4.10 CHARACTERIZING UNCERTAINTY IN PLUME DISPERSION MODELS

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INTRODUCTION

In a discussion on predictability, H. Tennekes stated that , "Because the atmosphere is a chaotic system in which all forecasts are divergent, particularly as far as the smaller scales of motion are concerned, we must insist that no forecast is complete without a preceding assessment of forecast skill. In the same spirit, no observation is complete without an appropriately sampled estimate of the variance of the properties observed, and no model calculation is complete without a calculation of the variance of the calculation."(see *Hooke et al*., 1990). In the current paper, we provide quantitative estimates of some of the major sources of uncertainty in plume dispersion modeling (e.g., variance of the model predictions) and then provide a preliminary assessment of their effects. The specific sources of uncertainty that are investigated are stochastic effects in the crosswind concentration profile, plume dispersion parameters, plume rise, and transport wind direction and speed.

DISCUSSION

Crosswind concentration profile variations

The widely-used Gaussian approximation for characterizing the crosswind distribution of mass of a dispersing plume as it is carried downwind provides a smoothed viewed of what is really seen in the world. *Irwin and Lee* (1996) analyzed the Prairie Grass data, as well as additional tracer data from the Kincaid power plant, which had a 183-m stack with a typical buoyant plume rise on the order of 200 m. They concluded that the scatter in the concentration values about the ensemble average Gaussian lateral profile can be characterized for both experimental data sets as having a log-normal distribution with a geometric standard deviation (GeoSD) on the order of 2.

The SCIPUFF model (*Sykes et al*., 1998) is one widely-used plume model that explicitly solves for the fluctuations in concentration internal to the plume as described above. Typically, the relative fluctuation (standard deviation divided by the mean) is simulated to be about 2 on the plume centerline, and is larger towards the edges of the plume. The SCIPUFF estimates of uncertainties are consistent with what has been independently found by the authors, as discussed in the previous paragraph. Note, SCIPUFF simulates additional sources of uncertainty which we have not investigated (e.g., uncertainty due to mesoscale wind fluctuations using inputs of wind speed variance and Lagrangian mesoscale integral scale, and uncertainty if the plume is located far from the wind observation site).

Dispersion parameter uncertainty

Irwin (1984) calculated the bias in the dispersion parameter estimates, and observed that the bias varied from one site to the next, and also calculated the random errors about the systematic bias at each site. To further explore these uncertainties, an analysis was conducted of the field experiments from 26 different sites listed and discussed in *Irwin* (1983). Nine of these sites involved elevated releases and the other 17 sites involved near-surface releases. The data were divided into four (4) groups: 1) elevated vertical dispersion values (5 sites), 2)

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elevated lateral dispersion values (4 sites), 3) near-surface vertical dispersion values (6 sites), and 4) near-surface lateral dispersion values (11 sites). For each experiment within each of the four groups we: 1) computed the average and geometric mean of ratio P/O, where P is the predicted and O is the observed dispersion, and 2) computed the standard deviation and geometric standard deviation of P/O ratio values. For the current analysis, Model 3 as described in *Irwin* (1983) was used for the predictions. Table 1 summarizes the results obtained from the analysis described. A log-normal distribution was seen to be a reasonable characterization for all of the random error distributions, even though a normal distribution is seen to be indicated at 10 experiment sites (see notations in Table 1). We looked to see if a large bias in the P/O ratio correlated with larger scatter in the random errors as reflected in the geometric standard deviation values, but such was not seen. We looked to see if the bias or geometric standard deviations in the vertical and lateral dispersion were correlated but such was not seen.

If we assume that the random biases and random errors come from independent log-normal distributions, we can model the uncertainty by expressing the dispersion parameters as $\sigma_{y,z} = b_{y,z} \cdot r_{y,z} \cdot \sigma^o_{y,z}$, where the subscripts y and z respectively refer to the lateral and vertical dispersion, b and r are random bias and error factors, $\sigma^o_{y,z}$ is the model's estimate of the dispersion, and $\sigma_{y,z}$ is the observed dispersion, including the effects of uncertainty. We can use the Table 1 results to characterize the distributions of b and r. We can characterize the 26 biases as a log-normal distribution with a GeoSD of 1.35 (e.g., $b_{y,z}$), and we can characterize the 26 GeoSD values by their average, 1.51 (e.g., $r_{y,z}$,). Note, a log-normal distribution with a GeoSD of 1.50 means 90 %of the values are within a factor of 2.

Hanna's (2002) informal expert elicitation concerning uncertainties in σ_y and σ_z and his reanalysis of *Draxler's* (1984) observations of σ_y and σ_z in many field experiments confirm the uncertainty magnitudes suggested above. Six developers of widely-used Gaussian dispersion models were asked to estimate the uncertainties, expressed as 90 % confidence bounds, in σ_y and σ_z. The six experts agreed that the uncertainties in both components were about a factor of two to three for hourly-averaged observations.

Draxler (1984) provides reviews of field observations of dispersion from many sites. The figures in *Draxler's* (1984) chapter were analyzed by *Hanna* (2002) to determine the range of the scatter of the points in the σ_y and σ_z plots. For the 18 figures with relevant data, there is seen to be a consistent factor of about 10 (i.e., an order of magnitude) range of variation in the plotted points from a best-fit line across all the figures. That is, for a given median σ_y or σ_z estimate (as from a best-fit line) at a given downwind distance or travel time and for a given stability, the observed σ_y or σ_z values cover an order of magnitude range. This corresponds to an uncertainty of about a factor of 3. A range of a factor of five would encompass nearly all of the observations, so we recommend that "random" σ_y or σ_z values should be no more than a factor of five away from the median value. The probabilities of values inside the factor of five range can be increased by the area of the CDF curve outside of the factor of five range. Furthermore, as stated above, the 90% range (i.e., from the 5th to the 95th percentiles) is approximately a factor of two.

It is seen that the independent assessments of uncertainties of σ_y and σ_z summarized in Table 1 and by *Hanna* (2002) produced similar estimates of uncertainty (about ± factor of two); however, since both studies used similar field data sets, this result is expected.

Plume rise uncertainty

Analysis of Figures 4 and 5 of *Erbrink* (1994), suggest the P/O plume rise ratio values can be characterized as having a log-normal distribution with a GeoSD of 2.10. Use of vertical profiles of the wind and temperature at 30 meter intervals reduces the uncertainty in the P/O plume rise ratios as characterized by a GeoSD from 2.10 to 1.48. Table 5.1 of *Briggs* (1969) list 22 plume rise estimates from 17 sites. Analysis of these estimates suggest that the distribution of P/O plume rise ratios can be characterized by log-normal distribution with a GeoSD of 1.34. Combining the results from *Erbrink* (1994) and *Briggs* (1969) suggest the uncertainty in the plume rise can be characterized as a random bias that follows a log-normal distribution with a GeoSD of order 1.34, and the random error that follows a log-normal distribution with a GeoSD of order 2.0.

Transport wind direction and speed uncertainty

There is indirect evidence through the comparison of observations with predictions from mesoscale meteorological modeling of what the uncertainties might be in characterizing the transport wind direction and speed. Hanna and Yang (2001) compared winds predicted for a nine-day period by the RAMS and MM5 meteorological models for the 12-km OTAG grid in the eastern US. For these comparisons, the root mean squared error (rmse) was less than 1.9 m/s for wind speed and on the order of 60 degrees for wind direction. They also compared MM5 predictions for a 4-day period for the 4-km grid in the central California SARMAP domain where four dimensional data assimilation (FDDA) was employed. For these comparisons, the rmse was 2.5 m/s for the wind speed and 66 degrees for the wind direction.

These results are consistent with comparison of MM5 10-m predictions made for the contiguous US for 2001 with observations from 785 sites for the period June 21 – September 21, 2001, where the average rmse over all 785 sites was determined to be 1.7 m/s for wind speed and 64 degrees for the wind direction. From analysis of the MM5 comparisons for 2001, it was determined that for the wind speed standard deviation of the site to site biases was 0.74 m/s and the average over the 785 sites of the standard deviations of the residuals was 1.5 m/s. For the wind direction, the standard deviation of the site to site biases was 16 degrees and the average of the standard deviations of the residuals was 61 degrees.

For the following list of experiments there was sufficient information to directly compare the transport wind direction (as indicated by a wind direction sensor near the release) with the actual transport directions (as indicated by the location of the center of mass of the tracer at each downwind arc): Project Prairie Grass, Green Glow, Hanford 30, Hanford 64, Hanford 67. The Hanford 64 involved releases at 26 m, and the Hanford 67 involved releases at 2 m, 26 m and 56 m. The wind sensor transport direction uncertainties could be characterized as a random overall bias for all releases during an experiment which was superimposed upon a random error that varied from one release to the next. The random bias followed a normal distribution with a standard deviation of about 4 degrees, and the random error followed a normal distribution with a standard deviation of about 2 degrees. These uncertainties in transport direction are substantially less for the tracer experiments than were determined in the MM5 comparisons. So we might be tempted to conclude that the uncertainties determined for these tracer experiments represents a lower bound on the wind speed and transport uncertainties, whereas the RAMS and MM5 comparisons provide evidence that much larger uncertainties are possible. Since these tracer experiments generally involved releases near the ground over simple terrain and on-site research-grade wind data were available, then these would be expected to represent minima. When the Kincaid tracer data are subjected to the same analysis, then a standard deviation of 20 degrees is found. However, the Kincaid plume was from a tall stack and plume rise was substantial, so the wind observation from a tower at a height of about 100 m was not representative of the wind at a height of several hundred meters, where the plume was located.

Combining the results from the studies discussed above suggest the uncertainty in the wind speed and wind directions can be envisioned as having a random bias that varies from one site to the next, and a random error at each site about the site bias. The random bias in wind speed is envisioned as following a normal distribution with a standard deviation of order 0.5 m/s, and the random bias in the wind direction is envisioned as following a normal distribution with a standard deviation of order 10 degrees. The random error in wind speed and direction can be simulated as errors in the North-South and East-West components which are envisioned to follow a normal distribution with a standard deviation of order 1.0 m/s for each component.

Propagation of uncertainties
Monte Carlo (MC) simulations were conducted to assess the sensitivity of the maximum concentration to random biases and errors. Using the Gaussian plume formula for the centerline concentration downwind from an elevated point source, with no mixing depth (ie unbounded above), we assumed the following values: median wind speed = 3 m/s, median $\sigma_y = \sigma_z$ = 150 m, median plume rise = 25 m, and stack height = 25 m. The random bias and random error were specified in the dispersion parameters, plume rise and wind speed as outlined in the preceding paragraphs (but we forced the wind direction to never change). One-hundred "years" having 8760 hours each were simulated, and the resulting MC concentrations were divided by the median concentration (ie, concentration obtained with no errors). The results are summarized in Table 2, and the "averaging" times are determined as block averages (ie, they do not overlap). The resulting uncertainty distribution in the maximum concentration was seen to follow a log-normal distribution which can be summarized by the geometric standard deviation. This synthetic numerical experiment allows us to view in particular the impact of random bias and random errors as averaging time increases in a world where the dispersive conditions (on average) never change.

CONCLUSIONS
It is concluded that normal error distributions can be used to characterize wind speed and wind direction uncertainties, whereas log-normal error distributions can be used for the rest of the sources of uncertainty. The total uncertainty in the model inputs and formulations is viewed as a combination of random biases and random errors. The random errors (about some bias) have the greatest impact on hourly concentration values, while random bias errors have the greatest impact on the long-term concentration values. Left for future investigation is the problem of developing a means for propagating uncertainty in the winds that develops dynamically consistent wind fields.

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Table 1. Summary of comparison of Model 3 (Irwin, 1983) predictions of vertical and lateral dispersion parameters with field data from 26 sites. GeoSD is the geometric standard deviation.

Elevated Lateral Dispersion Sites

Experiment Site	Number	Bias	GeoSD
Hanford(67)-56m	68	1.00	1.52
Hanford(67)-26m	210	0.81	1.51
NRTS	96	0.92	1.23
Karlsruhe	39	0.61	2.37*
Hanford	57	0.90	1.19
Suffield	104	1.08	1.43

Elevated Vertical Dispersion Sites

Experiment Site	Number	Bias	GeoSD
Agesta	24	1.09	1.39
Karlsruhe	87	1.03	2.04*
Porton	9	0.93	1.46
Hanford	19	1.46	1.49
NRTS	96	1.49	1.36*

Near-Surface Lateral Dispersion Sites

Experiment Site	Number	Bias	GeoSD
Mt. Iron	161	2.07	1.92*
NRTS-B	44	0.91	1.24
NRTS-A	84	1.24	1.39
Hanford 30	117	0.90	1.40*
Green Glow	86	0.82	1.51
Prairie Grass	315	1.12	1.68*
Dry Gulch	266	1.72	1.62
Ocean Breeze	172	1.78	1.44*
Round Hill II	30	1.38	1.29
Round Hill I	72	1.13	1.41
Handord(67)-2m	104	1.00	1.49*

Near-Surface Vertical Dispersion Sites

Experiment Sites	Number	Bias	GeoSD
NRTS-B	42	0.57	1.90
NRTS-A	46	1.26	2.32
Prairie Grass	203	1.24	1.63*
Round Hill I	52	1.03	1.40*

Values with * denote cases where a Normal distribution best characterizes the random errors, but for which, we also found a log-normal distribution fits nearly as well.

Table 2. The geometric standard deviation in maximum surface concentration values derived from Monte Carlo simulation of 100 "years" with constant average dispersion and wind conditions. The speed was 3 m/s, stack height was 25 m, plume rise was 25 m, vertical and lateral dispersion was 150 m, and no uncertainties were allowed in the wind direction.

Averaging Time	Random Errors	Random Biases	Random Errors and Biases
1-hr	2.59	2.07	3.36
3-hr	1.80	1.79	2.04
24-hr	1.26	1.62	1.56
30-days	1.05	1.59	1.46
Annual	1.02	1.59	1.46

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