SOURCE TERM ESTIMATION WITH REALISTIC SENSOR DATA

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1. INTRODUCTION

The Defense Threat Reduction Agency (DTRA) mission is to protect America and its allies by providing the capabilities to reduce, eliminate, counter the threat, and mitigate effects of incidents associated with weapons of mass destruction (Defense Threat Reduction Agency, 2008). Such incidents include an intentional release of hazardous chemical, biological, nuclear, or radioactive (CBNR) material into the atmosphere. To achieve this it is important to be able to predict the transport and dispersion of these materials. Sometimes however, there is inadequate source information to perform those predictions; therefore it becomes necessary to characterize the source of an airborne contaminant from remote measurements of the resulting concentration field. There has been extensive work on methods for back-calculating source characteristics. For example, Rao (2007) reviews methods that include adjoint and tangent linear models, Kalman filters, and variational data assimilation, among others. Some previous work uses genetic algorithms (GAs) to optimize source characteristics (Allen et al. 2006, 2007, Haupt 2005, Haupt et. al. 2006, 2007a, 2007b, 2007c, and Long et. al. 2008). Several of the previous papers examine the effect of adding noise to the data to simulate errors in the sensor data, input parameters, and the effects of atmospheric turbulence.

This study conducts similar tests using computational fluid dynamics (CFD) data to study the impact of turbulence on the accuracy of the source characterization. Such testing is necessary to simulate turbulence because these eddies distort the smoothed Gaussian puff shape the model would predict. This distortion makes it difficult to fit data to a Gaussian model and thus retrieve the source characteristics. Using CFD data is appropriate because although real observations should be used for maximum verisimilitude they are very difficult to come by as well as expensive. For this study we wish to use these data to back-calculate the source location by means of a GA, and then find the global optimum with the Nelder-Mead downhill simplex algorithm (NMDS) (Nelder and Mead 1965). The GA used with the NMDS is referred to as a Hybrid GA.

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2. DATA

The Eulerian/semi-Lagrangian (EULAG) CDF model uses a Large Eddy Simulation (LES) approach to solve the partial differential equations governing turbulent fluid flow. The resulting CFD data simulate the transport and dispersion of a single puff during a daytime release with an unstable boundary layer for a five minute time period.

The concentration data are sampled throughout the domain, but the values used for this study are only taken from sensor locations. We use the mean concentration value between 0-20 meter heights. The sensor configuration follows the setup used during the Fusing Sensor Information from Observing Networks (FUSION) Field Trial (FFT 07).

3. EXPERIMENTAL METHODS

To use this dataset with a Gaussian puff model in conjunction with the Hybrid GA, a single value for wind speed and direction are required. To achieve this single value wind speed and direction fields were averaged over space (x,y) to view the variations in height as a function of time. The mean wind speed and direction profiles indicated 1) that the lowest 80 meters are where the largest variation in the wind speed occurs and 2) that there is minimal wind direction variation throughout the 290 meter vertical domain over time. Figure 1 shows the lowest 80 meter region as the area that most influences the puff. Therefore, the wind speed and direction for this study were determined by taking the mean over the x,y and 0-80 meter vertical domain. These are then used as known parameters for the back-calculator model.

With the calculation of wind speed and direction, all of the parameters needed to back-calculate source location are known. The Hybrid GA is then used to back-calculate the source location. The median of ten Monte Carlo runs and the mean of ten ensemble runs are used to determine the mean absolute error (MAE) of the most likely location.

4. RESULTS

The Hybrid GA with the Gaussian puff model as configured is not sufficient for back-calculating a reasonable solution. We hypothesize that wind shear significantly deforms the puff. Thus, another variation of the Gaussian puff model is considered, a Sheared Gaussian puff model that includes a nondimensional shear factor (Konopka 1995, Walcek 2004).

The Sheared Gaussian puff model is then coupled with the Hybrid GA. The Sheared Gaussian puff model differs from the regular Gaussian model in that it more accurately accounts for the along-wind dispersion improving the back-calculation of the "y" location. Unfortunately, computation of the "x" location has degraded. We do not consider either configuration adequate at the present time. Note that we may be discerning the inherent mismatch in modeling a specific realization (the LES data) with an ensemble average model (represented by the Gaussian puff model). Figure 1 was created of the along wind perspective of the CFD data and it displayed the non-Gaussian nature of this turbulent data. Figures 2-4 of the CFD data at three different times for constant height levels were also created and it appears as if various puffs materialize at these different height levels. Thus, using a puff model such as SCIPUFF, which includes puff splitting, may be necessary to capture the behavior of realistic turbulent dispersion.

CONCLUSIONS

This study looks at the impact of using LES generated concentration data for the sensor input. This aspect of the study adds realism by simulating a specific potential realization of turbulent dispersion in a fully three dimensional sheared wind field. Our initial numerical experiments reveal the difficulty of determining the source of a more realistic puff.

Current experimental scenarios include altering GA and wind parameters to understand the dynamics between a Gaussian puff model and turbulent data. Another approach is to re-evaluate the physics of the shear Gaussian puff model and seek alterations that more closely simulate a sheared puff in a turbulent environment.

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REFERENCES

Allen, C. T., G. S. Young, and S. E. Haupt, 2006: Improving Pollutant Source Characterization by Optimizing Meteorological Data with a Genetic Algorithm, Atmos. Environ., 41, 2283-2289.

Allen, C. T., S.E. Haupt, and G.S. Young, 2007: Source Characterization with a Receptor/Dispersion Model Coupled with a Genetic Algorithm, Journal of Applied Meteorology and Climatology, 46, 273-287

Defense Threat Reduction Agency, cited 2008: Mission statement. [Available online at http://www.dtra.mil/about/mission.cfm]

Haupt, S. E., 2005: A Demonstration of Coupled Receptor/Dispersion Modeling with a Genetic Algorithm. Atmos. Environ., 39, 7181-7189.

Haupt, S. E., G. S. Young, and C. T. Allen, 2006: Validation of a Receptor/Dispersion Model with a Genetic Algorithm Using Synthetic Data. J. Appl. Meteor. 45, 476-490.

Konopka, P. 1995: Gaussian solutions for anisotropic diffusion in linear shear flow. J. Non-Equilib. Thermo-dyn. 20, 78-91.

Long, K.J., S.E. Haupt, and G.S. Young, 2008: Optimizing Source Characteristics and Meteorological Data Describing a Contaminant Release with a Genetic Algorithm. Submitted to Optimization and Engineering.

Nelder, J. A. and R. Mead, 1965: A Simplex Method for Function Minimization. Computer Journal, 7, 308-313.

Rao, .S., 2007: Source estimation methods for atmospheric dispersion, Atmos. Env. 41, 6963-6973.

Walcek, L.C., 2004: A Gaussian dispersion/plume model explicitly accounting for wind shear, 13th Conference on the Applications of Air Pollution Meteorology with the Air and Waste Management Assoc, Vancouver/BC, Canada Amer. Meteor. Soc., CD-ROM, 79742.

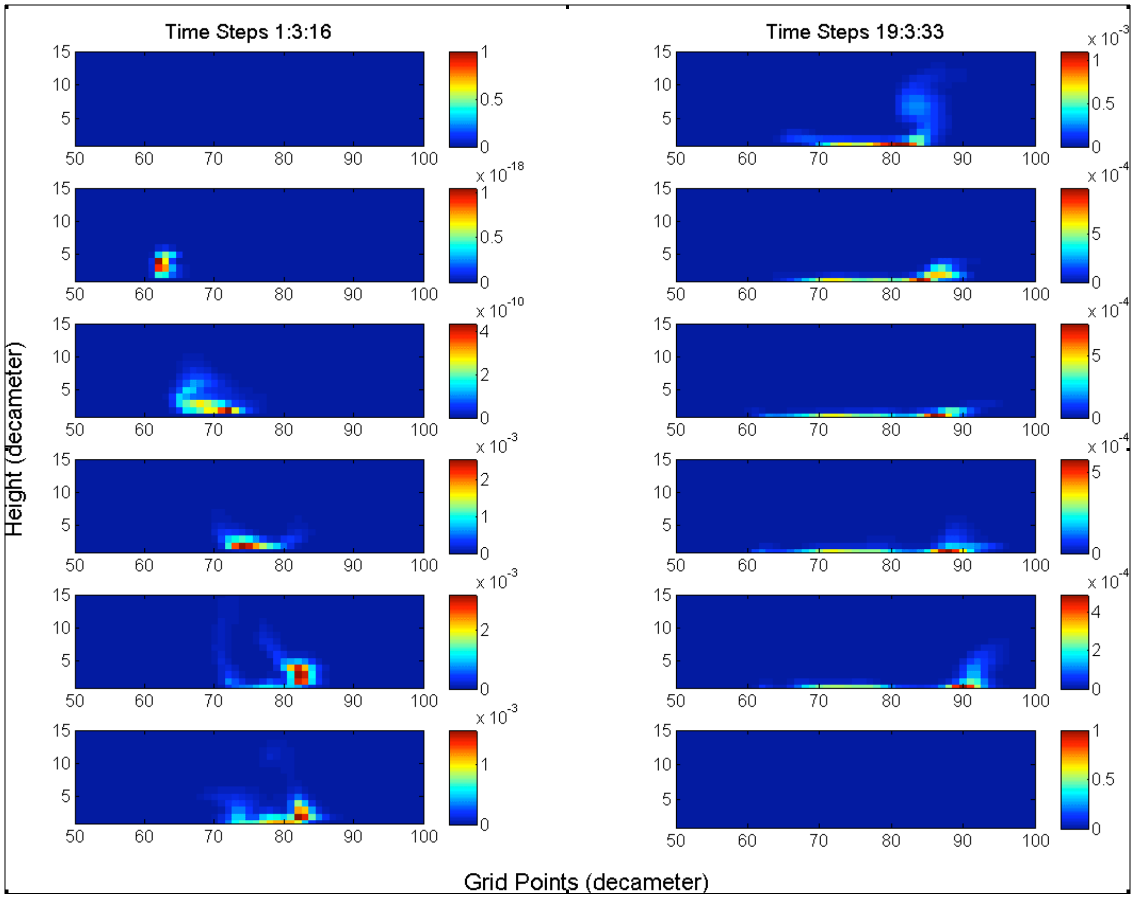

Figure 1. Along wind perspective of CFD concentration data at the 80th x direction grid point, for five minutes at 30 second intervals.

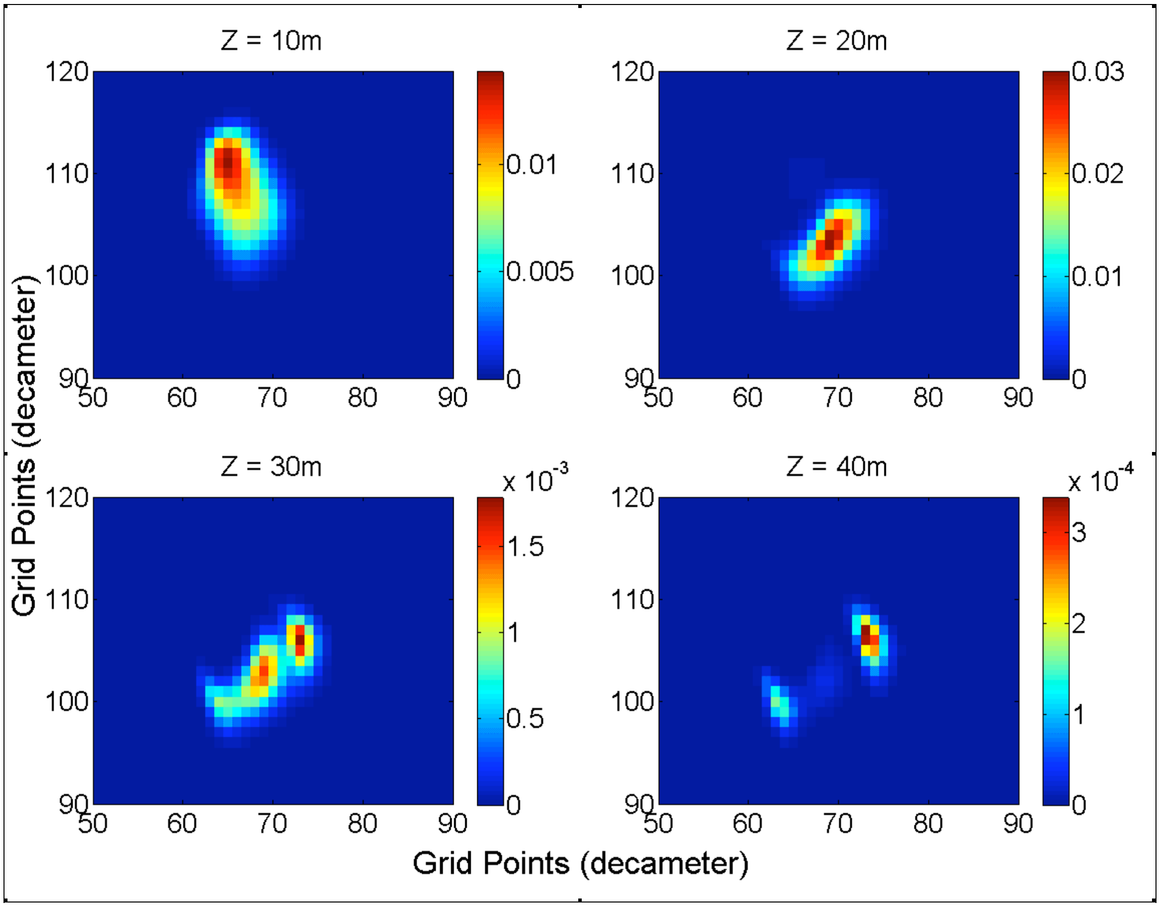

Figure 2. Concentration CFD data at 10, 20, 30 and 40 meter height levels at 40 seconds.

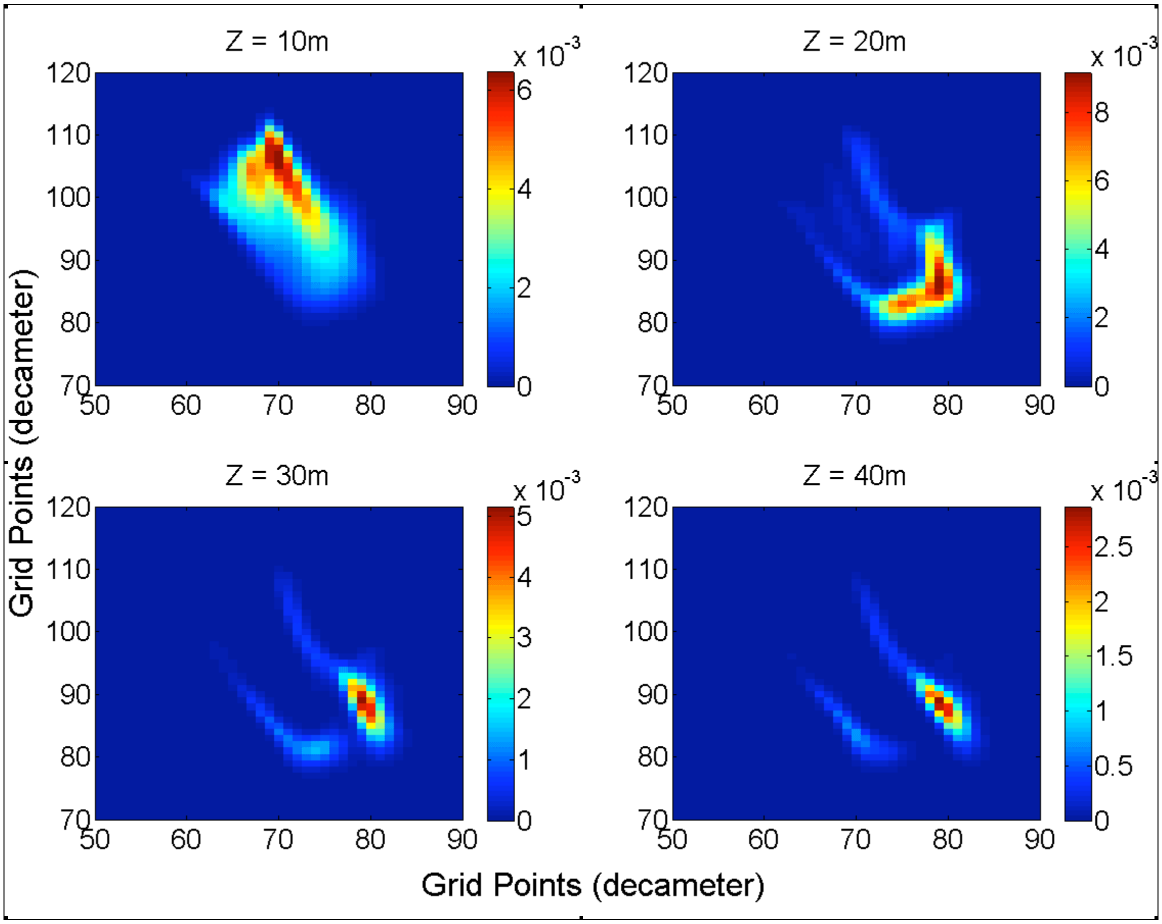

Figure 3. Concentration CFD data at 10, 20, 30 and 40 meter height levels at 90 seconds.

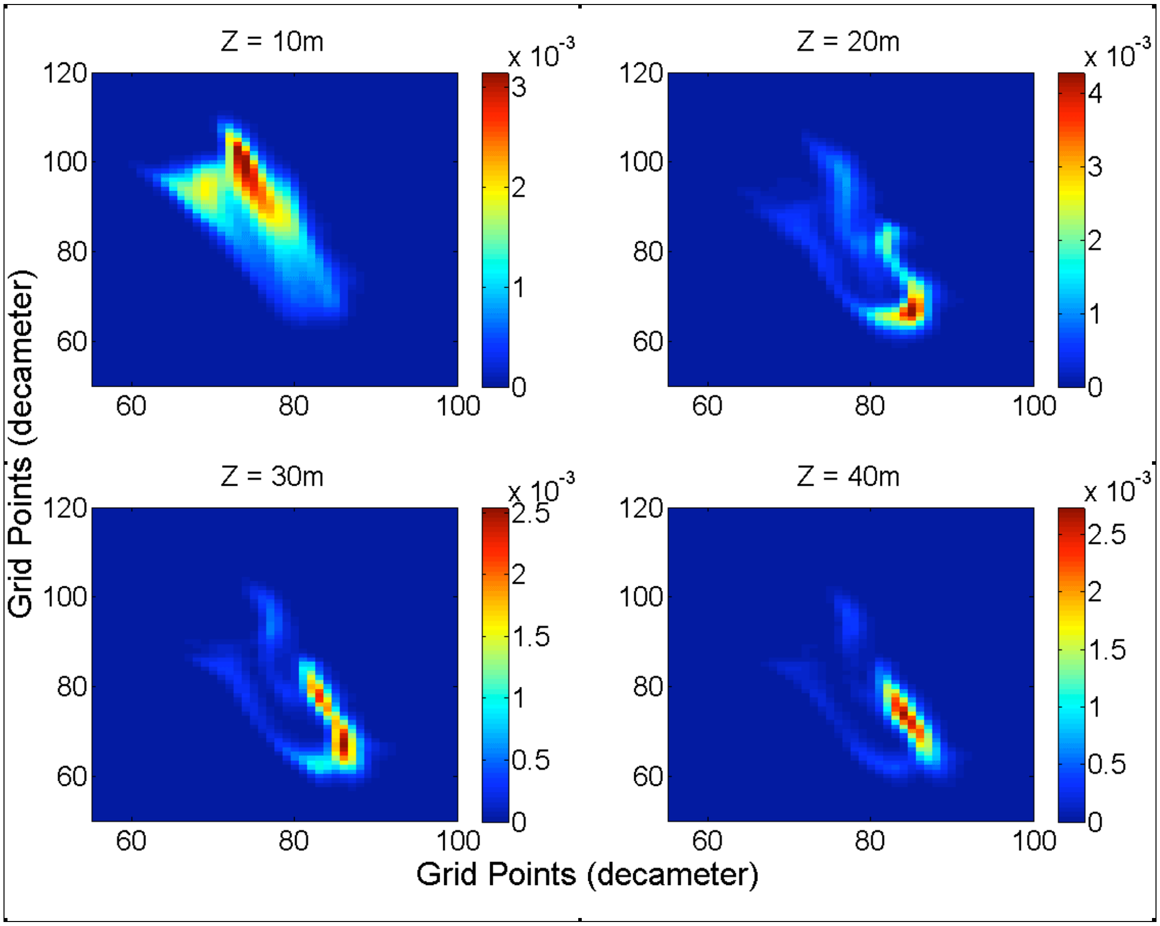

Figure 4. Concentration CFD data at 10, 20, 30 and 40 meter height levels at 140 seconds.