

# SIMULATED REGIONAL PM<sub>10</sub> DISPERSION FROM AGRICULTURAL TILLING OPERATIONS USING HYSPLIT

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**ABSTRACT.** Particulate matter (PM) of aerodynamic diameter less than or equal to 10  $\mu\text{m}$  (PM<sub>10</sub>) is regulated by the U.S. Environmental Protection Agency (EPA) as part of the National Ambient Air Quality Standards (NAAQS). This article reports on the calibration and evaluation of the HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) version 4.9 model to simulate regional dust dispersion from a disking operation. Disking operations in a cotton field in Las Cruces, New Mexico, were conducted, and boundary layer PM<sub>10</sub> concentrations were sampled using a DustTrak sampler on an airplane flown at altitudes between 200 and 500 m and several kilometers downwind. Using North American Mesoscale (NAM) forecast meteorological data (NAM12km, 12 km resolution) with vertical profiles, the model is capable of reasonably simulating regional PM<sub>10</sub> dispersion (simulated data = 1.048  $\times$  measured data with  $R^2 = 0.85$ ).

**Keywords.** Agricultural operation, HYSPLIT, PM<sub>10</sub>, Regional, Simulation, Tilling.

Particulate matter (PM) of aerodynamic diameter of less than or equal to 10  $\mu\text{m}$  (PM<sub>10</sub>) is regulated by the U.S. Environmental Protection Agency (EPA) as part of the National Ambient Air Quality Standards (NAAQS). PM<sub>10</sub> emitted from agricultural field operations (e.g., disking, listing, leveling, planting, harvesting) is first dispersed downwind in the near-field in high-concentration plumes and is then dispersed in lower concentrations farther downwind in the far-field (i.e., >1 km) (Hanna et al., 1982). A near-field dynamic model to estimate PM<sub>10</sub> dispersion was developed and validated (Wang et al., 2008, 2009). This model can be used to estimate the PM<sub>10</sub> concentration for people working and living immediately downwind of the agricultural field operation (0 to 3 km). A far-field regional model is needed to estimate the PM<sub>10</sub> dispersion from agri-

cultural operations for people working and living 3 to 50 km downwind.

The objective of this study was to calibrate and evaluate HYSPLIT for regional PM<sub>10</sub> dispersion simulations from agricultural field operations using forecast meteorological data.

Most pollutant dispersion models can be broadly classified as steady-state or dynamic. Steady-state models assume that the environmental conditions (e.g., wind direction and speed, and atmospheric stability) are fixed during a long simulation period (e.g., 1 h). Steady-state models can be used for industrial pollutant dispersions (e.g., smokestack dispersion) and other steady-state environments. The regulatory air quality models (Fugitive Dust Model, FDM; Industrial Source Complex Model, ISC3) at EPA are steady-state models that follow a Gaussian distribution to simulate dispersion ([www.weblakes.com/lakeepa1.html](http://www.weblakes.com/lakeepa1.html)). CALPUF (California Puff) Dispersion Modeling System), another Gaussian dispersion model, performed better than the ISC3 model, but a difference in magnitudes of predicted to measured concentrations of SO<sub>2</sub> was found (Sabah et al., 2010).

Dynamic models simulate pollutant dispersion using dynamic environmental conditions. HYSPLIT, a dynamic simulation model, is more complex than the steady-state models. The highest frequency of the input atmospheric data and simulation step can be 1 min. The short simulation step of the HYSPLIT model is more appropriate for PM<sub>10</sub> dispersion simulations from agricultural operations because of their dynamic meteorological conditions (Draxler and Hess, 1998). The model currently calculates dispersion using several methods, but the latest version has an option to use a Lagrangian particle model in which many particles are released over the duration of the simulation and the advective motion of each particle has an added random component according to the atmospheric turbulence at that time. The model has a minimum time step of 1 min (Draxler and Hess, 1997) even though meteorological driving data for wind speed and turbulence variance in the vertical direction are not available at

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# 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  $\leq 10 \mu\text{m}$  ( $\text{PM}_{10}$ ) 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.

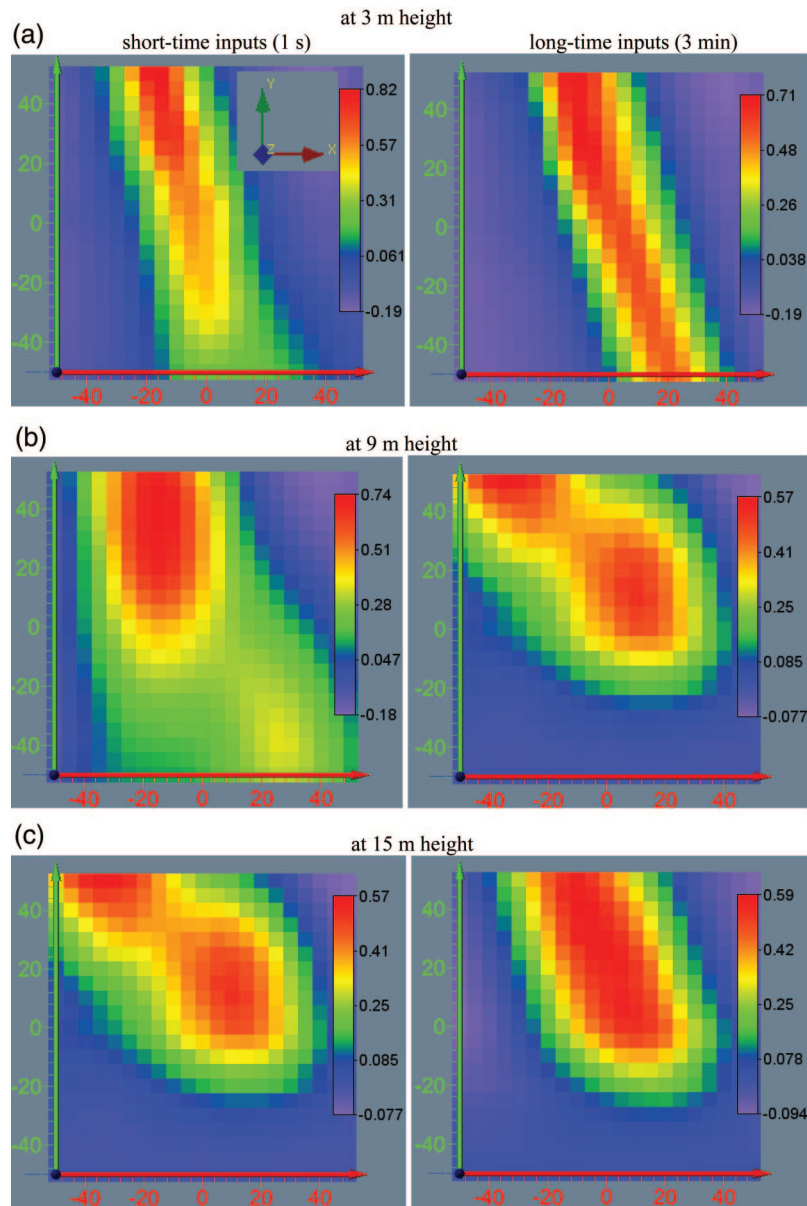
## INTRODUCTION

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.<sup>1–15</sup> 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.<sup>16</sup> Lagrangian models explicitly consider the diffusion of material in the near- and far-field.<sup>16</sup> Lagrangian models have been used to detail the variability of the subgrid concentrations in Eulerian grids to examine human exposure to toxins.<sup>15</sup> This ability to detail spatial variability is quite valuable in agricultural settings and was the reason Wang et al.<sup>17</sup> 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.<sup>18</sup> 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  $\text{PM}_{10}$  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  $\text{PM}_{10}$  dispersions for other agricultural operations and other moving sources (e.g., road dust).



**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  $1.41 \text{ m} \cdot \text{sec}^{-1}$ . The simulation time period was 152 sec,  $u^* = 0.50 \text{ m} \cdot \text{sec}^{-1}$ ,  $L = -40.5 \text{ m}$ , and wind direction =  $14.4^\circ$ .

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<sup>27</sup> proposed that the constancy of the wind,  $k$ , defined as the mean vector wind velocity divided by the mean scalar wind speed,  $\bar{V}/\bar{V}$ , 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  $180^\circ$ . 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  $18^\circ$  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.

# Local Dust Emission Factors for Agricultural Tilling Operations

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**Abstract:** Dust emission factors for regional- and local-scale simulations of particulate matter with diameters less than or equal to 10  $\mu\text{m}$  ( $\text{PM}_{10}$ ) dispersion from agricultural operations are not generally available. This article presents a modification of the U.S. Environmental Protection Agency AP-42 approach to better calculate aerosol emission factors of  $\text{PM}_{10}$  for agricultural tilling operations. For the modification, we added the variables soil moisture, operation type, and crop type based on experimental and literature data to estimate local emission factors. Field experiments to measure the  $\text{PM}_{10}$  emissions from rolling, disking, listing, planting, and harvesting cotton (*Gossypium hirsutum* L.) were conducted. Data from these field experiments plus literature data were used to isolate the effects of soil moisture and operation type on the emissions. Literature data were then used to add different crop and operation types.

**Key words:** Agricultural operation, AP-42, emission factor,  $\text{PM}_{10}$ , source strength, tilling.

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The U.S. Environmental Protection Agency (EPA) defines an *air emission factor* as “a representative value that relates the quantity of a pollutant released to the atmosphere with an activity associated with the release of that pollutant” (EPA, 1985). Emission factors are generally used to estimate the long-term ensemble (or population) emissions of a specific activity by multiplying the emission factor by the rate of the pollution-emitting activity. These general emission factors are not sufficient to estimate local agricultural emission rates where operation type, crop type, and soil moisture variations can affect the emissions of individual operations by orders of magnitude. This article considers these variations in the case of agricultural tilling operations.

The EPA specifies the calculation of  $\text{PM}_{10}$  (particulate matter with diameters  $\leq 10 \mu\text{m}$ ) emission factors for agricultural tilling operations as a power function of soil texture only:

$$E = 112.98 s^{0.6} \quad (1)$$

where  $E$  is the  $\text{PM}_{10}$  emission factor (milligrams per square meter) and  $s$  is the silt fraction (proportion of particles  $< 75 \mu\text{m}$  in diameter) of surface soil (0–10 cm of depth) (proportion, grams per gram). This silt fraction's definition is different from the definition commonly used by geologists and soil scientists

who usually consider silt as particles from 2 to 50  $\mu\text{m}$  and clay as particles from 0 to 2  $\mu\text{m}$  (EPA, 1985). This equation for fugitive dust was developed by the Midwest Research Institute in 1983 and adopted by the EPA in the fourth edition of AP-42 (EPA, 1985; Cowherd and Englehart, 1984).

The California Air Resources Board (CARB) has adopted empirical  $\text{PM}_{10}$  emission factors for several types of agricultural operations (Flocchini and James, 2001). The CARB emission factors separate agricultural operations into categories. For example, disking, tilling, and chiseling are combined in one category and have one single emission factor, 1.2 (lbs acre-pass<sup>-1</sup>; i.e., 134.8 mg m<sup>-2</sup>); land planing and floating (leveling the tops of furrowed rows before planting) are also combined in one category with an emission factor of 12.5 (lbs acre-pass<sup>-1</sup>; i.e., 1,404.5 mg s<sup>-2</sup>).

We have measured (Hiscox et al., 2007) and modeled (Wang et al., 2008) the  $\text{PM}_{10}$  exposure of workers in and near fields during agricultural operations in the lower Rio Grande Valley of New Mexico. To use our model (Wang et al., 2008) broadly in other environmental conditions, we need to estimate emission rates under different conditions without making *in situ* emission factor measurements. Therefore, we have developed, and describe in this article, modifications for the method described in Eq.(1) to add the variables soil moisture, crop type, and operation type, which allow the extension of our measured emission factors to other environmental conditions.

## MATERIALS AND METHODS

In 2005 and 2008, field experiments were conducted to quantify airborne particle emission factors from different agricultural operations (rolling, disking, listing, planting, and harvesting) in cotton fields at New Mexico State University Leyendecker Plant Science Center in Las Cruces, NM (32.2°N, 106.8°W; elevation, 1,180 m). To supplement the experimental data, literature data from Holmén et al. (2001) and Cassel et al. (2003) were also used.

## Experiments

Rolling, listing, planting, and disking operations were conducted in March and April of 2005, and disking operations were repeated in March of 2008 in Experimental Field 1 (100 m  $\times$  246 m) in the experimental cotton fields shown in Fig. 1. The operation sequence was deliberately conducted as normal and was the same as that used every year at the New Mexico State University farm, which mimics the most common sequencing in the Mesilla Valley region of New Mexico. On November 7, 2005, a harvesting operation was conducted in Experimental Field 2 (80 m  $\times$  210 m). The soil types for both fields were a mixture of Armijo clay loam (fine, Montmorillonitic, Thermic Typic Torrets) and Harkey loam (coarse-silty, mixed [calcareous], Thermic Typic Torrifluvents) (the fraction of  $> 75\text{-}\mu\text{m}$  particles, 0.43; the fraction  $> 2\text{-}\mu\text{m}$  and  $< 75\text{-}\mu\text{m}$  particles, 0.23; the fraction of  $\leq 2\text{-}\mu\text{m}$  particles, 0.34) (USDA, 2005).

A three-dimensional sonic anemometer (CSAT3, Campbell Scientific Inc, Logan, UT) was located at 1.5 m height at the field edge and measured, at 20-Hz sampling rates, the wind component velocities and air temperature. From these data, average

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# Application of an atmospheric gene flow model for assessing environmental risks from transgenic corn crops

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**Abstract:** Gene flow data from experiments under limited environmental conditions (e.g. wind speed and direction, atmospheric stability) have only provided limited information for gene flow risk management. It is necessary to apply models to predict the gene flow under a complete set of possible environmental conditions to inform farmers, seed companies, government agencies, and researchers about the risks and potential prevention and precaution methods. In this paper, the previous validated gene flow model developed by the authors was used to predict gene flow from genetically modified (GM) corn crops. The model was used to simulate potential gene flow from GM corn sources of different sizes from one plant area of 0.1 m<sup>2</sup> to an area 3.1×10<sup>6</sup> m<sup>2</sup> under normal weather conditions. In addition, the model was also used to predict the potential gene flow for different source strengths, atmospheric conditions, buffer heights, buffer field sizes, and pollen settling speeds from 10,000 m<sup>2</sup> sources. The model simulations have provided gene flow information for risk management under the above conditions and have shown that the source sizes, source strengths, buffer heights, buffer sizes, atmospheric conditions, and pollen settling speeds had important effects on gene flow. While the atmospheric conditions and pollen settling speeds cannot be controlled, choosing appropriate buffer heights and sizes will effectively prevent gene flow. The lost seed control is crucial to limit gene flow because even a GM corn plant can result in a grand total deposition flux of 646,272 grains/m<sup>2</sup>, an outcrossing ratio of 0.016, and outcrossed seed of 110 kernels/m<sup>2</sup> at 0.8 m from the plant in the non-target field under normal atmospheric conditions.

**Keywords:** model, risk management, crops, corn, pollen, gene flow, random walk, outcrossing

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## 1 Introduction

Since the first introduction of a genetically altered microscopic bacterium for devouring oil spills in 1971<sup>[1]</sup>, DNA technology (popularly referred to as genetic engineering or genetic modification) development and application have rapidly accelerated, especially in

agricultural and pharmaceutical processes and products. In agriculture, scientists use recombinant DNA technology to introduce genes for a desired trait from either the same or different species to produce novel (transgenic) plants with special characteristics to resist particular diseases, chemicals, or environmental stress for higher yields and/or better quality (U.S. Congress Office of Technology Assessment, 1992). It is estimated that in 2006, approximately 53.4 million hectares of land were planted with transgenic plants in the United States<sup>[2]</sup>.

Transgenic corn was one of the first four pest-resistant crops to flow from the industrial R&D pipeline to commercial production. It is estimated that one-third of all cornfields in the United States are planted

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