Using stochastic NWP ensembles for volcanic ash transport and dispersion model outcomes

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Abstract

Ash clouds ejected into the atmosphere by volcanic eruption extend over large areas and can travel thousands of kilometers from the source volcano, disrupting air traffic and posing a significant hazard to air travel. They are spread by winds as diffuse clouds of small particles having insufficient reflectance for detection by weather radars onboard aircraft. The PUFF model simulated the ash transport and dispersion for the eruption of Eyjafjallajokull, Island which had a peak ash emission in the period 15-20 April 2010. An important input parameter for such simulations are wind fields. They represent one of the major sources for uncertainties in ash transport and dispersion simulations. Ensemble methods are considered to be an effective way to estimate the probability density function of future states of the atmosphere by addressing uncertainties present in initial conditions and in model approximations. To generate localized wind ensemble we are using the Weather Research and Forecast (WRF) model with various initial conditions. We examine the spatial variability of the wind fields as well as their uncertainty by using two methods to simulate uncertainty on initial conditions.

I. GEFS Ensemble

GEFS ensembles account for uncertainty in the initial conditions using the breeding vectors approach [1]. The breeding method is based on the idea that the analysis that we get out of the data assimilation cycle will accumulate growing errors when it is recycled from one data assimilation cycle to the next. We are using the 21 GEFS ensemble.

GEFS Ensemble Members

Figure : Wind direction in deg, lat 60.13 and lon -1.18, April 17 2010 00Z

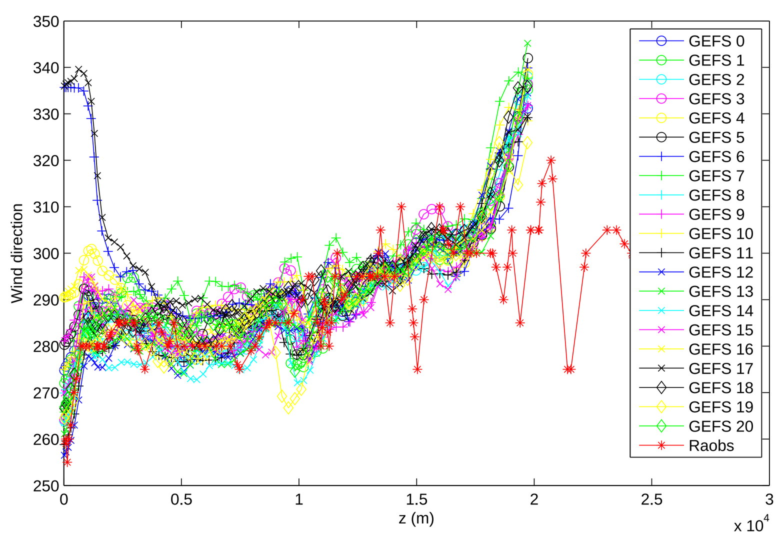
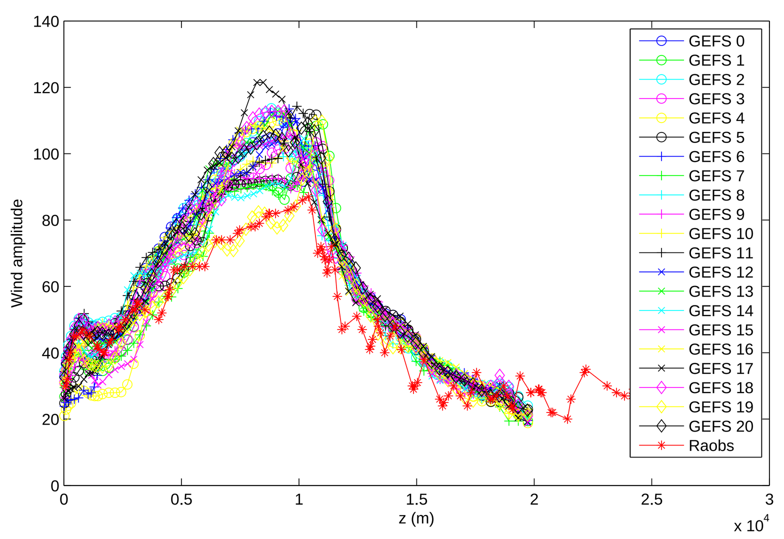


Figure : Wind amplitude in knots, lat 60.13 and lon -1.18, April 17 2010 00Z

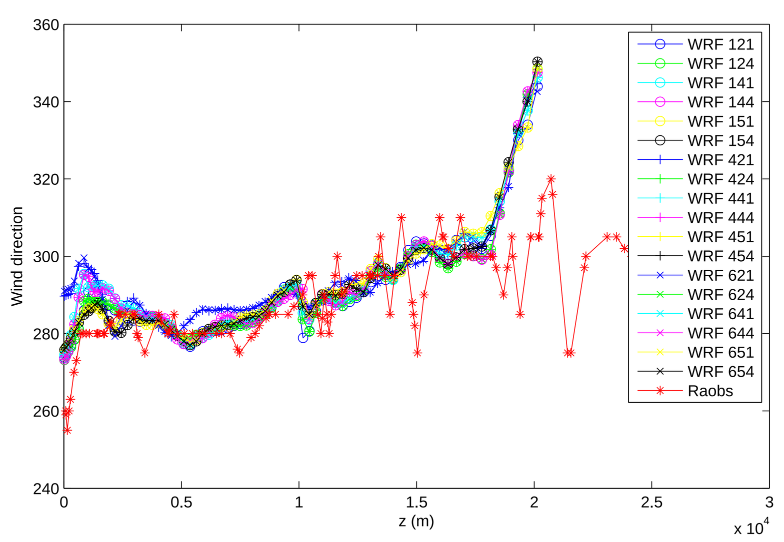


II. Multi-model Ensemble

To account for uncertainties due to model imperfections, a set of model physics runs can be conducted. The members of the WRF ensemble can be considered as independent estimated wind speeds. However, these estimates may not be equally likely and hence the ensemble needs to be calibrated using the BMA technique.

Multi-model Ensemble Members

Figure : Wind direction in deg, lat 60.13 and lon -1.18, April 17 2010 00Z



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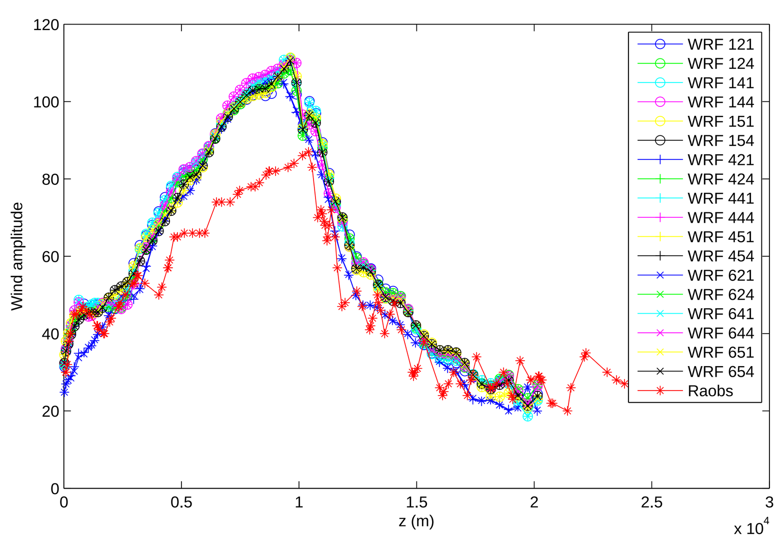


Bayesian Model Averaging (BMA) [2]

The BMA predictive PDF of the weather quantity to be forecast is a weighted average of PDFs defined around each individual bias-corrected ensemble member. The weather quantity to be forecast, y, is wind whose behavior can be estimated by a gamma distribution [2]. A Gamma distribution, $g_k(y \mid f_k)$, is defined around each individual forecast, f_k, conditional on f_k being the best forecast in the ensemble. The BMA predictive PDF is then a conditional probability for a forecast quantity y given K model forecasts $f_1, \ldots, f_k$, and is given by:

$$p(y \mid f_1, \ldots, f_k) = \sum_{k=1}^{K} w_k g_k(y \mid \tilde{f}_k)$$

where w_k is the posterior probability of forecast k being the best one, and is based on forecast k's skill in the training period. The component gamma PDF of wind speed is given by:

$$g_k(y \mid f_k) = \frac{1}{\beta_k^{\alpha_k}\Gamma(\alpha_k)} y^{\alpha_k - 1} \exp(-y/\beta_k)$$

with

$$\mu_k = b_{0k} + b_{1k} f_k$$

and

$$\sigma_k = c_{0k} + c_{1k} f_k$$

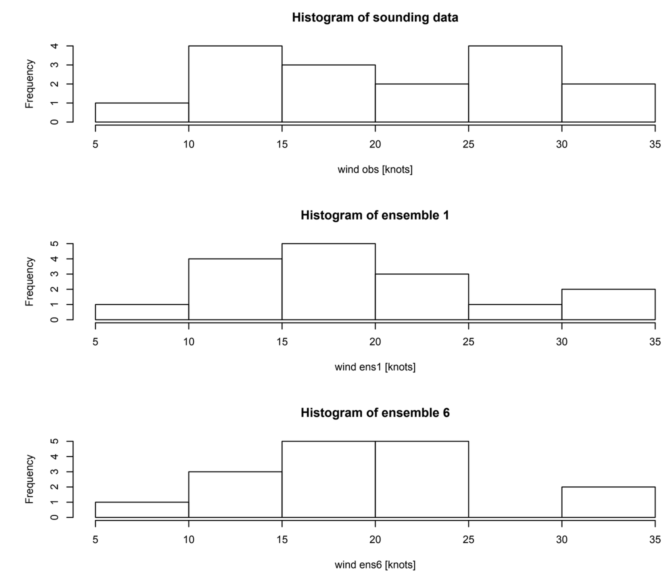
where $\mu_k = \alpha_k\beta_k$ is the mean of the distribution, and $\sigma_k = \sqrt{\alpha_k}\beta_k$. It is assumed that the standard deviation is constant across all ensemble members $\rightarrow c_{0k}$ and c_{1k} terms are replaced with c_0 and c_1.

Multi-model Ensemble Members

Table : Combinations of WRF model parameters. Microphysics: 1, Kessler; 4, 5-moment; 6, 6-moment. PBL: 2, Mellor-Yamada-Janjic; 4, Quasi-Normal Scale Elimination; 5, Niino Level 2.5. K: 1, Constant; 4, 2D deformation.

Microphysics	PBL	K
1	2	1
1	2	4
1	4	1
1	4	4
1	5	1
4	2	1
6	2	1

Figure : Observational data compared to two ensembles.



Results

Figure : BMA predictive PDF - Sounding LERW

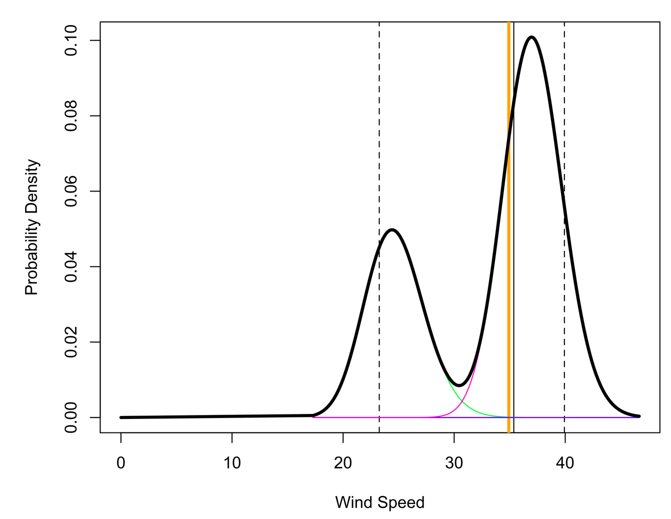
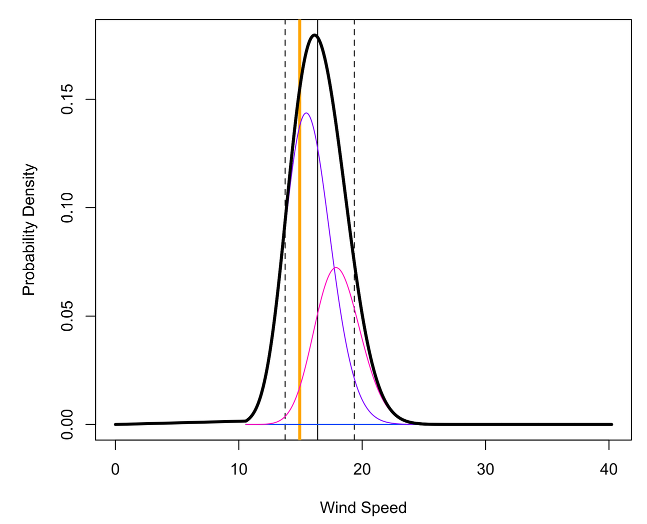


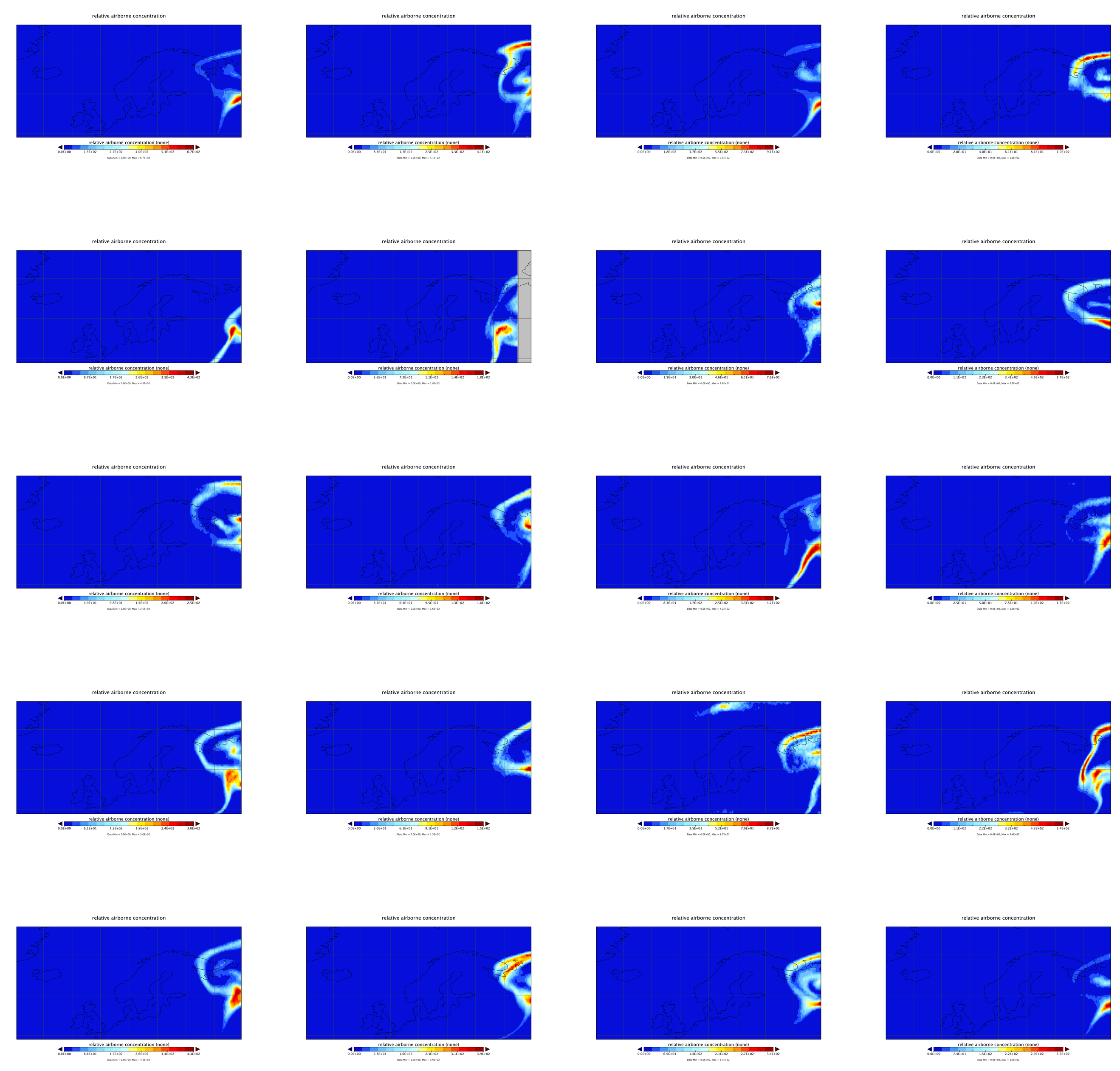
Figure : BMA predictive PDF - Sounding Praha



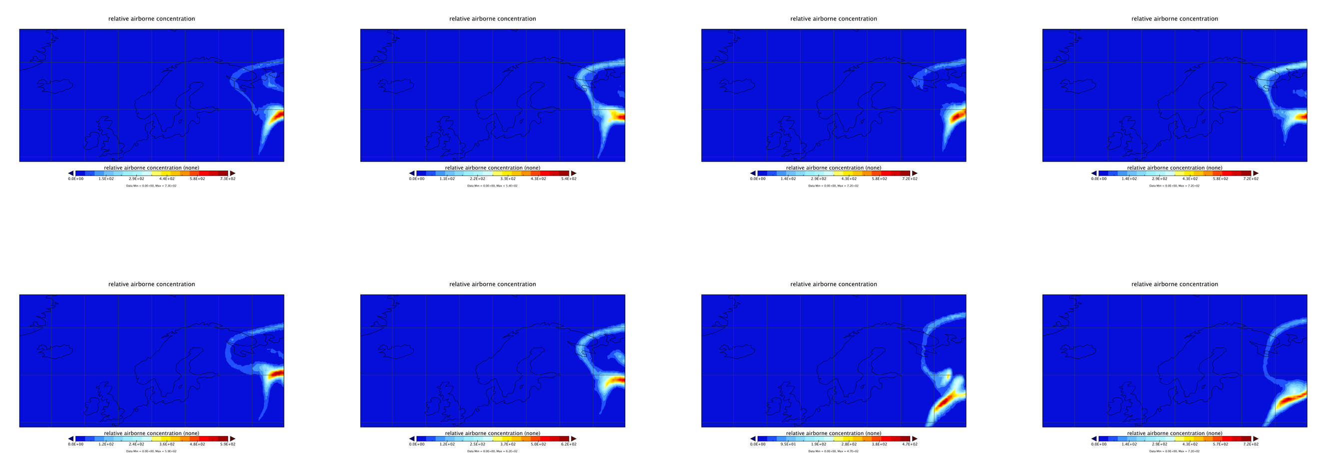
References

1. Toth, Z. and Kalnay, E. (1997) Ensemble forecasting at NCEP and the breeding method. Mon. Wea. Rev., 126, 3292-3302
2. Sloughter, J.M., Gneiting, T. and Raftery, E. (2010) Probabilistic wind speed forecasting using ensembles and Bayesian Model Averaging. J. of the Amer.Stat. Assoc., 105

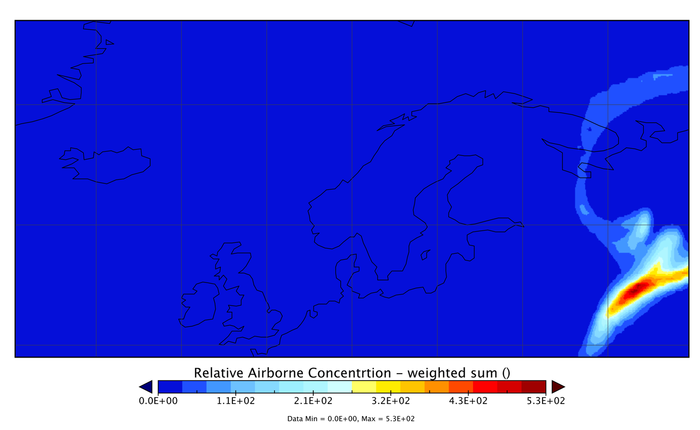
Puff Output - GEFS



Puff Output - Multi-model



BMA - Multi-model mean



Conclusions

We have used two methods to account for wind uncertainty in ash transport modeling: GEFS ensemble and WRF Multi-model ensemble. BMA was used to estimate weights for the mult-model ensemble, allowing us to calculate moments. Our next step is to explore methods for combining the results of the GEFS and multi-model ensembles.