Modeling nuclear accidents using an atmospheric transport model and the particle filter

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1. Introduction

In the event of a nuclear accident at a power plant, a good insight in the spatial distribution of radiation is important for taking countermeasures. A useful tool in this setting is an atmospheric transport model. These models (e.g. Brandt et al. 2000) simulate the spread of radiation accounting for, among others, wind direction, wind speed, stability of the atmosphere and radioactive decay. In addition to the model, information comes from radiation monitoring networks. The challenge that faces the modeller is to model the spread of radiation combining the information from the the atmospheric transport model and the monitoring network.

The most basic approach is to let the modeller make an expert judgement of the parameters given the observations from the monitoring network and his own experience. A more formal and objective approach would be to calibrate the model on the observations (e.g. Haupt et al. 2009). Alternatively, a probabilistic approach is to use sequential data assimilation. This involves defining the uncertainty in the model and the observations and how these develop in time. At any given time the best model, given the data, can be obtained from this. Data assimilation techniques include the extended kalman filter (Rojas-Palma et al. 2003) and the ensemble kalman filter (Zheng et al. 2010). The main drawback of the kalman type algorithms is that they do not perform well for non-linear models (Simon 2006), such as atmospheric transport models.

A popular data assimilation method, well suited for nonlinear models is the particle filter (Risfic et al. 2004). The particle filter samples parameter settings from probability distributions of the model inputs, generating a set of possible model solutions. Comparing those possible solutions to observations allows the particle filter to choose which solution performs well, and should be allowed to continue while bad performing solutions are eliminated. This process is called *resampling* in particle filter terms. The particle filter is a numerical Bayesian estimator, estimating the best probability distribution of the model given the observations.

In this paper we present results of using an atmospheric transport model in combination with a particle filter. The results involves using the ETEX tracer dataset. We compare a Monte Carlo approach, no monitoring network observations are used for assimilation, to two particle filter runs with increasing amounts of data used for assimilation. In this case Monte Carlo acts as a base line, allowing us to estimate the performance of the particle filter.

2. Background

2.1 ETEX tracer dataset

During the ETEX experiment, a non-reactive tracer (PMCH) was released into the atmosphere on two seperate occasions (Nodop et al. 1998) at Rennes located in the North-West of France. In this study we focus on the first ETEX release. At 16:00 GTC on October 23 1994 the first release of tracer started and lasted for 12 hours. During the experiment a network of 168 stations across Europe monitored the spread of the PMCH, recording the amount of PMCH above background levels in ng/m^3. Nodop et al. (1998) gives a very detailed description of both ETEX releases.

2.2 NPK-PUFF model

The NPK-PUFF (Verver and de Leeuw 1992) model is used to simulate the spread of PMCH following the release. NPK-PUFF is a so called Lagrangian puff atmospheric transport model. The model solve the continuous release of radioactive material by releasing so called puffs every timestep (Brandt et al. 2000). These puffs are gaussian shaped ellipsoids that are advected according to meteorological information. The puffs grow as they travel. In addition, processes such radioactive decay are also taken into account.

2.2 Particle Filter implementation

The particle filter samples from the probability distributions of the input parameters, e.g. wind speed and wind direction, to create a set of possible model outcomes, particles. When observations are available, this set of particles is compared to the observations, calculating the performance of each particle. Well performing particles are copied and poorly performing particles are eliminated. In this way the best model outcome, given the observations, is obtained.

In this study we chose to treat following model inputs randomly: wind direction, wind speed and lateral diffusion of the radiation. For the wind direction for each particle we drew a rotation angle form a normal distribution with zero mean and standard deviation of 20 degrees. This rotation angle was used to rotate the entire wind field. For the wind speed we uniformly drew a factor from the range 0.5 to 2, taking care to get an equal amount of samples between 0.5 to 1 and 1 to 2. In regard to the lateral growth we uniformly drew between 1/3 and 3. Resulting in particles that vary in diffusion rate between three times as slow and three times as fast as the standard NPK-PUFF diffusion rate.

When calculating the performance of each particle, we used the normal weight function as described in Simon (2006). We used 300 particles in our analysis. Using less particles speeds up calculations. However, the risk of having too little particles to accurately describe the probability density functions of the input variables also increases. The amount of 300 particles presented a good compromise. For resampling we used the Sequential Importance Resampling scheme described by Gordon et al. (1993).

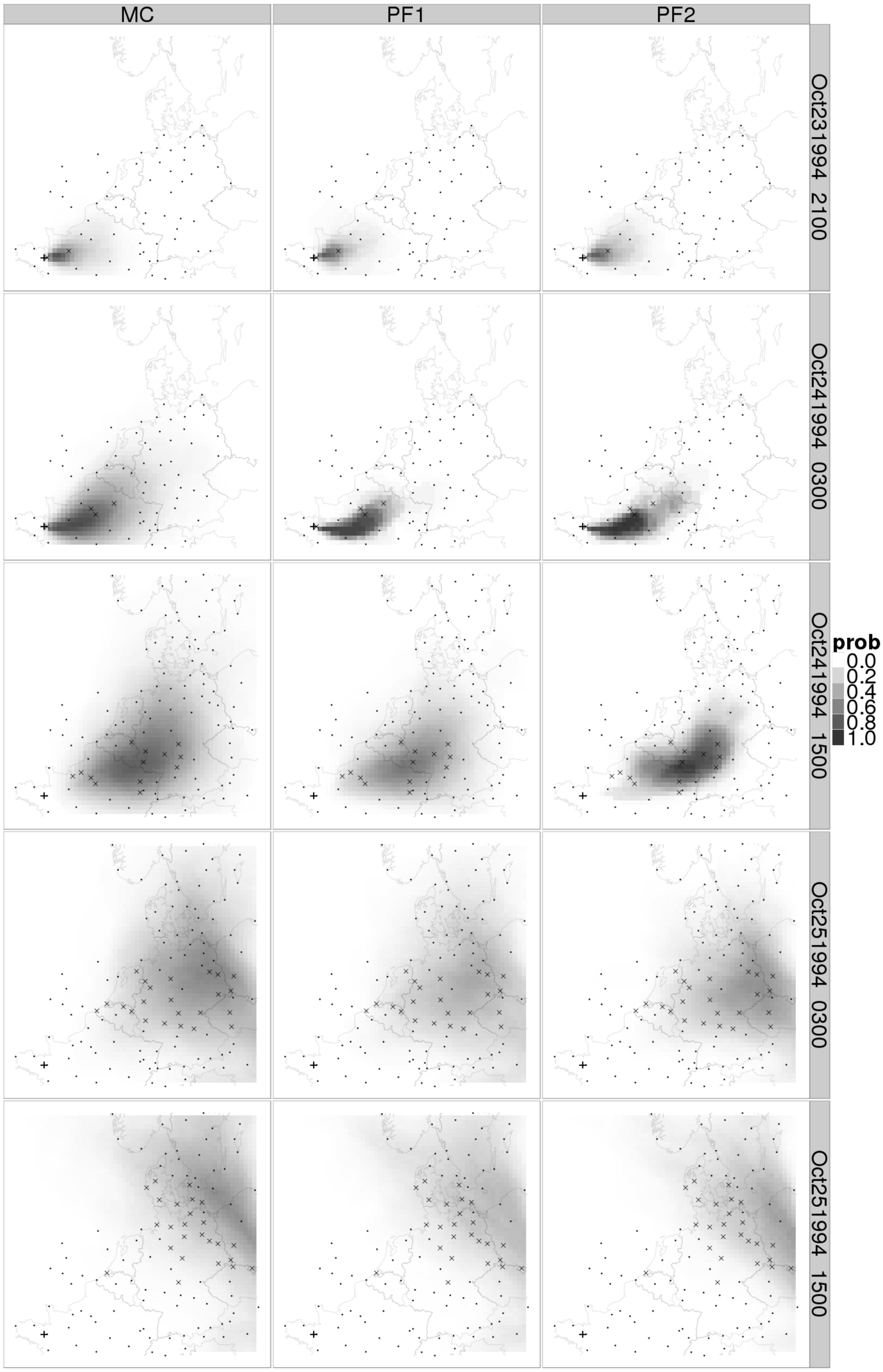

Figure 1: Development in time (rows) of the exceedance probability of 0.1 ng/m^3 for the three modeling options (columns). The dots mark observations below the threshold and the crosses mark observations above the threshold. The large cross shows the release location.

3. Preliminary results

In this paper we compared three runs that consist of a set of possible model outcomes. One is Monte Carlo (MC), which does not use any data to update the model. The other two use the particle filter, where one uses observations on three moments in time (PF1) and the other on seven (PF2). Figure 1 shows these runs in a lattice of spatial plots, where the color represents the probability of exceeding 0.1 ng/m^3. The columns in the lattice of plots show the different runs, the rows show different time steps. By using this low threshold the maps show the spatial extent of the set of particles. In addition to the color, the observations from the monitoring network are also shown. Dots are observations below the threshold and crosses above the threshold. Important to note is that run PF1 stops assimilating data at the second row in figure 1 and run PF2 at the third row.

From figure 1 it is obvious that the particle filter keeps the set of model outcomes closer to the observed values, presenting a much better estimate of the spatial distribution of radiation levels. Run PF2 performs better than PF1 after row number two, which is to be expected because in that case observations are still used to improve the model. The last row in figure 1 shows that after some time the improvement of assimilating data becomes smaller.

Figure 2 shows the development of the Mean Squared Error through time for the three runs. The vertical lines represent times that data is used to improve the model. This figure supports the results from figure 1, PF1 and PF2 outperform MC when data is assimilated. After a while the improvement of assimilating data is gone.

4. Preliminary conclusions

In this study the NPK-PUFF atmospheric transport model was used to simulate the spatial distribution of PMCH tracer follwing its release. Three scenarios were generated, where one used no data to improve the model (Monte Carlo) and the other two where particle runs with increasing amounts of observations. Comparing these three scenarios to the observed PMCH tracer observations allowed us to asses the performance of the particle filter.

The preliminary results from this study show that the particle filter is successful in modelling the spread of a tracer following a release. In addition, it also shows an improved performance to Monte Carlo which does not use observations to improve the model outcomes.

Our focus for future research will be on how to make decisions, e.g. evacuation, based on the results from the particle filter. Issues in this context include how to make a boolean decision based on a probability distribution and see how errors in the model and errors in the inputs of the model impact the decision.

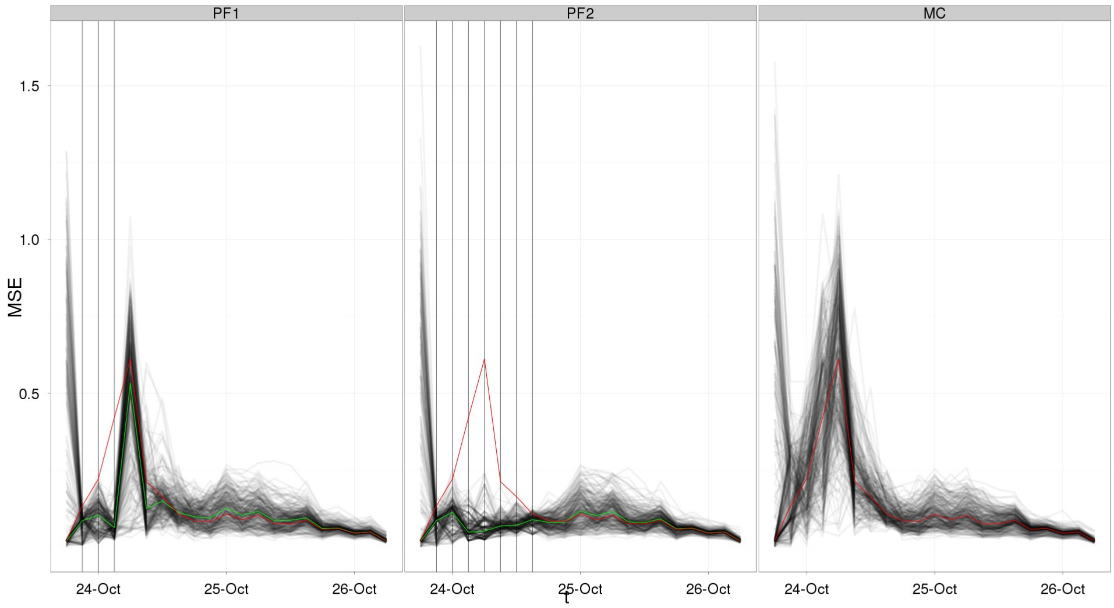

Figure 2: Development of Mean Squared Error in time. Vertical lines represent assimilation moments.

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