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Dynamic Data-Driven Event Reconstruction for Atmospheric Releases

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Dynamic Data-Driven Event Reconstruction for Atmospheric Releases

(A collaborative effort between Computation, Energy & Environment, NHI and Engineering)

Accidental or terrorist releases of hazardous materials into the atmosphere can impact large populations and cause significant loss of life or property damage. Plume predictions have been shown to be extremely valuable in guiding an effective and timely response. The two greatest sources of uncertainty in the prediction of the consequences of hazardous atmospheric releases result from poorly characterized source terms and lack of knowledge about the state of the atmosphere as reflected in the available meteorological data. We have developed a new event reconstruction methodology that provides probabilistic source term estimates from field measurement data for both accidental and clandestine releases.

Accurate plume dispersion prediction requires the following questions to be answered: What was released? When was it released? How much material was released? Where was it released? We have developed a dynamic-data-driven event reconstruction capability that couples data and predictive methods through Bayesian inference to obtain a solution to this inverse problem. The solution consists of a probability distribution of unknown source term parameters. For consequence assessment, we then use this probability distribution to construct a “composite” forward plume prediction that accounts for the uncertainties in the source term. Since in most cases of practical significance it is impossible to find a closed form solution, Bayesian inference is accomplished by utilizing stochastic sampling methods. This approach takes into consideration both measurement and forward model errors and thus incorporates all the sources of uncertainty in the solution to the inverse problem. Stochastic sampling methods have the additional advantage of being suitable for problems characterized by a non-Gaussian distribution of source term parameters and for cases in which the underlying dynamical system is nonlinear.

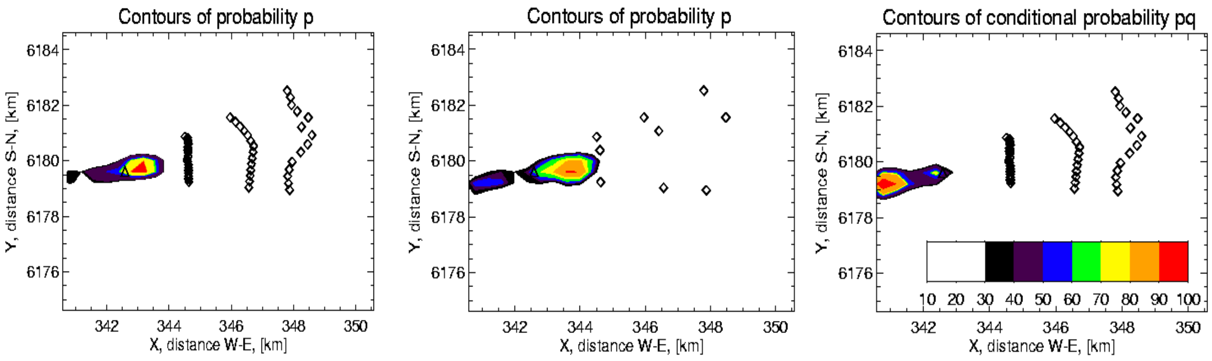
We initially developed a Markov Chain Monte Carlo (MCMC) stochastic methodology and demonstrated its effectiveness by reconstructing a wide range of release scenarios, using synthetic as well as real-world data. Data for evaluation of our event reconstruction capability were drawn from the short-range Prairie Grass, Copenhagen, and Joint Urban 2003 field experiments and a continental-scale real-world accidental release in Algeciras, Spain. The method was tested using a variety of forward models, including a Gaussian puff dispersion model INPUFF, the regional-to-continental scale Lagrangian dispersion model LODI (the work-horse real-time operational dispersion model used by the National Atmospheric Release Advisory Center), the empirical urban model UDM, and the building-scale computational fluid dynamics code FEM3MP. The robustness of the Bayesian methodology was demonstrated via the use of subsets of the available concentration data and by introducing error into some of the measurements (Fig. 1). These tests showed that the Bayesian approach is capable of providing reliable estimates of source characteristics even in cases of limited or significantly corrupted data. An example of an urban release scenario is shown in Fig. 2

For more effective treatment of strongly time-dependent problems, we developed a Sequential Monte Carlo (SMC) approach. To achieve the best performance under a wide range of conditions we combined SMC and MCMC sampling into a hybrid methodology. We compared the effectiveness and advantages of this approach relative to MCMC using a set of synthetic data examples.

We created a modular, scalable computational framework to accommodate the full set of stochastic methodologies (e.g., MCMC, SMC, hybrid stochastic algorithms, "Green's function", "reciprocal" methods), as well as a selection of key classes of dispersion models. This design provides a clear separation of stochastic algorithms from predictive models and supports parallelization at both the stochastic algorithm and individual model level. In other words, it supports a parallel stochastic algorithm (e.g., SMC) that invokes parallel forward models. The framework is written in Python and utilizes pyMPI. It invokes forward models either through system calls or as shared objects.

Our dynamic-data-driven event reconstruction capability seamlessly integrates observational data streams with predictive models, in order to provide the best possible estimates of unknown source-term parameters, as well as optimal and timely situation analyses consistent with both models and data.

This new methodology is shown to be both flexible and robust, adaptable for use with any atmospheric dispersion model, and suitable for use in operational emergency response applications.



(a) (b) (c)

Figure 1. An example of event reconstruction using an operational three-dimensional Lagrangian particle dispersion model and data from the Copenhagen field tracer experiment. In all of the panels, color contours represent the probability distribution of the source location; the actual source is denoted with a triangle, while the sensors are denoted with diamonds. In panel (a) event reconstruction using data from all 51 sensors is presented; in panel (b) source characterization based on data from only nine sensors is presented – notice that the confidence interval is larger than in case (a), indicating higher uncertainty; in panel (c) results obtained using all 51 sensors out of which 30% of the sensors were broken in some way (i.e., giving false positives, false negatives, or stuck on a wrong concentration) are shown – the effect of inaccurate data is evident through the bias in the solution; however the robustness of the methodology is demonstrated.

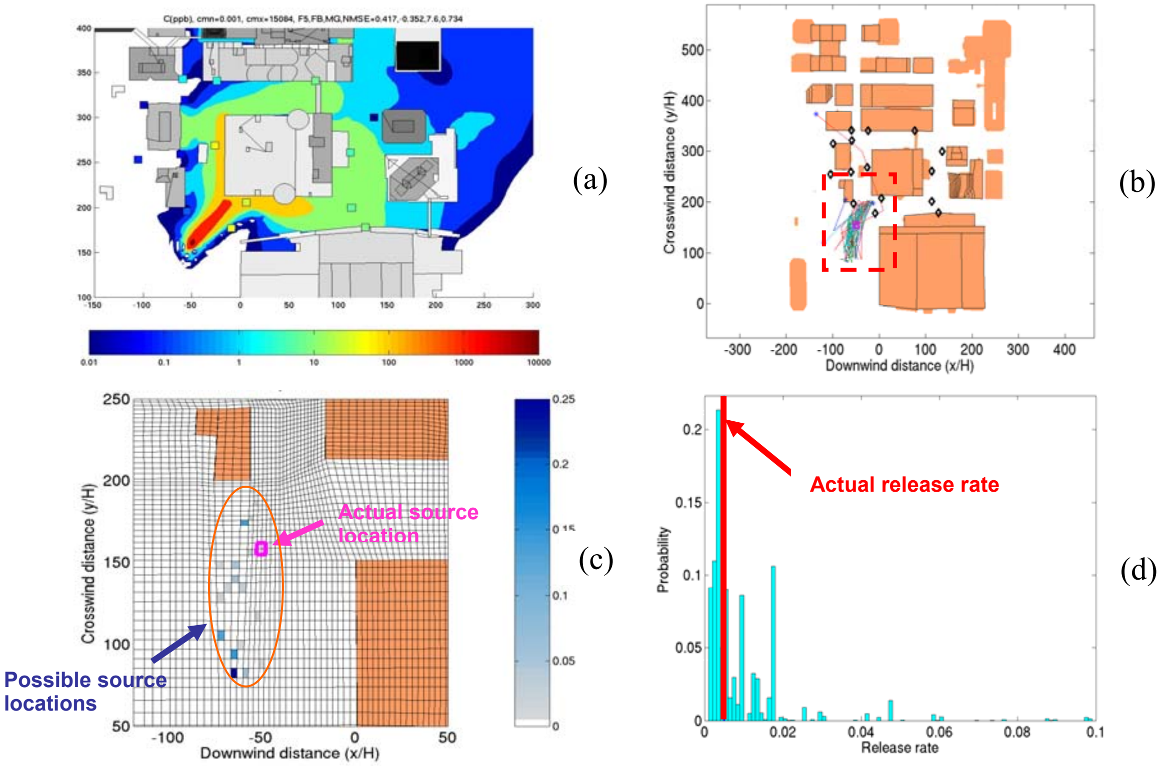


Figure 2. An example of event reconstruction for a release in an urban environment using a three-dimensional computational fluid dynamics code and concentration measurements from the field tracer experiment Joint Urban 2003 in Oklahoma City. In panel (b) four Markov Chains exploring source location are presented; panel (c) presents a magnification of a red dashed-line rectangle from panel (b) with probability distribution of source location presented as colored squares, where gray color represent low value of probability density and dark blue color represents high value of probability density; the pink rectangle denotes the actual source location; in panel (d) the probability distribution (histogram) of the source release rate is presented; the red line denotes actual release rate.

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