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UNCERTAINTY STUDIES ON AN ATMOSPHERIC DISPERSION MODEL WITH MONTE CARLO METHOD

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Abstract: The atmospheric dispersion models developed at IRSN (Institute for Radiation Protection and Nuclear Safety) are used in emergency situations to evaluate the environmental and healthcare consequences due to an accidental release of radionuclides. Simulations contain uncertainties, which come from models' errors and approximations and from input data (source terms and meteorological data). It is therefore critical to understand, quantify the uncertainties attached to simulations, develop tools and methods to take them into account in the recommendations made to the authorities during a nuclear emergency situation and thus better protect the population.

Currently, the simulations are carried out in a purely deterministic way: the input data as well as the model configuration are chosen and produce a single result. The uncertainties can be represented by an ensemble of simulations, obtained by perturbing the uncertain parameters and by using meteorological ensemble forecasts. The first step in uncertainty modeling is to perturb the parameters. These input parameters are perturbed according to given normal or log-normal distributions. For weather and source terms, we took advantage of ensembles and randomly sampled from them.This makes it possible to obtain an ensemble of entries that broadly covers the input space. The following step is to evaluate the outputs and carry out uncertainty quantification studies. Two questions arise: How does the result respond to a change in the input variables? How can we describe the quality of our ensemble? The comparison between simulations and observations makes it possible to qualify the ensemble, using tools such as rank histograms.

This study presents Monte Carlo simulations for the Fukushima accident case with the Eulerian transport model ldX. It follows the work of Périllat et al. (2017). Simulations are carried out by using the meteorological ensemble forecasts of the European Center for Medium-range Weather Forecast (ECMWF), an ensemble of 6 source terms, and random perturbations on the other inputs. Simulations are compared to radiological observations of activity concentration, dose rate and airborne deposition measurements collected in Japan.

Key words: *Uncertainty, atmospheric dispersion, Monte Carlo.*

INTRODUCTION

Uncertainties in atmospheric dispersion models can be due to different sources : input variables (weather forecasting, source term), physical parameters (deposition velocity, diffusion and scavenging coefficient, etc.), model approximations (representativeness and numerical errors). At the same time, environmental observations are also subject to errors. Therefore, understanding and quantifying these uncertainties is not trivial. Meteorological data is one of the utmost sources of uncertainties. Meteorological ensembles are used on a regular basis to evaluate uncertainties associated to aweather forecasts. Although uncertainties related to dispersion applications may be underestimated by these ensembles, Périllat et al. (2016) already showed the usefulness of this kind of ensembles to simulate the Fukushima accident. However, propagating meteorological ensembles is not sufficient to take into account all uncertainties, that is, create an ensemble spread enough for all radiological observations to be encompassed by the results. The source term, including the amount of emitted radionuclides and timings of releases, is also known as a major source of uncertainties in an accidental situation, both *a priori* (as a forecast) and *a posteriori* (as shown by the Fukushima accident). In this study, an ensemble of seven source terms based on the literature was used, with additional perturbations on some release parameters.

Based on the Fukushima disaster (2011), this study sets up a method to evaluate the uncertainties of the weather forecasting ensemble given by ECMWF (European Centre for Medium-Range Weather Forecasts), and propagate them in the dispersion model, as well as those due to source term and physical parameters, by Monte Carlo method. It complements the study of Périllat et al (2017) which uses similar methods and data but is focused on the local scale. Here, the simulation domain encompasses the whole Japan, and an Eulerian long-range transport model is used. In addition, the validation step deals with the uncertainties in the observations. Here, several questions arise : How can we compare the results of the model with the observations? How can we take into account the errors of the measurements? How can we assess the quality inour dispersion ensemble?

WEATHER ECMWF ENSEMBLE

First, we evaluate the meteorological. The ECMWF provides an ensemble of meteorological forecasts, which contains 50 members with 0.25° of horizontal resolution and three-hour time step. These meteorological data are made of 12 to 36-hour forecasts retrieved for each simulated day (the overall simulation period is three weeks). The ensemble used for date J comes from an analysis ensemble at noon of date J-1 and it is only used between 0h and 21h of date J. This allows to construct an ensemble of weather forecasts slightly more scattered than a more recent ensemble. This also avoids small physical inconsistencies that may arise at the assimilation time. Furthermore, a delay of several hours between the weather forecast assimilation update and its availability for dispersion use is representative of the conditions of an emergency crisis.

With the help of the meteorological observations from the network AMeDAS[1], we obtained a set of more than 600 measurement stations everywhere in Japan. We qualified the weather forecasting ensemble via the time series and the rank histograms for some variables : temperature at 2 m, rain, wind module and wind direction at 10 m. Since the meteorological resolution is quite large (about 25 km x 25 km), any cell can contain different reliefs and several measurement stations. If in one cell, the first station is in the valley and the other in the mountain, the observations can behave differently. Furthermore, the meteorological simulation gives the spatial mean of the whole cell. For this reason, in every grid cell, we compared the ECMWF forecasts with the averages across all the stations.

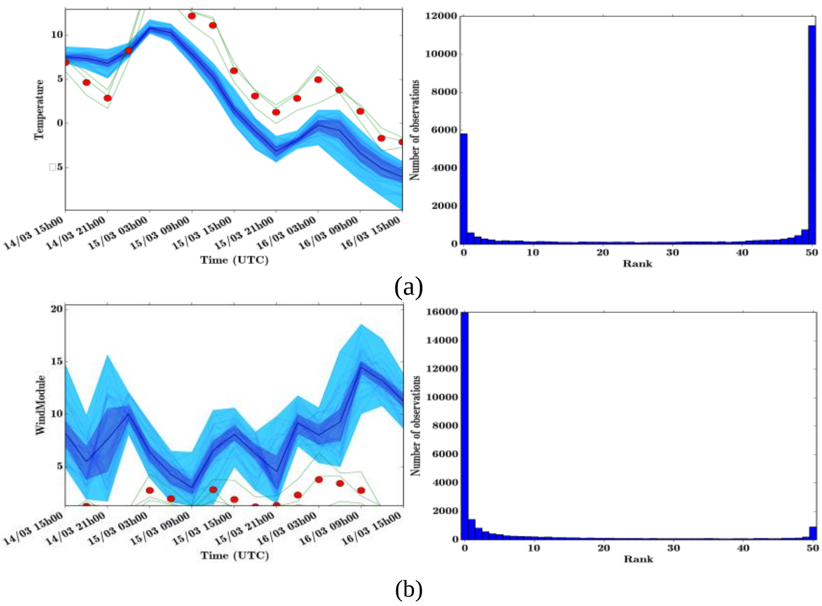

Figure 1. Comparison to observations and rank histograms for the variables 2-m temperature (a), 10-m wind module (b) in cell 571, which contains three stations : Nagiso (longitude = 137.62°, latitude = 35.61°), Ena (137.403°, 35.45°) and Nakatsugawa (137.49°, 35.48°). The red points are the spatial means of observations in this cell, the green lines are the observations at the three previous stations and the blue band is the ensemble envelop.

In **Figure 1**, the rank histograms are both U-shaped, even though averaging across the stations in each grid cell (**Figure 1**) helped. This means that the meteorological ensemble is under-dispersed and does not catch all uncertainties. U-shaped diagrams are usual in meteorological applications, since model errors

[1] Automated Meteorological Data Acquisition System (http://www.jma.go.jp/en/amedas/)

and physical approximations are not perfectly represented, especially within the atmospheric boundary layer. Another reason may be the role of representativeness error in the model-to-data comparison but also to meteorological observations errors. According to Bowler et al. (2009), we can take the measurement error into account by perturbing each member of the ensemble by a random number following a Gaussian distribution with zero mean and standard deviation equal to that of the observational error. For precipitation, a log-normal distribution with zero mean and standard deviation of 0.1 mm/h is suggested but the rank diagram did not improve. That could be explained by the difference in accuracy between Japanese and European rain gauges. We have then applied a perturbation following a uniform distribution for the precipitation, based on the Japanese rain gauge precision (0.5 mm/h). The perturbation values are given in **Table 1**.

Table 1 Meteorological observation errors following Bowler and Mylne (2009)

Variables	Distributions	Standard deviation or error range
Temperature	Gaussian	1.5 K
Wind module	Gaussian	1.7 m/s
Precipitation	Uniform	[-0.5 mm/h, 0.5 mm/h]

As shown in **Figure 2**, the previous perturbations make the ensemble more scattered and therefore, it better covers the observations. The outliers of rank diagrams shrink as well, but a bias remains, which probably arises from representativeness issues.

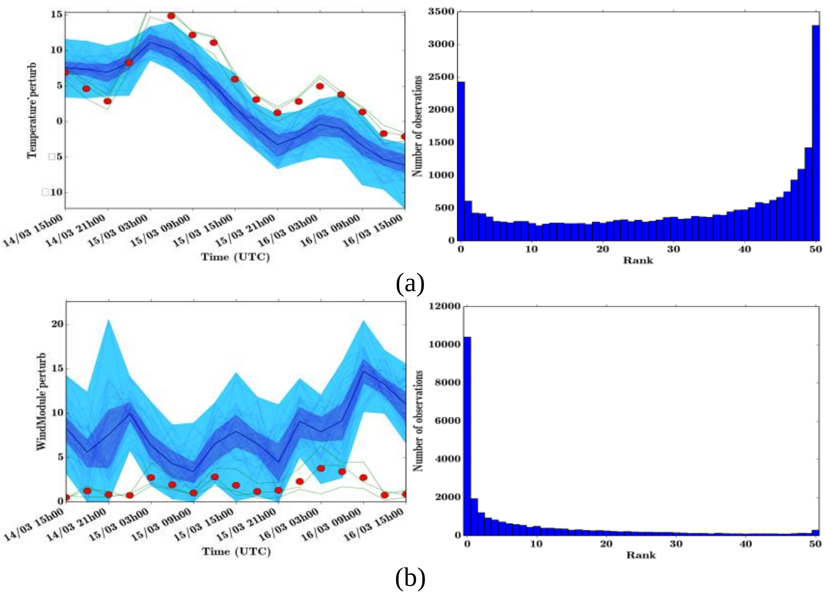

Figure 2. Comparison to observations and rank diagrams of perturbed meteorological ensemble for 2-m temperature (a) and 10-m wind module (b) of the same cell as in Figure 1 (cell number 571).

MONTE CARLO PERTURBATIONS

Once all sources of uncertainties have been identified and evaluated to the best of our knowledge, we sample them according to given probability distributions. As shown in **Table 2**, we have reused the same variation as Girard et al. (2014), except for the meteorological variables whose uncertainties are already represented by the 50 members of the ECMWF ensemble. A set of seven source terms from the literature and from IRSN studies was used. All of these are a posteriori source terms, derived from radiological measurements and dispersion modeling (reverse or inverse methods).

Table 2 Monte Carlo perturbation of ldX inputs

Variables	Methods	Variation spaces
Emission factors	Log-normal	[1/3, 3]
Source elevation (m)	Discrete	[20, 100, 220, 340]
Emission delay (hours)	Truncated normal	[-6, 6]
Weather forecast member	Discrete	[1, 50]

Source term	Discrete	[Katata, Terada, Mathieu and al., Saunier and al., IRSN inversion 1, IRSN inversion 2]
Scavenging factor a (s^{-1})	Uniform	[10^{-7}, 10^{-4}]
Scavenging exponent b	Uniform	[0.6, 1]
Vertical diffusion	Uniform	[1/3, 3]
Horizontal diffusion	Uniform	[0, 1.5] x 10^{4}
Dry deposition velocity (m/s)	Uniform	[5 x 10^{-4}, 5 x 10^{-3}]

RESULTS OF LDX

The long distance model ldX is an adaptation of Polair3D, an Eulerian advection-diffusion-transport model, used for nuclear emergencies by IRSN. In output, we are interested in the concentration of radionuclides in the atmosphere (air activity concentration in Bq/m^3), their deposited amount on the ground (deposition in Bq/m^2), as well as the gamma dose rate (radiation emitted from nuclides both in the air and on the ground, in Gy/h). Following the Fukushima disaster numerous measurements of these three categories were available throughout Japan. They are used here for the evaluation of an ensemble of 200 Monte Carlo simulations. In activity comparisons, the simulations tend to highly overestimate the plume during the first major contamination episode (14 – 16 March) and underestimate the second one (20 – 22 March). The rank diagram is largely U-shaped (**Figure 3**). This can most probably be explained by representativeness errors. Unfortunately, the spatial coverage of monitoring stations is not sufficient to successfully use spatial averaging, as for the meteorological observations. While some cells contain several stations, they tend to be clustered in the same area of the grid cell. For gamma dose rates, the simulations have difficulties to identify the start of wet deposition. This can be explained by the uncertainties in the simulation of the light rains, which can be responsible for a large increase in dose rate due to wet scavenging. Besides, gamma dose rate stations also suffer from an uneven distribution over the Japanese territory and a high redundancy in time, which hinders the interpretation of the rank diagram (**Figure 4**). Finally, the spatial coverage of deposition is very good and, although there is still the problem of information redundancy between neighbouring points, the rank diagram is largely better (**Figure 5**). However, the rank map of **Figure 5** presents a strong underestimation in steeply contaminated area.

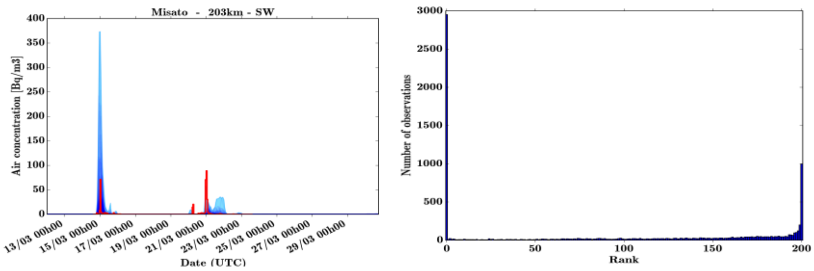

Figure 3. Concentration of Caesium 137 at Misato (203 km to the south-west of source) and the rank diagram of Cs-137 activities.

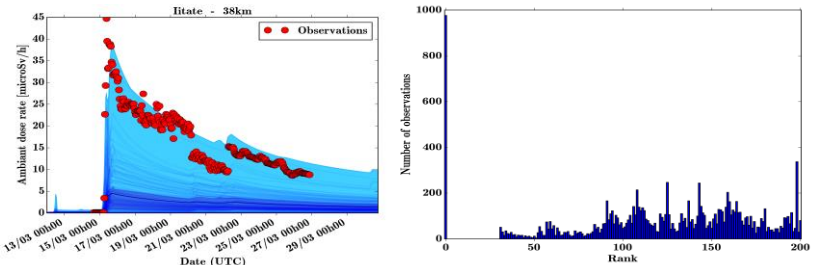

Figure 4. Gamma dose rate of caesium 137 at Iitate (38 km to the south-west of source) and rank diagram of dose rate.

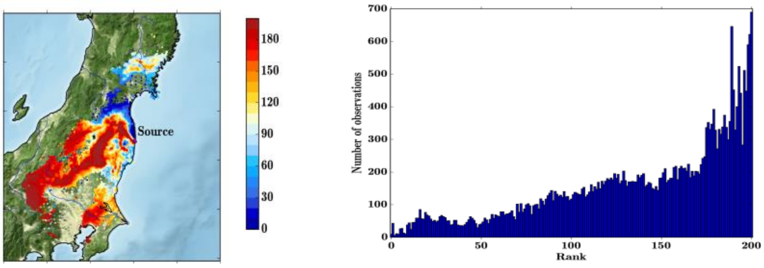

Figure 5. Rank map and rank diagram of the final deposition of Caesium 137. The rank map represents the rank of observation with respect to the weather ensemble. When a point is red, all members of the ensemble are below the observation. When the point is blue, the observation is below all members of the ensemble.

CONCLUSION

Meteorological ensembles were successfully combined with a Monte Carlo method for dispersion simulations of the Fukushima accident. This allowed to take into account all sources of uncertainties and compare the results with radiological observations. These comparisons show that our *a priori* knowledge of input uncertainties is not sufficient to properly encompass all observations. Source term uncertainties and errors on light rains, for instance, are probably not well modeled. Besides, representativeness and measurement errors are not taken into account. The comparison to meteorological observations showed that these two kinds of errors are essential and cannot be neglected in model-to-data comparisons. Thus, an important improvement will be to take into account errors in observations of volume activity, dose rate and deposition and also the spatial and temporal redundancy of measurements. Once the uncertain variables of the model are identified, their distributions can be inferred by applying a calibration method on the basis of the observations. A study based on Bayesian calibration and ensemble indicators is planned.

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