THE RELATIVE ACCURACY OF DRIFTSIM WHEN USED AS A REAL-TIME SPRAY DRIFT PREDICTOR

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ABSTRACT. *Increasing regulation of spray drift has led to the development of real-time drift monitoring systems that present drift potential to applicators so that drift reduction spraying techniques can be implemented on an as-needed basis. The central component in each of these state-of-the-art systems is a drift prediction model. A real-time drift monitoring system was developed using look-up tables produced from simulations of a random-walk model (FLUENT via DRIFTSIM). The predictive accuracy of this system, evaluated as the difference between predicted drift and in-field measured drift, was compared to alternative prediction models to determine the suitability of random-walk models for real-time drift prediction. DRIFTSIM was found to produce a significantly more accurate representation of real-time predicted drift when compared to four of the six alternative models tested. No significant difference in predictive accuracy was found when comparing DRIFTSIM to the two other models. When compared to alternative models at incremented distances downwind from the point of spraying, DRIFTSIM's predictions were found to be overall more accurate up to 10 m from the boom edge; however, three alternative models provided more accurate predictions for long-distance drift (20 to 50 m from the boom). These results suggest the potential of using DRIFTSIM in future real-time drift monitoring for increased accuracy and performance. However, additional development is needed to improve far-field (>10 m downwind of an application) drift prediction accuracy.*

Keywords. *Drift prediction, DRIFTSIM, Random-walk model, Spray drift.*

Spray drift, the airborne off-target movement of pesticides, results in reduced application rates, non-target damage, and environmental concerns. In 2009, the U.S. Environmental Protection Agency (EPA) proposed a revision to its current spray drift regulatory standards that, if passed, would require more straightforward wording on pesticide labels. The intent of this language is to provide applicators with more specific information regarding methods for safe application of a pesticide, as well as to establish clear-cut boundaries for the enforcement of drift regulations (EPA, 2009). With these revisions comes a heightened motivation for applicators to implement drift reduction technologies in order to protect non-target organisms from contamination.

The state-of-the-art in drift reduction technologies are systems that provide applicators with real-time drift potential information, allowing the applicator to alter spraying practices on-the-go to reduce drift. Potential for drift damage to non-target organisms is constantly changing during a spraying event, as weather conditions and the position of the sprayer relative to sensitive organisms vary over time and location. The goal of real-time drift prediction systems is to allow drift reduction methods to be implemented on an as-needed basis rather than being used on a field as a whole. By implementing measures as-needed, applicators can spray to maximize pesticide efficacy when the potential for drift damage is low, and then alter methods to reduce drift when the potential is high.

The central components of state-of-the-art drift evaluating systems are algorithms that predict drift. In addition to being accurate, these methods of drift prediction must be computationally inexpensive to achieve fast run times (and thus fast prediction update rates) on standard field computers.

Both regression models and analytical models have been proposed by researchers to represent and predict drift phenomena. Regression models are derived from data sets generated by either in-field or wind tunnel testing (Smith et al., 2000; Nuyttens et al., 2007). Analytical drift prediction models describe mechanistic, physical phenomena rather than numerical relationships. Most analytically derived models can be classified as either plume or random-walk, which differ in their mode of action for tracking the liquid volume leaving the sprayer. Random-walk prediction models are much more commonly used in ground application situations. These models track individual droplets from the point at which they exit the nozzle until either the water within the droplet completely evaporates or the droplet deposits within the field. Droplet trajectories are evaluated in a numerical, Lagrangian flow fashion, meaning that the change in the droplet's position and velocity is tracked dur-

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ing small time steps during which the droplet is acted upon by wind, drag, gravity, and statistical parameter influences (Thompson and Ley, 1983; Miller and Hadfield, 1989; Hall, 1975).

Regression models, when compared to analytical models, are much less computationally expensive, as they typically rely on a single equation to calculate predicted drift. The major limitation of such models is their narrow scope, which is constrained by the range of the operating conditions for which drift testing was conducted (Smith et al., 2000). Analytical models for drift prediction have increased in popularity over the last several decades as technology has advanced to the point where simulations can be performed on personal computers. In contrast to regression models, analytical models have a much wider range of application, as they are derived from mechanistic relationships. The major limitation of analytical models when used for real-time drift prediction is the computing time required for simulation, which leads to limited predictive resolution over time. For example, the random walk model of Baetens et al. (2007) required 18 h of simulation time in ANSYS to establish droplet trajectories.

State-of-the-art drift potential monitors currently apply mechanistic models, either plume or modified random-walk models, because they provide reasonable update rates (when compared to more extensive random-walk models) while still having a broad scope of application (Lebeau et al., 2009; Hewitt et al 2002). As full-scale random-walk models have been found to be highly accurate in predicting drift from ground applications (Thompson and Ley, 1983; Miller and Hadfield, 1989; Holterman et al., 1997; Baetens et al. 2007), it is desirable to incorporate such models within real-time drift monitoring systems.

DRIFTSIM, developed by Zhu et al. (1995), is a user-friendly, drift prediction software program that relies on random-walk model based predictions. DRIFTSIM was developed specifically for ground applications and has become a highly recognized and applied tool for the management of drift by extension personnel and regulatory agencies (White, 2006). To reduce DRIFTSIM's computing time requirements, Zhu et al. (1995) performed and recorded the results of over 2 million random-walk drift simulations within FLUENT, a computation fluid dynamics program. Drift distances of individual particles resulting from each simulation, along with weather and application conditions applied within the simulation, are stored in look-up tables within DRIFTSIM. DRIFTSIM recalls the results of random-walk simulations from the look-up tables, resulting in a highly efficient application of random-walk based predictions. This development by Zhu et al. (1995) of extensive random-walk model look-up tables established the possibility of incorporating random-walk predictions within real-time drift prediction.

Although DRIFTSIM is regarded as a highly accurate method for predicting drift of ground applications, little testing has been done to form a basis for this perception. Reichard et al. (1992) evaluated the base random-walk model within FLUENT through wind tunnel testing. The model within FLUENT was found to be highly accurate in predicting drift; the greatest difference between predicted and experimental drift was 5.4%. However, the greatest drift distance evaluated within the testing was only 2 m. Reichard et al. (1992) concluded that additional testing is required in order to determine the capabilities of the model for predictions at greater distances.

The overall goal of this research was to evaluate the predictive accuracy of DRIFTSIM when used for real-time, in-field spray drift prediction. Specific objectives were as follows:

- Develop an algorithm that converts the drift distances predicted by DRIFTSIM look-up tables to ground deposition levels for application in a real-time spray drift monitoring system.
- Statistically compare the predictive accuracy of DRIFTSIM to alternative regression models.
- Determine the suitability of DRIFTSIM for use as a real-time drift prediction model.

Methods and Materials

Algorithm Development

An algorithm was written using C++ to recall the drift distance of a droplet from the look-up tables generated by Zhu et al. (1995) given real-time weather (temperature, humidity, wind speed, and wind direction) and application conditions (droplet spectrum of nozzle, boom height, and nozzle operating pressure). As opposed to drift distance, the models by Hewitt et al. (2002) and Lebeau et al. (2009) predict and present drift in the more intuitive and usable form of deposition (volume per unit area). An algorithm to accompany the look-up routine was developed to convert drift distances to depositions for full-boom spraying. This algorithm relies on a discretely represented nozzle spectrum characterizing the nozzles (ten droplet size classes were used within the algorithm), sprayer boom length, and nozzle spacing in calculating this deposition. Given the sprayer position within the field and the wind direction, the algorithm spatially places the deposited drift.

The developed algorithm, implemented on a laptop computer, was interfaced with sensors required to evaluate weather and application conditions for real-time drift prediction. A Maretron weather station (Maretron, Inc., Phoenix, Ariz.) provided temperature, humidity, wind speed, and wind direction at an update rate of 2 Hz. Boom height was obtained through the instrumentation of an ultrasonic sensor (model PING))), Parallax, Inc., Rocklin, Cal.), also at a rate of 2 Hz. An EZ-Guide 500 receiver (Trimble Navigation, Ltd., Sunnyvale, Cal.) provided uncorrected GPS inputs. To further increase the GPS accuracy, a Slingshot RTK modem (Raven Industries, Sioux Falls, S.D.) was used to provide GPS correction through the Iowa CORS network. All sensor variables were input serially to the prediction algorithm run on the laptop. Based on the computing speed of the computer, the program updates the predicted drift at a rate of 0.5 Hz, with the most recent operating conditions applied for prediction as droplets are sprayed.

The real-time prediction system was installed on a Spra-Coupe 7650 sprayer (AGCO, Duluth, Ga.) for testing. Vari-

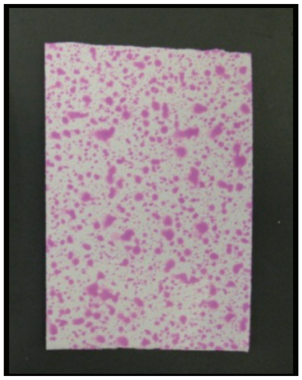

Figure 1. Dyed Kromekote card.

target nozzles (Delavan AgSpray Products, Mendota Heights, Minn.) were implemented on the test vehicle. The Varitarget nozzle was chosen for testing because it was designed to produce little variability in nozzle spectrum as the pressure and flow rate through the nozzle are varied. Duggupati (2007) evaluated the nozzle spectrum characteristics of the Varitarget nozzle and found constant spray quality based on ASABE Standard 572.1 (*ASABE Standards*, 2010a) over nozzle pressures from 10 to 50 psi. It was thus assumed throughout the testing that the nozzle spectrum used to characterize the fine nozzle on board the sprayer was constant.

Field Measurements

Testing was conducted in the fall of 2010 at the Iowa State University Agricultural Engineering and Agronomy Research Farm. Individual tests consisted of spraying a single swath along a straight ("A-B") line. Measurement of experimental deposition levels was performed according to ASABE Standard S561.1 (*ASABE Standards*, 2010b). White Kromekote paper cut into 2 cm × 3 cm sections served as experimental drift collectors in the testing. Collection cards were placed flat on bare ground per the ASABE standard. The sprayed volume was water with a 0.275% concentration of Tracer hot pink dye (Precision Laboratories, Waukegan, Ill.), as used by Hanna et al. (2009). The dye-Kromekote paper (fig. 1) method produces a droplet stain with a distinct edge and is a popular approach in extensive collection experiments (Barry et al., 1978; Maksymiuk and Moore, 1962).

The field layout for predictive accuracy testing is shown in figure 2. Cards were placed 0 to 50 m from the edge of the boom in 2 m increments, thus constituting a "card vector" of 26 cards. Ten card vectors were placed in the field for each set of test conditions, with 50 m between each card vector. This 50 m spacing allows for wind direction variability up to 45° without deposition from a single card vector overlapping an adjacent card vector per ASABE Standard S561.1. Test days were selected based on wind direction, wind direction stability, and wind speed to satisfy the test design criteria. In order to maintain the desired card vector spacing to prevent overlap, field dimensions required either due north or due south wind directions. Wind direction variations from due north or south of less than 20° were desirable to reduce the potential for overlap on adjacent card vectors.

A significant limitation of in-field testing is the inability to vary and select weather conditions at will. In evaluating the predictive accuracy of a model, conclusions can only be drawn for the set of conditions encountered during testing. It was determined that the scope of the predictive accuracy testing would be limited to typical operating conditions. To provide variability and increased understanding of the predictive ability, four general sets of operating conditions were selected to serve as treatments, with wind speed and boom height as the two principle subjects of variability. While boom heights could be changed manually, wind conditions were varied by spraying on different days based on weather forecasts. A Varitarget "fine" nozzle type was selected for testing, as it produces high drift potential cases. The evaluated nozzle spectrum, which was implemented within the prediction algorithm, is shown in figure 3.

Four tests were conducted in order to include a wide range of operating conditions by which to evaluate DRIFTSIM's ability to accurately predict drift. Although real-time conditions were monitored throughout the tests and varied widely, the average operating conditions for each of the four tests are shown in table 1. The application rate was held constant throughout the tests at 70 L ha^{-1}. The sprayer travel speed was also held constant throughout the tests at 8 km h^{-1}.

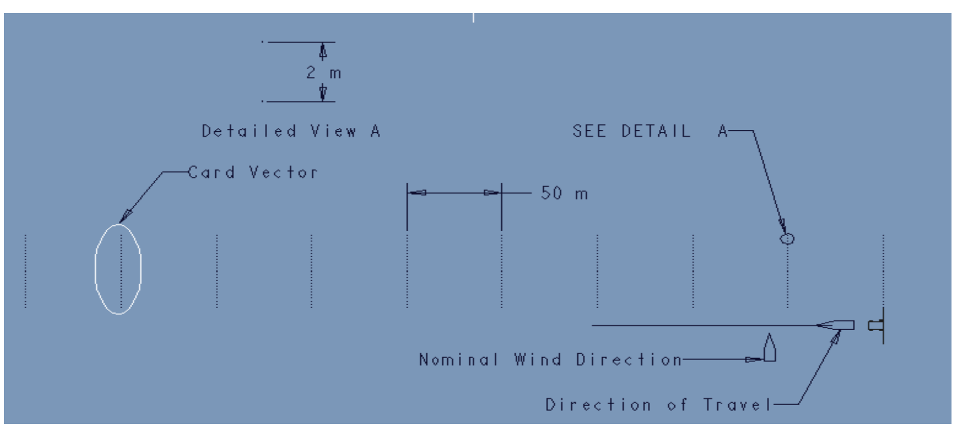

Figure 2. Field layout and card placement in model accuracy testing.

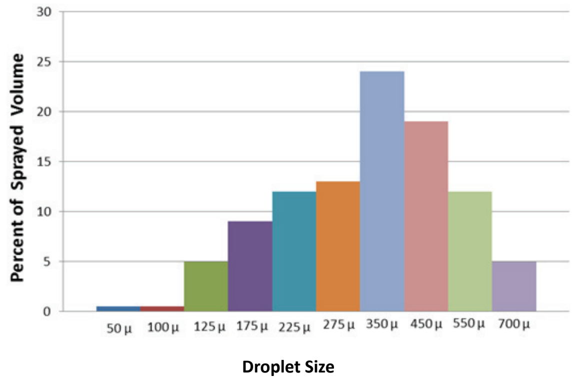

Figure 3. Evaluated nozzle spectrum of the Varitarget "fine" nozzle used in testing.

Table 1. Average operating conditions recorded during each of the four tests. Wind directions are relative to perpendicular to card vectors. Standard deviations are shown in parentheses for wind speed and direction.

Test	Temp. (°C)	RH (%)	Wind Speed ($m\ s^{-1}$)	Wind Direction (deg.)	Boom Height (m)	Pressure (kPa)	Nozzle Type
1	22.5	52.7	3.9 (1.1)	4.0 (13.5)	1.2	162.1	Fine
2	22.5	52.6	1.2 (0.4)	4.0 (14.8)	1.0	236.5	Fine
3	11.2	67.2	5.4 (1.17)	-7.0 (16.0)	1.2	216.0	Fine
4	12.2	61.3	6.4 (1.87)	-15.0 (19.3)	1.2	160.7	Fine

Kromekote cards containing depositions were collected 30 min after spraying to provide adequate drying time. Depositions on the field-collected cards were measured using DropletScan software (WRK of Arkansas, Lonoke, Ark.). DropletScan measures the deposition on card surfaces (reported as $L\ ha^{-1}$ or $gal\ acre^{-1}$) through the application of image processing algorithms to scanned images (Whitney, 2003). The accuracy of DropletScan is highly dependent on the use of a spread factor representative of the liquid-paper interface. Barry et al. (1978) developed relationships between spot diameters, as measured under the microscope, and pre-deposition droplet diameters controlled through the use of a vibrating reed apparatus. With the DropletScan and scanner setup used to analyze the depositions, droplets as small as 50 µm in diameter could be accurately measured. As droplets smaller than 50 µm comprise a very small percentage of both the sprayed and deposited volume (the exact percentage is variable depending on the specific nozzle and environmental conditions), errors resulting from the inability to accurately detect or measure such droplets were deemed minimal for the analysis.

An algorithm was added to the drift prediction program to store predicted drift within a ".txt" file, along with latitude and longitude, thus providing a position of the stored deposition. Predicted depositions were compared statistically to experimental depositions occurring at the same spatial position through paired difference t-tests.

The predictive ability of DRIFTSIM was statistically compared to that of six alternative models. Although it was desirable to compare real-time drift predicted by a random-walk model (DRIFTSIM) to that predicted by current state-of-the-art plume and simplified random-walk models, such alternative models were not available for simulation, as they are still in development. All alternative models considered within the accuracy analysis were regression models. Two models developed by Smith et al. (2000) were included within the analysis, termed Smith 1 and Smith 2. These models differed in the specific independent variables used to predict drift. The third model was developed by Nuyttens et al. (2007) in Belgium for drift prediction. The fourth model is a more general model developed by Wolf and Caldwell (2001), which is currently used in Canada by PMRA for regulatory purposes. The drift model developed by Wolf and Caldwell (2001) presents deposition as a function of distance, with alternative coefficients used in prediction for discrete operating conditions. As drift cannot be evaluated continuously, the Wolf and Caldwell (2001) model was only compared to DRIFTSIM for test 1, which closely matched the conditions for which the Wolf and Caldwell (2001) model is applicable. The fifth model was developed by Ganzelmeier et al. (1995) for use in drift evaluation in Germany, while the sixth model was developed in the Netherlands by Holterman et al. (1997).

The required independent variables, which were stored in real-time during testing, were applied to each of the six prediction models to produce predicted deposition profiles for each model. The predicted drift from each model was linked with spatial coordinates based on the position of the sprayer. Each set of operating conditions was recorded during testing, thus creating six unique predictions of drift for each test case for comparison to the experimental deposition resulting from each test case.

RESULTS

QUALITATIVE COMPARISON OF DRIFTSIM TO THE ALTERNATIVE MODELS

A qualitative comparison of drift from each of the seven prediction models (DRIFTSIM and the six alternative models) to the experimental deposition is shown in figure 4. The deposition shown is averaged at each of the 26 distances downwind from the boom edge for test 1 only. Results from test 1 were indicative of the other three tests. The logarithmic representation of deposition allows viewing of both the relatively high depositions near the boom edge and the low depositions at greater distances from the boom. Minimum depositions were truncated to -2 (i.e., log(0.01)),

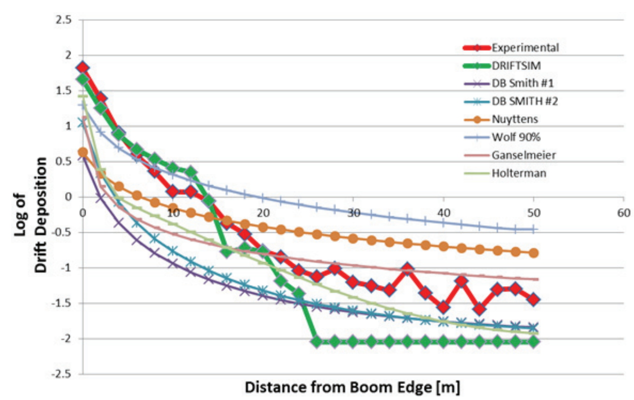

Figure 4. Qualitative comparison of predictions by DRIFTSIM to alternative models and experimental depositions averaged at each distance from the boom edge for test 1.

based on the limiting resolution of DropletScan.

As shown by the qualitative comparison in figure 4, DRIFTSIM provided the most accurate representation of drift near the boom edge (from 0 to 20 m). At greater distances from the boom edge (>20 m), DRIFTSIM underpredicted drift. For all distances greater than 26 m from the boom edge, DRIFTSIM predicted that no drift would be deposited. It is of note that, in this study and specifically figure 4, only deposited drift from 0 to 50 m was predicted and measured. It is hypothesized that the underrepresentation of DRIFTSIM-predicted deposition at distances greater than 20 m is due to a high emphasis on the evaporation of very fine droplets prior to deposition within the model. However, an analysis to evaluate this claim was not included in this study.

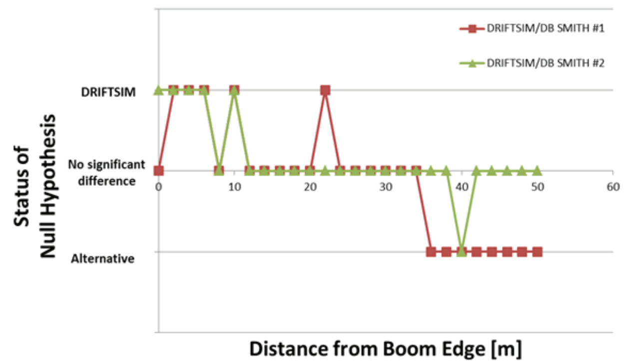

Figure 5. Status of null hypothesis at each distance from the boom edge when comparing predictive accuracy of DRIFTSIM to the two models by Smith et al. (2000).

Statistical Comparison of DRIFTSIM to the Alternative Models

Deposition levels (both predicted and experimental) at each distance from the boom edge were normalized by dividing the respective deposition at a distance by the average experimental deposition (from the four tests) at the same distance. Although the average experimental deposition is derived from the results of testing, in statistical application it can be viewed as an independent scaling factor. Predictive ability (accuracy) within the statistical testing was defined as the absolute difference between the normalized predicted drift deposition and the normalized experimental deposition. Predictive accuracy between models was statistically compared at each of the 26 distances from the boom edge, for each of the four tests individually, and overall.

At each distance from the boom edge, the predictive accuracy of DRIFTSIM was statistically compared to the predictive accuracy of each of the alternative models. A paired difference t-test was applied in order to reduce the local variability caused by changing weather conditions at each of the ten card vectors. The null hypothesis within the statistical testing was that there is no significant difference between the accuracy of the two models being compared. Two alternative hypotheses (the difference between DRIFTSIM's accuracy and the alternative model's accuracy is greater than zero, and the difference between the accuracy of the two models is less than zero) were applied individually to determine which of the two models was significantly more accurate in cases where a non-zero difference existed. Results of the statistical comparisons between DRIFTSIM and each of the alternative models are shown in figures 5 through 7. On the vertical axes in the figures, the state of the null hypothesis is displayed with discrete values of DRIFTSIM being significantly more accurate, the alternative model being significantly more accurate, or no significant difference between the models.

Figure 5 displays the status of the null hypothesis at each distance for the boom edge, comparing the accuracies of DRIFTSIM to the two regression models of Smith et al. (2000). For the majority of the near-boom cases (0 to 10 m from the boom edge), DRIFTSIM was significantly more accurate than both of the Smith et al. (2000) models. From 12 to 36 m from the boom edge, no overall significant difference was found between DRIFTSIM and the Smith et al. (2000) models. In predicting far-field drift, the Smith 1 model was found to be significantly more accurate than DRIFTSIM, while for the majority of far-field distances there was no significant difference between the Smith 2 model and DRIFTSIM.

In a similar manner, a statistical comparison of DRIFTSIM to the models by Nuyttens et al. (2007) and Wolf and Caldwell (2001) is shown in figure 6. The model by Wolf and Caldwell (2001) is based on spraying with a specific set of operating conditions. Thus, it does not contain the flexibility of the other alternative models in terms of numerous independent variables. The model (based on the coefficients used) specifically pertains to spraying using a pull-type sprayer, 0.6 m boom height, fine droplet spectrum, and wind speeds averaging 4.3 m s^{-1}. Although the droplet spectrum and wind speed were close to those encountered in test 1, a boom height of 1.2 m was applied during testing. These deviations from the target application of the Wolf and Caldwell (2001) model likely led to decreased accuracy in representing field depositions. DRIFTSIM proved to be significantly more accurate from 14 to 50 m. Little statistical difference in predictive accuracy was seen when comparing DRIFTSIM to the model by Nuyttens et al. (2007) except very near the boom edge (0 to 6 m), where DRIFTSIM's predictions were more accurate. As air assistance is a popular application approach in Europe, the base data used by Nuyttens et al. (2007) were generated using air assistance spraying, which is widely regarded as an effective measure to reduce drift. As was the

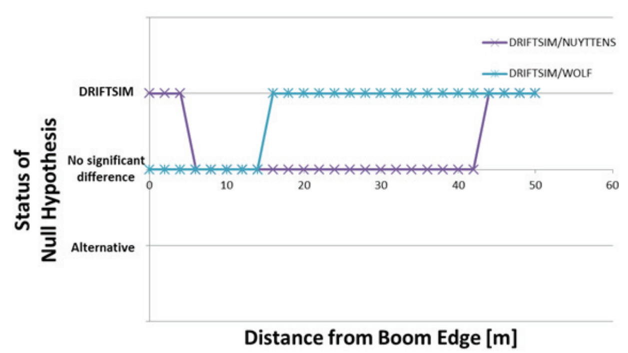

Figure 6. Status of null hypothesis in comparing predictive accuracy of DRIFTSIM to models by Nuyttens et al. (2007) and Wolf and Caldwell (2001).

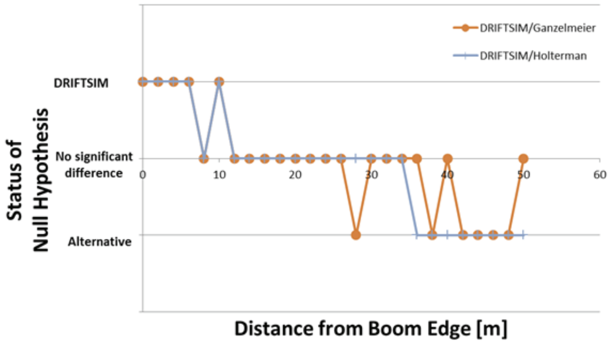

Figure 7. Status of null hypothesis when comparing predictive accuracy of DRIFTSIM to models by Ganzelmeier et al. (1995) and Holterman et al. (1997).

case with the Wolf and Caldwell (2001) model, this specificity of model derivation and application was likely responsible for the deviation from experimental depositions.

Figure 7 presents the results of the null hypothesis when comparing the accuracy of DRIFTSIM to models by Ganzelmeier et al. (1995) and Holterman et al. (1997). For the majority of the near-boom cases, DRIFTSIM proved to be significantly more accurate than either of the two alternative models. For large distances from the boom edge (>36 m), the converse is true, as the Ganzelmeier et al. (1995) and Holterman et al. (1997) models both provided a significantly more accurate prediction of drift. Over the middle region (12 to 36 m), no significant difference was found between the models. As was the case with the Wolf and Caldwell (2001) model, both of these models are rigid models in that they are not functions of weather or sprayer operation, but rather distance from the boom edge exclusively. The dataset from which Ganzelmeier et al. (1995) derived their regression model was highly diverse. However, conditions that were in "good agriculture practice" were sought for all test cases (i.e., low wind speed, low boom height, larger droplet sizes). Therefore, the model would not contain the generality necessary to accurately predict drift for "high drift potential" cases, which were experienced in the field tests.

General Quantitative Comparison of DRIFTSIM to Alternative Models

While distance-specific testing provides insight into certain model strengths or weaknesses, it does not provide a definite conclusion on which model is more accurate across the entire 0 to 50 m distance. To provide a more general, overall view of predictive accuracy, DRIFTSIM's predictive accuracy was compared statistically to the alternative models based on observational units of entire card vectors (i.e., 0 to 50 m downwind). An unbiased measure of deposition was defined to quantify deposition within a card vector as follows:

$$\text{Observational unit} = \sum_{i=1}^{26} \frac{Depostion_i}{Avg.\ Experimental\ Depostion_i} \quad (1)$$

where $Depostion_i$ is the predicted or experimental percent deposition (depending on the subset analyzed) at card i within the card vector, and $Avg.\ Experimental\ Depostion_i$ is the average percent deposition at each card i distance within the specific test, calculated based on the ten cards at the card i position.

As in the distance-specific statistical testing, DRIFTSIM's predictive accuracy was compared to that of the alternative models through a paired difference t-test. Testing was conducted for each of the four tests individually and combined (overall). Results of the statistical testing are shown in table 2. For each of the tests, the model that was significantly more accurate is shown. Overall, DRIFTSIM proved to be significantly more accurate than the models by Smith et al. (2000), Ganzelmeier et al. (1995), and Holterman et al. (1997). The null hypothesis, that there is no difference between the accuracy of DRIFTSIM and the alternative model, could not be rejected when comparing DRIFTSIM to the Smith 2 model and the Nuyttens et al. (2007) model.

Conclusions

The following conclusions were drawn from this work:

DRIFTSIM is better suited to predicting near-field drift (0 to 10 m from the boom edge) when compared to the alternative models, as evidenced by the significantly more accurate predictions within this region.

DRIFTSIM did not present more accurate representations of drift in the intermediate or far-field (20 to 50 m from the boom edge) regions. Several alternative models (i.e., Smith et al., 2000; Holterman et al., 1997; and Ganzelmeier et al., 1995) proved to be significantly more accurate in predicting far-field drift. The decreased accuracy in the far-field region may be due to a high model emphasis on the evaporation of very fine droplets, leading to low deposition levels from 20 to 50 m downwind of an application.

When considering applying DRIFTSIM in predicting drift for an application, its limited predictive accuracy over the 20 to 50 m region must not be ignored. For in-field applications, the significance of predictive accuracy in a cer-

Table 2. Status of null hypothesis comparing overall predictive accuracy of DRIFTSIM to six alternative models.

	Hypothesis Conclusion				
Comparison	Test 1	Test 2	Test 3	Test 4	Overall
DRIFTSIM/Smith 1	DRIFTSIM	Smith	DRIFTSIM	DRIFTSIM	DRIFTSIM
DRIFTSIM/Smith 2	-[a]	-	-	-	-
DRIFTSIM/Nuyttens et al. (2007)	DRIFTSIM	DRIFTSIM	-	-	-
DRIFTSIM/Wolf and Caldwell (2001)	DRIFTSIM	NA[b]	NA	NA	NA
DRIFTSIM/Ganzelmeier et al. (1995)	-	-	DRIFTSIM	-	DRIFTSIM
DRIFTSIM/Holterman et al. (1997)	DRIFTSIM	Holterman	DRIFTSIM	DRIFTSIM	DRIFTSIM

[a] Indicates cases no significant difference was found between the models.
[b] Comparison to the Wolf and Caldwell (2001) model was conducted for test 1 only, as conditions were not applicable for the other test cases.

tain region, i.e., either the near field (0 to 10 m) or far-field (20 to 50 m), will be dictated by the sensitivity and potential for damage to that region. In applications where predictive accuracy in the far-field region is of particular concerns, alternative models that are more accurate for this region should be considered.

When compared to the alternative models, DRIFTSIM appears potentially suitable for use as a real-time spray drift predictor when an accurate representation of far-field drift is unnecessary. However, additional testing at a greater variety of operating conditions is required to determine its full extent of application.

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