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The Diversity and Determinants of Fungicide Programs for Hop Powdery Mildew

Jae Young Hwang,[1] Sharmodeep Bhattacharyya,[2] Shirshendu Chatterjee,[3] Thomas L. Marsh,[4] Joshua F. Pedro,[3] and David H. Gent[1,†]

[1] United States Department of Agriculture-Agricultural Research Service, Forage Seed and Cereal Research Unit, Corvallis, OR 97331, U.S.A.
[2] Department of Statistics, Oregon State University, Corvallis, OR 97331, U.S.A.
[3] Department of Mathematics, City University of New York, New York City, NY 10031, U.S.A.
[4] School of Economic Sciences, Washington State University, Pullman, WA 99163, U.S.A.

Abstract

Plant disease monitoring metadata are a rich source of information for predicting pesticide use and costs on individual fields, farms, or regionally. Pesticide use patterns for management of hop powdery mildew (*Podosphaera macularis*) in Oregon were summarized by frequency of use of active ingredients and Fungicide Resistance Action Committee (FRAC) code. There was extensive variation in the frequency of use of specific active ingredients and FRAC codes among growers, ranging from a mean of 0 to 2.41 applications per yard. All growers used fungicides with FRAC codes 7/11 and 13; all but one grower used fungicide FRAC codes M02, NC, 3, and 11. Among fungicides with a moderate to high risk of developing resistance (FRAC codes 3, 5, 7, 7/11 premix, 11, or 13), the mean number of applications was ≤1.35 per yard across all growers and never exceeded four applications within a given yard. Hierarchical cluster analysis identified that the diverse use patterns could be categorized into three groups, which we define as pesticide programs. We fitted a random forest regression model and used Shapley values to quantify the importance of fungicide program in predicting the number of active ingredients applied and their costs relative to other known factors that influence these outcomes in individual yards. Pesticide program was the third most important variable predicting annual costs and the fifth most important predictor for the number of active ingredients applied. We also found hints that growers may switch between one of the three pesticide programs depending on the incidence of powdery mildew.

Keywords: epidemiology, field crops, fungi

Fungicides are a cornerstone of disease management in numerous crops (Gianessi and Reigner 2006). In certain high-value crops, most of the harvestable yield may be attributed to fungicide use, and all or nearly all of the production of some crops may be treated with fungicides (Gianessi and Reigner 2006). This is a common situation for powdery mildews, and it is clear that fungicide use is important for enhancing yield and quality and permitting production of powdery mildew–susceptible cultivars with desirable agronomic characteristics (Hollomon and Wheeler 2002). At the same time, reduction of risks caused by pesticide pollution is a major goal for agricultural policy (Möhring et al. 2020). The proportion of cropland area used to produce permanent crops (e.g., grapevine or tree fruit) in particular can be associated with increased risk of pesticide pollution (Wuepper et al. 2023). Thus, there is a need to understand patterns of pesticide use and their determinants to gain insights into production situations and growers' management practices that may minimize pesticide use (Lechenet et al. 2016; Wuepper et al. 2023).

One of the crops in the United States reported to have 100% of the production treated with fungicides is hop (*Humulus lupulus*) (Gianessi and Reigner 2006). An estimated 69% of the yield of hop is dependent on fungicides, with downy mildew (caused by *Pseudoperonospora humuli*) and powdery mildew (caused by the *Podosphaera macularis*) being the two primary targets (Gianessi and Reigner 2005). Powdery mildew occurs on hop throughout the Pacific Northwest, the primary production region for hops in the United States (Hop Growers of America 2024). The disease proliferates during the moderate to warm temperatures that normally dominate the spring and summer months in this region (Gent et al. 2022; Mahaffee et al. 2003; Peetz et al. 2009; Turechek et al. 2001). Crop damage occurs primarily from infection of inflorescences and developing cones (Gent et al. 2014; Royle 1978), which may reduce both yield and quality owing to discoloration, decreased levels of bittering acids, and the potential development of off-flavors during brewing (Gent et al. 2014; Hysert et al. 1998; Royle 1978).

Hop growers use both fungicides and herbicides for disease management, the latter being applied as part of cultural practices that manage plant growth to reduce inoculum and modify the environment to be less favorable for powdery mildew (Gent et al. 2008, 2012, 2019b; Laurie et al. 2023; Probst et al. 2016; Royle 1978). There can be substantial variability in how growers approach disease management (Dušek et al. 2023; Essling et al. 2021; Hwang et al. 2024). This naturally motivates one to understand pesticide use patterns, their determinants, and outcomes in terms of costs, efficacy, or other metrics. Simple descriptive summaries of pesticide use serve an important role in establishing a base level of knowledge to assess if growers follow recommended best practices for disease and resistance management and thus can help better target extension and educational efforts (Essling et al. 2021; Oliver et al. 2024). Beyond generating a descriptive understanding of practices, in-depth analysis of pesticide use patterns may also reveal variates that predict conditions where growers may apply more or less active ingredients or incur more or less costs (Andert et al. 2015). In previous studies with hop powdery mildew, we identified multiple covariates related

†Corresponding author: D. H. Gent; dave.gent@usda.gov

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to growers' spring pruning practices, cultivar susceptibility, the strain of the pathogen first found in a yard, and the centrality of a given yard in the network of other yards that are related to the number of active ingredients applied and their costs (Hwang et al. 2024). Collectively, these factors moderate disease severity, which is the causal effect that increases pesticide use and its associated costs as an exposure-response relationship.

In crops that are treated repeatedly, fungicides are often applied in various rotations or mixtures at specific times during a growing season (Essling et al. 2021; Oliver et al. 2024). Specific pesticide use patterns are commonly referred to as a pesticide program or disease management program (see, for example, Oliver et al. 2024). In our previous research of pesticide use by hop growers (Hwang et al. 2024), we considered only the count of the number of active ingredients applied or annual costs of the doses of the active ingredients as the response variables. This was because fungicide use patterns for hop powdery mildew are quite diverse and complex owing to the number of applications made and various combinations of fungicides growers may apply. Indeed, one of the primary challenges with analyzing pesticide use data is identifying use patterns and cogently summarizing the complex mixes of different pesticides applied. Consequently, analyses often rely on descriptive statistics that summarize the mean or distribution of applications made in total or of individual pesticides or a given biochemical mode of action (Andert et al. 2015; Essling et al. 2021; Hwang et al. 2024; Oliver et al. 2024). Data-reduction methods could be useful for condensing the multidimensional use of pesticide into a small number of interpretable summaries (Dušek et al. 2023). Beyond descriptive summaries, modeling of grower behavior based on covariates such as production practices, weather, or disease risk may provide deeper different insights into factors correlated with or determining pesticide use (Delcour et al. 2015; Lybbert et al. 2016).

In this research, we sought to address several questions related to hop growers' pesticide use practices to understand current fungicide use patterns. First, what are the most commonly applied pesticides in the management of powdery mildew? Second, is there evidence of specific combinations of pesticides in programs that growers routinely follow? And thirdly, how do growers' pesticide programs contribute to their overall pesticide use and costs relative to known variates related to these outcomes? In answering these questions, we extend our previous analyses (Hwang et al. 2024) and find hints of situation-specific pesticide programs growers adopt for hop powdery mildew depending on disease levels.

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 we give only a brief summary here. The observational unit was an individual hop within a year. A census sample was conducted by sampling every hop yard on every hop farm in the eastern extent of the Oregon hop production region during each year from 2014 to 2017. All cultivars were assessed independent of their susceptibility to powdery mildew. We used data from seven to nine farms sampled per year, spanning from near the cities of Silverton to Hubbard. We evaluated a total of 103 yards in 2014, 118 in 2015, 112 in 2016, and 125 in 2017.

The incidence of hop plants with powdery mildew was evaluated using a modification of cluster sampling methods described previously (Turechek and Mahaffee 2004; Turechek et al. 2001). Monthly from April to July, each individual yard was visited and divided into strata of 20 rows, and two strata per yard were sampled by evaluating 50 to 200 hills (simplified to plants herein) in one transect (row) per strata. We assessed each plant visually and recorded the number of plants harboring a shoot associated with myceliogenic perennation of *P. macularis* (i.e., a flag shoot) or colonies of *P. macularis*. Potential covariates associated with disease levels were collected during the time of disease assessments or later, including cultivar susceptibility to powdery mildew, the race (strain) of the pathogen present in a yard when disease was first detected, various network centrality measures, selected cultural practices, and the physical location of yards. Each cultivar was assigned a 0 to 5 ordinal score for its susceptibility to the two pathogenic races of *P. macularis* relevant at the time of the surveys, as described in Laurie et al. (2023).

The initial strain of *P. macularis* in each hop yard was determined as being virulent or not on the powdery mildew resistance factor dubbed R6, as described in Gent et al. (Gent et al. 2019a). We assigned a dummy variable of "1" if the initial strain of the pathogen was non–V6-virulent and "2" if the pathogen was V6-virulent. The initial strain was undefined if powdery mildew did not occur in a yard or, in a small number of instances (13 hop yards), the initial strain was not measured unambiguously. In these instances, we coded the initial strain as "0."

The thoroughness of spring pruning was rated using a 1 to 5 ordinal score as described in Laurie et al. (2023), with low values indicating that more of the foliage and stems were removed or killed. Spring pruning is known to be correlated with the incidence of hop plants with powdery mildew and fungicide use (Gent et al. 2019b; Hwang et al. 2024; Laurie et al. 2023).

P. macularis is readily disseminated by wind and can spread from yard to yard within a region (Gent et al. 2019a). The centrality of each hop yard in an inferred disease-spreading network was expressed using the outward degree centrality presented in Gent et al. (2019a). The outward degree centrality for a given hop yard is the sum of all outward-directed edges from that yard to other yards in the geographical extent of interest. Outward degree centrality was estimated for monthly time transitions of May to June and June to July for each network of yards planted to cultivars affected by V6-virulent or non–V6-virulent strains of *P. macularis* as described previously (Gent et al. 2019a). We also considered the centroid of all yards and divided the landscape into four equidistant quadrants from this central reference point and assigned a dummy variable to represent the general position of each yard in the landscape.

We obtained pesticide application records from each grower for all yards sampled from 2014 to 2017. We calculated the total number of fungicide and also herbicide active ingredients relevant for powdery mildew management applied by growers in a given year and their estimated costs per hectare as described previously (Hwang et al. 2024). As we noted previously, herbicides are relevant for management of powdery mildew because of the importance of defoliation of the first shoots that emerge and, later in spring and summer, removal of superfluous basal foliage (Gent et al. 2016; Probst et al. 2016). The pesticide application records contained active ingredients representing 17 fungicides and three herbicides. We obtained price quotes for these pesticides from three vendors in western Oregon that routinely service hop producers. Quotes were obtained in 2021 and reflected nominal prices for 2014, 2015, 2016, or 2017, where available. We estimated real prices using 2022 as the base by adjusting the nominal prices by the producer price index from the U.S. Bureau of Labor Statistics and then averaged over all available prices to obtain a single real price per unit.

Descriptive summary of pesticide use

Descriptive statistics were calculated to understand variability in use of each of the pesticide active ingredients identified in the pesticide application records. We calculated the mean number of applications of each active ingredient per yard aggregated by year, cultivar, grower, and grower × year. We visualized the data in heat maps. We also classified each pesticide by Fungicide Resistance Action Committee (FRAC) or Herbicide Resistance Action Committee (HRAC) code to understand how frequently each was used and how this varied by grower. We then calculated the mean, minimum, and maximum number of applications by grower to obtain baseline data on the use of each pesticide within a FRAC or HRAC group.

Hierarchical cluster analysis

The specific combinations of pesticide applied were quite diverse and challenging to summarize using only descriptive summaries. We conducted two-way hierarchical cluster analysis to identify groupings of similar pesticide use frequencies from growers' pesticide application records, what we refer to as programs. In short, the objective of our cluster analyses was to sort pesticide active ingredients that growers applied into groups in a way that the degree of relationship between any two variables was maximal if they follow the same group and minimal otherwise (Inekwe et al. 2020; Li et al. 2011).

Hierarchical clustering involves a series of calculations that combine observations into a hierarchy (Everitt et al. 2011). We used an agglomerative method based on the Euclidean distance between clusters using complete linkage (Jafarzadegan et al. 2019; Nielsen 2016). This approach tends to produce more compact clusters (Glasbey 1987). The optimal number of clusters was identified as that which maximized the average silhouette coefficient (Inekwe et al. 2020; Ogbuabor and Ugwoke 2018). We implemented these analyses using NbClust package in R version 4.3.0.

As we explain below, hierarchical cluster analysis identified that growers' pesticide use frequencies were best described by three groups. We refer to these three groups as pesticide use programs. We analyzed the frequency of use of each active ingredient within each group by analysis of variance. Means of active ingredient in each subgroup were separated by Fisher's least significant difference test at $P = 0.05$ (Lee and Lee 2018).

Random forest predictions

After identifying pesticide use programs from the hierarchical cluster analysis, we sought to understand (i) whether the programs were predictive of the total number of active ingredients applied or annual costs and (ii) the relative importance of pesticide program given the other known variates that influence these outcomes. We chose a random forest estimation because of its ability to identify relevant features in a multidimensional data set containing both categorical and continuous predictors (Verikas et al. 2011). We assigned a categorical variable to each of the groups identified in the hierarchical cluster analysis and then fit a random forest regression model (Abellán et al. 2017; Domingues et al. 2022). We used K-fold cross-validation by splitting our data into a training set and a testing set and then iteratively fitting the model five times, each time training the model with data from four of the folds and evaluating the model with data from the fifth fold.

The relevant features in a random forest are useful for interpretation of the model and for ensuring an accurate prediction model. In the ensemble tree model, the total reduction of loss contributed by all splits for a given feature is used to calculate feature importance (Theerthagiri and Vidya 2022). That is, when a regression model is formed with random forests, it allows one to obtain information on how each feature contributes to an average decrease in error in the regression model process (Kim and Kim 2022). Recursive feature elimination is a feature selection technique used for finding the optimal subset from a larger set of features (Theerthagiri and Vidya 2022). In recursive feature elimination, a model is trained on the entire data set to estimate the weight of each feature, the importance scores of all features are calculated using predetermined importance indices, and those features with the lowest importance score are eliminated. This process is applied recursively until the only variables remaining are those most relevant to predicting the outcome variable. Among the various feature selection models available, we used recursive feature elimination and cross-validation (RFECV). RFECV combines recursive feature elimination and cross-validation for optimal feature selection that maximizes the performance of the model (Awad and Fraihat 2023). RFECV excels in automatically determining the optimal feature selection and is robust to random noise in a data set, making it stable and reliable for the chosen feature subset (Xu et al. 2023). We compared the predicted value with the actual value for the annual cost of pesticides or the number of pesticide active ingredients after RFECV.

We then calculated Shapley additive explanation (SHAP) values for the final random forest model (Lundberg and Lee 2017). SHAP values are a measure of the contribution of each input variable on model predictions and help explain the root causes behind each prediction (Deb and Smith 2021). SHAP values can also identify whether the contribution of each feature is positive or negative to the outcome variable (Mangalathu et al. 2020). We used Python scikit-learn 3.1 to conduct these analyses.

Causal exposure-response function

The mean seasonal incidence of powdery mildew has a causal effect on the number of fungicide active ingredients applied and their associated cost (Hwang et al. 2024). This relationship is well explained by a linear exposure-response function. However, it is not known if or how this exposure-response function varies depending on the specific pesticide use program growers apply. To understand whether this relationship is sensitive to the pesticide use program growers apply, we fit causal exposure-response functions for each of the three pesticide use programs we identified through hierarchical cluster analysis. We used the subset of variables selected by RFECV in the random forest regression as the pre-exposure covariates. Before fitting the exposure-response function, we first attempted to adjust for potential confounding by calculating a generalized propensity score (Hirano and Imbens 2004; Wu et al. 2022). We also conducted a covariate balance test to check whether covariate balancing reduced confounding of variables related to both the treatment and the outcome (Lunt et al. 2009). We then estimated three causal exposure-response functions, one for each of the populations of hop yards that received one of the three pesticide programs we identified in the cluster analysis. We fit the causal exposure-response functions using the R package CausalGPS (Khoshnevis et al. 2023).

Results

Descriptive summary

There was variation by year and grower in the number of pesticide applications made and the specific active ingredients applied. Aggregated over grower, the number of times each of the 20 active ingredients were used per yard varied somewhat by year (Fig. 1). Use of certain active ingredients per yard tended to decline from 2014 to 2017, such as with copper formulated as a copper diammonia diacetate complex, the premix of boscalid + pyraclostrobin, and the herbicide paraquat declining from 1.96 to 0.71, 0.62 to 0.10, and 0.57 to 0.35 applications per yard, respectively. In contrast, use of fluopyram, the premix of fluopyram + trifloxystrobin, metrafenone, and the biofungicide containing *Reynoutria sachalinensis* extract tended to increase from 2014 to 2017 (0 to 0.31, 0 to 0.23, 0 to 0.47, and 0.14 to 1.83 applications per yard, respectively).

The most frequently used fungicide varied by year, with copper formulated as a diammonia diacetate complex being most the most frequently applied in 2014 (1.96 applications per yard), trifloxystrobin in 2015 (0.95 applications per yard), quinoxyfen in 2016 (0.95 applications per yard), and the biofungicide derived from an *Reynoutria sachalinensis* extract in 2017 (1.83 applications per yard). Quinoxyfen was the most broadly used fungicide, being applied to every cultivar except Mosaic. Copper formulated as a copper diammonia diacetate complex was used across 33 of the 35 cultivars. Among herbicides, carfentrazone was the most used herbicide in every year (1.55 to 2.14 application per yard). Carfentrazone was also applied to more cultivars (32) than either flumioxazin (29) or paraquat (27).

Individual growers tended to apply different pesticides in different years. For example, grower 1 applied nine active ingredients (in at least one yard) in 2014, six in 2015, four in 2016, and seven in 2017; only three of the active ingredients were applied in every year by grower 1 (Fig. 1). Although there was grower and year-specific variation in pesticide use, quinoxyfen and carfentrazone were notably two of the most consistently used active ingredients across all yards, independent of grower and year. Only one grower did not apply quinoxyfen or carfentrazone to at least one yard in every year.

There was also variability at the grower level when we aggregated active ingredients by FRAC or HRAC codes (Table 1). Overall, among growers the mean number of applications of a particular mode of action code ranged from 0 to 2.41 (FRAC M02) per yard, with a maximum value in an individual yard of 7 (FRAC P05). All growers used fungicides with FRAC codes 7/11 (as a premix) and 13 in at least one yard; all but one grower used fungicides with FRAC codes M02, NC, 3, and 11 in at least one yard (Table 1). All growers applied herbicides with HRAC code 14 in at least one yard. Among the fungicides with a moderate to high risk of developing resistance (FRAC codes 3, 5, 7, 7/11 premix, 11, or 13), the mean number of applications was ≤1.35 per yard across growers and never exceeded four applications within a given hop yard (Table 1). Herbicides within each HRAC code were applied on average 0 to 1.83 times per yard depending on the grower. At the extreme, as many as seven applications of HRAC code 14 herbicides were applied in a given hop yard.

Hierarchical cluster analysis

We found evidence that growers apply specific combinations of pesticides in identifiable patterns. We identified maximal support for three clusters of pesticides programs (Fig. 2), with slightly less support for two, four, five, or six clusters (Supplementary Fig. S1). The number of yards contained within each cluster was relatively balanced (141 to 190 yards; Supplementary Table S1). The three programs varied significantly in the frequency of use of many active ingredients (Table 2). A distinguishing feature of program group 3 was that it used nonsynthetic fungicides more often than synthetic fungicides. Yards that received program group 3 were treated significantly more often with sulfur (mean 2.11; $P < 0.001$) and potassium bicarbonate (mean 0.70; $P < 0.001$) than yards that received the other programs. Correspondingly, yards in program group 3 never received more applications of any particular herbicide or synthetic fungicide as compared with program groups 1 or 2, with the exception of fluopyram/trifloxystrobin (mean 0.17 applications versus ≤0.04; $P < 0.001$). Program groups 1 and 2 in contrast were characterized by low (mean 0.25, group 1) or intermediate (mean 0.72, group 2) use of sulfur but higher use of most synthetic fungicides. Program groups 1 and 2 differed in the use patterns of the specific nonsynthetic and synthetic fungicides that were applied. As compared with program group 1, program group 2 made more frequent use of triflumizole (0.52 versus 0.26), fluopyram (0.21 versus 0), the biofungicide containing *Reynoutria sachalinensis* (1.88 versus 0.07), and the herbicides carfentrazone (2.54 versus 1.13) and flumioxazin (0.61 versus 0.43). Program group 1, in contrast, made more frequent use of a specific formulation of copper (1.96 versus 0.45), mineral oils (1.04 versus 0.08), quinoxyfen (1.19 versus 0.94), and trifloxystrobin (1.02 versus 0.54) (Table 2).

The general characteristics of yards that we categorized into the three pesticide program groups varied in several ways (Table 3; Supplementary Fig. S2). The total number of active ingredients applied per yard was similar between the three groups, ranging from

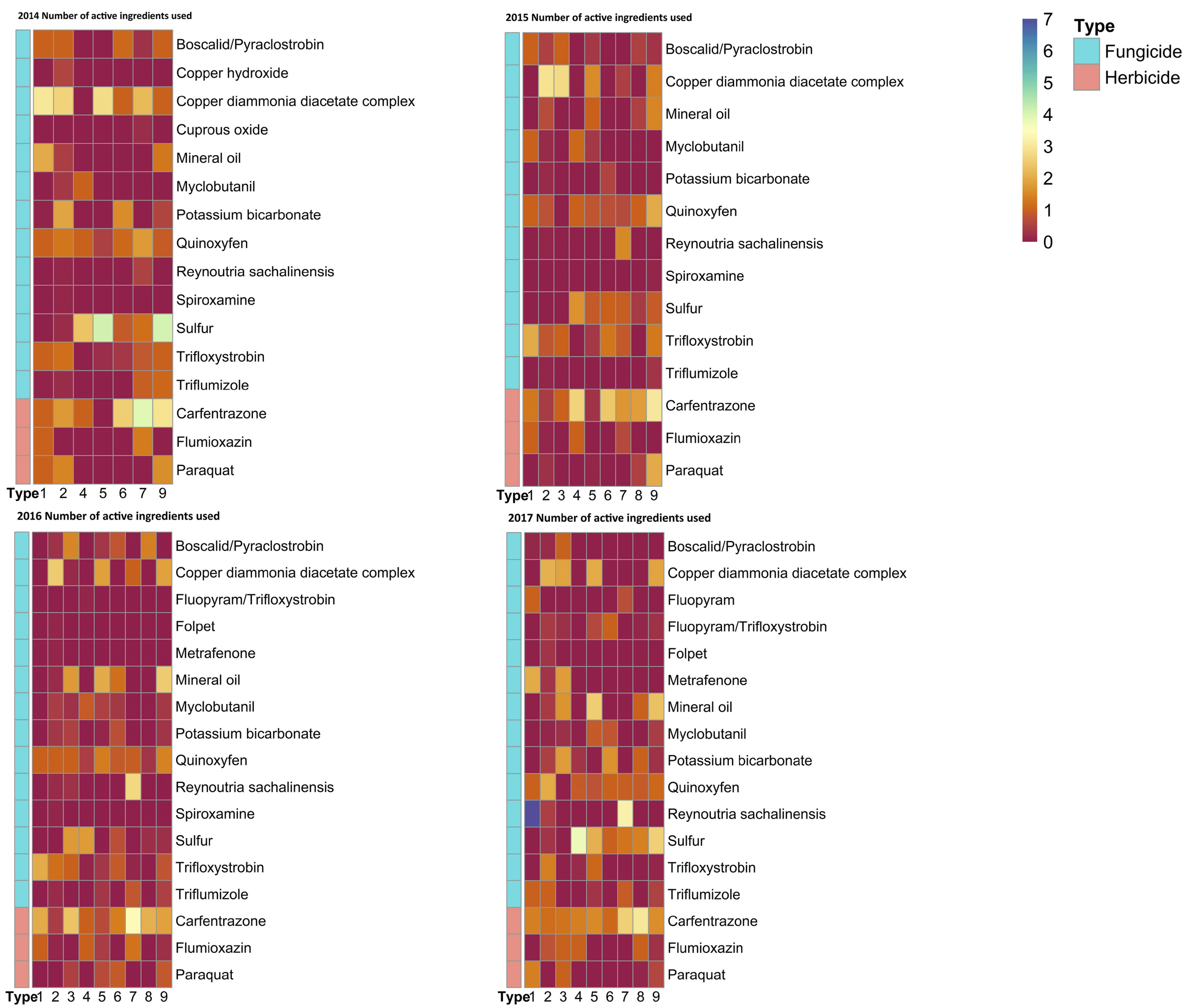

Fig. 1. Mean number of applications of fungicide and herbicide active ingredients applied per hop yard used to manage hop powdery mildew by Oregon hop growers (numbered 1 to 9) during 2014 to 2017.

9.09 (SD 3.65) with program group 3 to 9.74 (SD 4.18) with program group 2. Although the number of active ingredients applied was generally similar, the annual costs were least expensive ($353.34 per ha, SD $262.14) with group 3 and most expensive ($500.37 per ha, SD $226.25) with group 1 (Table 3).

Disease pressure varied among yards within each pesticide program group, with the mean seasonal disease incidence being highest in yards in group 1 (0.07), lowest in group 2 (0.01), and intermediate in group 3 (0.03) (Fig. 3). This was generally reflected in the mean monthly disease incidence as well (Table 3). Based on the present analysis, we cannot discern causal effects of the three programs on mean seasonal disease incidence. Covariates that potentially moderate mean seasonal disease incidence tended to vary between yards that received one of the three pesticide programs (Table 3; Supplementary Fig. S2). We also observed an association between position in the landscape and the tendency for a hop yard to receive program groups 1, 2, or 3. Yards in the northwest quadrant of the production area were overrepresented in the least costly program group 3, yards in the northeast quadrant were overrepresented in the costliest program group 1, and yards in the southeast quadrant mostly received the intermediately priced program group 2 (Supplementary Fig. S2).

Random forest predictions

We compared the original variables with the selected variables after RFECV, and predictive accuracies for random forests were similar based on mean absolute error (27.27 versus 27.32 with the original and selected variables, respectively, for annual costs; 2.39 with both variable sets for active ingredients). The model with reduced variables after RFECV had an R^2 in training of 0.75 for annual costs and 0.80 for active ingredients (Fig. 4), indicating acceptable predictive accuracy.

Table 1. Mean (minimum and maximum) number of applications of fungicides and herbicides aggregated by hop grower in Oregon during 2014 to 2017

FRAC or HRAC code[z]	Active ingredient	Grower								
		1	2	3	4	5	6	7	8	9
M01	Copper hydroxide Copper diammonia diacetate complex Cuprous oxide	0.27 (0, 3)	0.88 (0, 5)	0.46 (0, 3)	0	0.67 (0, 4)	0.08 (0, 1)	0.32 (0, 5)	0	0.51 (0, 3)
M02	Sulfur	0	0.12 (0, 2)	0.67 (0, 2)	2.41 (1, 4)	1.70 (0, 6)	0.90 (0, 1)	0.87 (0, 3)	0.72 (0, 4)	1.94 (0, 5)
M04	Folpet	0	0.10 (0, 2)	0	0	0	0	0	0	0
P05	*Reynoutria sachalinensis* extract	1.79 (0, 7)	0.20 (0, 2)	0.10 (0, 1)	0	0	0	1.97 (0, 5)	0	0
3	Myclobutanil Triflumizole	0.26 (0, 1)	0.31 (0, 2)	0.10 (0, 2)	0.36 (0, 2)	0.33 (0, 2)	0.15 (0, 2)	0.33 (0, 2)	0	0.39 (0, 3)
5	Spiroxamine	0	0.04 (0, 1)	0	0	0	0	0	0	0.01 (0, 1)
7	Fluopyram	0.26 (0, 1)	0	0	0	0	0	0.18 (0, 1)	0	0
7/11	Fluopyram/trifloxystrobin Boscalid/pyraclostrobin	0.27 (0, 1)	0.28 (0, 3)	0.64 (0, 2)	0.01 (0, 1)	0.17 (0, 1)	0.36 (0, 2)	0.03 (0, 1)	0.31 (0, 2)	0.19 (0, 1)
11	Trifloxystrobin	1.22 (0, 2)	1.14 (0, 3)	0.57 (0, 1)	0.06 (0, 1)	0.52 (0, 2)	0.63 (0, 2)	0.47 (0, 1)	0	0.81 (0, 2)
13	Quinoxyfen	1.00 (1, 1)	1.27 (0, 3)	0.38 (0, 1)	0.83 (0, 2)	0.87 (0, 2)	0.93 (0, 2)	1.07 (0, 4)	0.75 (0, 2)	1.35 (0, 2)
14	Carfentrazone Flumioxazin	1.07 (0, 2)	0.58 (0, 4)	1.02 (0, 4)	1.12 (0, 3)	0.39 (0, 2)	0.93 (0, 3)	1.83 (0, 7)	1.36 (0, 4)	1.24 (0, 5)
22	Paraquat	0.62 (0, 2)	0.39 (0, 3)	0.62 (0, 2)	0	0.20 (0, 1)	0.22 (0, 1)	0	0.19 (0, 1)	1.26 (0, 4)
50	Metrafenone	0.51 (0, 2)	0.10 (0, 1)	0.76 (0, 2)	0	0	0	0	0	0
NC (not classified)	Potassium bicarbonate Mineral oil	0.27 (0, 2)	0.55 (0, 5)	1.17 (0, 4)	0.04 (0, 3)	0.75 (0, 4)	0.70 (0, 2)	0	0.45 (0, 4)	1.08 (0, 5)

[z] FRAC = Fungicide Resistance Action Committee; HRAC = Herbicide Resistance Action Committee.

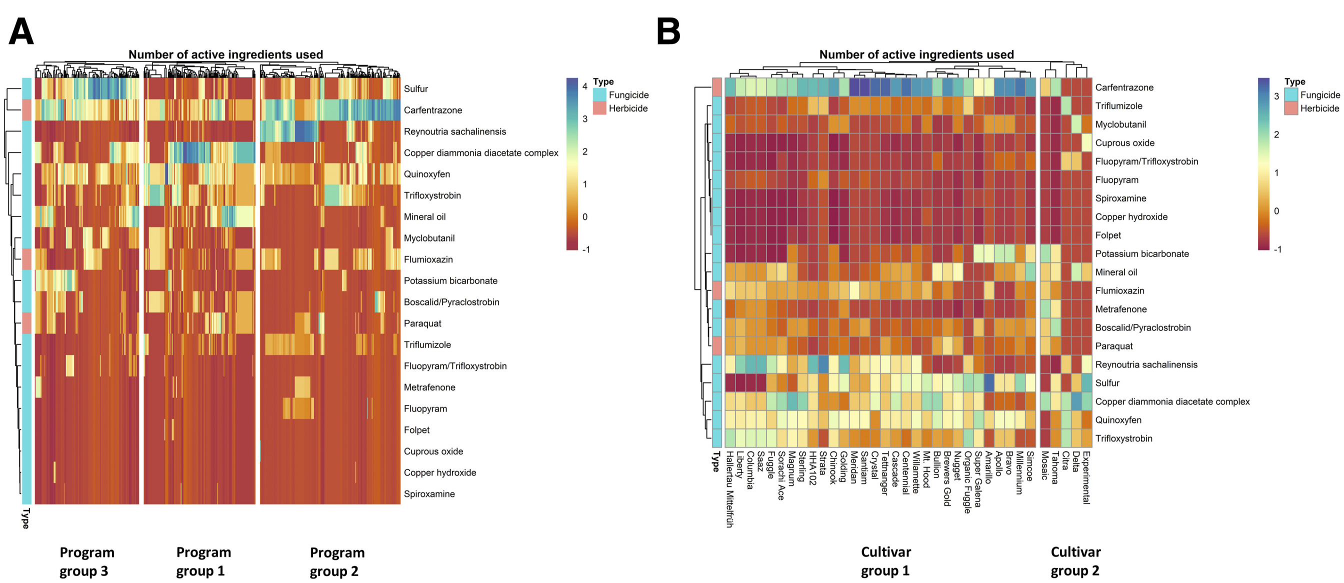

Fig. 2. Two-way hierarchical cluster analysis of fungicide and herbicide active ingredients used to manage powdery mildew by Oregon hop growers during 2014 to 2017. Analyses were conducted by hop yard (**A**) or by cultivar (**B**).

The specific pesticide programs growers applied were important predictors of their annual costs and the number of active ingredients they applied. Variable importance ranged from near 0 to 0.19, and those variables with importance <0.01 were not selected (Table 4). Among the variables retained in the model, pruning thoroughness, as expected (Hwang et al. 2024), was the most important variable for both annual cost and active ingredients. The next most important variables related to disease incidence, either as the seasonal mean incidence or during June or July, and the pesticide program group (Table 4). Pesticide program group was the second most important variable in the model for annual cost (variable importance 0.08) and fourth most important for the number of active ingredients applied (variable importance 0.09).

Based on SHAP values, the order of importance of variables on predictions varied depending on whether the outcome variable was the number of active ingredients applied or annual costs (Fig. 5). Again, pruning thoroughness was the most important variable influencing predictions for both annual costs and the number of active ingredients. Larger feature values had negative SHAP values, meaning that poor thoroughness of pruning had a high negative contribution to the predictions for both outcome variables. Relatively low monthly or mean seasonal powdery mildew incidence lowered the predicted annual cost or number of active ingredients applied.

Based on SHAP values, pesticide program group was the third most important variable impacting predictions of annual costs and the fifth most important variable for the number of active ingredients applied (Fig. 5). Program group 3, which made more frequent use of sulfur and generally less frequent use of synthetic fungicides, had a large negative impact on model predictions for annual cost but had a small positive effect on the number of active ingredients applied. Program groups 1 and 2, which made more frequent use of certain synthetic fungicides but few applications of sulfur, both increased predicted annual costs. Program groups 1 and 2 differed in their impact on the number of active ingredients applied, though. Fewer active ingredients were predicted when program group 1 was used, but more were predicted when program group 2 was used.

Table 2. Mean number of applications of each pesticide active ingredient by program group[z]

Program group 1		Program group 2		Program group 3	
Active ingredient	**Mean number of applications**	**Active ingredient**	**Mean number of applications**	**Active ingredient**	**Mean number of applications**
Copper diammonia	1.96 a	Carfentrazone	2.64 a	Sulfur	2.11 a
Quinoxyfen	1.19 a	*Reynoutria sachalinensis*	1.88 a	Carfentrazone	1.51 b
Carfentrazone	1.13 c	Quinoxyfen	0.94 b	Quinoxyfen	0.87 b
Mineral oil	1.04 a	Sulfur	0.72 b	Copper diammonia	0.82 b
Trifloxystrobin	1.02 a	Flumioxazin	0.61 a	Mineral oil	0.82 a
Paraquat	0.53 a	Trifloxystrobin	0.54 b	Potassium bicarbonate	0.7 a
Boscalid	0.5 a	Triflumizole	0.52 a	Trifloxystrobin	0.41 b
Flumioxazin	0.43 b	Copper diammonia	0.45 c	Boscalid	0.4 a
Myclobutanil	0.32 a	Paraquat	0.28 b	Myclobutanil	0.4 a
Triflumizole	0.26 b	Metrafenone	0.22 b	Flumioxazin	0.31 b
Sulfur	0.25 c	Fluopyram	0.21 a	Paraquat	0.27 b
Potassium bicarbonate	0.17 b	Boscalid	0.15 b	Fluopyram/trifloxystrobin	0.17 a
Reynoutria sachalinensis	0.07 b	Mineral oil	0.08 b	Metrafenone	0.11 b
Fluopyram/trifloxystrobin	0.04 b	Myclobutanil	0.05 b	Triflumizole	0.09 c
Folpet	0.03 a	Potassium bicarbonate	0.05 b	Copper hydroxide	0.03
Metrafenone	0.03 a	Cuprous oxide	0.02	*Reynoutria sachalinensis*	0.02 b
Spiroxamine	0.01	Copper hydroxide	0.01	Cuprous oxide	0
Copper hydroxide	0	Fluopyram/trifloxystrobin	0 b	Fluopyram	0 b
Cuprous oxide	0	Folpet	0 b	Folpet	0 b
Fluopyram	0 b	Spiroxamine	0	Spiroxamine	0

[z] Letters indicate significant differences for a given active ingredient between program groups based on analysis of variance (least significant difference test with $P = 0.05$). Lack of letters indicate group effects were not significantly different.

Table 3. Mean and standard deviation (SD) of variables associated with 458 hop yards clustered into three pesticide program groups

	All		Group 1		Group 2		Group 3	
Variable (form)	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Annual cost (USD per ha)	444.38	275.93	500.37	226.25	470.13	305.28	353.34	262.14
Active ingredients (count)	9.43	3.88	9.38	3.71	9.74	4.18	9.09	3.65
Susceptibility V6 strains (0 to 5)	2.74	1.32	2.85	1.29	2.39	1.35	3.07	1.20
Susceptibility non-V6 strains (0 to 5)	1.85	1.50	1.87	1.54	1.91	1.42	1.74	1.54
Seasonal disease incidence (proportion)	0.03	0.09	0.07	0.12	0.01	0.06	0.03	0.07
Flag shoot incidence (proportion)	0.0003	0.0020	0.0004	0.0025	0.0002	0.0019	0.0002	0.0014
Pruning thoroughness (1 to 5)	2.99	1.53	3.52	1.34	3.12	1.51	2.27	1.47
Initial strain (0/1/2)	0.74	0.91	0.97	0.90	0.45	0.78	0.88	0.99
Disease incidence April (proportion)	0.0004	0.0044	0.0006	0.0032	0.0005	0.0060	0.0003	0.0027
Disease incidence May (proportion)	0.0033	0.0254	0.01	0.04	0.00	0.02	0.00	0.02
Disease incidence June (proportion)	0.07	0.19	0.14	0.25	0.03	0.13	0.04	0.17
Disease incidence July (proportion)	0.07	0.18	0.13	0.26	0.02	0.10	0.06	0.14
Degree centrality June R6 (count)	0.26	1.59	0.41	1.78	0.13	1.46	0.26	1.55
Degree centrality July R6 (count)	1.02	3.47	1.62	3.72	0.56	3.30	0.99	3.34
Degree centrality June non-R6 (count)	0.28	1.79	0.43	2.04	0.24	2.03	0.17	1.02
Degree centrality July non-R6 (count)	0.50	1.88	0.93	2.32	0.24	1.33	0.38	1.91

Exposure-response function

We fit exposure-response functions to hop yard observations for each of the three pesticide program groups after attempting to balance covariates to understand how annual costs and the number of active ingredients scaled with disease exposure level (Fig. 6). The outcome rate for all pesticide program groups had a linear relationship with disease exposure level. However, each pesticide program group had different ranges of disease exposure levels. This indicates that growers applied each of the programs under a different range of mean seasonal disease incidence. The covariate balance tests failed for pesticide program group 1 for both the number of active ingredients applied and annual costs (Supplementary Fig. S3) using a nominal threshold value of 0.3 (a moderate confounding effect of the covariate) (Zhu et al. 2015). Therefore, assumptions of the exposure-response functions were not satisfied, and the validity of the models for pesticide program group 1 was questionable.

Discussion

Fungicides are a mainstay of disease management on hop throughout the Pacific Northwest (Gianessi and Reigner 2006), and our research contributes to several questions about hop growers' pesticide use practices. First, we established that there is large diversity in the specific pesticides applied and frequency of their application that varies by year, by grower, and even by the same grower between years. Notwithstanding this diversity, we identified the pesticides that are most frequently and most broadly applied for powdery mildew management. Second, whereas there is much diversity in growers' pesticide use patterns, we find evidence that growers apply specific combinations of pesticides in identifiable patterns. We identified three general programs that best explain the frequency of use of specific combinations of pesticides. Third, we demonstrate that growers' use of one of the three identified pesticide programs is among the most important variable determining the number of active ingredients they apply and their annual

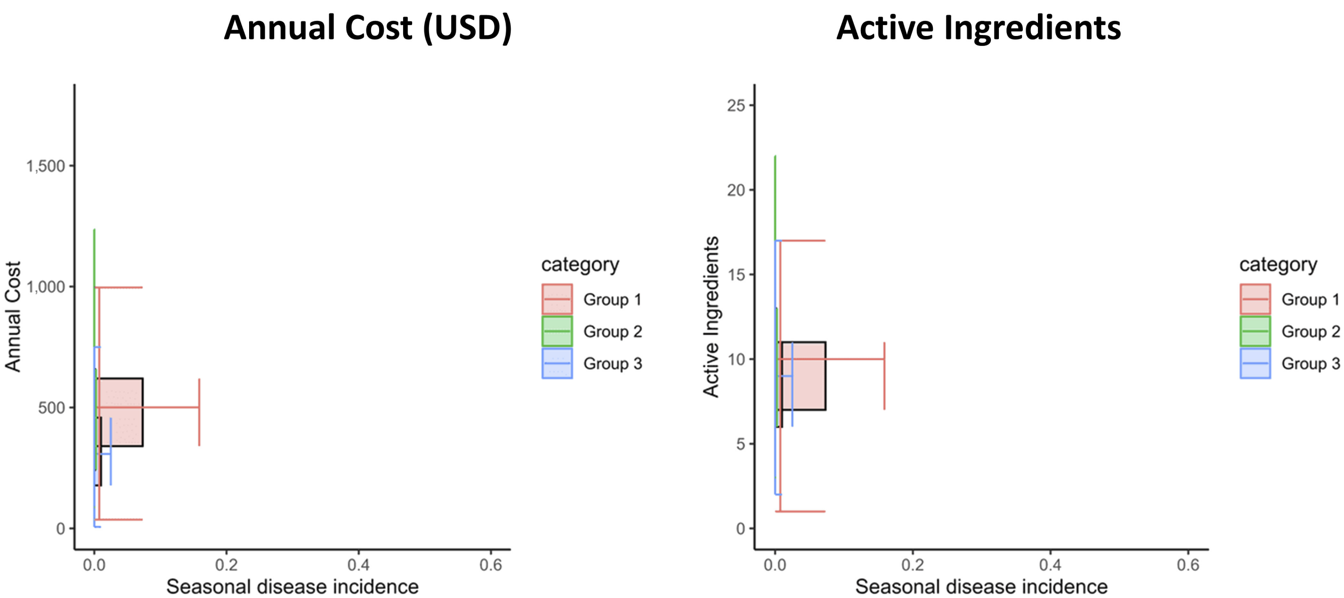

Fig. 3. Double boxplots expressing the distribution of the seasonal mean incidence of powdery mildew (as a proportion) and the associated annual costs of pesticides (left) or number of active ingredients (right) applied by hop producers.

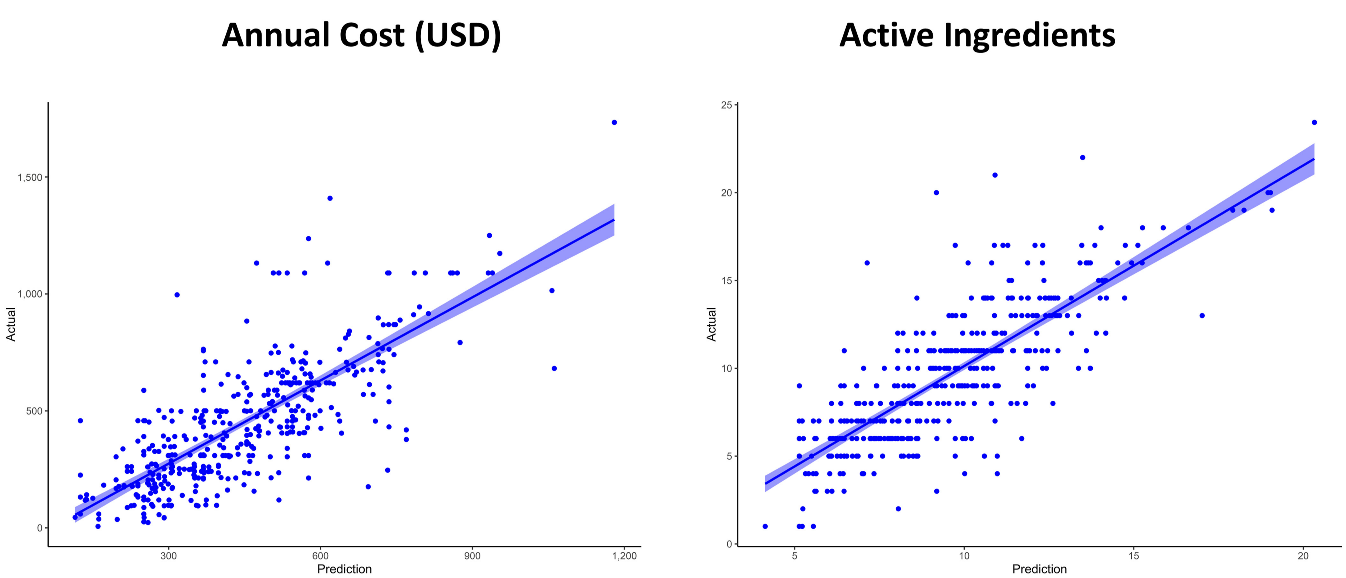

Fig. 4. Predicted versus observed values from a random forest regression for the annual cost of pesticides (left) or the number of pesticide active ingredients (right) applied by Oregon hop growers for management of powdery mildew.

costs. We also find evidence that growers apply each fungicide program only under a specific range of disease levels.

Growers use diverse pesticide strategies but make consistent use of quinoxyfen and carfentrazone

There is much variability in the individual pesticides that growers apply for management of powdery mildew. Standardized pesticide management programs are sometimes followed for certain diseases or complexes of diseases, such as seed treatments or fungicide applications during specific periods of host susceptibility (Ayesha et al. 2021; Barro et al. 2019; Gadoury et al. 2012). Standardized programs can be more difficult to adopt in higher value crops when repeated fungicide applications are made over a relatively long period of the season (Essling et al. 2021; Oliver et al. 2024). Farm-level effects can also be important in explaining variation in pesticide use (Andert et al. 2015). In the current data set, growers changed use of specific products over time for reasons that are not fully clear. This could reflect new pesticides becoming registered for use on hop, such as with the fluopyram-containing products in 2016 or metrafenone in late 2014, or changes in maximum residue levels in key export markets (Handford et al. 2015).

Table 4. Variable importance coefficient and selected variables by recursive feature elimination and cross-validation (RFECV)[z]

	Annual cost		Active ingredients	
Feature	**Variable importance**	**Selected by RFECV**	**Variable importance**	**Selected by RFECV**
Disease incidence April	0.03	True	0.01	False
Disease incidence May	0.01	True	0.01	False
Disease incidence June	0.06	True	0.07	True
Disease incidence July	0.05	True	0.11	True
Seasonal disease incidence	0.08	True	0.10	True
Susceptibility to V6 strains	0.06	True	0.03	True
Susceptibility to non-V6 strains	0.08	True	0.04	True
Initial strain	0.03	True	0.05	True
Pruning thoroughness	0.19	True	0.17	True
Flag shoot incidence	0.02	True	0.01	False
Degree centrality June R6	0.00	False	0.00	False
Degree centrality July R6	0.02	True	0.07	True
Degree centrality June non-R6	0.00	False	0.00	False
Degree centrality July non-R6	0.04	True	0.04	True
Northwest quadrant	0.07	True	0.06	True
Northeast quadrant	0.02	True	0.01	False
Southwest quadrant	0.04	True	0.02	True
Southeast quadrant	0.03	True	0.03	True
Program group	0.08	True	0.09	True

[z] Variables selected by RFECV are noted as "true" and eliminated variables are noted as "false."

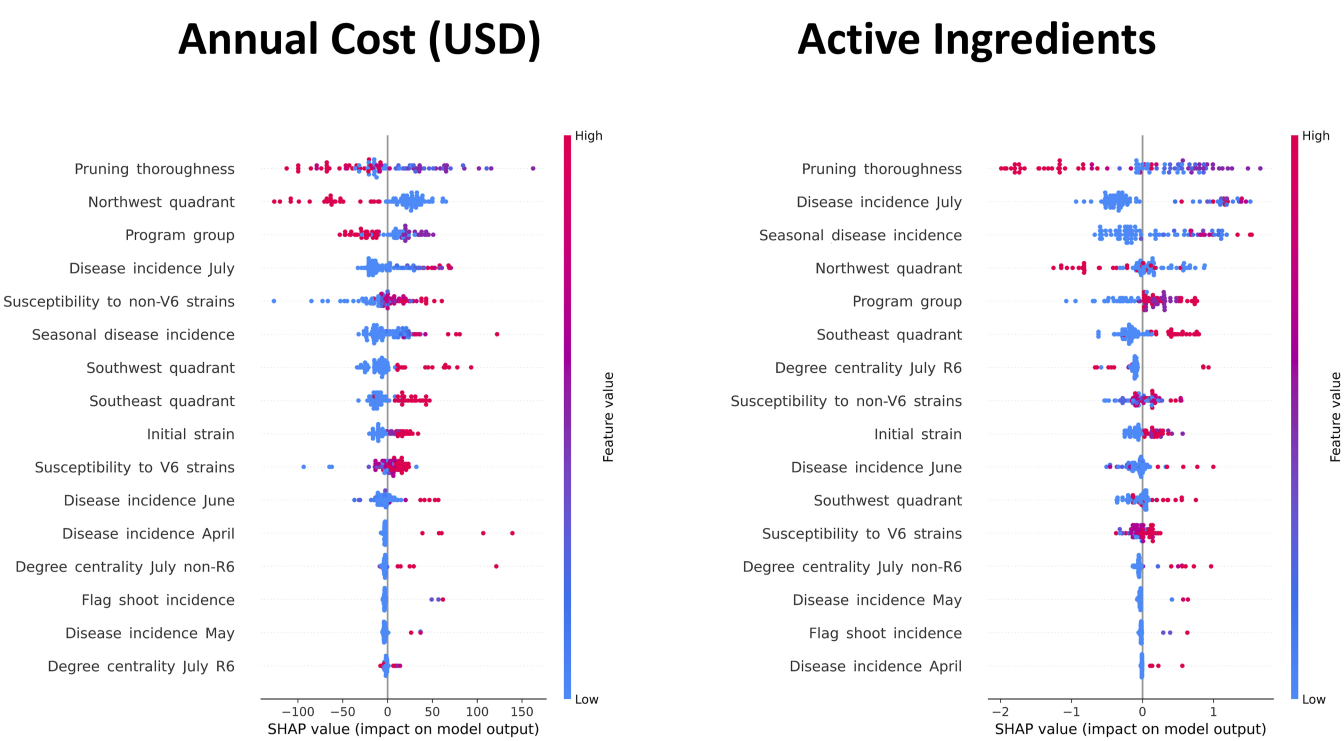

Fig. 5. Shapley additive explanation (SHAP) values of annual costs of pesticides and the number of pesticide active ingredients applied for management of powdery mildew by Oregon hop growers during 2014 to 2017. The *y*-axis indicates the feature names in descending order of importance. The *x*-axis indicates the SHAP value, and the color of the value shows whether an observation has a higher or lower value than other observations for that variable. The color of each point on the graph indicates the value of the corresponding feature, with red indicating high values and blue indicating low values for a given feature.

The pesticide application records contained active ingredients representing 17 fungicides and three herbicides relevant for powdery mildew management. Although pesticide usage varied by year and grower, two active ingredients that were used frequently and relatively consistently across all years were quinoxyfen and carfentrazone (Fig. 1). Growers made on average 0.67 to 2.87 applications of carfentrazone per hop yard and 0.75 to 1.35 applications of quinoxyfen per hop yard. Use of the desiccant herbicide carfentrazone use may reflect the centrality of thorough pruning for reducing the incidence of flag shoots (Gent et al. 2012, 2019b), whereas quinoxyfen use may reflect the efficacy of this fungicide for managing the cone phase of powdery mildew (Nelson et al. 2015). Beyond quinoxyfen, though, there was notable variation and grower-specific use patterns of most FRAC codes with the exception of the premix of FRAC 7/11 (Table 1). For instance, some growers used FRAC M02 (sulfur) relatively often (2.41 applications per yard) whereas others did not use FRAC M02 at all during 2014 to 2017.

The descriptive analysis of pesticide use provides a base level of knowledge to assess if hop growers follow best practices for disease management related to fungicide resistance management that can inform future educational efforts and policy. Growers in general appear to be following best practices for fungicide resistance management related to limiting the use of a given mode of action associated with a moderate to high risk of resistance development (Corkley et al. 2022). Although usage of the various FRAC codes depended on the specific grower, on average none of the growers made more than 1.35 applications per yard of any FRAC code or premixes with a moderate to high risk of resistance development (Table 1). Furthermore, in only five instances was a FRAC code with moderate to high risk applied in more than two applications in a given yard. Although growers appear to be following best management practices for limiting use of any given mode of action, the relatively consistent use of quinoxyfen across farms, cultivars, and years suggests that this fungicide may be a priority for future resistance monitoring. Furthermore, there may be an area for education on resistance management as related to use of multisite fungicides, notably FRAC M02 (sulfur). Growers that applied sulfur comparatively less often made comparatively more frequent use of synthetic fungicides with a moderate to high risk of resistance development, which may hasten resistance development.

Growers' pesticide use patterns indicate three general programs

Although pesticide programs were complex and quite diverse, application of hierarchical cluster analysis enabled us to find evidence of three general programs that growers used.

The programs varied based on the relative use of sulfur or other nonsynthetic fungicides and differing combinations of specific synthetic fungicides and herbicides used in powdery mildew management. Four of the five most commonly applied fungicides in program group 3 were nonsynthetic materials: sulfur, copper, mineral oil, and potassium bicarbonate. Program group 3 also had lower use of every synthetic fungicide than program group 1 and, for most active ingredients, program group 2 (Table 2). Given the higher costs of synthetic fungicides relative to sulfur and other nonsynthetic fungicides (Hwang et al. 2024), this explains why the annual costs varied by program group, even though the mean number of active ingredients applied was similar.

It is likely that fungicide use patterns are also influenced by restrictions on tank mixes or rotations dictated by the manufacturers' label. This may lead to technology lock-in, in which a grower's previous pesticide choice may make it difficult to switch to certain other alternatives. For example, the use of sulfur-based fungicides may preclude the use of mineral oils for a certain period of time because of label requirements related to minimizing phytotoxicity. Presence of downy mildew, the other major foliar disease of hop in the Pacific Northwest (Gent et al. 2012), could also shape growers' decisions on pesticide selection because certain fungicides may affect both diseases (Nelson et al. 2015). Unfortunately, we do not have estimates of the presence or severity of downy mildew in the present data set. An expanded analysis considering both diseases would be illuminating for understanding how pesticide use patterns change in response to dual epidemics.

The mean seasonal incidence of powdery mildew varied in hop yards that received one of the pesticide programs group (Table 3; Fig. 3). However, discerning cause and effect with the present data set is difficult because our analyses are focused on annual outcomes. Measurements of disease and pesticide selections over time are needed to make causal inferences about the effectiveness of the pesticide programs. Our analyses do provide new direction for future research to quantify the effectiveness of the three approaches that growers tended to take in their disease management.

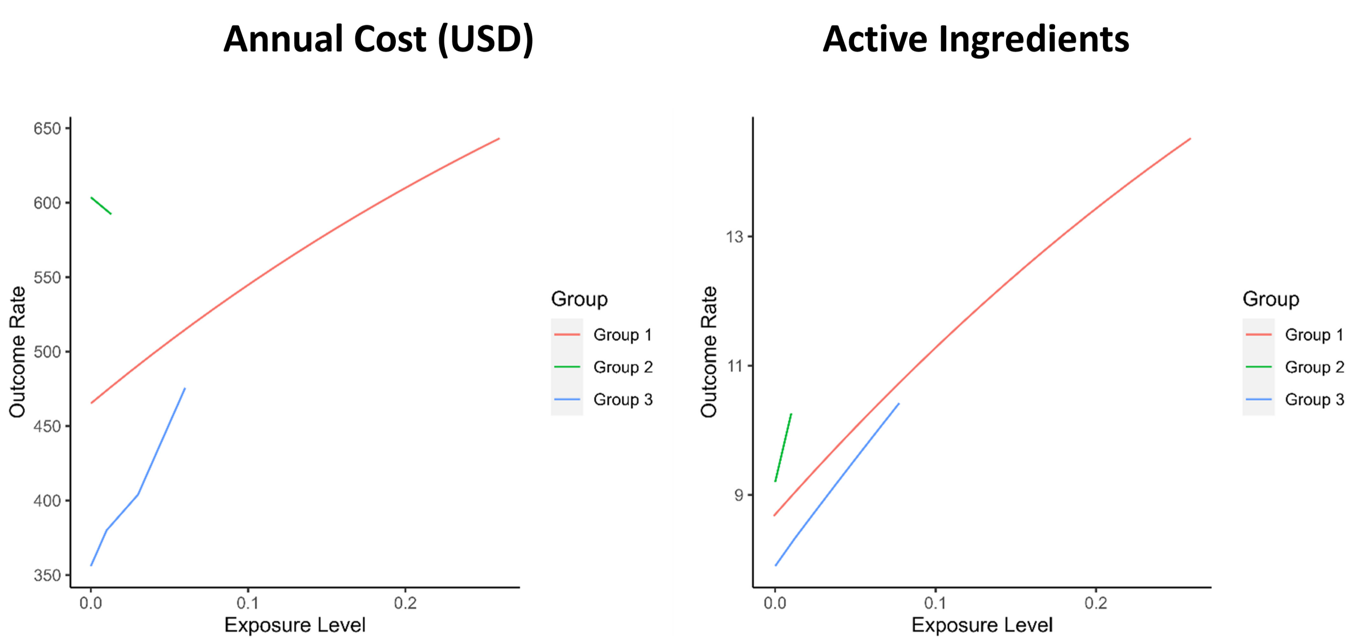

Fig. 6. Exposure response function of annual costs of pesticides (left) and the number of pesticide active ingredients (right) applied by Oregon hop growers for management of powdery mildew. Groups refer to pesticide program groups identified through hierarchical cluster analysis. Exposure level represents the seasonal mean incidence of plants with powdery mildew. Note that the exposure levels varied depending on the program group.

Growers' pesticide program is an important predictor of overall pesticide use and costs

A contribution of the current study is that we find evidence that pesticide program group is comparatively important relative to other factors known to influence pesticide use and costs, such as pruning thoroughness, cultivar susceptibility to powdery mildew, and levels of disease in spring (Table 4; Fig. 5). The SHAP values indicate that growers that applied program group 3 increase the predicted number of active constituents applied but also lowered their annual costs. This is expected given the more common use of inorganic fungicides in program group 3 (sulfur, copper, mineral oil, and potassium bicarbonate) that have generally shorter reapplication intervals than synthetic fungicides but also tend to be less expensive.

For both active ingredients and annual costs, the other variables identified as most important based on SHAP values were related to thoroughness of spring pruning, position in the landscape, and disease incidence in July or seasonally. We draw particular attention to spring pruning thoroughness. This practice is an antecedent of disease development and was the most influential variable for both outcome variables, varying by more than one ordinal value in each pesticide program group. We note that pesticide program group 1 had the least thorough pruning (mean 3.52) and had the largest predicted annual costs ($500.27 per ha), whereas program group 3 had the most thorough pruning (mean 2.27) and least predicted annual costs ($353.34). Previous research found an association between the thoroughness of spring pruning and when growers made the first fungicide application of the season (Gent et al. 2012). In that study, growers on average delayed their first fungicide application for powdery mildew by approximately 2 weeks when pruning was conducted thoroughly versus other categories (Gent et al. 2012). In the present study, we also found an association between the pesticide program group that was applied and the date of the first fungicide application of the year. Growers adopting pesticide program group 1, 2, or 3 made the first fungicide application of the year on average on 27 April, 17 May, and 5 May, respectively. In contrast, the date of the last fungicide application was approximately similar across the pesticide program groups (23 to 26 July). Our present study indicates that thorough spring pruning not only delays the timing of the first application but that growers also reduce the total number of active ingredients they apply and also the type of active ingredients when pruning is conducted thoroughly. This cultural practice, therefore, may have economic benefits as well as longer-term benefits for delaying fungicide resistance because growers tend to make fewer applications of synthetic fungicides with higher risks of developing resistance when pruning is conducted most thoroughly. Additionally, thorough spring pruning may derivatively reduce the risk of crops exceeding maximum residue limits (Handford et al. 2015) in export markets because the overall reduced use of synthetic fungicides in a pesticide program is correlated with the thoroughness of spring pruning.

Growers apply a specific fungicide program under a specific range of disease levels

Spring pruning thoroughness and other important variables in the random forest regression are related directly or indirectly to disease incidence (Probst et al. 2016; Royle 1978). This motivated our attempt to fit causal exposure response functions for each pesticide program group because mean seasonal incidence of powdery mildew has a direct causal relationship with fungicide use and costs (Hwang et al. 2024). Multiple attempts to balance or match covariates failed to resolve covariate imbalance in the data set, and the assumption of overlap for all values of potential confounders and weak unconfoundedness were not satisfied. Causal inference, therefore, is not possible for the fitted exposure response functions. Although causal inference is not possible, the shape of the exposure response functions and range of seasonal mean incidence of plants with powdery mildew is potentially informative. It is apparent that yards that receive one of the three pesticide programs vary in the mean incidence of powdery mildew (Fig. 3) and the range of disease incidence (Fig. 6). The tendency is that the number of active ingredients applied, and annual costs incurred, increase linearly with the seasonal mean incidence of plants with powdery mildew, independent of the pesticide program group applied by a grower. The restricted range of seasonal mean disease incidence where program group 2 and program group 3 were applied hints at growers switching pesticide programs in response to disease pressure. Disease mitigation decisions often change or are assumed to change with disease prevalence or information on disease risk (Cascante-Vega et al. 2022; Garcia-Figuera et al. 2021; Lybbert et al. 2016; Murray-Watson et al. 2022). In our companion study, we conduct follow-up analyses to understand when hop growers switch pesticide programs and identify factors associated with switching behavior. Such analyses could guide future research to design and identify fungicide programs tailored to disease exposure levels, which our analyses indicate could reduce both cost and use of synthetic fungicides.

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