Health & Ecological Risk Assessment

Impact of Wind Speed and Direction and Key Meteorological Parameters on Potential Pesticide Drift Mass Loadings from Sequential Aerial Applications

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ABSTRACT

Pesticide spray drift is potentially a significant source of exposure to off-target, adjacent aquatic habitats. To estimate the magnitude of pesticide drift from aerial or ground applications, regulatory agencies in North America, Europe, and elsewhere rely on spray drift models to predict spray drift deposition for risk assessments. Refined assessments should ultimately depend on best-available data for exposure modeling. However, when developing lower tier "screening" assessments designed to indicate whether further refinement is needed, regulators often make conservative assumptions with a resulting increased level of uncertainty in estimating environmental exposure or risk. In the United States, it is generally accepted that, to ensure conservative regulatory assessments, it is reasonable to assume that the wind speed might be 4.47 m/s (10 miles per hour [mph]), the relative humidity and temperature are highly conducive to drift, and the wind is blowing directly toward a receiving water for any given single spray event in a season. However, what is the probability these conditions will all co-occur for each of 4 sequential spray events spaced a week apart (common practice for insecticides)? The refined approach in the present study investigates this question using hourly meteorological data sets for 5 United States Environmental Protection Agency (USEPA) standard crop scenarios to understand how real-world data can reduce unnecessary uncertainty for sequential applications. The impact of wind speeds, temperatures, relative humidity, and wind direction at different times of day on annual drift loadings has been examined using a stepwise process for comparison with corresponding regulatory default loading estimates. The impacts on drift estimates were significant; interestingly, the time of day of the applications impacted variability more than did the selected crop scenario. When all these real-world factors were considered, estimated 30-y total drift loads ranged from 2% to 5% greater than the default estimate (2 of 30 cases due to high afternoon wind speeds) to 51% to 86% reductions (25 of 30 cases) with an overall average reduction of 63%. *Integr Environ Assess Manag* 2020;16:197–210. © 2019 The Authors. *Integrated Environmental Assessment and Management* published by Wiley Periodicals, Inc. on behalf of Society of Environmental Toxicology & Chemistry (SETAC)

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INTRODUCTION

Spray drift deposition resulting from pesticide applications is a potential source of exposure to off-target, adjacent habitats. To determine the magnitude of off-target spray drift that occurs from aerial or ground applications, regulatory agencies in North America, Europe, and other parts of the world rely on spray drift models to predict spray drift as

a part of their environmental risk assessments. As such, both the development and parameterization of these models are important for determining the most appropriate off-target drift percentages to use in regulatory risk assessments. Previous field study analyses demonstrated that wind speed and other meteorological factors have a major effect on spray drift deposition (Payne and Thompson 1992; Bird et al. 2002; Teske et al. 2003; Wang and Rautman 2008). Consequently, in the United States, standard US Environmental Protection Agency (USEPA) Tier II surface water exposure modeling uses default conservative drift-related parameters (wind speed, temperature, and relative humidity) as inputs into the AgDRIFT model (version 2.1.1) to represent a single high-exposure condition over a 30-y simulation for both single applications and for every aerial

application of a sequence of pesticide applications during a season (USEPA 2012; White et al. 2013). As an additional conservative assumption, all applications are assumed to be applied with the wind blowing at a relatively high speed toward the receiving water body. For a single application, this is probably not an unreasonable hypothesis to ensure conservative parameterization for a standard exposure modeling crop scenario. However, the probability of this combination of circumstances occurring for every one of a seasonal series of multiple applications (which are common on many insecticide and fungicide labels) will decrease significantly as the number of applications within a growing season increases. In the real world, the likelihood of multiple sequential aerial applications spaced days apart and all experiencing identical and adverse meteorological conditions is vanishingly low. Moreover, assuming this co-occurrence of sequential spray applications with adverse wind conditions will happen every year for 30 y is an even less realistic proposition. For pesticide registrations within the European Union (EU), the FOrum for the Coordination of pesticide fate models and their USe (FOCUS) Task Force provides guidance for regulatory exposure modeling (FOCUS 2001, 2014; EFSA PPR 2013). For an EU regulatory risk assessment with a sequence of pesticide applications, FOCUS recommends reducing the drift percent of each individual application as the number of applications increases (e.g., for corn at a 1-m distance to water body, the drift is 2.8% for a single application, 2.4% for 2 applications, 1.9% for 4 applications, and 1.5% for 8 applications).

The main objective of the present study was to examine the conservative USEPA drift assumptions for sequential aerial applications using a stepwise drift refinement approach. To achieve this goal, a detailed analysis of the impact of real-world climatic conditions on estimated annual drift mass loads from multiple applications for a select set of USEPA regulatory crop-specific scenarios using a standard generic aerial application regime was compared to USEPA default drift mass loads.

Another objective of the present study was to analyze the variability of hourly measured climate parameters throughout the 24-h day (in 4-h increments). This evaluation allowed comparison of how the climate parameters changed throughout the day across locations and how this impacted the drift estimated by the AgDRIFT model and the resulting annual drift mass loadings. According to Hoffman and Salyani (1996), studies have shown that diurnal timing of spray applications can have significant effect on off-target spray drift due to the variation in climatic factors throughout the day; and therefore, spray timing is often used to mitigate potential drift risk (USEPA 2017). In general, drift loads are lower for nighttime (lower wind speed and temperatures and higher relative humidity, which are associated with lower drift) as compared to daytime (higher wind speed and temperature and lower relative humidity, which are associated with higher drift) (Hoffman and Salyani 1996).

Interestingly, there was not a great deal of data published on spray drift in the last decade. More recent research on spray drift has often been focused on spray drift reduction technologies (Jackson et al. 2012; Hilz and Vermeer 2013; USEPA 2018a). In addition, model improvement continues in government organizations in the United States (Teske et al. 2011, 2018, 2019) and in Canada (Wolf et al. 1993; Wolf and Caldwell 2001).

METHODS AND RESULTS

The USEPA guidance for standard Tier II exposure assessments requires off-target drift to be computed with the AgDRIFT model (version 2.1.1) (USEPA 2012) or with the precomputed drift values in the guidance document (White et al. 2013). The AgDRIFT model is a modified version of the AGricultural DISPersal model (AGDISP) and was jointly developed by the US Department of Agriculture's Forest Service and the Spray Drift Task Force (SDTF). AgDRIFT is capable of estimating spray drift deposition for pesticide spray buffer evaluations and was adopted by USEPA for use in regulatory modeling. Two significant improvements involving the step size algorithm and droplet evaporation assumptions have been made to the AGDISP model since the adoption of AgDRIFT by USEPA (Teske et al. 2011, 2018, 2019); however, the latest version 2.1.1 of AgDRIFT used by USEPA for regulatory modeling has not been updated with these improvements. Therefore, the current version of AgDRIFT consistently overpredicts drift estimates compared to the AGDISP model, which now better fits the data set developed by the SDTF.

AgDRIFT consists of a Tier I approach for ground, airblast, and aerial applications and Tier II and Tier III approaches for aerial applications only. For standard USEPA exposure modeling, the default droplet size for AgDRIFT Tier I aerial applications corresponds to those from a nozzle that delivers droplets classified as American Society of Agricultural and Biological Engineers (ASABE, incorrectly referred to as ASAE in AgDRIFT) Fine to Medium droplet size, assuming no drift setback buffer resulting in an application with off-target drift load of 12.5% of the nominal application rate entering an immediately adjacent rectangular receiving water (1 ha; 63.61 m × 157.2 m). The parameters for the AgDRIFT Tier I and Tier II aerial (agricultural) simulations are provided in Supplemental Data Table SI-1. In order to mitigate the predicted off-target drift from an application, USEPA may require a drift setback buffer or a specific droplet size range to be included on a product label. The AgDRIFT Tier I aerial simulations can be repeated using a coarser droplet size and/or a setback buffer distance. For example, when a label mandates a 45.7-m (150-ft) drift setback buffer and an ASABE Medium Coarse droplet size, then the percent off-target drift decreases to 1.97%. Thus, it is possible to use the AgDRIFT Tier I aerial model approach to take account of common drift mitigation requirements; however, simple logic suggests that other standard assumptions underlying these model runs (especially those regarding wind speed and direction) will often contribute very significant conservatism under real-world conditions. The present study utilizes the AgDRIFT Tier II aerial model

approach to provide a thorough analysis to determine the potential impact of these assumptions. In standard USEPA exposure assessments, the drift loading to the standard pond assumes the following:

1) that the wind is always blowing toward the off-target receiving water body,
2) that the wind speed is 4.47 m/s (10 mph), and
3) that the temperature and relative humidity are 30 °C (86 °F) and 50%, respectively.

For any single aerial application, although the combination of circumstances listed above clearly remains a high-end exposure case, it is probably not an unreasonable hypothesis to include in a scenario given that there is a finite probability that these variables could co-occur in this adverse manner. However, the probability of this combination of factors co-occurring for each of a sequence of multiple applications (which are common on pesticide labels and which are therefore a key element in aquatic exposure assessments for most crops with potential pest or disease problems) will become increasingly lower as the number of applications within a growing season increases. This evaluation examines this hypothesis with 3 steps of drift modeling refinements: 1) historical climate data including wind speed, temperature, and relative humidity; 2) historical wind direction data; and 3) combined wind speed, temperature, relative humidity, and wind direction data. The progressive impact that these steps of refined drift modeling have on the mass loading into the off-target receiving water body are shown. These 3 climate-related analyses were conducted for 5 crop scenarios for a single generic pesticide which already has droplet size and no-spray buffer restrictions.

Although factors such as the pesticide K_{OC} and half-life in a water body will often impact the potential time course of exposure concentrations resulting from drift (and runoff) off-target transport, the present analysis was designed simply to investigate the impact of wind speed, relative humidity, temperature, and wind direction on estimates of potential off-target drift transport. Consequently, the present analysis standardized the numbers of applications, application intervals, and application rates in order to examine the effect of real-world combinations of drift-related weather parameters recorded at 5 National Oceanic and Atmospheric Administration (NOAA) Solar and Meteorological Surface Observation Network (SAMSON) weather stations (NOAA 2013) representing different seasonal start dates (due to different crop emergence dates) and regional climatic regimes.

Default modeling approach

For the present study, 5 USEPA regulatory standard scenarios within the Pesticide Water Calculator (PWC, version 1.52) (USEPA 2016) model and their standard crop weather station locations were selected for the evaluation of the impact of the wind speed, temperature, relative humidity, and wind direction on off-target drift mass loadings onto an off-target area or water body. The USEPA standard scenarios

utilized in the present analysis were CA Tomato, CA Melon, FL Turf, IN Corn, and NJ Melon (USEPA 2016). The locations of the weather stations were Fresno, California (CA Tomato and CA Melon); Daytona Beach, Florida (FL Turf); Indianapolis, Indiana (IN Corn); and Wilmington, Delaware (NJ Melon), USA; details are provided in the Supplemental Data. These scenarios were selected for the present study due to having relatively low erosion vulnerability and reflecting a range of regional climates. It is important to note that the CA weather station is the same for both the tomato and melon scenarios; however, the application timing and associated weather parameters for each of these scenarios differ due to the crop emergence date within each scenario (CA Tomato is March 1st and CA Melon is May 16th).

Modeling simulated a generic pyrethroid active ingredient; specific application patterns for each scenario are provided in detail in Supplemental Data Table SI-2. The application pattern for the default assumptions modeling included 4 sequential aerial applications at a nominal rate of 0.1 kg/ha (similar to pyrethroid label rates) and a 7-d interval starting 7 d prior to the crop emergence date specified in each scenario. For the present study, the default assumption aerial off-target drift percent reflects an ASABE medium to coarse nozzle refinement and a drift setback buffer of 45.7 m (150 ft) resulting in a default drift of 1.97% for each application using the standard assumptions about temperature (30 °C or 86 °F), relative humidity (50%), and wind speed (4.47 m/s or 10 mph) and direction (toward the water body). Annual drift mass loads and the resulting 30-y drift mass loads (based on 1961–1990 weather data) were calculated for each of the 5 scenarios.

Estimating annual off-target drift loads

Estimation of annual off-target drift loads for the higher tier drift modeling in the present study was conducted in 3 steps. The first investigates the impacts of 3 key climatic AgDRIFT model inputs (wind speed, ambient temperature, and relative humidity) on multiple sequences of days. The second simply evaluates the likelihood that all applications are made with the wind blowing in the prevalent direction of the off-target water body. The third step combines Step 1 and Step 2. The detailed methodology for each of these steps is provided in the following sections.

Step 1: Drift load analysis: Wind speed, temperature, and relative humidity. The first refinement investigated was the combined impact of wind speed, temperature, and relative humidity as a single parameter. As wind speed and temperature increase, drift increases, and as relative humidity increases, drift decreases. The default assumption drift computed from AgDRIFT has a calculated drift of 1.97%. Examples of the influence of wind speed, temperature, and relative humidity on off-target drift are shown in the following list. Keeping other parameters at default values,

- if temperature decreases to 24 °C (75 °F), drift decreases to 1.84%;

- if wind speed decreases to 2.24 m/s (5 mph), drift decreases to 1.72%;
- if relative humidity increases to 75%, drift decreases to 1.58%; and
- if all of the above variations are combined, drift decreases significantly to 0.86%.

All crop scenarios had 7 application sets with 4 applications at a 7-d interval; weekly insecticide treatments may be required for severe infestations and are often permitted on product labels. To obtain sufficient distributional data to properly sample the potential combinations of climate data relevant for each crop–location combination, it was assumed that, in addition to the designated starting application date (e.g., 7 d prior to crop emergence) there was a window of alternative start dates, each 1 d later than the previous one. For each crop scenario, alternative start dates were identified until the next day fell on the date scheduled for the second aerial application corresponding to the original start date. The first application in Set 1 for CA Tomato is made on 22 February, CA Melon on 9 May, FL Turf on 25 January, IN Corn on 8 May, and NJ Melon on 24 April (see Supplemental Data Table SI-3 for all application dates and sets). Consequently, wind speed, temperature, and relative humidity combinations to be used as inputs for AgDRIFT were retrieved from the USEPA hourly SAMSON weather data for the individual weather stations associated with each standard crop scenario (USEPA 2018b). Temperature data were rounded to the nearest multiple of 5 °F, relative humidity was rounded to the nearest multiple of 5%, and wind speed was rounded to the nearest integer speed (mph). Given that these parameters can vary systematically throughout the day, the effect of time-of-day was examined in each crop scenario analysis using values separated by 4 h by obtaining the measured wind speed, temperature, and relative humidity for 6 set times of day (0400, 0800, 1200, 1600, 2000, and 2400 h) on each of the prescribed application days to give 6 equivalent time sets of co-occurring weather measurements for each sequence of application days (i.e., applications at 0400 h on every application day, at 0800 h on every application day, etc.). An initial analysis showed the same general pattern of wind speed and direction for the 6 selected hours versus all 24 h for each of the scenario's weather stations, indicating the 6 selected hours are representative of all 24 h for each scenario. It is important to note that the CA Tomato and CA Melon scenarios share the same weather station for regulatory modeling; however, because their application windows are different, they generated 2 entirely independent data sets.

Additionally, the frequency and percentage of applications that occur when wind speeds are exceeding 6.71 m/s (15 mph) across each of the same 5 scenarios were evaluated. As expected, the results vary considerably across the scenarios with the highest 6.71 m/s (15 mph) exceedance frequencies associated with the midday hours for the FL Turf, IN Corn, and NJ Melon scenarios. The data for

these analyses is provided in detail in Supplemental Data Table SI-4.

The extracted data were processed to produce model inputs; temperatures below 0 °C (32 °F) were truncated at 0 °C. Wind speeds exceeding 6.71 m/s (15 mph) were capped at 6.71 m/s due to pyrethroid labels restricting applications to wind speeds equal to or below 6.71 m/s. This process was repeated for all 30 y of the weather set used for each crop scenario. Table 1 compares the 30-y mean climate parameter values for all 6 application hours of Set 1 application dates for the 5 scenarios with the default regulatory assumptions (see Supplemental Data Table SI-5 for all sets of data). In general, compared to the 30-y average values of drift parameters for those dates for each scenario, the 4.47 m/s (10 mph) wind speed default is slightly overestimated, the 30 °C (86 °F) default temperature is considerably warmer, and the 50% relative humidity assumption is generally an underestimate.

Each time-period–day combination of wind speed, temperature, and relative humidity for a given year was then processed using the AgDRIFT model (version 2.1.1) using the Tier II Aerial option and run with an ASABE Medium to Coarse droplet size (required on pyrethroid product labels). The percent of off-target drift was then calculated by the "Toolbox-Aquatic Assessment" using the "EPA-Defined Pond" with a 45.7-m (150-ft) nonsprayed buffer distance to the water body. Those setback buffer distance and the droplet size parameters reflect mandated pyrethroid label requirements. For Step 1, it was assumed that the wind was blowing directly toward the water body on each application day and time. This process was repeated for all 30 y of the weather set used for each crop scenario.

Using the off-target drift percent calculated from AgDRIFT for each application, the resulting drift load estimates (drift percent × 0.1 kg/ha application rate × 1-ha surface area of pond) were then summed for all aerial applications in that year separately for each time of day. These annual drift load estimates from each of the 30 individual years were each divided by the annual default assumption drift load (4 applications at 0.1 kg/ha with 1.97% drift). The resulting ratios were then ranked and plotted as annual exceedance probabilities to produce a set of 6 distributions of expected annual drift load ratios (one for each 4-h application time of day). The individual drift loads for each individual year could then be compared with the drift load used for default assumption model runs in which 100% of the theoretical annual maximum AgDRIFT load was transported to the receiving water on every occasion in every year. This process was repeated 6 times for each of the alternative start dates to produce 7 application sets of output. As an example, Figure 1 shows these results for 4 CA Tomato scenario application sets and Figure 2 shows Application Set 1 for the other 4 scenarios. Similar figures for all application sets for each scenario are provided in Supplemental Data Figures SI-1 to SI-5.

The off-target drift load results displayed in Figure 1 and Figure 2 plot the loads versus the exceedance probability

Table 1. Example 30-y average values of climatic drift parameters for CA, FL, IN, and NJ weather stations at 6 times (0400, 0800, 1200, 1600, 2000, and 2400 h) on 4 Set 1 application dates

Weather parameter	Scenario	Representative hour (Set 1)[a]						All times for Set 1
		0400	0800	1200	1600	2000	2400	
Wind speed, m/s (Default = 4.47 m/s or 10 mph)	CA Tomato	2.67	2.79	3.45	3.88	2.91	2.70	3.07
	CA Melon	3.15	3.41	3.48	4.40	4.74	4.35	3.92
	FL Turf	2.86	3.26	5.18	5.35	3.53	3.30	3.91
	IN Corn	3.35	4.17	5.13	5.33	4.24	3.74	4.33
	NJ Melon	3.61	4.51	5.37	5.57	4.51	3.92	4.58
Temperature, °C (Default = 30 °C or 86 °F)	CA Tomato	7.6	8.7	15.6	17.7	12.7	9.3	12.0
	CA Melon	13.6	18.5	26.0	28.6	23.1	17.1	21.1
	FL Turf	11.3	12.2	18.7	19.1	14.8	13.2	14.9
	IN Corn	13.4	15.8	20.8	22.2	19.0	15.3	17.8
	NJ Melon	10.6	13.6	17.9	18.4	14.8	12.1	14.6
Relative humidity, % (Default = 50%)	CA Tomato	87.9	82.1	57.7	47.9	68.3	81.9	71.0
	CA Melon	70.7	54.3	33.9	26.3	37.7	55.3	46.4
	FL Turf	84.8	83.2	61.4	60.0	77.4	82.7	74.9
	IN Corn	83.4	76.5	59.9	53.9	62.8	76.0	68.8
	NJ Melon	78.7	69.8	55.9	55.6	66.9	75.0	67.0

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; mph = miles per hour; NJ = New Jersey, USA.
[a]Only 1 application set (Set 1) is shown (additional application set and scenario data are in Supplemental Data). Averages were computed assuming a maximum wind speed of 6.71 m/s (15 mph) and lower temperature limit of 0 °C (32 °F).
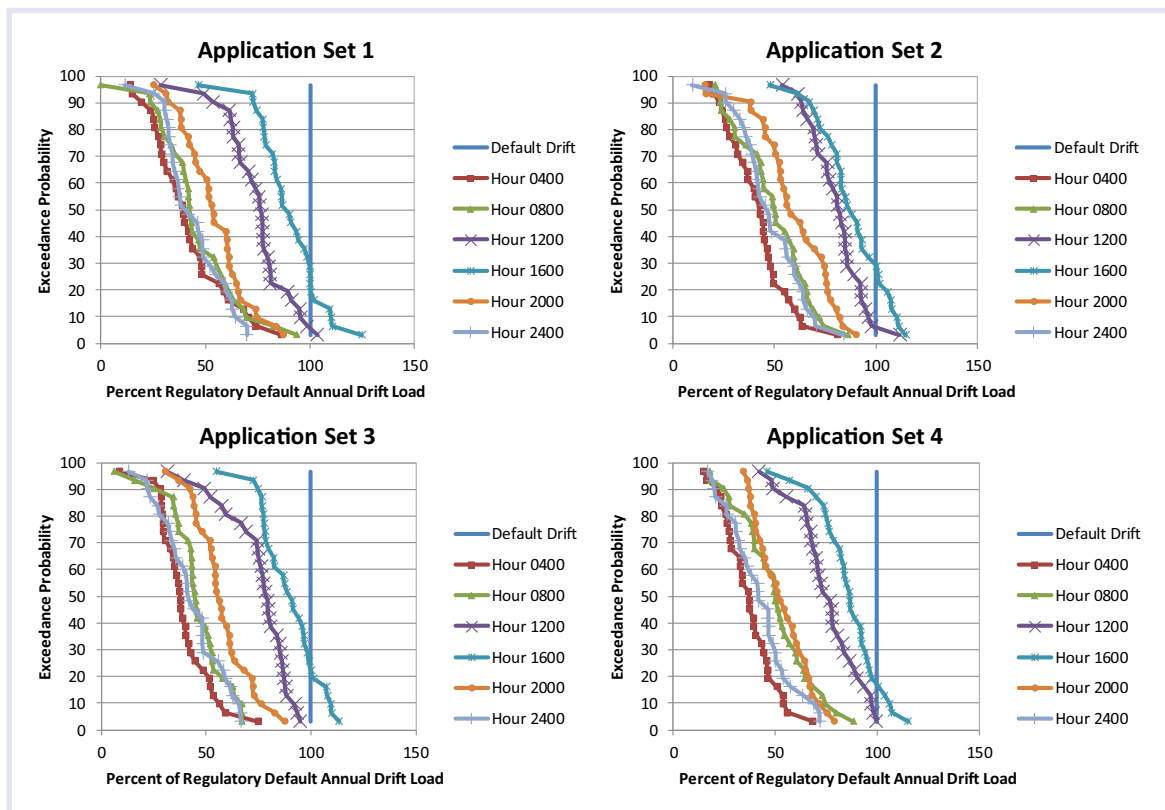
Figure 1. AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times based on wind speed, temperature, and relative humidity data from the CA Tomato scenario (only Sets 1–4 are shown; however, similar patterns are seen for Sets 5–7 (see Supplemental Data Figure SI-1). CA = California, USA.
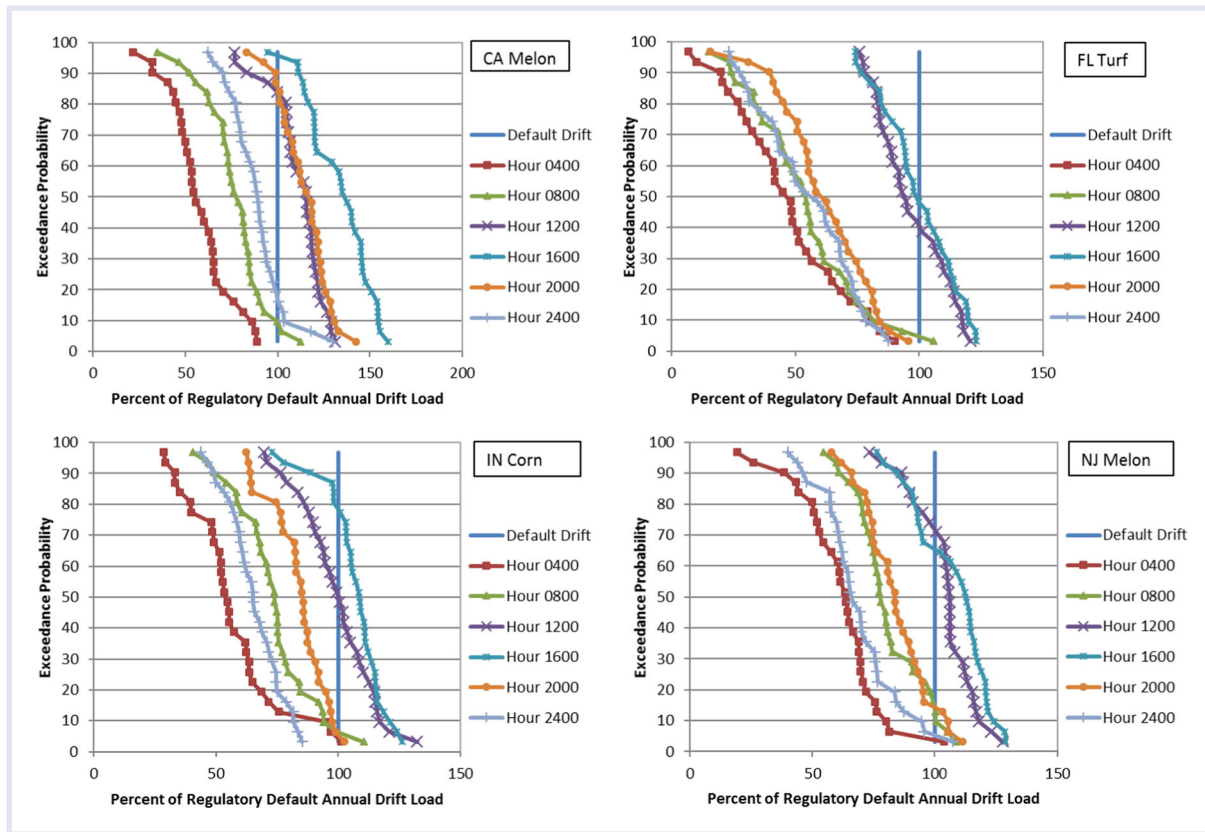
Figure 2. AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times based on wind speed, temperature, and relative humidity data from the CA Melon, FL Turf, IN Corn, and NJ Melon scenarios (Application Set 1 only; remaining sets provided in Supplemental Data Figures SI-2 to SI-5). CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.

(Haan 1977). In the default assumption simulations, every year generated the same aerial drift load; these default assumption distributions are therefore vertical lines with every load being 100% of the standard AgDRIFT load. The remaining lines reflect the ranked distribution of total aerial drift loads across 30 y for each of the 6 times of day. As an example of interpretation, using Application Set 1 in Figure 1 and considering the 0800 h distribution, the graphic shows that every other year (50th percentile probability) the drift load will be below 50% of the load estimated by the default modeling. For all 30 y, the drift load at 0800 h is always below the default estimate. The distribution profiles for each of the application times across each of the applications sets appear relatively similar. This indicates that the climatic variability between sets is not substantial for the CA Tomato scenario. Likewise, the other crop scenarios had similar distribution profiles as well across their respective application sets, and these are shown in the Supplemental Data.

By examining each set in Figure 1, it is apparent that if aerial applications are made at 1200 h or 1600 h, part of the upper end of the predicted annual drift load distribution exceeds the estimated default drift load. However, even where this occurs, the majority of the annual loads (and, in every case, for the 0400, 0800, 2000, and 2400 h application timings) will be below the estimated default

assumption load for the CA Tomato scenario, sometimes by a very significant margin.

The results of the annual off-target drift load analyses in Figure 1 and Figure 2 and the related figures in the Supplemental Data provide some interesting insights, including a real world data-based confirmation of the conventional wisdom that applications made around noon and during the afternoon hours are more likely to be subject to higher wind speeds and drift loads.

Table 2 provides the range of annual AgDRIFT drift load estimates based on wind speed, temperature, and relative humidity across 30 y (1961–1990) of applications for Set 1 of each scenario (effectively reflecting the maximum, minimum, and mean drift loads for each line plotted in Figure 1 and Figure 2). As expected from the figures, there are a few maximum annual drift loadings across the application times and scenarios that slightly exceed the estimated annual drift load based upon the default assumption. However, when comparing the mean values, the vast majority of application times had predicted annual drift loads at or below the default assumption. Only application times of 1200, 1600, and 2000 h had mean annual drift loading values above the default estimate for three of the scenarios (CA Melon, IN Corn, and NJ Melon) which is consistent with wind speeds typically being higher during the afternoon hours. Table 3 compares the cumulative summed aerial 30-y drift loads for

Table 2. Range of annual AgDRIFT drift load estimates (kg) for Application Set 1 for each scenario wind speed, temperature, and relative humidity data

Crop scenario		Range of annual drift loadings (kg) for Application Set 1 (based on 30 y of applications)						Default estimate[a]
		0400	0800	1200	1600	2000	2400	
CA Tomato	Minimum	0.0011	0.0000	0.0022	0.0037	0.0020	0.0009	0.00788
	Maximum	0.0068	0.0074	0.0082	0.0098	0.0069	0.0055	
	Mean	0.0033	0.0036	0.0059	0.0071	0.0043	0.0035	
CA Melon	Minimum	0.0017	0.0027	0.0060	0.0074	0.0066	0.0049	0.00788
	Maximum	0.0070	0.0089	0.0103	0.0126	0.0112	0.0102	
	Mean	0.0045	0.0060	0.0088	0.0105	0.0090	0.0070	
FL Turf	Minimum	0.0005	0.0012	0.0060	0.0059	0.0012	0.0018	0.00788
	Maximum	0.0071	0.0083	0.0095	0.0097	0.0075	0.0069	
	Mean	0.0037	0.0042	0.0076	0.0079	0.0048	0.0043	
IN Corn	Minimum	0.0023	0.0032	0.0055	0.0058	0.0049	0.0034	0.00788
	Maximum	0.0080	0.0087	0.0104	0.0099	0.0081	0.0067	
	Mean	0.0045	0.0058	0.0078	0.0084	0.0066	0.0052	
NJ Melon	Minimum	0.0015	0.0043	0.0058	0.0060	0.0046	0.0032	0.00788
	Maximum	0.0082	0.0086	0.0101	0.0102	0.0088	0.0085	
	Mean	0.0048	0.0064	0.0082	0.0085	0.0066	0.0054	

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.
[a]Default regulatory assumption annual drift mass load = drift fraction × number of applications × rate (kg) (0.0197 × 4 × 0.1 = 0.00788 kg).

Table 3. Percent difference relative to default modeling of cumulative 30-y AgDRIFT aerial drift load estimates and those for selected[a] scenario application sets based on real-world hourly wind speed, temperature, and relative humidity data

Crop scenario	Application set	Aerial application hour (percent difference relative to default 30-y drift load)[b]					
		0400	0800	1200	1600	2000	2400
CA Tomato	1	−59%	−55%	−26%	−10%	−46%	−56%
	2	−58%	−51%	−19%	−12%	−41%	−52%
	3	−61%	−55%	−25%	−11%	−43%	−57%
	4	−63%	−50%	−25%	−14%	−47%	−58%
	5	−61%	−56%	−23%	−13%	−45%	−59%
	6	−63%	−56%	−24%	−12%	−46%	−56%
	7	−64%	−56%	−25%	−12%	−42%	−56%
CA Melon	1	−42%	−24%	11%	34%	14%	−12%
FL Turf	1	−53%	−46%	−3%	0%	−39%	−45%
IN Corn	1	−44%	−27%	−1%	7%	−16%	−34%
NJ Melon	1	−39%	−19%	4%	7%	−16%	−31%

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.
[a]Complete data are provided in Supplemental Data Tables SI-6 and SI-7.
[b]A decrease from the 30-y estimated drift mass using default assumptions is represented by a negative percentage and an increase is represented by a positive percentage.

all sets for CA Tomato and Set 1 for the remaining scenarios with the load estimated using default assumptions. The values are expressed as percentage differences from the regulatory default assumption 30-y total drift mass load of 0.236 kg (30 × 0.00788). As an example of interpretation, for CA Tomato Application Set 1 0800 h value of −55%, this indicates a reduction in the 30-y drift load of 55% from the default estimate, that is, a reduction factor of 2.2-fold ((100/100 − 55) = 2.2).

Table 3 suggests that, although there are mass load differences between locations for a given application time, the differences between application times at a given location may be even greater. However, the range of the difference is rather small across the application sets (i.e., Sets 1–7) indicating that, generally, drift-related parameters vary diurnally in similar manner at similar times of the year. This trend was observed for the other 4 scenarios for which full tables are provided in the Supplemental Data. It is important to point out that there are a few occasions (i.e., CA Melon 1200, 1600, and 2000 h) in which the wind speed, temperature, and relative humidity generate drift mass loadings that are slightly higher than the drift mass derived using default assumptions. These are likely a result of a combination of higher wind speeds, higher temperatures, and lower relative humidity (i.e., >4.47 m/s (10 mph), >30 °C (86 °F), <50%, respectively) during those times of the day with higher wind speed probably being the dominant factor.

Step 2: Drift load analysis: Wind direction. In addition to the assumptions about wind speed, ambient temperature, and relative humidity previously discussed, standard USEPA Tier II modeling assumes the wind is always blowing toward the receiving water body, which is clearly conservative for even a 30-y simulation of a single application to a single field. However, in the real world, at the catchment scale, this default assumption becomes even less probable because multiple fields will all have different orientations relative to the receiving water body (or bodies) and thus, even on a simulated single spray day, the wind is unlikely to direct drift to the receiving water body from all fields. As with the other drift-related parameters examined in Step 1, wind direction can also vary systematically throughout the day. Therefore, the effect of time-of-day was again accounted for in each crop scenario using directions separated by the same 4-h intervals by obtaining an approximation of the wind direction (in degrees) for the same 6 times of day (0400, 0800, 1200, 1600, 2000, and 2400 h) on each aerial application day to give 6 equivalent time sets of sequential wind directions for each application day.

To generate off-target drift mass loads that account for wind direction, the prevailing wind direction was abstracted from the scenario-specific weather station data used in Step 1. The methodology used to determine the prevailing wind direction (expressed as a 90-degree range) for each application time (Set 1 only) for each scenario is described in the Supplemental Data. Table 4 summarizes the variation in

Table 4. Prevailing wind direction for the 6 application times at each scenario location over 30 y of applications

Hour	Wind direction (degrees, averaged across all sets)				
	CA Tomato	CA Melon	FL Turf	IN Corn	NJ Melon
0400	300	320	320	230	310
0800	110	310	320	230	320
1200	140	290	270	230	320
1600	320	300	20	230	300
2000	310	300	140	200	180
2400	310	310	250	200	300

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.

the prevailing wind direction for each application time across each of the scenarios.

Figure 3 shows the count of years (out of the 30 y evaluated) that have a specified number of the 4 applications made when the wind was blowing within ±45 degrees of the prevailing wind direction. For example, of all the scenarios, only CA Tomato had a single year when all 4 applications were made when the wind was within ±45 degrees of the prevailing direction. The CA Melon scenario had the most consistent wind direction with 3 out of 4 applications within ±45 degrees of the prevailing wind occurring in 14 out of 30 y.

The Step 2 drift mass load analysis was conducted for each of the application times for 30 y but for Application Set 1 only, given that the Step 1 analysis strongly suggested that there is little difference between sets within the same season. If the wind direction for an application was ±45 degrees from the prevailing direction, the drift load was assumed to be 100% of the default estimated load; if not, the load was assumed to be 0%. The resulting directional drift load estimates were then accumulated for each aerial application in that year for each time period. These summed drift load estimates from each of the 30 individual years were each then processed as before to express the data as a percentage of the default estimated drift load to be plotted
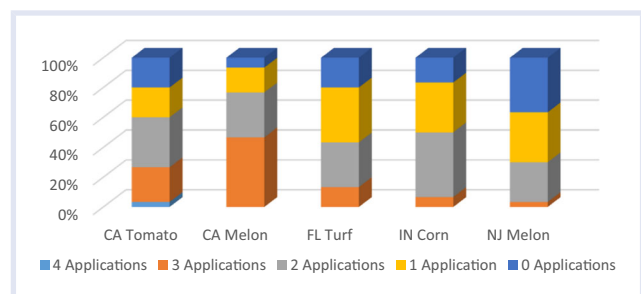
Figure 3. The number of years (out of 30) with annual applications in the same direction (±45 degrees) of as the prevailing wind for Application Set 1 (0800 h) for 5 crop scenarios based on wind direction data.
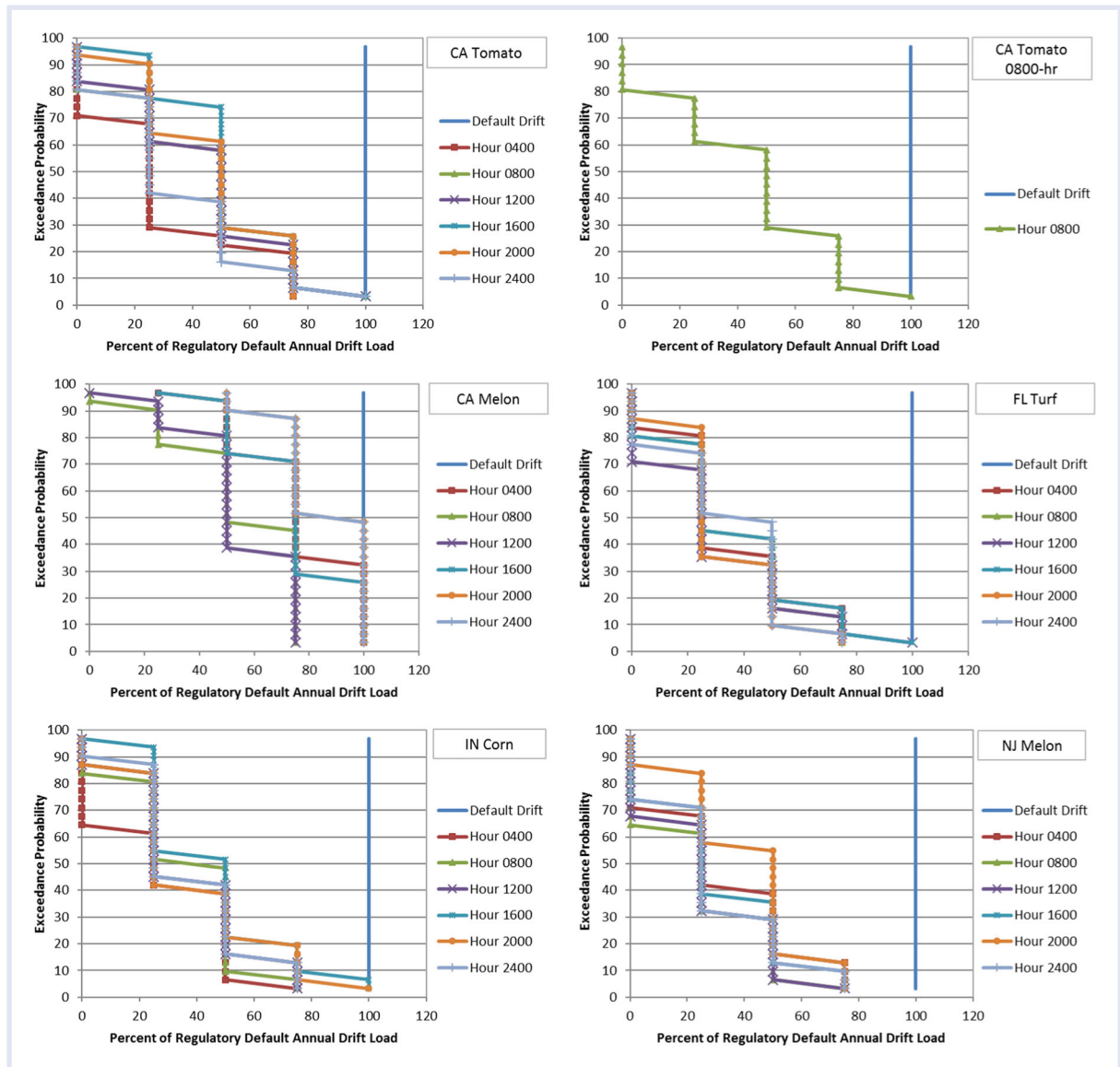
Figure 4. AgDRIFT estimated drift loadings for Set 1 sequential aerial applications (4) for 6 application times of day based on wind direction for 5 crop scenarios (assuming all other factors affecting drift load remain unchanged).

as a probability distribution for comparison with the load derived from default parameters (100% of the theoretical maximum AgDRIFT load on every occasion in every year). This process was repeated for Set 1 of each of the 5 crop scenarios in the present study (Figure 4). With 4 applications simulated, there are only 5 possible outcomes from the directional analysis (0%, 25%, 50%, 75%, or 100% of the default drift load) depending on the number of applications that occur when the wind direction approximates the prevailing direction; this causes the stair-step appearance of the graphs in Figure 4. Using the CA Tomato Application Set 1 shown in Figure 4 as an example and considering the 0800 h distribution (a separate graphic of the 0800 h data is provided for clarity), every other year (50th probability) the drift load is 50% of the default estimated load. For 29 out of the 30 y of simulations, the drift load at 0800 h is below the default estimate.

Figure 4 shows that considering wind direction will only reduce estimates of off-target drift load relative to the default assumption that conservatively assumes the wind is always in the direction of the off-target water body for every aerial application in a sequence. The 5 crop scenario charts indicate that the probability that all 4 applications will occur when the wind blows in the same direction is low at any of the times of day. Excluding CA Melon, the probability of even 3 of the 4 applications occurring with the prevailing wind direction is less than 25% for each of the 6 application times. CA Melon is the exception with the 0400, 1600, and 2400 h applications having the wind blowing in the same direction for all 4 events in approximately 25% to 50% of the 30 y. This might be because the time of year for the CA Melon applications (May) corresponds to a more consistent prevailing wind than for the other scenario locations and timing.

Table 5. Percent difference relative to default modeling of cumulative 30-y aerial AgDRIFT drift load estimates for Application Set 1 based on wind direction

Crop scenario	Aerial application hour (percent difference relative to default 30-y drift load)[a]					
	0400	0800	1200	1600	2000	2400
CA Tomato	−71%	−58%	−58%	−49%	−54%	−66%
CA Melon	−24%	−46%	−46%	−26%	−15%	−15%
FL Turf	−66%	−66%	−70%	−64%	−68%	−67%
IN Corn	−73%	−65%	−64%	−56%	−63%	−63%
NJ Melon	−69%	−76%	−75%	−70%	−61%	−72%

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.
[a]A decrease from the 30-y default assumption drift mass is represented by a negative percentage, and an increase is represented by a positive percentage.

Table 5 provides the cumulative summed aerial 30-y drift loads for each of the scenarios based upon the default assumptions alongside the relative 30-y drift load percent differences for the estimated drift loads for Application Set 1 based on wind direction. For example, the FL Turf 0800 h load is reduced by 66% indicating a reduction in the 30-y drift load of 66% relative to the default estimate (i.e., a reduction factor of 2.9-fold).

Table 5 shows that the natural variation in wind direction (across 30 y [1961–1990] at each of the locations) for 4 sequential weekly applications at a range of times of day results in substantial reductions compared to the estimated 30-y drift mass loading derived using default assumptions. The CA Melon scenario had the smallest percent difference with reductions of 15% to 46%, with the other 4 scenarios showing a much greater impact resulting in a range of 49% to 76% reduction relative to the default.

Step 3: Drift load analysis: Combined climate parameters. The next step in the present study was to evaluate the combined impact of wind speed, temperature, and relative humidity together with wind direction data. Because the wind direction analysis considered only Set 1 for each scenario, the combined parameter analysis also examined only the Set 1 sequence. The process of calculating the drift load estimates for the combined analysis was the same as it was for the wind direction analysis, with the following modifications. Applications made with a wind direction within ±45 degrees of the prevailing wind direction were considered as receiving an off-target drift load estimated on the basis of the wind speed, temperature, and relative humidity for that specific application day and time (i.e., the Step 1 load). If the wind was from any other direction, the drift load was considered to be zero.

The same process was followed to generate percent differences from the default estimated load, and these were then ranked and plotted as exceedance probabilities (Haan 1977) to produce 6 distributions of expected annual drift load ratios (Figure 5). Considering the 0800 h distribution

from CA Tomato Application Set 1, the figure shows that every other year (50th probability) the drift load will be about 20% of the load based on the default model assumptions. Interestingly, for all 180 estimated loads across 30 y for CA Tomato, only 1 (1600 h application) exceeds the default drift load estimate.

Table 6 provides the cumulative summed aerial 30-y drift loads for each scenario based upon the default model assumptions alongside the Step 3 relative 30-y drift load percent differences estimated for Application Set 1. It shows that the CA Tomato 0800 h drift load is reduced by 79%, corresponding to a reduction factor of 4.8-fold.

Table 6 shows that the impact of all 4 drift-related climate variables across each of the scenarios and application times was a substantial reduction of the estimated 30-y drift mass loading in all cases except the 1600 h and 2000 h application times of the CA Melon scenario. The percent difference relative to the default 30-y drift mass load estimate for the other 4 scenarios ranged from 50% to 86% reduction across all times of day, whereas the range for CA Melon was a slight increase of 5% to a reduction of 53%. Despite sharing the same weather station, the CA Tomato and CA Melon simulations generated appreciably different drift loads due to the differing application windows.

Wind speed and direction analysis

The present study also investigated relationships between wind direction and wind speed given that any correlation between these factors could systematically impact drift load estimates. Wind rose plots demonstrating those relationships are provided in the Supplemental Data. The CA Melon and CA Tomato had very different wind roses even though it was the same weather station indicating the variability of wind direction throughout the year. The results suggest that, for a given location, winds with speeds >4.47 m/s (10 mph) (i.e., those likely to cause higher off-target drift) may be more strongly associated with just one or a few directions than slower speed winds. This would be expected to make wind direction an even more significant variable for the higher drift load events.

DISCUSSION AND CONCLUSIONS

The results from the present analysis demonstrate the impact that real-world climatic data (wind speed, temperature, relative humidity, and wind direction) can have on the estimation of off-target drift mass deposition across 5 USEPA standard crop scenarios, especially when compared to estimates based on regulatory default assumptions. Step 1 showed that incorporating wind speed, temperature, and relative humidity data results in greater reductions in estimated off-target drift deposition for morning and evening application times due to lower wind speed and temperatures and higher relative humidity. Estimated drift loads for 7 sequences of 4 applications spaced 7 d apart, but which started on 7 successive days, gave very similar 30-y drift loading patterns. This suggests that weather patterns are consistent within a monthly period
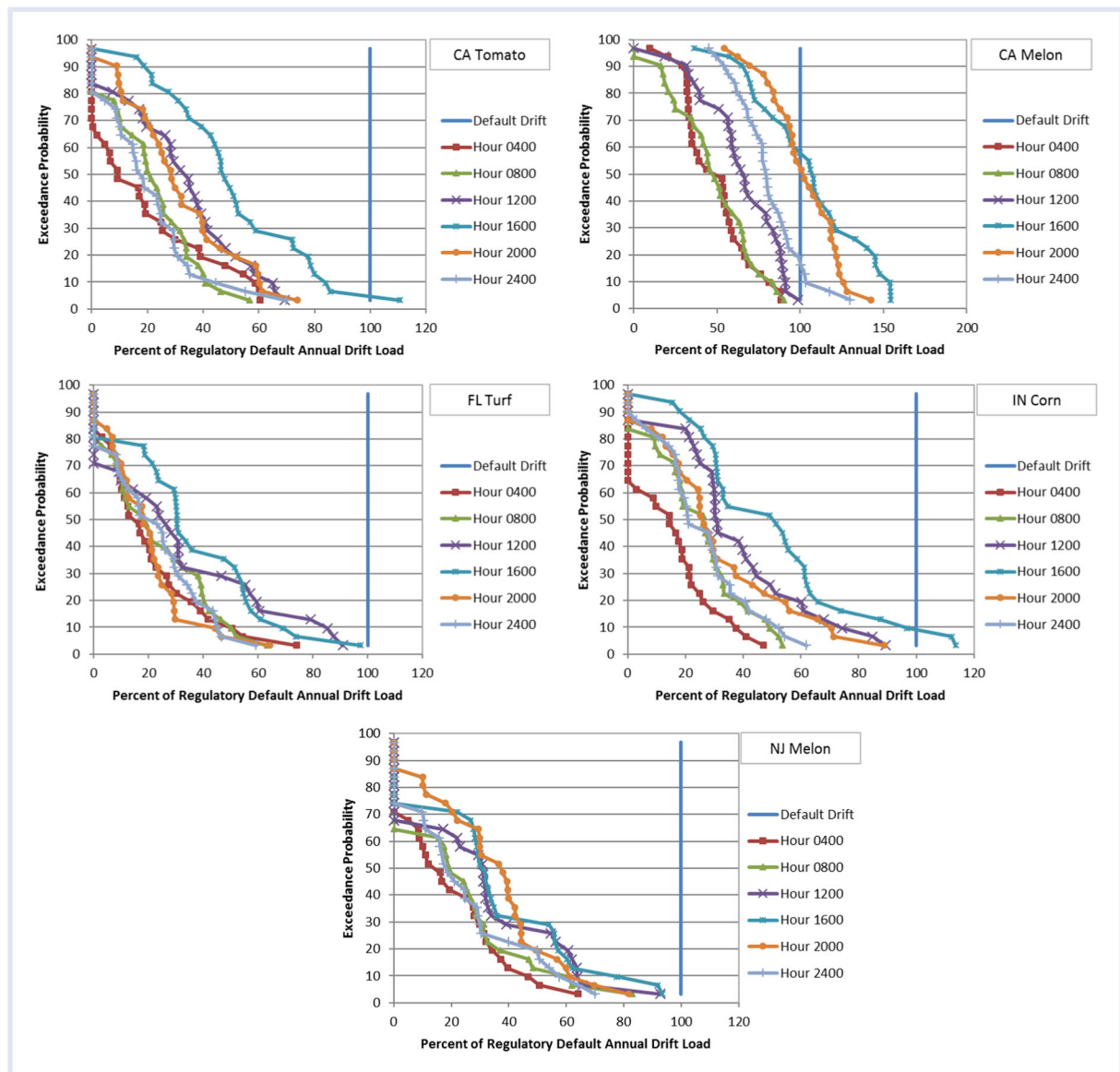
Figure 5. AgDRIFT estimated drift loadings for Application Set 1 sequential aerial applications for 6 application times of day based on combined climate data for 5 crop scenarios.

when examined on a 30-y time scale. Wind direction also has a considerable impact on the estimated 30-y drift mass loading across almost all scenarios and times of day. When all 4 parameters are used as model inputs, their combined effect is increased. For 4 scenarios, the estimated drift loads were reduced from 50% to 86% relative to the regulatory default estimate. However, for CA Melon, 2 times of day generated estimates very slightly higher than the default (2% and 5%), whereas the remainder showed reductions between 19% to 53%. Further analyses indicated that wind speed and direction at a given location and season may be associated, which would further increase the significance of wind direction for some higher risk events.

Current USEPA modeling methodology for assessing regulatory ecological or drinking water exposure uses default drift-related parameters (wind speed, temperature, and relative humidity) to estimate off-target drift deposition

representing a single high-exposure condition for every application of a sequence of pesticide applications over a 30-y simulation (Teske et al. 2003; USEPA 2012). Additionally, every application simulation assumes the wind is blowing directly toward the receiving water body. Results from the present analysis show that, when there are multiple applications in a sequence, the cumulative likelihood of the high-exposure condition applying to all applications is much lower. The present study shows how using realistic climate data to estimate off-target drift loading reduces unnecessary uncertainty and substantially reduces the expected drift mass loading compared to using regulatory defaults. Given the range of scenarios evaluated in the present analysis, it is reasonable to assume similar impacts across all USEPA crop scenarios.

The AgDRIFT model includes a multiple application assessment (MAA) tool for estimating the probabilistic impact

Table 6. Percent differences from default assumption modeling of summed 30-y aerial AgDRIFT drift load estimates for Application Set 1 based on the Step 3 analysis for 5 crop scenarios

Crop scenario	Aerial application hour (percent difference from default estimate 30-y drift mass load)[a]					
	0400	0800	1200	1600	2000	2400
CA Tomato	−82%	−79%	−68%	−50%	−69%	−80%
CA Melon	−51%	−53%	−36%	5%	2%	−19%
FL Turf	−80%	−78%	−70%	−66%	−81%	−79%
IN Corn	−86%	−76%	−63%	−51%	−69%	−75%
NJ Melon	−81%	−78%	−71%	−67%	−67%	−77%

CA = California, USA; FL = Florida, USA; IN = Indiana, USA; NJ = New Jersey, USA.
[a]A decrease from the 30-y default estimated drift mass is represented by a negative percentage and an increase is represented by a positive percentage.

of wind speed and direction changes on sequential applications to the same spray area (USEPA 2012). However, this tool is not currently considered by USEPA for regulatory risk assessments. The MAA tool computes a drift fraction based on the weather station location (using wind speed, temperature, and relative humidity), wind direction, and number of applications. For example, in Fresno, California with 4 applications in February and March, maximum wind speed of 7 m/s (15.7 mph), medium to coarse droplets, and 45.7-m (150-ft) setback there was a drift of 0.62% from the Tier II Aerial MAA tool compared to 1.97% drift from the USEPA default approach. This results in a reduction of 68% drift mass over the sequence of 4 applications each year over 30 y, which is similar to the CA Tomato Step 3 analyses (71% reduction). Interestingly, this comparison between MAA output and the results from the present study suggest that the MAA tool already included in AgDRIFT would be a simple way to incorporate refined approaches associated with wind speed and direction into spray drift risk assessments.

Another study, which was conducted at the watershed level (Winchell et al. 2018), investigated the impact of incorporating several site-specific parameters in a stepwise approach (i.e., annual application data, field-scale application data, observed wind direction and speed, and stream geometry) as refined modeling inputs from a screening-level approach. The resulting concentrations were compared to observed field data, and the greatest model improvements were associated with the wind speed and wind direction parameters (Winchell et al. 2018).

The present study approach only considers the effect of real-world conditions for multiple applications; refined drift simulations must also incorporate other factors such as mandated spray nozzle impacts on droplet size distributions, aerial application boom specification, the inclusion of droplet size modifying adjuvants, and requirements for no-spray buffers.

In the real world, at the catchment scale, this default assumption regarding wind direction becomes even less probable because multiple fields growing the crop of interest will all have different orientations relative to any receiving water bodies and thus, even on a simulated single spray day, the wind (which will have a uniform direction at the catchment scale) is extremely unlikely to direct drift to the receiving water body from all fields being treated.

Even though the present study approach refines the realism of off-target drift mass loadings, these estimates should still be considered conservative due to additional factors. These factors include natural wider buffer areas, natural wind breaks, the effect of trees and brush at filtering droplets, water surface in receiving waters being below land level and uncropped roadways, and the fact that multiple fields on the same farm are unlikely to be sprayed simultaneously. For example, a spatial analysis examining some of these factors was previously evaluated in the high cotton-producing Yazoo County, Mississippi, USA (Hendley et al. 2001). Results from that study show 92% of ponds in this region have no cotton grown within a 60-m buffer area, and only 2% of the ponds have cotton present in all directions around the ponds and within a 120-m buffer area (Hendley et al. 2001). Results also show that the composition of these buffer areas found between agriculture and water bodies were comprised of 78% to 87% dense trees, sparse trees, or brush, depending on the type of water body, thus reducing the expected loading of off-target drift into nearby water bodies (Hendley et al. 2001) due to filtering of the drift before entry. Similar results were obtained for orchard terrestrial environments in Europe (Thomas et al. 2016).

Additionally, the significance of drift entry may be overestimated relative to runoff because it is extremely episodic and will occur only for those fields that are near water on a few days of each year and then only when conditions are adverse (i.e., in cases where a field is near a water body, and wind speed is significant and blowing toward the pond with no natural vegetation in the way). In contrast, runoff will occur from all fields, and the resulting runoff (albeit without a lot of deposited sediment) will reach "receiving waters" on potentially many more occasions each year.

The present analysis was limited to the AgDRIFT modeling input parameters used by USEPA in standard regulatory risk assessments; however, other parameters such as type of aircraft, nozzle types, release heights, swath widths, and other environmental conditions could be evaluated for potential impact on off-target drift deposition as well. The authors speculate an analysis of these other parameters would result in similar conclusions that the uncertainty associated with the conservative approaches used in USEPA regulatory modeling could be improved with the use of site-specific real-world data.

consisting of member companies AMVAC Chemical Corp., BASF Crop Protection, Bayer CropScience, FMC Corporation, Syngenta Crop Protection, and Valent USA. The authors conducted all work directly for or as contractors to the primary registrants of the pyrethroids.

Data Availability Statement—Data and associated calculation tools for this manuscript are available as supplemental files or from corresponding author Dean Desmarteau (desmarteaud@waterborne-env.com) upon request.

SUPPLEMENTAL DATA

Supplemental information provides additional data and analysis not included in the manuscript.

Figure SI-1. Ranked Sets 1 to 7 AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times of day based on historical wind speed, temperature, and relative humidity data across 30 y for the CA Tomato scenario.

Figure SI-2. Ranked Sets 1 to 7 AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times of day based on historical wind speed, temperature, and relative humidity data across 30 y for the CA Melon scenario.

Figure SI-3. Ranked Sets 1 to 7 AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times of day based on historical wind speed, temperature, and relative humidity data across 30 y for the FL Turf scenario.

Figure SI-4. Ranked Sets 1 to 7 AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times of day based on historical wind speed, temperature, and relative humidity data across 30 y for the IN Corn scenario.

Figure SI-5. Ranked Sets 1 to 7 AgDRIFT estimated drift loadings for sequential aerial applications for 6 application times of day based on historical wind speed, temperature, and relative humidity data across 30 y for the NJ Melon scenario.

Figure SI-6. CA Tomato 30-y wind rose plots for all sets for 0400, 0800, 1200, 1600, 2000, and 2400 h.

Figure SI-7. CA Melon 30-y wind rose plots for all sets for 0400, 0800, 1200, 1600, 2000, and 2400 h.

Figure SI-8. FL Turf 30-y wind rose plots for all sets for 0400, 0800, 1200, 1600, 2000, and 2400 h.

Figure SI-9. IN Corn 30-y wind rose plots for all sets for 0400, 0800, 1200, 1600, 2000, and 2400 h.

Figure SI-10. NJ Melon 30-y wind rose plots for all sets for 0400, 0800, 1200, 1600, 2000, and 2400 h.

Table SI-1. AgDRIFT Tier I/Tier II aerial simulation parameters.

Table SI-2. Application use pattern modeling inputs.

Table SI-3. Aerial application timing regimes for all scenarios.

Table SI-4. Number and percentage of days when hourly wind speed exceeds 6.71 m/s (15 mph) across 30 y.

Table SI-5. Thirty-year averages for wind-related drift parameters for CA, FL, IN, and NJ weather stations at 6 hours.

Table SI-6. Cumulative 30-y aerial AgDRIFT drift loads for all scenario application sets based on historical wind speed, temperature, and relative humidity.

Table SI-7. Percent difference relative to default modeling of cumulative 30-y aerial AgDRIFT drift load estimates for all scenario application sets based on historical wind speed, temperature, and relative humidity data.

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