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Sustainable Pest Management Under Uncertainty:
A Dynamic Bioeconomic Analysis of Lowbush Blueberry Production[1]

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Abstract

Spotted Wing Drosophila (SWD) is an invasive pest that infests soft-skinned fruits and has resulted in large pest management costs for growers in the U.S. In this study, we analyze sustainable SWD pest management for lowbush blueberry production in Maine. We develop and apply a novel dynamic bioeconomic analysis framework that combines numerical dynamic optimization and dynamic structural econometric estimation. Our preliminary results suggest that a sustainable pest control alternative -- early harvesting -- can be part of an optimal management strategy, and that spraying insecticide is not optimal in most cases when pest pressure is low. We also find that the actual behavior of growers is rationalized by a very high perceived spray cost and as well as a high perceived yield loss from infestation from medium-high levels of SWD. Furthermore, even after conditioning on growers' beliefs, the preliminary results still show a positive deadweight loss to actual pest management decisions. In particular, preliminary results show that, given growers' beliefs and perceptions, and in contrast to their actual spraying and harvesting decisions, the optimal SWD strategy still tends to include early harvesting and very little if any spraying. The results of this research has the potential to provide timely information to stakeholders regarding optimal management strategies; improve growers' welfare and sustainability; as well as shed light on the field of bioeconomics for pest management.

Keywords: pest management, agriculture, sustainability, insecticide, pesticide, farmer behavior
***JEL* codes:** Q12, Q57, Q16, Q18

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1. Introduction

Spotted Wing Drosophila (SWD), or *Drosophila suzukii*, is an invasive pest that infests soft-skinned fruit such as berries and has resulted in large pest management costs for berry growers in the U.S. since it was first detected in 2008 (Walsh et al. 2011; Cini, Ioriatti and Anfora 2012; Asplen et al. 2015a). Unlike most of the Drosophila species, female SWD have a unique serrated ovipositor which allows them to lay eggs under the ripening or unripe fruit skin and causes direct damage to soft-skinned fruit (Asplen et al. 2015b). High-value fruit crops such as blueberries are the most affected by SWD. Fruit buyers generally have very low tolerance with infested fruits; in fresh or exporting markets, the whole shipment is rejected if any infestation is found. The economic loss from SWD has been severe. An over $500 million losses was estimated for the west coast berry industry (Bolda, Goodhue and Zalom 2010).

To protect their crops from SWD infestation, domestic growers have increased their use of insecticide applications (Bolda et al. 2010; Walsh et al. 2011; Cini et al. 2012). The management costs of intensive insecticide applications are high (Farnsworth et al. 2017; Drummond, Ballman and Collins 2019), however, and recent research suggests that growers may be over-spraying when the pest pressure is low (Yeh et al. 2020). Moreover, increased insecticide usage due to SWD may also lead to insecticide resistance (Farnsworth et al. 2017; Gress and Zalom 2018), and has drawn environmental and health concerns (Sexton 2007).

The resulting high production costs and environmental concerns have led the industry and researchers to evaluate alternative pest management strategies (Farnsworth et al. 2017). Possible sustainable SWD control alternatives include exclusion netting, frequent harvesting, or early harvesting, among other strategies (Leach, Van Timmeren and Isaacs 2016; Leach et al. 2018; Rendon and Walton 2019; Rendon et al. 2020; Stockton et al. 2020). Nonetheless, given the high

penalty associated with infestation, the majority of the growers still tend to cling to an intensive calendar-based spraying schedule to control SWD, although it may not be the best management practice.

In this paper, we focus on lowbush blueberry production in Maine. Maine is the third largest state in domestic blueberry production volume (U.S. Department of Agriculture 2019), and produces over 90% of lowbush blueberry in the U.S. Given the climate of the region, SWD is a mid-to-late season pest. Unlike highbush blueberry production, which has multiple harvests per season, lowbush blueberry growers only harvest once per season. As a result, for lowbush blueberry growers in Maine, a unique sustainable pest control alternative to calendar-based insecticide applications is to harvest earlier to avoid the higher pest pressure later in the season. The tradeoff for early harvesting, however, is that growers may incur revenue loss from any prematurely harvested unripe fruit that is sorted out in the processing line (Drummond et al. 2018). The optimal pest management strategy is further complicated by the uncertainty growers face regarding the pest pressure and the corresponding infestation, which affect their profits.

We examine the following research questions: What is the optimal SWD management strategy? Are growers currently following the optimal SWD management strategy? Is sustainable pest control a part of the optimal strategy? How can we incentivize growers to adopt sustainable management strategies?

In order to answer these research questions, we develop a novel dynamic bioeconomic analysis framework of lowbush blueberry production to analyze sustainable SWD pest management under uncertainty. We apply our multi-stage dynamic bioeconomic analysis framework to a unique dataset of 92 lowbush blueberry farms in Maine to investigate the optimal SWD management strategy, the resulting welfare changes, and grower behavior.

Our dynamic bioeconomic analysis framework combines numerical dynamic optimization and dynamic structural econometric estimation, and consists of three stages. In the first stage, we construct a numerical bioeconomic model to solve for the dynamically optimal management strategy, and compare optimal decisions predicted by our model with actual decisions made by growers. In the second stage, we develop a dynamic structural econometric model that accounts for the unobservable factors when growers make actual choices, and estimate the structural parameters econometrically using the data. Our structural model enables us to ascertain what parameters, beliefs, and perceptions would rationalize the decisions growers have actually made. In the third stage, we parameterize our numerical bioeconomic model from Stage 1 using our structural parameter estimates from Stage 2 in order to determine the optimal strategy given growers' beliefs, and to assess whether the actual decisions made by growers are optimal given their beliefs as determined in Stage 2.

We model the grower's decision-making problem over a growing season as a finite-horizon stochastic dynamic optimization problem. Each week during the growing season, the grower makes decisions about whether to spray insecticide to control SWD and whether to harvest. Once the grower decides to harvest, the decision is irreversible and the grower receives the revenues from harvest (which is the yield net of any loss from SWD, times price) at the time of harvest. The decision-making problem is dynamic because blueberry yields, SWD population, and infestation levels vary over time and are affected by the previous management decisions implemented by the grower. The model is stochastic given the uncertainty faced by growers regarding SWD population, infestation, and weather. The grower's problem is therefore one of investment under uncertainty (Dixit and Pindyck 1994).

The numerical bioeconomic model we develop in the first stage is a finite-horizon stochastic dynamic programming problem that solves for the dynamically optimal management strategy. The state variables include the observed SWD larval and adult population, the interval since the last insecticide application, precipitation, and temperature. SWD larval population, SWD adult population, and weather all evolve stochastically. We non-parametrically estimate separate stochastic transition densities for the SWD population during the early-, mid-, and late-season using the data. The distributions for stochastic precipitation and temperature, which we allow to vary by time of season, are estimated using empirical averages in the actual data. The interval since the last insecticide application evolves deterministically. We solve the finite-horizon dynamic programming model via backwards iteration in order to determine the dynamically optimal management strategy. We compare the optimal decisions predicted by our model with the actual decisions made by growers in the data, and assess whether and by how much growers can increase their welfare by employing the optimal strategy.

One key assumption we make when inferring optimality using the numerical bioeconomic model is that growers' perceptions and beliefs about spraying costs and infestation loss are the same as those we use in our model. Although we calibrate the spraying costs and infestation loss parameters in our numerical bioeconomic model based on actual data and SWD studies of infestation, it is possible that growers may have different perceptions and beliefs about spraying costs and infestation loss. If growers view certain parameters differently than what the model assumes, then the optimal strategy given their beliefs would differ from what is suggested by the numerical bioeconomic optimization.

To address this, in the second stage of our study, we estimate a dynamic structural model to estimate the parameters that underlie the decision-making of Maine lowbush blueberry growers.

Our dynamic structural econometric model builds upon our numerical bioeconomic model, and additionally accounts for unobservable state variables growers observe (but we do not observe) when they make their spraying and harvesting decisions. We estimate several parameters econometrically using the data, including the yield losses due to SWD infestation and the perceived spray costs. Building on the nested fixed point maximum likelihood estimation technique developed by Rust (1987), we solve for the structural parameters using a maximum likelihood estimation that nests a backwards iteration to solve for the continuation values and conditional choice probabilities for each evaluation of the likelihood function. Our dynamic structural econometric model enables us to ascertain what parameters, beliefs, and perceptions would rationalize the decisions growers actually made.

In the third stage of our analysis, we apply the structural parameters estimated at the second stage to the numerical model built in the first stage in order to solve for the optimal strategies conditional on growers' beliefs. Then, taking growers' beliefs as given, we recalculate welfare using the third-stage composite model to assess whether and by how much growers can increase their welfare by employing the optimal strategy.

The contribution of this study is twofold. First, our dynamic bioeconomic analysis of the optimality of SWD management strategies as well as their welfare and sustainability have important implications for growers and policymakers. We not only assess the optimality of sustainable pest management alternatives for this severe pest issue, but also provide actionable results for growers to improve their welfare.

Our second contribution is methodological. Programming- or optimization-based bioeconomic models have the drawback of simplying or assuming the behavior and beliefs of decision-makers (Janssen and van Ittersum 2007). To the best of our knowledge, our paper is one

of the few studies in the field of bioeconomics that incorporate a dynamic structural econometric estimation of grower's behavior into numerical optimization. By including the structural estimates of growers' beliefs and perceptions, our novel multi-stage dynamic bioeconomic analysis framework enables us to propose possible improvements in management practices that align with growers' beliefs and perceptions. The results from the structural estimation also provide relevant information for other research related to the grower's decision-making of pest management.

Our research has the potential to not only provide timely information to stakeholders regarding optimal management strategies, but also shed light on the literature on the bioeconomics of pest management.

2. Previous Literature

This study contributes to various strands of the literature. In this section, we first discuss the studies related to the economics of SWD. Then, we review previous studies on pest management with the focus of those using bioeconomic models. Lastly, we discuss dynamic structural econometric model and related applications in the literature.

Since SWD becomes an established pest in the U.S., there is a growing body of studies examining the economic impacts it brought to the industry (Bolda et al. 2010; Goodhue et al. 2011; Farnsworth et al. 2017; Yeh et al. 2020). Although pest management decisions are made at the farm level, farm-level SWD control decisions are not well understood in economic research. The only two related studies are Fan et al. (2020) and Yeh et al. (2020). Fan et al. (2020) develop a Bayesian bioeconomic model to whether monitoring based integrated pest management strategies perform better in terms of minimizing the costs. Both Fan et al. (2020) and Yeh et al. (2020) use simulation-based approaches to rank and compare how different pest control strategies perform.

This study relates to a broader literature on the economics of pest management. Past economic research has studied how producers deal with pest issues from various aspects. Production-oriented studies focus on estimating the productivity change or functional form of including pesticide as damage-control input in the crop production (Carrasco-Tauber and Moffitt 1992; Kuosmanen, Pemsl and Wesseler 2006; Sexton 2007; Chambers, Karagiannis and Tzouvelekas 2010), while other studies focus on the welfare implication related to pesticide usage, such as the environmental externalities and health impacts (Sunding and Zivin 2000; Sexton 2007; Grogan and Goodhue 2012; Waterfield and Zilberman 2012). Given the negative externalities associated with pesticide applications, researchers also assess how to incentivize pesticide reduction in various settings (Lohr, Park and Higley 1999; Falconer and Hodge 2000; Jacquet, Butault and Guichard 2011). For instance, Jacquet, Butault and Guichard (2011) simulate the effect of pesticide reduction and suggest threshold of cutting pesticide without reducing farm income.

As pest control decisions are highly related to ecological and environmental factors, bioeconomic models provide an integrated framework to evaluate optimal pest control decisions. Given the intertwined feedback links between the biological and economic systems, bioeconomic modeling is generally challenging and the modeling approach highly depends on the nature of the problem (Finnoff et al. 2005; Smith 2008; Kling et al. 2016). For the case of optimal farm-level pest management, the majority of bioeconomic studies are based on mathematical programming or optimization with a certain objective such as profit-maximization (Falconer and Hodge 2000; Buysse, Van Huylenbroeck and Lauwers 2007; de Frahan et al. 2007; Mérel and Howitt 2014). One caveat of this type of bioeconomic model is that it often neglects the behavioral factors of producers and thus producers may not desire to manage their production according to the optimal model outcome (Janssen and van Ittersum 2007). Previous researches suggest the importance of

acknowledging not only the parameters in the bio-system but also producer's behavior in decision making in the bioeconomic studies (Falconer and Hodge 2000; Smith 2008; Chen, Jayaprakash and Irwin 2012).

Dynamic structural econometric models provide great flexibility for researchers to estimate behavioral parameters under various circumstances. Dynamic discrete choice models have been applied in various economic research topics (Hotz and Miller 1993; Rust 1987; Timmins 2002; Arcidiacono and Miller 2011). Specifically, applications in agriculture include disease management (Carroll et al. 2020a; Sambucci, Lin Lawell and Lybbert 2019; Carroll et al. 2020b) and land use (Scott 2018). For instance, Carroll et al. (2020b) apply a dynamic structural model for lettuce crops disease control in California to evaluate outcomes between long-term and short-term decision-makers. Although farm managers generally make pest management decisions within the production season on a weekly basis, the use of the dynamic discrete choice model to understand the within-season decision-making of pest control is rare in the literature, which could be due to data limitation.

Previous research by Misra and Nair (2011) provide evidence that innovative dynamic structural econometric models can help significantly improve decision-making and outcomes. In their study, Misra and Nair (2011) develop and apply a dynamic structural econometric model to data on the US sales force of a large contact lens manufacturer to design sales-force compensation schemes to increase the firm's profits. Their recommendations were then implemented at the firm, resulting in an increase in annual revenues of about $12 million. Our research strives to similarly improve decision-making and outcomes by growers managing SWD.

This study contributes to the literature in various aspects. First, synthesis papers such as Kling et al. (2016) point out that there is a still lack of economic models of decision making

coupled with the biophysical system to provide policy-relevant implications. The integrated framework proposed in this study suggests a novel way of incorporating producer's perception into bioeconomic research, which sheds light on this strand of work. Moreover, as discussed earlier, structural estimation of grower's within-season pest management behavior is hard to find in the economic research, and thus the structural estimation itself provides valuable understanding of grower's pest control behavior. In addition, this study also possesses empirical contributions regarding the problem of SWD and the optimal management correspondingly. Farm-level analyses conducted by Fan et al. (2020) and Yeh et al. (2020) infer best SWD control with simulations, whereas this is the only study that solves for the optimal SWD control strategy and makes welfare inference.

3. Data

We obtain our field data from 92 lowbush blueberry fields in Maine with SWD larva and adult observations. Wild blueberry production employs a two-year production cycle. The first year is solely for field preparation (vegetative), while the second year is for harvesting (fruit-bearing). In the dataset, each farm reported data from one fruit-bearing year over the period 2012 to 2017. The adult SWD population was monitored with sticky traps in the field, while larvas were observed using fruit sampling (see Drummond et al. (2019) for details on the data collection). There are 19 farms out of the 92 total that are organic farms.

Given that each farm-year reported slightly different observation intervals and time lengths, we linearly postulate the uneven observations into a total of 18 weeks (June 1 to Sep 30), which is when the wild blueberries are generally susceptible to SWD infestation. Then, we subset the data into the same discrete time step (weekly) for calibration and estimation, given that grower usually

makes weekly decisions in practice. The weather data is compiled using the farm locations from PRISM.[2]

4. Numerical Bioeconomic Model

Our numerical bioeconomic model is a finite-horizon stochastic dynamic programming problem. Each week t, conditional on the past decisions and the observed pest level, the grower makes decisions on whether to spray insecticide to control SWD or whether to harvest to receive the corresponding payoffs (i.e. revenue from selling the berries). Once the grower decides to harvest, the decision is irreversible, and the grower receives payoff at the harvesting period. Thus, the choice variable a_t is a vector consisting of the choice of harvesting (h_t) and choice of spraying (s_t), and takes one of three possible values: $a_t \equiv (h_t, s_t) \in \{(1,0), (0,0), (0,1)\}$. The option of harvesting while spraying is not included in the analysis given that growers generally avoid applying insecticide at the same time of harvesting to comply with the regulated maximum pesticide residue levels; as a consequence, we do not observe growers harvesting and spraying during the same week in the data.

The state variable vector $state_t$ in the optimization model is a tuple consisting of state variables measuring the population levels of SWD, weather variables, and the interval since the last insecticide application. The population dynamics of SWD is accounted by using the six-level discretized observed larva ($y_{larva,t}$) and the dummy variable of the observed adult SWD ($y_{adult,t}$). The observed larva is assumed to directly influence a percentage loss in yield, which affects grower's per-period payoff. The expected crop revenue π_t from harvesting at week *t* is a function

[2] http://www.prism.oregonstate.edu/

of baseline yield at week t, the expected percentage losses in production due to larval infestation ($\text{loss}(\text{y}_{\text{larva,t}})$), and price.

$$\pi_t(y_{larva,t}) = yield_t \cdot E\left(1 - loss(y_{larva,t})\right) \cdot price.$$

The state tuple also includes the three-level spraying intervals for insecticide application, which can take value as 1 if sprayed at t; 2 if not spray but still within effective periods of past insecticide applications (i.e. sprayed at $t-1$ or $t-2$); or 3 if not spray and not in effective periods of past insecticide applications. Finally, we include two weather-related dummy variables, the weekly accumulated precipitation and maximal temperature, as studies have shown that precipitation may affect spraying efficacy while the temperature may affect the SWD population dynamics (Tochen et al. 2014; Wiman et al. 2014; Hamby et al. 2016; Gautam et al. 2016; Van Timmeren et al. 2017). We use 2mm and 27 degree Celsius as the thresholds for the dummy variables for accumulated precipitation and the maximal temperature, respectively.

The Bellman equation of the grower's dynamic programming problem includes the entire stream of expected payoffs from the three possible choices at a given time: (1) harvest, (2) not harvest and not spray, and (3) not harvest but spray. The Bellman equation can be mathematically specified as:

$$\begin{aligned} V_t(state_t) = \max_{h_t, s_t}\{ \quad & h_t \cdot \pi_t(y_{larva,t}), \\ & (1-h_t)(1-s_t) \cdot \beta \cdot E(V_{t+1}(state_{t+1}) | state_t, \text{s}_\text{t} = 0, \text{h}_\text{t} = 0), \\ & (1-h_t) \cdot s_t \cdot \beta \cdot E(V_{t+1}(state_{t+1}) | state_t, \text{s}_\text{t} = 1, \text{h}_\text{t} = 0) - s_t \cdot \text{spraycost} \quad \} \end{aligned}$$

We assume that grower's utility is linear to the per period payoff (i.e. we assume that $U(\pi_t(\text{state}_\text{t})) = \pi_t(\text{state}_\text{t})$). The value function $V_t(state_t)$ denotes the value function at time *t* given the level of state variable tuple ($state_t$), and gives the optimized value of the present discounted value of the entire stream of expected per-period payoffs from time *t* until the remainder of the season when the spraying and harvesting decisions are chosen optimally, conditional on

choosing optimally in the remaining time periods. β denotes the weekly discount factor. $E(\mathrm{V}_{t+1}(state_{t+1})|state_t, \mathrm{s}_t, \mathrm{h}_t = 0)$ is the continuation value from not harvesting, which is the expected value of the value function next period, conditional on not harvesting this period, where the expectations are taken over the stochastic population transition from the current state to the next state. We assume that the continuation value from waiting instead of harvesting in the final week of the season is 0: $E(\mathrm{V}_{t+1}(state_{t+1})|state_t, \mathrm{s}_t, \mathrm{h}_t = 0) = 0$. We solve for the value function for each week *t* via backwards iteration.

We assume that the state variables follow a first-order Markov process. The transition densities $Pr(state_{t+1}|state_t, \mathrm{a}_t)$ governing the evolution of state variables from one period to the next given the state variable and choice variable this period is calculated as follows. For SWD population dynamics (i.e. $y_{larva,t}$ and $y_{adult,t}$), we use nonparametric estimation to account for the transition densities of population levels conditional on spraying decision, weather variables, and spraying interval variable. We separate the 18-week season equally into three periods, and the transition densities are estimated separately for early-, mid- and late-season. There is a total of 10 transition densities calculated for the SWD dynamics.[3] The distributions for stochastic precipitation and temperature, which we allow to vary by time of season, are estimated using empirical averages in the actual data. The spraying interval variable evolves deterministically as a function of this period's action and the value of the previous spraying interval variable.

The transition densities we estimate non-parametrically and use for our numerical model and structural econometric models are consistent with models of SWD dynamics. Our estimated

[3] The detail breakdown of the 10 transition densities is as follow. If spraying interval = 1 (i.e. spray), then the densities are further conditioned on the precipitation as it affects the spraying efficacy. We only observed spraying behavior in mid-season. If spraying interval = 3 (i.e. not spray and is not within effective periods of past insecticide applications), then we condition the densities on temperature, and separated the densities for early, mid, and late season. For spraying interval = 2 (i.e. not spray but within effective periods of past insecticide applications), we calculate the densities separately for mid and late season, but we do not further conditional on other conditions given the limited data variation.

transition densitions show that, during the mid-season, if the farmer either has never sprayed yet or is past the effective periods of past insecticide application, there is higher probability of SWD larva to increase if the farmer does not spray. Also during the mid-season, spraying diminishes the probability of SWD getting worse, especially when rain does not wash it away. We also find that when temperature is very hot, this makes it more likely for SWD to decline, which is consistent with studies that show that SWD mortality rate increases dramatically if the temperature exceeds 27 degrees C (Tochen et al. 2014).

The values of key model parameters in the optimization model are drawn for a representative lowbush blueberry farm in Maine based on various sources. The grower is a price taker and we draw the average price at $0.26 per lb (U.S. Department of Agriculture 2019). We assume an annual discount rate of 0.9 and calculate the weekly discount factor accordingly. The assumed yield of a healthy berry field is at 4,000 lbs per acre. The cost of spraying ($spraycost$) is $40 per acre (Esau 2019).

The relationship between week of harvest and the yield (i.e., $yield_t$) is proxied by the percentage of ripeness estimated based on Julian date in Drummond et al. (2019):

$$\%\, ripe\ fruit = 100/\left(1 + e^{(30.903 - 0.159 \cdot JulianDate)}\right)$$

for weeks $first\_ripe\_week$=9 and later; prior to weeks $first\_ripe\_week$=9, the percentage of ripeness is 0. According to this function for fruit ripeness, fruit reaches close to its maximum maturity around weeks 11-12 of the 18-week season.

Based on expert opinion and extension reports (Burrack 2014; De Ros et al. 2015; DiGiacomo et al. 2019; Drummond, Ballamn, et al. 2019; Yeh, Drummond and Gomez 2019; Yeh et al. 2020), the percentage production loss ($loss\left(y_{larva,t}\right)$) is related to the level of larval

infestation, but they are not perfectly colinear (Table 1) since it is difficult to completely sort out infested fruits from the healthy ones and may incurs higher production costs in reality.

As explained below, we conduct sensitivity analysis that vary the values of key model parameters, and find that the results of our numerical model are robust to a reasonable range of values for these parameters.

5. Dynamic Structural Econometric Model

To understand the beliefs and perceptions of growers that underlie and rationalize their spraying and harvesting decisions as revealed in the data, we nest the numerical bioeconomic model within the structural econometric model adapted from Rust (1987). Our dynamic structural econometric model builds upon our numerical bioeconomic model, and additionally accounts for unobservable state variables growers observe (but we do not observe) when they make their spraying and harvesting decisions.

The vector of structural parameters θ we estimate relates to costs induced by SWD, including the five tiers of infestation loss and the spraying cost. We rewrite the value function and per-period payoff for grower i as follows:

$$
\begin{aligned}
V_{it}(state_{it}) &= \max_{a_{it}} \{ \quad u_{0,it}(state_{it}, a_{it}, \theta) + \epsilon_{a_{it}} + \beta \cdot E(V_{i,t+1}(state_{i,t+1}|a_{it})) \} \\
&= \max_{h_{it}, s_{it}} \{ \quad h_{it} \cdot \pi_{it}(y_{larva,t}, \theta) + \varepsilon_{1it}, \\
&\qquad\qquad \varepsilon_{2it} + (1 - h_{it})(1 - s_{it}) \cdot \beta \cdot E(V_{t+1}(state_{i,t+1})|s_{it} = 0), \\
&\qquad\qquad \varepsilon_{3it} + (1 - h_{it}) \cdot s_{it} \cdot \beta \cdot E(V_{t+1}(state_{i,t+1})|s_{it} = 1) - s_{it} \cdot spraycost \quad \}
\end{aligned}
$$

$$
\pi_{it}(y_{larva,t}, \theta) = yield_t \cdot E\left(1 - loss(y_{larva,i,t})\right) \cdot price
$$

The per-period payoff to each choice a_{it} has a deterministic component and a stochastic component. The deterministic component, $u_{0,it}(state_{it}, a_{it}, \theta)$, of the per-period payoff is 0 when

there is no harvest. The deterministic component of the per-period payoff to action 1, when there is harvest, is $\pi_{it}(y_{larva,t}, \theta)$. The stochastic component to the per-period payoff to each action is an unobserved shock, $\epsilon_{a_{it}}$, associated with that action choice a_{it} that is assumed to be distributed i.i.d. extreme value across time, farms, and actions. The likelihood function, $\mathcal{L}(\theta) = \Pi_i \Pi_t Prob(a_{it}|state_{it}, \theta)$, is a function of the conditional choice probabilities, $Prob(a_{it}|state_{it}, \theta)$.

$$Prob_t(a_{it}|state_{it}, \theta) = \frac{exp\left(u_{0,it}(state_{it}, a_{it}, \theta) + \beta V_t^c(state_{it}, a_{it}, \theta)\right)}{\Sigma_a exp\left(u_{0,it}(state_{it}, a_{it}, \theta) + \beta V_t^c(state_{it}, a_{it}, \theta)\right)}$$

The continuation value, $V_t^c(state_{it}, a_{it}, \theta)$, under the assumption of the extreme value distribution of the error terms, is given by:

$$V_t^c(state_{it}, a_{it}, \theta) = E_{state,t}\left[E_\epsilon\left[\max_a\left(u_{0,it}(state_{it}, a_{it}, \theta) + \beta V_t^c(state_{it}, a_{it}, \theta)\right)\right]\right]$$

$$= E_{state,t}\left[ln\Sigma_a exp\left(u_{0,it}(state_{it}, a_{it}, \theta) + \beta V_t^c(state_{it}, a_{it}, \theta)\right)\right].$$

Thus, we can construct the maximum likelihood estimation with the below log-likelihood function:

$$L(\theta) = ln\mathcal{L}(\theta) = \Sigma_i \Sigma_t ln\left(Prob_t(a_{it}|state_{it}, \theta)\right).$$

Building on the nested fixed point maximum likelihood estimation technique developed by Rust (1987), we solve for the structural parameters using a maximum likelihood estimation that nests a backwards iteration to solve for the continuation values and conditional choice probabilities for each evaluation of the likelihood function.

Identification of the parameters θ comes from the differences between per-period payoffs across different action choices, which in finite horizon dynamic discrete choice models are identified when the discount factor β, the distribution of the choice-specific shocks ε_{it}, and the

final period continuation value are fixed (Rust 1994; Magnac and Thesmar 2002; Abbring 2010). In particular, because the discount factor β and the distribution of the choice-specific shocks ε_{it} are fixed and the final period continuation value is zero, the parameters in our model are identified because each term in the deterministic component $u_{0,it}(state_{it}, a_{it}, \theta)$ of the per-period payoff depends on the action a_{it} being taken at time *t*, and therefore varies based on the action taken; as a consequence, the parameters do not cancel out in the differences between per-period payoffs across different action choices and are therefore identified. For example, the $spraycost$ parameter is identified in the difference between the per-period payoff from choosing to spray and the per-period payoff from any action choice a_{it} that does not involve spraying.

Standard errors are formed by a nonparametric bootstrap. Farms are randomly drawn from the data set with replacement to generate 100 independent panels each with the same number of farms as in the original data set. The structural model is run on each of the new panels. The standard errors are then formed by taking the standard deviation of the parameter estimates from each of the panels.

6. Preliminary Results and Discussion

In this section, we first discuss the optimal management strategies and welfare solved by the numerical model, then we discuss the structural estimates and the welfare reassessment conditional on the growers' beliefs.

6.1. Optimal management strategies and welfare

The numerical bioeconomic model solves for the policy function and value function for each week, which specify the optimal strategy as a function of state variable at each week. Under

the base case specification, we find that for most weeks with low SWD population, it is not optimal to spray insecticide. Spraying is only optimal in some cases when SWD is high and the farm either has never sprayed or has passed the effective periods of past insecticide applications.

We also find that harvesting can be optimal as early as week 10 for a few states. These states tend to be states in which SWD adult index is high and when the interval since last spray is high. Thus, early harvesting can be part of an optimal SWD management strategy when SWD is high. We also find that harvesting is optimal for almost all state tuples starting week 12 onwards. In the base case specification, fruit reaches its maximum maturity around weeks 11-12.

Our preliminary results therefore suggest that a sustainable pest control alternative -- early harvesting -- can be part of an optimal management strategy, and that spraying insecticide is not optimal in most cases when pest pressure is low.

We use our numerical model to compare the welfare from the optimal strategy predicted by our model with the welfare from the actual decisions made by growers in the data. We define welfare as the present discounted value (PDV) of the entire stream of per-period payoffs over the entire season for the farm. Our numerical bioeconomic model solves for the value function for each week, which specifies the welfare the farm would receive as a function of state variables if it followed the optimal strategy. Using our numerical bioeconomic model, we can thus infer actual welfare, optimal welfare, and deadweight loss. We calculate actual welfare using observed actions and states of each farm. The optimal welfare, as given by the value function evaluated at on the initial observed states, is the maximum expected PDV of the entire stream of per-period payoffs the farm could have received that year if it followed the optimal strategy. We calculate the deadweight loss from the growers' actual actions as optimal welfare minus actual welfare. The

average actual welfare is estimated at $826.7 per acre (Table 2). The optimal welfare is on average $963.6 per acre across all farms. The mean deadweight loss across all farms is $136.9 per acre.

Since the optimal strategy maximizes the expected welfare of farmers, some farms have an actual welfare that exceeds optimal welfare owing to actual realized draws of stochastic state variables. Nevertheless, the deadweight loss to actual decisions would be decreased and welfare increased on average and in expectation if the farmers pursued the optimal spray and harvest strategy instead.

We also use our numerical model to compare the optimal decisions predicted by our model with the actual decisions made by growers in the data. For each farm in our data set, we run 100 simulations of the optimal spray and harvest strategies start with the actual observed states for that farm at the first week, and forward simulating using our policy function and transition densities. For each farm for each week of each simulation, we infer the action using the policy function solved from the numerical optimization, and we draw from the estimated transition densities to simulate the transition of the states from one week to the next.

Using the simulated trajectories from each farm, we plot the average optimal probabilities of spraying and harvesting at each time period, and compare with the actual spraying and harvesting decisions made in the data (Figure 1). The average probabilities of actual spray and actual harvest refer to the averages across the observed actions employed by the growers, while the average probabilities of optimal spray and optimal harvest are calculated by averaging over the 100 simulated trajectories for each farm. Both probabilities are averaged across the 92 farms. The results indicate that the probability of spraying in the observed data is much higher than is optimal. The optimal harvest timing is also shown to peak around week 10 to week 12, which is earlier than the actual harvest periods around week 12 to week 15.

Our results are robust to alternative specifications that vary crop price, spray cost, the variance in crop prices, and the discretization of SWD and infestation loss. Our results are also fairly similar to alternative specifications that vary percentage yield loss based on infestation level, transition density week cutoff, and first harvestable week (Figure A1 in Appendix).

6.2. Structural parameters of grower's behavior

The preliminary results for the structural parameters from our structural econometric model are summarized in Table 3a. The cumulation of infestation loss tiers indicates the percentage of yield loss given the observed larval infestation level. The results show that growers perceive that there will be a 100% loss in yield if there is a medium-high level of SWD larva (i.e., between 5 and 10% observed larval infestation) or higher. In contrast, as seen in Table 1 for the yield loss that we use in our numerical model, expert opinion and extension reports show that the yield loss for a medium-high level of SWD larva (i.e., between 5 and 10% observed larval infestation) is only 50% (Burrack 2014; De Ros et al. 2015; DiGiacomo et al. 2019; Drummond, Ballamn, et al. 2019; Yeh et al. 2019; Yeh et al. 2020).

In addition, results show that growers perceive the cost associated with spraying to be very high, at $2,966.17 per acre, which is significant at a 5% level. In contrast, the actual spray cost (i.e., that we use in our numerical model) is $40 per acre.

Growers are therefore making decisions as if they face a spray cost (monetary or otherwise) of $2,966.17 and high yield losses from medium-high levels of SWD larva. In other words, growers' actual decisions are rationalized by a spray cost (monetary or otherwise) of $2,966.17 and high yield losses from medium-high levels of SWD larva.

We also try an alternative specification of our structural model in which we use coarser bins for larva and larval infestation. As seen in Table 3b, our results are robust. Once again, we find that growers perceive that there will be a 100% loss in yield if the observed larval infestation is 5% or higher. Our results also show once again that growers perceive the cost associated with spraying to be very high, this time at a statistically significant $2,965.83 per acre.

6.3. Optimal strategies conditional on structural parameters

Using our structural estimates, we reassess the optimal strategy for the growers given their beliefs and perceptions.

Figure 2 plots the optimal strategies given the beliefs and perceptions of growers, and compares them with the actual spraying and harvesting decisions made by growers in the data. As we obtain high perceived spray costs from the structural estimates, when we reassess the numerical model with structural estimates, the policy function indicates that spraying is never an optimal strategy under any state. We also find that harvesting is optimal for most state tuples starting week 12 onwards. Moreover, given the beliefs of growers, harvesting is not optimal for some states. Thus, given growers' beliefs and perceptions, early harvesting can be part of the optimal SWD strategy while spraying is not.

Given the growers' perceived high spraying costs, the average actual welfare is negative due to the high spraying cost, at -$1,643.20. In constrast, the average optimal welfare given the growers' beliefs is $985.30. Thus, even conditional on growers' beliefs, growers experience an average deadweight loss of $2,638.50 across farms. The positive deadweight loss indicates that, even under the grower's perceptions of SWD-related costs, their actual choices were still not optimal and could be improved (Table 2).

Figure 3 compares the actual decisions with the optimal strategy given the beliefs and perceptions of growers when also accounting for unobservable state variables growers observe (but we do not observe) when they make their spraying and harvesting decisions, as given by the optimal choice probabilities. The qualitative results are similar: given growers' beliefs, the optimal mixed strategy places a very low and almost negligible probability on spraying, and a higher probability on early harvesting than was pursued by the growers' in the data.

7. Conclusion and Next Steps

In this paper, we develop a novel dynamic bioeconomic analysis framework that combines numerical dynamic optimization and dynamic structural econometric estimation to analyze optimal SWD management for wild blueberry production in Maine.

Results from our numerical bioeconomic model provide valuable insights to the optimal pest management. Our preliminary results suggest that a sustainable pest control option -- early harvesting -- can be part of the optimal strategy. For weeks with low SWD population, insecticide application is not optimal in most cases.

We find that the actual spraying and harvesting decisions of growers are not optimal. Of the farms that actually spray, the optimal spray often tends to be later than actual (first) spray. The optimal harvest tends to be earlier than actual harvest for most (but not all) farms. Under base case parameters, there is a deadweight loss to actual decisions that would be decreased on average and in expectation if the farmers pursued the optimal spray and harvest strategy instead.

Since the optimal strategy maximizes the expected welfare of farmers, some farms have an actual welfare that exceeds optimal welfare owing to actual realized draws of stochastic state variables. Nevertheless, the deadweight loss to actual decisions would be decreased and welfare

increased on average and in expectation if the farmers pursued the optimal spray and harvest strategy instead.

We employ a dynamic structural econometric model in this study to understand growers' behavior, perceptions, and beliefs. We find a very high perceived cost related to spraying, and the structural estimation also suggests that, for the case of lowbush blueberry in Maine, growers do not perceive much yield loss when the larval infestation is under 5%. However, growers perceive a 100% loss when the infestation is over the 5% threshold. According to expert opinion and extension reports (Burrack 2014; De Ros et al. 2015; DiGiacomo et al. 2019; Drummond, Ballamn, et al. 2019; Yeh et al. 2019; Yeh et al. 2020), however, the yield loss when the larval infestation is between 5% and 10% is only 50%. Thus, the actual behavior of growers is rationalized by a very high perceived spray cost, much higher than the actual spray cost; as well as a different (and possibly incorrect) perception of percentage yield loss based on infestation. Our results suggest that a reason that most growers are very proactive in pest control in reality may be that they view a total loss from a small percentage of SWD infestation.

Nevertheless, when we condition on the beliefs of the growers and solve for the optimal SWD strategy conditional on their beliefs, we find that there still exists positive deadweight loss to the actual decisions being made by growers. In other words, there is still room for welfare improvement even after considering grower's perceptions in making decisions. In particular, given growers' beliefs and perceptions, and in contrast to their actual spraying and harvesting decisions, the optimal SWD strategy still tends to include early harvesting and very little if any spraying.

Our preliminary results suggest some possible ways to improve the optimality of actual SWD management strategies of farmers and therefore their welfare and sustainability. These

include: providing grower with information about actual spray costs and percentage yield loss based on infestation; providing growers with information about early harvest as an optimal management strategy; providing growers with incentives to incentivize early harvest as a possible strategy; and mitigating any possible barriers to the use of early harvest as a SWD management strategy.

This study contributes to the literature and has valuable policy implications regarding the sustainability of pest control. Methodologically, this is a very unique bioeconomic study that combines structural estimations of grower's behavior with numerical optimization, which is rarely viable in within-season farm-level bioeconomic research. Our results provide actionable suggestions to growers on choosing an optimal pest control strategy that can improve their welfare and sustainability. The results can also be used to provide information on incentivizing sustainable strategy and mitigating possible barriers of adoption. Our next step is to incorporate risk aversion into the analysis, to simulate counterfactual analyses for scenarios such as insecticide resistance, and to have more understanding about welfare changes related to the adoption of sustainable practices.

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Table 1. Assumed production loss based on observed larval infestation

Observed larval infestation	Index for y_{larva}	Percentage of production loss ($loss_t$)
0% or less than 0.3%	0 and 1	0%
Between 0.3% and 1%	2	10%
Between 1% and 5%	3	30%
Between 5% and 10%	4	50%
More than 10%	5	80%

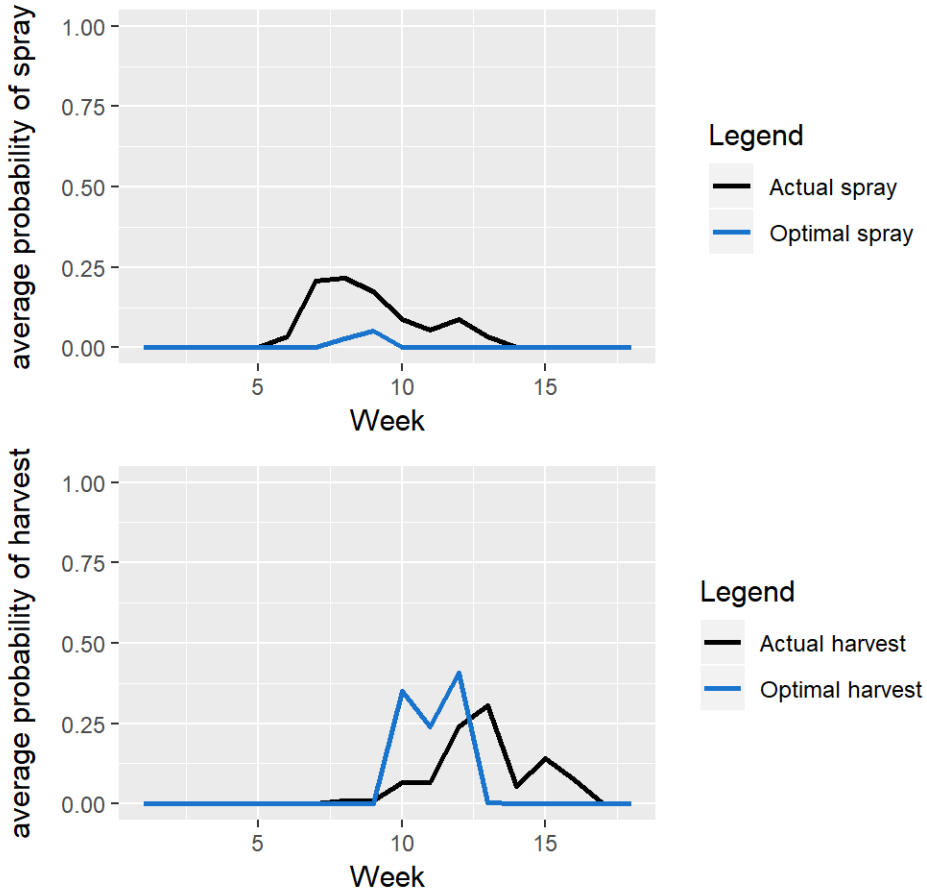
Notes: The production loss based on observed larval infestation is based on expert opinion and extension reports (Burrack 2014; De Ros et al. 2015; DiGiacomo et al. 2019; Drummond, Ballamn, et al. 2019; Yeh et al. 2019; Yeh et al. 2020).

Table 2. Average welfare across farms

	Results from using base-case parameter values	Results from using structural estimates of parameters
Actual welfare ($/acre)	826.7	-1,653.2
	(217.9)	(2520.4)
Optimal welfare ($/acre)	963.6	985.3
	(0.2)	(0.0)
Deadweight loss ($/acre)	**136.9**	**2,638.5**
	(217.9)	**(2520.4)**

Notes: Table reports average values across farms. Standard deviations across farms are in parentheses. We define welfare as the present discounted value (PDV) of the entire stream of per-period payoffs over the entire season for the farm. We calculate actual welfare using observed actions and states of each farm. The optimal welfare, as given by the value function evaluated at on the initial observed states, is the maximum expected PDV of the entire stream of per-period payoffs the farm could have received that year if it followed the optimal strategy. We calculate the deadweight loss from the growers' actual actions as optimal welfare minus actual welfare.

Figure 1: Optimal vs. actual probabilities of spraying and harvesting



Notes: Figure compares the optimal and actual average probabilities of spraying and harvesting. The optimal average probabilities of spraying and harvesting are given by averaging over 100 simulations for each farm using the policy function from our numerical model and the non-parametrically estimated transition densities, and then averaging over all farms.

Table 3a. Structural parameter estimates

	Parameter Estimate
Infestation loss tier 1 (Infestation ≤ 0.3%)	0.000
	(0.000)
Infestation loss tier 2 (0.3%< Infestation ≤ 1%)	0.000
	(0.065)
Infestation loss tier 3 (1%< Infestation ≤ 5%)	0.000
	(0.046)
Infestation loss tier 4 (5%< Infestation ≤ 10%)	1.000***
	(0.191)
Infestation loss tier 5 (10% < Infestation)	0.000
	(0.166)
Spray cost ($ per acre)	2,966.17***
	(96.123)

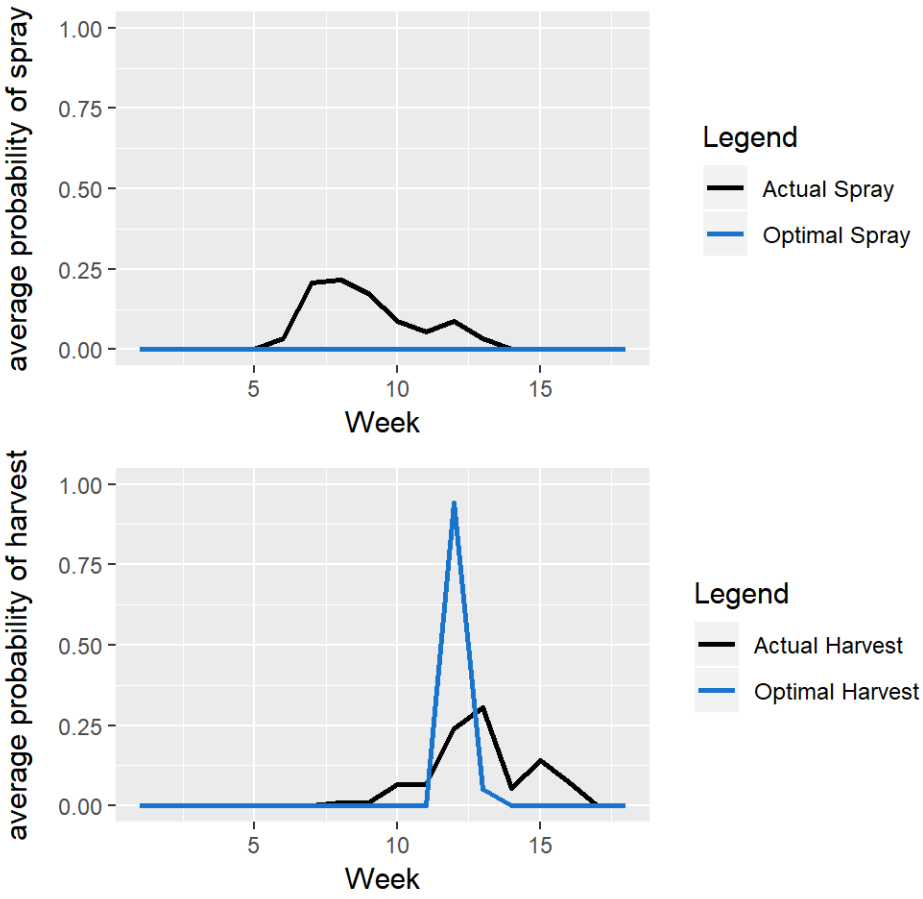
Notes: Infestation is the observed larval infestation. Bootstrapped standard errors in parentheses.
Significance: *** 0.1%; **1%; *5%

Table 3b. Structural parameter estimates: Robustness with coarser bins for larva and larval infestation

	Parameter Estimate
Infestation loss tier 1 (Infestation ≤ 0.3%)	0.000
	(0.000)
Infestation loss tier 2 (0.3%< Infestation ≤ 1%)	0.000
	(0.171)
Infestation loss tier 3 (1%< Infestation ≤ 5%)	0.000
	(0.045)
Infestation loss tier 4 (5%< Infestation)	1.000***
	(0.177)
Spray cost ($ per acre)	2,965.83***
	(96.121)

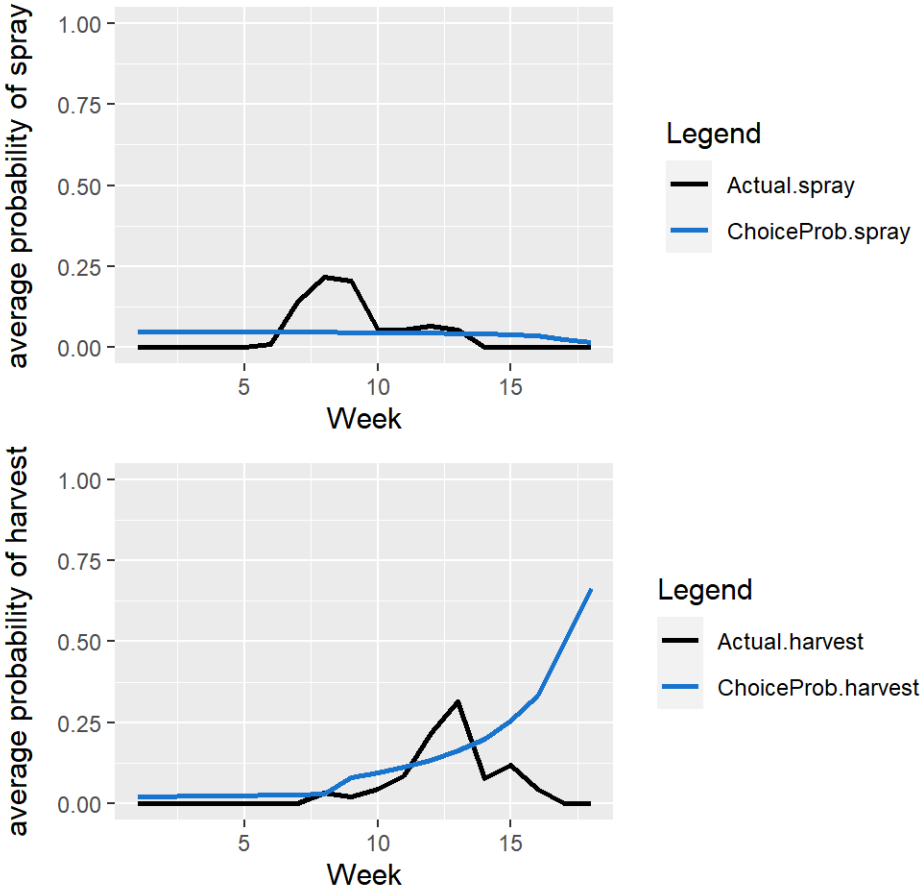
Notes: Infestation is the observed larval infestation. Bootstrapped standard errors in parentheses.
Significance: *** 0.1%; **1%; *5%

Figure 2: Optimal probabilities of spraying and harvesting conditional on growers' beliefs and perceptions



Notes: Figure compares the optimal and actual average probabilities of spraying and harvesting, conditional on growers' beliefs. The optimal average probabilities of spraying and harvesting conditional on growers' beliefs use the parameters estimated from the structural model, and are given by averaging over 100 simulations for each farm using the policy function from solving our numerical model using the parameters estimated from the structural model and the non-parametrically estimated transition densities, and then averaging over all farms.

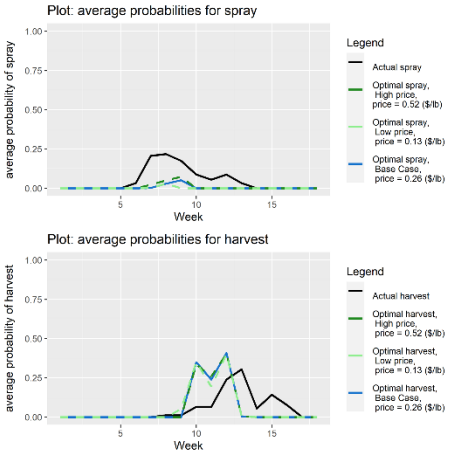
Figure 3: Optimal probabilities of spraying and harvesting conditional on growers' beliefs and perceptions when also accounting for unboservable state variables



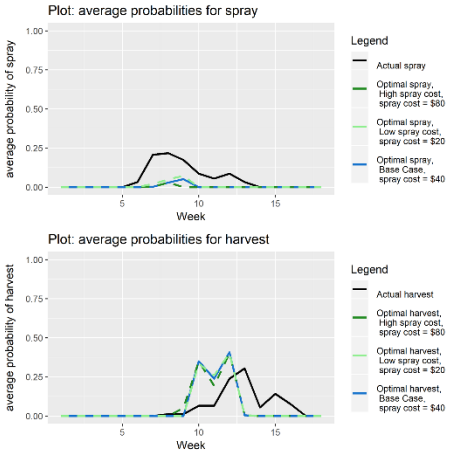
Notes: Figure compares the optimal and actual average probabilities of spraying and harvesting, conditional on growers' beliefs and when also accounting for unboservable state variables.

Appendix

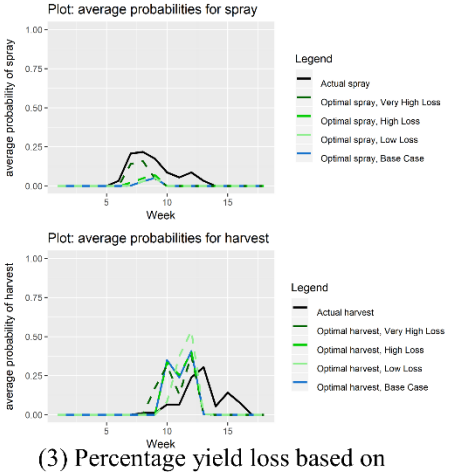
Figure A1. Numerical Model Robustnesss



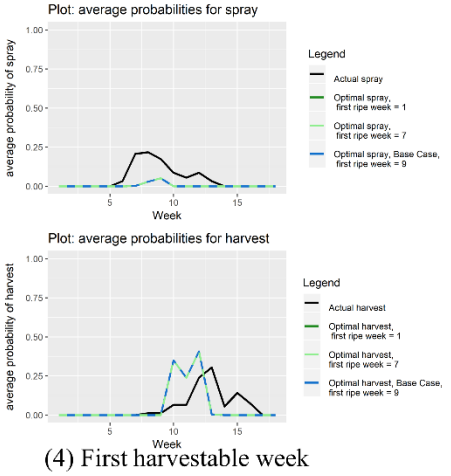
(1) Crop price



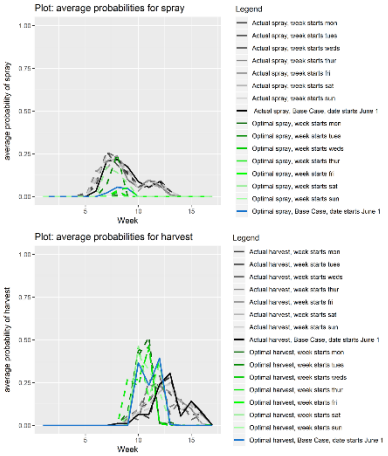
(2) Spray cost



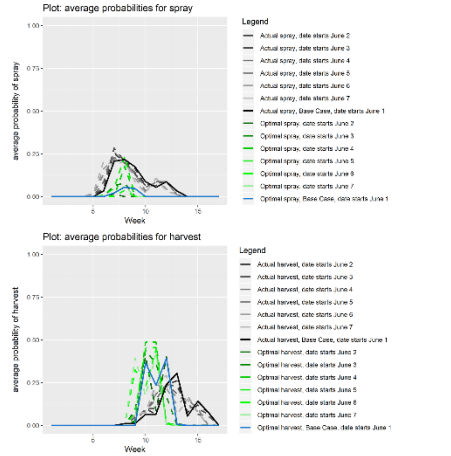
(3) Percentage yield loss based on infestation



(4) First harvestable week



(5) Week definition by day



(6) Week definition by starting date (June 1- June 7)