A Comparison of Lagrangian Model Estimates to Light Detection and Ranging (LIDAR) Measurements of Dust Plumes from Field Tilling

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ABSTRACT
A Lagrangian particle model has been adapted to examine human exposures to particulate matter $\leq 10 \mu m (PM_{10})$ in agricultural settings. This paper reports the performance of the model in comparison to extensive measurements by elastic LIDAR (light detection and ranging). For the first time, the LIDAR measurements allowed spatially distributed and time dynamic measurements to be used to test the predictions of a field-scale model. The model outputs, which are three-dimensional concentration distribution maps from an agricultural disking operation, were compared with the LIDAR-scanned images. The peak cross-correlation coefficient and the offset distance of the measured and simulated plumes were used to quantify both the intensity and location accuracy. The appropriate time averaging and changes in accuracy with height of the plume were examined. Inputs of friction velocity, Monin–Obukhov length, and wind direction (1 sec) were measured with a three-axis sonic anemometer at a single point in the field (at 1.5-m height). The Lagrangian model of Wang et al. predicted the near-field concentrations of dust plumes emitted from a field disking operation with an overall accuracy of approximately 0.67 at 3-m height. Its average offset distance when compared with LIDAR measurements was approximately 38 m, which was 6% of the average plume moving distance during the simulation periods. The model is driven by weather measurements, and its near-field accuracy is highest when input time averages approach the turbulent flow time scale (3–70 sec). The model accuracy decreases with height because of smoothing and errors in the input wind field, which is modeled rather than measured at heights greater than the measurement anemometer. The wind steadiness parameter ($S$) can be used to quantify the combined effects of wind speed and direction on model accuracy.

INTRODUCTION
Particulate matter (PM) is regulated by the U.S. Environmental Protection Agency (EPA) as part of the National Ambient Air Quality Standards. Eulerian and Lagrangian models are widely used to simulate transport of PM and other pollutants.1–15 Eulerian models for estimating scalar transfer by turbulence have been limited by their inability to accurately model the dispersion of material from near-field sources.16 Lagrangian models explicitly consider the diffusion of material in the near- and far-field.16 Lagrangian models have been used to detail the variability of the subgrid concentrations in Eulerian grids to examine human exposure to toxins.15 This ability to detail spatial variability is quite valuable in agricultural settings and was the reason Wang et al.17 adapted a Lagrangian model for agriculture dust dispersion.

In agricultural, construction, and other settings where soil is frequently disturbed, little is known about the frequency and intensity of aerosol doses received at short distances away from the disturbance because of the transient nature of local dust plumes and the difficulties in making accurate concentration measurements in dynamic plumes.18 Thus, specific field, crop, and weather-related best management practices to minimize dust exposure in agriculture have not been defined. The authors

IMPLICATIONS
A Lagrangian model has been demonstrated to have the potential to estimate near-field $PM_{10}$ dispersion from agricultural disking operations. The major model improvements over traditional plume models are that it can simulate moving sources and plume meander. Therefore this technique can be used to provide accurate $PM_{10}$ dispersions for other agricultural operations and other moving sources (e.g., road dust).
have adapted the Lagrangian particle model of Wilson and Shum\textsuperscript{6} to estimate the dynamic plumes and aerosol concentrations of PM \(\leq 10\ \mu\text{m} (\text{PM}_{10})\) generated by agricultural field operations.\textsuperscript{9} The authors hope to use this model to evaluate management practices across the entire range of field crops, soils, moisture, weather conditions, and locations in the United States and elsewhere.

Before this can be done, the model’s accuracy and use protocols must be established. Hiscox et al.\textsuperscript{19} used an aerosol light detection and ranging (LIDAR) to accurately measure dynamic dust concentrations and calculate near-field human exposures from a field disking operation. The purpose of this paper is to compare these direct LIDAR measurements of dust plume movement and dynamic concentrations to these model-generated measurements to quantify the accuracy and precision of the model predictions.

The wind statistics inputs (e.g., friction velocity, \(u^*\) (m \(\cdot\) sec\(^{-1}\)); Monin–Obukhov length, \(L\) (m), and wind direction (degrees). In each time step, the model simulates particle flights in three dimensions on the basis of the wind turbulences calculated from the wind statistics and a Markov chain algorithm. The concentration (mg \(\cdot\) m\(^{-3}\)) at a location at time \(t\) (sec) is estimated by calculating the mass of the particles in a unit volume cube at the location at time \(t\) (details are in Wang et al.\textsuperscript{17}).

**METHODOLOGY**

**Model Description**

A dynamic Lagrangian, local field-scale model of dust dispersion from an agricultural disking operation was developed and presented in Wang et al.\textsuperscript{17} Distribution of aerosol particles of different sizes that remained airborne after a few meters was measured in this experiment by Holmén et al.\textsuperscript{18} They showed that over 96% of the airborne material generated in this disking operation was equal to or smaller than 10 \(\mu\text{m}\). (Field-scale and near-field are used interchangeably in this paper and mean that the simulation domain is \(< 1000\ \text{m}\) in the horizontal direction and \(< 100\ \text{m}\) in the vertical direction.) The atmospheric inputs for the model are the 1-sec wind statistics: friction velocity, \(u^*\) (m \(\cdot\) sec\(^{-1}\)); Monin–Obukhov length, \(L\) (m), and wind direction (degrees). In each time step, the model simulates particle flights in three dimensions on the basis of the wind turbulences calculated from the wind statistics and a Markov chain algorithm. The concentration (mg \(\cdot\) m\(^{-3}\)) at a location at time \(t\) (sec) is estimated by calculating the mass of the particles in a unit volume cube at the location at time \(t\) (details are in Wang et al.\textsuperscript{17}).

**Field Experiments**

The model was used to simulate the dynamic dust dispersion experiments of disking operations in an irrigated cotton field near Las Cruces, NM, described by Holmén et al.\textsuperscript{18} and Hiscox et al.\textsuperscript{19} The experimental field was approximately 2.8 ha. Figure 1 presents an aerial photo of the site annotated with the location of the field and instrumentation. Experimental field 1 was used in the spring of 2005 to measure dust emissions from field preparation and planting operations. On March 31, 2005, the field was worked for disking operations. The field was a mixture of Armijo clay loam and Harkey loam soil types. The average soil moisture was 28%.

![Figure 1. Experimental farm with field and sensor locations.](image)

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\(\text{PM}_{10}\)
A three-dimensional sonic anemometer (CSAT3, Campbell Scientific, Inc.) was located at a height of 1.5 m at the field edge to measure the 20-Hz wind component velocities and temperature \((u, v, w, T)\). The friction velocity \(u^*\), Monin–Obukhov length \(L\), and wind direction were obtained for each sampling pass at each second.

Dust plume size, shape, and movement were measured remotely with the University of Connecticut’s portable backscatter elastic LIDAR at approximately 4-s intervals for each horizontal-slice scan. The LIDAR specifications are listed in Hiscox et al.\(^{21}\) The LIDAR is capable of scanning in horizontal or vertical planes. For this disk operation, a series of horizontal slices was designed to scan the entire plume. The lowest elevation of the scan was a horizontal slice just above the field, and successive slices were collected at increasing elevations of approximately 3-m intervals. A full scan consisted of 15 successive slices were collected at increasing elevations of the scan was a horizontal slice just above the field, and was repeated 5–6 times for each pass depending on the dust’s persistence. The slices from each scan were combined in LIDAR data analysis software to characterize the dust’s persistence. The slices from each scan were combined in LIDAR data analysis software to characterize the dust’s persistence.

Complete LIDAR, sampler, and micrometeorology data were available for 13 disking passes. The model was run four times for each pass using four different time averages of the input micrometeorology data (1 sec, and 3, 30, and 60 min). Input data for the averaging periods of 3, 30, and 60 min are presented in Table 1. The 1-sec input data are not shown because of the size of the dataset.

The model concentration outputs were compared with the LIDAR scans by comparing LIDAR-measured to model-calculated horizontal arrays (hereafter called maps) of aerosol concentration at three different heights above ground (3, 9, and 15 m). At each height, the comparison statistics were the two-dimensional lagged cross-correlation coefficient, \(E_{i,j}^{(x,y)}\) and the offset distances of the peak coefficients. The coordinates \((x, y)\) of the coefficient represent the lagged distances in the two horizontal directions in the concentration data matrix, where \(x\) was in the tractor traveling direction and \(y\) was normal to the traveling direction (Cartesian coordinate system) (Figure 2). The simulated data for each map were shifted in \(x\) and \(y\) directions (step length = 5 m) in the two directions, then the corresponding correlation coefficient \(E_{i,j}^{(x,y)}\) of the overlapped parts of the simulated and the measured data was calculated. The two-dimensional shifted cross-correlation coefficient, \(E_{i,j}^{(x,y)}\), is (after Mayor et al.\(^{24}\))

\[
E_{i,j}^{(x,y)} = \frac{\sum a_{i,j} b_{i,j} - \left( \sum a_{i,j} \right) \left( \sum b_{i,j} \right)}{\sqrt{\sum a_{i,j}^2 - \left( \sum a_{i,j} \right)^2} \sqrt{\sum b_{i,j}^2 - \left( \sum b_{i,j} \right)^2}}^{1/2}
\]

where \(a\) (in the shifted simulated data) and \(b\) (in the measured data) are the overlapped matrices; \(i, j\) are the indices in either matrix (i.e., \(a_{i,j}\) and \(b_{i,j}\) are the element of the \(i\)th row and \(j\)th column in either matrix); and \(N\) is the number of points in either the \(a\) or \(b\) matrix. Comparison of these coefficient plots and the offset distances of the peak coefficient allowed us to quantify how closely
matched were the distribution and location of spatial clustering in the modeled and measured plumes. The peak correlation coefficient shows how close the particle distribution spatial patterns were between the modeled and the measured plumes; and the offset distance shows the location difference between the two plumes, measured and modeled (Figure 3). The best/worst match will be when that peak correlation coefficient is 1/0 and offset distance is 0/infinite.

RESULTS
A sample visualization of the simulation versus LIDAR measurement is plotted in Figure 4. These simulation output maps are from the 1-sec inputs (data not shown) and 3-min inputs (shown in Table 1) compared with the measured LIDAR maps for run no. 6.

In this simulation, the cross-correlation coefficients between the measured and the simulated plumes are plotted in Figure 3. At 3-m height, the peak correlation was 0.82 using 1-sec average input data versus 0.71 using 3-min average input data. At 9 m, the peak coefficients were 0.74 versus 0.57, and at 15 m, the peak coefficients were 0.57 versus 0.59 for the 1-sec and 3-min average input data, respectively. Generally, the accuracy of the model prediction decreased with an increase in height and averaging time, as demonstrated by the decreasing cross-correlation coefficients.

At 3 m, in the simulation of short-time inputs the offset distances were $x = -15$ m (horizontally on the maps) and $y = 50$ m (vertically) (the coordinates for the highest correlation coefficient) (Figure 5). This means that the simulated plume at 3 m was 15 m off of the measured
toward the \( x \) negative direction and 50 m off toward to the \( y \) positive direction, which is a total vector offset distance of 52.2 m (Figures 4 and 5).

Correlation coefficient maps were calculated at three heights above ground, 3, 9, and 15 m, and at four different averaging times for the input weather variables, 1 sec and 3, 30, and 60 min. The summary statistics are presented in Table 2, in which all of the values are 13-run averages and run-to-run variation. The average correlation coefficients range from 0.67 to 0.48. There is an average 23% decrease in correlation between the measured and modeled plumes with a height increase of from 3 to 15 m. They also show an average 7% decrease at 3-m height when averaging time is increased from 1 sec to 60 min. Thus, the model prediction of concentration is poorer with increasing height and increasing averaging time.

Table 2 also presents the run-to-run variability of the correlation coefficients expressed as the coefficient of variation (CV = standard deviation/mean). These statistics show a relative increase in average variation of 20% with each 3-m increase in height, and an increase of 13% with each increase in averaging time (1 sec to 3 min, 10%; 3–30 min, 11%; 30–60 min, 18%). Thus, the random error of the model prediction of concentrations increases with increases in height and averaging time.

Table 2 presents the average absolute offset distance, which is the horizontal distance between the measured and modeled plume center. These ranged from 35.1 to 49.4 m. There was no detectable change with time averages, but there was an average 8% decrease (improvement) in the offset distance with each 6-m height increase. The variability of the offset distance again shows no consistent change with different time averages but indicates an average 70% increase in the variability with each 6-m height increase.

**DISCUSSION**

The predictions of plume dispersion presented above are an improvement over previous work presented in the literature. Stein and Wyngaard\(^2\) noted that the “inherent uncertainty” in the dispersion process, because of the stochastic nature of the turbulence of the atmosphere, is defined as the ratio of their root mean square difference in a measurement period and the ensemble average of aerosol concentrations. They noted that previous experiments

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**Figure 3.** Illustration of the peak correlation coefficient and the offset distance calculations. Panel a shows the measured plume. Graphs b–e show different peak correlation values and offset distances for different simulated plumes.
generally showed the values of the inherent uncertainty in pollutant dispersion from a near-surface source in the atmosphere boundary layer exceed 50% for an averaging time on the order of 1 hr. This maximum would be expected to increase with shorter averaging times. Therefore, compared with previous work the average peak coefficient of 0.67 at a height of 3 m in this study is an improvement on previous work. In general, the model concentration errors are due to the model smoothing the actual LIDAR-measured concentrations. The model individually handles each dust particle, whereas the LIDAR showed that the dust actually moved in clumps of various sizes. Further improvement of the model predictions would have to include the mechanisms that define these clumps. Also, dynamic wind data at multiple horizontal locations and multiple heights need to be measured or modeled to overcome the rapid spatial structure changes in the wind field.

The ratio of offset distance to the downwind plume moving distance is the parameter used to measure the location difference of the modeled and measured plumes. Its magnitude is due to the accuracy of the plume location, which is primarily dependent on the variability of the wind direction and speed. On the basis of the average measured wind speed (4.8 m \cdot sec^{-1}) and the average simulation time (126 sec), the average plume moving distance was 602 m (\approx 4.8 \times 126). The average offset distance was 38 m; therefore, the ratio was only 38/602, or 6%.

The wind speed and direction are never constant over short averaging times. Therefore plumes are advected and dispersed in the near-field by nearly instantaneous fluctuations driven by turbulent structures. It is therefore important to use time averages of the wind measurements that reflect the time scale that is most influential in dispersing the plumes in the region of interest. The surface layer time scale \( (z/u^*)^2 \) ranged from 3 to 7 sec at a height of 1.5 m up to approximately 70 sec at a height of 15 m. This indicates that the predictable lifetime of wind eddies was at least an order of magnitude shorter than the 3 min it took to disk one pass across the field. Thus, as the input weather data are averaged over greater and greater time periods, the short-term wind field structure is lost and only its statistical properties are maintained if the wind field time series is statistically stationary. The increases in error of the model predictions of concentration that were positively correlated with increased time averages are likely due to the longer time averages smoothing the

**Figure 4.** The comparison of model simulation of (a, d, g) short-time (1-sec) inputs, (b, e, h) LIDAR observation, and (c, f, i) model simulation of long-time (3 min) inputs of instantaneous normalized dust concentration (dimensionless) at 3-, 9-, and 15-m heights from a disking operation at 152 sec after tractor was started. LIDAR and simulated concentration data were divided by their maximum value at each height. The tractor traveled from right to left. Tractor start point was (246,0). Tractor speed was 1.41 m \cdot sec^{-1}. The simulation time period was 152 sec, \( u^* = 0.50 \) m \cdot sec^{-1}, \( L = -40.5 \) m, and wind direction = 14.4°.
short-term fluctuations of wind direction and speed. The higher concentration prediction errors that were positively correlated with increased height are most likely due to errors in the model predictions of the wind properties at the higher elevations because they were only measured at a single height (1.5 m).

Wind direction fluctuations and associated wind speed fluctuations are the mechanisms that move the plume horizontally back and forth in the meandering process. To classify these fluctuations of the wind direction and speed, a wind steadiness parameter ($S$) was used that combines these two. Singer\textsuperscript{27} proposed that the constancy of the wind, $k$, defined as the mean vector wind velocity divided by the mean scalar wind speed, $V/V$, can be used for classification purposes. The range of $k$ is from 0 to 1. A value of 1 means the wind direction did not change over the averaging period. A value of 0 means a completely symmetrical wind speed and direction distribution during the averaging period. The steadiness factor, $S$, is defined as

$$S = \frac{2}{\pi} \arcsin (k) \quad (2)$$

The equation transforms the constancy into a linear function. The angular deviations range from 0 to 180°. If $k$ is 1 then $S$ is 1, and if $k$ is 0 then $S$ is 0. A change of 0.1 in $S$ represents a deviation in the wind of 18° over the averaging period. The average $S$ for each of the input runs and averaging time lengths are presented in Table 1.

Similar plots of $u^*$ (not shown) demonstrate that longer time averages smooth the variation in wind turbulence intensity but do not change the overall average.

Figure 5. Sample two-dimensional cross correlation between the LIDAR-measured and the modeled dust concentration (short-time inputs vs. long-time inputs) at (a–c) 3-, (d–f) 9-, and (g–i) 15-m height. Tractor traveled from right to left. Tractor start point was at (246,0). Tractor speed was 1.41 m·sec$^{-1}$. The simulation time period was 152 sec, $u^* = 0.50$ m·sec$^{-1}$, $L = -40.5$ m, and wind direction = 14.4°.
Also, there is little difference between the 30 and 60 min averages as expected in a fully developed convective boundary layer.26

The combination of wind speed variations and wind direction bias in the wind steadiness parameter (S) shows an overall decrease in wind steadiness with increased averaging times (Figure 6), which explains the decrease in concentration prediction accuracy with longer time averages.

The run-to-run values of wind direction are plotted in Figure 7 for the different averaging times and show a wind veer (clockwise movement) with longer-term averages. This is interpreted to mean that the longer time series of wind direction were not stationary and likely were the cause of the large regular offset distances.

In this study, the wind was very steady (steadiness > 0.9); that is, wind direction and wind speed did not change much. This resulted in little model performance difference between the 1-sec and 3-min average input runs. When wind is not steady (steadiness value is low), the model performance from 1-sec inputs would have better performance than that from the long-time average inputs. It should be noted that the availability of a LIDAR made nearly instantaneous measurements of concentration in the air possible. This has not been previously available to test dispersion models at the local scale. Thus the short-time-average predictions could be tested in this project.

The wind data measurements were limited to one point at the field edge. Because of the spatial variations of the dynamic wind field where specific structures had a lifetime on the order of seconds, the 1-sec inputs captured the plume meanders during the 3-min pass on those occasions in which the driving eddies were translated from the anemometer to the tractor or vice versa. But for much of the time, this was not the case. Therefore, there was little difference between the 1-sec and 3-min average input results. This suggests that dynamic wind data at multiple horizontal locations and multiple heights, measured or modeled, are likely to improve the model performance in the near-field.

CONCLUSIONS

The Lagrangian model of Wang et al.17 predicted the near-field concentrations of dust plumes emitted from a

Table 2. Overall means and run-to-run variation of concentration (peak correlation coefficient) and offset distance (modeled vs. LIDAR-measured).

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<th>Error Measure</th>
<th>Height (m)</th>
<th>1 sec</th>
<th>3 min</th>
<th>30 min</th>
<th>60 min</th>
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<tr>
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<td></td>
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<td>42.3</td>
<td>49.4</td>
<td>42.7</td>
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<td>39.1</td>
<td>37</td>
</tr>
<tr>
<td>CV of distance offset</td>
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<td>0.25</td>
<td>0.27</td>
<td>0.20</td>
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<td></td>
<td>9</td>
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<td>0.36</td>
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<tr>
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<td>0.64</td>
<td>0.61</td>
<td>0.62</td>
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<tr>
<td>Peak correlation coefficient (PCC)</td>
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<td>0.66</td>
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</tr>
<tr>
<td></td>
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<td>0.48</td>
<td>0.54</td>
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<tr>
<td>CV of PCC</td>
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<tr>
<td>Wind steadiness</td>
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<td>0.98</td>
<td>0.94</td>
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Figure 6. Run-to-run wind steadiness for 3-, 30-, and 60-min inputs.

Figure 7. Run-to-run wind direction with different time averages.
field disking operation with an overall accuracy of approximately 0.67 at a height of 3 m. Its average offset distance when compared with LIDAR measurements was approximately 38 m. The model is driven by weather measurements, and its near-field accuracy is highest when input time averages approach the turbulent flow time scale (3–70 sec). The wind steadiness parameter ($S$) can be used to quantify the combined effects of wind speed and direction on model accuracy.

The Lagrangian model presented here is a significant improvement to the state of the art for simulating near-field $PM_{10}$ dispersion from a disking operation. The improvements are primarily due to the inclusion of moving sources and inputs of weather parameters averaged to the surface layer time scale (3–70 sec). However, the model accuracy decreases with height because one-point wind data measurements at a height of 1.5 m cannot represent the wind field well at higher heights. The model was parameterized for the near-field surface layer. Therefore, the model should not be used to simulate regional (horizontally $> 1000$ m and vertically $> 100$ m) dust dispersion.

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