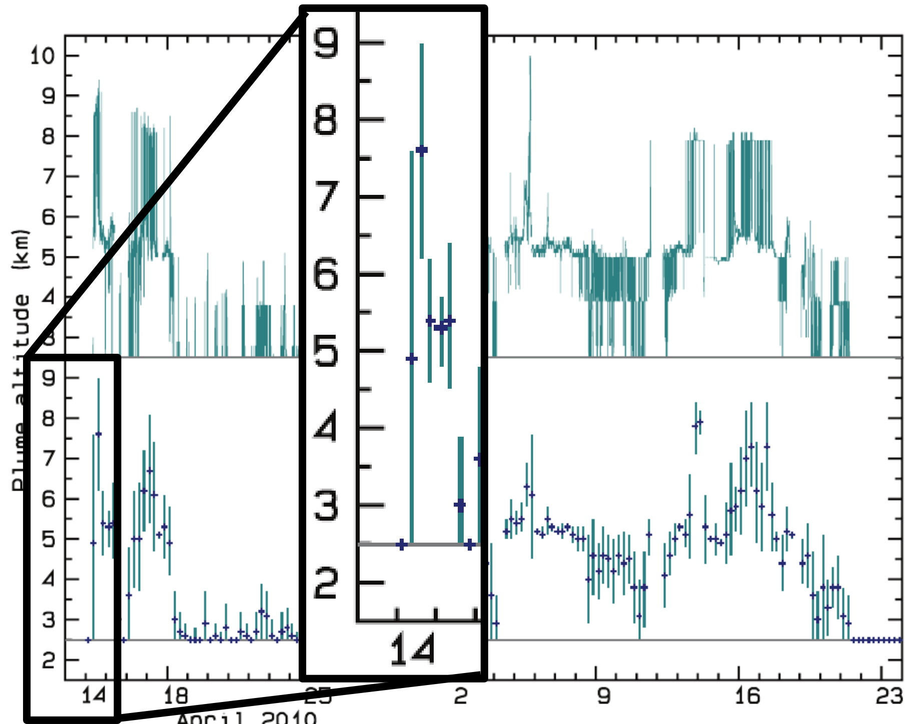

Radar observations at Keflavik
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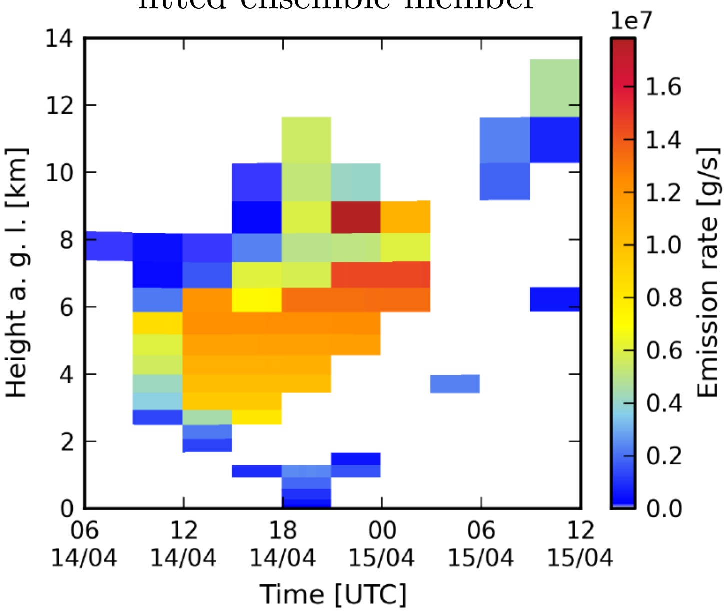
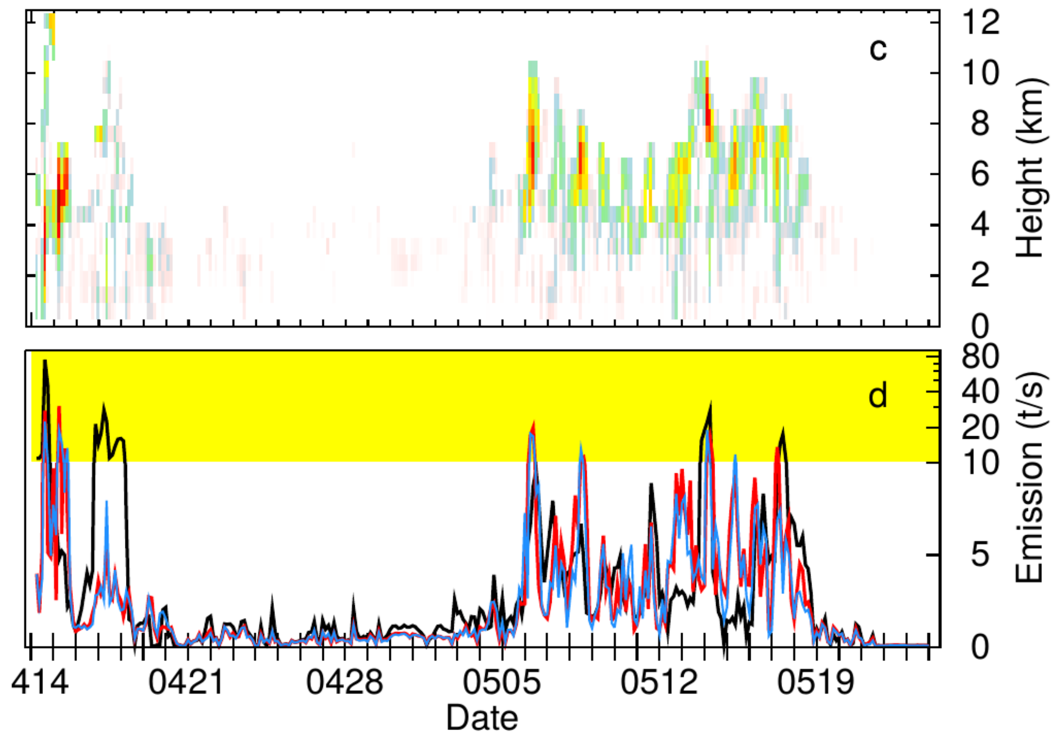


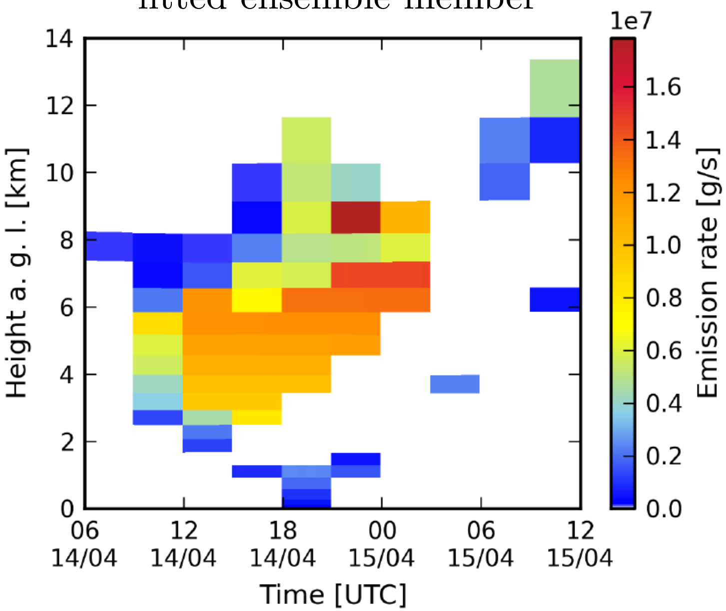


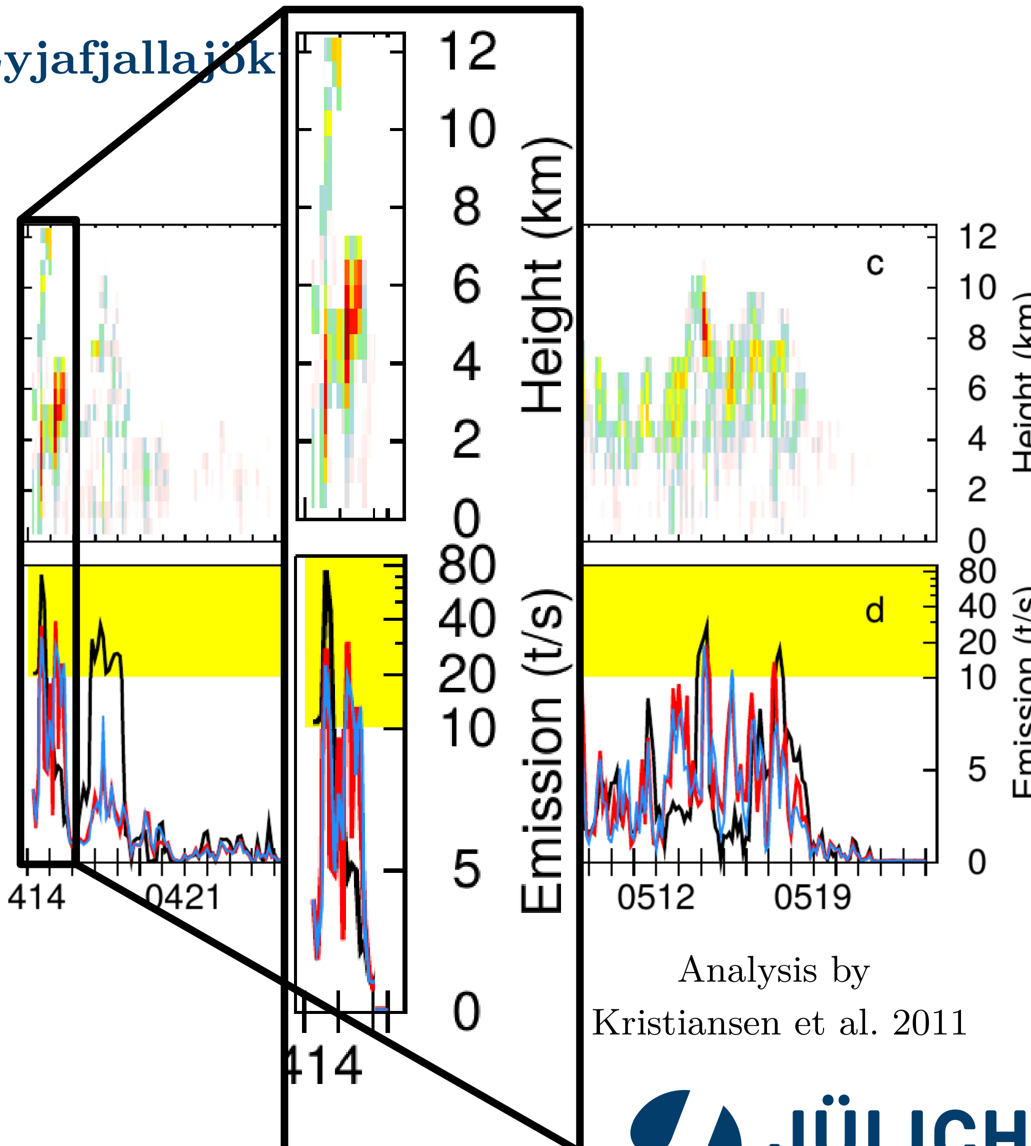
Analysis by Kristiansen et al. 2011

RESULTS

Observability application to Eyjafjallajök

Emission profile of the best fitted ensemble member





Analysis by
Kristiansen et al. 2011

CONCLUSION & OUTLOOK

Conclusions

- Development of a stochastic system (ESIAS) for volcanic ash emission estimation
- Sensitivity tests show dependence of analysis on wind conditions
  - Strong winds: reliable analysis
  - Weak winds: deficiencies in both, analysis and error representation
- Application to real volcanic eruption shows good estimation of emission profile
- High dependence on available observations

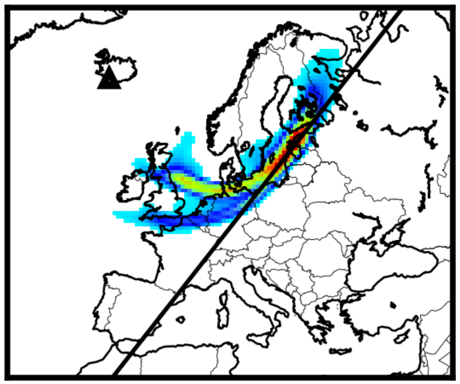
Outlook

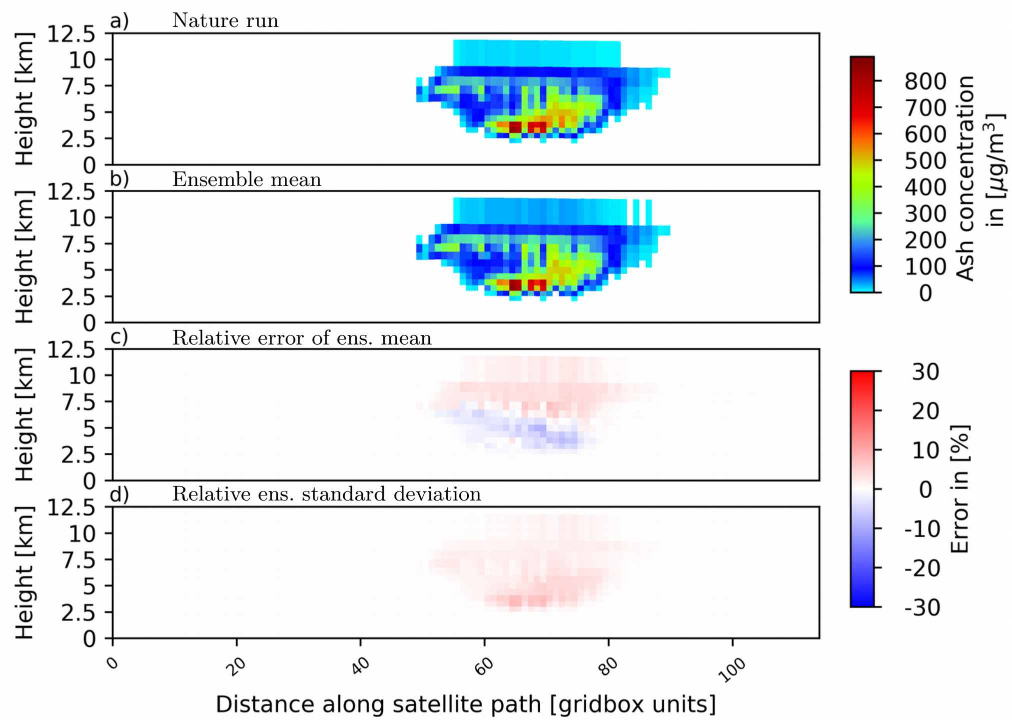
- Integration of meteorological ensemble for further error representation
- Extension of stochastic model to more complex emission scenarios (forest fires, Saharan dust events)
- Increase computational efficiency

RESULTS

Sensitivity analysis / Potential and limitations

Volcanic ash cloud at 16/04/2010, 06 UTC
(6h forecast after end of assimilation window)





Strong wind case (15/04/2010)

- Vertical cross section along satellite path
- Distingiushing of second elevated ash layer by ensemble mean
- Relative mean error of the order of relative ensemble standard deviation

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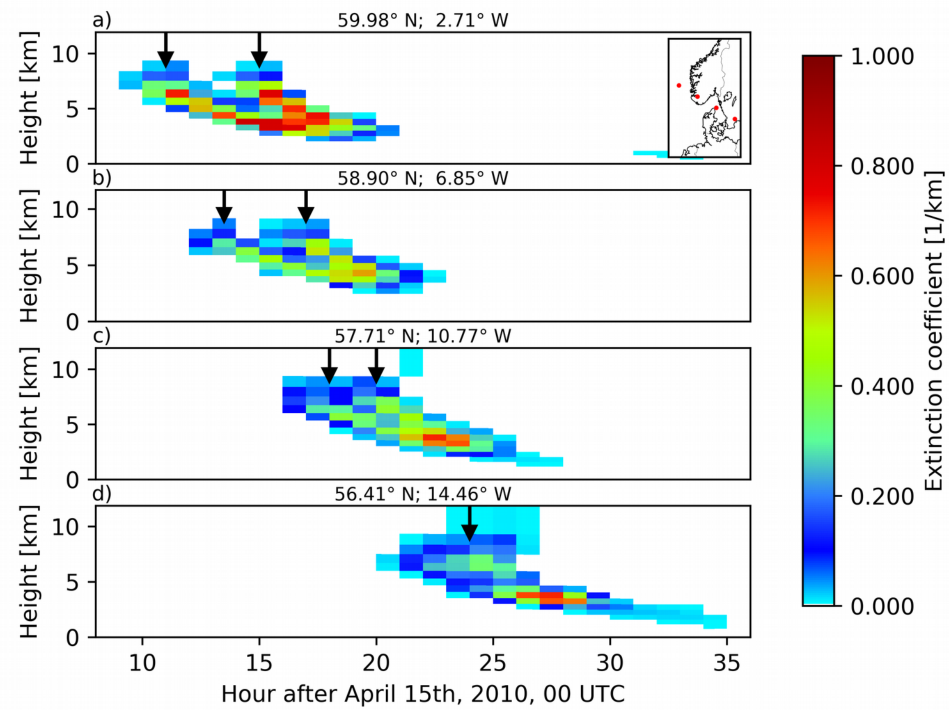
RESULTS

Sensitivity analysis / Convergence of both ash clouds

Strong wind case (15/04/2010)

- Two high concentration areas of volcanic ash converge at approx. April, 16th, 00 UTC (24h after simulation start)
- After convergence no separation of the two regions possible
- No improvement of analysis by increasing the assimilation window length beyond 24 hours



Extinction coefficient $\left(\eta = \frac{M}{\alpha} \approx 1.45\, g/m^2\right)$ of volcanic ash of nature run volcanic ash concentrations at four selected positions

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