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Fungicide Selection, Disease Risk, and Grower Switching Behavior

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Abstract

Disease management may require multiple decisions by growers on whether to apply a pesticide, the frequency of applications, and also the type of pesticide to use. We developed models for estimating the probability of switching behavior by hop growers related to use of nonsynthetic or synthetic fungicides, or mixtures thereof, for hop powdery mildew (*Podosphaera macularis*). Growers used nonsynthetic fungicides alone in 61.5% of their applications, later switching to synthetic fungicides or mixtures of the two in 21.5 or 17.0% of their total applications, respectively. Binary logistic regression predicted that the likelihood of switching fungicide type was associated with use of a nonsynthetic fungicide in the first application of the year and how early in the season growers made that application. The predicted probability of switching increased proportionate to the incidence of plants with powdery mildew but with a weaker effect. Multinomial logistic regression modeling of switching between nonsynthetic, synthetic, or mixtures of fungicides indicated a complex pattern of switching behavior. A random forest classification algorithm identified the most important variables in the multinomial logistic regression model as time of year, individual grower effects, the date of the first application, seasonal mean disease incidence, thoroughness of spring pruning, and cultivar susceptibility to two races of the fungus. Overall, our analyses indicate that growers switch from nonsynthetic fungicides to more active (and more expensive) synthetic fungicides or mixtures thereof at critical periods of crop susceptibility and when expected or observed disease incidence increases. Reducing the use of synthetic fungicide inputs may be closely linked to disease risk mitigation, as risk mitigation is indissolubly linked to growers' decisions to switch to these more potent fungicides or fungicide mixtures.

Keywords: epidemiology, fungi, hops

Growers face multiple decisions when managing foliar diseases with repeating cycles (Pfender et al. 2011). Among these decisions, a grower must choose when to begin intervention, the timing and frequency of repeated treatment, and what fungicide or fungicides to use. The choice of what fungicide or mixtures of fungicides to use may have immediate consequences for the effectiveness of management efforts, input costs, and the likelihood of large variances in revenue should their intervention efforts fail. These decisions also have longer-term consequences: how quickly fungicide resistance develops in a population based on frequency of use of a given mode of action (van den Bosch et al. 2014), environmental impacts on nontarget organisms (Tang et al. 2021), and, potentially, market access owing to pesticide residues (Handford et al. 2015).

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Societal and regulatory pressures to reduce the risk of agricultural pesticides are increasing (Lamichhane et al. 2016). There is particular concern and scrutiny surrounding synthetic pesticides as well as more hazardous nonsynthetic pesticides (Finger and Möhring 2024). The U.S. Government Code of Federal Regulations defines a synthetic as "a substance formulated or manufactured by a chemical process or by a process that chemically changes a substance extracted from naturally occurring plant, animal, or mineral sources, except that such term shall not apply to substances created by naturally occurring biological processes" (National Archives 2024). Nonsynthetic refers to a pesticidal substance that is derived from mineral, plant, or animal matter and does not undergo a synthetic process. This class of pesticides includes biopesticides and elements occurring naturally in the environment, such as sulfur or copper. There is much interest in quantifying when and why growers apply a given fungicide and their tactical decisions to switch the fungicide type they are using. Understanding the drivers of these decisions may uncover opportunities for reducing the use of synthetic fungicides or refine future research and educational outreach. This is an important but challenging undertaking because how growers manage risk and adjust their management is multidimensional (Garcia-Figuera et al. 2021; Lybbert et al. 2016; McRoberts et al. 2011).

Switching is a well-known and studied area of social and consumer behavior (Fanning et al. 2010) that refers to changing a product or service in favor of another (Hirschman 1970). Although economic researchers often study switching behavior focused on costs, marketing scholars approach the related concept of inertia (Klemperer 1995; Six et al. 2017). Companies increasingly emphasize retaining customers by preventing defection as building partnerships with their customers for their long-term profitability and survival (Chakravarty et al. 2004). Several studies in economic epidemiology considered changes in pest management decisions owing to obtaining new information on disease or pest forecasts or direct observation of pest levels (Lybbert et al. 2016; Mumford and Norton 1984; Swinton and King 1994). For pesticide resistance management, the ultimate goal of minimizing or delaying resistance level in the pest population is often driven by identifying cost-effective switching tactics (Fitri et al. 2021; Jutsum et al. 1998). Variables that may influence switching are diverse and include satisfaction and quality of current services, value, the cost or perceived cost of switching, attitudes, the attractiveness of alternatives, trust, commitment, social influences, and variety seeking (Bansal et al. 2005). These variables may be binned into categories of positive, negative, or "mooring" variables in a push-pull-mooring framework of switching adopted from migration models (Bansal et al. 2005). Negative factors act to push people to alternatives. Positive factors pull people to alternatives. Personal and social factors act as mooring variables that may either facilitate or suppress changes.

A motivating pathosystem for understanding determinants of switching behavior related to pesticide use is provided by hop powdery mildew, caused by the fungus *Podosphaera macularis*. The disease typifies many foliar diseases of high-value crops in which fungicides are a routine component of disease management. Powdery mildew is one of the costliest and potentially damaging diseases of hop (*Humulus lupulus*) in the Pacific Northwest (Mahaffee et al. 2009a) where most production of the crop occurs in the United States (Barth et al. 1994). Hop is a long-lived perennial produced for its strobiles, colloquially referred to as cones (Mahaffee et al. 2009b). Crop damage can be caused by reductions in yield or quality, the latter potentially rendering crops unsalable should powdery mildew cause unacceptable damage to the appearance or brewing qualities of cones (Gent et al. 2014; Hysert et al. 1998). Host resistance to powdery mildew exists, but market factors and brewer demand largely dictate the cultivars that growers must produce (Mahaffee et al. 2009a; Royle 1978). Multiple pathogenic races of *P. macularis* now exist that can overcome important sources of host resistance (Block et al. 2021; Gent et al. 2017; Wolfenbarger et al. 2016). Therefore, disease management is centered on cultural practices that reduce inoculum density (Gent et al. 2019b; Probst et al. 2016; Royle 1978), which are supplemented by repeated applications of fungicides. As with many high-value crops, a diversity of fungicides is used to manage the disease, including synthetic fungicides with specific modes of action prone to fungicide resistance and various nonsynthetic fungicides that tend to be less expensive and have lower risks of fungicide resistance but have shorter periods of residual control (Hwang et al. 2024).

The number of active ingredients applied for management of hop powdery mildew is associated with numerous covariates related to specific cultural practices, cultivar susceptibility to the disease, geographic effects, and disease levels in the early phases of disease outbreaks. Fundamentally, these factors predict pesticide use intensity—and the closely correlated costs growers incur—because they mediate or moderate pathogen pressure (Hwang et al. 2024). Accordingly, there is not a single fungicide program used for managing powdery mildew. Fungicide use patterns for the disease are complex and involve varying numbers of active ingredients in diverse combinations that can be resolved into three general programs (Hwang et al. 2025). In some programs, growers tend to apply a combination of fungicides with more frequent use of nonsynthetic fungicides, such as sulfur, whereas other programs rely on a greater number of synthetic fungicides. When growers choose a given program appears to be situation-dependent, as attempts to balance or match covariates in previous studies failed to resolve covariate imbalance because of inherent endogeneity between variables (Hwang et al. 2025). This suggests that hop growers may actively switch pesticide programs based on disease levels or other factors, such as the presence of other diseases or pests that may necessitate different fungicides for tank mix compatibility.

Our specific interest here is in identifying determinants that underly growers' decisions to switch the type of fungicides they use. To this end, we use binary and multinomial logistic regression models to predict switching behavior. We also quantify the variable importance of predictors using a novel random forest classification algorithm. Our results point to disease risk mitigation as an overriding driver of growers' fungicide choice.

Materials and Methods

Data collection and data set

A full description of methods for disease assessment and the disease data set is presented in Gent et al. (2019a) and Hwang et al. (2024 and 2025); only a succinct summary is presented here. Disease data were collected from a census sample of every hop yard on every hop farm in the eastern extent of the Oregon hop production region during each year of 2014 to 2017. We considered data from a total of 103 yards in 2014, 118 in 2015, 112 in 2016, and 125 in 2017. From March to August each year, 8 to 10 farms were used to analyze different types of fungicide application use. As we describe below, we fit logistic regression models only using data from April through July because most covariates were assessed during this period. We considered data from eight farms in the regression analysis because for two farms we had data from only 10 or 31 yards.

The incidence of hop plants with powdery mildew was evaluated monthly from April to July using a modification of cluster sampling methods described previously (Turechek et al. 2001; Turechek and Mahaffee 2004). The incidence of plants with evidence of bud perennation by *P. macularis* (a flag shoot) was assessed during ratings in April and May (Gent et al. 2019b; Laurie et al. 2023). Each cultivar was assigned a 0 to 5 ordinal value for its susceptibility to two pathogenic races of *P. macularis*, denoted as V6 virulent or non-V6 virulent (Gent et al. 2019a), as described in Laurie et al. (2023). The thoroughness of the cultural practice of spring pruning was rated using a 1 to 5 ordinal value as described previously (Laurie et al. 2023), with low values indicating that more of the foliage and stems were removed or killed and thus *P. macularis* was less likely to perennate in that yard (Gent et al. 2019b).

Descriptive summary of pesticide use

We obtained pesticide application records from each grower for all yards sampled from 2014 to 2017 (Hwang et al. 2025). The pesticide records contained 17 fungicide active ingredients (Hwang et al. 2025). We classified each fungicide application made in each yard as synthetic, nonsynthetic, or a mixture of both based on the FRAC code (Supplementary Table S1). Operationally, we considered folpet nonsynthetic given its FRAC code (M 04) and general use pattern. We calculated simple descriptive statistics to understand the mean, SEs, and the range for each subgroup of the covariates we considered, as we describe below.

To understand growers' switching from one of the three fungicide categories (nonsynthetic, synthetic, or mixture), we needed to define a baseline to identify switching from that baseline. We defined the baseline as the category of the first fungicide application of the growing season. We then summed the number of fungicide active ingredients applied for each category. To understand the general relationships between variables, we created double box plots for the date of the first fungicide application of the year, the mean day when applications were made, and seasonal mean disease incidence for each category of fungicide type.

Logistic regression

We used logistic regression to predict switching between the categories of fungicide type after ensuring appropriate fit of a logistic model, as we describe later. We first considered switching as a binary event, where changing from the baseline fungicide type, or in a later application, was considered a switching event (coded as "1") and no change was considered a nonevent (coded as "0"). For concreteness, a sequence of fungicide categories nonsynthetic/nonsynthetic/synthetic/mixture/mixture would consist of two switches, the first from a nonsynthetic to synthetic fungicide and the second from a synthetic to a mixture. There is a long history of applying random utility models that link switching decisions to logistic regression (McFadden 2001). We fit a binary logistic regression model to understand factors predictive of switching behavior (Peng et al. 2002). Logistic regression applies a logit transformation to the outcome variable to linearize the relationship to the predictor variables in the form:

$$Logit(\pi) = \log(odds) = \ln\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

Taking the antilog of the above equation on both sides, one derives an equation to investigate the predicted probability of the occurrence of the outcome variable as follows:

$$\pi = Probability(Y|X_1 = x_1, X_2 = x_2, \ldots, X_k = x_k) = \frac{e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k}}{1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k}}$$

where π is the probability of the outcome variable or event, switching behavior in our application. The parameters α and βs are typically estimated by maximum likelihood. Although the relationship between logit (π) and the predictor X_s is linear, association between the probability of Y and X_s is nonlinear. For this reason, log transformation of the odds in the logit equation is necessary to establish a linear relationship between the binary dependent variable and its predictor(s). The predictor variables considered are given in Table 1, plus additional dummies variables for "Year" and "Grower."

Because we considered three classes of fungicide type (synthetic, nonsynthetic, and a mixture of both), we also considered a multinomial logistic regression. A multinomial logistic regression model does not assume normality, linearity, or homoscedasticity, but does assume independence among the dependent variable choices. Furthermore, multinomial logistic regression does not assume perfect separation of the categories (Heinze 2006). We considered the same predictor variables in the multinomial logistic regression. The response variable was switching from a synthetic, nonsynthetic, or mixture to one of the other fungicide types.

Several caveats are in order. For both the binary and multinomial logistic regression models, we do not model grower risk preferences explicitly but rather point out that that risky behavior may be partially determined or embedded (in an uncertain way) in other covariates. Second, a property of logistic regression is the independence of irrelevant alternatives, meaning that the addition or removal of an alternative option does not impact the preferences of the remaining options. The advantages and disadvantages of this property are discussed in McFadden (2001). We also assume that the three fungicide types we consider encompass all possible choices for fungicides and therefore satisfy the assumption of independence of irrelevant alternatives. Finally, we do not explicitly account for potential endogeneity as the primary focus of this model is not causal in nature but rather predictive of underlying epidemiological factors and exogenous determinants (Fanning et al. 2010). Moreover, we lack a suitable instrumental variable correlated with the outcome variable but not the predictors (Lokshin and Sajaia 2004).

Variables included were selected by stepwise selection to avoid model overfitting and identify a subset of predictors based on their statistical significance (Matsuhashi et al. 2020). We fit models in R using the stepAIC function from the MASS package (Zhang 2016). We calculated a variance inflation factor (VIF) to measure potential multicollinearity among the predictors (Supplementary Fig. S1). We retained independent predictor variables that had VIF less than 2 and were not strongly correlated with each other (Supplementary Fig. S2).

We implemented a novel variable-selection algorithm for finding the final set of variables using a random forest classification algorithm. The classifier is used as a "black box" but returns a feature ranking of predictors based on mean reduction in impurity (Kursa and Rudnicki 2010). We implemented the random forest classifier using the Boruta package in R. The algorithm comprises the following steps:

1. Extend the data set by adding copies of all predictors.
2. Shuffle the added attributes to eliminate their correlation with the outcome variable to create so-called shadow attributes.
3. Run a random forest classifier on the extended data set and aggregate the computed z-scores.
4. Find the maximum z-score among the shadow attributes (MZSA) and identify all attributes that scored better than MZSA.
5. For each attribute with irrelevant importance, perform a two-sided test of equality with the MZSA.

Table 1. Summary statistics and mean (minimum and maximum) by fungicide type applied by hop growers in Oregon during 2014 to 2017

	Total					Nonsynthetic		
Variable (form)	Mean	SD	Min	Max	Synthetic	Mean ± SD (range)	Mixture	F test[a]
Spray date (day of year)	147.1	23.4	64	187	160 ± 18 (117–187)	138 ± 22 (64–187)	163 ± 15 (128–186)	256.5***
First spray date (day of year)	120.9	17.7	64	183	127 ± 21 (64–183)	119 ± 17 (64–159)	121 ± 14 (66–157)	26.0***
Disease incidence (proportion)	0.08	0.2	0	1	0.06 ± 0.18 (0–1)	0.05 ± 0.17 (0–1)	0.17 ± 0.28 (0–1)	39.1***
Disease incidence in May (proportion)	0.005	0.03	0	0.38	0.0046 ± 0.03 (0–0.38)	0.004 ± 0.02 (0–0.38)	0.007 ± 0.03 (0–0.38)	1.7
Flag shoot incidence (proportion)	0.0002	0.003	0	0.08	0.00008 ± 0.001 (0–0.03)	0.0003 ± 0.003 (0–0.08)	0	1.8
Previous flag shoot incidence (proportion)	0.0002	0.003	0	0.08	0.00029 ± 0.0029 (0–0.03)	0.0002 ± 0.003 (0–0.08)	0.00009 ± 0.0009 (0–0.012)	0.4
Pruning thoroughness (1–5 ordinal)	2.9	1.5	1	5	3.4 ± 1.5 (1–5)	2.8 ± 1.5 (1–5)	2.9 ± 1.3 (1–5)	20.9***
Susceptibility V6 strains (0–5 ordinal)	2.8	1.3	0	5	2.6 ± 1.3 (0–5)	2.8 ± 1.3 (0–5)	3.2 ± 1.2 (0–5)	16.3***
Susceptibility non-V6 strains (0–5 ordinal)	1.8	1.5	0	4	2.1 ± 1.4 (0–4)	1.7 ± 1.5 (0–4)	1.7 ± 1.6 (0–4)	7.2***
N	1,585				342	975	268	

[a] F tests indicate a difference in means between the groups synthetic, nonsynthetic, and mixture based on an analysis of variance. Asterisks indicate statistical significance at $P \leq 0.01$.

6. Consider the attributes that have importance significantly lower than MZSA as irrelevant and eliminate these from the data set.
7. Consider the attributes which have a value significantly higher than MZSA as relevant.
8. Eliminate all shadow attributes.
9. Repeat the procedure until relevance is assigned for all the attributes.

We compared the parsimony, prediction accuracy, and goodness of fit of the full and reduced models by calculating the Akaike information criterion (AIC), deviance, and McFadden's pseudo-R^2 (Hughes et al. 2019). We also plotted and inspected the receiver operating characteristic (ROC) curves, measured the area under the ROC curve, and calculated the Kolmogorov-Smirnov statistic as general measures of predictive accuracy and predictive power. All data and code needed to reproduce the analysis are available at https://github.com/ComputationalCrew/2025-Switching-Behavior.

Results

Descriptive summary of pesticide use

There was variation by month and year in the number of pesticide applications made. Aggregated over grower by year, the average and standardized values for monthly pesticide application made from 2014 to 2017 varied: 0.08 ± 0.35 for March, 0.47 ± 0.71 for April, 1.90 ± 1.38 for May, 1.84 ± 1.59 for June, 1.93 ± 1.29 for July, and 0.40 ± 0.61 for August. Growers used the most fungicide active ingredients in May, June, and July, and usually these were a single active ingredient, whether a synthetic or nonsynthetic fungicide (Supplementary Table S2). Independent of month, growers rarely applied tank mixes of more than one synthetic fungicide (0.2% of applications) active ingredient. Growers tank-mixed multiple nonsynthetic fungicides more often, but this was still relatively uncommon (6.5% of applications). Most mixtures involved only one synthetic and one nonsynthetic fungicide (20.7% of applications). There was also interannual variation in fungicide use, with the

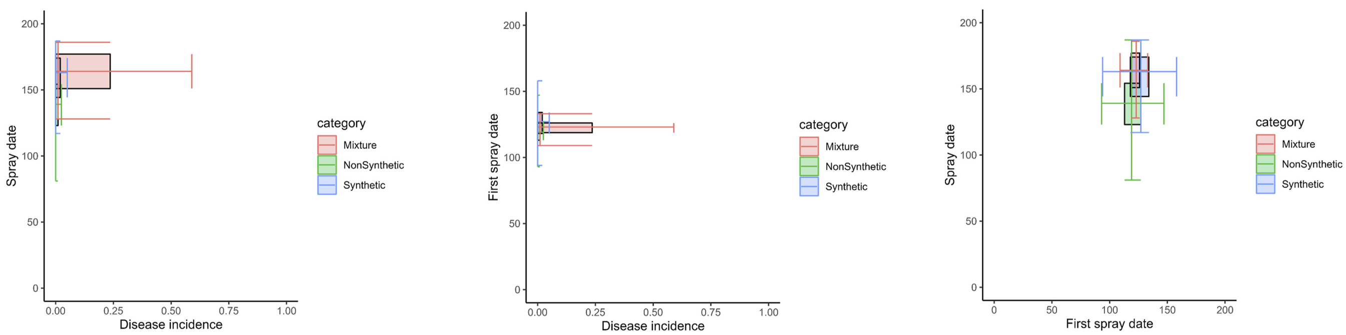

Fig. 1. Double boxplots expressing the distribution of the seasonal mean incidence of hop plants with powdery mildew (as a proportion) and fungicide spray date (left), first spray date (middle), or the distribution of spray date and first spray date (right). The first (baseline) fungicide application type is excluded in this visualization.

Table 2. Number (percentage) of applications of fungicide applied for hop powdery mildew for each type of fungicide and switching behavior[a]

Covariate[b]	N → N	N → S	N → M	S → S	S → N	S → M	M → M	M → N	M → S
N	493	157	125	94	82	39	101	35	29
Pruning thoroughness									
1	148 (55.8)	31 (11.7)	35 (13.2)	17 (6.4)	9 (3.4)	4 (1.5)	13 (4.9)	8 (3)	0 (0)
2	89 (41.4)	42 (19.5)	18 (8.4)	14 (6.5)	20 (9.3)	7 (3.3)	16 (7.4)	4 (1.9)	5 (2.3)
3	101 (35.7)	41 (14.5)	35 (12.4)	7 (2.5)	20 (7.1)	16 (5.7)	42 (14.8)	5 (1.8)	16 (5.7)
4	69 (48.6)	13 (9.2)	14 (9.9)	13 (9.2)	5 (3.5)	6 (4.2)	14 (9.9)	4 (2.8)	4 (2.8)
5	86 (34.4)	30 (12)	23 (9.2)	43 (17.2)	28 (11.2)	6 (2.4)	16 (6.4)	14 (5.6)	4 (1.6)
Susceptibility V6 strains									
0	29 (46.8)	13 (21)	2 (3.2)	3 (4.8)	11 (17.7)	0 (0)	2 (3.2)	0 (0)	2 (3.2)
1	87 (42.9)	29 (14.3)	12 (5.9)	24 (11.8)	15 (7.4)	12 (5.9)	15 (7.4)	2 (1)	7 (3.4)
2	37 (44.6)	11 (13.3)	8 (9.6)	13 (15.7)	3 (3.6)	4 (4.8)	4 (4.8)	1 (1.2)	2 (2.4)
3	155 (46)	52 (15.4)	28 (8.3)	25 (7.4)	38 (11.3)	7 (2.1)	18 (5.3)	8 (2.4)	6 (1.8)
4	174 (39.6)	45 (10.3)	72 (16.4)	26 (5.9)	14 (3.2)	14 (3.2)	59 (13.4)	23 (5.2)	12 (2.7)
5	11 (35.5)	7 (22.6)	3 (9.7)	3 (9.7)	1 (3.2)	2 (6.5)	3 (9.7)	1 (3.2)	0 (0)
Susceptibility non-V6 strains									
0	172 (45.1)	46 (12.1)	57 (15)	16 (4.2)	20 (5.2)	5 (1.3)	43 (11.3)	19 (5)	3 (0.8)
1	86 (42.6)	29 (14.4)	12 (5.9)	24 (11.9)	15 (7.4)	12 (5.9)	15 (7.4)	2 (1)	7 (3.5)
2	23 (38.3)	7 (11.7)	6 (10)	11 (18.3)	2 (3.3)	4 (6.7)	4 (6.7)	1 (1.7)	2 (3.3)
3	155 (46)	52 (15.4)	28 (8.3)	25 (7.4)	38 (11.3)	7 (2.1)	18 (5.3)	8 (2.4)	6 (1.8)
4	57 (32.6)	23 (13.1)	22 (12.6)	18 (10.3)	7 (4)	11 (6.3)	21 (12)	5 (2.9)	11 (6.3)
Synthetic[c]									
0	493 (80.8)	0 (0)	0 (0)	0 (0)	82 (13.4)	0 (0)	0 (0)	35 (5.7)	0 (0)
1	0 (0)	157 (28.8)	125 (22.9)	94 (17.2)	0 (0)	39 (7.2)	101 (18.5)	0 (0)	29 (5.3)
Nonsynthetic[c]									
0	0 (0)	157 (56.1)	0 (0)	94 (33.6)	0 (0)	0 (0)	0 (0)	0 (0)	29 (10.4)
1	388 (51)	0 (0)	123 (16.2)	0 (0)	81 (10.6)	39 (5.1)	100 (13.1)	30 (3.9)	0 (0)
2	102 (91.9)	0 (0)	2 (1.8)	0 (0)	1 (0.9)	0 (0)	1 (0.9)	5 (4.5)	0 (0)
3	3 (100)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)

[a] There were a total of N = 1,155 observations of fungicide applications from all years and hop yards, excluding the first (baseline) application. M = mixture; N = nonsynthetic; S = synthetic. Arrows indicate the direction of switching between the three fungicide types. Values in parentheses are the percentage for each subgroup.
[b] Variable descriptions are as described in the Materials and Methods.
[c] Synthetic and nonsynthetic are categorical variables that denote the count of active ingredients of each type applied in the given sequence of applications.

number of fungicide active ingredients applied declining from 2014 to 2016 and then increasing in 2017.

Growers made their first fungicide application as early as 5 March (day of year 64) and as late as 6 July (day of year 187), with the average first application on 30 April (day of year 120) (Table 1). Aggregated over the type of fungicide active ingredient, growers frequently used nonsynthetic fungicides earlier in the growing season (mean application 18 May, day of year 138 ± 22) as compared with synthetic fungicides (9 June; day of year 160 ± 18) or mixtures (12 June; day of year 163 ± 15) (Table 1). The overall tendency to use nonsynthetic fungicides earlier in the season was in part related to the tendency for growers to make their first application of the season earlier when using nonsynthetic fungicides (Fig. 1; Table 1). Growers used nonsynthetic or synthetic fungicides alone when seasonal mean disease incidence was lowest (0.06 ± 0.1 and 0.05 ± 0.1, respectively) and tended toward mixtures when disease incidence was greater (0.17 ± 0.28) (Fig. 1; Table 1). Nonsynthetic fungicides alone were used in 61.5% of applications, whereas 21.5% of applications were synthetic fungicides alone and 17.0% were mixtures (Table 1). Growers appeared to apply mixtures of fungicides preferentially on cultivars that were more susceptible to V6-virulent races of *P. macularis* (Tables 1 and 2). This corresponded with the greater use of mixtures associated with a higher incidence of powdery mildew.

The most frequent changes in the type of fungicide used was switching from nonsynthetic to synthetic (13.5% of application) or mixtures (10.8%). Switching from a synthetic fungicide or mixture to a nonsynthetic fungicide occurred relatively infrequently (7.1 and 3.0% of applications, respectively; Table 2). Growers rarely applied multiple synthetic active ingredients concurrently. Nonsynthetic fungicides were typically applied as a single active ingredient (81.4% of applications) versus two or three active ingredients (18.6% of applications) (Table 2).

Logistic regression

Binary logistic regression. Following stepwise selection, the final model for predicting whether growers switched their type of fungicide included variables for the day of year when the spray was made, day of the first spray, seasonal mean disease incidence, disease

Table 3. Summary for binary logistic regression models and important variables identified by a random forest classifier algorithm in the Boruta package[a]

	Full model					Stepwise selection model				
Parameter	Estimate	SE	*Z* value	*P* value	Variable importance	Estimate	SE	*Z* value	*P* value	Variable importance
(Intercept)	−1.16	0.46	−2.50	0.01	–	−1.05	0.22	−4.81	<0.001	–
Spray date	0.49	0.09	5.57	<0.001	57.1	0.49	0.09	5.64	<0.001	78.1
First spray date	−0.37	0.10	−3.78	<0.001	35.5	−0.36	0.10	−3.82	<0.001	46.0
Disease incidence	0.27	0.10	2.70	0.01	18.2	0.24	0.09	2.67	0.01	24.4
Disease incidence in May	−0.15	0.09	−1.64	0.10	–	−0.14	0.09	−1.59	0.11	–
Flag shoot incidence	0.05	0.09	0.59	0.56	–	–	–	–	–	–
Previous flag shoot incidence	−0.05	0.10	−0.46	0.65	–	–	–	–	–	–
Synthetic	0.84	0.11	7.89	<0.001	52.3	0.83	0.10	8.03	<0.001	67.5
Nonsynthetic	−0.29	0.10	−2.83	0.004	23.3	−0.28	0.10	−2.77	0.01	24.0
Pruning thoroughness	–	–	–	–	18.7	–	–	–	–	–
2	0.16	0.25	0.62	0.54	–	–	–	–	–	–
3	0.45	0.24	1.83	0.07	–	–	–	–	–	–
4	−0.17	0.32	−0.52	0.60	–	–	–	–	–	–
5	0.25	0.28	0.89	0.37	–	–	–	–	–	–
Susceptibility V6 strains	–	–	–	–	3.6	–	–	–	–	–
1	−12.20	535.41	−0.02	0.98	–	–	–	–	–	–
2	−0.29	0.67	−0.44	0.66	–	–	–	–	–	–
3	−0.03	0.35	−0.08	0.93	–	–	–	–	–	–
4	−0.04	0.39	−0.11	0.91	–	–	–	–	–	–
5	−0.35	0.62	−0.57	0.57	–	–	–	–	–	–
Susceptibility non-V6 strains	–	–	–	–	5.6	–	–	–	–	–
1	12.00	535.41	0.02	0.98	–	–	–	–	–	–
2	0.05	0.68	0.07	0.95	–	–	–	–	–	–
3	–	–	–	–	–	–	–	–	–	–
4	−0.01	0.29	−0.03	0.98	–	–	–	–	–	–
Year	–	–	–	–	22.5	–	–	–	–	31.9
2015	−0.30	0.23	−1.30	0.20	–	−0.25	0.22	−1.13	0.26	–
2016	0.35	0.25	1.41	0.16	–	0.44	0.24	1.82	0.07	–
2017	0.03	0.20	0.14	0.89	–	0.09	0.19	0.44	0.66	–
Grower	–	–	–	–	30.6	–	–	–	–	45.6
2	0.37	0.30	1.22	0.22	–	0.27	0.28	0.97	0.33	–
3	0.57	0.44	1.30	0.19	–	0.55	0.42	1.32	0.19	–
4	0.47	0.42	1.13	0.26	–	0.30	0.35	0.84	0.40	–
5	0.16	0.34	0.48	0.63	–	0.03	0.30	0.08	0.93	–
6	1.66	0.46	3.64	<0.001	–	1.58	0.43	3.67	<0.001	–
7	1.44	0.28	5.22	<0.001	–	1.40	0.25	5.58	<0.001	–
8	0.03	0.32	0.10	0.92	–	0.02	0.28	0.08	0.94	–
Model fit	AIC	1,229.0			–	–	1,210.5			–
	Null deviance	1,558.6 on 1,154 df			–	–	1,558.6 on 1,154 df			–
	Residual deviance	1,167.0 on 1,124 df			–	–	1,176.5 on 1,138 df			–
	LR test	391.6 ($P \leq 0.001$)			–	–	382.08 ($P \leq 0.001$)			–
	McFadden's R^2	0.2512			–	–	0.2451			–
N	–	–	–	–	1,155	–	–	–	–	–

[a] *P* values indicate whether parameter estimates are significantly different from 0 as inferred from the *Z*-score. AIC = Akaike information criterion; LR = likelihood ratio.

incidence in May, and whether the grower was applying a synthetic (switching from a nonsynthetic or mixture) or nonsynthetic fungicide (switching from a synthetic fungicide or mixture). Additionally, dummy variables for year and grower also were significant (Table 3). Variables not retained in the final model after applying the random forest classifier algorithm were related to the incidence of plants with powdery mildew in May, the incidence of plants with flag shoots, the thoroughness of pruning in spring, and susceptibility to two races of *P. macularis.*

The AIC and residual deviance indicated the model constructed using stepwise selection was more parsimonious and had superior predictive power as compared with the full model (Table 3). McFadden's pseudo-R^2 was approximately 0.25 for both models, indicating a moderate and comparable level of predictive power or resolution (Alemi et al. 2023; Hemmert et al. 2018). The area under the ROC curve for the full model and stepwise selection model were similar, 0.82 and 0.81, respectively (Supplementary Fig. S3). The Kolmogorov-Smirnov statistics for the full model and stepwise selection model were, respectively, 54 and 51%, indicating only a slight reduction in the predictive power of the reduced model compared with the full model.

Variable importance based on a random forest classification identified the most important variables as, in descending order, day of year when the spray was made (variable importance 78.1), whether the grower was switching to a synthetic fungicide (67.5), the day of year of the first spray (46.0), grower (45.6), year (31.9), seasonal mean disease incidence (24.4), and whether the grower was switching to a nonsynthetic fungicide (24.0) (Table 3). The relative risk ratio for these predictors also varied. Holding other variables at their mean or baseline, growers were 2.31 times more likely to switch to synthetic fungicide, and they were 0.74 times less likely to switch to a nonsynthetic fungicide. An increase of 1 day of when an application was made increased the relative risk ratio for switching by 1.60. This effect was most apparent after approximately 5 May (day of year 125), mostly independent of whether disease was present or not (Fig. 2). Growers that made their first application later in the season also were more likely to switch fungicide type (Fig. 2). A one-unit increase in the seasonal mean incidence of plants with powdery mildew increased the relative risk ratio for switching by 1.30. The predicted probability of switching increased with the incidence of plants with disease until approximately 0.5 incidence (Fig. 2). The relative risk ratio estimates for grower 6 and grower 7 indicated they were 4.2 to 5.3 times more likely to switch their type of fungicide use as compared with grower 1 (the baseline reference); other grower-specific effects were not significant.

Multinomial logistic regression. The final model constructed after stepwise variable selection was more parsimonious based on AIC (1,909.8 versus 1,885.7) and had similar predictive power based on McFadden's pseudo-R^2 (0.39 for both models) (Table 4; Supplementary Table S3). The residual deviance was smaller with the reduced model (1,135.4) versus the full model (1,155.3).

All potential predictors in the full model were also included in the stepwise selection model. However, previous incidence of flag shoots was removed from the final model based on the random forest classification algorithm in the Boruta package (Table 4). Cultivar susceptibility to two strains of *P. macularis*, spring pruning thoroughness, the incidence of flag shoots in the current month, the incidence of flag shoots in the previous month, and the incidence of plants with powdery mildew in May were significant in the multinomial model although these variables were not significant in the binary model. The variables that appeared both in the reduced multinomial and binary logistic regression models had generally similar variable importance (Tables 3 and 4). A notable exception was that grower-specific effects were somewhat more important in the multinomial model as compared with the binary model (Table 4).

Holding year and grower-specific effects constant (Table 4), there was a large log odds of switching to a mixture from one of the other groups as the season progressed. Growers were increasingly likely to switch to a synthetic fungicide or mixture after early May (Fig. 2). With each day, the log odds of switching to a mixture increased by 0.44 or 2 depending on the baseline fungicide type (Table 4). In yards

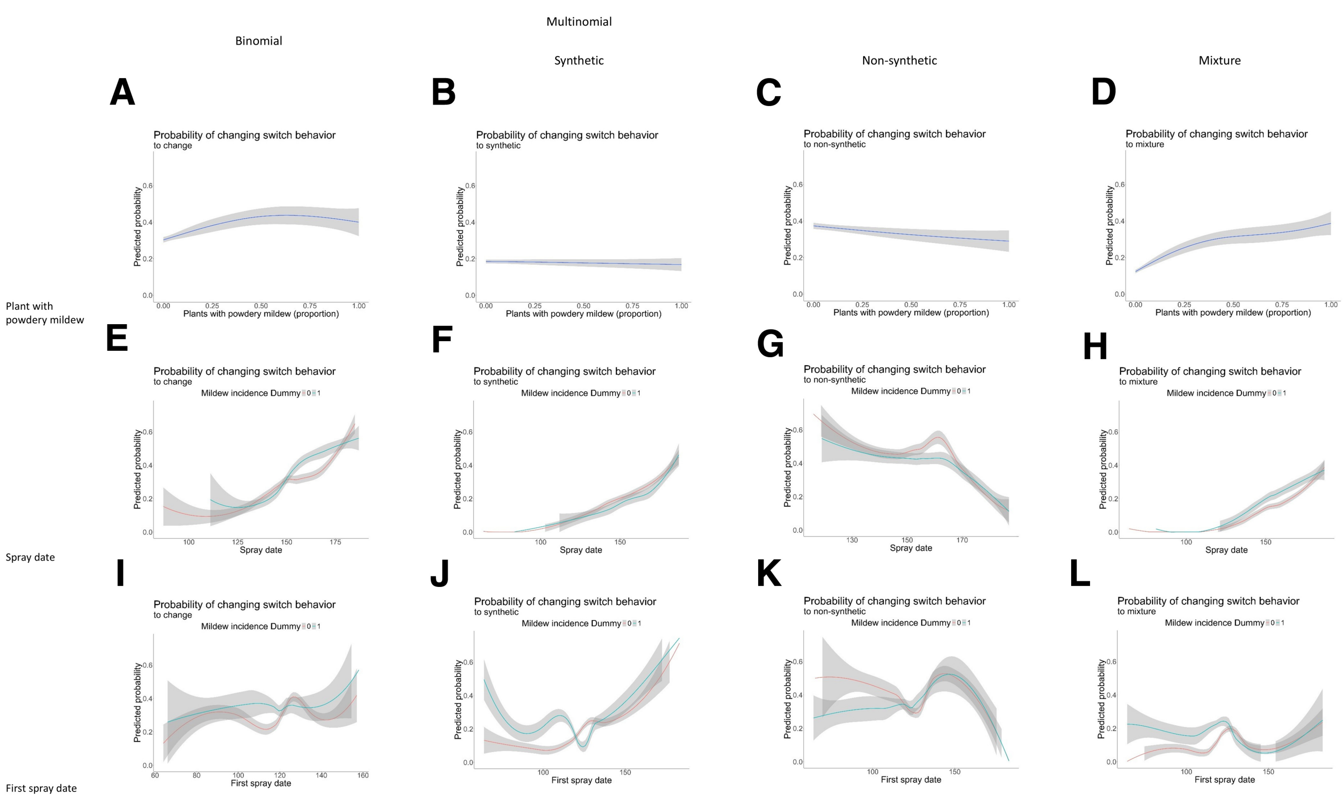

Fig. 2. Predicted probabilities of binomial **(A, E, and I)** and multinomial **(B, C, D, F, G, H, J, K, and L)** logistic regression models for selected variables that predict grower switching behavior related to the type of fungicide applied for hop powdery mildew (A to D), spray date (E to H), and first spray date (I to L) in Oregon during 2014 to 2017. Shaded areas are 95% confidence intervals.

where growers made their first application relatively early with a nonsynthetic fungicide, they were more likely to switch to a synthetic fungicide (log odds 0.31) and less likely to change to mixture (log odds −0.32) as compared with growers who made their first application relatively late. Growers increasingly switched from applying only nonsynthetic or synthetic fungicides to mixtures of the two as disease incidence increased (Fig. 2).

Either relatively low (ordinal value = 1) or relatively high (ordinal value = 4) cultivar susceptibility to powdery mildew was predictive of switching for multiple types of fungicides (Table 4). For example, the log odds of switching from a nonsynthetic fungicide to a fungicide mixture increased by 1.30 when cultivar susceptibility to V6-virulent strains of *P. macularis* increased from 0 to 4 on the ordinal scale (Table 4). In contrast, the log odds decreased by 29 for the same change for cultivars rated as partially resistant (ordinal value 1). The effect of seasonal mean incidence of plants with powdery mildew differed depending on the specific type of switching from one fungicide to another fungicide. For example, a one-unit increase in the seasonal mean incidence of plants with powdery mildew resulted in a 58% increase in the relative risk ratio of switching to a mixture of fungicides versus a nonsynthetic fungicide while causing an 8% increase in the odds of switching to a synthetic fungicide versus a nonsynthetic fungicide. Where cultivar susceptibility was a significant effect, the predicted probability of switching had similar directional responses to increasing incidence of powdery mildew but varied in the rate of change (Fig. 3). Spring pruning thoroughness was not a significant variable for predicting switching but was nonetheless identified by the Boruta algorithm as having moderate variable importance (24.9). Plots of predicted probability of switching by pruning thoroughness category did not indicate a consistent pattern of switching between fungicide types (Supplementary Fig. S4).

Discussion

Growers may change both the number of active ingredients they use (Hwang et al. 2024) and also the type of pesticide in response to or in anticipation of disease. Growers' decisions on pesticide use and switching is of central importance for understanding their disease management tactics and identifying areas to target for reducing use of more hazardous pesticides. In the motivating pathosystem, we found switching behavior to be multiphasic and to be affected by year- and grower-specific effects with uncertain causal effects. Notwithstanding these effects, the other variates predictive of switching from nonsynthetic fungicides to more active (and more expensive) synthetic fungicides or mixtures thereof hint at risk mitigation as an overarching driver and pulling factor of these decisions, as is common in much of agricultural pest management (Gent et al. 2013; Lybbert et al. 2016; Mumford and Norton 1984; Wearing 1988).

In support of this conclusion, we note that time of year (variable spray date) and switching to a synthetic fungicide or mixture thereof (variable synthetic) as the two variables with the greatest variable importance in both forms of the logistic regression models. That is, growers switched from a typical baseline program of nonsynthetic fungicides to more potent (Nelson et al. 2015) and more expensive (Hwang et al. 2024) alternatives as the season progressed. The most serious damage from powdery mildew to hop results from infection during bloom and juvenile stages of cone development (Gent et al. 2014; Royle 1978; Twomey et al. 2015), with bloom normally occurring shortly after the summer solstice (Neve 1991). Just preceding these crop stages, growers most often switched from nonsynthetic fungicides to alternatives. The incidence of plants with powdery mildew increases from early spring to early summer with increasingly favorable weather for the disease, plant growth, and

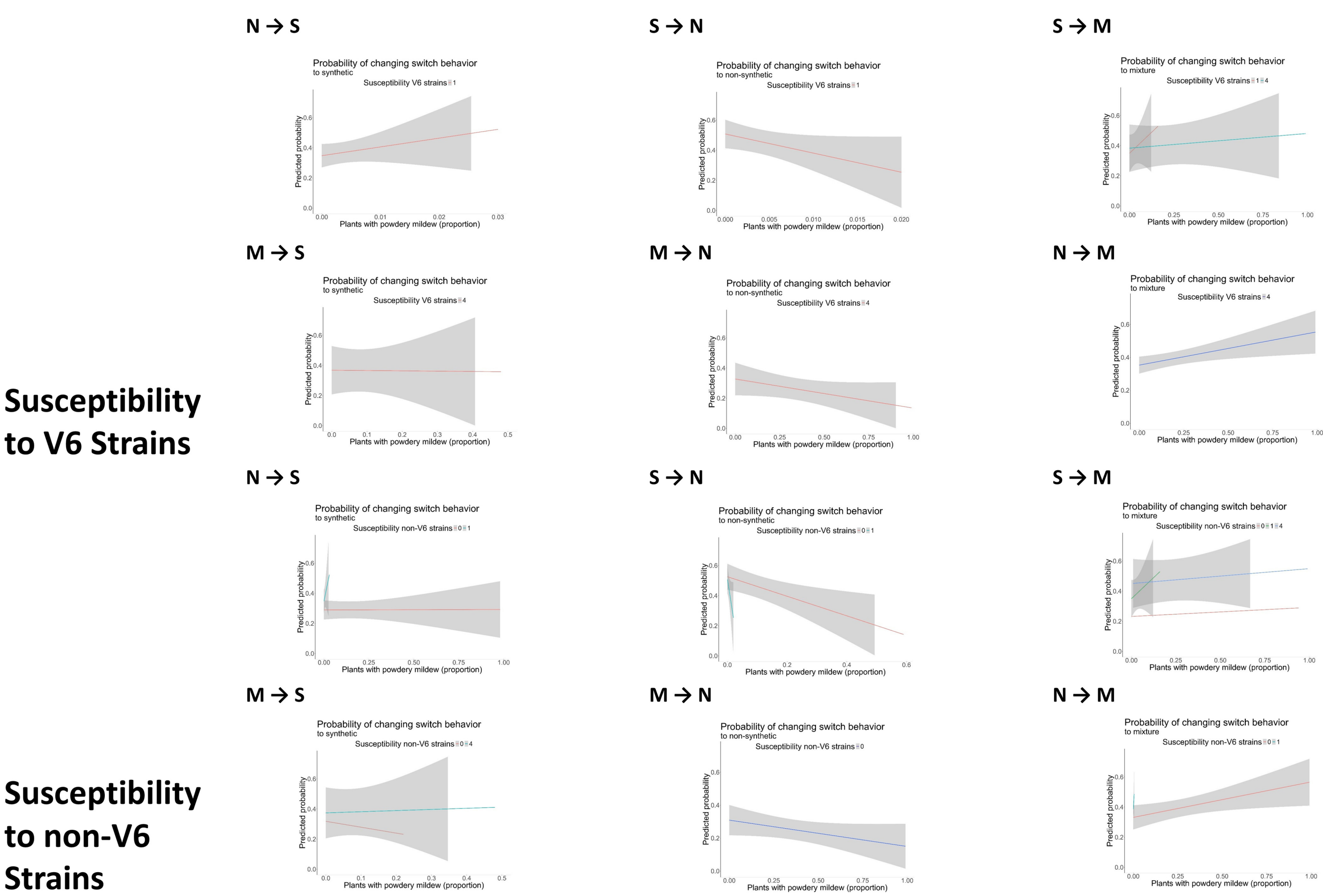

Fig. 3. Predicted probabilities of growers switching between different types of fungicides applied for hop powdery mildew estimated from a multinomial logistic regression model for significant covariates related to cultivar susceptibility. Data are presented for two strains of *Podosphaera macularis* that differ in V6 virulence. Shaded areas are 95% confidence intervals. M = mixture; N = nonsynthetic; S = synthetic.

increasing regional inoculum source strength (Gent et al. 2019a, 2024; Turechek et al. 2001). Crop developmental stage (as inferred from spray date) and disease incidence are correlated, but not strongly so (Supplementary Fig. S2). Although mean seasonal disease incidence is predictive of the total number of active ingredients applied (Hwang et al. 2024) and the general fungicide program applied (Hwang et al. 2025), it is not strongly predictive of grower switching behavior. Indeed, growers also switched fungicide type when disease incidence was relatively low. Switching to synthetic fungicides appears to be mostly preventative based on time of year (Fig. 2E), whereas switching to mixtures is more sensitive to the presence or incidence of powdery mildew (Fig. 2D). These findings confirm previous studies that suggested that general pesticide programs or strategies employed for this disease may be driven by disease pressure (Hwang et al. 2025).

Considerations of crop quality, phytotoxicity, and other pests also may influence switching behavior. Sulfur is one of the most applied nonsynthetic fungicides for powdery mildew on multiple

Table 4. Summary for a multinomial logistic regression model after stepwise variable selection and important variables identified by a random forest classifier algorithm in the Boruta package[a]

	Synthetic				Nonsynthetic				Mixture				
	Nonsynthetic		Mixture		Synthetic		Mixture		Nonsynthetic		Synthetic		
Parameter	Log (OR)	*P* value	Log (OR)	*P* value	Log (OR)	*P* value	Log (OR)	*P* value	Log (OR)	*P* value	Log (OR)	*P* value	Variable importance
(Intercept)	−0.73	0.13	−1.8	0.01	0.73	0.13	−1.1	0.13	1	0.2	1.8	0.01	–
Spray date	−1.6	<0.001	0.44	0.001	1.6	<0.001	2	<0.001	−2	<0.001	−0.44	0.001	75.8
First spray date	−0.31	0.004	−0.63	<0.001	0.31	0.004	−0.32	0.017	0.32	0.017	0.63	<0.001	40.3
Susceptibility V6 strains	–	–	–	–	–	–	–	–	–	–	–	–	15.8
1	10	<0.001	−8.1	<0.001	−8.1	<0.001	−29	<0.001	50	<0.001	−4.5	<0.001	–
2	0.53	0.5	0.87	0.4	−0.53	0.5	0.34	0.8	−0.34	0.8	−0.87	0.4	–
3	0.06	0.7	0.23	0.5	−0.06	0.7	0.17	0.6	−0.17	0.6	−0.23	0.5	–
4	0.46	0.3	1.7	0.01	−0.46	0.3	1.3	0.051	−1.3	0.05	−1.7	0.01	–
5	0.08	>0.9	1.2	0.2	−0.08	>0.9	1.1	0.2	−1.1	0.2	−1.2	0.2	–
Susceptibility non-V6 strains	–	–	–	–	–	–	–	–	–	–	–	–	14.9
1	−9.9	<0.001	8.4	<0.001	8	<0.001	29	<0.001	−51	<0.001	4.2	<0.001	–
2	−0.9	0.2	−0.57	0.6	0.9	0.2	0.34	0.7	−0.33	0.7	0.57	0.6	–
3	0.06	0.7	0.23	0.5	−0.06	0.7	0.17	0.6	−0.17	0.6	−0.23	0.5	–
4	−0.51	0.14	−0.95	0.01	0.51	0.14	−0.44	0.2	0.44	0.2	0.95	0.01	–
Pruning thoroughness	–	–	–	–	–	–	–	–	–	–	–	–	24.9
2	0.14	0.6	−0.06	0.9	−0.14	0.6	−0.2	0.5	0.2	0.5	0.06	0.9	–
3	0.35	0.2	0.4	0.3	−0.35	0.2	0.04	0.9	−0.04	0.9	−0.4	0.3	–
4	0.46	0.2	0.15	0.7	−0.46	0.2	−0.31	0.4	0.31	0.4	−0.15	0.7	–
5	0.13	0.7	−0.27	0.5	−0.13	0.7	−0.4	0.3	0.4	0.3	0.27	0.5	–
Disease incidence	−0.08	0.5	0.37	0.003	0.08	0.5	0.46	<0.001	−0.46	<0.001	−0.37	0.003	28.5
Disease incidence in May	−0.02	0.9	0.01	>0.9	0.02	0.9	0.04	0.7	−0.04	0.7	−0.01	>0.9	6.3
Flag shoot incidence	0.18	0.3	−8	<0.001	−0.18	0.3	−8.5	<0.001	7.6	<0.001	7.4	<0.001	4.3
Previous flag shoot incidence	−0.03	0.8	−0.06	0.7	0.03	0.8	−0.04	0.8	0.04	0.8	0.06	0.7	–
Year	–	–	–	–	–	–	–	–	–	–	–	–	36.6
2015	−1.6	<0.001	−1.3	<0.001	1.6	<0.001	0.31	0.3	−0.31	0.3	1.3	<0.001	–
2016	−0.3	0.3	1.2	0.001	0.3	0.3	1.5	<0.001	−1.5	<0.001	−1.2	0.001	–
2017	0.45	0.046	1.3	<0.001	−0.45	0.046	0.82	0.001	−0.82	0.001	−1.3	<0.001	–
Grower	–	–	–	–	–	–	–	–	–	–	–	–	59.8
2	0.69	0.035	−2.3	<0.001	−0.69	0.035	−3	<0.001	3	<0.001	2.3	<0.001	–
3	3	<0.001	1.5	0.026	−3	<0.001	−1.4	0.005	1.4	0.005	−1.5	0.026	–
4	3	<0.001	−0.78	0.2	−3	<0.001	−3.8	<0.001	3.8	<0.001	0.78	0.2	–
5	5.5	<0.001	3.1	0.003	−5.5	<0.001	−2.4	<0.001	2.4	<0.001	−3.1	0.003	–
6	3.5	<0.001	0.6	0.2	−3.5	<0.001	−2.9	<0.001	2.9	<0.001	−0.6	0.2	–
7	2.3	<0.001	−2.2	<0.001	−2.3	<0.001	−4.5	<0.001	4.5	<0.001	2.2	<0.001	–
8	4.2	<0.001	0.73	0.13	−4.2	<0.001	−3.5	<0.001	3.5	<0.001	−0.73	0.13	–
Model fit	AIC	–	–	–	–	–	1,885.7	–	–	–	–	–	–
	Residual deviance	–	–	–	–	–	1,813.7	–	–	–	–	–	–
	LR test	–	–	–	–	–	1,135.4 ($P \leq 0.001$)	–	–	–	–	–	–
	McFadden's R^2	–	–	–	–	–	0.3917	–	–	–	–	–	–
N	–	–	–	–	–	–	1,585	–	–	–	–	–	–

[a] The baseline fungicide type (synthetic, nonsynthetic, or mixture) is shown in the top row of the table. Switching from the baseline to another fungicide type is as indicated in the second row of the table. Log (OR) is log odds ratio. *P* values indicate whether the log odds ratio is significantly different from 0 (which transforms to an odd ratio of 1). AIC = Akaike information criterion; LR = likelihood ratio.

crops (Essling et al. 2021), including hop (Hwang et al. 2025). Use of sulfur is restricted by many brewers after bloom (typically early summer) because of concerns about residues carrying through and causing organoleptic defects in the end product (Gent et al. 2009). Use of sulfur after approximately mid-June can also exacerbate outbreaks of two-spotted spider mite (*Tetranychus urticae*), one of the most important arthropod pests of this crop (Gent et al. 2009; Woods et al. 2012). Nonetheless, switching from nonsynthetic fungicides to a synthetic-only alternative or a mixture occurred at approximately the same rate (Tables 2 and 4), even though other nonsynthetic fungicides (such as mineral oils) may also exacerbate spider mite outbreaks (Gent et al. 2009). Therefore, although growers may have switched away from sulfur specifically, they still included nonsynthetic fungicides in tank mixes in roughly half of their later-season applications. The decision to switch from a nonsynthetic fungicide to a mixture may also be motivated by fungicide resistance management considerations, as disease levels are typically maximal in late spring and early summer (Gent et al. 2014, 2024). Our companion analysis of the same data set indicates that growers, in general, did not overuse any given FRAC group with a moderate to high risk of resistance (Hwang et al. 2025). However, time of year (spray date) was a more important variable than disease incidence in the random forest classification. This suggests to us that disease protection rather than resistance management may be the primary motivation for using fungicide mixtures later in the season. Resistance management may be an ancillary, but fortuitous, benefit of disease risk mitigation with fungicide mixtures.

Holding other factors constant, growers were less likely to switch their fungicide type in yards where the first fungicide application was made relatively late in spring. This is because these growers typically began their program with a synthetic fungicide rather than a less potent nonsynthetic fungicide (Fig. 1; Table 1). We observed again that this strategy was not strongly influenced by the presence of powdery mildew (Fig. 2I–L). A perceived threat of disease given the lack of protection from prior fungicide application may prompt growers to begin their program with synthetic fungicides, pointing again to risk mitigation as a central feature of fungicide selection.

Cultivar susceptibility to powdery mildew was not consistently predictive of switching behavior; cultivar susceptibility was nonsignificant in the binomial model and only weakly important in the multinomial model (Tables 3 and 4). In the multinomial model, cultivar susceptibility was only important for select combinations of cultivar susceptibility categories and types of switching. For the more common types of switching from nonsynthetic to synthetic or nonsynthetic to mixtures, the predicted probability of switching increased with the mean seasonal incidence of powdery mildew (Fig. 3). However, the effect was not consistent across cultivars or the types of switching we considered. Previous analyses also found that growers often responded to powdery mildew similarly across cultivars with quite different levels of susceptibility to powdery mildew (Hwang et al. 2024). Follow-up studies and analyses are needed to understand the reasons why growers' disease management programs do not appear to scale commensurately with cultivar susceptibility. This also leads to questions about whether this is a specific case of a more general phenomenon of growers making "insurance" sprays on cultivars with partial resistance and, if so, the potential versus actual pecuniary value of partial disease resistance given grower risk aversion (Fuller et al. 2014).

Apart from programs better tailored by cultivar, our analyses also provide guidance on where to focus future efforts to reduce the use of synthetic fungicides in particular and fungicide use in general. Growers rely heavily on nonsynthetic fungicides in the earliest months of the growing season but do switch to or tank mix with synthetic fungicides later in the season. There is thus a need to identify use patterns of current nonsynthetic fungicides or alternatives that could reduce or replace their synthetic counterparts. As the use of mixtures is sensitive to disease presence and disease incidence, identifying the causes of relatively high disease levels in a subset of yards could better target intervention. Indeed, probable causes are known from our previous analyses with the same data set (Hwang et al. 2024, 2025).

Two other sidebars are worth noting. Although our analyses describe and predict when growers switch their fungicide use, we cannot assess with the present data the impact of these switches on disease control or economic value. Presumably, disease control was superior (Gent et al. 2008; Nelson et al. 2015), but yard-level comparisons would be important to quantify the benefits. Second, the limited use of synthetic fungicides alone, as compared with use in mixtures, is broadly consistent with strategies for delaying fungicide risk management (van den Bosch et al. 2014). The effectiveness of a mixture for fungicide resistance management depends on the relative effectiveness of the specific fungicides in the mixture and dosage (Elderfield et al. 2018; Hobbelen et al. 2011; Taylor and Cunniffe 2023). Synthetic fungicides and mixtures were mostly likely to be used late in the season when pathogen pressure was relatively high (Gent et al. 2024). Critical examination of the specific mixtures used is warranted to identify appropriate combinations and doses for delaying fungicide resistance management.

Acknowledgments

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