

US EPA ARCHIVE DOCUMENT

**Background Document for the Scientific Advisory Panel on Ground Hydraulic
Applications:**

**Downwind Deposition Tolerance Bounds for Ground Hydraulic Boom Sprayers
July 23, 1999**

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I. Summary

The Environmental Fate and Effects Division (EFED) of the Office of Pesticide Programs (OPP) currently assumes a fixed amount (1%) of drift to aquatic habitats and terrestrial plants from ground hydraulic boom pesticide applications. To develop a tool which could be used to estimate downwind drift from boom applications at a range of distances, the Spray Drift Task Force's (SDTF) data set was analyzed and used to develop four generic deposition curves to form a basis for estimating drift. As part of an ongoing peer review effort, EFED seeks the opinions of the Scientific Advisory Panel (SAP) regarding the ground hydraulic data and their potential use. The deposition curves from the data are proposed to be used in risk management for such purposes as setting buffer zones, placing limits on drop size, and placing limits on boom heights. There may be cases where EPA finds that estimated deposition from spray drift (using these curves) would present an unreasonable risk that cannot be mitigated to acceptable levels. In such cases, EPA may decide not to register a particular use on the basis of this assessment.

Boom height and droplet size are the two most important measured factors influencing drift from ground hydraulic sprayers in the SDTF pesticide drift database. Wind speed was not important except with a nozzle generating a fine droplet size spectrum [volume median diameter (VMD) 171 μ m].

Downwind deposition at 8 m ranged from 0.16 to 9.5% of the target application rate. At 400 m deposition did not exceed 0.05% of the application rate. The lowest deposition was achieved with a nozzle producing the coarsest spray at the lowest boom height. The highest deposition occurred with a nozzle producing the finest spray and the highest boom height, a configuration which is stated to be atypical.

Analysis of the downwind deposition results included curve fitting and ANOVA followed by the development of bounded deposition curves. The relationship between downwind deposition and distance was fit for each treatment to a simple two parameter, a and b , exponential decay function. The specific function was chosen because it showed a good fit to the field data. ANOVA results for a and b suggested that the treatments could be grouped into four categories based on two degrees of spray coarseness and two boom heights. For each grouping (*e.g.* coarse spray/low boom), the range of deposition values was determined at set distances. These ranges were then used to set bounds with set levels of confidence. Bounded deposition curves of this type are proposed for use in estimating spray drift deposition for risk assessments.

II. Introduction

EFED risk assessments normally assume a fixed amount of spray drift from ground boom applications. The default deposition value input for exposure assessment is 1%. For terrestrial plants there is no distance associated with this 1%. In aquatic assessments 1% of the application rate is estimated to reach a 63 m wide, one hectare pond immediately adjacent to the field. This value is used for all types of boom sprayers at all boom heights. No value is presently used to

assess deposition to ponds farther from the edge of the field making it difficult to assess risk reduction from the use of buffer zones. There is an immediate need within EFED for a model which provides more information on how sprayer type, sprayer configuration, and distance affect downwind drift.

In 1992 and 1993 the SDTF, a consortium of pesticide registrants, conducted a detailed study of off-target deposition of pesticides resulting from ground hydraulic sprayers. The data resulting from this study was the subject of an open data review workshop in December 1998 at which time experts in the area of spray drift from academia, government, and industry were asked to comment on the strengths and weaknesses of the data set. A discussion of the spray drift study is presented here along with the results of the peer review workshop and a proposed method for using the data to estimate spray drift. EFED believes the proposed method presented here offers a scientific basis for estimating potential downwind deposition and is an improvement over the current assumption. In environmental risk assessments, the quantity of estimated drift is important in defining risks to terrestrial and aquatic plants, terrestrial and aquatic animals, and contamination of drinking water sources. If accepted, estimated drift levels from the proposed curves would be incorporated into pre-existing models and protocols for estimating environmental risk. Deposition estimates may be used in human exposure assessments as well. The Health Effects Division (HED) of OPP is preparing protocols to calculate human exposures from pesticide deposition. The source of the deposition estimates for HED's protocols is not final, but EFED predictions based on the methods described here will be considered.

Pesticide drift, as defined by the Association of American Pesticide Control Officials, is the physical movement of pesticide through the air at the time of pesticide application or soon thereafter from the target site to any non- or off-target site. This definition intentionally excludes off-site movement of pesticides due to volatilization and other secondary causes. Under the Federal Insecticide, Fungicide and Rodenticide Act (FIFRA) pesticide registrants are required to submit study data on the propensity of their products to result in off-target deposition. In the past this requirement has been dealt with on a chemical by chemical basis. However, since drift potential of pesticides is largely independent of the chemistry of the active ingredient, the SDTF came forward and agreed to carry out a number of studies to approach the FIFRA requirement generically. The studies performed by the SDTF have been divided into categories by application method: aerial, ground hydraulic, chemigation and orchard airblast. This discussion of the SDTF ground hydraulic studies and proposed tolerance curves emphasizes data collected on horizontal deposition.

OPP poses the following questions to the SAP regarding the SDTF ground hydraulic deposition curves generated from these studies, and the use of these curves in risk assessments:

1. Do the data provide a sound basis from which to generate deposition curves which can be used in risk assessments?
2. What significant limitations, if any, exist in the ground hydraulic and orchard data in terms of:

- a) application equipment (e.g., nozzles, sprayers)?
 - b) meteorological conditions (e.g., temperature, humidity, wind speed)?
 - c) site conditions (e.g., terrain, crop canopy)?
 - d) reliability of deposition data (e.g., tank mix tracer concentrations, analytical recoveries)?
3. Is the method used for generating the deposition curves appropriate given the data from which they were developed?
4. Does the SAP agree that the proposed approach is an improvement over the current methods used by OPP to predict deposition from off-target spray drift?
5. Given the available information, do the 95th percentile values for the deposition curves appear:
- a. justified? Are additional correction factors required?
 - b. realistic? Do the percentile calculations overestimate “real world” levels?

III. Overall Study Design

A. Background

The objective of the studies was to generate data on pesticide drift during application with ground hydraulic sprayers. EPA expected that the data would be suitable for assessing the function of application parameters on the magnitude of drift and for developing a method for estimating deposition for inclusion in exposure assessments.

Two field studies were conducted in the high plains region of Texas during 1992 and 1993. Weather conditions at the field site were chosen to range from cool and dry to hot and dry. The study site consisted of several fields at varying angles to one another. The application sites consisted of an open, level field of mowed grass (10 cm). On a given day, a field was chosen so that the wind was as close to perpendicular as possible from collection lines. Applications consisted of four parallel swaths each measuring 13.7 m by 305 m. Collection lines were placed perpendicular to the swaths and consisted of three parallel rows of collection equipment spaced at regular distances from the field's edge. Horizontal and vertical alpha cellulose cards and low volume polyurethane air samplers were used to measure different aspects of drift. Samples collected in different lines provided information on the variability at given distances. Deposition measurements were also made in the treated fields within swaths as a measure of application efficiency and as a confirmation of application rate. Samples were collected within 30 minutes of application, sealed in clear Kapak bags, placed on dry ice, and taken to a freezer trailer for storage.

Aspects of the application equipment were varied to assess their relative importance. Variation consisted of four nozzles types, two boom heights, and two application rates (which were varied

by adjusting the ground speed of the tractor). The droplet size spectrum for each nozzle was determined at the pressure used in the field study. Spray volumes used in the field trials ranged from less than 3 gal/acre to 27 gal/acre.

A “standard” treatment was applied simultaneously with each “variable” treatment made so that a covariate statistical approach might be used in analyzing the results. All variable treatments used malathion as a tracer while standard treatments used diazinon. Diazinon and malathion levels were measured on the same cards. The standard treatment was to be used to correct the variable treatment application for meteorological conditions allowing an evaluation of the effects of the equipment variables on off-site drift and deposition. The statistical approach used in performing the covariate correction for meteorological effects is described in detail in the summary and integration report (I94-001). However, since in general the relationship between deposition and meteorological variables did not appear significant the correction was not applied to the data before performing additional analysis. The standard case remains very valuable in evaluating drift response to meteorological variables. The decision to use uncorrected data in the evaluation of effects of equipment variable was appropriate.

Also submitted with the field studies were an Integration and Summary of the 1992 and 1993 Field Studies and two studies for atomization droplet size spectra.

B. Validity of the Generic Approach

The SDTF studies are based on the hypothesis that spray drift occurs independently of the chemical identity of the active ingredient. However, the physical properties of the spray tank mixture are considered to be important by affecting the droplet size spectra. To apply data from the SDTF studies generically, drift must occur independently of active ingredient and be predominately related to application scenario conditions. One of the underlying requirements for using this approach is that the active ingredient must not volatilize significantly from the carrier or the collection media. In the SDTF studies, the vapor pressure of the tracers is high enough that some volatilization likely occurred, but given the short amount of time from the beginning of the applications to the collection of the drift collection cards it is unlikely that this was a major source on error.

Table 1. Properties of the tracers		
	Tracers	
Properties	malathion	diazinon
Water solubility (mg/l)	145	40
Vapor pressure (torr)	4×10^{-5}	1.4×10^{-4}
Henry's Law constant (atm-m ³ /mol)	1.2×10^{-7}	1.4×10^{-6}
Hydrolysis half-lives (days)	pH 5: 107 pH 7: 6 pH 9: 0.5	pH 5: 12 pH 7: stable (138 days) pH 9: stable (77 days)
Aerobic aquatic metab. half-lives (days)	1.1 (water portion)	8 (water portion)
Anaerobic aquatic metab. half-lives (days)	2.5	4
soil photolysis (days)	>30	17-34

IV. Range of Conditions

The following table derived from the SDTF integrated report shows the treatments included in the field studies.

Table 2. Application equipment parameters

Appl. Vol. (gal/acre)	Pressure (psi)	Boom Height (in)	Nozzle (type)	Ground Speed (mph)
Standard Treatments				
24	40	20	8004	5
Variable Treatments				
23	20	50	8010LP	15
9	20	20	8004LP	15
27	20	20	8004LP	5
8	40	20	8004	15
23	40	50	8004	5
2.6	55	50	TX6	15
2.6	55	20	TX6	15
8	55	20	TX6	5

A. Equipment and Practices

Applications were made with two Spra Coupe (Model 220) ground hydraulic sprayers equipped with centrifugal pumps and 13.7 m booms. Nozzles were spaced 51 cm apart. Boom height was normally 51 cm (20 in) but was 127 cm (50 in) in some treatments. Four types of nozzles were studied, each at a single pressure. The nozzles and pressures were the 8004LP, 8010LP, 8004 and TX6 nozzles at 20, 20, 40, and 55 psi, respectively.

The ground speed of the tractor was either 5 or 15 mph. Faster speed resulted in a lower volume applied per unit area. The application rate varied from 2.6 gal/acre (with the TX6 at 15 mph) to 27 gal/acre (with the 8004LP at 5 mph). These rates range from ultra low volume to medium volume.

With the exception of standard treatments, each variable application was replicated once. Every variable application was accompanied by a standard treatment which was applied by another sprayer following or preceding the sprayer making the variable treatment. The application variables of the standard treatment were held constant. Standard treatments were conducted with

8004 nozzles, 0.51 m boom, 40 psi and a tractor speed of 5 mph which is stated to be representative of standard agricultural practice.

No information was provided to justify the selection of the application equipment or operating parameters as representative of those in common use. In order for the study results to be useful in exposure assessments the study design needs to represent the range of conditions occurring in agriculture.

B. Carriers/Formulations

The material exiting the nozzles was referred to as the test substance. All variable treatments used an emulsifiable concentrate of malathion (Malathion 57EC) in a water carrier containing phosphate buffer to enhance tracer stability. Two metals (Mo and Mn) were also included for potential use as tracers but not analyzed because the pesticide tracers were considered adequate. Standard treatments were identical to variable treatment except that an emulsifiable concentrate of diazinon was used instead of malathion.

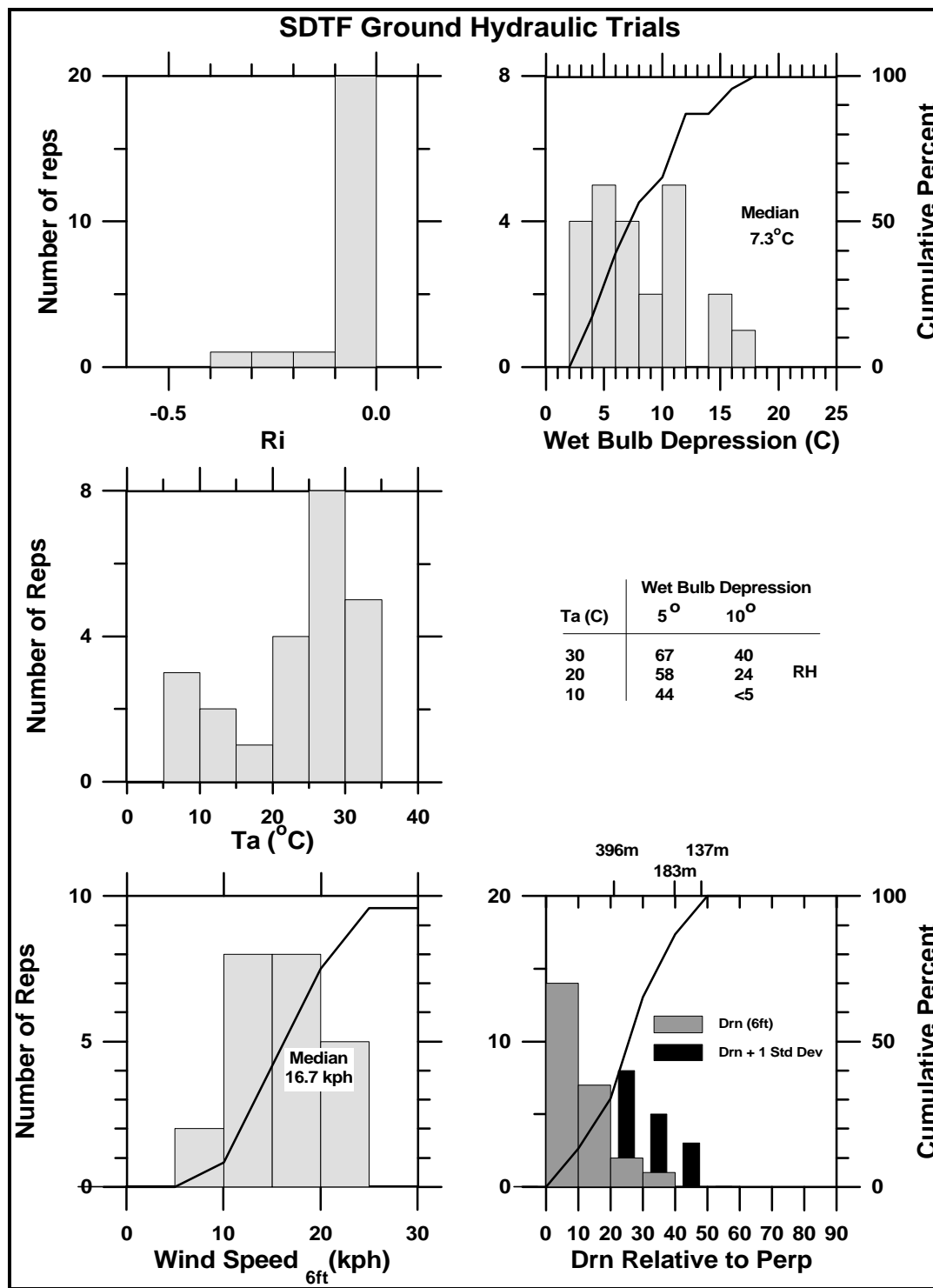
The range of test substances examined in the hydraulic ground spray field and atomization studies was small. The substances were limited to water solutions. Oil solutions which might be used in a ULV application were not examined.

C. Meteorology

The field studies were conducted during different seasons to incorporate hot and cool conditions. During the 1992 study, temperatures ranged from the 70's to 90's (°F) with percent relative humidities ranging from 30's to 80's. During the 1993 studies conditions were cooler and drier with temperatures ranging from the 40's to 80's (°F) and percent relative humidities ranging from single digits to 60's.

Wind speeds were lower during the 1992 studies, usually under 10 mph and always under 12 mph. The wind speeds during the 1993 study were always greater than 10 mph and on two occasions exceeded 20 mph.

Figure 1. Meteorological conditions during the ground hydraulic field trials. (From R.E. Mickle's review of the SDTF data).



Wind angle relative to the field being treated was defined as the angle between the average wind direction and the collection lines perpendicular to the field. A wind blowing perpendicular to the field, parallel to the collection lines would have a wind angle of zero. Final wind direction results were averaged from two measurement stations each at 1.83 m above the ground. Applications were only performed when the wind angle was less than 20 degrees. Wind did shift during application on occasion so that the wind angle could be as high as 33 degrees.

The Richardson number is a measure of atmospheric stability and is sometimes related to drift potential. Conditions during both the 1992 and 1993 field studies were relatively unstable, with Richardson number values close to -0.08. During one treatment in each field study, the Richardson number equaled or was less than -0.2. Larger (positive) Richardson numbers indicate that the atmosphere is stable, generally results in higher drift potential. Thus the effect of atmospheric stability was not assessed because the range of conditions was small and very stable conditions were not examined.

V. Evaluation of Data Quality

A. Tracer Stability and Spike Recovery

Field spikes and stability tests were performed with both malathion and diazinon. Spikes were made with an aqueous buffered tracer solution like that used in the treatments. Field spikes on alpha cellulose collectors were performed at high and low levels; approximately 34 and 0.1% of the application rate, respectively. The low spike was most representative of deposition data. Spikes were either frozen immediately (unweathered) or placed in the field, upwind of the treatment during the application and drift period (weathered). Due to human error, some spike solution concentrations were reported to be incorrect resulting in concentrations below the limit of quantitation. Recovery data from these treatments is not available. With correctly fortified samples, recoveries were generally greater than 80%. The largest change in recovery correlated with weathering was with diazinon spiked at the low level where the spike recovery was 83%. No adjustments were made to SDTF results to adjust for spike recovery efficiency.

Since samples were frozen for a period of 2 to 6 months before analysis, a frozen storage stability test for malathion and diazinon was conducted. A single storage stability test was conducted for all field studies raising some concern that pH of frozen field study samples which was likely affected by the carrier pH was not replicated in the storage stability study. Stability of the two tracers was measured at 0, 1, 6, and 12 months and similar results were found for the two tracers. At six months malathion stability was approximately 90% (with 89% recovery) and 65% (with 102% recovery) at low and high fortification levels, respectively. At six months diazinon stability was approximately 93% (with 86% recovery) and 60% (with 93% recovery) at low and high fortification levels, respectively. These results suggest that some degradation likely occurred on collection cards with higher tracer levels stored for 6 months. No corrections were made in test results for degradation.

There is concern that chemical tracer instability may have affected the quality of the deposition data. The tracers are volatile and not particularly stable, especially under alkaline conditions (see

Figure 2. Spike recoveries. (From R.E. Mickle's review of the SDTF data.)

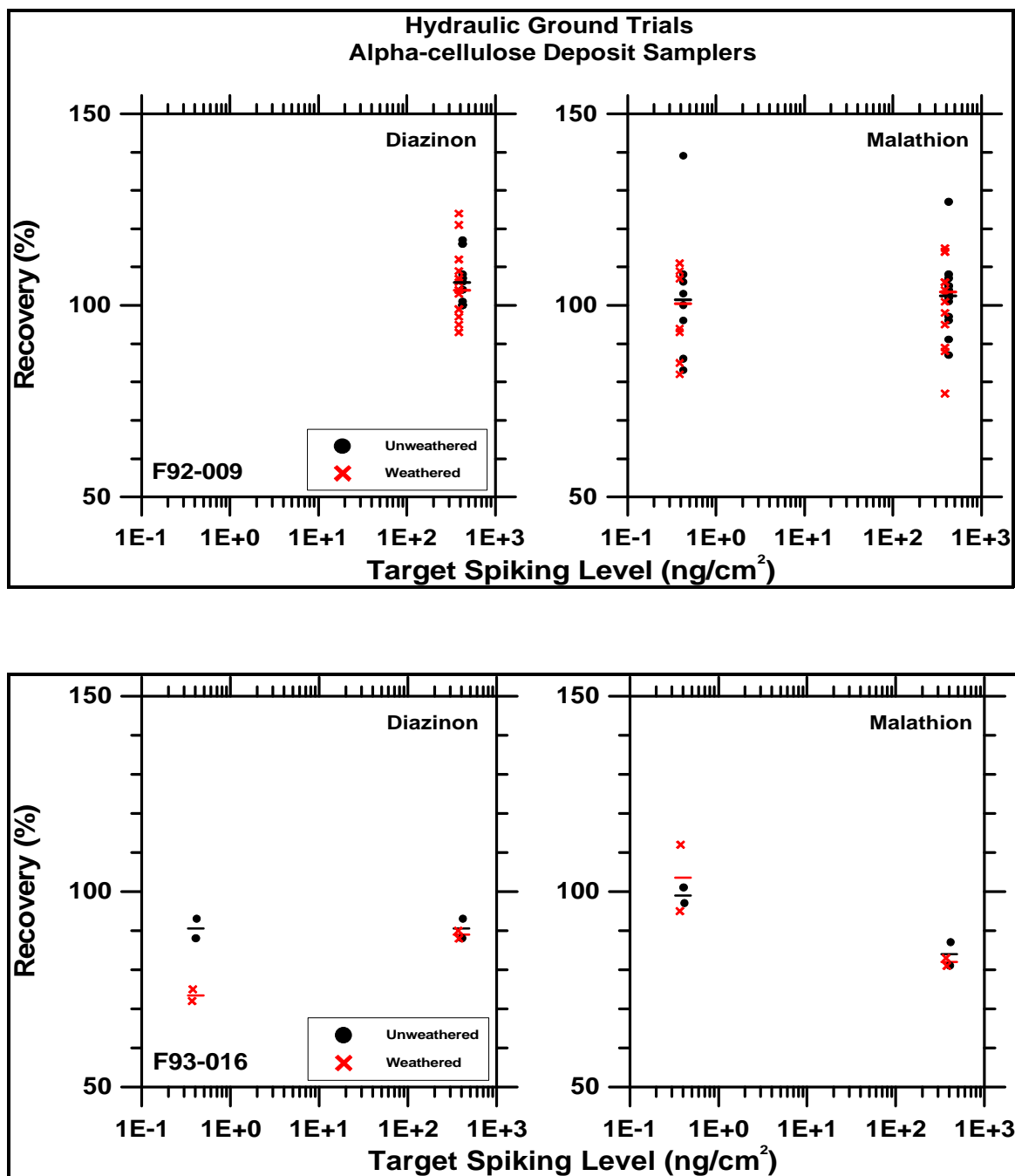


Table 1). Malathion is susceptible not only to hydrolysis at alkaline pH (half life at pH 9: 0.5 days), but also to aquatic metabolism under aerobic conditions (half life: 1.1 days). Although diazinon does not hydrolyze under alkaline hydrolysis, volatilization is expected to play a larger role in the dissipation of this compound relative to malathion. The vapor pressures of diazinon and malathion are 1.3×10^{-4} torr and 4×10^{-5} torr, respectively. The field trials conducted at high temperatures are likely to show a greater loss of diazinon because the vapor pressure of diazinon nearly doubles for every 5°C increase in temperature from 20 to 40°C (68-104°F).

Loss of tracer through volatilization, hydrolysis, and/or metabolism could result in significant underestimates in deposition.

B. Deposition

1. Collectors

Horizontal alpha cellulose cards were used in this study to collect deposition expected on aquatic and terrestrial habitats. Three parallel rows of cards were laid perpendicular and downwind from the treated field. In each collection line cards were placed at 8, 15, 23, 30, 46, 61, 91, 137, 183 and 396 m from the field's edge. Each line also contained four cards placed in the field within treatment swaths. In the 1992 field study, cards in each collection line were analyzed separately. In the 1993 field study, cards at most distances were consolidated with cards from other collection lines at the same distance to be analyzed as composite samples. The individual cards from each line at 30, 91 and 183 m were analyzed separately and provided an estimate of variation between different collection lines. The variation between collection lines was different in the two field studies. In the 1993 study when wind was greater the average standard deviation was 20% of the mean. In 1992, when wind speeds were lower, the average standard deviation was 11% of the mean.

When the prevailing wind direction was close to perpendicular to the field, collection lines were placed at the center of the downwind edge. The study protocol allowed for a wind angle of up to 30 degrees if the collection lines were moved closer to the downwind side of the treatment zone. A wind angle of up to 20 degrees was considered acceptable for the collection lines placed outward from the middle of the treatment zone. Wind variability was measured during the drift period and if the average direction did not intercept the most downwind collectors the treatment was repeated.

2. Wind Speed and Direction

Variability in wind direction was greater during the 1992 study when winds were slower. In 1992 and 1993 the standard deviations of wind direction averaged 17.5 and 10.9 degrees respectively. Wind speed also varied during the spray and drift periods with higher variation observed during the 1992 season when winds were slower. Wind speeds were determined from measurements made every second during the application and drift period and averaged. The standard deviation

of wind speed at a height of 2 m averaged 26.4% and 16.6% of the average during the drift periods in the 1992 and 1993 seasons, respectively.

Shifting wind direction and wind speed leads to the possibility of underestimating deposition in the far field. The movement of the drift cloud from the treatment area may not fully impact the far field collectors when wind direction and speed during the application and drift period fluctuate. With larger deviations in wind direction and wind speed there is an increased probability that the drift cloud will be carried predominately to one side of the collector lines.

3. Tank Mix Analyses

Variation in tank mix concentrations increases uncertainty in application rate and deposition results. Tank mix tracer levels were analyzed separately and compared with theoretical tank mix concentrations. Results ranged from 71 to 115% of the theoretical concentration. Mean tank concentration results from analyses for malathion used in variable treatments were 95 and 92% pre- and postapplication. Mean tank concentrations for diazinon used in standard treatments were 84 and 76% pre- and postapplication. Based on the high in-swath deposition measurements (see mass balance below) it is possible that the tank mix analyses may not accurately represent the true concentrations. However, if the tank mix analyses are more accurate than the theoretical values, deposition measurements would be under estimated, particularly in standard treatments.

C. Mass Accounting

A detailed mass accounting was not performed with the data from the ground spray field studies. In-swath deposition measurements showed high deposition in the treatment zone. In fact, most in-swath deposition measurements from horizontal alpha cellulose cards accounted for more than 100% of the theoretical application rate. Deposition measurements outside the treatment area were low, usually not exceeding 1% of the application rate at a given distance.

D. Atomization

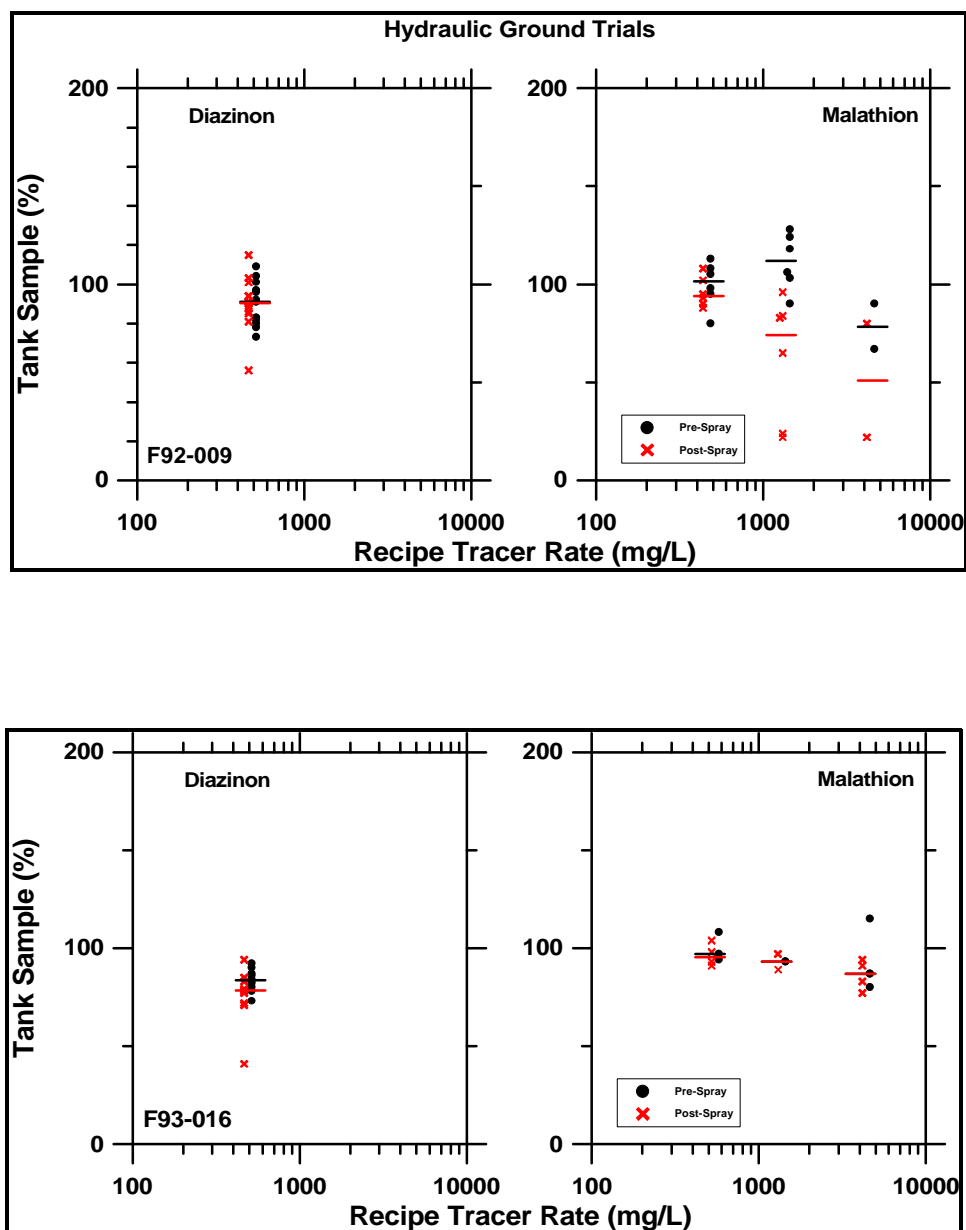
Two studies assessed the droplet size spectrum produced by equipment used in field studies. Drop size spectra were expressed as the droplet diameter at which half of the spray volume exists in droplets of smaller diameter ($D_{v0.5}$) and the volume percentage of spray in droplets with diameters less than $141\mu\text{m}$ ($V_{<141}$) which are considered to be drift prone. The test substance was the same as that used in field studies.

The nozzles, pressures and resulting droplet spectra with a 15 mph wind speed were as follows.

Table 3. Nozzles and spray characteristics.

Nozzle	Pressure (psi)	$V_{<141}$ (%)	$D_{v0.5}$ (μm)
8010LP	20	1	762
8004LP	20	2	486
8004	40	5	358
TX6	55	26	175

Figure 3. Spray tank tracer concentrations. (From R.E. Mickle's review of the SDTF data.)



Slightly smaller drop sizes were reported for some nozzles under wind tunnel conditions with low air speed (5 mph). This small difference is likely due to the fact that smaller droplets slow faster than large droplets after leaving the nozzle leading to a cloud of droplets close to the nozzle opening and an over estimate of the relative proportion of fine drops.

The 8004 nozzle was used for the standard treatments and is reported by the SDTF to be most representative of a typical ground sprayer but no grower or applicator input was provided. The nozzle with the highest proportion of drift prone droplets was the TX6. The SDTF reports that this nozzle may be used to for good penetration and coverage of a crop canopy or for low volume sprays without a crop canopy.

The nozzle with the largest drop size spectrum is the 8010LP and is used for some turf applications (Hurto *et al* 1987).

VI. Variable Responses

Downwind deposition is summarized in the following table adapted from the SDTF integrated report. Each row of deposition results averages the measurements from replicate treatments in the given wind speed range. Treatments with TX6 nozzles at 0.51 m boom height are displayed separately for different wind speeds because of divergent results.

Table 4. Downwind deposition and application parameters.

V _{<141} (%)	Nozzle	Wind Speed Range (mph)	Boom Ht. (m)	Downwind Distance (m)									
				7.6	15.2	22.9	30.5	45.7	61.0	91.4	137	183	396
				mean % of application rate									
1	8010LP	6-15	0.51	0.16	0.09	0.05	0.03	0.02	0.01	0.01	0.003	<0.002	<0.002
1	8010LP	11-15	1.27	1.15	0.48	0.31	0.14	0.1	0.07	0.06	0.014	0.007	0.002
2	8004LP	5-20	0.51	0.49	0.31	0.16	0.12	0.09	0.06	0.03	0.020	0.012	0.004
5	8004	6-11	0.51	0.50	0.37	0.26	0.19	0.13	0.10	0.05	0.036	0.022	0.007
5	8004	9-10	1.27	1.22	0.81	0.36	0.25	0.13	0.09	0.05	0.028	0.022	0.004
26	TX6	6-9	0.51	1.05	0.46	0.33	0.25	0.15	0.14	0.08	0.046	0.032	0.014
26	TX6	11	0.51	3.34	1.38	0.94	0.43	0.38	0.30	0.14	0.088	0.054	0.014
26	TX6	13	0.51	9.50	7.1	4.07	2.48	1.12	0.94	0.38	0.142	0.068	0.006

Drop size and boom height were the two most important factors influencing downwind deposition. The three nozzles which were examined at 0.51 and 1.27 m (8010LP, 8004, TX6) all produced greater downwind deposition with the higher boom. With a 1.27 m boom, drift at 8 m increased by 144% to 618% with 8004 and 8010LP nozzles, respectively. It is interesting that the largest relative effect was observed with the nozzle producing the coarsest spray.

Wind speed exerted the largest effect on the fine spray produced by the TX6 nozzles (Figure 4, top). The SDTF integrated report shows no significant correlation between wind speed and deposition for all the standard treatments examined together but the deposition from standard treatments conducted contemporaneously with the TX6 treatments appear to have a weak correlation to wind speed (Figure 4, bottom). The 8004 nozzle used in standard treatments produces a coarser spray than the TX6. It is likely that the fine drop size spectrum produced by the TX6 nozzle relative to the other nozzles makes it more sensitive to wind.

Previous studies have reported a relationship between deposition and wind speed so the lack of correlation in with the large standard treatment data set is somewhat surprising. It is possible the fairly high scatter in the data may mask the results. For the 24 standard case studies, deposition at 8 m ranges from 0.147 to 0.926 % of the application rate, and at 30 m the deposition ranges from 0.033 to 0.312 %. Figure 5 shows a plot of deposition as a function of wind speed at 8 m down wind. An inspection of this graph suggests that the deposition may, in fact, increase with increasing wind speed up to 11 - 12 mph, and then decrease as wind speed increases above that level. For example while a regression for the whole range of data yields an $R^2 = 0$, a regression on the 18 values below 12 mph yields an $R^2 = 0.44$.

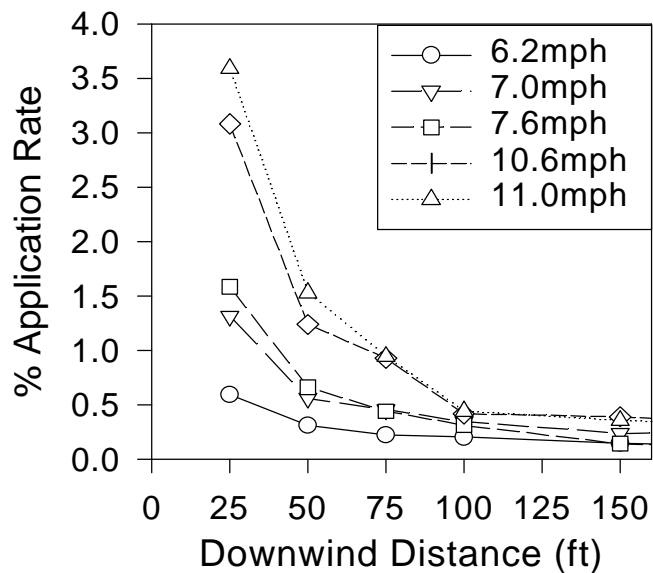
The only meteorological variable which appears to be correlated with deposition at all downwind distances were temperature. Temperature and deposition at two downwind distances in standard treatments are plotted in Figure 6. The mechanism behind the correlation is not clear. If the cause was water evaporation from droplets decreasing drop size, it might also be expected that percent humidity would inversely correlate with drift but upon graphical analysis, this relationship was not apparent. Because wind speed and other meteorological parameters did not correlate strongly with drift, the value of using a covariate approach was diminished.

Richardson number and deposition at two downwind distances in standard treatments are plotted in Figure 7. The range of Richardson numbers examined in the studies was small, between -0.01 and -0.10, except for two more extreme cases at -0.29 and -0.37. The correlations are driven almost entirely by the two lowest measurements decreasing the significance of the observation.

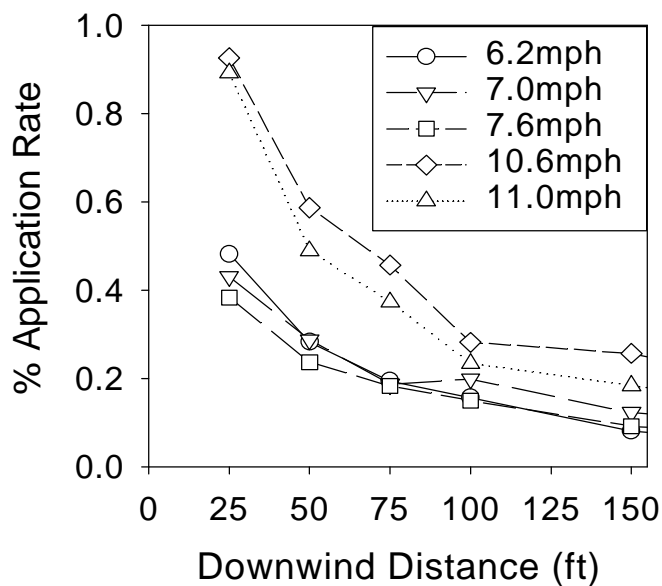
Figure 4.

TX6 nozzle treatments, standard treatments (with 8004 nozzles) applied under the same conditions, and the effect of wind speed on downwind deposition.

**Windspeed and
Deposition
with TX6 Nozzles**



**Windspeed and
Deposition
with 8004
Nozzles**



Droplet size is postulated to be one of the primary application variables controlling off-site pesticide drift. Nozzles used in the ground spray studies produced a large range of VMDs (164 μm -755 μm). Overall, there is a significantly higher off-site deposition from the small droplet applications than the large ones. An alternate graphical presentation of this effect is shown in Figures 8 - 10, illustrating the response of deposition to VMD at 8 m, 30 m, and 90 m down wind for the low boom conditions of the variable case applications. There is a clear relationship to drop size at all three measurement stations downwind.

The TX6 nozzles, which produces the finest spray (VMD 171 μm), when used at a 1.27 m boom height resulted in the highest level of drift observed in the study: 9.5% at 8 m and 2.5% at 30 m. Using a high boom and fine spray in the absence of a crop canopy does not represent normal use. It was included as a worst case scenario that is unlikely to occur because of its poor application efficiency in the absence of a crop canopy. The high boom height with the fine spray resulted in the highest variability of in-swath deposition. The mean deposition and standard deviations were 88% and 36.1%, respectively, of the expected application rate across all measurements in both replicates.

VII. General Comments of the Peer Reviewers

The reports of the December 1998 peer review workshop on the SDTF ground hydraulic boom studies are included in the background material for the SAP. The reviewer's comments provide an understanding of the strengths and weaknesses of SDTF studies.

Most of the reviewers gave positive overall comments on the studies and their results. The scale and level of detail of studies were generally considered to be laudable.

Positive comments included the statements below with referenced page numbers in parentheses:

D. Ken Giles: "The measurement techniques were very well developed and documented, likely due to the GLP requirement. Collection surfaces, recoveries, sample weathering and meteorological measurements represent a high standard of work, easily meeting the standards for scientific publication." (page 3)

"There is a tremendous amount of useful data generated from this work." (page 2)

Sandra L. Bird: "The ground sprayer studies seem to cover a significant range of application parameters." (Page 19)

"Overall, the ground spray data base may be rich enough to form a basis for regulatory assessment." (Page 18)

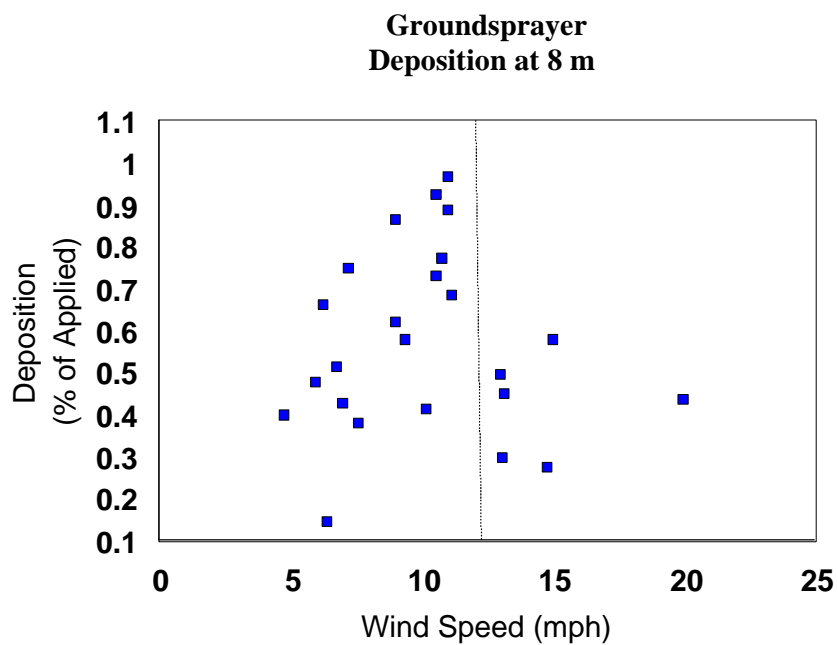


Figure 5. Deposition as a Function of Wind Speed at 8 m

Figure 6.

Off-Target Deposition and Temperature

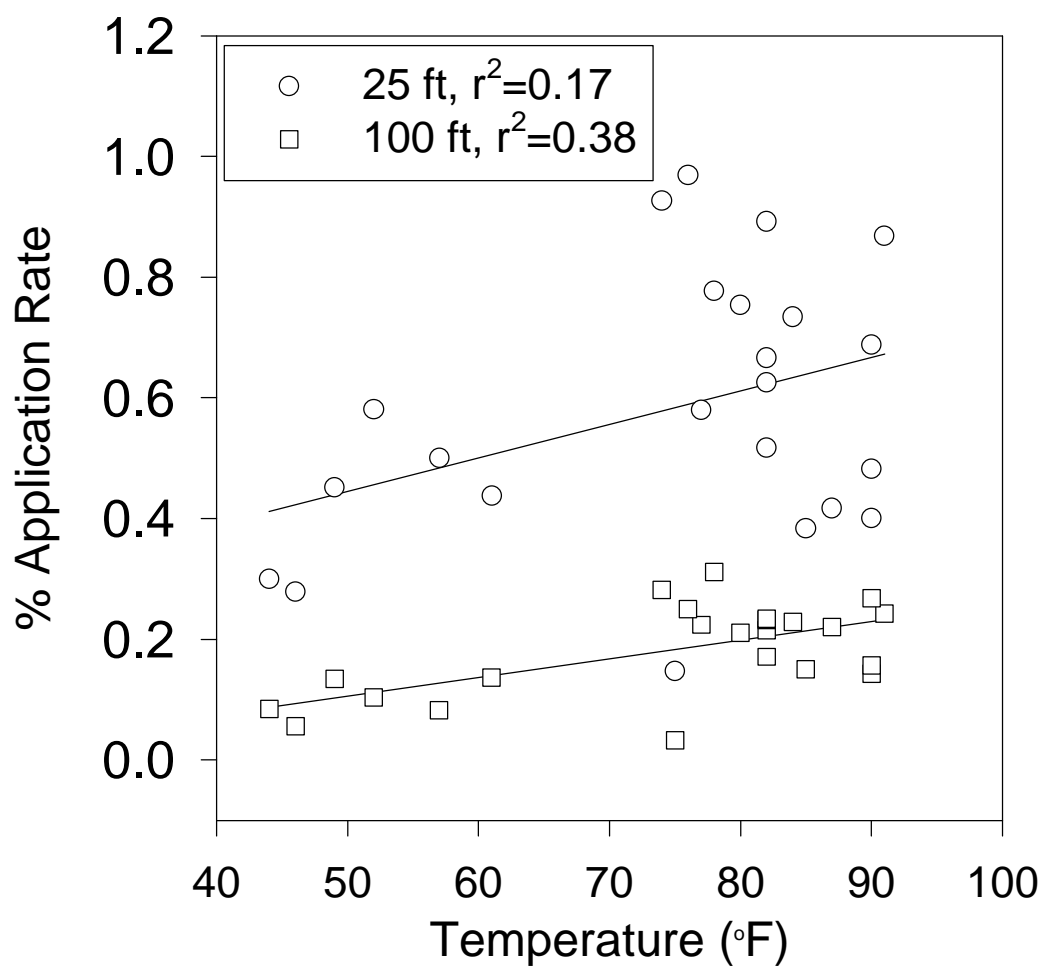
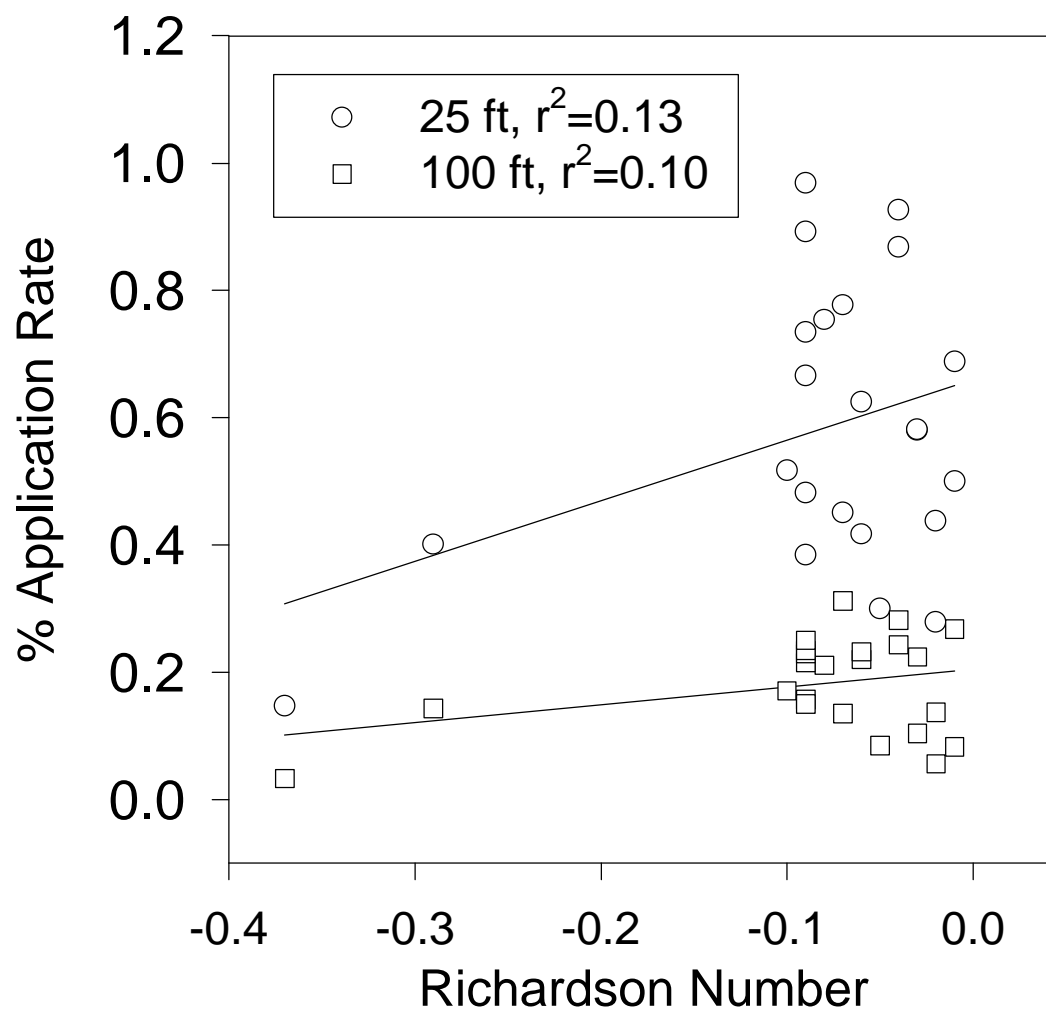


Figure 7.

Off-Target Deposition and Richardson Number



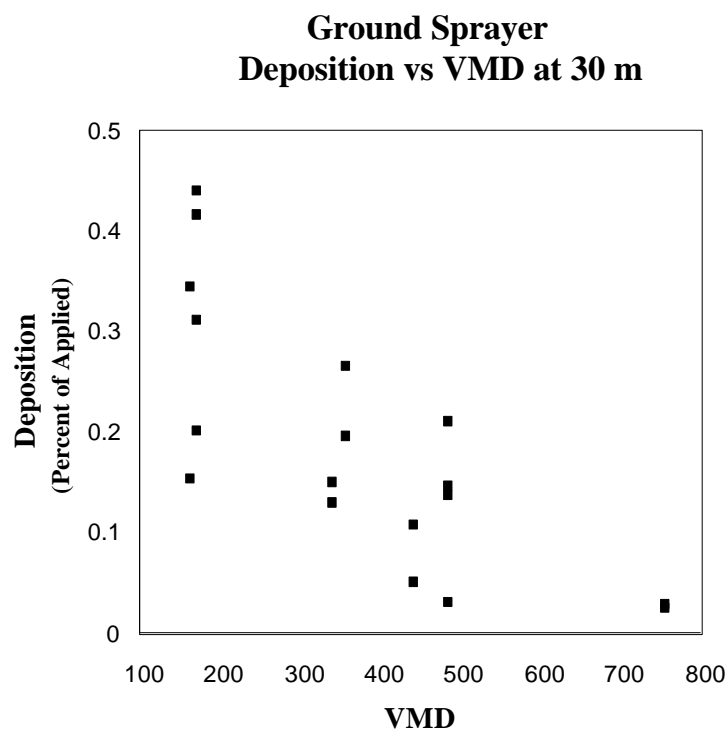


Figure 8. Deposition as a Function of VMD at 30 m.

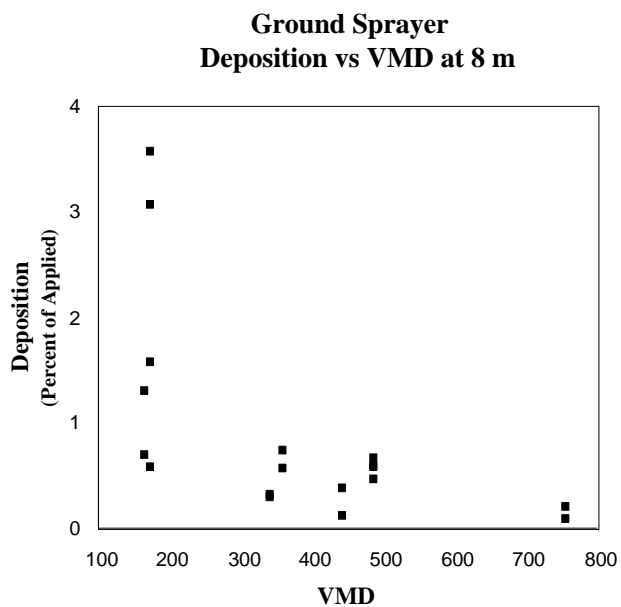


Figure 9. Deposition as a Function of VMD at 8 m.

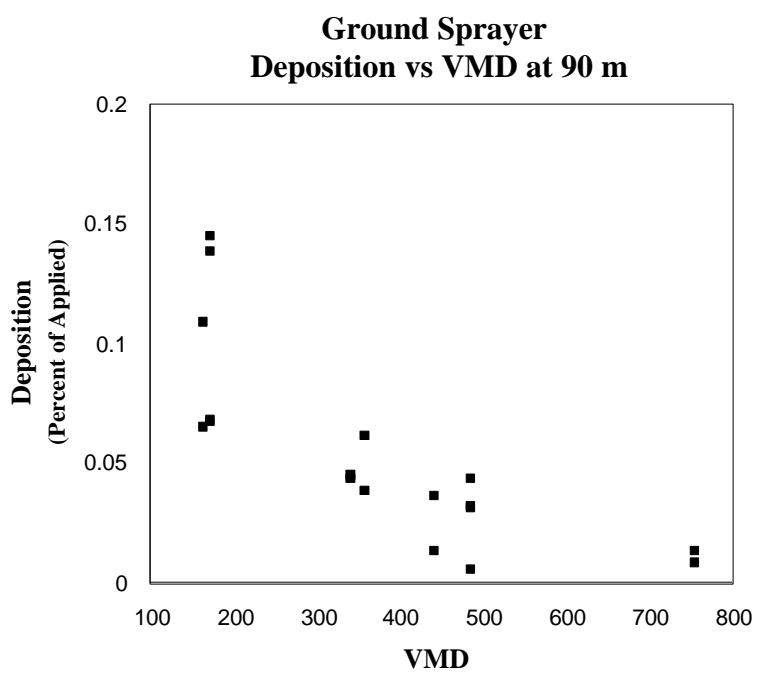


Figure 10. Deposition as a Function of VMD at 90 m.

Wayne Coates: “In general the reports appear scientifically sound in terms of the analytical and data collection methods, the statistical analyses, and the interpretation that has been presented....” (Page 2)

Terrell Barry: “The data in the report appears sound in terms of the basic study design, analytical methods and data collection techniques.” (Page 1)

Criticisms of the studies included the following statements:

D. Ken Giles: “The studies appeared to establish “typical” or limiting values for spray drift more than they provided an understanding of how the factors specifically affect drift.” (Page 3)

Sandra L. Bird: “The lack of collectors within 8 m of the field is a major limitation of the data set for use in doing exposure calculations.” (Page 18)

“Overall, the data quality is good, but the lack of adequate spike data is of concern, particularly for the low rate collectors.” (Page 18)

“One difficulty with both the ground spray and chemigation data is the lack of applicator survey data to allow a firmer specification of the standard practices, which in turn would be helpful for constructing a 95th percentile bound.” (Page 19)

Wayne Coates: “... the number of field runs that were conducted was minimal/inadequate.” (Page 2)

“The wide range in [tank mix] recoveries could indicate problems with the methodology.” (Page 4)

R.E. Mickle: “If anything, the ground application studies suffered from the limited number of repetitions conducted within each of the variable categories. Given the limited number of trials, efforts should be made to incorporate other field studies into the data base where possible.” (Page 4)

“The SDTF should either conduct supplementary trials to resolve recovery problems or use the results to produce bias or uncertainty bounds at different deposit levels.” (Page 7)

“Although these trials have spanned a large range of operational variables, a limited number of trials were actually carried out with different nozzles. Also few replicates were conducted at different meteorological conditions making it difficult to statistically develop representative curves.” (Page 15)

Terrell Barry: “The biggest potential limitation of the data set for predicting off-site exposure is

the lack of applications at lower wind speeds. Potential confounding factors in the data set are the collection efficiency of the alpha cellulose at higher wind speeds and the effect of the wind angle on results.” (Page 1)

After presentations at the peer review workshop, there was a discussion on the use of the data for regulatory purposes. The peer reviewers were receptive to using percentile curves similar to the example reported by Terrell Barry for the purposes of predicting potential deposition levels.

VIII. Data Analysis and Exposure Assessment

A. Overview of the Approach.

The approach used for evaluation of ground spray studies was similar to that used for the orchard and vineyard studies (presented separately). For the benefit of those who may have reviewed the orchard and vineyard report first, we note the following main differences. First, here we have included a more extensive statistical analysis of predictors of drift, which uses as input the curve parameters (denoted a and b , as for the orchard studies) calculated for individual applications (Sections 3 and 4 on evaluation of drift predictors for standard and variable treatments). Second, while the calculation of tolerance bounds (Section 5) here has relied on the same curve fitting procedure has been used for the evaluation of drift predictors (the approximate OLS approach, Sections 2).

As with the orchard and vineyard studies, the first step in our approach was to reduce the data for each application by fitting a smooth curve relating deposition (%) to distance, independently for each application. Regarding the details of this step, note that there are two primary kinds of questions about spray drift:

- 1) What proportion of the applied material is initially deposited off-site (near field) and what factors influence the magnitude of that initial deposition?
- 2) What is the rate of decline in proportion of applied material with increasing distance downwind and what factors influence that rate of decline?

These questions can be approached by fitting a curve of the following form:

$$\text{deposition}(\% \text{ appl}) = e^a e^{b\sqrt{x}} = \exp(a + b\sqrt{x})$$

where: x = distance downwind, adjusted for wind angle,

$\% \text{ app.rate}$ = the deposition measured at each downwind distance,

a = a parameter estimate providing the initial deposition at $x = 0$,

b = a $\% \text{ app rate}$ decline parameter.

For the ground spray data, this equation tended to fit well (high R^2). The parameter, a , provides the estimate of the initial deposition off-site (near field) through the model term e^a . The value of a will be larger when the initial deposition rate is higher. For example, a fit equation with $a = 2.0$ has a larger initial deposition than a fit equation with $a = 1.0$. The value of the initial deposition parameter, a , may be zero (indicating an initial deposition of 1% of applied rate) or negative (indicating an initial deposition of less than 1% of the applied rate). The parameter, b , is similar to a rate constant, describing the rate at which the deposition declines with increasing distance from the field. Larger negative values of the decline parameter, b , will be found under conditions where there is rapid decrease in the observed %app.rate with increasing distance from the field. For example, a fit equation with $b = -0.30$ has a more rapid rate of decline in deposition than a fit equation with $b = -0.10$. The empirical function above integrates the information contained in the downwind transects for each applications.

A curve of the general form indicated was fitted to the distance-deposition data, separately for each application. The results of this step, consisting of one pair of parameter estimates (a , b) per application, were used as input for subsequent analyses.

An obvious alternative would be to restrict attention to those distances actually evaluated in the study, and evaluate the observations separately for each distance. As noted, the approach based on curve fitting was helpful in interpreting the data because different kinds of affects can be isolated by the parameters a and b .

Some exposure calculations may require interpolation of exposure at distances not measured directly. Also, after distances have been adjusted for wind angle we no longer have collections of measurements at the same distance. Therefore the curve fitting approach places the data in a more uniform and manageable form. Finally, if we assume that deposition decreases as some smooth function of distance from the edge of the field, then in principle some information on deposition at a given distance is provided by the measurements at adjacent distances. Provided that the curves fit well, this information is retrieved by the curve fitting approach.

The equation we have chosen is not necessarily the only choice for an empirical equation to represent the decline observed in deposition on a down wind transect. Other equations with the same general form but different scaling of distance (e.g. x , $\ln(x)$) could also be chosen. However, the chosen equation fit well to all applications. Other, more complex, empirical equations might provide an even better fit of the field data. However, the simple empirical equation shown above was employed because it has only two parameters that are easily interpreted while still adequately representing the field data. The parameters of this function can be examined separately to study the effect of meteorological factors on the magnitude of the initial deposition and the rate of decline. In addition, if there are differences between the variable treatments in the initial deposition and/or the rate of decline, the parameters for the empirical equations can be used to detect those differences.

There were 24 standard applications and 24 variable treatment applications in the SDTF study.

Initially, the weather data for one treatment, 09-06 rep 4, was missing. This made it impossible to use the cosine adjustment on the downwind distances. Therefore, the results for both the standard and the variable treatment for that application was deleted from the data set. Determinations of tolerance bounds (discussed below) included these treatments.

B. Distance-Deposition Curves - Regression Methods.

For each application, we fit a curve of the form $y = \exp(a + b \cdot x)$. Before curve fitting, the distances were adjusted for wind angle to yield estimates of the distance from the point of origin to the point of measurement, in the direction of the wind. If wind angle is expressed as degrees normal to the crop rows (e.g., an angle of 0 represents wind perpendicular to the rows), then the adjustment is to divide by the cosine of wind angle.

A different curve fitting approach was used for the results in Sections 3 and 4 than for Section 5 (Tolerance bounds). The approach used for Sections 3 and 4 was based on minimizing absolute deviations while that for Section 5 was based on minimizing relative deviations, as explained in greater detail below. The explanation for this difference in procedures is that both kinds of analyses were initially conducted using the first approach (based on absolute deviations). During the evaluation of the orchard results (presented separately), EFED participants found large relative deviations and opted for an approach that would place more emphasis on minimizing relative deviations. The relative deviations were less significant for the ground spray data than for the orchard data, but tolerance bounds for ground spray have been recalculated using the approach applied with orchard data, largely for uniformity. However it was concluded that the statistical analyses in Sections 3 and 4 are still valid and useful.

For the calculation of tolerance bounds (Section 5) the curve fitting approach was to regress the natural logarithm of deposition against the square-root of distance. When regression is carried out with the dependent variable transformed logarithmically, the tendency is for deviations to be weighted according to the relative deviation (observed/predicted) whereas least-squares in the original scale would weight based on absolute deviation. It should be noted that if there is a definite preference for predicting *arithmetic mean* deposition (versus all other central-tendency parameters) back-transforming the results of a regression from the log scale will not be ideal for that purpose. However, EFED participants concluded that there was no strong basis for a specific preference for prediction of the arithmetic mean in this situation.

Before fitting curves, nondetect observations were processed as follows. Nondetects were either deleted from the analysis, or kept and replaced with half the detection limit, according to the following criteria: (1) A nondetect was kept whenever there was a detection at a more distant measurement station; (2) If there were nondetects beyond all the detection distances, only one was kept (the one closest to the field edge).

The regression approach just described places relatively high weight on the smallest observations. The results in Section 4 (evaluation of drift predictors) were also obtained by regressing $\ln(y)$

against x , but a weighted regression procedure was used with weights of y^2 . This procedure has the effect of placing similar weights on absolute deviations of a given magnitude (see Appendix 2). Our experience with the orchard spray studies confirms that this procedure often substantially increases R^2 (in the scale of %deposition). The approach is available in TableCurve Windows 1.12 (Jandel, 1992) software, which was used for the curve fitting. The chosen equation showed high R^2 values (deposition scale) for the fits to all 46 applications (Appendices 4). In addition, all 46 equations predicted downwind deposition within a factor of two at all sampling distances. Other equations with this general form did not perform as well for all 46 applications.

An alternative would have been to directly optimize the sum of squared residuals using nonlinear optimization methods. If that approach had been used, numerical difficulties for a small percentage of the curves might have proved a significant obstacle. Curves of the general type used here have been considered somewhat problematic from the standpoint of nonlinear regression (Ross, 1990, particular Section 7.2.4).

All nondetects were kept in the analysis, replaced by half the detection limit. There were relatively few nondetects (e.g., compared to the situation with the orchard studies), so we do not believe the results will be very sensitive to minor differences in the handling of nondetects. More rigorous approaches may be considered, from the statistical literature on analysis of censored data.

C. Predictors of Drift: Standard Treatments

Analysis of the 23 standard applications was performed first. The relationship between the values of two empirical model parameters and the meteorological variables were examined. Initial analysis consisted of examining the meteorological variables for multicollinearity. As expected, the wind speeds at the various heights were highly correlated. Therefore, only wind speed at the 2 m height was retained in the analysis. Also as expected, the standard deviation of the wind direction was highly correlated with the wind speed (high wind speed tends to be associated with low standard deviation of wind direction). Therefore, the standard deviation of the wind direction was removed.

The final meteorological variables included were wind speed at 2 m, relative humidity, Richardson Number, and the wind angle. Although the distances were corrected for wind angle, it was included because this variable gives an indirect measure of the change in the source from a 55m x 305m rectangle to some other effective shape, depending upon the size of the wind angle. As mentioned in the integrated report, two of the applications showed Richardson Numbers significantly larger than the remaining 23 applications. These two applications were eliminated from the general analysis. One application showed a wind speed of 22 mph. This application was also eliminated from the analysis. This left a total of 20 standard treatments for the remainder of the analysis.

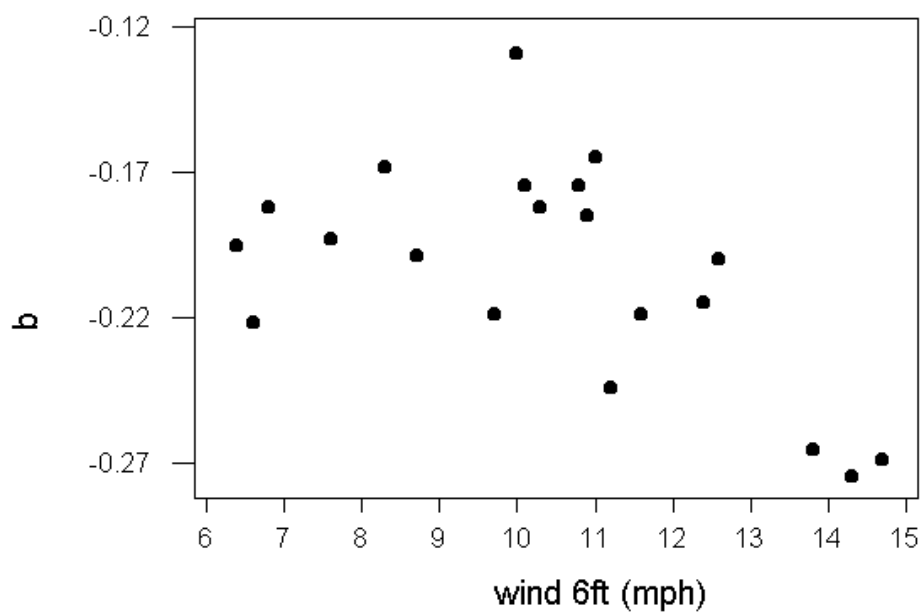
The value of the initial deposition parameter, a , was not significantly correlated to any of the

meteorological variables. This result is consistent with the conclusion in the integrated report and is most likely due to the small difference between the 20 applications in initial deposition at 8 m and 15 m. However, the value of b , the %app rate decline parameter, was significantly correlated to wind speed at 2 m ($r=-0.548$, $p=0.012$), and the wind angle ($r=0.589$, $p=0.006$). As wind speed increased the value of b became larger, negative. Therefore, at higher wind speeds the rate of decline in deposition with distance tended to increase (larger negative, more rapid decline) (Figure 11). This trend is particularly evident in at wind speeds above 11mph and is contrary to the expected trend of a more rapid rate of decline with distance at slower wind speeds due to faster settling of droplets closer to the source. All the wind speeds in these trials were above 6 mph so evaluation of the rate of decline in deposition at lower wind speeds was not possible. The more rapid rate of decline with higher wind speed may be due to lower collection efficiency of the alpha-cellulose cards at higher wind speed (wind speed exceeding approximately 11 mph).

Figure 12 shows the significant positive trend of the value of the decline parameter, b , with wind angle. As the wind angle increased, the value of the decline parameter also increased, so the rate of decline decreased. This is also contrary to the expected trend. Theoretically, for the same application conditions and wind speed, as wind angle increases the initial deposition parameter, a , should increase (larger initial deposition) and the decline parameter should decrease (become larger negative, more rapid decline). This is due to the changing source geometry from a rectangle 50 meters deep to a triangle of varying length (longer than 50 meters), depending upon the size of the wind angle. The near field will receive more deposition as the angle increases between 0° and 30° (the largest deviation from perpendicular allowed by the study protocol). The far field will receive less as the wind angle increases between 0° and 30°. When the wind angle becomes large, some far field deposition cards may not receive any deposition. These changes will lead to a larger initial deposition parameter, a , and a smaller decline parameter, b (larger negative, more rapid decline).

These theoretical results are complicated by the moving source (the ground rig moving side to side in relation to the wind angle), but, the basic relationship should hold. An explanation for the results evident in Figure 12 is that for this set of applications, wind angle and wind speed are negatively correlated $R = -0.406$, $p = 0.076$. The applications with highest wind speeds also had small wind angles. In addition, as is usually the case, the highest wind speeds were accompanied by the small standard deviation of wind direction $R = -0.903$, $p = 0.00$). It is likely that the positive correlation of the decline parameter, b , with wind angle is an indirect representation of the wind speed effect and not a wind angle effect. This is further supported by the observation that deposition (%applied) at 183 m and 396 m are not correlated with wind angle $R = 0.275$, $p = 0.240$ and $r = -0.024$, $p = 0.919$, respectively). It should be noted that only four of the 20 applications showed a wind angle larger than 15°.

Figure 11. Decline parameter, b , for 20 standard ground rig treatments versus wind speed. Ground rig data from Appendix I of the SDTF integrated report.



Per R. Mickle's (1998) suggestion, the wind angle values may be adjusted to account indirectly for potentially larger deviations from 0° than the mean wind angle during the application. The adjustment, (wind angle + 1 std deviation of wind direction), can be used as an informal analysis. When this adjustment is made, there is still a lack of correlation between the wind angle and far field deposition at 183 m and 396 m ($r = 0.385$, $p = 0.093$ and $r = 0.088$, $p = 0.713$, respectively).

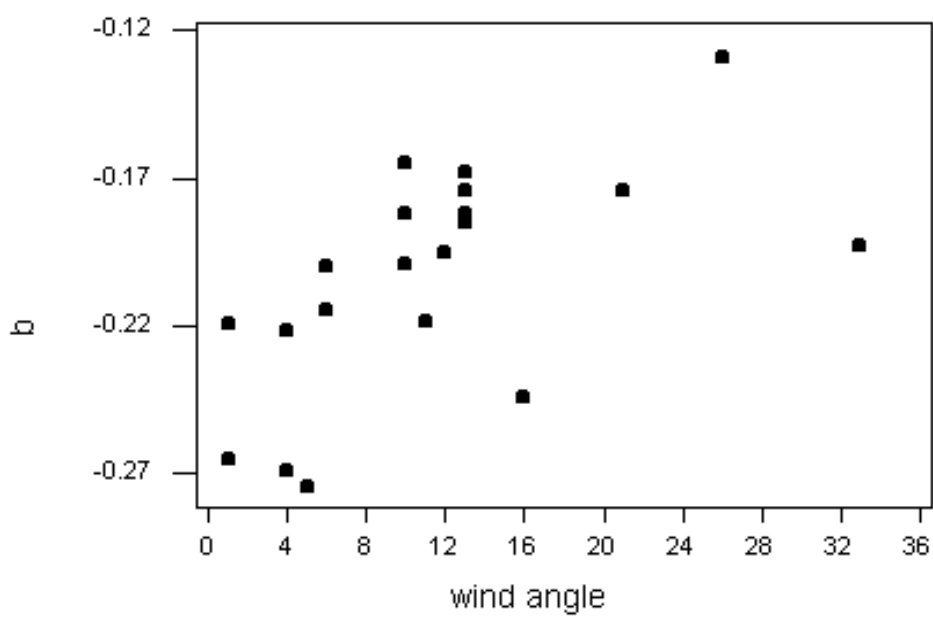
Twelve of the 20 applications empirically modeled were conducted in 1992 when all three lines at all distances were collected and analyzed. The % applied results reported in the integrated report, and empirically modeled here, are averages of those three lines. That averaging process will tend to smooth out some of the wind angle effects for the 1992 data. The remaining 8 applications conducted in 1993 had only three of the ten downwind locations sampled by three lines. Therefore, some of the down wind sites were averages and some were center line on the idealized rectangular source.

A more detailed analysis is required to quantitatively evaluate the wind angle effect. It may be desirable in the future to remove the far field deposition result (396 m) for all 20 applications and re-examine the model parameters. However, because of the lack of correlation between the far field deposition and the wind angle, it is unlikely that the model parameters will change substantially or that the major conclusions will change.

D. Predictors of Drift: Variable Treatments

The same decline function used for the standard ground treatments was fit for the 23 individual applications. Results are shown in Table 2. Separate two way analysis of variance was performed on the equation parameters (a and b), using sprayer type and boom height as factors. For the initial deposition parameter, a , the ANOVA results indicate a significant difference between sprayers ($F=10.63$, $p=0.00$) and boom height ($F=17.31$, $p = 0.00$) but no interaction between the two factors ($F=1.74$, $p = 0.20$). Figure 13 shows the value of the initial deposition parameter for the variable treatments, using the VMD as the label for each sprayer. As indicated by the ANOVA results, the results shown in the figure below indicate that both sprayer (represented by VMD) and boom height significantly influence the value of the initial deposition parameter, a , and that their influence is additive. The value of the initial deposition parameter, a , for the three sprayers, 8004, 8004LP and 8101LP are not significantly different. The TX6 sprayer, with the VMD of 171 μm shows a significantly higher amount of initial deposition, relative to the remaining three sprayers. This effect is independent of boom height. The higher initial deposition for the 1.27 m boom height is also apparent in Figure 13. The ANOVA results indicate a uniform increase in the value of the initial deposition parameter, a , with the increase to the higher boom height for all three sprayers. The low boom mean $a = 0.720$ and the high boom mean $a = 1.88$. The mean uniform increase in the value of the initial deposition parameter, a , can be estimated as $1.88 - 0.72 = 1.16$.

Figure 12. Value of the decline parameter, b , for the 20 standard ground rig treatments versus the wind angle during the applications. Data from Appendix I of the integrated report.



The ANOVA results for the decline rate parameter, b , showed no significant differences for either sprayer or boom heights. Interpreting the rate of decline is difficult because of the high wind speeds (greater than 10 mph) present in 14 of the 23 applications. As discussed in the standard treatment section, there is a potential effect of wind speed on the collection efficiency of the horizontal alpha cellulose collectors. Figure 14 shows the same trend of a more rapid rate decline in deposition with increased distance as wind speed increases. There is a weak correlation between the value of the decline parameter, b , and wind speed ($R = -0.405$, $p = 0.078$). The weaker correlation is expected because of the increased variation in the decline parameter values due to the differences between the variable treatments. As discussed in the standard treatment section, the observed trend is contrary to the expected trend of the most rapid rate of decline being associated with slower wind speeds due to more rapid settling of droplets closer to the field.

E. Tolerance Bounds

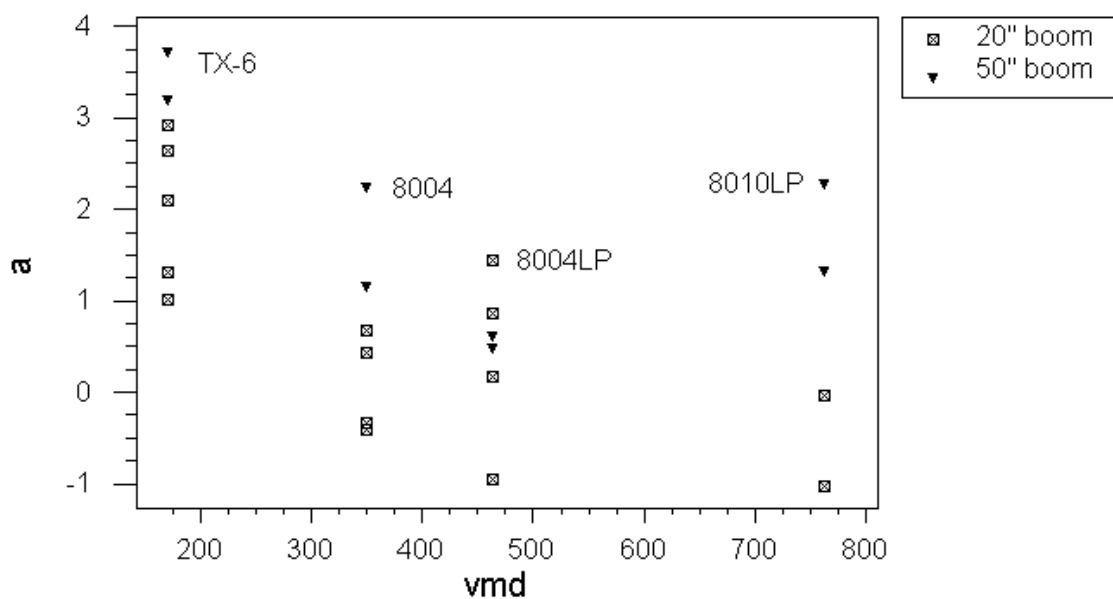
An upper tolerance bound covers a percentile β of the distribution, with confidence γ . In our calculations, a single tolerance bound applies to a combination of percentile of distribution ($\beta = 95\%$, 99%), and confidence coefficient ($\gamma = 65\%$, 75% , 85% , 95%), distance from edge of field ($x = 5$ m, 10 m, 20 m, ..., 250 m), and treatment grouping (groupings numbered $1, \dots, \#gr$).

The procedure used for calculating tolerance bound was identical to the procedure used for calculating tolerance bounds for the orchard studies (presented separately):

To calculate a bound for deposition at given distance (x), the first step was to plug the estimates of a and b (calculated as described above using regression of deposition against distance) into the formula for deposition: If a_i and b_i denote the estimates for the i th application, deposition at distance x is estimated by $\exp(a_i + b_i x)$ for the i th application. The resulting estimates of %appl were then used as input for the calculation of tolerance bounds. The calculations for upper-bound deposition for a given treatment group used the mean deposition for applications in that treatment group; however, the *same coefficient of variation* was assumed to apply for *each* treatment group, a point that we now develop. Based on that assumption, we used the same estimated coefficient of variation for each grouping except for the medium-low/coarse category.

The medium-low coarse category was evaluated completely independently of the other categories because the group consisted mostly of “standards” which were matched with treatments in the other categories. Pooling across all categories would have involved violation of an assumption of statistical independence.

Figure 13. The value of the initial deposition parameter, a , for the variable treatments (indicated by VMD). Data from Appendix I of the integrated report..

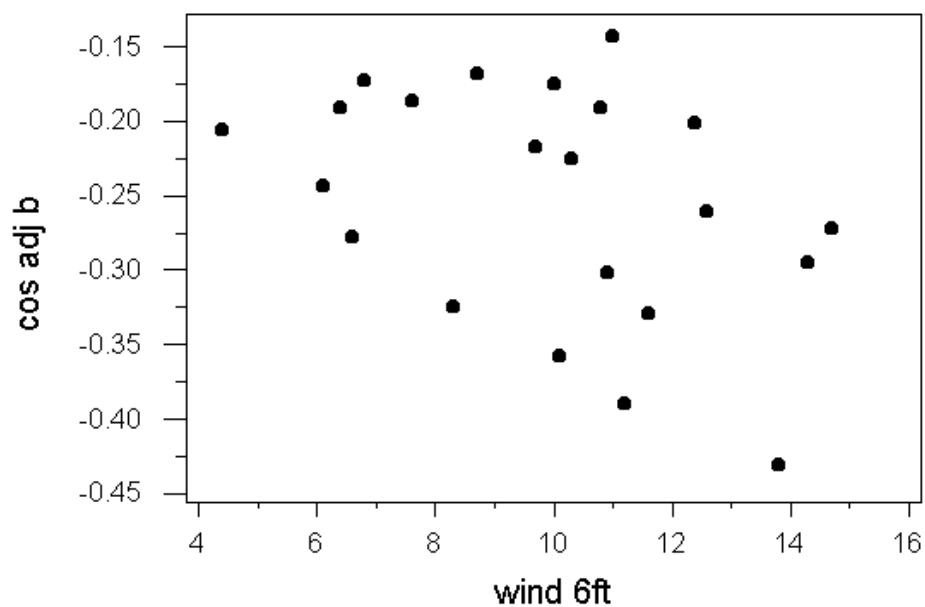


The assumptions of our approach are that the distribution is normal within each grouping (as usual in ANOVA); however *in lieu* of the familiar assumption of equal variances, we assume an equal coefficient of variation (for groups other than the medium-low/coarse group). The (assumed common) coefficient of variation was estimated using a formula that pools (in a sense, averages) the sample coefficients from the individual groups. The formula for pooling coefficient of variation estimates is a special case of the “moment estimator” given by McCullagh and Nelder (1989).

To calculate tolerance bounds based on the equal-CV assumption, we adapt a well-known procedure based on the noncentral- t distribution (Guttman, 1970). The technical appendix develops the algorithm and provides a SAS program (SAS Inst., Inc.). When there is a single sample, the equal-variance and equal-CV approaches are identical and exact. When there are multiple samples, the equal-variance formulae are exact while the equal-CV approach is approximate. For the equal-CV approach, the approximation is of a type that we think is customary, amounting to replacing an unknown group mean by a sample mean. The approximation is expected to be better for groups with a larger sample size. In view of the fact that the result is approximate, a Monte Carlo experiment may be considered in order to evaluate the quality of the approximation, particularly for small N .

Figures 15 through 18 below display the statistical results for each of the four ground spray categories. Displayed on the graphs are the mean and 95th percentile (95 % confidence) deposition versus distance curves and the deposition measurements from the field studies. Similar to the orchard results, the 95th percentile curve generally intersects more data points at small and large distances. At mid range distances the data points generally fall farther beneath the 95th percentile estimate. The overall proximity of the 95th percentile to the data in each of the categories suggests that it is not overly conservative and is likely not a literal 95th percentile in terms of data scatter.

Figure 14. The value of the decline parameter, b , for the variable treatments versus wind speed.



Data from Appendix I of the integrated report

Figure 15.

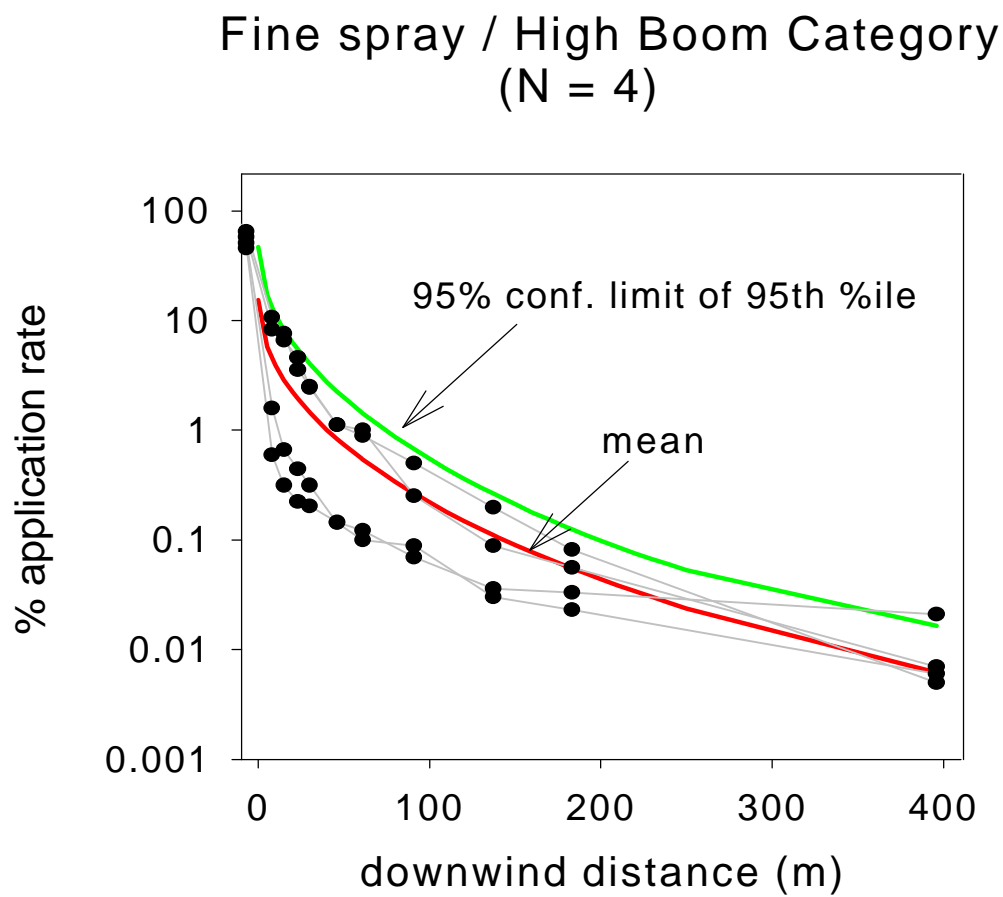


Figure 16.

Fine spray / Low Boom Category
(N = 4)

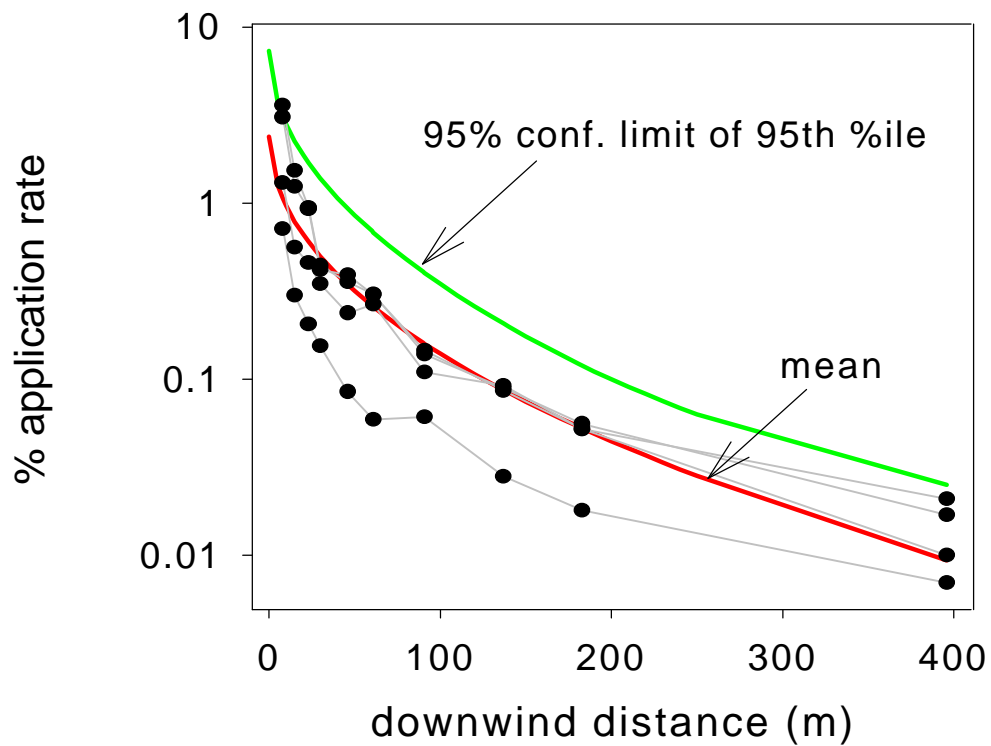


Figure 17.

Medium-coarse spray / High Boom
Category (N = 8)

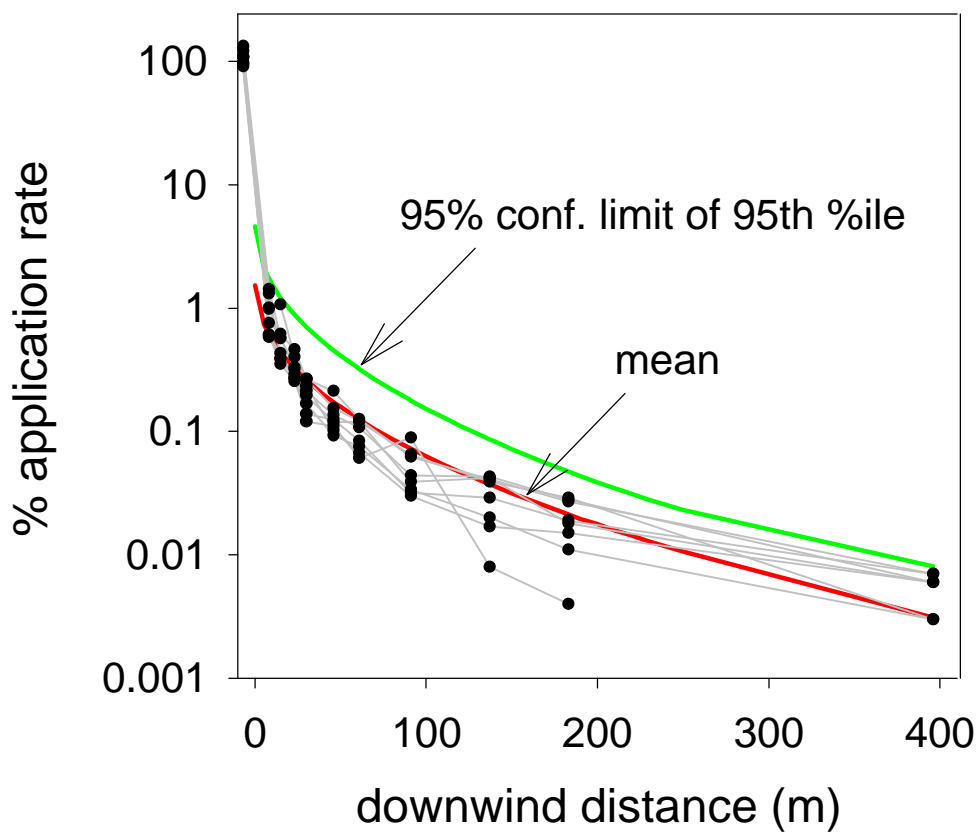
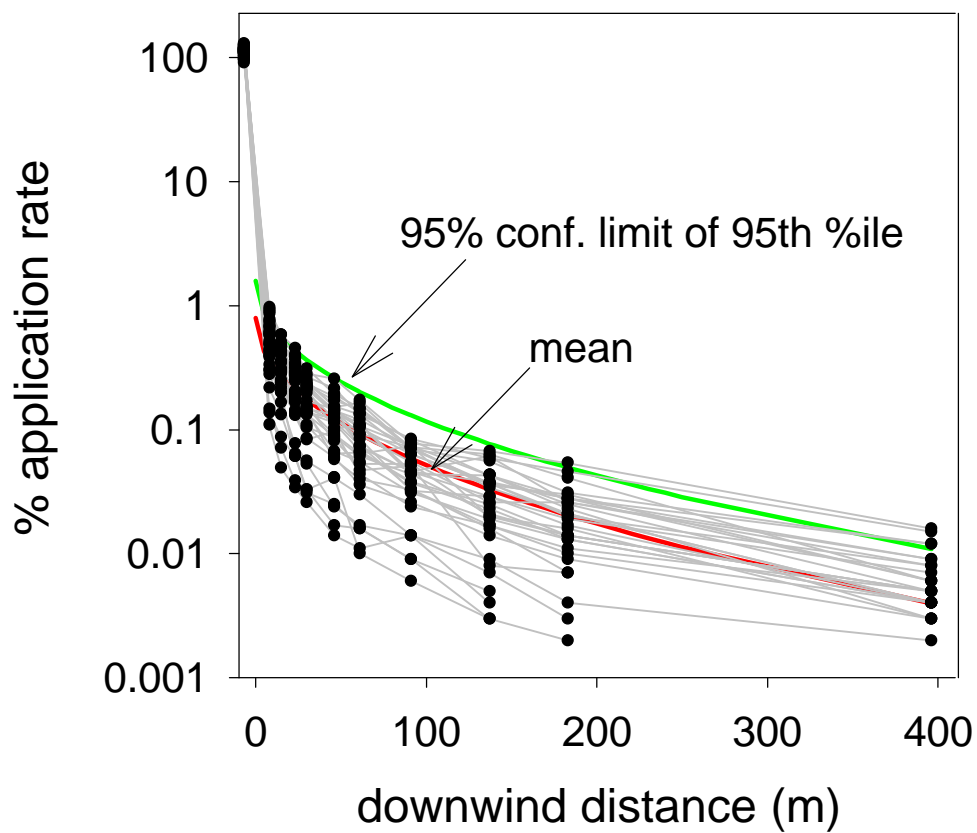


Figure 18.

Medium-coarse spray / Low Boom
Category (N = 34)



F. Possible Refinements of the Statistical Procedures

The following text is identical in the ground spray document and the airblast/orchard document. Material on inside applications applies only to the airblast/orchard studies.

We note several important limitations of the bounds reported here. Here some of the issues are discussed in fairly general terms. EFED and the authors of this report are considering some refinements. However, we realize that in view of the limited quantity of data, the value of refinements will need to be weighed against the possible value added.

Refinements of the curve-fitting step. We have used a statistical approach that involves fitting a curve to the deposition results for each application. This step may be refined in two ways. First, the specific curve we have fitted tends to under-predict for the locations most distant from the field edge. Therefore we may consider fitting somewhat more flexible curves. Second, a more rigorous treatment of the nondetects may be adopted from the statistical literature on analysis of censored data. The development of a more refined regression approach is likely to be an iterative process.

Incorporating the residual variation from individual regression curves. For our tolerance bound calculations the measured values of deposition were replaced with values predicted using regression equations, which were fitted to the data from individual applications. Since measured values vary from the predictions, a more refined approach would make use of the *residual variances*. For a single regression curve, the residual variance estimate quantifies the variation of individual data points from the regression line. A relatively challenging approach would involve applying spatial statistical methods to the data from the individual collectors. That approach would take into account spatial auto-correlation as well as the magnitude of residual variance at the level of individual collectors.

Bounds for integrated deposition. The bounds reported here apply to deposition (% of applied) at a given distance from the edge of the field, for a series of distances. An aquatic exposure assessment would require that we integrate the deposition-distance curve over the surface area of a water body, to calculate mass deposition into the water body. In order to place an upper bound on integrated exposure, an obvious approach would be to define an “upper bound deposition curve” as the set of upper bounds over distance, and integrate the upper bound curve. An alternative which may be somewhat more rigorous would be to integrate each of the fitted curves separately and apply a tolerance bound calculation to the values that result.

It is likely that each variation of the exposure indices will suggest modifications for the procedure for calculating statistical bounds. Therefore it is desirable to refine the exposure estimates as much as possible before putting in much more work on the calculation of statistical bounds. With regard to higher-tier assessments, we note that flexible Monte Carlo procedures have been proposed in the risk assessment literature, that appear to address the statistical error in a manner analogous to our use of tolerance bounds (hierarchical Monte Carlo, see e.g., Brattin et al., 1996,

or bootstrap methods).

Scaling from row to field. The bounds reported here apply to the deposition expected to result from a single pass of an applicator through the field. If we are to estimate the deposition from spraying a whole field, it seems that the deposition at a given distance from the edge of the field would be calculated by summing contributions from drift originating at different points within the field. If the deposition from spraying a single row has a normal distribution (as assumed for the computations reported here), the distribution of the sum from several rows will also have a normal distribution.

It does not seem reasonable to suppose that the deposition from two rows will be statistically independent, given that adjacent rows are likely to be treated during the same period of a single day. Appropriate handling of correlations would need to be worked out by formal analysis. However we provide some general remarks on the handling of correlations.

First, the issue of correlations can be confusing because of the distinction between the correlations in the data versus in the field. Depending on how the data were collected, the former may or may not be viewed as estimating the latter. For example, it appears that the data cannot be used to estimate the correlation of deposition from outside rows and inside rows in the orchard airblast studies: In the design of the orchard studies a substantial period might elapse between the tests with outside and inside rows. It appears that ignoring a positive correlation would underestimate the variance of total deposition. For example, for two rows with deposition D_1 and D_2 , we have

$$\text{variance}(D_1 + D_2) = \text{variance}(D_1) + \text{variance}(D_2) + 2 * \text{covariance}(D_1, D_2).$$

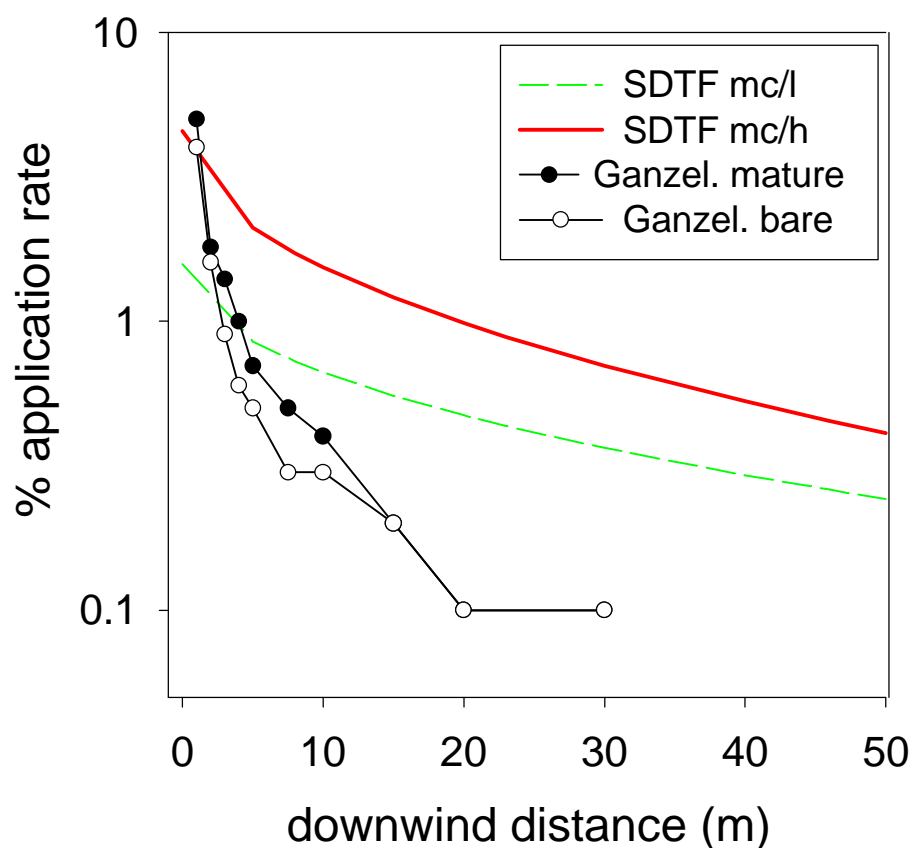
The more positive the correlation, the less likely a high deposition from one row will be compensated by a low deposition from the next.

Second, correlations may affect statistical confidence intervals by determining, in effect, the amount of independent data: If two variables (say A and B) are correlated so that B can be predicted to some degree based on knowledge of A, then measuring B adds less information, beyond what is provided by A, relative to the case where the variables are independent. Thus it seems that ignoring correlations may result in statistical bounds that are too narrow: one effectively assumes more data than is actually available.

Random effects models. The bound procedure assumed that all applications in a given treatment grouping are independent, when actually most of the applications are paired with the same treatment given to replicates in a pair. An alternative would be to use an approach that recognizes explicitly two “levels” of variation (between replicates in a replicate-pair, among replicate pairs in a treatment grouping). This approach would probably widen the statistical bounds somewhat. This could be justified on the grounds that measurements under a wider variety of conditions is likely to be more valuable than repeated measurement under very similar conditions. Development of tolerance bounds for random effects models could involve

considerable effort: Straightforward procedures appear to be available only for some special cases (e.g, Bhaumik and Kulkarni, 1996). An acceptable expedient may be simply to average the results for pairs of replicate pairs, and take N to be the number of pairs or unpaired treatments.

Ganzelmeier-SDTF 95th %tile Comparison



Consideration may be given to the use of formal meta-analysis methods, to combine the Spray Drift Task Force data with data from other spray drift studies. Issues involved in combining data are beyond the scope of this report. However, we note that random effects approach could be valuable by allowing a distribution of differences among studies. Random effects models are in fact an important tool in current meta-analysis methodology (e.g., Normand, 1995).

Alternatives to distance-by-distance bound calculation. The bounds calculated here require that the group means and pooled CV be calculated separately for each distance, although the calculations for each distance are based on the same set of a and b estimates from the curve-fits. It is possible that some greater flexibility will be obtained by working with a bivariate distribution for the two parameters, and developing ways to translate the results into the scale of deposition. Evidently, this can be simplified if the parameters can be assumed to vary independently. We have done some work towards such an approach.

Monte Carlo simulation to evaluate statistical procedures. A Monte Carlo experiment may be considered to evaluate the approximate tolerance bounds. This would naturally be done after most conceptual issues are settled.

IX. Ganzelmeier Drift Studies from Field Crops

A number of drift studies conducted in Germany for registration purposes have been summarized (Ganzelmeier et al 1995). The data collected from drift studies to field crops included eight treatments to bare ground plots and an equal number of treatments to mature cereals of undefined species. Boom height and drop size information for the applications were not given. The volume applied per acre (~ 32 gallons per acre) and the application speed (3.7 mph) suggest that a relatively coarse spray may have been used. The highest volume applied in the SDTF studies was 27 gallons per acre with the 8004LP nozzle at a speed of 5 mph.

In general the SDTF studies measured downwind drift under a larger range of conditions (see table below). Some SDTF trials were conducted under higher wind speeds, higher temperatures, and lower humidity, which are considered to cause higher levels of drift.

The Ganzelmeier data were analyzed to produce a 95th percentile value at each distance deposition was measured. Graphically comparing the 95th percentile of the Ganzelmeier data to that derived from the SDTF data (see figure below) shows some similarity close to the field's edge. However, the SDTF curve is extrapolated at distances less than 8 m and therefore may not be accurate. At distances where deposition was measured in the SDTF studies, the SDTF 95th percentile is much higher than the Ganzelmeier data at greater distances which may be caused by the higher drift conditions used in the SDTF studies.

Table 5. Comparison of Ganzelmeier and SDTF application conditions.

parameter	Ganzelmeier	SDTF
wind speed range (mph)	2-8	5-20
temperature (°F)	50-63	40-95
humidity (% relative)	60-85	<10-85
downwind distance (m)	1-30	8-400

Figure 19.

Comparison of the SDTF 95th percentile medium-coarse low boom (mc/l) and high boom (mc/h) categories with the Ganzelmeier 95th percentile values for the bare ground and mature cereal data. Boom height and drop spectrum were not available for the Ganzelmeier data set.

X. EFED's Present Drift Estimation and SDTF 95th Percentile Curves

For deposition input into EFED exposure assessments related to ground boom pesticide applications, the current assumption is that 1% of the application rate drifts into a 1 hectare pond immediately adjacent to a 10 hectare field. For terrestrial plants, a drift exposure estimate of 1% is used without an associated distance. The hypothetical pond is 63 m wide, 2 m deep, and has an approximate volume of 2×10^7 liters. The pesticide concentration in the pond from a 1 kg / hectare application to the field is equivalent to the direct application of 0.01 kg to the pond or an estimated screening concentration of 0.5 µg/l.

The 95th percentile curve of the SDTF data does not allow integration to the edge of the field without extrapolation to distances less than 8 m. The ground boom field trials used 8 m as the closest measurement distance.

Using the SDTF 95th percentile curves it is possible to estimate aquatic concentrations resulting

from spray drift in hypothetical ponds beginning 8 m or farther from the field edge. The estimated concentration is useful as a rough comparison of how the SDTF data compares EFED's current practice, but, since only a few swaths were sprayed, it does not account for a field size of 10 hectares. For estimation with the fine / low boom category, if deposition is assumed decrease linearly between 8 and 70 m (using deposition values from the tolerance table in the appendices) the overall deposition would be 1.8%. When diluted into 20 million liters, the estimated screening concentration for a 1 kg / hectare application would be approximately 0.92 µg/l. If the edge of the pond is 70 m from the orchard and extends to 130 m from the orchards edge, the estimated screening concentration resulting from 0.40% of the application rate would be approximately 0.20 µg/l.

XI. References

General References

Ganzelmeier, I.H., D. Rautman, R. Spangenberg, M. Streloke, M. Herrmann, H.-J. Wenzelburger, and H.-F. Walter. 1995. Studies on the spray drift of plant protection products, Results of a test program carried out throughout the Federal Republic of Germany. Blackwell Wissenschafts-Verlag GmbH Berlin/Wien.

Hewitt, A.J. 1995. *Atomization droplet size spectra for spray drift formulations: 1992 field trial conditions*. SDTF study no. A92-005. MRID 43657601.

Hewitt, A.J. 1994. *Spray Drift Task Force atomization droplet size spectra for spray drift test substances: 1993 field trial conditions*. SDTF study no. A93-008. MRID 43757802.

Hurto, K.A. 1987. Application and spray pattern characteristics of the ChemLawn 4GPM spraying system used by lawncare. *Proceedings of the Northeast Weed Science Society*. Vol. 42, p. 164-165.

Johnson, D.R. 1994. *Spray Drift Task Force 1992 ground field study in Texas*. SDTF study no. F92-009. MRID 43493801.

Johnson, D.R. 1994. *Spray Drift Task Force 1993 ground field study in Texas*. SDTF study no. F93-016. MRID 43493802.

Johnson, D.R. 1995. *Drift from applications with ground hydraulic sprayers: Integration and summary of 1992 and 1993 field studies*. SDTF study no. I94-001. MRID 43508001.

Statistical References

Bhaumik, D.K. and P.M. Kulkarni. 1996. A simple and exact method for constructing tolerance

intervals for the one-way ANOVA with random effects. *Amer. Statistician*. 50(4):319-323.

Brattin, W.J., Barry, T.M., and Chiu, N. 1996. Monte Carlo modeling with uncertain probability distributions. *HERA* 2:820-840.

Gilbert, R.O. 1987. *Statistical Methods for Environmental Pollution Monitoring*. Van Nostrand Reinhold.

Guttman, I. 1970. *Statistical Tolerance Regions: Classical and Bayesian*. Charles Griffin and Co.

Hahn, G.J., and Meeker, W.Q. 1991. *Statistical Intervals: A Guide for Practitioners*. Wiley.

McCullagh, P. and Nelder J.A. 1989. *Generalized Linear Models*. 2nd edition. Chapman and Hall.

Normand, S.-L. T. 1995. Meta-analysis software: a comparative review. *Amer. Statistician*. 49(3):297-308.

Weissberg, A., and G.H. Beatty. 1960. Tables of tolerance limit factor for normal distributions. *Technometrics* 2:483-500.

Wild, P., Hordan, R., Leplay, A., and Vincent, R. 1996. Confidence intervals for probabilities of exceeding threshold limits with censored log-normal data. *Environmetrics* 7:247-249.

Appendices

Appendix 1: Noncentral- t tolerance bounds under equal variance and equal coefficient of variation assumptions

The material in this appendix is identical in the documents for orchard/airblast and ground spray.

Notation, General linear model theory (GLMT). We use the following conventional notation to describe distributions:

χ_v^2 chi-square distribution with v degrees of freedom, or a random value with that distribution;

$N(\mu, \sigma^2)$ normal distribution with mean μ and variance σ^2 , or a random value with that distribution;

$\Phi(x)$ cumulative distribution function (CDF) for a $N(0,1)$ distribution;

$\Phi^{-1}(x)$ inverse-CDF for a $N(0,1)$ distribution.

We assume that the data are in $\#gr$ groups with N_i values in the i th group. We assume that values in the i th group are iid normal with mean μ_i and variance σ_i^2 .

Let y_{ij} = the value of the j th observation in the i th group, $j=1, \dots, N_i$, $i=1, \dots, \#gr$;
 y_i = sample mean for the i th group, $i=1, \dots, \#gr$;
 s_i^2 = sample variance for the i th group, $i=1, \dots, \#gr$.

All of the theory used here is shared with the derivation of familiar parametric confidence bounds for the mean of a normal distribution based on the Student t distribution. Here, where a result from this basic theory is used, this is indicated by “GLMT.”

Pooling variances and pooling coefficients of variation. As background, it is useful to review the familiar situation involving multiple groups (say $\#gr$ groups), with an assumption that the within-group variance is equal across groups, i.e., we assume $\sigma_1^2 = \sigma_2^2 = \dots = \sigma_{\#gr}^2 = \sigma^2$. The common variance σ^2 can be estimated by the ANOVA error mean square (MS_E) which effectively averages the sample variances over groups:

$$MS_E = v^{-1} \sum_i df_i s_i^2 \text{ (summing over groups)}$$

where df_i = degrees of freedom for the i th group = $N_i - 1$;
 v = total degrees of freedom = $\sum_i df_i$.

Then $v \cdot MS_E / \sigma^2$ has a χ_v^2 distribution and is statistically independent of the sample means (GLMT).

For the situation involving an equal coefficient of variation (CV), we use a special case of the “moment estimator” described by McCullagh and Nelder (1989). Instead of assuming an equal variance in each group we assume an equal CV. In other words we assume:

$$\sigma_1 / \mu_1 = \sigma_2 / \mu_2 = \dots = \sigma_{\#gr} / \mu_{\#gr} = CV$$

or

$$\sigma_i = \mu_i \cdot CV, \quad i = 1, \dots, \#gr.$$

For situations such as this where some functional relationship is assumed to relate the variance to the mean it is common to use a weighted regression approach. In this case the ideal weights would weight observations in the i th group proportionally to μ_i^{-2} (GLMT). Unfortunately the ideal weights then depend on the unknown true group means $\mu_1, \dots, \mu_{\#gr}$.

The weighted means equal the unweighted means because the ideal weights change among but not within groups. Regarding variance estimation, we note that as a rule of thumb weighted regression procedures involve replacing the familiar regression sums of squares (SS) with weighted SS. Considering in particular the following weighted SS for residuals:

$$\begin{aligned} WSS_E &= \sum_{i=1}^{\#gr} \sum_{j=1}^{N_i} \mu_i^{-2} (y_{ij} - \bar{y}_i)^2 \\ &= \sum_{i=1}^{\#gr} df_i (s_i / \mu_i)^2 \end{aligned}$$

In general, the method of moments involves setting a statistic equal to its expected value. We have exactly that $E(WSS_E) = v \cdot CV^2$ (GLMT). Therefore, for an approximate method of moments estimator in this situation we make the approximation

$$WSS_E \approx \sum_{i=1}^{\#gr} df_i (s_i / \bar{y}_i)^2 = v \cdot (CV^*)^2$$

where CV^* is our estimate of the common within-group coefficient of variation. Hence $CV^* = [v^{-1} \sum df_i (CV_i^*)^2]^{1/2}$ where CV_i^* is the sample coefficient of variation for the i th group. The coefficient of variation is pooled by squaring the sample CV's, averaging (weighting by degrees of freedom) and finally taking the square root.

Noncentral- t tolerance bounds: the equal variance case. In the familiar situation involving a common within-group variance σ^2 the β th percentile for the i th group has the general form $\mu_i + z_\beta \sigma$ where $z_\beta = \Phi^{-1}(\beta)$.

For the i th group, we may use a bound of the general form $y_i + k \cdot s$, where s is the estimated within

group variance (equal for all groups). Therefore the problem of finding a bound that covers percentile β with confidence γ amounts to solving for k in the expression:

$$\text{pr} [y_i + k \cdot s \geq \mu_i + z_\beta \sigma] = \gamma$$

The exact solution in the equal variance situation is well known (e.g., Guttman, 1970) but it is useful to review the solution here as background for an approximate solution for the equal-CV situation. The event $y_i + k \cdot s_i \geq \mu_i + z_\beta \sigma$ above is equivalent to:

$$[(\mu_i - y_i) + z_\beta \sigma] / s \leq k.$$

On the left side, divide numerator and denominator by $\sigma/\sqrt{N_i}$, which is the standard deviation of y_i :

$$[(\mu_i - y_i)/(\sigma/\sqrt{N_i}) + z_\beta \sqrt{N_i}] / (s\sqrt{N_i}/\sigma) \leq k.$$

or

$$N(z_\beta \sqrt{N_i}, 1) / \sqrt{(\chi_v^2 / v)} \leq k\sqrt{N_i}$$

where the numerator and denominator random variables are statistically independent (GLMT). By the definition of a noncentral- t random variable, the event of interest is:

$$T(z_\beta \sqrt{N_i}, v) \leq k\sqrt{N_i}$$

where $T(\delta, v)$ denotes a noncentral- t random variable with noncentrality parameter δ and degrees of freedom v .

Therefore the following algorithm (which is easily programmed in SAS) yields a bound that covers percentile β with exact confidence γ :

- (1) Calculate $z_\beta = \Phi^{-1}(\beta)$.
(The SAS function PROBIT may be used.)
- (2) Calculate the noncentrality parameter $\delta = z_\beta \sqrt{N_i}$.
- (3) Find the appropriate critical value of a noncentral $T(\delta, v)$ distribution, say t^* that satisfies $\text{Pr}[T(\delta, v) \leq t^*] = \gamma$.
(The SAS function TINV may be used.)
- (4) $k = t^* / \sqrt{N_i}$.
- (5) The bound is $y_i + k \cdot s$ where $s = \sqrt{\text{MS}_E}$.

Noncentral- t tolerance bounds: the equal-CV case. In the equal-CV situation, we pursue an analogy with the equal-variances situation and try to solve at least approximately for k in the expression:

$$\text{pr} \{ y_i + k \cdot \sigma_i^* \geq \mu_i + z_\beta \sigma_i \} = \gamma$$

where $\sigma_i = \text{CV} \cdot \mu_i$ is the true standard deviation in the i th group,

$\sigma_i^* = CV^* \cdot y_i$ is suggested as an estimator of σ_i ,
 CV^* is the pooled coefficient of variation described above.

Using the same steps as for the equal variance situation, we require:

$$\text{pr} \{ N(z_p \sqrt{N_i}, 1) / (\sigma_i^* / \sigma_i) \leq k \sqrt{N_i} \} = \gamma,$$

Regarding the distribution of the ratio σ_i^* / σ_i , we have:

$$\frac{\sigma_i^*}{\sigma_i} = \frac{\bar{y}_i \cdot CV^*}{\mu_i \cdot CV} = \frac{\bar{y}_i \cdot \left(\frac{1}{v} \sum df_i s_i^2 \bar{y}_i^{-2} \right)^{1/2}}{\mu_i \cdot CV}$$

For an approximation, we substitute the sample means (y_i , known) for the true means (μ_i , unknown), which after some rearrangement and GLMT gives $\sigma_i^* / \sigma_i \approx \sqrt{(\chi_v^2 / v)}$. This suggests, as an approximation, using σ_i^* in place of s in the algorithm described above, for the equal variance situation. If we make this approximation, technically the denominator will deviate from the desired function of a χ^2 distribution, and also the numerator and denominator are not evidently independent, which are conditions for the ratio to have the noncentral- t distribution.

The algorithm differs from the algorithm for the equal variances case only at Step 5:

- (5) The bound is $y_i + k \cdot \sigma_i^*$ where $\sigma_i^* = CV^* \cdot y_i$.

The following SAS code was used:

```

** ===== ** ;
** Program SASTOL.SAS (SAS) : Tolerance bound calculations for ** ;
** the equal-CV model.  D.Farrar, 6/99 ** ;
** ** ;
** The program calculates tolerance bounds using SAS functions for the ** ;
** normal and noncentral t distributions.  It does not calculate the ** ;
** pooled CV. The pooled CV is an input. ** ;
** ** ;
** Input fields: ** ;
** ----- ** ;
** The first 2 input fields are not used in the calculations.  They are ** ;
** there because I just wanted them carried along into the output. ** ;
** ** ;
** PERC - percentile to estimate or bound on (=BETA) ** ;
** N - number of observations on which mean is based ** ;
** DF - number of degrees of freedom on which CV is based, ** ;
** not necessarily N-1 ** ;
** CV - coefficient of variation, possibly pooled over groups. ** ;
** ** ;
** Output fields: ** ;
** ----- ** ;
** PERTILE - point estimate of the percentile identified by input ** ;
** variable PERC ** ;
** TOL[P] - bound that covers percenile PERC with confidence P% ** ;
** ** ;
** ===== ** ;

TITLE1 "Tolerance bounds for deposition by distance";
FILENAME IDATA '[insert file name]';

FOOTNOTE "Bound TOL[P%] covers percentile (PERC) with confidence P%";
NODATE PAGESIZE=100 ;
*INPUT VARIABLES : GROUP X PERC N DF MEAN CV ;
DATA;
  INFILE IDATA ;
  INPUT GROUP X PERC N DF MEAN CV ;
  Z = PROBIT( PERC ) ; * critical value of N(0,1) distr ;
  NCP = Z*SQRT(N); * noncentrality parameter ;
  S = MEAN*CV ; * estimate of standard deviation ;
  PERCtile= MEAN + Z*S ; * point estimate of PERCentile ;
  TOL65 = MEAN + S*TINV(.65,DF,NCP) / SQRT(N); * tolerance bounds ;
  TOL75 = MEAN + S*TINV(.75,DF,NCP) / SQRT(N);
  TOL85 = MEAN + S*TINV(.85,DF,NCP) / SQRT(N);
  TOL95 = MEAN + S*TINV(.95,DF,NCP) / SQRT(N);
PROC SORT; BY GROUP PERC X ;
PROC PRINT NOOBS ;
  VAR X N DF MEAN CV PERTILE TOL65 TOL75 TOL85 TOL95 ;
  BY GROUP PERC ;
  PAGEBY GROUP;
RUN;

```


Appendix 2: Approximate ordinary least squares algorithm used in curve fitting step.

We calculated estimates of a and b using an approximate ordinary least squares (OLS) approach. For the present situation, the exact OLS approach would be to determine values of a and b that minimize the sum of squared residuals:

$$SS_R = \sum_{i=1}^n [y_i - f(x_i; a, b)]^2$$

where x_1, \dots, x_n denote distances and y_1, \dots, y_n denote corresponding deposition measurements.

For the type of function we are considering, minimization of SSR requires numerical optimization. Difficulties with the numerical optimization for a small fraction of applications could cause significant inconvenience. The following approximate OLS approach does not require numerical optimization. We note the following approximation of SS_R :

$$\begin{aligned} SS_R &\approx \sum_{i=1}^n \frac{[\ln(y_i) - \ln(f(x_i; a, b))]^2}{[d \ln(y_i) / d y_i]^2} \\ &= \sum_{i=1}^n [\ln(y_i) - (a + b\sqrt{x_i})]^2 y_i^2 \end{aligned}$$

Accordingly, we optimize the last expression. This solution is obtained without recourse to numerical optimization, by weighted linear regression of log deposition against the square-root of distance, weighting by the square of measured deposition. The approach is available in TableCurve Windows 1.12 (Jandel, 1992) software, which was used for the curve fitting.

As discussed in the body of the report, the approximate OLS approach was only for a, b estimates for the statistical analysis of drift predictors. For the calculation of tolerance bounds, we have relied on parameter estimates computed by unweighted regression of $\ln(y)$ on x .

Appendix 3: Tables of Tolerance Bounds

Using the procedure outlined in Appendix 1, tolerance bounds have been calculated corresponding to percentiles 95% and 99%, with confidence levels 65%, 75%, 85%, and 95%. Computations were based on the SAS program given in Appendix 1.

Variables in output are as follows:

GROUP	1 for F/H; 2 for F/L; 3 for M/H; 4 for M/L
PERC	percent for percentiles that we want to estimate or bound (95%, 99%)
X	distance in meters
N	number of observations used to calculate a mean
DF	number of degrees of freedom used to calculate a pooled CV
MEAN	mean deposition for applications in a given group and distance
CV	pooled coefficient of variation for a given distance
PERCTILE	percentile point estimate
TOL65 etc.	tolerance bound with confidence 65%, etc.

Tolerance bounds for deposition by distance
Treatment applications

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17:32 Friday, May 28, 1999

----- GROUP=1 PERC=0.95 -----									
X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	4	11	15.3200	0.68617	32.6108	35.7427	37.9509	40.9991	47.0345
5	4	11	5.8139	0.64518	11.9838	13.1014	13.8894	14.9770	17.1306
8	4	11	4.5032	0.63484	9.2055	10.0573	10.6578	11.4868	13.1281
10	4	11	3.9004	0.62904	7.9361	8.6671	9.1825	9.8940	11.3026
15	4	11	2.8744	0.61673	5.7904	6.3185	6.6909	7.2050	8.2228
20	4	11	2.2241	0.60629	4.4422	4.8439	5.1272	5.5182	6.2924
23	4	11	1.9370	0.60060	3.8505	4.1971	4.4415	4.7789	5.4468
30	4	11	1.4492	0.58842	2.8519	3.1060	3.2851	3.5324	4.0220
30	4	11	1.4492	0.58842	2.8519	3.1060	3.2851	3.5324	4.0220
40	4	11	1.0122	0.57280	1.9659	2.1386	2.2604	2.4285	2.7614
46	4	11	0.8346	0.56407	1.6089	1.7492	1.8481	1.9846	2.2549
50	4	11	0.7392	0.55845	1.4183	1.5413	1.6280	1.7477	1.9847
60	4	11	0.5574	0.54493	1.0570	1.1475	1.2113	1.2994	1.4737
61	4	11	0.5426	0.54361	1.0279	1.1157	1.1777	1.2633	1.4326
70	4	11	0.4306	0.53200	0.8075	0.8757	0.9239	0.9903	1.1218
80	4	11	0.3393	0.51955	0.6292	0.6817	0.7187	0.7698	0.8710
90	4	11	0.2716	0.50751	0.4983	0.5393	0.5683	0.6083	0.6874
91	4	11	0.2658	0.50633	0.4872	0.5273	0.5555	0.5946	0.6718
100	4	11	0.2204	0.49588	0.4001	0.4327	0.4556	0.4873	0.5500
110	4	11	0.1809	0.48467	0.3251	0.3513	0.3697	0.3951	0.4454
120	4	11	0.1500	0.47392	0.2670	0.2882	0.3031	0.3237	0.3646
130	4	11	0.1256	0.46369	0.2213	0.2387	0.2509	0.2678	0.3012
137	4	11	0.1114	0.45688	0.1951	0.2103	0.2210	0.2357	0.2650
140	4	11	0.1059	0.45405	0.1851	0.1994	0.2095	0.2235	0.2511
150	4	11	0.0900	0.44509	0.1560	0.1679	0.1763	0.1880	0.2110
160	4	11	0.0770	0.43688	0.1324	0.1424	0.1495	0.1593	0.1786
170	4	11	0.0663	0.42952	0.1132	0.1217	0.1277	0.1359	0.1523
180	4	11	0.0574	0.42310	0.0974	0.1046	0.1097	0.1168	0.1307
183	4	11	0.0551	0.42137	0.0932	0.1001	0.1050	0.1117	0.1250
190	4	11	0.0500	0.41771	0.0843	0.0905	0.0949	0.1010	0.1130
200	4	11	0.0437	0.41344	0.0734	0.0788	0.0826	0.0878	0.0982
210	4	11	0.0384	0.41035	0.0643	0.0690	0.0723	0.0769	0.0859
220	4	11	0.0339	0.40850	0.0566	0.0608	0.0637	0.0677	0.0756
230	4	11	0.0300	0.40794	0.0502	0.0538	0.0564	0.0599	0.0670
240	4	11	0.0267	0.40870	0.0446	0.0479	0.0502	0.0533	0.0596
250	4	11	0.0238	0.41077	0.0399	0.0428	0.0449	0.0477	0.0533
396	4	11	0.0062	0.55425	0.0118	0.0129	0.0136	0.0146	0.0166

----- GROUP=1 PERC=0.99 -----

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	4	11	15.3200	0.68617	39.7747	43.5797	46.1948	49.8439	57.1688
5	4	11	5.8139	0.64518	14.5401	15.8979	16.8310	18.1331	20.7469
8	4	11	4.5032	0.63484	11.1538	12.1886	12.8998	13.8922	15.8842
10	4	11	3.9004	0.62904	9.6082	10.4963	11.1066	11.9584	13.6680
15	4	11	2.8744	0.61673	6.9985	7.6402	8.0812	8.6966	9.9318
20	4	11	2.2241	0.60629	5.3611	5.8492	6.1847	6.6528	7.5924
23	4	11	1.9370	0.60060	4.6434	5.0645	5.3539	5.7577	6.5683
30	4	11	1.4492	0.58842	3.4331	3.7417	3.9539	4.2499	4.8441
30	4	11	1.4492	0.58842	3.4331	3.7417	3.9539	4.2499	4.8441
40	4	11	1.0122	0.57280	2.3610	2.5709	2.7151	2.9164	3.3204
46	4	11	0.8346	0.56407	1.9298	2.1002	2.2173	2.3807	2.7087
50	4	11	0.7392	0.55845	1.6996	1.8490	1.9517	2.0950	2.3827
60	4	11	0.5574	0.54493	1.2640	1.3739	1.4495	1.5549	1.7666
61	4	11	0.5426	0.54361	1.2289	1.3357	1.4091	1.5115	1.7170
70	4	11	0.4306	0.53200	0.9636	1.0465	1.1035	1.1831	1.3427
80	4	11	0.3393	0.51955	0.7493	0.8131	0.8569	0.9181	1.0409
90	4	11	0.2716	0.50751	0.5922	0.6421	0.6764	0.7242	0.8203
91	4	11	0.2658	0.50633	0.5789	0.6276	0.6611	0.7078	0.8016
100	4	11	0.2204	0.49588	0.4746	0.5141	0.5413	0.5792	0.6554
110	4	11	0.1809	0.48467	0.3849	0.4166	0.4384	0.4689	0.5300
120	4	11	0.1500	0.47392	0.3155	0.3412	0.3589	0.3836	0.4331
130	4	11	0.1256	0.46369	0.2610	0.2821	0.2966	0.3168	0.3574
137	4	11	0.1114	0.45688	0.2298	0.2482	0.2609	0.2786	0.3140
140	4	11	0.1059	0.45405	0.2179	0.2353	0.2472	0.2639	0.2975
150	4	11	0.0900	0.44509	0.1833	0.1978	0.2078	0.2217	0.2496
160	4	11	0.0770	0.43688	0.1554	0.1675	0.1759	0.1876	0.2111
170	4	11	0.0663	0.42952	0.1326	0.1429	0.1500	0.1599	0.1797
180	4	11	0.0574	0.42310	0.1139	0.1227	0.1288	0.1372	0.1541
183	4	11	0.0551	0.42137	0.1090	0.1174	0.1232	0.1312	0.1474
190	4	11	0.0500	0.41771	0.0985	0.1061	0.1113	0.1185	0.1331
200	4	11	0.0437	0.41344	0.0857	0.0923	0.0968	0.1031	0.1156
210	4	11	0.0384	0.41035	0.0751	0.0808	0.0847	0.0901	0.1011
220	4	11	0.0339	0.40850	0.0661	0.0711	0.0745	0.0793	0.0890
230	4	11	0.0300	0.40794	0.0585	0.0629	0.0660	0.0702	0.0788
240	4	11	0.0267	0.40870	0.0521	0.0560	0.0587	0.0625	0.0701
250	4	11	0.0238	0.41077	0.0466	0.0501	0.0526	0.0559	0.0628
396	4	11	0.0062	0.55425	0.0142	0.0154	0.0163	0.0175	0.0199

Bound TOL[P%] covers percentile (PERC) with confidence P%
 Tolerance bounds for deposition by distance
 Treatment applications

17:32 Friday, May 28, 1999

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----- GROUP=2 PERC=0.95 -----									
X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	4	11	2.39186	0.68617	5.09142	5.58039	5.92517	6.40107	7.34335
5	4	11	1.25785	0.64518	2.59271	2.83450	3.00498	3.24030	3.70623
8	4	11	1.06172	0.63484	2.17039	2.37120	2.51279	2.70823	3.09521
10	4	11	0.96512	0.62904	1.96371	2.14459	2.27212	2.44816	2.79673
15	4	11	0.78801	0.61673	1.58740	1.73219	1.83429	1.97521	2.25424
20	4	11	0.66446	0.60629	1.32709	1.44711	1.53174	1.64856	1.87985
23	4	11	0.60606	0.60060	1.20478	1.31322	1.38969	1.49523	1.70422
30	4	11	0.49952	0.58842	0.98299	1.07056	1.13231	1.21754	1.38630
30	4	11	0.49952	0.58842	0.98299	1.07056	1.13231	1.21754	1.38630
40	4	11	0.39303	0.57280	0.76333	0.83041	0.87770	0.94298	1.07223
46	4	11	0.34539	0.56407	0.66584	0.72388	0.76481	0.82130	0.93315
50	4	11	0.31838	0.55845	0.61084	0.66381	0.70117	0.75272	0.85480
60	4	11	0.26331	0.54493	0.49932	0.54207	0.57221	0.61382	0.69620
61	4	11	0.25859	0.54361	0.48982	0.53170	0.56123	0.60200	0.68271
70	4	11	0.22121	0.53200	0.41477	0.44983	0.47456	0.50868	0.57625
80	4	11	0.18816	0.51955	0.34895	0.37808	0.39861	0.42696	0.48309
90	4	11	0.16168	0.50751	0.29665	0.32110	0.33834	0.36213	0.40924
91	4	11	0.15933	0.50633	0.29202	0.31606	0.33300	0.35640	0.40271
100	4	11	0.14012	0.49588	0.25441	0.27511	0.28971	0.30985	0.34975
110	4	11	0.12232	0.48467	0.21983	0.23749	0.24995	0.26714	0.30118
120	4	11	0.10745	0.47392	0.19122	0.20639	0.21709	0.23185	0.26109
130	4	11	0.09492	0.46369	0.16731	0.18042	0.18967	0.20243	0.22770
137	4	11	0.08728	0.45688	0.15287	0.16475	0.17313	0.18469	0.20759
140	4	11	0.08426	0.45405	0.14718	0.15858	0.16662	0.17771	0.19968
150	4	11	0.07512	0.44509	0.13012	0.14008	0.14710	0.15680	0.17599
160	4	11	0.06724	0.43688	0.11556	0.12431	0.13048	0.13900	0.15587
170	4	11	0.06040	0.42952	0.10308	0.11081	0.11626	0.12378	0.13868
180	4	11	0.05444	0.42310	0.09233	0.09919	0.10403	0.11071	0.12393
183	4	11	0.05280	0.42137	0.08940	0.09603	0.10070	0.10715	0.11993
190	4	11	0.04921	0.41771	0.08303	0.08915	0.09347	0.09943	0.11124
200	4	11	0.04461	0.41344	0.07495	0.08045	0.08432	0.08967	0.10026
210	4	11	0.04055	0.41035	0.06791	0.07287	0.07637	0.08119	0.09074
220	4	11	0.03694	0.40850	0.06176	0.06625	0.06942	0.07380	0.08246
230	4	11	0.03373	0.40794	0.05636	0.06046	0.06335	0.06734	0.07524
240	4	11	0.03086	0.40870	0.05160	0.05536	0.05801	0.06167	0.06891
250	4	11	0.02829	0.41077	0.04740	0.05086	0.05331	0.05668	0.06335
396	4	11	0.00940	0.55425	0.01797	0.01953	0.02062	0.02213	0.02512

----- GROUP=2 PERC=0.99 -----

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	4	11	2.39186	0.68617	6.20990	6.80397	7.21225	7.78198	8.92559
5	4	11	1.25785	0.64518	3.14577	3.43952	3.64141	3.92312	4.48861
8	4	11	1.06172	0.63484	2.62973	2.87370	3.04137	3.27535	3.74501
10	4	11	0.96512	0.62904	2.37745	2.59720	2.74823	2.95898	3.38201
15	4	11	0.78801	0.61673	1.91860	2.09452	2.21541	2.38412	2.72276
20	4	11	0.66446	0.60629	1.60163	1.74745	1.84767	1.98752	2.26823
23	4	11	0.60606	0.60060	1.45284	1.58459	1.67514	1.80150	2.05513
30	4	11	0.49952	0.58842	1.18331	1.28970	1.36282	1.46485	1.66966
30	4	11	0.49952	0.58842	1.18331	1.28970	1.36282	1.46485	1.66966
40	4	11	0.39303	0.57280	0.91676	0.99825	1.05425	1.13240	1.28927
46	4	11	0.34539	0.56407	0.79861	0.86913	0.91759	0.98522	1.12097
50	4	11	0.31838	0.55845	0.73201	0.79637	0.84060	0.90232	1.02622
60	4	11	0.26331	0.54493	0.59710	0.64904	0.68474	0.73454	0.83453
61	4	11	0.25859	0.54361	0.58562	0.63651	0.67148	0.72028	0.81823
70	4	11	0.22121	0.53200	0.49497	0.53757	0.56685	0.60770	0.68970
80	4	11	0.18816	0.51955	0.41557	0.45096	0.47528	0.50921	0.57733
90	4	11	0.16168	0.50751	0.35257	0.38227	0.40269	0.43117	0.48835
91	4	11	0.15933	0.50633	0.34700	0.37620	0.39627	0.42427	0.48049
100	4	11	0.14012	0.49588	0.30176	0.32691	0.34420	0.36832	0.41673
110	4	11	0.12232	0.48467	0.26023	0.28169	0.29644	0.31702	0.35833
120	4	11	0.10745	0.47392	0.22592	0.24435	0.25702	0.27470	0.31018
130	4	11	0.09492	0.46369	0.19731	0.21324	0.22419	0.23946	0.27013
137	4	11	0.08728	0.45688	0.18005	0.19448	0.20440	0.21824	0.24603
140	4	11	0.08426	0.45405	0.17325	0.18710	0.19662	0.20990	0.23656
150	4	11	0.07512	0.44509	0.15290	0.16501	0.17332	0.18493	0.20823
160	4	11	0.06724	0.43688	0.13558	0.14621	0.15352	0.16372	0.18419
170	4	11	0.06040	0.42952	0.12076	0.13015	0.13661	0.14561	0.16369
180	4	11	0.05444	0.42310	0.10803	0.11636	0.12209	0.13009	0.14614
183	4	11	0.05280	0.42137	0.10456	0.11261	0.11815	0.12587	0.14138
190	4	11	0.04921	0.41771	0.09704	0.10448	0.10959	0.11673	0.13105
200	4	11	0.04461	0.41344	0.08752	0.09420	0.09879	0.10519	0.11804
210	4	11	0.04055	0.41035	0.07925	0.08528	0.08941	0.09519	0.10678
220	4	11	0.03694	0.40850	0.07204	0.07750	0.08126	0.08650	0.09701
230	4	11	0.03373	0.40794	0.06573	0.07071	0.07414	0.07891	0.08850
240	4	11	0.03086	0.40870	0.06020	0.06476	0.06790	0.07228	0.08107
250	4	11	0.02829	0.41077	0.05532	0.05953	0.06242	0.06645	0.07455
396	4	11	0.00940	0.55425	0.02152	0.02341	0.02471	0.02652	0.03015

Bound TOL[P%] covers percentile (PERC) with confidence P%
 Tolerance bounds for deposition by distance
 Treatment applications

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 17:32 Friday, May 28, 1999

----- GROUP=3 PERC=0.95 -----									
X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	6	11	1.52930	0.68617	3.25535	3.53945	3.73684	4.01111	4.55874
5	6	11	0.73653	0.64518	1.51815	1.64681	1.73619	1.86040	2.10839
8	6	11	0.60808	0.63484	1.24304	1.34756	1.42017	1.52107	1.72253
10	6	11	0.54601	0.62904	1.11095	1.20394	1.26855	1.35832	1.53756
15	6	11	0.43450	0.61673	0.87527	0.94782	0.99822	1.06827	1.20811
20	6	11	0.35868	0.60629	0.71637	0.77524	0.81615	0.87299	0.98647
23	6	11	0.32347	0.60060	0.64303	0.69562	0.73217	0.78295	0.88433
30	6	11	0.26042	0.58842	0.51248	0.55397	0.58279	0.62284	0.70281
30	6	11	0.26042	0.58842	0.51248	0.55397	0.58279	0.62284	0.70281
40	6	11	0.19912	0.57280	0.38673	0.41761	0.43907	0.46888	0.52840
46	6	11	0.17234	0.56407	0.33224	0.35856	0.37685	0.40226	0.45299
50	6	11	0.15736	0.55845	0.30192	0.32571	0.34224	0.36521	0.41107
60	6	11	0.12731	0.54493	0.24142	0.26020	0.27325	0.29138	0.32759
61	6	11	0.12477	0.54361	0.23633	0.25470	0.26746	0.28518	0.32058
70	6	11	0.10483	0.53200	0.19657	0.21167	0.22216	0.23674	0.26585
80	6	11	0.08755	0.51955	0.16236	0.17467	0.18323	0.19512	0.21886
90	6	11	0.07395	0.50751	0.13568	0.14584	0.15290	0.16271	0.18229
91	6	11	0.07275	0.50633	0.13334	0.14331	0.15024	0.15987	0.17909
100	6	11	0.06306	0.49588	0.11450	0.12297	0.12885	0.13702	0.15334
110	6	11	0.05422	0.48467	0.09744	0.10456	0.10950	0.11637	0.13008
120	6	11	0.04695	0.47392	0.08354	0.08957	0.09375	0.09957	0.11118
130	6	11	0.04090	0.46369	0.07209	0.07723	0.08080	0.08575	0.09565
137	6	11	0.03726	0.45688	0.06526	0.06987	0.07307	0.07752	0.08640
140	6	11	0.03583	0.45405	0.06259	0.06699	0.07005	0.07430	0.08279
150	6	11	0.03154	0.44509	0.05463	0.05843	0.06107	0.06474	0.07206
160	6	11	0.02789	0.43688	0.04792	0.05122	0.05351	0.05670	0.06305
170	6	11	0.02475	0.42952	0.04224	0.04512	0.04712	0.04990	0.05545
180	6	11	0.02205	0.42310	0.03740	0.03993	0.04168	0.04412	0.04899
183	6	11	0.02132	0.42137	0.03609	0.03852	0.04021	0.04256	0.04725
190	6	11	0.01971	0.41771	0.03326	0.03549	0.03704	0.03919	0.04349
200	6	11	0.01768	0.41344	0.02970	0.03168	0.03305	0.03496	0.03877
210	6	11	0.01589	0.41035	0.02662	0.02839	0.02962	0.03132	0.03472
220	6	11	0.01433	0.40850	0.02396	0.02554	0.02664	0.02817	0.03123
230	6	11	0.01295	0.40794	0.02164	0.02307	0.02407	0.02545	0.02820
240	6	11	0.01173	0.40870	0.01962	0.02092	0.02182	0.02307	0.02558
250	6	11	0.01065	0.41077	0.01785	0.01903	0.01985	0.02100	0.02328
396	6	11	0.00312	0.55425	0.00596	0.00643	0.00675	0.00721	0.00811

----- GROUP=3 PERC=0.99 -----

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	6	11	1.52930	0.68617	3.97048	4.32690	4.56818	4.90662	5.59035
5	6	11	0.73653	0.64518	1.84200	2.00340	2.11266	2.26592	2.57554
8	6	11	0.60808	0.63484	1.50612	1.63724	1.72600	1.85050	2.10203
10	6	11	0.54601	0.62904	1.34502	1.46168	1.54065	1.65142	1.87521
15	6	11	0.43450	0.61673	1.05789	1.14891	1.21052	1.29695	1.47155
20	6	11	0.35868	0.60629	0.86457	0.93843	0.98843	1.05857	1.20026
23	6	11	0.32347	0.60060	0.77542	0.84141	0.88608	0.94874	1.07532
30	6	11	0.26042	0.58842	0.61691	0.66896	0.70419	0.75362	0.85346
30	6	11	0.26042	0.58842	0.61691	0.66896	0.70419	0.75362	0.85346
40	6	11	0.19912	0.57280	0.46446	0.50320	0.52943	0.56622	0.64053
46	6	11	0.17234	0.56407	0.39850	0.43151	0.45387	0.48522	0.54856
50	6	11	0.15736	0.55845	0.36181	0.39165	0.41186	0.44020	0.49746
60	6	11	0.12731	0.54493	0.28870	0.31226	0.32821	0.35059	0.39579
61	6	11	0.12477	0.54361	0.28256	0.30559	0.32119	0.34307	0.38726
70	6	11	0.10483	0.53200	0.23458	0.25352	0.26635	0.28434	0.32067
80	6	11	0.08755	0.51955	0.19336	0.20881	0.21926	0.23393	0.26357
90	6	11	0.07395	0.50751	0.16126	0.17400	0.18263	0.19474	0.21919
91	6	11	0.07275	0.50633	0.15844	0.17095	0.17942	0.19130	0.21531
100	6	11	0.06306	0.49588	0.13581	0.14643	0.15362	0.16371	0.18408
110	6	11	0.05422	0.48467	0.11535	0.12428	0.13032	0.13880	0.15592
120	6	11	0.04695	0.47392	0.09870	0.10626	0.11138	0.11855	0.13305
130	6	11	0.04090	0.46369	0.08502	0.09146	0.09582	0.10194	0.11429
137	6	11	0.03726	0.45688	0.07686	0.08264	0.08656	0.09205	0.10314
140	6	11	0.03583	0.45405	0.07367	0.07920	0.08294	0.08818	0.09878
150	6	11	0.03154	0.44509	0.06419	0.06896	0.07219	0.07672	0.08586
160	6	11	0.02789	0.43688	0.05623	0.06036	0.06316	0.06709	0.07503
170	6	11	0.02475	0.42952	0.04949	0.05310	0.05554	0.05897	0.06590
180	6	11	0.02205	0.42310	0.04376	0.04693	0.04907	0.05208	0.05816
183	6	11	0.02132	0.42137	0.04221	0.04526	0.04733	0.05023	0.05608
190	6	11	0.01971	0.41771	0.03887	0.04167	0.04356	0.04622	0.05158
200	6	11	0.01768	0.41344	0.03468	0.03716	0.03884	0.04120	0.04596
210	6	11	0.01589	0.41035	0.03107	0.03328	0.03478	0.03689	0.04114
220	6	11	0.01433	0.40850	0.02795	0.02994	0.03128	0.03317	0.03698
230	6	11	0.01295	0.40794	0.02524	0.02704	0.02825	0.02996	0.03340
240	6	11	0.01173	0.40870	0.02289	0.02452	0.02562	0.02716	0.03029
250	6	11	0.01065	0.41077	0.02083	0.02231	0.02332	0.02473	0.02758
396	6	11	0.00312	0.55425	0.00714	0.00773	0.00812	0.00868	0.00981

Bound TOL[P%] covers percentile (PERC) with confidence P%

Tolerance bounds for deposition by distance
Standard applications7
17:32 Friday, May 28, 1999

----- GROUP=4 PERC=0.95 -----									
X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	33	32	0.80136	0.44559	1.38869	1.43313	1.46418	1.50550	1.58201
5	33	32	0.42664	0.45705	0.74739	0.77166	0.78861	0.81118	0.85296
8	33	32	0.36174	0.46269	0.63705	0.65788	0.67243	0.69180	0.72767
10	33	32	0.32973	0.46624	0.58260	0.60173	0.61510	0.63289	0.66583
15	33	32	0.27091	0.47461	0.48240	0.49840	0.50958	0.52446	0.55201
20	33	32	0.22974	0.48242	0.41204	0.42583	0.43547	0.44829	0.47204
23	33	32	0.21022	0.48690	0.37859	0.39133	0.40022	0.41207	0.43400
30	33	32	0.17451	0.49687	0.31713	0.32792	0.33546	0.34549	0.36407
30	33	32	0.17451	0.49687	0.31713	0.32792	0.33546	0.34549	0.36407
40	33	32	0.13860	0.51018	0.25491	0.26371	0.26986	0.27804	0.29319
46	33	32	0.12245	0.51775	0.22672	0.23461	0.24012	0.24746	0.26104
50	33	32	0.11326	0.52265	0.21063	0.21799	0.22314	0.22999	0.24267
60	33	32	0.09444	0.53445	0.17746	0.18374	0.18813	0.19397	0.20478
61	33	32	0.09282	0.53560	0.17459	0.18078	0.18510	0.19086	0.20151
70	33	32	0.07995	0.54572	0.15172	0.15716	0.16095	0.16600	0.17535
80	33	32	0.06851	0.55654	0.13123	0.13598	0.13929	0.14371	0.15188
90	33	32	0.05929	0.56696	0.11459	0.11877	0.12169	0.12558	0.13279
91	33	32	0.05847	0.56798	0.11309	0.11723	0.12011	0.12396	0.13107
100	33	32	0.05174	0.57704	0.10084	0.10456	0.10715	0.11061	0.11700
110	33	32	0.04546	0.58682	0.08934	0.09266	0.09498	0.09807	0.10378
120	33	32	0.04019	0.59633	0.07961	0.08259	0.08468	0.08745	0.09258
130	33	32	0.03572	0.60559	0.07130	0.07399	0.07587	0.07837	0.08301
137	33	32	0.03298	0.61195	0.06618	0.06869	0.07045	0.07278	0.07711
140	33	32	0.03190	0.61464	0.06414	0.06658	0.06829	0.07055	0.07475
150	33	32	0.02860	0.62348	0.05793	0.06015	0.06170	0.06377	0.06759
160	33	32	0.02575	0.63214	0.05251	0.05454	0.05595	0.05784	0.06133
170	33	32	0.02325	0.64062	0.04776	0.04961	0.05091	0.05263	0.05582
180	33	32	0.02107	0.64895	0.04356	0.04526	0.04645	0.04803	0.05096
183	33	32	0.02047	0.65142	0.04240	0.04406	0.04522	0.04676	0.04962
190	33	32	0.01915	0.65713	0.03984	0.04141	0.04250	0.04396	0.04665
200	33	32	0.01744	0.66517	0.03653	0.03797	0.03898	0.04032	0.04281
210	33	32	0.01593	0.67307	0.03357	0.03490	0.03584	0.03708	0.03938
220	33	32	0.01458	0.68086	0.03092	0.03215	0.03302	0.03416	0.03629
230	33	32	0.01338	0.68853	0.02853	0.02968	0.03048	0.03154	0.03352
240	33	32	0.01230	0.69609	0.02638	0.02744	0.02819	0.02918	0.03101
250	33	32	0.01132	0.70354	0.02443	0.02542	0.02611	0.02704	0.02874
396	33	32	0.00398	0.80316	0.00925	0.00964	0.00992	0.01029	0.01098

----- GROUP=4 PERC=0.99 -----

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0	33	32	0.80136	0.44559	1.63204	1.68939	1.72882	1.78154	1.87974
5	33	32	0.42664	0.45705	0.88028	0.91160	0.93313	0.96192	1.01555
8	33	32	0.36174	0.46269	0.75112	0.77800	0.79648	0.82119	0.86722
10	33	32	0.32973	0.46624	0.68737	0.71206	0.72903	0.75173	0.79401
15	33	32	0.27091	0.47461	0.57002	0.59067	0.60487	0.62386	0.65922
20	33	32	0.22974	0.48242	0.48757	0.50537	0.51761	0.53397	0.56445
23	33	32	0.21022	0.48690	0.44834	0.46478	0.47609	0.49120	0.51935
30	33	32	0.17451	0.49687	0.37622	0.39014	0.39972	0.41252	0.43637
30	33	32	0.17451	0.49687	0.37622	0.39014	0.39972	0.41252	0.43637
40	33	32	0.13860	0.51018	0.30310	0.31446	0.32226	0.33270	0.35215
46	33	32	0.12245	0.51775	0.26993	0.28011	0.28711	0.29647	0.31390
50	33	32	0.11326	0.52265	0.25097	0.26047	0.26701	0.27575	0.29203
60	33	32	0.09444	0.53445	0.21185	0.21996	0.22553	0.23299	0.24687
61	33	32	0.09282	0.53560	0.20847	0.21646	0.22195	0.22929	0.24296
70	33	32	0.07995	0.54572	0.18146	0.18847	0.19329	0.19973	0.21173
80	33	32	0.06851	0.55654	0.15722	0.16334	0.16756	0.17319	0.18367
90	33	32	0.05929	0.56696	0.13750	0.14289	0.14661	0.15157	0.16082
91	33	32	0.05847	0.56798	0.13573	0.14106	0.14473	0.14963	0.15876
100	33	32	0.05174	0.57704	0.12119	0.12598	0.12928	0.13369	0.14190
110	33	32	0.04546	0.58682	0.10752	0.11180	0.11475	0.11869	0.12603
120	33	32	0.04019	0.59633	0.09594	0.09979	0.10244	0.10598	0.11257
130	33	32	0.03572	0.60559	0.08604	0.08951	0.09190	0.09510	0.10104
137	33	32	0.03298	0.61195	0.07993	0.08318	0.08541	0.08839	0.09394
140	33	32	0.03190	0.61464	0.07750	0.08065	0.08281	0.08571	0.09110
150	33	32	0.02860	0.62348	0.07009	0.07295	0.07492	0.07755	0.08246
160	33	32	0.02575	0.63214	0.06361	0.06622	0.06802	0.07042	0.07489
170	33	32	0.02325	0.64062	0.05791	0.06030	0.06195	0.06415	0.06824
180	33	32	0.02107	0.64895	0.05288	0.05507	0.05658	0.05860	0.06236
183	33	32	0.02047	0.65142	0.05148	0.05362	0.05510	0.05707	0.06073
190	33	32	0.01915	0.65713	0.04841	0.05043	0.05182	0.05368	0.05714
200	33	32	0.01744	0.66517	0.04444	0.04630	0.04758	0.04929	0.05248
210	33	32	0.01593	0.67307	0.04088	0.04260	0.04378	0.04537	0.04832
220	33	32	0.01458	0.68086	0.03768	0.03928	0.04037	0.04184	0.04457
230	33	32	0.01338	0.68853	0.03481	0.03629	0.03730	0.03866	0.04120
240	33	32	0.01230	0.69609	0.03221	0.03359	0.03453	0.03579	0.03815
250	33	32	0.01132	0.70354	0.02986	0.03114	0.03202	0.03319	0.03539
396	33	32	0.00398	0.80316	0.01143	0.01194	0.01229	0.01277	0.01365

Bound TOL[P%] covers percentile (PERC) with confidence P%

Appendix 4

Table 1 Estimates of the mean initial deposition parameter, a , and the decline parameter, b , for the standard ground spray applications. (As used for the evaluation of drift predictors, based on approximate OLS.)

Treatment Number	a	b	R^2
0902-4	0.84811	-0.22987	98.3%
0903-3	0.89126	-0.21893	96.4%
0903-4	0.35653	-0.22209	99.3%
0904-1	0.28504	-0.18673	99.1%
0904-2	0.55595	-0.19951	99.1%
0905-1	0.81917	-0.18485	98.8%
0905-2	0.65919	-0.17912	99.4%
0906-1	-0.13815	-0.17256	98.4%
0907-1	0.02662	-0.14388	92.8%
0907-4	0.35703	-0.18689	99.3%
0908-2	0.45783	-0.16747	99.3%
0908-3	0.52157	-0.20192	99.1%
1602-1	-0.11750	-0.21602	99.4%
1602-2	0.33776	-0.20081	91.9%
1603-2	0.62683	-0.18963	98.7%
1603-3	0.96412	-0.22269	98.8%
1604-2	0.62143	-0.26539	97.2%
1605-1	0.78492	-0.26950	98.9%
1605-2	1.20011	-0.25392	98.6%
1606-1	0.09721	-0.27566	98.6%

Table 2. Estimates of the mean initial deposition parameter, a , and the decline parameter, b , for the variable ground spray treatments. (As used for the evaluation of drift predictors, based on approximate OLS.)

Sprayer	Boom Height (in)	a	b	R^2
8010LP	20	-0.0276	-0.2965	98.4%
8010LP	20	-1.0300	-0.2474	96.1%
8010LP	50	1.3359	-0.2722	97.6%
8010LP	50	2.2727	-0.4054	97.9%
8040LP	20	-0.9492	-0.2081	99.4%
8040LP	20	0.1689	-0.2224	98.2%
8040LP	20	0.8594	-0.2407	95.0%
8040LP	20	1.4356	-0.4310	98.8%
8040LP	50	0.6164	-0.2291	98.9%
8040LP	50	0.4813	-0.1956	99.3%
8040	20	0.6686	-0.1770	97.9%
8040	20	0.4240	-0.1955	99.3%
8040	20	-0.3984	-0.1449	99.5%
8040	20	-0.3388	-0.1708	99.4%
8040	50	1.159	-0.1947	85.8%
8040	50	2.251	-0.3827	99.5%
TX6	20	1.313	-0.2175	93.0%
TX6	20	1.006	-0.2786	97.1%
TX6	20	2.101	-0.3327	99.1%
TX6	20	2.636	-0.3094	97.5%
TX6	20	2.926	-0.3349	98.7%
TX6	50	3.196	-0.2029	96.5%
TX6	50	3.726	-0.2626	97.9%

Table ##. Results of curve fitting for each application, as used for the tolerance bound calculations.

Treatment Category	Year	Treatment ##	Regression Results			
			R ²		Parameter Estimates	
			$\ln v, \ln \hat{v}^{[1]}$	$v, \hat{v}^{[2]}$	<i>a</i>	<i>b</i>
fine/high	1992	106	94.3%	87.8%	0.622	-0.313
			90.2%	87.9%	-0.509	-0.197
	1993	102	99.5%	97.1%	3.402	-0.436
			97.6%	98.2%	3.360	-0.446
fine/low	1993	103	96.4%	86.3%	1.348	-0.311
			92.8%	84.1%	1.287	-0.294
	1992	103	94.7%	84.2%	0.338	-0.228
			92.6%	82.9%	-0.365	-0.255
medium/high	1992	104	97.3%	97.8%	0.366	-0.283
			96.1%	96.9%	-0.088	-0.268
	1992	107	97.2%	88.8%	0.753	-0.319
			88.0%	85.2%	0.264	-0.306
	1993	105	94.1%	95.5%	0.727	-0.414
			93.8%	81.2%	0.281	-0.331
medium/low	1992	0102r3	98.8%	98.2%	-0.172	-0.344
		0102r4	95.8%	96.6%	0.131	-0.337
		0103r3	95.4%	88.2%	0.008	-0.241
		0103r4	95.2%	94.3%	-0.420	-0.268
		0104r1	98.1%	98.3%	-0.052	-0.286
		0104r2	95.5%	94.6%	-0.081	-0.250
		0105r1	95.4%	94.6%	0.213	-0.233
		0105r2	98.7%	98.6%	0.381	-0.274
		0106r1	98.1%	97.3%	-0.352	-0.277
		0106r4	96.0%	96.4%	-0.489	-0.231
		0107r1	98.9%	94.0%	-0.066	-0.246
		0107r4	97.3%	96.1%	-0.191	-0.236
		0108r2	96.9%	96.7%	-0.021	-0.223
		0108r3	99.2%	97.2%	0.105	-0.283
	1993	0102r1	95.9%	95.9%	-0.824	-0.273
		0102r2	93.9%	91.6%	-0.343	-0.286
		0103r2	99.2%	97.9%	0.391	-0.302
		0103r3	98.9%	95.0%	0.387	-0.292
		0104r1	96.6%	95.3%	-0.431	-0.265
		0104r2	90.1%	86.6%	-0.656	-0.266
		0105r1	96.9%	95.3%	0.112	-0.369
		0105r2	95.5%	91.2%	0.221	-0.275
	1992	0106r1	93.1%	90.4%	-1.073	-0.292
		0106r4	96.2%	94.7%	-1.066	-0.400
		102	97.1%	97.5%	-1.457	-0.292
			96.6%	91.9%	-0.635	-0.240
	1992	108	95.6%	97.0%	-0.810	-0.196

Treatment Category	Year	Treatment ##	Regression Results			
			R ²		Parameter Estimates	
			$\ln v, \ln \hat{v}^{[1]}$	$v, \hat{v}^{[2]}$	<i>a</i>	<i>b</i>
		108	97.9%	98.0%	-0.718	-0.241
	1993	104	93.6%	91.6%	-0.004	-0.311
			84.7%	82.6%	-0.952	-0.358
	1993	106	98.3%	97.6%	-0.388	-0.474
			93.2%	92.2%	-1.456	-0.368
	1992	105	93.2%	92.5%	-0.290	-0.259
			97.1%	96.9%	-0.043	-0.263

1 R² for the regression of \ln deposition against square-root of distance. This is optimized by the values of *a* and *b* displayed.

2 The predicted values from the regression were back-transformed to the scale of %deposition, and we report the the squared correlation with the untransformed measurements of %deposition. This is not optimized by the displayed values of *a* and *b*.