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

Cities on Volcanoes 12, Antigua Guatemala

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Introduction and motivation

- Atmospheric dispersion models can provide realistic distributions of airborne volcanic ash and gases or tephra deposits
- Traditionally, operational forecast systems rely on volcanic ash transport and dispersal (VATD) models to produce deterministic forecasts
- Ensemble modelling poses new challenges: we explore approaches for dealing with large volumes of ensemble data, data interpretation and applications

Why ensemble modelling?

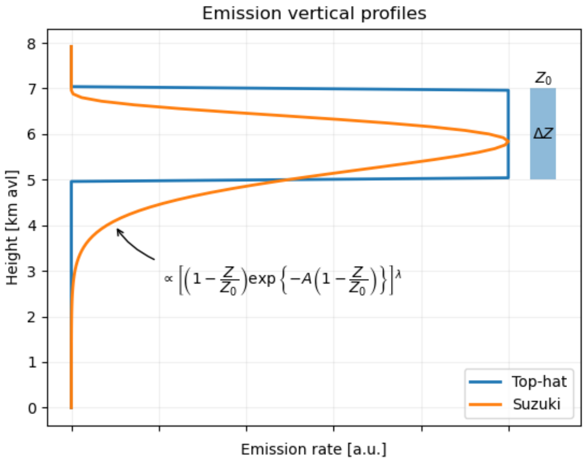
- **Uncertainty in model input parameters:** Deterministic models are highly sensitive to uncertain model input parameters (e.g. eruption source parameters) and meteorological fields. We can take into account these uncertainties using ensemble modelling
- **Quantification of model output uncertainty:** 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

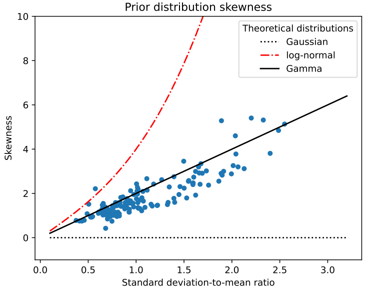
Outputs:
- Ash/gases concentration
- Column mass loading
- Top cloud height
- Deposit mass loading

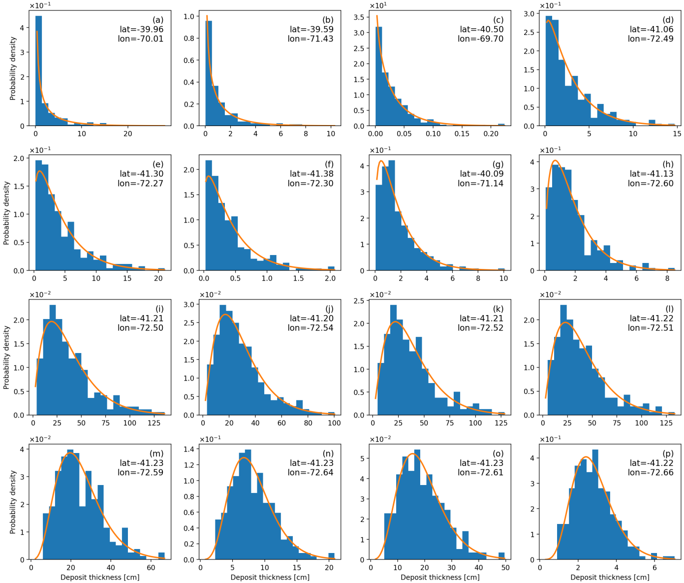


Ensemble simulations: Probability distribution

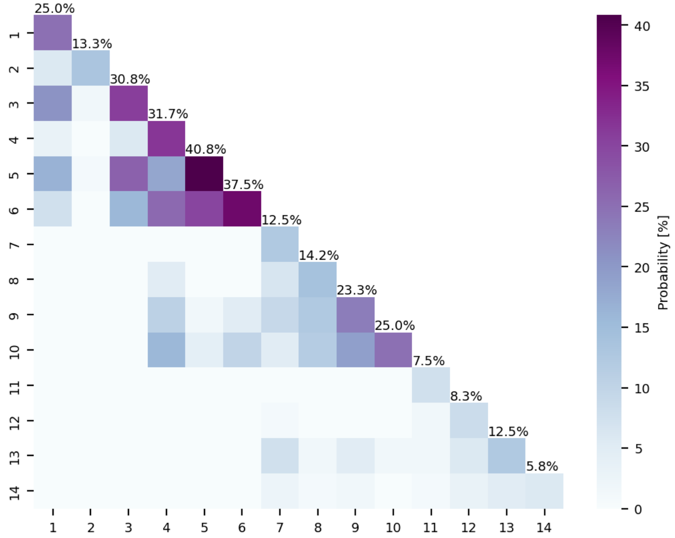
The gamma distribution provides a good approximation to the ensemble distribution:

- $\overline{y} < \sigma_y \rightarrow$ mode$=0$
- $\overline{y} > \sigma_y \rightarrow$ mode>0
- Right-skewed probability distributions





Ensemble data complexity reduction



Run configuration:

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

Traditional products:

- Ensemble mean
- Ensemble spread
- Exceedance probability

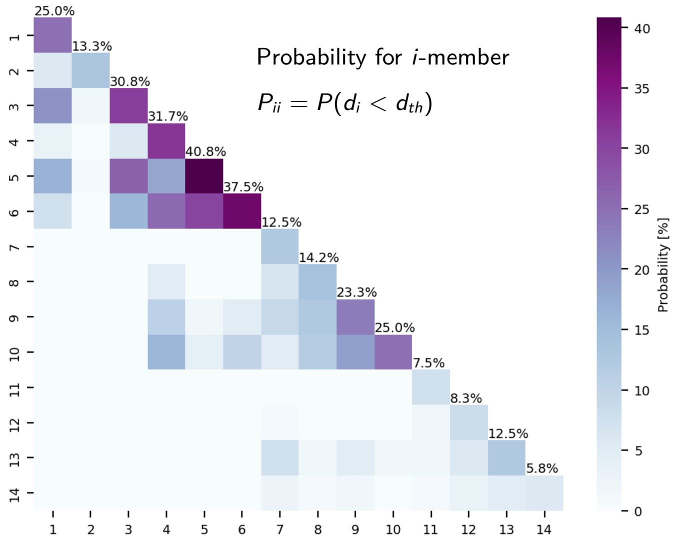
Complexity reduction:

- 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:
$120 \to 14$

Ensemble data complexity reduction



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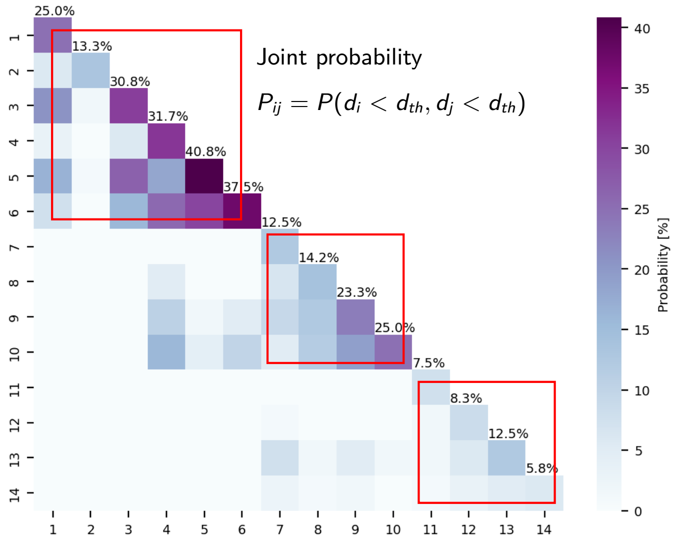

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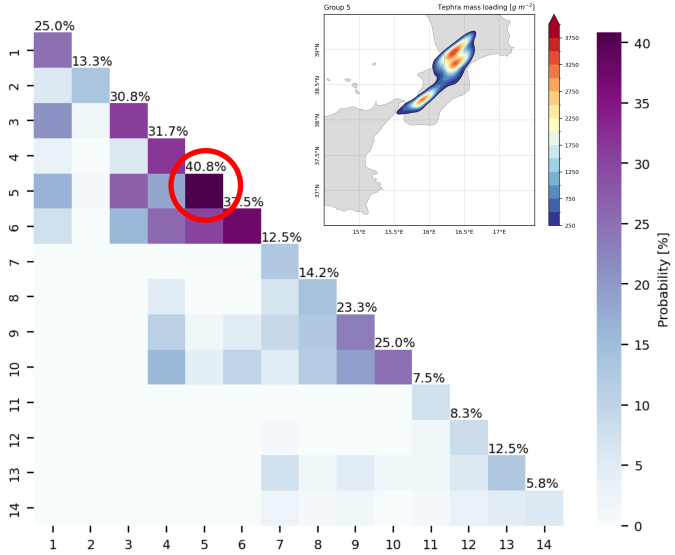

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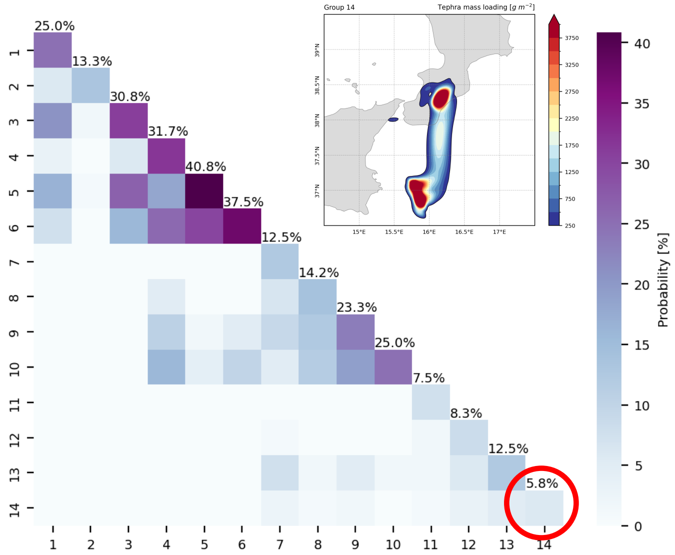

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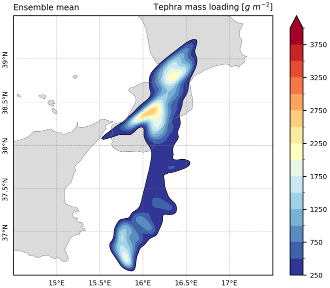
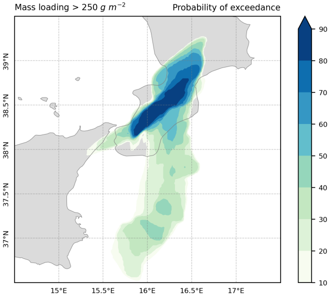
Comparison of model products

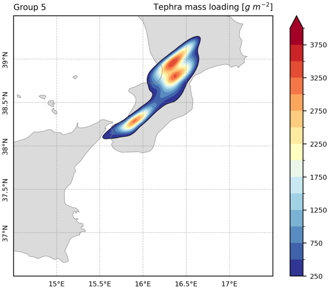


Traditional products

← Ensemble mean

Probability of exceedance →

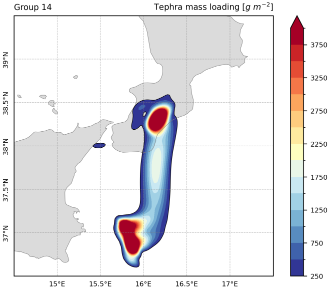




Reduced ensemble

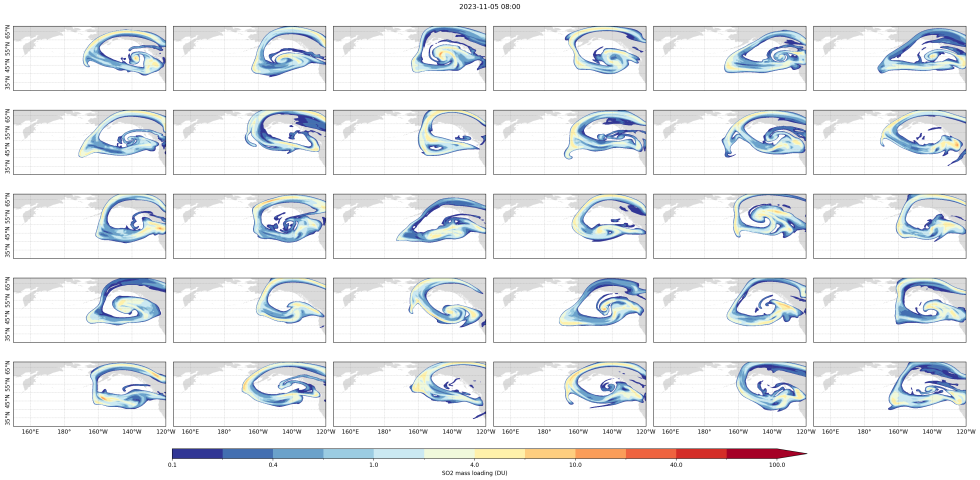
← High probability state (41%)

Low probability state (6%) →



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



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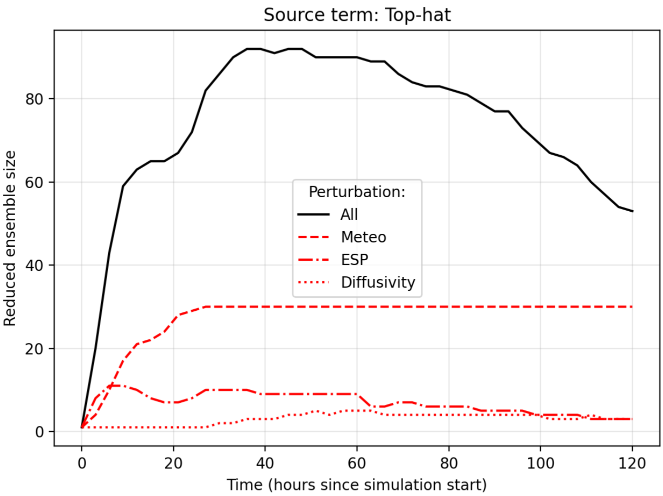


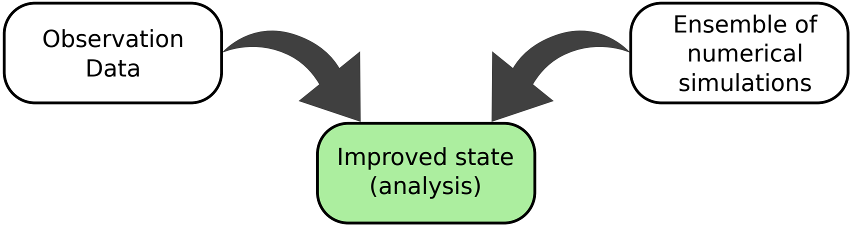
- Minimum ensemble size required
- Sensitivity

	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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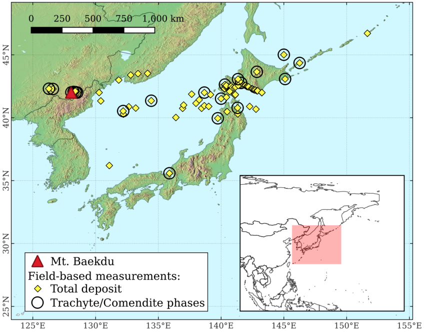
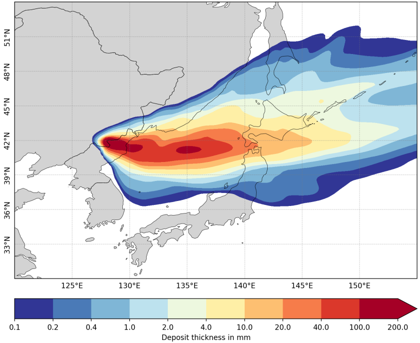


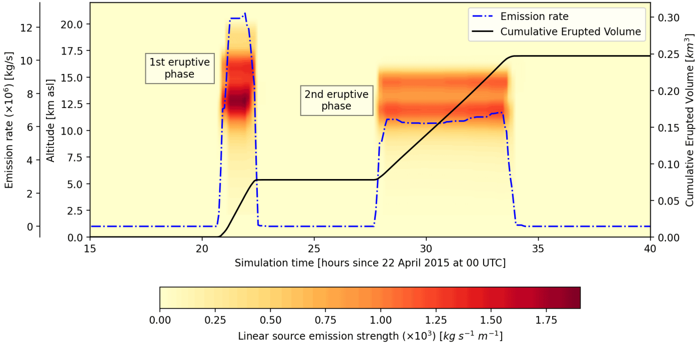


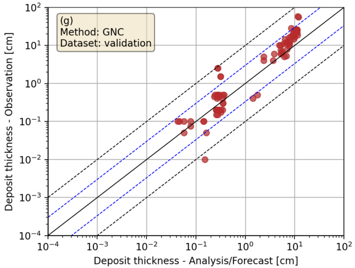
Millennium eruption

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 are useful?
  - Whenever the ESP or meteorological conditions have large uncertainties
  - If forecast errors must be quantified
  - If observations are available to be assimilated
  - When the emission source needs to be characterised
- How should the ensemble be constructed? Which variables should be perturbed? What's the minimum ensemble size required?
  - We gave a preliminary insight into which parameters are the most sensitive
  - What is the minimum ensemble size corresponding to each case
- How interpret and deal with large volumes of ensemble data? Which probabilistic output products are relevant?
  - We proposed a complexity reduction technique in order to identify qualitatively different states in the ensemble
  - We obtained approximate solutions of the physical model, including the state that is most likely to be sampled, and assigned a probability to each state
  - These physically consistent states can be compared directly with satellite images
- Are the traditional assimilation methods suitable for the atmospheric dispersion of volcanic species?
  - Traditional data assimilation methods lead to suboptimal performance in the case VATD models
  - We propose a new ensemble-based data assimilation method which outperforms the classical EnKF method when is applied to VATD models