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EXTENDED ABSTRACT

Ensemble atmospheric dispersion modelling of a near-range selenium-75 emission

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Introduction

On May 15th, 2019, an incident in a hot cell at the Belgian Reactor 2 (BR2) on the SCK CEN campus in Mol led to the accidental release of radioactive selenium-75 (Se-75) into the atmosphere via the facility’s ventilation stack. The release originated from a Se-75 capsule under production, with an initial puff discharging approximately 1.49 10^{10} Bq of Se-75, followed by residual emissions at orders-of-magnitude lower levels over subsequent months.

Two releases stages could be identified: the initial puff and the residual release. The initial puff was detected by the TELERAD network — a nationwide radiological surveillance and early-warning system comprising gamma dose rate sensors. The residual release was composed by trace Se-75 concentrations, which were later identified on aerosol filters in northwestern France by the Institute for Radiological Protection and Nuclear Safety.

Previous investigations by Frankemölle et al. (2022) and De Meutter and Hoffman (2020) examined both the source term reconstruction and local-scale dispersion of Se-75, employing atmospheric dispersion models to analyse both the initial puff and residual release. Frankemölle et al. (2022) specifically conducted Gaussian plume simulations using on-site meteorological data and validated their results by comparing modelled ambient dose equivalent rates with observations from Belgium's TELERAD monitoring network[1]. These comparisons demonstrated that the simulations provide a consistent representation of Se-75's near-range dispersion patterns.

This previous work demonstrated the effectiveness of Gaussian dispersion models in simulating local-scale transport for well-characterized releases. However, when using dispersion models to predict hazardous material concentrations near release sites, it is

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1 While simulations were performed for both release stages, the current study focuses exclusively on the initial puff

equally important to quantify the associated prediction uncertainties. Ensemble Dispersion Modeling (EDM) addresses this need by running multiple dispersion simulations (ensemble members) and analysing their statistical distribution, providing a probabilistic perspective on potential dispersion patterns (Galmarini et al., 2004). Among the various EDM methodologies available, this study specifically examines two key approaches: (1) a multi-model ensemble technique and (2) the use of ensemble meteorological fields as input to the dispersion model.

A key challenge in uncertainty quantification is ensemble under-dispersion (or overconfidence), where the ensemble members fail to capture the full range of uncertainties inherent to the predictions. This issue is particularly pronounced at short spatial scales, where perturbations in initial conditions have limited time to develop. While various techniques exist to enhance ensemble spread — some involving complex mathematical formulations that increase model complexity — this study explores two straightforward approaches: (1) incorporating earlier ensemble forecast initializations into the meteorological inputs (e.g. increasing the lead time of the forecast), and (2) examining how a multi-model strategy affects dispersion uncertainty. These methods provide practical alternatives to more computationally intensive solutions while effectively addressing under-dispersion.

Methodology

This study employs two complementary dispersion modelling approaches: the Lagrangian particle model FLEXPART (Pisso et al., 2019) and a Gaussian plume formulation. FLEXPART simulates atmospheric transport through stochastic tracking of fictitious particles, incorporating processes of advection, convection, and deposition driven by ECMWF meteorological inputs. The Gaussian plume implementation was developed using the GaussianDispersion.jl Julia package, employing standard Pasquill-Gifford stability classifications with Briggs dispersion coefficients. Both models were forced with consistent wind fields interpolated from the same ECMWF datasets, ensuring comparable boundary conditions for model intercomparison.

An array of gamma dose rate detectors monitors the vicinity of the BR2 facility. Figure 1 shows their geographical distribution alongside the time-integrated concentration (TIC) field from our deterministic FLEXPART simulation. These detectors provide 10-min-average measurements of the ambient dose equivalent rate $\dot{H}^*(10)$(Sv/s). To enable direct comparison with the dispersion model outputs, we converted simulated concentration fields to dose rates using the Healy and Baker (1968) formulation for air kerma rate calculation, subsequently applying the ICRP 74 (ICRP, 1996) conversion coefficients to obtain ambient dose equivalent rates. This methodology follows the approach detailed in Frankemölle et al. (2022).

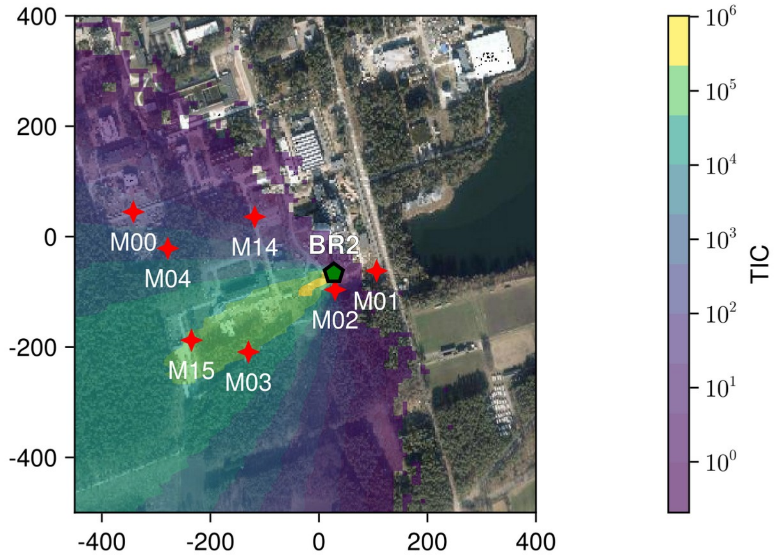

Figure 1: Time Integrated Concentration (TIC) [Bq s/m³] of the FLEXPART deterministic simulation in the vicinity of the release, with the locations of the gamma dose rate detectors and the BR2 facility. The spatial unit is in meter.

The dispersion models were driven by meteorological inputs from ECMWF's operational archive, including both deterministic forecasts and Ensemble Prediction System (EPS) data. The EPS comprises 50 ensemble members available at 3-hourly intervals, each serving as input for separate dispersion simulations with both models. To enhance the ensemble size, we incorporated four additional forecasts initialized at 12-hour intervals prior to the first initialization time (2019-05-15 at 00:00, 2019-05-14 at 12:00, 2019-05-14 at 00:00, 2019-05-13 at 12:00, and 2019-05-13 at 00:00). This approach expanded the total number of dispersion ensemble members to 250 per model. From this ensemble, we derived key statistical metrics including the ensemble mean, the ensemble spread (quantified as the standard deviation from the mean) and the coefficient of variation (defined as the ensemble standard deviation normalized by the mean).

Results

Figure 2 presents the ensemble dispersion simulation results, focusing on TELERAD stations IMR/M03, IMR/M04, and IMR/M15 where measurements exceeded the statistical detection threshold. While IMR/M02 did not meet this threshold, it was included as its signal reveals noteworthy features (discussed subsequently). The results demonstrate consistently greater ensemble spread in the Gaussian plume model compared to FLEXPART, indicating higher sensitivity to meteorological variations with this parameterization. Notably, the highest uncertainty occurs at IMR/M02 - a station initially excluded from formal analysis due to statistically insignificant signals, yet whose measurements show partial temporal alignment with the simulated plume passage (see Section 3.3.2 of Frankemölle et al. (2022) for more details). We can also see that the measurements often falls outside of the standard deviation zone, which means a somewhat under-dispersiveness of the ensemble, even for the most dispersive ensemble.

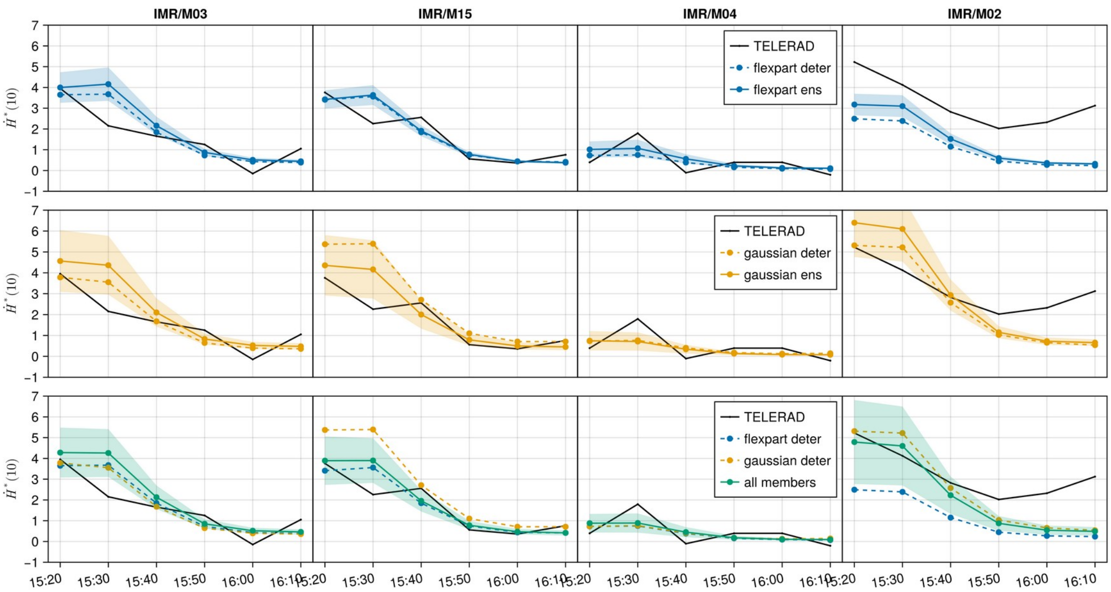

Figure 2: Comparison of background-subtracted ambient dose equivalent rates (in nSV/hour) between TELERAD measurements and ensemble simulations. Black solid lines represent TELERAD measurements, while dashed lines show deterministic simulation results. Ensemble means are depicted as solid coloured lines (blue: FLEXPART; orange: Gaussian plume; green: combined ensemble), with shaded bands indicating the ensemble spread (±1 standard deviation).

To evaluate the influence of forecast lead time on ensemble uncertainty, we calculated the time- and station-averaged coefficient of variation (the ratio of ensemble standard deviation to the mean), presented in Figure 3. The results indicate a systematic increase in Ensemble Dispersion Model (EDM) uncertainty with longer lead times, a trend that generally correlates with the rising uncertainty in the ECMWF wind speed ensemble. However, a misalignment between EDM and wind speed spread is observed at specific lead times (especially 36h and 48h), likely attributable to nonlinearities introduced by the integration process required to convert Se-75 concentration fields to gamma dose rates. Furthermore, the analysis reveals that utilizing accumulated ensembles, as opposed to individual forecast initializations ensemble, has a minimal impact on the overall spread magnitude. The increase in coefficient of variation culminates in a 41% enhancement for the full ensemble (green line on Figure 3) compared to using only the most recent forecast, while the highest uncertainty amplification reaches 152% when comparing the longer lead time of the full ensemble to the lowest lead time of FLEXPART.

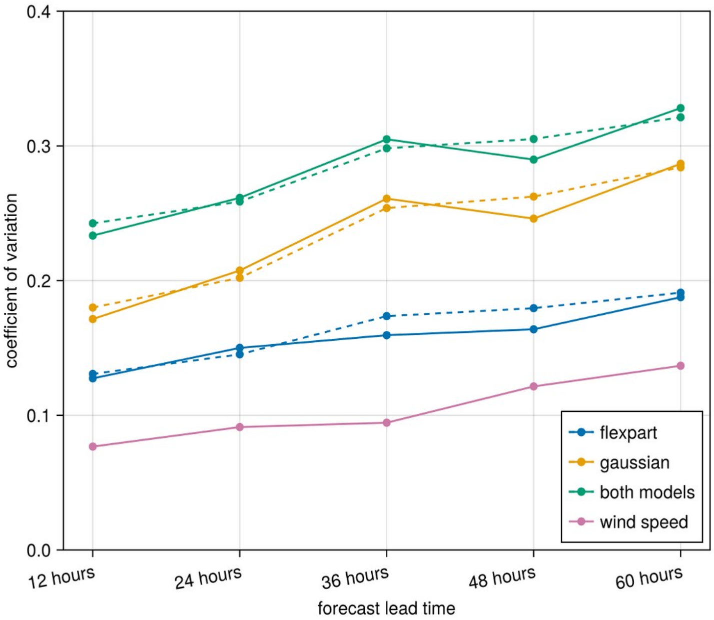

Figure 3: Temporal and spatial average of the ensemble coefficient of variation across all valid detection stations as a function of forecast lead time. Solid lines represent values calculated from individual ensemble forecasts (e.g., a single initialization time), while dashed lines show results from progressively accumulated ensemble forecasts (multiple initialization times). The results for the EDM are shown, along with the wind speed from the ECMWF ensemble.

Conclusion

This study investigated strategies for enhancing ensemble spread in short-range atmospheric dispersion modelling through multi-model integration and the incorporation of multiple forecast initializations. Our findings demonstrate that both approaches effectively increase ensemble dispersion.

Despite these enhancements, the ensembles remained under-dispersive, suggesting that further expansion of the ensemble—potentially through additional forecast initializations—may be necessary. Future work should determine whether spread continues to increase with additional members or eventually reaches an asymptotic limit. While this study provided brief qualitative insights into ensemble skill, the limited observational dataset (n=24) precluded robust quantitative evaluation using standard metrics like rank histograms or RMSE. A definitive assessment of how these methodologies impact predictive skill will require application to a more extensive set of well-characterized release events.

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