Background Document for the Scientific Advisory Panel on Orchard Airblast:

Downwind Deposition Tolerance Bounds for Orchards

July 23, 1999

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I. Summary

The Environmental Fate and Effects Division (EFED) of the Office of Pesticide Programs (OPP) currently has no model for estimating spray drift from orchard airblast applications. Consequently, EFED's environmental risk assessments include standard estimates drift. To develop a tool which could be used to estimate downwind drift at a range of distances the Spray Drift Task Force's (SDTF) data set was analyzed and used to develop two generic deposition curves. These curves are proposed to form the basis of a method for estimating drift from orchard airblast applications. As part of an ongoing peer review effort, EFED seeks the opinions of the Scientific Advisory Panel (SAP) regarding the orchard data and their potential regulatory use. The deposition curves from the data are proposed to be used in risk management for setting buffer zones. 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.

The SDTF, a coalition of pesticide registrants, performed airblast studies that quantified drift from pesticide applications in eight distinct orchard environments. Meteorological conditions, atomization data, drift measurements and grower interviews were collected in support of these studies as well as information on analytical recovery and tracer stability. The application equipment chosen was supposed to represent that most commonly used. The effects of canopy spacing, size and density were suggested to be the most important factors affecting drift. Deposition levels were not, however, quantitatively related to measured variables. No corrections were made to account for losses of pesticide tracer due to degradation or extraction recovery.

In order to consolidate the SDTF data set into a form useful for assessing downwind drift, deposition data were grouped into high drift potential orchards and low drift potential orchards. Orchard groupings are hypothetical categories of different orchards based on their relative potential to allow drift. The high drift grouping is composed of data from orchards containing tall trees (pecans), dense canopies (citrus), spaced canopies (young orchards), and dormant trees. The low drift grouping is composed of data from medium canopy densities (apple and almond) and 2 meter high vineyards. The development of these groupings was based on observed deposition values from individual orchards and physical characteristics expected to result in higher drift.

Mean deposition versus distance curves and corresponding tolerance bounds were developed for the high and low groupings. Statistical analysis was performed by fitting individual applications with a simple exponential decay function and then using the calculated depositions from the function to estimate variability at a range of distances to determine tolerance bounds.

Data for each tree crop type (*e.g.,* almonds) were collected from a single orchard, minimizing variability. Analyzing deposition values across groups of different orchard types increases variability which helps to offset the lack of variability in the study design.

Grouping also is intended to allow the data to be bridged to represent more orchard types than those included in the SDTF study orchards. Orchard groupings are intended to be used as surrogates for other orchard types with similar physical parameters (*e.g.*, height, canopy density, canopy spacing). If data are provided to define the physical characteristics for an orchard type of a species or variety not included in the high or low groupings, it should be possible to categorize the orchard into an existing grouping.

II. Introduction

EFED risk assessments normally estimate a fixed amount of spray drift from orchard airblast applications. The aquatic exposure scenario for airblast uses a standard 5% of the application rate which deposits on a 64 meter wide, one hectare pond immediately adjacent to the orchard. This value is used for all types of orchards and application equipment. No value is presently used to assess deposition to ponds farther from the edge of the orchard 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 orchard type and distance affect downwind drift.

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 conditionally 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 chemical nature of the active ingredient, the SDTF has carried 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 review of the SDTF orchard airblast studies emphasizes data collected on horizontal surfaces.

During 1993 and 1994 the SDTF conducted drift studies on orchard airblast applications. Their data was submitted to EPA in the form of several reports. In December 1998, a scientific peer review workshop was organized by EFED. Scientists participating in the workshop were asked to review the SDTF studies for airblast, ground hydraulic, and chemigation application methods. The questions posed to reviewers were:

1. Are the reports scientifically sound in terms of study design, analytical methods, data collection, statistical analysis and interpretation.

2. Do the data support the generic approach used by the SDTF, i.e., is drift independent of the chemistry of the active ingredient?

3. How do atomization studies on spray mixtures relate to field studies?

4. What are the limitations of the data set for predicting potential exposure of non-target organisms to pesticide drift?

5. What factors most influence off-target spray drift of pesticides?

6. To what extent can the data be related to drift that might result from typical airblast and ground spray pesticide applications?

The overall view expressed by the participants from academia and government research and regulatory institutions was that the quality of the data was high relative to other drift studies and the data were acceptable to use for risk assessment purposes. All reviewers felt that canopy type and structure are particularly important factors in orchard spray drift and that the SDTF database contains a very good range and mix of canopy architectures. The sprayers selected for the studies were considered typical of those used across the country and were appropriate for the selected canopy conditions. Environmental conditions (wind speed, humidity, etc) were also considered important. When the studies are taken as a whole, the range of conditions is quite good. However, the range of conditions for any individual canopy study was somewhat limited. One comment made by nearly every reviewer was that very little statistical evaluation of the data had been conducted by the SDTF. This comment led to the undertaking of the statistical work and deposition curve development presented is this report. An attempt was made to capture the criticisms and concerns of the peer reviewers and include them in integrated form. In addition, several figures included here are adapted from those of the peer reviewers. Individual reports of the peer reviewers are included in the background material for this report.

OPP poses the following questions to the SAP regarding the Spray Drift Task Force orchard studies, the deposition curves generated from these studies, and the use of these curves in risk assessments and risk management:

1. What significant limitations, if any, exist in the 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)?

2. Is the method used for generating the deposition curves appropriate given the data from which they were developed?

3. 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?

4. 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?

5. Will the outlined method for incrementally increasing orchard size by summing depositions from inside treatments with increasing offsets be appropriate for adjusting results to varying sized orchards?

6. Are the given orchards groupings (high and low) reasonable for:
   a. statistical purposes?
   b. risk assessment purposes?

7. Do the data provide a sound basis from which to generate deposition curves which can be used in risk assessment and risk management?

III. Overall Study Design

A. Background

The SDTF produced four studies on drift and atomization from airblast applications under different field conditions with varying equipment. Three studies conducted on orchards in different states were: 1994 Orchard Airblast Study on Pecans in Georgia, 1994 Orchard Airblast Field Study on Citrus in Florida, and 1993 Airblast Study in California. In addition to the field studies, studies on the droplet size spectrum produced by equipment similar or identical to that used in field studies and a report integrating the results from the different studies were also produced. Surveys from 59 growers and applicators from nine states provided information on practices used in airblast pesticide application. Interviews included questions on types of equipment used, crops and commodities, future and present orchard spacing and application techniques.

Airblast applications are distinct from other application methods in the equipment used and the crops treated. Since orchard airblast applications are directed into the canopy from inside the orchard, it is logical to assume that the canopy type is likely to affect the movement of the pesticide. Field study designs were chosen to provide an array of canopy types, heights, and spacings so that the effects of the physical environment on spray drift could be assessed. Air movement through canopies is likely to vary depending on the type and growth stage of orchard being treated; thus several orchards (apple, grape, almonds, oranges, grapefruit, and pecans) were studied to identify potential differences affecting the magnitude of drift. Aspects of airblast applications which were examined in SDTF studies for their effects on spray drift are outlined below:

- ! The largest trees studied were mature pecan trees (20-21 m tall). Applications to large trees require that the pesticide formulation be projected from the airblast apparatus to the tree tops, pushing the pesticide spray to great heights. Because the lateral distance traveled by pesticide drift is related to spray height, it is important to examine drift resulting from applications to tall trees.

- The smallest trees studied were small grapefruit trees (~2 m tall). Small trees may just require lateral projection of the pesticide from the airblast apparatus minimizing the height of the spray; but small, immature trees have larger spaces between the trees within rows. Larger spaces are expected to result in greater air flow and thus may increase drift. The relatively large space (~2.3 m) between the small grapefruit canopies provided a test of this physical parameter relative to the other orchards where the trees were in contact.

- Since pesticides may be applied to trees lacking foliage, drift resulting from applications to dormant apple trees was studied. (Foliated apple trees were also examined.) Drift is likely to be affected by the absence of leaves on the trees allowing relatively unrestricted air movement through the canopy.

- Airblast and mist blowers are different application equipment which may be used in similar orchard settings. Drift from mist blower application to grapefruit was studied and compared to results from airblast applications. Drift from wrap-around sprayer use in a vineyard was also measured.

- The droplet size spectrum of the pesticide formulation produced during application has been identified by the SDTF and many independent researchers as an important factor affecting drift, particularly with aerial applications. The droplet size spectra produced by airblast and mist blower equipment similar or identical to that used in field studies was determined under a range of conditions to determine the importance of equipment and configuration on the production particles with high drift potential.

Drift from spraying the first few rows of the orchard (outside treatments) and drift from the next few rows further in the orchard (inside treatments) were determined separately. For inside treatments with tree fruits (see figure below) the sprayer traveled between the third and sixth tree rows spraying on both sides. For outside treatments spraying took place from the outer most edge, spraying inward, through the third row of trees. With grapes, the distance between rows was smaller and the outside treatments and inside treatments consisted of spraying the outermost four rows on both sides and the next four rows, respectively.

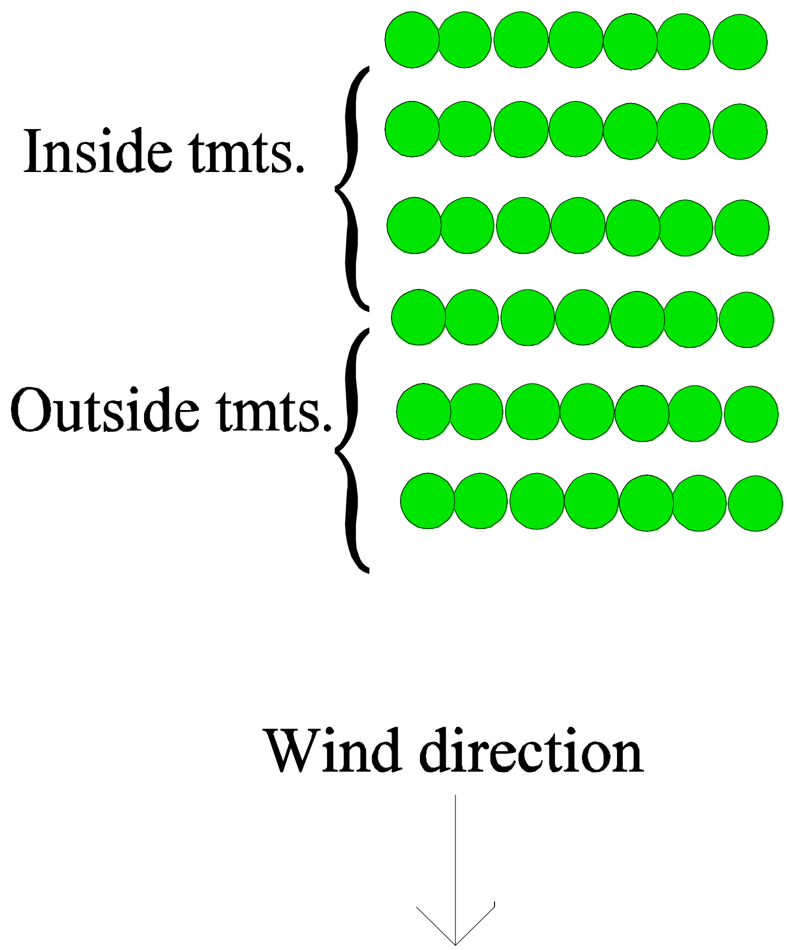
B. Methods

Drift was measured using horizontal and vertical alpha cellulose collection cards, polyurethane foam (PUF) low volume air samplers, and polyester strings downwind from the application area. Malathion and carbaryl were used as tracers to quantify drift. The horizontal cards after extraction and analysis by GC (malathion) or HPLC (carbaryl) provided data on the amount of deposition of the pesticide application. Vertically hung polyester strings provided data on the profile of the drift cloud. Drift samples were collected at regular distances from 0 to 549 m in three rows, perpendicular to the rows of the orchard, downwind,10-20 minutes after application was completed. Additional sampling stations at 549 m were spread parallel to the orchard in order to capture the most drift possible.

The application rate of malathion in the orchards was not determined directly. Although in pesticide field studies it is common practice to measure application rate directly by measuring horizontal deposition in the field, no such measurements were made in these studies. Instead, the amount of tracer used per acre was calculated from the tracer concentration of the tank mix (determined from the known volumes of water and tracer added), determining the volume sprayed (tanks were calibrated to subtract the volume remaining in the tank after application from the initial volume), and the acreage sprayed. Deposition data collected from inside the orchard, had it been collected, could have confirmed calculated application rates. However, given the heterogeneous three dimensional environment of orchards, spacings between trees and the intended deposition onto trees, it is possible that measurements made on orchard floors would be erratic and difficult to interpret. The absence of confirmatory measurements inside the orchard increases the importance of accurately defining tank mix tracer concentrations which were problematic (see Tracer Stability and Spike Recovery below).

Figure 1

Inside and outside treatment areas for tree fruit.
(View from above)



C. Validity of Generic Approach

In SDTF aerial application studies, a generic approach focusing on droplet size was validated. Production of small, light droplets was identified as a critical factor affecting drift in aerial applications. Droplet size is determined by the physical properties of the tank mix, the application equipment and operating conditions. Physical properties such as dynamic surface tension and viscosity, which are important in determining drift potential, are not greatly affected by the active ingredient. Thus, in most cases, drift can be assessed independently of the pesticide in the formulation.

Contrary to aerial applications, airblast applications occur within a varying three dimensional environment of an orchard which affects air current movement as well as spray interception. The heterogeneous environment of orchards varies with the type and age of the trees within it and with the season. These complexities had to be addressed in the airblast drift study design and did not allow a generic approach across different crop types as in the aerial application studies. The results of the airblast studies must be considered relative to where the spray was applied.

IV. Range of Conditions

A. Equipment and Practices

The application equipment chosen was intended to be representative of current practices. Models examined in the SDTF studies were 1) the Wilbur-Ellis sprayer with Albuz AM7 hollow cone ceramic nozzle tips (as used in the California and Florida orchards), 2) the FMC John Bean Model 9300 CP axial fan blast sprayer fitted with hollow cone ceramic nozzles (as used in the Georgia Pecan field study), 3) AGTec mist blowers with AGTec mist blower nozzle tips, and 4) a wrap-around sprayer with unspecified nozzles used on grapes. The AGTec mist blower used in the droplet size spectrum study (model 400LPS) was not identical to the type used in the Florida and California field studies (model 500CS) but nozzles and configurations were identical and airstream velocities were similar.

It would be costly and impractical to test all airblast equipment used in US agriculture so the equipment chosen was supposed to represent that most commonly used. It is not clear, however, how this determination was made. Although interviewed growers and applicators were asked to specify application equipment, their responses of makes and models of airblast equipment were not stated in the report. It is also not clear what differences that may affect spray drift exist between models. Many growers surveyed stated a transition to tower sprayers which direct spray downward into trees. However, tower sprayers were not included in the studies.

Application equipment and techniques vary with the crop being treated. Growers tailor their application practices to suit the orchard receiving a pesticide treatment. Airblast treatments are conducted to give thorough coverage of leaves and bark with the spray mixture. Spray not contacting a tree is wasted so applications are usually directed at trees, with nozzles pointed away from or above the trees being turned off. Most growers report turning off outside nozzles as they turn corners, not using outward pointing nozzles on end rows and not using upper nozzles for small trees. The application methods used in the airblast field studies reflect the common practices reported in the interviews of growers and applicators.

B. Carriers/Formulations

Airblast pesticide applications generally consist of a formulated active ingredient in a water carrier that may or may not contain surfactant. Drift retardants were not used in field trials because none of the 59 growers interviewed used a drift retardant product in their applications. Airblast tank mixes are usually quite dilute due to the high application volume (50 to 1500 gallons/acre). Thus the range of physical properties for airblast applications is substantially smaller than for other application methods using more concentrated formulations.

In the SDTF airblast field studies, a water carrier containing phosphate buffer and pesticide tracer was used. The pesticides were used at rates lower than specified on their labels because multiple applications were performed on the same rows. The pesticides used as tracers were the organophosphate insecticide malathion (Florida, Georgia, California) and the methyl carbamate insecticide carbaryl (California) which are both susceptible to hydrolysis at alkaline pH. Phosphate buffer was added to the water carrier to reduce pH, increasing the stability of the tracers.

A different tank mix solution from that used in field studies was used in atomization studies (see Atomization below). However, given that airblast applications are normally dilute water solutions, the tank mix solutions used in field and atomization studies probably have similar properties to those used in general agriculture.

C. Meteorology

The most important meteorological condition affecting spray drift from pesticide applications is usually wind speed. Wind speed was measured both inside and outside the orchards at multiple heights. As expected, wind speed inside orchards is lower and varies less than outside. The wind speed range observed inside and outside each orchard is stated in Table 1.

Wind direction shifts were also measured during application and drift periods. Much of the variation in measurements from different replicates is likely due to wind direction and turbulence. During the application and drift periods, wind direction varied by a standard deviation of greater than 40 degrees and commonly varied by more than 15 degrees. Shifting wind and turbulence would be expected to greatly affect deposition at given collection sites. In addition to shifting wind conditions, some of the differences between replicate deposition measurements may be due to different wind angles during replicates.

Table 1. Orchard type and wind conditions inside and outside the orchard.

Orchard type	Wind speed (mph)	
	Inside	Outside
Pecans	0.6-1.5	3.4-8.7
Grapes	0.4-1.0	1.8-6.9
Almonds	0.4-1.1	4.1-6.1
Oranges	0.5-1.0	5.8-9.2
Apples	0.4-0.5	3.3-7.4
Apples (dormant)	0.5-6.2	2.2-12.2
Large Grapefruit	3.8-8.8*	3.6-9.1
Small Grapefruit	2.7-6.9*	3.4-7.3

*These measurements were made above tree height.

Wind angle also leads to a slight underestimation of drift at a given distance. The minimum distance which the drift cloud can travel to a collection point is the perpendicular distance from the orchard to the collector. This is the distance that was used to describe drift distances and correlated with magnitude of deposition in the SDTF integration report. The actual distance traveled would be slightly greater depending on the wind angle; 1.5% and 6% greater for angles of 10 and 20 degrees, respectively. Cosine corrected downwind distances can help compensate for wind angle.

The wind speeds which occurred during these studies cover most of the range under which growers reported they would make applications. Some growers stated, however, that they would make airblast applications in higher winds, with 23 mph reported as the highest.

Other meteorolgical data (humidity, temperature, solar radiation, and barometric pressure) were collected. Relative humidity and temperature, along with other factors, affect evaporation which decreases drop size while the application is airborne and may increase drift potential.

Richardson number (Ri) was used as a measurement of atmospheric stability in SDTF studies. Stable conditions, when there is little vertical mixing, are commonly associated with high drift levels. The majority of the field study data were collected under neutral or unstable conditions (Ri < 0.1). Since the SDTF data were collected under unstable conditions and stable conditions would be expected to result in higher drift levels, the use of the data should not be extended to stable conditions.

D. Orchards

Study sites were chosen so that prevailing winds blew perpendicular to orchard rows. A range of orchard types was chosen to represent the majority of orchards in US agriculture. The orchard environment is determined by a number factors including the age and /or size of the trees, the season (if the trees are deciduous), tree spacing, canopy density, leaf size, and pruning practices. The sites chosen represent a broad range of canopy types including dormant and small trees which were expected to pose the highest drift potential.

Canopy densities were quantitatively characterized using an instrument (LI-COR LAI-2000) with a wide angle lens to measure light in several locations in each orchard. The amount of light penetrating the canopies was used to quantify the density. The LAI-2000 instrument was used to calculate leaf area index (LAI) values (an estimate of leaf surface area above a unit area of soil) and diffuse noninterceptance (DIFN) (the percent of sky seen through the canopy). A high LAI and low DIFN indicate a dense canopy.

Other important orchard characteristics affecting drift are tree height and the amount of open area between trees (the open distance between canopies). The table below adapted from the SDTF integration report (MRID 43925701) shows the range of orchard conditions included in the field studies.

Table 2. Physical parameters of orchards included in the SDTF study. A high leaf area index (LAI) and low diffuse noninterceptance value (DIFN) indicate a dense canopy.

Crop	Avg crop height (m)	Approx. space betw. trees (m)	DIFN	LAI
dormant apples	4.3	3	0.776	0.30
grapes	1.8	0	0.278	1.52
almonds	7.9	0	0.259	1.57
apples	4.3	0	0.195	1.91
pecans	20.7	0	0.182	1.96
oranges	5.2	1	0.090	2.81
large grapefruit	4.6	0	0.089	2.77

small grapefruit	2.7	2.1-2.4	0.069	3.07

Growers comments suggested that there is a movement toward orchards with closely spaced trees pruned on the sides and the top. This geometry facilitates harvest by hand. The result would be more orchards with small trees and less space between trees. An orchard scenario of this sort was not examined in these studies.

V. Evaluation of Data Quality

A. Tracer Stability and Spike Recovery

The stability of the tracers was assessed in the tank mixes and on the collection media. Samples were taken from the spray tanks before and after applications. Tracer concentration measurements were compared to calculated values. At the time the reports were written, the stability test results had not undergone quality assurance. In some instances spikes appeared to undergo significant degradation, but confirmatory studies showed the tracers to be stable. No corrections for tracer degradation were used.

Any variability in tank mix concentration would directly impact the calculation for relative off-target deposition. Figure 2 summarizes the ratio of measured tank concentrations referenced to the mix recipe. Post-spray samples are offset slightly from pre-spray samples. Horizontal lines indicate the medians at different tracer rates. Analyzed tank samples showed considerable variability for all three studies ranging from the extremes of 17% and 125% of the mix formula. Generally, however, medians were within 20% of the mix formula. There appears to be no consistent bias with respect to tracer type or tracer rate. However, there tends to be a tendency for the means of the pre-spray samples to be higher than post-spray samples. Representatives of SDTF have attributed tank mix variability largely to poor mixing at the time of sampling and have thus justified the use of the tank mix formulae in calculating relative drift amounts. Environmental fate data show that the tracers used, malathion and carbaryl, have the potential to undergo alkaline hydrolysis and microbial degradation with half-lives in the order of days.

There is concern that chemical tracer instability may have affected the quality of the deposition data. Malathion has some potential to volatilize and is not particularly stable, especially under alkaline conditions (see Table 1, in Ground Boom SAP Background document). 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). The vapor pressure of malathion is 4×10^{-5} torr. Loss of tracer through volatization, hydrolysis, and/or metabolism could result in significant underestimates in deposition.

In addition to the above concerns, the results of the Georgia pecan study's tank mix stability are questionable. In the first treatment, tank mix data were problematic with low recoveries and high variability (17.0 and 68.4% recovery of expected tracer) and mishaps in sample handling (containers were reported to have broken) which made re-analysis impossible. The second treatment showed greater and more consistent recoveries with 63.2% and 81.1% for first and second replicates, respectively.

B. Field Fortifications on Collectors

High and low level field fortifications of tracers on collection media were used to assess the stability of tracers during the period from application to analysis. Tracers, dissolved in organic solvent, were placed on the collection media in a spot using a micropipette. Field spikes were either frozen immediately after adding the tracer (unweathered) or after the drift period (weathered). Spiked collection media were placed upwind from the application area to avoid contamination during spraying. Unspiked control samples measured possible contamination.

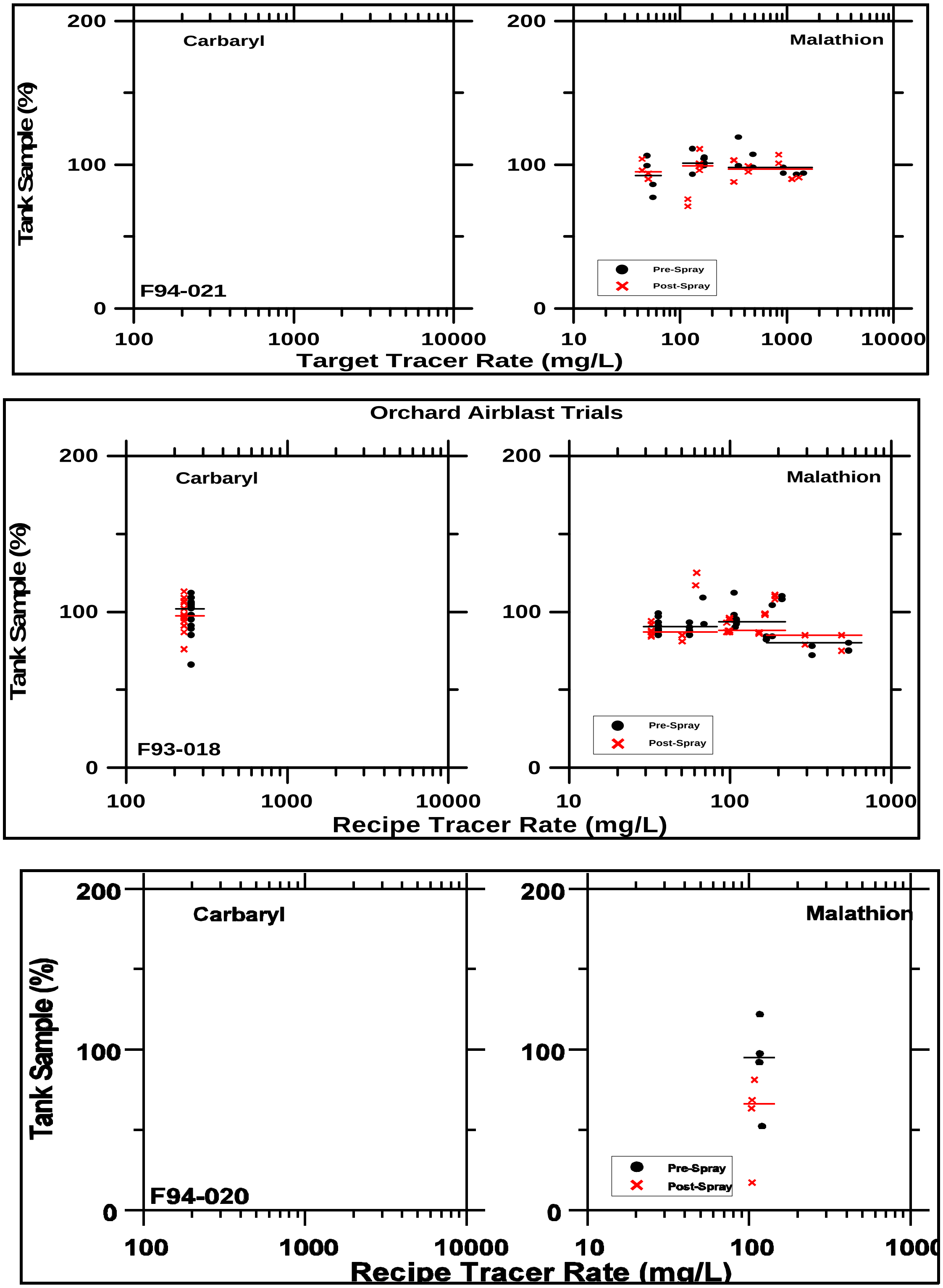
A potential weakness in the field fortification protocol is that the spikes were not performed using tank mix contents. By adding the fortification in an organic solvent the collection media was drier than that receiving tracer drift in the water carrier. Because the tracers used are susceptible to hydrolysis, damp conditions are expected to decrease tracer stability. This adds uncertainty, but because tank mix water was buffered to improve stability in the tank, stability on collection media may also have been enhanced.

Weathered and unweathered field fortification samples suggest that some tracer degraded during the study and storage time. Considerable range exists in recovery as a percentage of spiking level (see figure below). In the California study spikes from the tank mix were used but the amount of spiking material was calculated from the mix formula and not the measured concentration in the tank. In this instance, variability in the samples collected from the tank may increase measured recovery variability. However, the lab-prepared spikes in organic solvent showed only slightly less variability in recovery of malathion. Generally, higher fortification levels resulted in higher recoveries (80-105%) and lower fortification levels resulted in lower recoveries (65-85%). The apparent loss of tracer at low levels could result in a tendency of underestimating deposition in the far field. In the California, Florida, and Georgia studies the overall mean recoveries were 78%, 87%, and 89% of spikes on alpha cellulose collectors, respectively.

C. Deposition

For measurements made during a single application at the same distance, variation in measured deposition is relatively small. Horizontal deposition was measured on alpha cellulose cards at regular intervals down three collection lines perpendicular to orchard rows. Sampling units were comprised of three cards spaced 15 m apart but equidistant from the orchard's edge. Some sampling units were consolidated and analyzed as single samples. At other distances samples were analyzed individually which made it possible to assess variability between collection lines within single applications. Horizontal alpha cellulose cards which were analyzed separately had an average standard deviation of 22% for 144 sets of three cards.

Figure 2. Tank tracer analyses (from R.E. Mickle's review of SDTF data)



Deposition results showed high variability between replicate applications. Most applications scenarios were repeated once (airblast treatments of grapes and dormant apples were performed one time) and the results were averaged in SDTF tables and figures. Measurements of drift varied more between replicates of applications than within the same application. Expressed by percentage of the average deposition, replicates varied between 0.7 and 178%, with an average variation of 55.7%. Variation did not show a trend with distance from the orchard with the highest variation observed at the 50 m distance (averaging 75.5%).

Airblast and mist blower drift measurements were not made for inside rows of grapefruit trees. This adds uncertainty to the calculated levels of drift from young orchards with spaced trees. In other test orchards deposition from inside and outside treatments was measured separately and then added to determine total deposition. In the grapefruit orchard horizontal deposition measurements for inside treatments were not included in the study design so total deposition could not be calculated. In the absence of actual measurements, estimated values were calculated by extrapolating results from other orchards in the airblast study (excluding grapes, but including dormant apples). The SDTF assumed the average ratio of deposition from inside and outside treatments from other orchards would be similar to that in grapefruit and used this value to extrapolate inside treatment deposition from outside treatment deposition. In all orchards examined with inside and outside row treatments, deposition resulting from the outside row was several times higher than from inside rows in the near field but similar at greater downwind distances. In orchards such as small grapefruit where there is space between trees, overall drift and drift from inside rows may be higher than most orchards. Extrapolating drift data from orchards with different canopies, as was done with the grapefruit orchards, may underestimate actual drift from orchards with spaced trees. The estimated inside treatment data from grapefruit were not included in the orchard groupings used for statistical analyses.

D. Mass Accounting

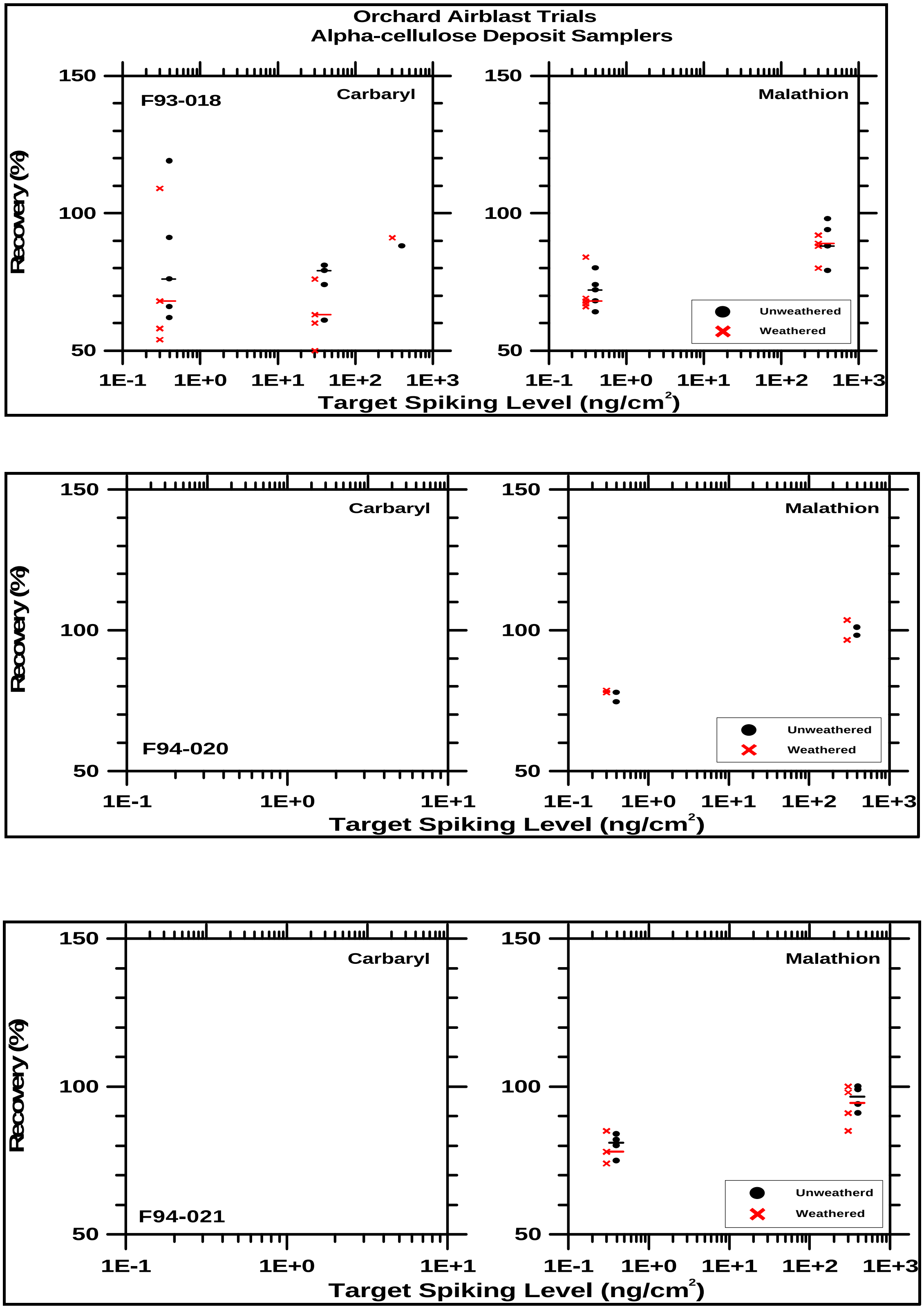
Calculating mass balance can be a useful check for determining a study's overall accounting of the pesticide sprayed. The mass balance of spray leaving orchards was calculated using string and horizontal deposition data. String data were used as the measure of drift leaving the orchard and traveling downwind at set distances. The sum of depositions on the vertical strings and the horizontal collectors was considered to reflect the total amount of drift at a given distance. Horizontal deposition integrated over a distance was assumed to decrease linearly between measurement stations which probably slightly overestimates drift. Using this approach the recoveries in the 0 to 30 m range ranged from 45 to 225% (or 73 to 143% when the highest and lowest values were dropped). In the 0 to 150 m interval the recoveries ranged from 52 to 109%. Recovery was lower for the mist blower than airblast.

E. Atomization

Atomization data show that airblast and mist blower equipment produce very fine sprays. Atomization studies were conducted with the Wilbur-Ellis airblast, FMC John Bean airblast, and AGTec mist blower equipment. (The wrap-around sprayer used in grape applications was not examined.) Droplet size spectra for the Wilbur-Ellis and AGTec equipment were determined using a Malvern 2600 laser diffraction particle size analyzer. The spectra from the FMC sprayer was analyzed with a Sympatec Vario/LA HELOS laser diffraction particle size analyzer which is reported to work on the same principle as the Malvern instrument. These two instruments were located at different facilities and were not tested against each other at the time of the reports. Corrections were made in the analyses by computer software for multiple scatterings of dense sprays close to nozzle tips.

The tank mix solutions used in the field studies were different from those used in the atomization studies. Pesticide tracers present in the field studies were not used in the Atomization Droplet Size Spectra for Airblast Sprayers (except for one non-GLP experiment containing malathion). Instead, water containing a non-ionic surfactant (Induce™, predominately containing alkyl aryl polyoxyalkane ethers) was used. This solution is expected to have a low dynamic surface tension (although the value was not determined) which would favor the formation of small, drift-prone droplets.

Figure 3. Spike recoveries (from R.E. Mickle's report).


Orchard Airblast Trials
Alpha-cellulose Deposit Samplers
F93-018
Carbaryl
Malathion
Recovery (%)
150
100
50
1E-1
1E+0
1E+1
1E+2
1E+3
Unweathered
Weathered
Target Spiking Level (ng/cm²)
F94-020
Carbaryl
Malathion
Unweathered
Weathered
Target Spiking Level (ng/cm²)
F94-021
Carbaryl
Malathion
Unweatherd
Weathered
Target Spiking Level (ng/cm²)

Atomization studies attempted to mimic droplet size spectra produced in field studies. However, some equipment and carriers varied between the field and atomization studies. The AGTec mist blower used in the droplet size spectrum study (model 400LPS) was not identical to the type used in the Florida and California field studies (model 500CS). However, because nozzles and configurations were identical and airstream velocities were similar, the SDTF suggested that the spectrum results would be similar.

Results from the atomization study showed the drop size spectrum of the Wilbur-Ellis apparatus under a range of operating conditions as well as spectra for the mist blower and FMC sprayer. 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 141µm ($V_{<141}$) which are considered to be most drift prone. The Wilbur-Ellis airblaster generally produced slightly finer sprays with smaller nozzles and higher pressures. Larger nozzle angle also resulted in a small increase in fine droplet production.

Atomization results most relevant to field studies are listed below with equipment and configurations producing finer spray listed first:

Table 3. Application equipment parameters.

crop	Equipment	pressure (psi)	$D_{v0.5}$	$V_{<141}$ (%)
grapefruit	AGTec mist blower	45	94	75
grape	Wilbur-Ellis	200	122	60
grapefruit	Wilbur-Ellis	250	128 to 132	55 to 56
almond	Wilbur-Ellis	200	137	55
apple	Wilbur-Ellis	145	134	53
orange	Wilbur-Ellis	200	144	51
pecan	FMC John Bean	200	146	48
grapefruit	Wilbur-Ellis	145	166 to 170	36 to 37
dormant apple	Wilbur-Ellis	145	172	37

The AGTec mist blower produced the finest droplets with more fines being produced at the top nozzles. With the exception of the mist blower, droplet size does not vary greatly among the airblast applications. Factors other than droplet size spectra are probably more important in affecting drift potential in most orchard airblast applications.

VI. Field Study Results

A. Rank of Crops by Drift Potential

Trends in drift potential appeared to be primarily correlated with canopy geometry and to a lesser extent the drop size spectrum.

Average deposition values from the SDTF studies are presented in the table below. Tree crops were ranked in the following order, from highest to lowest drift potential based on horizontal deposition at 15 m (50 ft). These data are shown graphically in the figure below.

Several factors which are likely to affect drift potential are inseparable and are related to canopy type. For example, spray equipment for pecans is configured to spray to the height of a tall orchard. Also, higher wind speeds are observed in dormant canopies. Thus, with these studies, it seems reasonable to rank relative drift potential by canopy type. Figure 2 suggests that drift from applications to different orchards varies with distance. The dormant apple orchards which had the highest level of drift at 15 m is near the lowest at 300 m. This effect is likely due to the absence of foliage resulting high deposition near the orchard combined with the slightly more coarse spray reducing far field deposition. Mist blower applications resulted in lower depositions at 15 m than high pressure airblast applications, but this trend was reversed at farther distances which is likely due to the small droplet size spectrum of the mist blower relative to airblast sprayers..

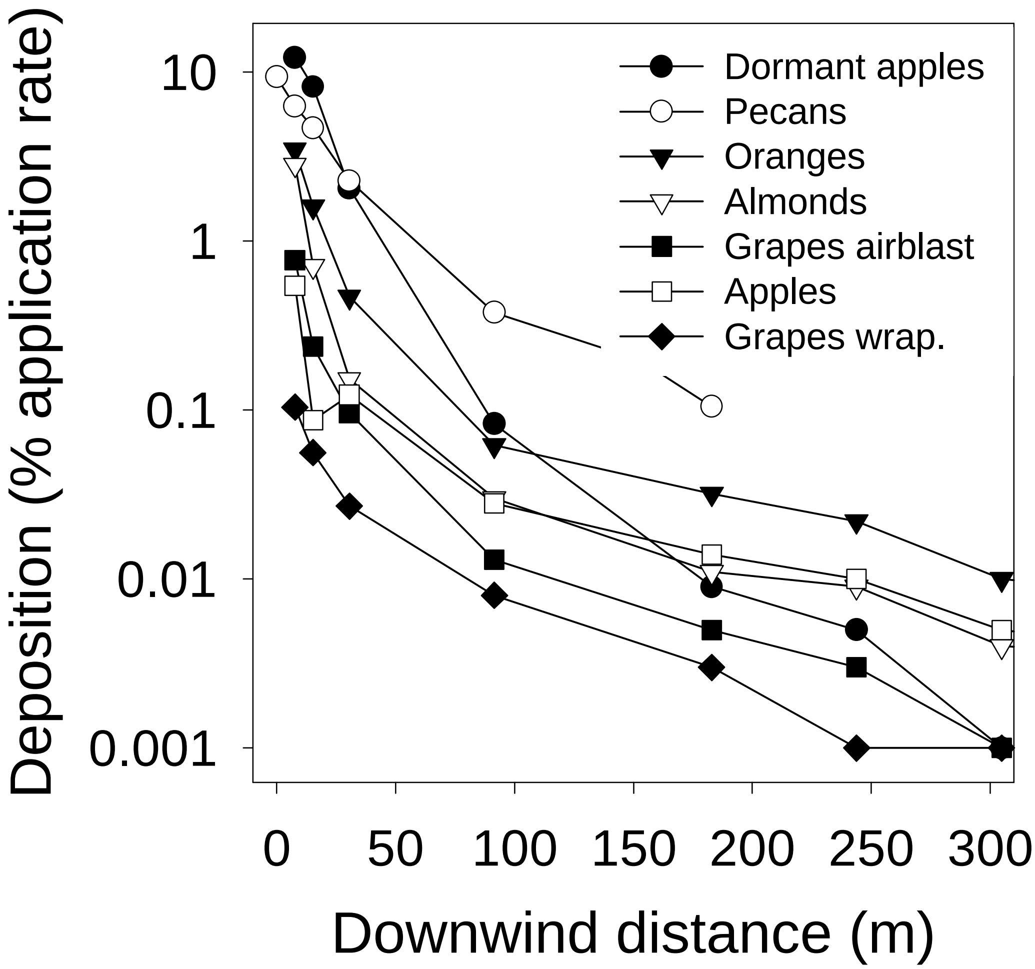
Table 4. Horizontal deposition from study orchards.

crop	canopy and spacing	Horizontal deposition (m)									
		0	7.6	15	30	91	752	183	244	305	549
		% application rate									
dormant apples	no leaves	-	12.2	8.9	2.05	0.083	-	0.009	.005	<0.002	<0.002
small grapefruit (high pressure airblast)	short, dense; large spacing	-	14.0*	6.35*	3.13*	0.191 *	-	0.025 *	-	-	-
pecans	very tall, moderately dense, no space between trees	9.35	6.26	4.68	2.27	0.378	0.198	0.105	-	-	-
large grapefruit (high pressure airblast)	dense; no space between trees	-	4.52*	3.95*	1.07*	0.121 *	-	0.005 *	-	-	-
small grapefruit (mistblower)	short, dense; large spacing	-	4.42*	2.78*	1.20*	0.151 *	-	0.064 *	-	-	-
large grapefruit (mist blower)	dense; no space between trees	-	2.29*	2.63*	0.992 *	0.144 *	-	0.038 *	-	-	-
oranges	dense; some space between trees	-	3.47	1.60	0.468	0.062	-	0.032	0.022	0.010	0.004
almonds	tall, low density; no space between trees	-	2.84	0.710	0.152	0.030	-	0.011	.009	0.004	0.003
grapes (with airblast)	short, low density; no space between vines	-	0.770	0.237	0.096	0.013	-	0.005	0.003	<0.002	<0.002
apples	moderate density, no space between trees	-	0.544	0.087	0.123	0.028	-	0.014	0.010	0.005	0.002
grapes (with wrap-around sprayer)	short, low density; no space between vines	-	0.104	0.056	0.027	0.008	-	0.003	<0.002	<0.002	<0.002

*The fraction of deposition arising from inside row treatments was calculated based on the relative contribution of inside treatments in other orchards.

Figure 4

Cumulative horizontal deposition from inside and outside treatments.



B. Rationale for Calculating Tolerance Bounds

Useful drift estimates for environmental risk assessments should provide a realistic upper bound for deposition levels which are expected to commonly occur. The values reported in the table above are useful in calculating the relative importance of canopy type on drift at a given distance. EFED believes the values are not directly appropriate for risk assessment because depositions are expected to regularly exceed the reported values for the following reasons:

1) The percentages reported are average values. Approximately half of all measurements would be expected to exceed those reported.

2) Only one replicate was performed so reported values may not represent accurate means. The variability between applications was frequently high with an average variation of 55.7% around the mean.

3) Replicates were not conducted in different orchards to assess variability within an orchard type.

4) Deposition was only measured perpendicular to rows. Downwind deposition parallel to rows might be higher due to less restricted air movement in this direction. Increased deposition was measured perpendicular to rows of trees with space between them relative to trees with continuous canopies. Based on this observation, less restricted air movement down rows of trees would also be expected which could result in higher drift along this axis.

5) Reported values were not adjusted for degradation. Although most tracer recoveries were reasonable, not accounting for the measured loss results in another factor which consistently reduces reported values.

6) Downwind distances did not account for wind angle. Reported values were correlated with distances perpendicular to the orchard, but actual drift distances are longer due to wind angle. This results in a small underestimate of drift for a given distance.

7) Other canopy types may be less effective at intercepting drift. Given the limited range of canopies that was practical to test in this study, it is not possible to extrapolate to all other canopies. For instance, it is not clear what drift could be expected from a banana orchard.

8) Drift resulting from inside treatments in grapefruit orchards was estimated from other orchards.

9) Only the outermost six rows (eight rows for grapes) were treated. Treating more rows would result in increased drift.

Each of the above factors must be considered when using these data *directly* for risk assessments. By placing bounds on the data and using correction factors, if necessary, the data set should be very useful in developing exposure assessments.

VII. General Comments of the Peer Reviewers

The reports of the December 1998 peer review workshop on the SDTF airblast 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:

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

"These studies represent a very comprehensive database on drift from orchard blast applications." (Page 1)

Robert D. Fox: "In summary, I believe these studies were well planned and conducted, and that the data obtained was useful as a data base of downwind deposits from spraying several tree-fruit canopies and vineyards." (Page 5)

"Measured deposit values were similar to values in other studies reported in the literature for similar canopies and sprayer treatment, when put on the same basis. No one else has measured droplet size spectra as accurately as this study. Or used such a wide range of canopies." (Page 5)

Steven G. Perry: "The overall study design was very good and scientifically sound. The studies contribute an excellent database representing drift and deposition over a wide range of canopies and a reasonable range of spray equipment." (Page 16)

Jodie D. Whitney: "With few exceptions, the SDTF results on drift deposition downwind of the orchard are very similar to those in the literature. Given the variability that exists in trying to make these measurements, my judgement is that the similarity of the results of the SDTF and other studies is very acceptable." (Page 4)

D. Ken Giles: "This is a good study. The data represent a dedicated, multi-year, multi-location effort to characterize airblast spraying, a diverse and difficult application technique used on very diverse crops." (Page 1)

Criticisms of the studies included the following statements:

Steven G. Perry: "... the range of meteorological conditions both for each canopy tested and over all the canopies is fairly limited." (Page 17)

Jodie D. Whitney: "The 2-replicate data in these studies provide only an indication of the experimental error and caution should be exercised comparing treatment means from 2 replications." (Page 2)

Robert D. Fox: "There was some variability in measured tank mix concentration. We also have difficulty in obtaining exact values of tank mix." (Page 2)

D. Ken Giles: "The study reports a low level of replication. Many applications were replicated only once while most were executed twice." (Page 5)

R.E. Mickle: "The SDTF should assess other studies with data closer to the application zone in order to establish representative deposit profiles from the application zone to 7.6 m if buffer zones of this size are important." (Page 4)

"The SDTF should address this problem [measured tank mix concentration variability] and either resolve the issue in terms of why the tank samples were not representative or use the data for developing uncertainty bounds for the data set." (Page 6)

"In order for these data to be related to potential exposure, the SDTF has to fully assess the potential losses due to collection efficiency and sample degradation." (Page 11)

Terrell Barry: "Potential limitations of the data set for predicting off-site exposure include the difficulty on interpreting the results due to confounding treatments with wind speeds and the lack of applications at lower wind speeds." (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 ground hydraulic boom applications. However, the complexity of the airblast data resulting from the importance and variability of canopy characteristics made the statistical development of deposition bounds more difficult than ground applications.

Some reviewers noted that although these extensive studies do not (and could not be expected to) include measurements of deposition under all possible combinations of canopy structure, sprayer characteristics, and environmental conditions, this data base (with its high quality measurements) fills much of the void in our orchard spray drift knowledge base. If utilized wisely, it was suggested that these data could serve as the basis for significant improvements in our current risk assessment methods. Limitations in the overall range of conditions studied would be factored into any deposition estimate based on this data.

VIII. Data Analysis for Exposure Assessment

A. Overview of Objectives and Issues.

For purposes of this report, we are concerned only with bounds that can be used in risk assessments that they are scientifically defensible. (An ideal assessment would be "probabilistic," i.e., would characterize the frequency or probability of exceeding given magnitudes of exposure or impact.)

We build from the idea of using a distribution percentile. However, in view of the limited quantity of data, we propose to use procedures that address not only variation in drift deposition (as represented by distribution percentiles), but also *statistical error* in estimating percentiles. A simple percentile would be calculated from a finite amount of more or less variable data, so there will be some uncertainty regarding the real percentile. This uncertainty can be addressed by calculating an upper bound for the percentile. A one-sided bound on a percentile can also be called a one-sided *tolerance bound*.

Use of a tolerance bound provides a statement of the general form "we have 85% confidence that 99% of values will not exceed ... [deposition value]" for a particular distance. We have actually calculated tolerance bounds for the 95th and 99th percentiles, using confidence coefficients 65%, 75%, 85%, and 95%, as a function of distance for outside rows. For example, use of the value with 65% confidence for a given percentile means the odds are about 2:1 that the bound will be higher than the true percentile. Note that with sufficient data, use of tolerance bounds converges to use of percentiles. Useful basic references on tolerance bounds include Hahn and Meeker (1991) and Gilbert (1987).

We have not evaluated the orchard data using statistical methods that we would consider if the study were "ideal" from the viewpoint of characterizing variation in drift. In the actual design of the orchard studies, a given treatment (combination of crop and application procedure) was evaluated twice in sequence in a single site and year. At a given study site and year the order of treatments was not randomized. We would consider a different statistical approach if each treatment had been applied at multiple sites within an appropriate geographic range. In that case some kind of "mixed" model might also be considered. This approach would recognize different levels of variation, e.g., variation within a site versus variation among sites, and would provide estimates of variation specific to different levels. (A split-plot model is an example of a mixed model.)

For the orchard data, one approach would be to assume that variation among sites and times does not matter. We have adopted an approach that we consider more cautious: We have assumed that within several rough groupings of treatments (described below), the variation observed in the orchard drift data will be higher than would be observed for any single treatment. Based on this assumption, we formed groupings of treatments and treated the variation within a grouping as statistically independent, although the variation observed results partly from different treatments. Among the treatments in a single category, this approach will likely be more protective for some than for others. We suggest that the approach represents some tradeoff between, on the one hand, recognizing some differences among treatments, and on the other, respecting the limits of the data for making fine distinctions.

B. Orchard Groupings

The characteristics of the different canopies associated with higher drift levels enable speculation as to the mechanism of increased off-site movement of application. Characteristics correlated with increased drift are stated below in order of importance with suggested mechanisms:

Table 5. Canopy characteristics proposed to be associated with drift.

Canopy Characteristic Associated with Drift	Possible Explanation
no leaves	less restricted air movement through the canopy results in higher wind speeds in the orchard.
space between trees	less restricted air movement around trees can carry application out of orchard.
tall canopy	projection of application to tall tree tops results in a higher drift cloud which takes longer to settle and thus travels farther.
dense canopies	blocking air flow through the canopy results in movement of wind above and around trees.

The effect of canopy density is opposite at high and very low densities. With no leaves drift is highest because air movement through the canopy is less restricted. With a dense canopy air movement is likely pushed above and around trees and results in higher drift than trees with moderate canopy density. Given the variable and contrary effects at high and very low densities it is not clear how drift would be affected from orchard canopy types not examined in the SDTF study.

In order to consolidate the SDTF results into a form useful for assessing downwind drift, deposition data were grouped to form two orchard groupings: a high drift potential group and low drift potential group (see table below). The high drift grouping is composed of data from orchards containing tall trees (pecans), dense canopies (citrus), spaced canopies (young orchards), and dormant trees. The low drift grouping is composed of data from medium canopy densities (apple and almond) and 2 meter high vineyards. The development of these orchard groupings was based on observed deposition values from individual orchards and physical characteristics expected to result in higher drift.

Initially three groups were created based on physical characteristics following the groupings in the SDTF model, AgDRIFT, which is empirically based on the same orchard data. Given that a natural grouping of orchards was not clearly apparent from deposition data, it seemed logical to group orchards based on their physical parameters as they are believed to relate to drift: Tall and dense trees are expected to result in high drift clouds which are prone to drift farther. Dormant and spaced trees are expected to allow relatively unrestricted air flow through the orchard increasing drift. Medium density and medium height canopies are expected to allow a combination of horizontal movement within the canopy and foliage capture of pesticide material such that drift beyond the canopy is less than that of tall, very dense, or very sparse canopies. Vineyards are expected to be effective in trapping drift because they have medium density canopies and because they are relatively low to the ground the resulting drift clouds do not travel far. However, graphical analysis showed the difference between the two higher drift canopy types was small (see figure below). Although the probable reasons why different orchards associated with high drift were different, the resulting magnitudes of drift were similar. Given the closeness of the mean values for tall/dense and spaced/dormant, it seemed appropriate to combine them to form a single high drift grouping. A low drift group was composed of the vineyard/medium group alone.

Table 6. SDTF orchards included in groupings.

Orchard grouping	Orchard type used in grouping
High drift	pecans (tall) small citrus (spaced trees) citrus (dense canopies) dormant apples (sparse)
Low drift	apples (medium density) almonds (medium density) grape vineyards (low height, medium density)

Given the distinctness of the mist blower and wraparound sprayer equipment, these data were not averaged with airblast data but placed in separate groups.

Since the study design generally included only one orchard type per commodity (*e.g.* one variety of apple tree in a single orchard) and did not test all types of orchard trees, the possibility exists that the test orchards do not reflect the true means and variation of orchards in the U.S. The lack of data defining the variability in individual orchard types (*e.g.* pecans) greatly increases the uncertainty in defining individual orchards, but upon grouping, random errors should be reduced through averaging. Random errors overestimating drift should tend to be compensated by random error resulting in underestimates.

Grouping minimizes error that would be generated from averaging the highest and lowest drift scenarios. Clearly pecan orchards are distinctly different from vineyards, and the two would be expected to result in very different levels of drift. Grouping is required because averaging of the highest and lowest drift potential scenarios would not accurately characterize drift potential indicated in the data.

Another intention of categorizing the data into groups was to bridge the data to estimate drift from orchards other than those included in the SDTF study orchards. Orchard groupings are intended to be used as surrogates for other orchard types with similar physical parameters (*e.g.* height, canopy density, canopy spacing) for which detailed drift data are not available. If data are provided to define the physical characteristics for an orchard type of a species or variety not included in the orchard grouping, it should be possible to categorize the orchard into an existing orchard grouping (*i.e.* high or low) and estimate drift without performing field studies for the specific orchard type.

Orchard groupings are intended to be flexible and to allow for the addition of significant, new data. As additional data become available from ongoing and future studies, it will be possible to redefine orchard groupings and update deposition values based on orchard physical parameters and applications methods. To encourage the development and use of drift-reducing technology, new groupings with lowered deposition values may be developed as quantitative drift study data become available. Orchard groupings reflecting lower drift levels may result in lower exposure levels in risk assessments.

IX. Statistical Procedures

A. Overview of Procedures.

The first step was to reduce the data for each application by fitting a smooth curve relating percent deposition to distance independently for each application. The purpose of this step was to reduce the data for a single application to a small number of curve parameters. In preliminary analyses, a specific function was found to fit well for most applications (e.g., for the most part yielding high R^2 values):

$$\text{deposition} = \exp\{a + b * (\text{distance}^{\wedge}0.5)\}$$

This function has two parameters: a parameter denoted *a* can be viewed as quantifying deposition close to the field edge. A second parameter *b* quantifies how rapidly deposition falls off with distance from the field edge. The function was fitted separately for each application, resulting in an estimate of *a* and an estimate of *b* for each application. The parameter estimates (for *a* and *b*) were used as input data for the subsequent analyses, the calculation of percentiles and statistical bounds. Additional details are given in Section 3 below.

The distance values used in the curve-fitting step were adjusted based on wind angle to provide an estimate of distance from the field edge, in the wind direction. In addition, distances for inside applications were adjusted based on the point of application inside the field. (See Section B below.)

The values of *a* and *b* for a given application were used to predict deposition at a given distance from the field edge. Because *a* and *b* have distinct values for each application, we also have a distinct prediction for each application, for a given distance from the field edge. *The predicted values at a given distance were used as a statistical sample to calculate a tolerance bound at that distance* using the procedures described in Section 4 below.

An obvious alternative would be, instead of using predicted values at a given distance, to restrict attention to those distances actually evaluated in the study, and calculate tolerance bounds based on the actual measurements rather than based on the values predicted from regression. However, some exposure calculations may require interpolation of exposure at distances not measured directly. Also, after distance has been adjusted for wind angle or (for inside rows) distance inside the field, we no longer have collections of measurements at the same distance. The regression 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 regression approach.

B. Adjustment of Distances to Measurement Points.

For the curve-fitting step (relating deposition to distance), the distances are from the point of application to the measurement station. For outside rows, the distances are between the field edge and the measurement station. For inside rows, an "inset" value is added to the distance, which is the distance between an inside row and the edge of the field. The inset values we have used for inside rows are tabulated below.

Table 7. Inset values for adjusting distances for inside applications

Study	Crop	Appl. Method	Inset (m)
Georgia/94	pecan	airblast	45.75
California/93	grapes	airblast,	14.4
		wraparound	14.4
	almonds	airblast	16.75
	orange	airblast	16.75
	apple	airblast	12.25
	dormant	airblast	12.25

Distances for inside treatments can also be modified using available information on wind angle. The wind angle was expressed as degrees 'relative to normal' (e.g., 0 degrees means that wind perpendicular to the crop rows). Wind angle values varied up to 69 degrees. The objective of a wind angle adjustment is to provide distance from the point of application (the field edge for outside rows, or a point within the field for inside rows) to the measurement point. Combining these calculations, distance relative to a point of origin is expressed, for inside and outside rows, by the formula:

$$x = \frac{\text{STADIST} + \text{INSET}}{\cos(\text{WINDDEG} * K)}$$

where STADIST = station distance from edge of field (m);
INSET = inset (m, >0) for inside rows, 0 for outside rows;
WINDDEG = wind angle in degrees from normal (see above);
K = proportionality constant, depending on whether the cos function is defined to operate on angles (*K*=1) or radians (*K*=ð/180).

C. Distance-Deposition Curves, Regression Methods.

For each application we fit a smooth curve relating deposition (denoted *y*, %application) to distance (denoted *x*, in meters). (Here *x* is assumed to be adjusted for 'inset' and wind angle as described above.) Generalizing the familiar formula for first-order degradation, a flexible family of functions is:

$$f(x; a, b) = \exp(a + b\, x^{p}) .$$

The value of *p*=0.5 was found to work well for the ground spray data (reported elsewhere), and in preliminary analyses we have found that choice to work well to the orchard data as well. The choice *p*=1, which corresponds to the first-order dissipation curve, appeared particularly poor in preliminary work. We have uniformly fitted the function with *p*=0.5 for the orchard data, i.e., the function we have fitted is

$$f(x; a, b) = \exp(a + b\sqrt{x}) .$$

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

For each application, the function given above was fitted by regressing the natural logarithm of deposition against the square-root of distance. This approach results in maximum R^2 when comparing predicted to observed values *in the log scale*.

In preliminary analyses we used approximate ordinary least squares (OLS) methods that maximize R^2 in the scale of %application. The basis for the preliminary approach was that the approach based on transformation might place too high weight on the smallest values, which are often equal to half the detection limit. However, we have concluded that in the specific context of pesticide drift analysis, the OLS approach results in unacceptable *proportional* errors, particularly for the more distant measurement locations. In other words, errors of a small fraction of percent of the application rate correspond to a many-fold difference between observed and predicted values. We note that whether proportional error or absolute error is more important depends on the application.

It should be noted that if we know that what we need is specifically the *arithmetic mean* deposition, back-transforming the results of a regression from the log scale will be somewhat inaccurate for that purpose. However, we concluded that there was no strong basis for a specific preference for prediction of the arithmetic mean for a given application, relative to other measures of central tendency.

Deposition data were available for distances up to 183 m for the GA and Fl studies, and up to 549 m for the CA study. To improve the fit of the curves, the data for 549 m were dropped for the CA study, so that we used distances up to 335 m for that study. These are distances from the field edge; distances used for inside applications will be larger.

D. Tolerance Bound Calculations.

An upper tolerance bound covers a percentile *â* of the distribution, with confidence ã. In our calculations, a single tolerance bound applies to a combination of percentile of distribution (*â* = 95%, 99%), and confidence coefficient (ã = 65%, 75%, 85%, 95%), distance from edge of field (*x* = 5 m, 10m, 20m, ..., 250 m), and treatment grouping. We have calculated tolerance bounds only based on the outside applications (not for the inside applications).

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 ith application, deposition at distance *x* is estimated by $\exp(a_i + b_i\sqrt{x})$ for the ith 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.

With regard to statistical assumptions, we initially concluded that a lognormal assumption would be simple and appropriate. However, the application of lognormal methods resulted in absurdly high estimates of percentiles, e.g., 99th percentile estimates that exceeded 100% of the application rate, when the actual measurements were generally less than 0.01%. We think it is useful to describe this outcome because lognormal assumptions are popular and sometimes appropriate in exposure assessment and such an approach is likely to be suggested from time to time for analysis of spray drift data.

The initial assumption of lognormality was based on preliminary graphical analysis (cumulative probability plots) which combined the data across treatments ignoring treatment groupings. (Treatment groupings were even more uncertain at the time than now.) While such plots definitely appeared more normal after log transformation, further study suggested an alternative interpretation, namely that variation was reasonably normal within groupings (as far as one can tell with the limited number of measurements per grouping) but variances were smaller in groups with smaller means. Logarithmic transformation seemed to result in a right tail of the distribution falling more abruptly than expected for the normal distribution. A Bartlett's test did not indicate significant differences in variance but the test is not specifically sensitive to situations where variance increases with the mean, and was implemented with a limited sample size.

With a large amount of data per grouping, the variance can be calculated separately for each grouping. However, we note that the coefficient of variation (standard deviation / mean) was reasonably similar across treatment groups. We considered it appropriate to develop a procedure based on the assumption of a common coefficient of variation. Thus 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. 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 fairly 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*.

X. Regression and Tolerance Bound Results

A. Results

Results of the regression step (regression of deposition against distance for each application) are displayed in Table 8. R^2 values were mostly higher than 95%. For two cases with R^2 below 80%, graphs of the raw data against distance indicated that the data was very variable so that no monotone curve would have yielded a high R^2.

Tolerance bounds are given in an Appendix, by percentile, confidence, distance, and treatment category.

Figures 5 and 6 show mean and 95th percentile curves compared to sample data from individual treatments. Each point is the average deposition on three horizontal alpha cellulose cards at a given distance from the edge of the orchard. Measurements made in the same application are connected by a line in the graphs.

Graphed data show a reasonable relationship relative to the curves. The mean curve may over predict mean deposition in the far field because the majority of points fall under the curve except at short distances. As expected, few points sit above the 95th percentile curve but enough that so this estimate is not unrealistically high. The apparent relationship between the field data and the curves suggest that the statistical approach described above would be appropriate for generic exposure estimates resulting from spray drift.

Table 8. Results of curve fitting for each application.

Study	**Treat-ment ##**	**Inside/ Outside**	**Crop**	**Device**	**Treat-ment Grouping [1]**	**Regression Results**			
						R^2		**Parameter Estimates**	
						ln *y*, ln *ŷ* [2]	***y*, *ŷ* [3]**	***a***	***b***
GA/94	1	out	pecan	airblast	1	94.1%	87.6%	2.751	-0.417
						92.1%	82.4%	2.550	-0.358
	2	in				50.1%	44.8%	0.750	-0.193
						62.4%	18.9%	1.104	-0.277
CA/93	102	out	grapes	airblast	3	94.0%	89.0%	0.302	-0.565
	103	in				98.0%	95.6%	-0.260	-0.337
	104	out		wraparound	5	99.1%	98.4%	-2.409	-0.336
						97.9%	90.1%	-1.239	-0.420
	105	in				99.5%	98.9%	-2.967	-0.279
						94.9%	87.0%	-2.336	-0.275
	107	out	almonds	airblast	3	90.6%	79.7%	0.910	-0.375
						91.7%	82.8%	1.068	-0.433
	108	in				95.4%	86.1%	-0.937	-0.284
						94.5%	94.4%	-0.398	-0.463
	110	out	orange	airblast	1	90.6%	93.4%	1.597	-0.377
						96.0%	92.4%	1.609	-0.433
	111	in				96.9%	98.0%	0.031	-0.255
						97.6%	94.3%	-0.211	-0.338
	116	out	apple	airblast	3	92.4%	76.0%	-0.747	-0.264
						72.1%	55.3%	-2.063	-0.253
	117	in				79.0%	59.7%	-1.355	-0.231
						63.8%	53.2%	-2.652	-0.188
	119	out	dormant apple	airblast	2	98.1%	95.7%	3.880	-0.611
	120	in				96.3%	92.8%	2.976	-0.558
FL	1	out	Large Citrus	airblast	1	91.9%	97.7%	3.565	-0.503
						99.3%	99.3%	3.318	-0.598
	4	out		mist blower	4	96.8%	96.9%	2.304	-0.487
						98.6%	96.9%	1.908	-0.432
	6	out	Sm.Citrus	airblast	2	98.7%	90.1%	4.017	-0.589
						99.3%	98.7%	3.578	-0.586
	9	out		mist blower	4	96.3%	94.9%	1.955	-0.399
						94.5%	77.0%	2.341	-0.438

[1] groupings: 1) large/dense; 2) dormant/young; 3) medium; 4) mistblower; 5) wraparound
[2] R^2 for the regression of ln deposition against square-root of distance. This is optimized by the values of *a* and *b* displayed.
[3] 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* .

Figure 5. High drift grouping, outside treatments: Predicted deposition and downwind distance relative to field data.

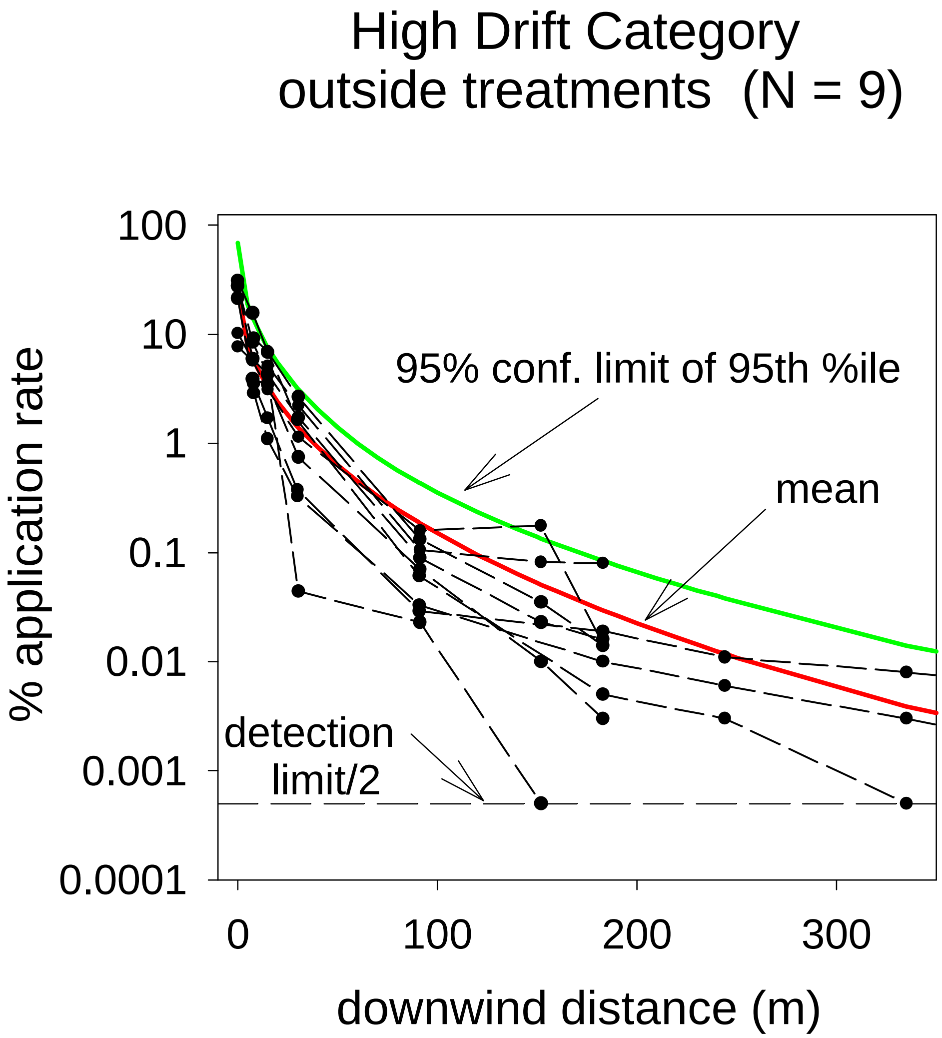
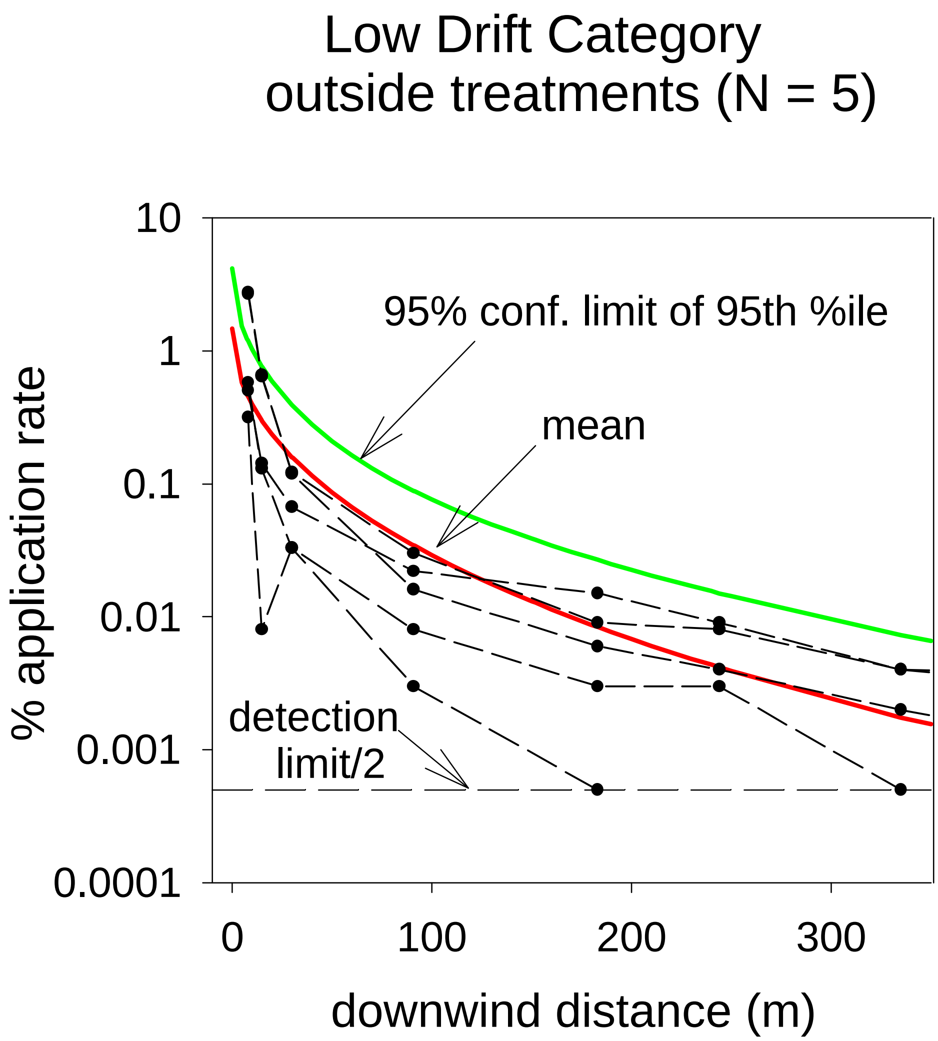


Figure 6. Low drift grouping, outside treatments: Predicted deposition and downwind distance relative to field data.



2. Limitations and Possible Refinements of the Deposition Bounds as used for orchard airblast studies and ground spray studies.

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 non-detects 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.

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.

XI. Ganzelmeier Data on Drift from Airblast Applications

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 fruit and vine crops included 61 treatments to fruit trees (31 early growth, 30 late growth stages) and 21 treatments to vineyards (10 early, 11 late stages). The results for orchards and vineyards were combined into early and late groupings. Comparisons between SDTF results and Ganzelmeier are limited in that quantitative canopy density measurements, tree type, orchard layout, treatment area size, and drop size information for the applications were not given in the Ganzelmeier report.

Table 9. Comparison of Ganzelmeier and SDTF application conditions for fruit and vine crops.

parameter	Ganzelmeier	SDTF
wind speed range (mph)	0.2-14*	1.8-12.2**
temperature (^{o}F)	36-77	55-103
humidity (% relative)	36-90	8-82
downwind distance (m)	3-50	0-550

* It is not clear whether wind speed measurements were made inside or outside orchards.
** From measurements outside the orchard.

The Ganzelmeier early and late grouping for orchards and vineyards 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 figures below) shows the Ganzelmeier to be similar to the SDTF but direct comparisons are limited by the factors listed above. It is likely that the Ganzelmeier early growth stages are likely similar to the SDTF dormant apple study and may be useful as a comparison to the high grouping of the SDTF data (see figure below). Since the canopy characteristics in the Ganzelmeier late grouping were not defined it is not clear which SDTF grouping is most reasonable for comparison. Since the SDTF high category represents more tree types it was used for comparison in the figure below. Ganzelmeier late grape is best compared to the SDTF low grouping which includes grape vineyards.

Figure 7. Comparison of SDTF “High” grouping to Ganzelmeier “Early” grouping.

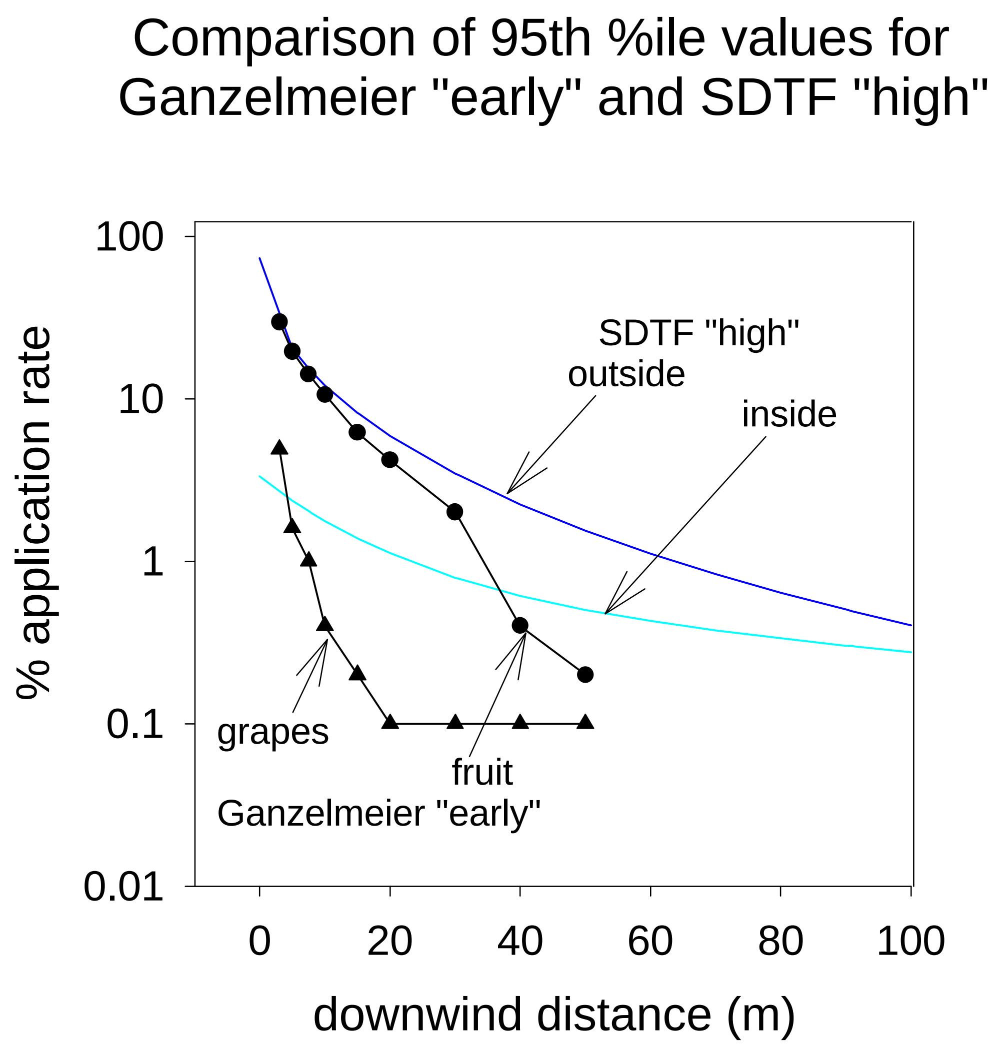


Figure 8. Comparison of SDTF “High” grouping to Ganzelmeier “Late” grouping.

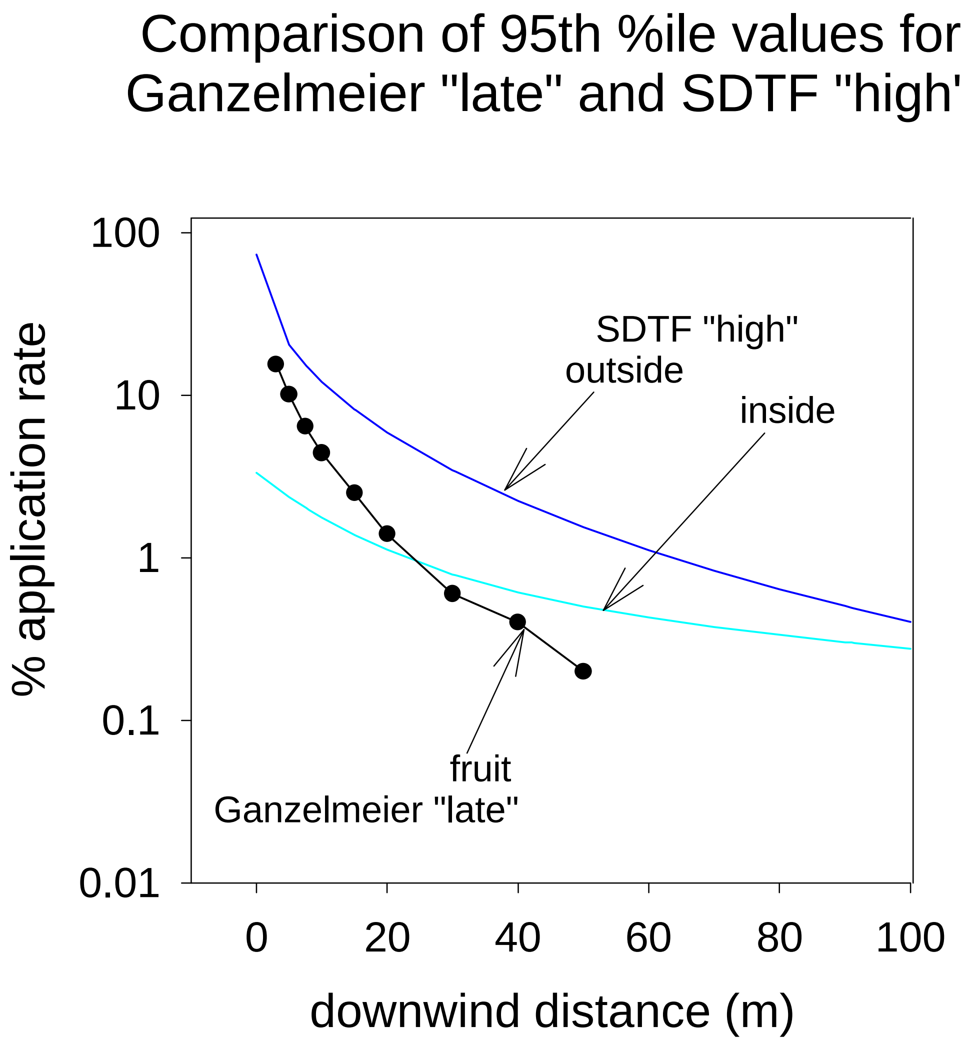
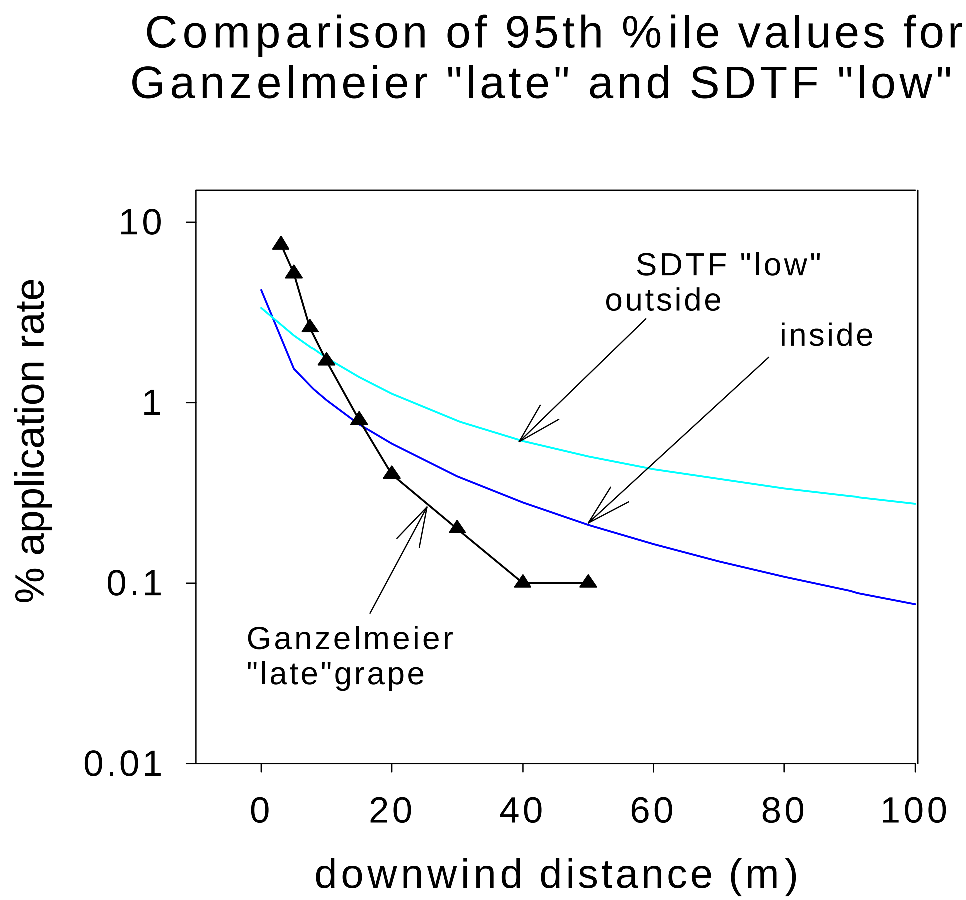


Figure 8. Comparison of SDTF "Low" grouping to Ganzelmeier "Late" grape grouping.



The graphical comparisons of the 95th percentiles of the Ganzelmeier and SDTF studies generally show similar results close to the treatment area, and higher deposition predicted by the SDTF curves at greater distances. The largest discrepancy in the near-field is from comparing "late grapes" to the SDTF "low" category (Figure 8). The apparent under-prediction of the SDTF data may be a result of the absence of SDTF deposition data in grapes at distances less that 8 m and the use of a one row width offset to define the edge of the field in the SDTF studies. The edge of the treatment area was not defined in the Ganzelmeier report.

The graphical comparisons presented above generally suggest that the 95th percentile curves generated from the SDTF data are protective.

XII. EFED's Present Drift Estimation and SDTF 95th Percentile Curve

For exposure assessments related to airblast pesticide applications, EFED currently assumes that 5% of the application rate drifts into a 1 hectare pond immediately adjacent to a 10 hectare orchard. The hypothetical pond is 63 m wide, 2 m deep, and has an approximate volume of $2x10^7$ liters. The pesticide concentration in the pond from a 1 kg / hectare application to the orchard is equivalent to the direct application of 0.05 kg to the pond or an estimated screening concentration of 2.5 ppb.

The 95th percentile curve of the SDTF data does not allow integration to the edge of the orchard without extrapolation to distances less than 8 m. Although some measurements were made at the edge of the orchards, most field trials used 8 m as the closest measurement to the orchards.

Using the SDTF 95th percentile curve from the outside applications it is possible to estimate aquatic concentrations in hypothetical ponds which beginning 8 m or farther from the orchard 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 rows of the orchards were sprayed for outside treatments, it does not account for an orchard size of 10 hectares. For estimation, if deposition is assumed decrease linearly between 8 and 70 m (see tolerance table in the appendices) the overall deposition would be 7.7%. When diluted into 20 million liters, the estimated screening concentration of a 1 kg / hectare application would be approximately 3.9 ppb. If the edge of the pond is 70 m from the orchard and extends to 130 m, the estimated screening concentration resulting from 0.53% of the application rate would be approximately 0.27 ppb.

XIII. References

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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:

$\div_{í}^{2}$ chi-square distribution with í degrees of freedom, or a random value with that distribution;

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

Ö(x) cumulative distribution function (CDF) for a N(0,1) distribution;

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

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

Let y_{ij} = the value of the jth observation in the ith group, j=1,...,N_i, i=1,...,#gr;

$\overline{y}_i$ = sample mean for the ith group, i=1,...,#gr;

s_i^2 = sample variance for the ith group, i=1,...,#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 $ó_1^2=ó_2^2=,...,=ó_{\#gr}^2=ó^2$. The common variance $ó^2$ can be estimated by the ANOVA error mean square (MS_E) which effectively averages the sample variances over groups:

$$MS_E = í^{-1} \Sigma_i \, df_i \, s_i^2 \text{ (summing over groups)}$$

where df_i = degrees of freedom for the ith group = N_i - 1;

í = total degrees of freedom = $\Sigma_i \, df_i$.

Then í $\cdot MS_E/ó^2$ has a $\div_{v}^{2}$ 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:

$$ó_1/ \mu_1 = ó_2/\mu_2 = \ldots = ó_{\#gr} / \mu_{\#gr} = CV$$

or

$$ó_i = \mu_i \cdot CV, \quad i = 1,\ldots,\#gr.$$

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 ith group proportionally to μ_i^{-2} (GLMT). Unfortunately the ideal weights then depend on the unknown true group means $\mu_1,\ldots,\mu_{\#gr}$.

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:

$$WSS_E = \sum_{i=1}^{\#gr} \sum_{j=1}^{N_i} \mu_i^{-2} (y_{ij} - \bar{y}_i)^2$$

$$= \sum_{i=1}^{\#gr} df_i (s_i / \mu_i)^2$$

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

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

where CV* is our estimate of the common within-group coefficient of variation. Hence $CV{*}=[í^{-1}\Sigma df_i (CV_i{*})^2]^{½}$ where $CV_i{*}$ is the sample coefficient of variation for the ith 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 ó ^{2} the *â*th percentile for the ith group has the general form μ_i+$z_{â}$ *ó* where $z_{â}$ = Ö$^{-1}$(*â*).

For the ith group, we may use a bound of the general form $\overline{y}_i + k{\cdot}s$, where *s* is the estimated within group variance (equal for all groups). Therefore the problem of finding a bound that covers percentile *â* with confidence ã amounts to solving for *k* in the expression:

$$\text{pr}\ [\ \overline{y}_i + k{\cdot}s \geq \mu_i + z_{â}\, ó\ ] = ã$$

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 $\overline{y}_i + k{\cdot}s_i \geq \mu_i + z_{â}\, ó$ above is equivalent to:

$$[(\ \mu_i - \overline{y}_i\ ) + z_{â}\, ó\ ]\ /\ s \leq k.$$

On the left side, divide numerator and denominator by *ó*/√N_i, which is the standard deviation of $\overline{y}_i$:

$$[(\ \mu_i - \overline{y}_i\ )/(ó/\sqrt{N_i}) + z_{â}\sqrt{N_i}\ ]\ /\ (\ s\sqrt{N_i}\ /\ ó\ ) \leq k.$$

or

$$N(z_{â}\sqrt{N_i}\ ,\ 1\ )\ /\ \sqrt{\ (\ ÷_i^{\,2}\ /\ í\ )} \leq k\sqrt{N_i}$$

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:

$$T\ (\ z_{â}\sqrt{N_i}\ ,\ í\ ) \leq\ k\sqrt{N_i}$$

where *T* (ä, í) denotes a noncentral-*t* random variable with noncentrality parameter ä and degrees of freedom í .

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

(1) Calculate $z_{â}$ = Ö$^{-1}$(*â*).
(The SAS function PROBIT may be used.)
(2) Calculate the noncentrality parameter ä = $z_{â}\ \sqrt{N_i}$.
(3) Find the appropriate critical value of a noncentral *T*(ä,í) distribution, say *t** that satisfies Pr[*T*(ä,í) ≤ *t**] = ã.
(The SAS function TINV may be used.)
(4) $k = t^* / \sqrt{N_i}$.
(5) The bound is $\overline{y}_i + k \cdot s$ where $s = \sqrt{MS_E}$.

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:

$$\text{pr}\ \{\ \overline{y}_{i} + k \cdot \text{ó}_{i}^{*} \geq \mu_{i} + z_{\hat{a}}\,\text{ó}_{i}\ \} = \text{ã}$$

where ó$_i$ = CV · μ_i is the true standard deviation in the ith group,
ó$_i$* = CV* · $\overline{y}_i$ is suggested as an estimator of ó$_i$,
CV* is the pooled coefficient of variation described above.

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

$$\text{pr}\ \{\ \text{N}(\ z_{\hat{a}}\sqrt{N_{i}}\ ,\ 1\ )\ /\ (\ \text{ó}_{i}^{*}\ /\ \text{ó}_{i}\ ) \leq k\sqrt{N_{i}}\ \} = \text{ã},$$

Regarding the distribution of the ratio ó$_i$*/ó$_i$, we have:

$$\frac{\text{ó}_{i}^{*}}{\text{ó}_{i}} = \frac{\overline{y}_{i}\ \cdot\ \text{CV}^{*}}{\mu_{i}\ \cdot\ \text{CV}} = \frac{\overline{y}_{i}\ \cdot\ \left(\frac{1}{\text{í}}\sum_{i}\ \text{df}_{i}\ s_{i}^{2}\ \overline{y}_{i}^{-2}\right)^{1/2}}{\mu_{i}\ \cdot\ \text{CV}}$$

For an approximation, we substitute the sample means ($\overline{y}_i$, known) for the true means (μ_i, unknown), which after some rearrangement and GLMT gives ó$_i$*/ó$_i$ ≈ $\sqrt{(\text{÷}_i^{2}/\text{í})}$ This suggests, as an approximation, using ó$_i$* 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 ÷^{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 $\overline{y}_i + k \cdot$ ó$_i$* where ó$_i$* = CV* · $\overline{y}_i$.

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:                                                       **
;
** --------------                                                       **
;
** PERCTILE - 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 PERCTILE TOL65 TOL75 TOL85 TOL95 ;
  BY GROUP PERC ;
  PAGEBY GROUP;
RUN;
```

Appendix 2: Tables of tolerance bounds for outside applications in the orchard airblast studies

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 the "high" group; 3 for the "low" group; 4 for mistblower applications; 5 for wraparound applications to grapes
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 32
Outside applications 11:15 Tuesday, June 1, 1999

------------------------------------- GROUP=1 PERC=0.95 -------------------------------------

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	9	16	26.7862	0.67238	56.4109	60.2399	62.9163	66.5591	73.5740
5.0	9	16	7.9477	0.60254	15.8245	16.8426	17.5542	18.5227	20.3879
7.6	9	16	6.0188	0.58736	11.8337	12.5852	13.1106	13.8256	15.2025
8.0	9	16	5.7940	0.58533	11.3723	12.0933	12.5972	13.2831	14.6041
10.0	9	16	4.8543	0.57609	9.4541	10.0486	10.4642	11.0298	12.1190
15.0	9	16	3.3403	0.55795	6.4059	6.8021	7.0790	7.4560	8.1819
15.2	9	16	3.2957	0.55733	6.3169	6.7074	6.9804	7.3519	8.0673
20.0	9	16	2.4453	0.54470	4.6362	4.9193	5.1173	5.3867	5.9054
30.0	9	16	1.4591	0.52821	2.7268	2.8907	3.0052	3.1611	3.4613
30.0	9	16	1.4591	0.52821	2.7268	2.8907	3.0052	3.1611	3.4613
30.5	9	16	1.4257	0.52766	2.6632	2.8231	2.9349	3.0871	3.3801
40.0	9	16	0.9508	0.52140	1.7662	1.8716	1.9453	2.0455	2.2386
50.0	9	16	0.6555	0.52184	1.2182	1.2909	1.3417	1.4109	1.5442
60.0	9	16	0.4705	0.52793	0.8790	0.9318	0.9687	1.0189	1.1157
70.0	9	16	0.3481	0.53843	0.6564	0.6962	0.7241	0.7620	0.8350
80.0	9	16	0.2638	0.55234	0.5036	0.5345	0.5562	0.5857	0.6424
90.0	9	16	0.2040	0.56885	0.3948	0.4195	0.4367	0.4602	0.5054
91.0	9	16	0.1990	0.57062	0.3857	0.4099	0.4267	0.4497	0.4939
91.4	9	16	0.1970	0.57133	0.3822	0.4061	0.4228	0.4456	0.4894
100.0	9	16	0.1603	0.58728	0.3152	0.3352	0.3492	0.3682	0.4049
110.0	9	16	0.1278	0.60712	0.2553	0.2718	0.2834	0.2991	0.3293
120.0	9	16	0.1031	0.62793	0.2095	0.2233	0.2329	0.2460	0.2712
130.0	9	16	0.0840	0.64937	0.1738	0.1854	0.1935	0.2045	0.2258
140.0	9	16	0.0692	0.67120	0.1455	0.1554	0.1623	0.1717	0.1898
150.0	9	16	0.0574	0.69319	0.1229	0.1313	0.1372	0.1453	0.1608
152.0	9	16	0.0554	0.69760	0.1189	0.1271	0.1328	0.1406	0.1557

160.0	9	16	0.0480	0.71520	0.1045	0.1118	0.1169	0.1238	0.1372
170.0	9	16	0.0404	0.73711	0.0894	0.0957	0.1002	0.1062	0.1178
180.0	9	16	0.0342	0.75881	0.0769	0.0825	0.0863	0.0916	0.1017
183.0	9	16	0.0326	0.76527	0.0736	0.0789	0.0826	0.0877	0.0974
190.0	9	16	0.0292	0.78025	0.0666	0.0714	0.0748	0.0794	0.0883
200.0	9	16	0.0250	0.80136	0.0579	0.0621	0.0651	0.0691	0.0769
210.0	9	16	0.0215	0.82212	0.0505	0.0543	0.0569	0.0605	0.0673
220.0	9	16	0.0186	0.84249	0.0443	0.0476	0.0499	0.0531	0.0592
230.0	9	16	0.0161	0.86246	0.0389	0.0419	0.0440	0.0468	0.0522
240.0	9	16	0.0140	0.88201	0.0344	0.0370	0.0388	0.0413	0.0461
244.0	9	16	0.0133	0.88971	0.0327	0.0352	0.0370	0.0394	0.0440
250.0	9	16	0.0123	0.90114	0.0304	0.0328	0.0344	0.0366	0.0409
335.0	9	16	0.0044	1.04706	0.0119	0.0129	0.0136	0.0145	0.0163
549.0	9	16	0.0006	1.31030	0.0018	0.0020	0.0021	0.0022	0.0025

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

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	9	16	26.7862	0.67238	68.6849	73.4632	76.7277	81.2069	89.9235
5.0	9	16	7.9477	0.60254	19.0880	20.3585	21.2264	22.4174	24.7350
7.6	9	16	6.0188	0.58736	14.2429	15.1808	15.8215	16.7007	18.4117
8.0	9	16	5.7940	0.58533	13.6834	14.5832	15.1979	16.0413	17.6826
10.0	9	16	4.8543	0.57609	11.3599	12.1018	12.6087	13.3042	14.6576
15.0	9	16	3.3403	0.55795	7.6760	8.1704	8.5082	8.9717	9.8737
15.2	9	16	3.2957	0.55733	7.5687	8.0560	8.3889	8.8457	9.7347
20.0	9	16	2.4453	0.54470	5.5439	5.8973	6.1387	6.4699	7.1146
30.0	9	16	1.4591	0.52821	3.2521	3.4565	3.5962	3.7879	4.1609
30.0	9	16	1.4591	0.52821	3.2521	3.4565	3.5962	3.7879	4.1609
30.5	9	16	1.4257	0.52766	3.1759	3.3755	3.5118	3.6989	4.0630
40.0	9	16	0.9508	0.52140	2.1040	2.2356	2.3254	2.4487	2.6886
50.0	9	16	0.6555	0.52184	1.4513	1.5421	1.6041	1.6891	1.8547
60.0	9	16	0.4705	0.52793	1.0483	1.1142	1.1592	1.2209	1.3411
70.0	9	16	0.3481	0.53843	0.7841	0.8338	0.8678	0.9144	1.0051
80.0	9	16	0.2638	0.55234	0.6029	0.6415	0.6680	0.7042	0.7747
90.0	9	16	0.2040	0.56885	0.4739	0.5047	0.5257	0.5546	0.6107
91.0	9	16	0.1990	0.57062	0.4631	0.4932	0.5138	0.5420	0.5970
91.4	9	16	0.1970	0.57133	0.4589	0.4887	0.5091	0.5371	0.5916
100.0	9	16	0.1603	0.58728	0.3793	0.4043	0.4213	0.4448	0.4903
110.0	9	16	0.1278	0.60712	0.3082	0.3288	0.3428	0.3621	0.3997
120.0	9	16	0.1031	0.62793	0.2536	0.2708	0.2825	0.2986	0.3300
130.0	9	16	0.0840	0.64937	0.2110	0.2255	0.2354	0.2489	0.2753
140.0	9	16	0.0692	0.67120	0.1772	0.1895	0.1979	0.2094	0.2319
150.0	9	16	0.0574	0.69319	0.1500	0.1605	0.1677	0.1776	0.1969
152.0	9	16	0.0554	0.69760	0.1452	0.1554	0.1624	0.1720	0.1907
160.0	9	16	0.0480	0.71520	0.1279	0.1370	0.1432	0.1517	0.1683
170.0	9	16	0.0404	0.73711	0.1097	0.1176	0.1230	0.1304	0.1448
180.0	9	16	0.0342	0.75881	0.0946	0.1015	0.1062	0.1127	0.1253
183.0	9	16	0.0326	0.76527	0.0906	0.0973	0.1018	0.1080	0.1201
190.0	9	16	0.0292	0.78025	0.0821	0.0881	0.0922	0.0979	0.1089
200.0	9	16	0.0250	0.80136	0.0715	0.0768	0.0804	0.0854	0.0951
210.0	9	16	0.0215	0.82212	0.0625	0.0672	0.0704	0.0748	0.0834
220.0	9	16	0.0186	0.84249	0.0549	0.0591	0.0619	0.0658	0.0734
230.0	9	16	0.0161	0.86246	0.0484	0.0521	0.0546	0.0581	0.0648
240.0	9	16	0.0140	0.88201	0.0428	0.0461	0.0483	0.0514	0.0574
244.0	9	16	0.0133	0.88971	0.0408	0.0439	0.0460	0.0490	0.0547
250.0	9	16	0.0123	0.90114	0.0379	0.0409	0.0429	0.0456	0.0510
335.0	9	16	0.0044	1.04706	0.0150	0.0162	0.0171	0.0182	0.0204
549.0	9	16	0.0006	1.31030	0.0023	0.0025	0.0027	0.0028	0.0032

--------------------------------------- GROUP=3 PERC=0.95 ---------------------------------------

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	5	16	1.46941	0.67238	3.09454	3.33855	3.51229	3.74677	4.19337
5.0	5	16	0.57926	0.60254	1.15335	1.23955	1.30093	1.38376	1.54153
7.6	5	16	0.46853	0.58736	0.92118	0.98915	1.03755	1.10286	1.22725
8.0	5	16	0.45512	0.58533	0.89330	0.95909	1.00594	1.06916	1.18958
10.0	5	16	0.39766	0.57609	0.77449	0.83107	0.87135	0.92572	1.02928
15.0	5	16	0.29906	0.55795	0.57352	0.61473	0.64407	0.68367	0.75910
15.2	5	16	0.29601	0.55733	0.56737	0.60811	0.63712	0.67628	0.75085
20.0	5	16	0.23577	0.54470	0.44701	0.47872	0.50131	0.53179	0.58984
30.0	5	16	0.15900	0.52821	0.29714	0.31788	0.33265	0.35258	0.39054
30.0	5	16	0.15900	0.52821	0.29714	0.31788	0.33265	0.35258	0.39054
30.5	5	16	0.15621	0.52766	0.29179	0.31215	0.32665	0.34621	0.38347
40.0	5	16	0.11461	0.52140	0.21290	0.22766	0.23817	0.25235	0.27936
50.0	5	16	0.08620	0.52184	0.16019	0.17130	0.17921	0.18989	0.21022
60.0	5	16	0.06682	0.52793	0.12485	0.13356	0.13977	0.14814	0.16409
70.0	5	16	0.05300	0.53843	0.09993	0.10698	0.11200	0.11877	0.13167
80.0	5	16	0.04280	0.55234	0.08168	0.08752	0.09168	0.09729	0.10798
90.0	5	16	0.03508	0.56885	0.06790	0.07283	0.07634	0.08107	0.09009
91.0	5	16	0.03441	0.57062	0.06671	0.07156	0.07501	0.07967	0.08855
91.4	5	16	0.03415	0.57133	0.06624	0.07106	0.07449	0.07912	0.08794
100.0	5	16	0.02911	0.58728	0.05723	0.06145	0.06445	0.06851	0.07624
110.0	5	16	0.02441	0.60712	0.04878	0.05244	0.05505	0.05857	0.06527
120.0	5	16	0.02066	0.62793	0.04199	0.04519	0.04747	0.05055	0.05642
130.0	5	16	0.01762	0.64937	0.03644	0.03927	0.04128	0.04399	0.04917
140.0	5	16	0.01514	0.67120	0.03185	0.03436	0.03615	0.03856	0.04315
150.0	5	16	0.01309	0.69319	0.02801	0.03025	0.03185	0.03400	0.03810
152.0	5	16	0.01272	0.69760	0.02732	0.02951	0.03107	0.03318	0.03719
160.0	5	16	0.01138	0.71520	0.02477	0.02678	0.02821	0.03014	0.03382
170.0	5	16	0.00995	0.73711	0.02200	0.02382	0.02510	0.02684	0.03016
180.0	5	16	0.00873	0.75881	0.01963	0.02127	0.02244	0.02401	0.02701
183.0	5	16	0.00841	0.76527	0.01899	0.02058	0.02171	0.02324	0.02614
190.0	5	16	0.00770	0.78025	0.01759	0.01907	0.02013	0.02156	0.02427
200.0	5	16	0.00682	0.80136	0.01581	0.01716	0.01812	0.01942	0.02189
210.0	5	16	0.00606	0.82212	0.01426	0.01549	0.01636	0.01755	0.01980
220.0	5	16	0.00541	0.84249	0.01290	0.01402	0.01482	0.01590	0.01796
230.0	5	16	0.00484	0.86246	0.01169	0.01272	0.01346	0.01445	0.01633
240.0	5	16	0.00434	0.88201	0.01063	0.01158	0.01225	0.01316	0.01489
244.0	5	16	0.00416	0.88971	0.01024	0.01116	0.01181	0.01268	0.01436
250.0	5	16	0.00390	0.90114	0.00969	0.01056	0.01118	0.01201	0.01360
335.0	5	16	0.00174	1.04706	0.00474	0.00519	0.00552	0.00595	0.00677
549.0	5	16	0.00036	1.31030	0.00114	0.00126	0.00134	0.00146	0.00167

-- GROUP=3 PERC=0.99 --

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	5	16	1.46941	0.67238	3.76785	4.05830	4.26060	4.53633	5.06826
5.0	5	16	0.57926	0.60254	1.39121	1.49381	1.56528	1.66268	1.85059
7.6	5	16	0.46853	0.58736	1.10873	1.18963	1.24598	1.32278	1.47094
8.0	5	16	0.45512	0.58533	1.07484	1.15316	1.20770	1.28205	1.42547
10.0	5	16	0.39766	0.57609	0.93061	0.99796	1.04487	1.10880	1.23214
15.0	5	16	0.29906	0.55795	0.68723	0.73628	0.77045	0.81702	0.90685
15.2	5	16	0.29601	0.55733	0.67980	0.72829	0.76207	0.80812	0.89694
20.0	5	16	0.23577	0.54470	0.53453	0.57228	0.59858	0.63442	0.70356
30.0	5	16	0.15900	0.52821	0.35437	0.37906	0.39626	0.41970	0.46491
30.0	5	16	0.15900	0.52821	0.35437	0.37906	0.39626	0.41970	0.46491
30.5	5	16	0.15621	0.52766	0.34797	0.37220	0.38908	0.41208	0.45646
40.0	5	16	0.11461	0.52140	0.25363	0.27119	0.28343	0.30010	0.33228
50.0	5	16	0.08620	0.52184	0.19085	0.20407	0.21329	0.22584	0.25006
60.0	5	16	0.06682	0.52793	0.14889	0.15926	0.16649	0.17633	0.19532
70.0	5	16	0.05300	0.53843	0.11938	0.12777	0.13361	0.14158	0.15694
80.0	5	16	0.04280	0.55234	0.09780	0.10474	0.10959	0.11618	0.12891
90.0	5	16	0.03508	0.56885	0.08150	0.08737	0.09145	0.09702	0.10776
91.0	5	16	0.03441	0.57062	0.08009	0.08586	0.08989	0.09537	0.10594
91.4	5	16	0.03415	0.57133	0.07954	0.08528	0.08927	0.09472	0.10522
100.0	5	16	0.02911	0.58728	0.06888	0.07390	0.07740	0.08217	0.09137
110.0	5	16	0.02441	0.60712	0.05888	0.06324	0.06627	0.07041	0.07839
120.0	5	16	0.02066	0.62793	0.05083	0.05464	0.05730	0.06092	0.06790
130.0	5	16	0.01762	0.64937	0.04424	0.04760	0.04995	0.05314	0.05930
140.0	5	16	0.01514	0.67120	0.03877	0.04176	0.04384	0.04668	0.05215
150.0	5	16	0.01309	0.69319	0.03419	0.03686	0.03872	0.04125	0.04613
152.0	5	16	0.01272	0.69760	0.03337	0.03597	0.03779	0.04027	0.04505
160.0	5	16	0.01138	0.71520	0.03031	0.03271	0.03437	0.03664	0.04103
170.0	5	16	0.00995	0.73711	0.02700	0.02916	0.03066	0.03270	0.03665
180.0	5	16	0.00873	0.75881	0.02415	0.02610	0.02746	0.02931	0.03287
183.0	5	16	0.00841	0.76527	0.02337	0.02527	0.02658	0.02838	0.03184
190.0	5	16	0.00770	0.78025	0.02168	0.02345	0.02468	0.02636	0.02959
200.0	5	16	0.00682	0.80136	0.01953	0.02114	0.02226	0.02379	0.02673
210.0	5	16	0.00606	0.82212	0.01765	0.01912	0.02014	0.02153	0.02421
220.0	5	16	0.00541	0.84249	0.01600	0.01734	0.01827	0.01954	0.02199
230.0	5	16	0.00484	0.86246	0.01454	0.01576	0.01662	0.01778	0.02003
240.0	5	16	0.00434	0.88201	0.01324	0.01436	0.01515	0.01622	0.01828
244.0	5	16	0.00416	0.88971	0.01276	0.01385	0.01461	0.01564	0.01763
250.0	5	16	0.00390	0.90114	0.01209	0.01312	0.01384	0.01482	0.01672
335.0	5	16	0.00174	1.04706	0.00599	0.00652	0.00690	0.00741	0.00839
549.0	5	16	0.00036	1.31030	0.00147	0.00161	0.00170	0.00183	0.00209

------------------------------------- GROUP=4 PERC=0.95 --------------------------------------

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	4	16	8.55057	0.67238	18.0072	19.5259	20.6141	22.0777	24.8529
5.0	4	16	3.18288	0.60254	6.3374	6.8440	7.2070	7.6952	8.6209
7.6	4	16	2.53036	0.58736	4.9750	5.3676	5.6489	6.0272	6.7446
8.0	4	16	2.45181	0.58533	4.8124	5.1915	5.4631	5.8284	6.5212
10.0	4	16	2.11680	0.57609	4.1227	4.4448	4.6756	4.9861	5.5747
15.0	4	16	1.54882	0.55795	2.9702	3.1985	3.3621	3.5821	3.9992
15.2	4	16	1.53141	0.55733	2.9353	3.1608	3.3223	3.5396	3.9516
20.0	4	16	1.19065	0.54470	2.2574	2.4287	2.5515	2.7166	3.0297
30.0	4	16	0.76651	0.52821	1.4325	1.5394	1.6161	1.7191	1.9146
30.0	4	16	0.76651	0.52821	1.4325	1.5394	1.6161	1.7191	1.9146
30.5	4	16	0.75141	0.52766	1.4036	1.5083	1.5834	1.6843	1.8757
40.0	4	16	0.52917	0.52140	0.9830	1.0559	1.1081	1.1783	1.3115
50.0	4	16	0.38200	0.52184	0.7099	0.7625	0.8003	0.8510	0.9472
60.0	4	16	0.28464	0.52793	0.5318	0.5715	0.6000	0.6382	0.7108
70.0	4	16	0.21726	0.53843	0.4097	0.4406	0.4627	0.4925	0.5490
80.0	4	16	0.16901	0.55234	0.3226	0.3472	0.3649	0.3886	0.4337
90.0	4	16	0.13353	0.56885	0.2585	0.2785	0.2929	0.3123	0.3489
91.0	4	16	0.13052	0.57062	0.2530	0.2727	0.2868	0.3058	0.3417
91.4	4	16	0.12934	0.57133	0.2509	0.2704	0.2844	0.3032	0.3389
100.0	4	16	0.10688	0.58728	0.2101	0.2267	0.2386	0.2546	0.2849
110.0	4	16	0.08651	0.60712	0.1729	0.1868	0.1967	0.2101	0.2354
120.0	4	16	0.07069	0.62793	0.1437	0.1554	0.1638	0.1751	0.1966
130.0	4	16	0.05826	0.64937	0.1205	0.1305	0.1376	0.1473	0.1655
140.0	4	16	0.04837	0.67120	0.1018	0.1103	0.1165	0.1248	0.1404
150.0	4	16	0.04043	0.69319	0.0865	0.0939	0.0992	0.1064	0.1199
152.0	4	16	0.03903	0.69760	0.0838	0.0910	0.0962	0.1031	0.1162
160.0	4	16	0.03400	0.71520	0.0740	0.0804	0.0850	0.0912	0.1029
170.0	4	16	0.02875	0.73711	0.0636	0.0692	0.0732	0.0786	0.0888
180.0	4	16	0.02443	0.75881	0.0549	0.0598	0.0633	0.0680	0.0770
183.0	4	16	0.02328	0.76527	0.0526	0.0573	0.0607	0.0652	0.0738
190.0	4	16	0.02085	0.78025	0.0476	0.0519	0.0550	0.0591	0.0670
200.0	4	16	0.01787	0.80136	0.0414	0.0452	0.0479	0.0516	0.0585
210.0	4	16	0.01538	0.82212	0.0362	0.0395	0.0419	0.0451	0.0512
220.0	4	16	0.01329	0.84249	0.0317	0.0347	0.0368	0.0396	0.0450
230.0	4	16	0.01151	0.86246	0.0278	0.0305	0.0324	0.0349	0.0397
240.0	4	16	0.01001	0.88201	0.0245	0.0269	0.0285	0.0308	0.0350
244.0	4	16	0.00947	0.88971	0.0233	0.0256	0.0272	0.0293	0.0334
250.0	4	16	0.00873	0.90114	0.0217	0.0237	0.0252	0.0272	0.0310
335.0	4	16	0.00301	1.04706	0.0082	0.0090	0.0096	0.0104	0.0119
549.0	4	16	0.00034	1.31030	0.0011	0.0012	0.0013	0.0014	0.0016

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

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	4	16	8.55057	0.67238	21.9253	23.7008	24.9467	26.6397	29.8931
5.0	4	16	3.18288	0.60254	7.6444	8.2367	8.6522	9.2170	10.3023
7.6	4	16	2.53036	0.58736	5.9878	6.4468	6.7689	7.2065	8.0476
8.0	4	16	2.45181	0.58533	5.7904	6.2336	6.5446	6.9672	7.7793
10.0	4	16	2.11680	0.57609	4.9537	5.3303	5.5946	5.9537	6.6438
15.0	4	16	1.54882	0.55795	3.5591	3.8260	4.0133	4.2678	4.7568
15.2	4	16	1.53141	0.55733	3.5170	3.7806	3.9655	4.2168	4.6998
20.0	4	16	1.19065	0.54470	2.6994	2.8997	3.0402	3.2312	3.5982
30.0	4	16	0.76651	0.52821	1.7084	1.8334	1.9212	2.0404	2.2695
30.0	4	16	0.76651	0.52821	1.7084	1.8334	1.9212	2.0404	2.2695
30.5	4	16	0.75141	0.52766	1.6738	1.7962	1.8822	1.9989	2.2233
40.0	4	16	0.52917	0.52140	1.1710	1.2562	1.3160	1.3973	1.5534
50.0	4	16	0.38200	0.52184	0.8457	0.9073	0.9505	1.0092	1.1220
60.0	4	16	0.28464	0.52793	0.6342	0.6806	0.7132	0.7575	0.8425
70.0	4	16	0.21726	0.53843	0.4894	0.5255	0.5509	0.5853	0.6515
80.0	4	16	0.16901	0.55234	0.3862	0.4150	0.4352	0.4627	0.5155
90.0	4	16	0.13353	0.56885	0.3102	0.3337	0.3502	0.3725	0.4155
91.0	4	16	0.13052	0.57062	0.3038	0.3268	0.3429	0.3648	0.4070
91.4	4	16	0.12934	0.57133	0.3012	0.3241	0.3401	0.3618	0.4037
100.0	4	16	0.10688	0.58728	0.2529	0.2723	0.2859	0.3044	0.3399
110.0	4	16	0.08651	0.60712	0.2087	0.2249	0.2363	0.2518	0.2815
120.0	4	16	0.07069	0.62793	0.1740	0.1877	0.1973	0.2104	0.2355
130.0	4	16	0.05826	0.64937	0.1463	0.1579	0.1661	0.1773	0.1987
140.0	4	16	0.04837	0.67120	0.1239	0.1339	0.1410	0.1505	0.1689
150.0	4	16	0.04043	0.69319	0.1056	0.1143	0.1204	0.1286	0.1445
152.0	4	16	0.03903	0.69760	0.1024	0.1108	0.1167	0.1247	0.1401
160.0	4	16	0.03400	0.71520	0.0906	0.0981	0.1033	0.1105	0.1243
170.0	4	16	0.02875	0.73711	0.0780	0.0846	0.0892	0.0954	0.1074
180.0	4	16	0.02443	0.75881	0.0675	0.0733	0.0773	0.0827	0.0932
183.0	4	16	0.02328	0.76527	0.0647	0.0702	0.0741	0.0793	0.0894
190.0	4	16	0.02085	0.78025	0.0587	0.0637	0.0672	0.0720	0.0812
200.0	4	16	0.01787	0.80136	0.0512	0.0556	0.0587	0.0629	0.0710
210.0	4	16	0.01538	0.82212	0.0448	0.0487	0.0514	0.0552	0.0623
220.0	4	16	0.01329	0.84249	0.0393	0.0428	0.0452	0.0485	0.0548
230.0	4	16	0.01151	0.86246	0.0346	0.0377	0.0398	0.0428	0.0484
240.0	4	16	0.01001	0.88201	0.0306	0.0333	0.0352	0.0378	0.0428
244.0	4	16	0.00947	0.88971	0.0291	0.0317	0.0335	0.0360	0.0408
250.0	4	16	0.00873	0.90114	0.0270	0.0295	0.0312	0.0335	0.0379
335.0	4	16	0.00301	1.04706	0.0103	0.0113	0.0120	0.0129	0.0147
549.0	4	16	0.00034	1.31030	0.0014	0.0015	0.0016	0.0017	0.0020

------------------------------------- GROUP=5 PERC=0.95 --------------------------------------

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	2	16	0.18976	0.67238	0.39963	0.44250	0.47373	0.51529	0.59301
5.0	2	16	0.07779	0.60254	0.15489	0.17064	0.18211	0.19738	0.22593
7.6	2	16	0.06327	0.58736	0.12439	0.13688	0.14597	0.15807	0.18071
8.0	2	16	0.06150	0.58533	0.12070	0.13280	0.14161	0.15333	0.17525
10.0	2	16	0.05388	0.57609	0.10493	0.11536	0.12296	0.13307	0.15197
15.0	2	16	0.04068	0.55795	0.07801	0.08564	0.09119	0.09858	0.11241
15.2	2	16	0.04027	0.55733	0.07718	0.08472	0.09021	0.09752	0.11119
20.0	2	16	0.03212	0.54470	0.06089	0.06677	0.07105	0.07675	0.08741
30.0	2	16	0.02163	0.52821	0.04043	0.04427	0.04706	0.05079	0.05774
30.0	2	16	0.02163	0.52821	0.04043	0.04427	0.04706	0.05079	0.05774
30.5	2	16	0.02125	0.52766	0.03969	0.04346	0.04621	0.04986	0.05669
40.0	2	16	0.01552	0.52140	0.02883	0.03155	0.03353	0.03617	0.04110
50.0	2	16	0.01160	0.52184	0.02155	0.02359	0.02507	0.02704	0.03073
60.0	2	16	0.00892	0.52793	0.01666	0.01824	0.01940	0.02093	0.02380
70.0	2	16	0.00701	0.53843	0.01322	0.01448	0.01541	0.01664	0.01894
80.0	2	16	0.00560	0.55234	0.01070	0.01174	0.01249	0.01350	0.01539
90.0	2	16	0.00454	0.56885	0.00880	0.00967	0.01030	0.01114	0.01272
91.0	2	16	0.00445	0.57062	0.00863	0.00949	0.01011	0.01094	0.01249
91.4	2	16	0.00442	0.57133	0.00857	0.00942	0.01004	0.01086	0.01239
100.0	2	16	0.00373	0.58728	0.00733	0.00807	0.00860	0.00932	0.01065
110.0	2	16	0.00309	0.60712	0.00618	0.00681	0.00727	0.00788	0.00902
120.0	2	16	0.00259	0.62793	0.00526	0.00580	0.00620	0.00673	0.00772
130.0	2	16	0.00218	0.64937	0.00451	0.00498	0.00533	0.00579	0.00665
140.0	2	16	0.00185	0.67120	0.00389	0.00431	0.00461	0.00501	0.00577
150.0	2	16	0.00158	0.69319	0.00338	0.00374	0.00401	0.00437	0.00503
152.0	2	16	0.00153	0.69760	0.00328	0.00364	0.00390	0.00425	0.00490
160.0	2	16	0.00135	0.71520	0.00295	0.00327	0.00351	0.00382	0.00441
170.0	2	16	0.00117	0.73711	0.00258	0.00287	0.00308	0.00336	0.00389
180.0	2	16	0.00101	0.75881	0.00227	0.00253	0.00272	0.00297	0.00344
183.0	2	16	0.00097	0.76527	0.00219	0.00244	0.00262	0.00286	0.00332
190.0	2	16	0.00088	0.78025	0.00201	0.00224	0.00241	0.00263	0.00305
200.0	2	16	0.00077	0.80136	0.00178	0.00199	0.00214	0.00234	0.00272
210.0	2	16	0.00067	0.82212	0.00159	0.00177	0.00191	0.00209	0.00243
220.0	2	16	0.00059	0.84249	0.00141	0.00158	0.00170	0.00187	0.00217
230.0	2	16	0.00052	0.86246	0.00127	0.00142	0.00153	0.00167	0.00195
240.0	2	16	0.00046	0.88201	0.00113	0.00127	0.00137	0.00150	0.00175
244.0	2	16	0.00044	0.88971	0.00109	0.00122	0.00131	0.00144	0.00168
250.0	2	16	0.00041	0.90114	0.00102	0.00114	0.00123	0.00135	0.00158
335.0	2	16	0.00016	1.04706	0.00044	0.00050	0.00054	0.00060	0.00070
549.0	2	16	0.00002	1.31030	0.00008	0.00009	0.00010	0.00011	0.00013

------------------------------------- GROUP=5 PERC=0.99 -------------------------------------

X	N	DF	MEAN	CV	PERCTILE	TOL65	TOL75	TOL85	TOL95
0.0	2	16	0.18976	0.67238	0.48658	0.53425	0.56841	0.61434	0.70144
5.0	2	16	0.07779	0.60254	0.18683	0.20434	0.21689	0.23376	0.26576
7.6	2	16	0.06327	0.58736	0.14971	0.16360	0.17354	0.18692	0.21229
8.0	2	16	0.06150	0.58533	0.14523	0.15868	0.16831	0.18127	0.20585
10.0	2	16	0.05388	0.57609	0.12608	0.13768	0.14599	0.15716	0.17835
15.0	2	16	0.04068	0.55795	0.09348	0.10196	0.10803	0.11620	0.13170
15.2	2	16	0.04027	0.55733	0.09247	0.10086	0.10687	0.11495	0.13027
20.0	2	16	0.03212	0.54470	0.07281	0.07935	0.08403	0.09033	0.10227
30.0	2	16	0.02163	0.52821	0.04821	0.05248	0.05554	0.05966	0.06746
30.0	2	16	0.02163	0.52821	0.04821	0.05248	0.05554	0.05966	0.06746
30.5	2	16	0.02125	0.52766	0.04733	0.05152	0.05453	0.05856	0.06622
40.0	2	16	0.01552	0.52140	0.03435	0.03737	0.03954	0.04245	0.04798
50.0	2	16	0.01160	0.52184	0.02568	0.02794	0.02956	0.03174	0.03587
60.0	2	16	0.00892	0.52793	0.01987	0.02163	0.02289	0.02459	0.02780
70.0	2	16	0.00701	0.53843	0.01579	0.01720	0.01821	0.01957	0.02214
80.0	2	16	0.00560	0.55234	0.01281	0.01396	0.01479	0.01591	0.01802
90.0	2	16	0.00454	0.56885	0.01056	0.01153	0.01222	0.01315	0.01491
91.0	2	16	0.00445	0.57062	0.01037	0.01132	0.01200	0.01291	0.01465
91.4	2	16	0.00442	0.57133	0.01029	0.01123	0.01191	0.01282	0.01454
100.0	2	16	0.00373	0.58728	0.00882	0.00964	0.01023	0.01102	0.01251
110.0	2	16	0.00309	0.60712	0.00746	0.00816	0.00866	0.00934	0.01062
120.0	2	16	0.00259	0.62793	0.00636	0.00697	0.00740	0.00799	0.00909
130.0	2	16	0.00218	0.64937	0.00547	0.00600	0.00638	0.00689	0.00785
140.0	2	16	0.00185	0.67120	0.00473	0.00520	0.00553	0.00598	0.00682
150.0	2	16	0.00158	0.69319	0.00412	0.00453	0.00482	0.00522	0.00596
152.0	2	16	0.00153	0.69760	0.00401	0.00441	0.00470	0.00508	0.00581
160.0	2	16	0.00135	0.71520	0.00361	0.00397	0.00423	0.00458	0.00524
170.0	2	16	0.00117	0.73711	0.00317	0.00349	0.00372	0.00403	0.00462
180.0	2	16	0.00101	0.75881	0.00280	0.00308	0.00329	0.00357	0.00409
183.0	2	16	0.00097	0.76527	0.00270	0.00297	0.00317	0.00344	0.00395
190.0	2	16	0.00088	0.78025	0.00248	0.00274	0.00292	0.00317	0.00364
200.0	2	16	0.00077	0.80136	0.00220	0.00243	0.00260	0.00282	0.00324
210.0	2	16	0.00067	0.82212	0.00196	0.00217	0.00232	0.00252	0.00290
220.0	2	16	0.00059	0.84249	0.00175	0.00194	0.00208	0.00225	0.00260
230.0	2	16	0.00052	0.86246	0.00157	0.00174	0.00186	0.00202	0.00233
240.0	2	16	0.00046	0.88201	0.00141	0.00156	0.00167	0.00182	0.00210
244.0	2	16	0.00044	0.88971	0.00135	0.00150	0.00161	0.00175	0.00201
250.0	2	16	0.00041	0.90114	0.00127	0.00141	0.00151	0.00164	0.00189
335.0	2	16	0.00016	1.04706	0.00056	0.00062	0.00067	0.00073	0.00084
549.0	2	16	0.00002	1.31030	0.00010	0.00011	0.00012	0.00013	0.00016

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