Ensemble atmospheric dispersion modelling of volcanic species: interpreting ensemble data and applications

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Introduction and motivation

- Customarily, operational forecast systems rely on volcanic ash transport and dispersal (VATD) models to produce deterministic forecasts
- ▶ We can generate realistic representations of the spatio-temporal distribution of airborne volcanic species (i.e. ash and gases) and tephra deposits using a physics-based approach
- ▶ In parallel, there has been a growing interest in ensemble approaches for modelling the atmospheric transport of volcanic aerosol and tephra in recent years
- ► This study explores different challenges involving ensemble modelling and proposes some approaches for dealing with ensemble data

Why ensemble modelling?

- ▶ Uncertainty in model input parameters: Deterministic models are highly sensitive to uncertain model input parameters (e.g. eruption source parameters) and meteorological fields. We can take into account these uncertainties using ensemble modelling
- Quantification of model output uncertainty: Ensemble-based modelling allows one to characterise and quantify model output uncertainties. In addition to traditional forecasting products, the associated errors can be provided
- ▶ Improvement of forecast skill: Real observations can be incorporated into dispersal models using ensemble-based data assimilation techniques
- Source inversion: Different techniques for source term inversion have been proposed based on ensemble modelling

Ensemble simulations

Numerical model:

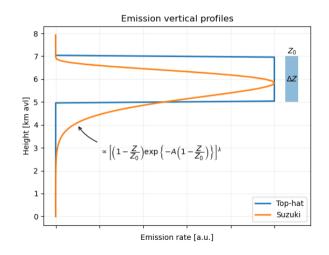
► FALL3D: model for atmospheric transport and deposition of particles and aerosols

Ensemble construction:

- ► Emission source parameters
- Grain size distribution
- Aggregation parameters
- Meteorological fields
- Diffusivity coefficients

Outputs:

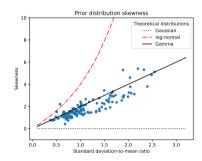
- ► Ash/gases concentration
- ► Column mass loading
- ► Top cloud height
- Deposit mass loading

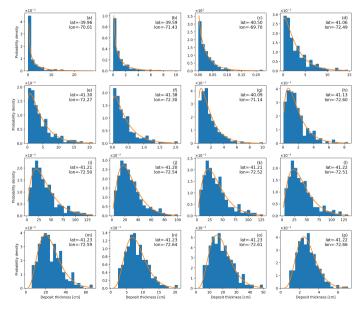


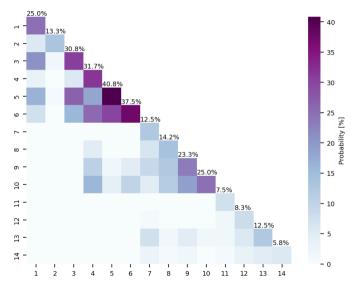
Ensemble simulations: Probability distribution

The gamma distribution provides a good approximation to the ensemble distribution:

- $ightharpoonup \overline{y} < \sigma_v
 ightarrow ext{mode=0}$
- $\overline{y} > \sigma_v \rightarrow \text{mode} > 0$
- Right-skewed probability distributions







Run configuration:

- ► Test case: 2015 Etna eruption
- Ensemble size = 120 members

Traditional products:

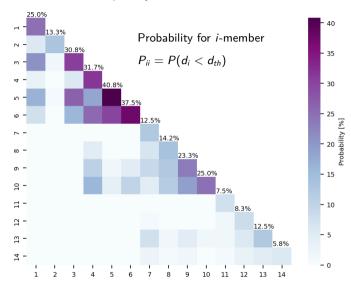
- Ensemble mean
- Ensemble spread
- ► Exceedance probability

Complexity reduction:

- Remove redundancy in the ensemble data
- We need to measure the distance d_{ij} between two model states i and j
- Ensemble members with similar distances are grouped

Reduced ensemble

Ensemble size reduction:



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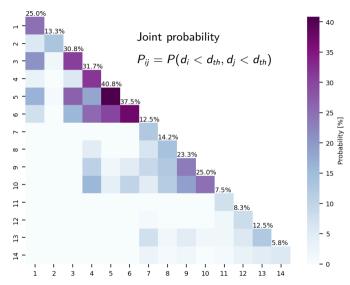
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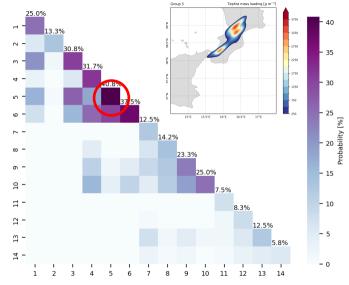
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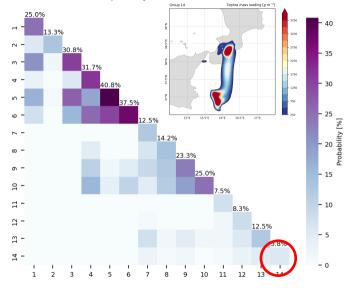
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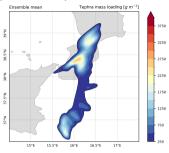
Complexity reduction:

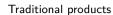
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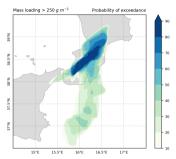
Comparison of products

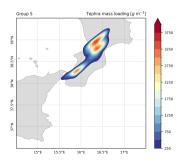




 $\leftarrow \ \mathsf{Ensemble} \ \mathsf{mean}$

Probability of exceedance \rightarrow

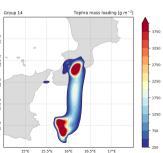




Reduced ensemble

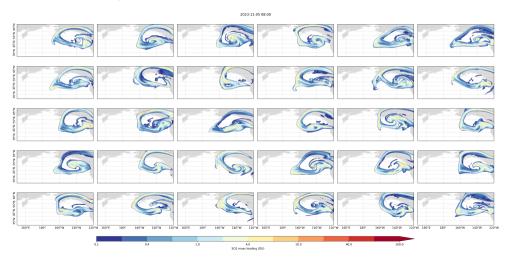
 $\leftarrow \mbox{ High probability} \\ \mbox{state (41\%)}$

Low probability state $(6\%) \rightarrow$

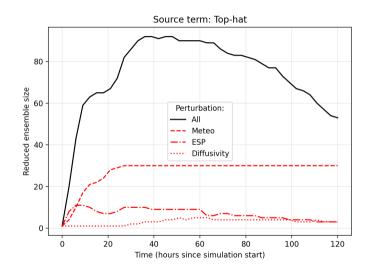


Sensitivity study

- ► Test case: SO2 cloud of the 2023 Klyuchevskoy eruption (Kamchatka Peninsula)
- ▶ Multiple ensemble simulations were performed perturbing single model parameters
- ▶ Size of the reduced ensemble as a measure of the variable sensitivity
- ► Ensemble size = 120 members



Sensitivity study



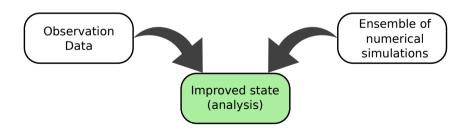
- Minimimum ensemble size required
- Sensitivity

	Short-term forecasting	Long-term forecasting
Meteo	Medium	High
Eruption Source Parameters	Medium	Medium
Diffusivity	Low	Low

Ensemble-based data assimilation

GNC method:

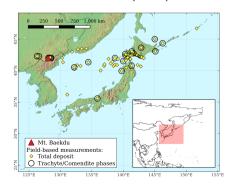
- ▶ We propose a heuristic first-order data assimilation method for lower-bounded (positive) variables
- ▶ The Gaussian with non-negative constraints (GNC) method assumes a multi-dimensional Gaussian probability distribution and a linear observation operator
- ▶ A non-negative quadratic programming problem is solved using an iterative approach
- ► This method leads to better results than other DA techniques, including the classical Ensemble Kalman Filter (EnKF)

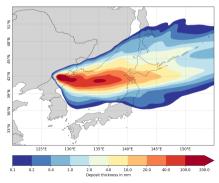


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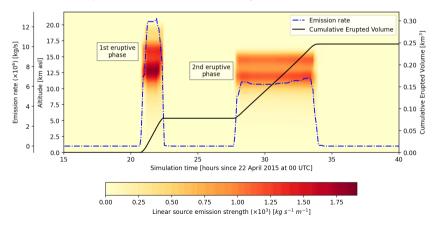


Millennium eruption

Reconstruction of the tephra fallout deposit of the 946 CE Millennium eruption of Changbaishan volcano assimilating deposit thickness data

Source term inversion

- ► A technique for emission source inversion based on the GNC method can be used to estimate the space—time distribution of the source
- Valid for problem with weak non-linearity effects



Calbuco eruption

Time evolution of emission rate profiles for the 2015 Calbuco eruption according to the source term inversion approach based on the GNC method

Conclusions

- ▶ When ensemble simulations should be performed instead of the deterministic simulations?
- ▶ How the ensemble should be constructed?
- ► Which variables should be perturbed?
- ▶ What's the minimum ensemble size required to properly represent the system state?
- How interpretate and deal with large volumes of ensemble data?
- Which probabilistic output products are relevant?
- ▶ Are the traditional assimilation methods suitable for the atmospheric dispersion of volcanic species?