Assessing the Impact of Meteorological Model Uncertainty on SCIPUFF AT&D Predictions

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Motivation

- Many physics-based atmospheric transport and dispersion (AT&D) models, e.g. SCIPUFF, derive their transporting wind field from meteorological (met) models *met model winds*
- These AT&D and met models are sophisticated interplays of physics and parameterizations that have evolved over many years *good T&D models*
- Given adequate initial and boundary conditions, these models can successfully reproduce dispersion episodes *sensitive to ics & bcs*
- In a limited domain model, an ensemble of simulations can be used to include the statistical effects of large-scale (*outer*) variability *dispersion uncertainty arises from met ensemble uncertainty*

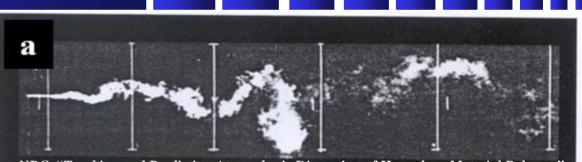


Background

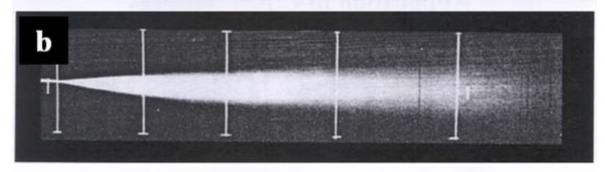
- *Realization* The actual wind field for a dispersion event
- *Statistic* Ensemble Mean Plume

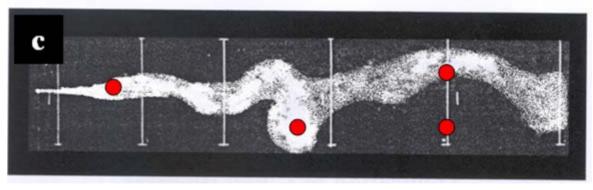
• Conditional Statistic Reduced uncertainty through NWP skill

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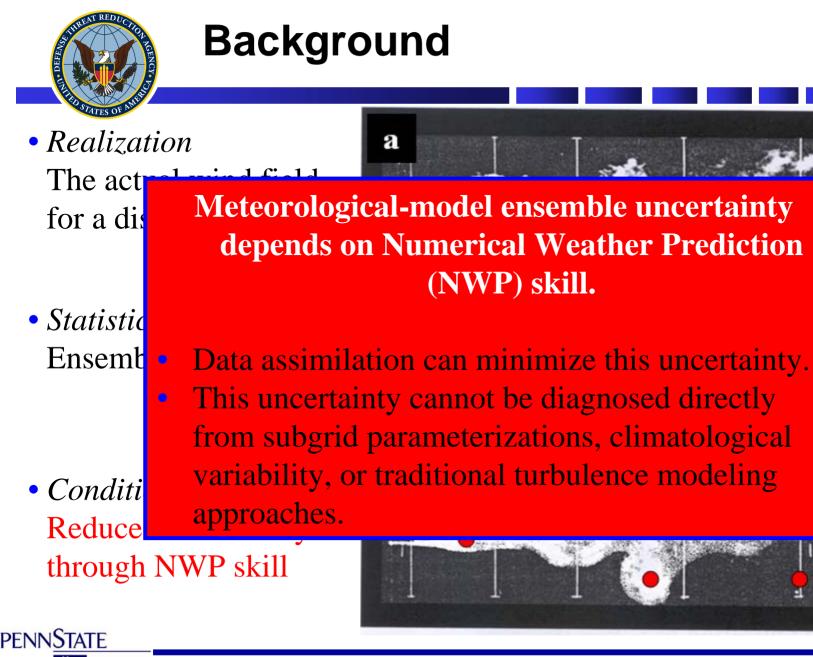


NRC, "Tracking and Prediction Atmospheric Dispersion of Hazardous Material Releases"





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Goal and Approach/Outline

To parameterize meteorological model uncertainty for dispersion

- Representation
 - Evaluate meteorological model uncertainty from meteorological model ensemble variability
- Theory
 - Use Taylor dispersion arguments applied to ensemble dispersion to define the uncertainty modeling parameters
- Evaluation
 - Diagnose the uncertainty parameters from ensemble data (this study & related work by Walter Kolczynski, PhD, PSU)
- Modeling

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– Develop operational models for the uncertainty parameters



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The Meteorological Ensemble

A fair weather day in Oklahoma

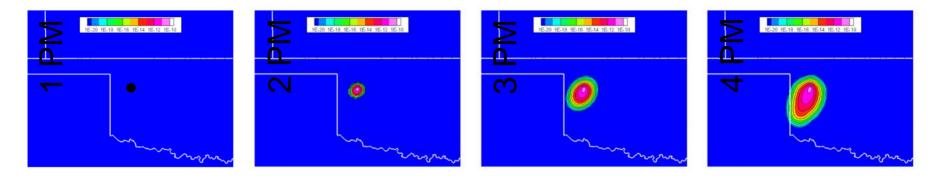
- Ensemble 1: used to evaluate uncertainty modeling parameters
 - A 29 member MM5 physics ensemble (PhD work of B. Reen, Penn State Meteorology) modeling the IHOP (International H2O Project) field experiment (<u>light winds & precip.</u>)
- Ensemble 2: used to motivate ensemble uncertainty
 - Research ensemble (11 members) intentionally constructed to emphasize wind-direction variability
- Other Ensembles: "*real-world*" *examples*
 - NCEP's SREF operational data
 - MM5 ensemble modeling the CAPTEX (Cross Appalachian Tracer Experiment) field study

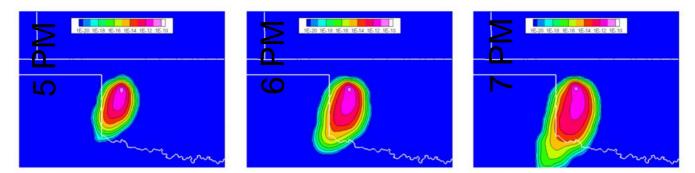
Baseline Member of Ensemble 2



6 Hr Release of C7F14; 1 PM to 7 PM Local Time; 5/29/2002

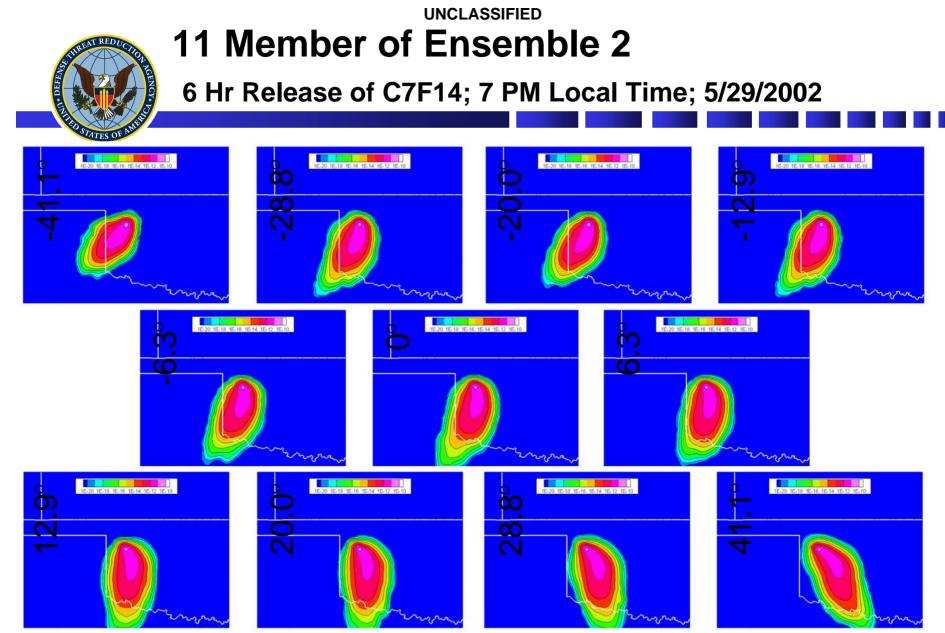
MM5 wind field; SCIPUFF dispersion model







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Members constructed to emphasize wind-angle uncertainty

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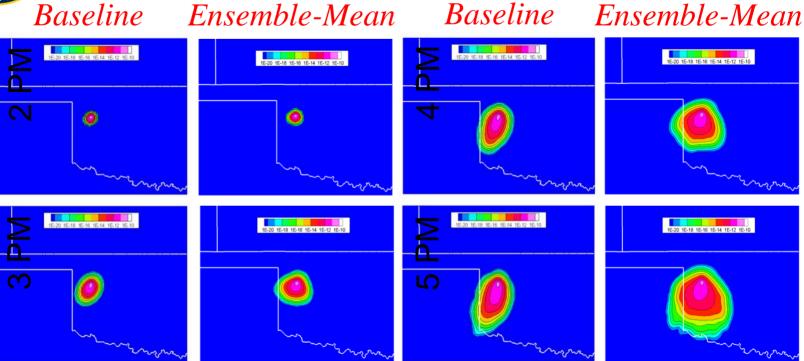
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UNCI ASSIFIED **Baseline/Ensemble-Mean Plumes**

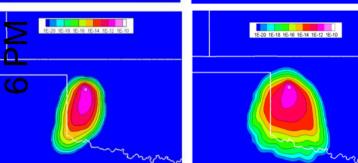
6 Hr C7F14 Release; 2 PM to 6 PM Local Time; 5/29/2002

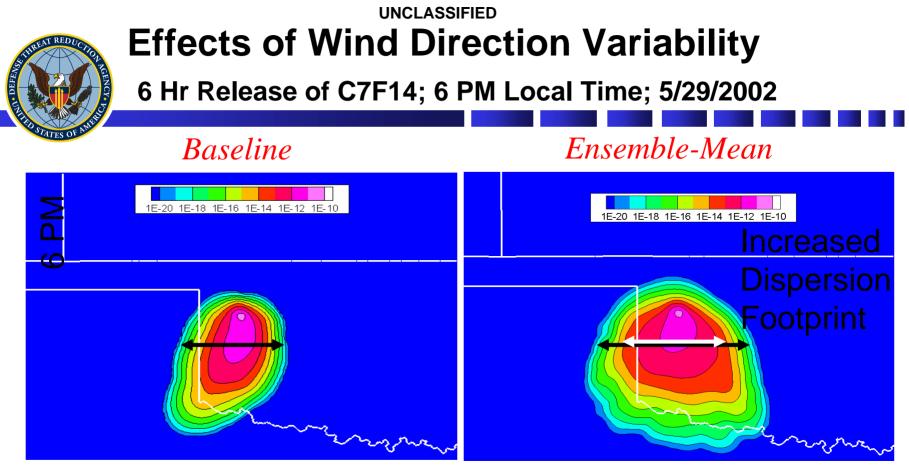
Baseline



• Member- and mean-plume footprint differences depict effects of ensemble uncertainty.

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- The mean-plume footprint is larger than the member plume footprint due to meteorological variability.
- The characteristic dispersion length, therefore, is larger.
- Planform differences between these plumes demonstrate the effects of meteorological uncertainty on dispersion.



Relation to Dispersion Uncertainty

Taylor-dispersion arguments can be used to relate dispersion uncertainty to meteorological model ensemble variability

- The theory describes dispersion in homogeneous environments.
- It isolates Lagrangian velocity and integral-time statistics as the relevant modeling parameters.
- They yield the ensemble-uncertainty model parameters.





Taylor Dispersion

This is a variant of the "Taylor dispersion" problem (Taylor, 1921). Its key parameter is the Lagrangian integral time scale τ_L ,

$$\tau_L = \frac{1}{\overline{v^2}} \int_0^\infty \overline{v(t)v(t+\tau)} d\tau.$$

The overbar represents the average over a large ensemble of dispersion realizations and v is the lateral velocity of a diffusing particle in coordinates aligned with the ensemble-mean flow.



Taylor Dispersion6 Hr C7F14 Release; 2 PM to 6 PM Local Time; 5/29/2002

 The plume width parameter σ has linear and parabolic growth asymptotes

$$\sigma(t) = (\overline{v^2})^{1/2} t, \quad t \ll \tau_L$$

$$\sigma(t) = (\overline{v^2}\tau_L)^{1/2} t^{1/2}, \quad t \gg \tau_L$$

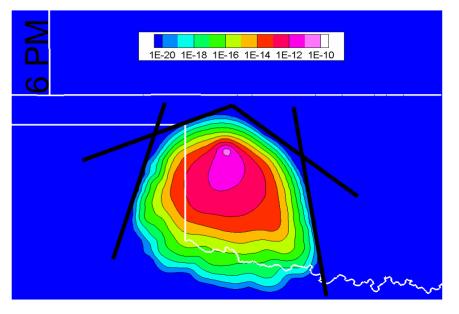
• A characteristic width parameter is

$$\Lambda \simeq \tau_L \times (\overline{v^2})^{1/2}$$

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Uncertainy modeling parameters

Ensemble-Mean

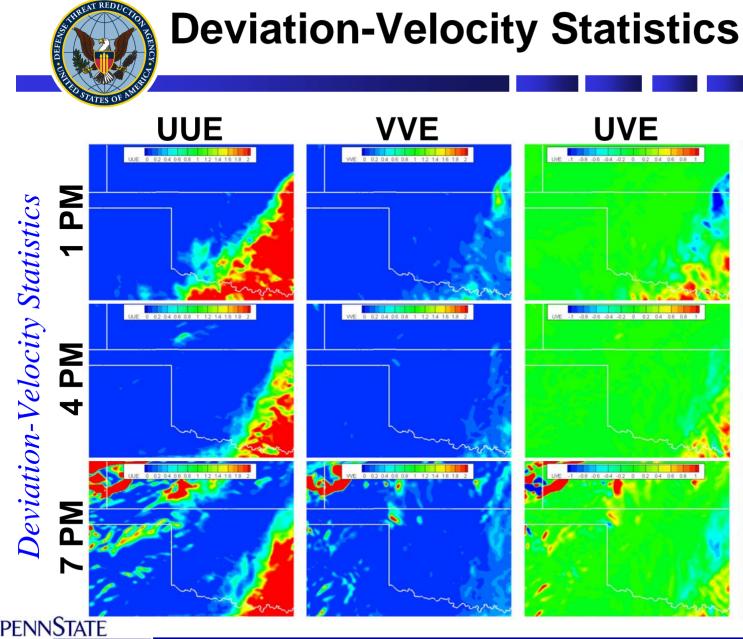




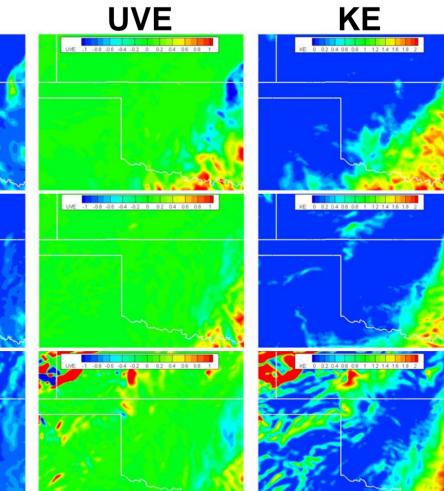
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Uncertainty Parameters

- SCIPUFF parameters UUE, VVE, and UVE can be diagnosed from ensemble deviation-velocity fields
- The Lagrangian integral time can be diagnosed from Lagrangian particle trajectories through the meteorological model data
- SCIPUFF parameter SLE can be diagnosed from the ensemble deviation velocities and the Lagrangian integral time SLE ~ τ_L (UUE+VVE)^{1/2}
- Direct evaluation of these parameters from meteorological data provides the "truth" for modeling efforts.



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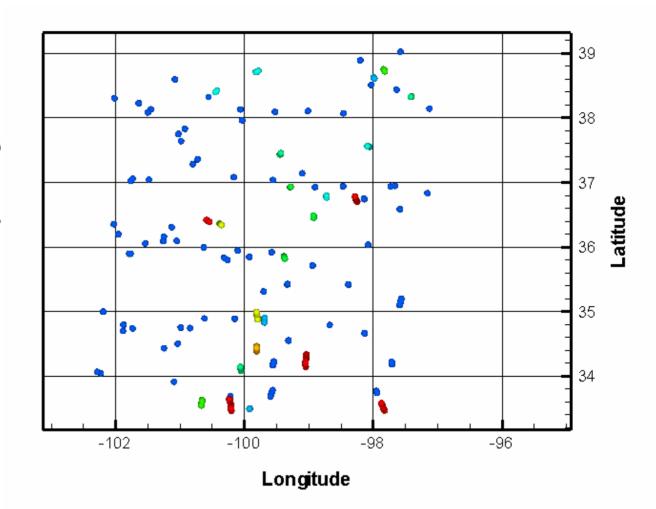
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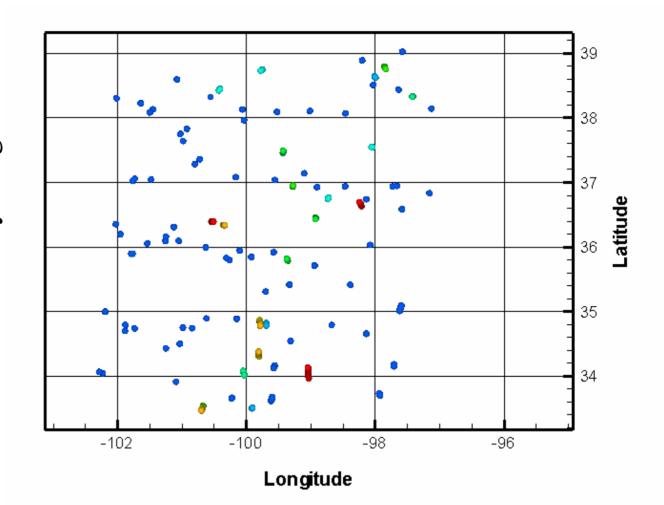


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Lagrangian Particle Trajectories





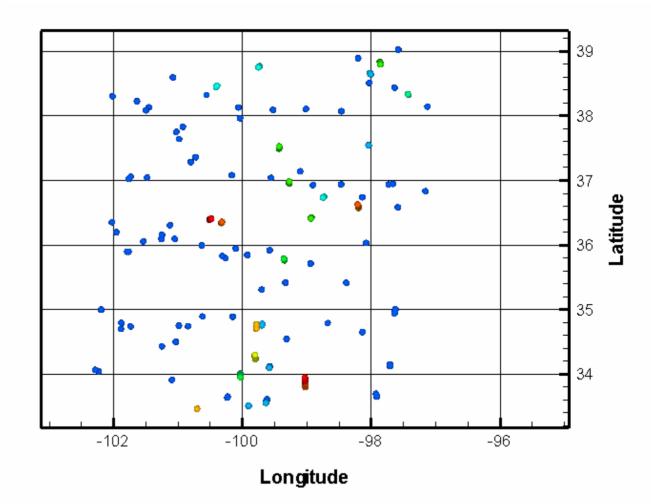
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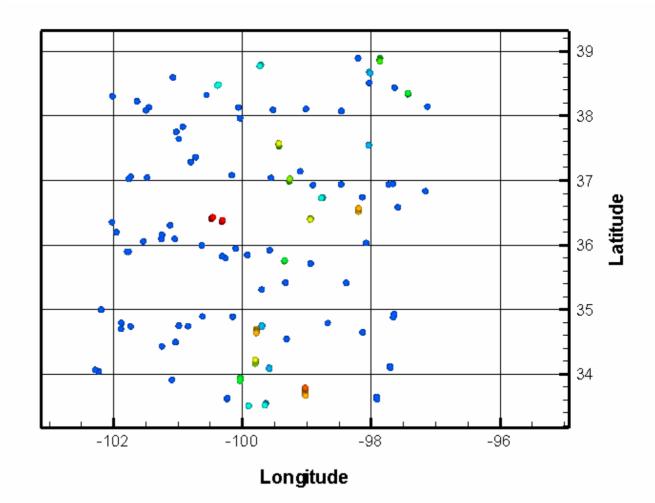




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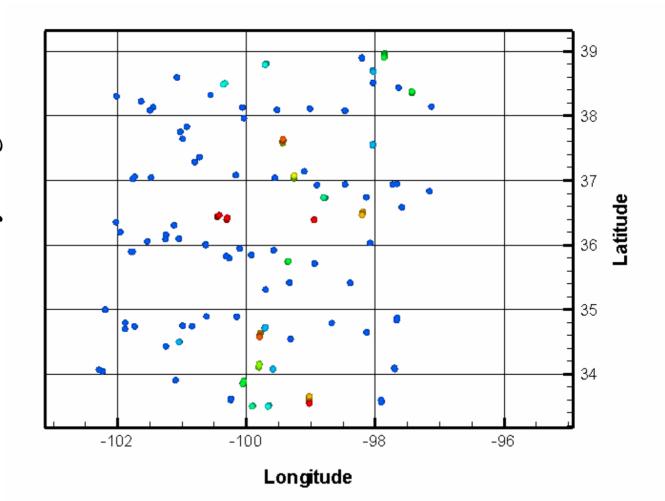




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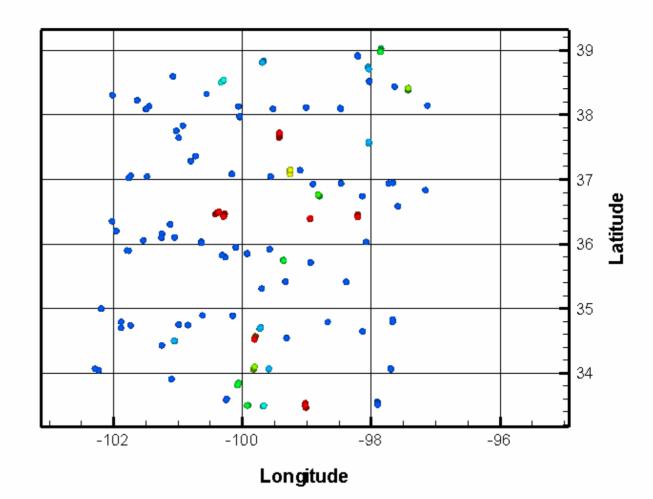




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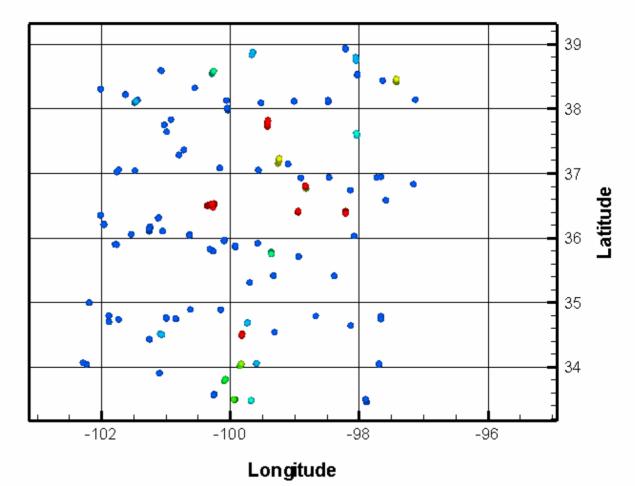




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Lagrangian Particle Histories

Fewer members with increasing time Δ 2 Ω Ω -2 ∍ > -6 -6 -8 -8 -10 L 20000 Time (s) -10 L 40000 20000 40000 Time (s)

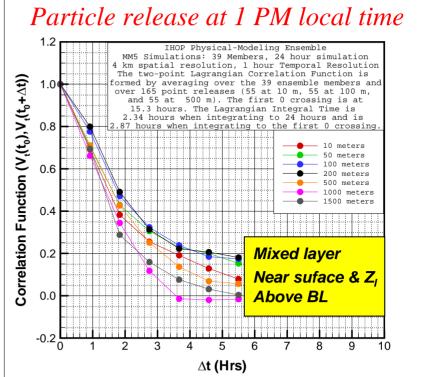
 Lagrangian Particle Data (Ensemble Members – black, Ensemble Mean – Red)



Lagrangian Particle Correlations

- The Lagrangian correlation functions were computed
 - <u>Ensemble averaging</u> for each release location and
 - <u>Spatial averaging</u> over release
 locations at the same height (to
 increase the sample contributing
 to the statistic)

Lateral Velocity Correlation Function





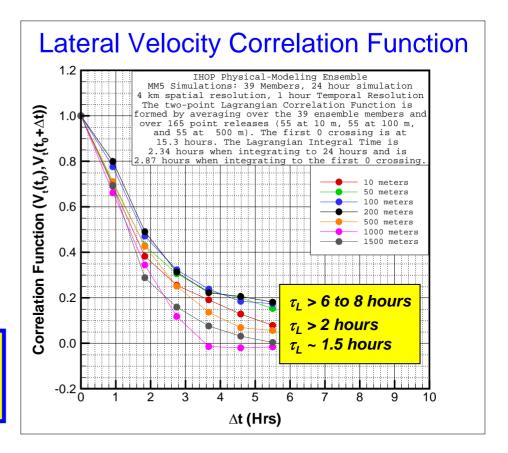


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Lagrangian Integral Times

By extrapolating the correlation curve to 0 followed by integration, estimates for the Lagrangian Integral Time, τ_L, as a function of height can be computed:

These data indicate that τ_L is larger than 6-8 hours





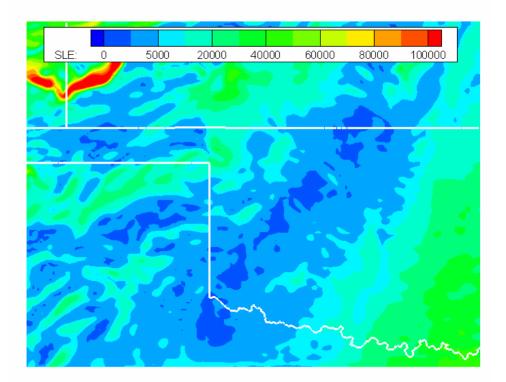
IHOP Great Plains Model

6 Hr C7F14 Release; 7 PM Local Time; 5/29/2002

- Using $\tau_L \sim 6-8$ hours, a field of SLE can be computed.
- The definition for SLE is a function of time and space.
- For this case,

 $0.0 \ km < SLE < 200 \ km$

large/small values depend on the local deviation velocities (on the uncertainty)



SLE

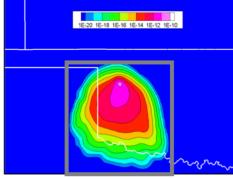


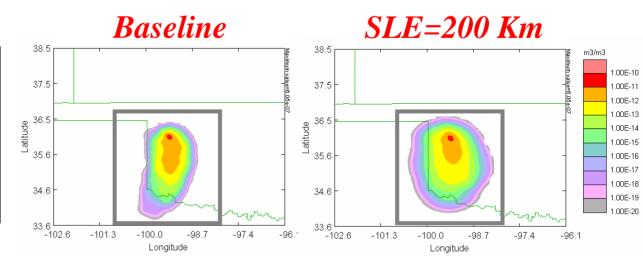


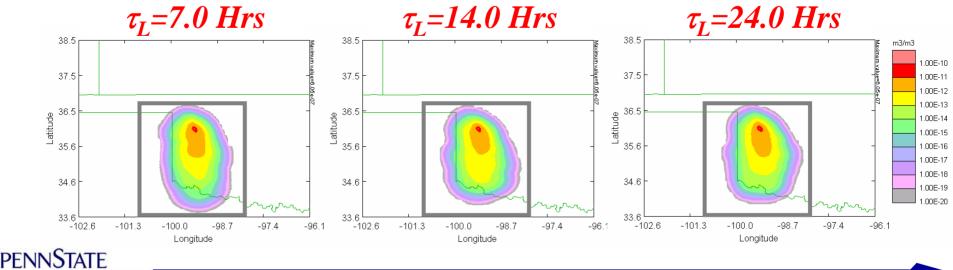
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SCIPUFF (Hazard Mode)











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Summary

- Taylor-dispersion arguments relate meteorological model variability to dispersion uncertainty
 - Modeling parameters depend on Eulerian ensemble deviationvelocity statistics and on the Lagrangian Integral Time
- Evaluation of the modeling parameters using a meteorological physics ensemble suggests
 - A Lagrangian Integral Time > 6 to 8 hours yielding SLE
 ranging from < 1 km to ~200 km under low wind & light rain
- Evaluation using SCIPUFF is ongoing.



Continued Work

- Further evaluation of the ensemble variability modeling parameters for geometrically and meteorologically complicated cases
 - CAPTEX (Cross Appalachian Tracer Experiment) field experiment
 - NCEP's SREF ensemble with weather and topography
- Model the uncertainty parameters using these meteorologicalensemble-computed fields as "truth"
 - This project
 - 2-point spatial correlations (W. Kolczynski/D. Stauffer, PSU)