Cost-effectiveness and Risk Assessment in Integrated Pest Management: The Case of Spotted Wing Drosophila

Working paper

Bingyan Dai, Cornell University, bd393@cornell.edu

Miguel Gómez, Cornell University, mig7@cornell.edu

Xiaoli Fan, University of Alberta, xiaoli@ualberta.ca

Binita Shrestha, Cornell University, bs687@cornell.edu

Gregory M. Loeb, Cornell University, gme1@cornell.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 2024

Abstract

Effectively managing pests and mitigating the negative externalities of pesticide applications require integrated pest management (IPM). IPM aims to discourage the development of pest populations while keeping pesticide usage at economically justified levels and minimizing risks to human health and the environment. However, more than half a century since its conception, IPM has not been adopted to a satisfactory extent. The high cost of practice and perceptions of increased risks associated with IPM have been identified as the most critical barriers to its adoption in the U.S. This study evaluates the cost-effectiveness and risks associated with the status quo strategy (i.e., calendar-based spraying) and five monitoring-based IPM strategies with two monitoring techniques (i.e., adult trapping and larva-sampling) for controlling a devastating invasive species affecting the soft-fruit industry in the U.S. (i.e., Spotted wing drosophila (SWD)). We utilize a Bayesian bioeconomic framework which incorporates both biological and economic uncertainties related to SWD control, focusing on conventional blueberry production in New York state. Our results indicate that the status quo strategy remains the optimal control strategy for profit-maximizing growers with the lowest expected total costs and the least variability in yield and total costs. While all monitoring-based spraying strategies result in higher expected total costs than the status quo approach, the expected total costs and risk level of the larva-sampling based IPM strategy show only a small difference compared to the status quo one. Policymakers could consider offering small incentives to cover this difference in expected total costs and encourage the adoption of improved IPM practices for sustainability. These findings contribute to the sustainable management of invasive species at the farm level and provide insights for policies aimed at promoting environmental-friendly and sustainable agricultural practices.

1. Introduction

Integrated pest management (IPM), created in the late 1950s (Deguine et al. 2021), is a science-based and sustainable decision-making process that utilizes information on pest biology, environmental data, and technology to manage pest damage in a way that minimizes economic costs and risks to people, property, natural resources, and the environment (White and Wetzstein 1995; Greene et al. 1985; Tait et al. 2021). Since 2000, four regional IPM centers funded by the USDA National Institute of Food and Agriculture were created to promote nationwide adoption of IPM in the United States (U.S.) (Balew et al. 2023). However, more than half a century after its conception, IPM has not been adopted to a satisfactory extent (Balew et al. 2023; Rasche et al. 2016; Creissen et al. 2019; Deguine et al. 2021), especially in fruit and vegetables (Greene et al. 1985; Wyckhuys et al. 2021).

The low levels of farmer adoption and insufficient diffusion of IPM technology are ascribed to different factors. The high cost of practice, and the perception of increased risks associated with IPM strategies are the most critical barriers to IPM adoption in the U.S. (Greene et al. 1985; Lane, Walker and Grantham 2023). Moreover, most growers are risk-averse, and those who are more risk averse are less likely to take such preventive measures due to less certain net return from IPM strategies (Wang and Finger 2023). Improved economic cost-benefit analysis that highlight profitability of IPM practices, therefore, is essential for promoting new and existing IPM innovations, which was also ranked as the most critically important way to increase IPM adoption by IPM professionals (Lane et al. 2023). With better cost-benefit analyses, economists can better predict which incentives might have the most impact on increasing IPM adoption. Other barriers, including difficulty of implementation and lack of awareness, could be mitigated by extension and education programs.

This research aims to evaluate the cost-effectiveness and risk level of a promising integrated pest management strategy for controlling a devastating invasive species affecting the soft-fruit industry in the U.S. (i.e., Spotted wing drosophila (SWD)). This study involved an interdisciplinary effort among agricultural economists and entomologists to acquire and analyze biological and economic data on SWD management in New York State. This research builds on previous work (Fan et al. 2020) by utilizing a Bayesian bioeconomic approach while concurrently devoting major attention to a monitoring-based IPM strategy with improved monitoring technique for controlling SWD and risk analysis with detailed biological and economic data.

Spotted-wing drosophila (SWD), native to Southeast Asia, is a devastating invasive pest of soft-skinned fruits (e.g., strawberries, cherries, blackberries, blueberries, raspberries, etc.). In the last ten years, SWD has expanded its range to affect all major American and European fruit production regions (Asplen et al. 2015). Infestation by SWD generates both direct and indirect economic impacts through yield losses, shorter shelf life of infested fruit, and increased management costs. It has estimated significant economic losses from SWD invasion in different regions within and among countries (Yeh et al. 2020; Farnsworth et al. 2017; De Ros et al. 2015).

Managing SWD is challenging with few current technologies that provide relief as a standalone option (Tait et al. 2021). Currently, growers of soft fruits rely on a single and aggressive management strategy: calendar-based insecticide applications (Farnsworth et al.

2017). However, this conventional method may exacerbate externalities from intensive use of insecticides, including water pollution, soil erosion, human health issues and insecticide resistance (Van Timmeren et al. 2018; Gress and Zalom 2019). Growers are urged to use an integrated pest management (IPM) approach to manage this highly adaptive insect. Effective IPM strategies could significantly reduce pesticide applications by integrating other control strategies, such as monitoring, sanitation, and biological and behavioral control (Tait et al. 2021). Among all existing IPM strategies for controlling SWD, monitoring-based control strategy is gaining increasing interest from both growers and entomologists due to its practicality and effectiveness.

In this study, we evaluate the risk and cost-effectiveness of an improved monitoring-based management strategy: larva sampling-based spraying strategy. Fan et al. (2020) studied the cost-effectiveness of a traditional monitoring-based strategy that utilizes adult trapping to guide spraying decisions. However, recent studies show that adult catches are a poor indication of pest population and fruit infestations (Tait et al. 2021). During summer months of harvesting season, when temperatures are warm and reproduction peaks, the population's life stage distribution is primarily skewed towards nonadult life stages (Grassi et al. 2018; Emiljanowicz et al. 2014). It indicates that targeting mobile adult flies may not be the most effective means of managing this pest. There are some regions where adult trap monitoring has been largely abandoned (Tait et al. 2021). Entomologists suggested to incorporate fruit sampling in the field to observe early life stages (i.e., egg and larva) of SWD, which could provide real-time information and a more accurate estimate of crop damage that growers can use to adjust insecticide applications (Farnsworth et al. 2017).

Bioeconomic modelling is favored for evaluating the economic performance of integrated pest management strategies as it enables simultaneous accounting of the economic and ecological aspects of the problem (Sanchirico and Wilen 1999; Epanchin-Niell and Wilen 2012; Chalak, Polyakov and Pannell 2017; Fan et al. 2020; Yeh et al. 2023). The economic injury level is determined by dynamic biological and economic parameters, which can be highly variable and uncertain. SWD population and infestation intensity are largely affected by local climatic conditions and the availability of host fruit, implying that varying climatic conditions could significantly impact SWD-related yield losses and profits (Farnsworth et al. 2017). Understanding uncertain SWD population dynamics, coupled with crop susceptibility, is especially important to help guide grower management practices. To incorporate key uncertainties, we extended a Bayesian bioeconomic model (Fan et al. 2020) that integrate farm-level cost-benefit analysis with a dynamic population model parameterized using the most recent data on the presence of SWD and weather conditions in New York State.

With observed SWD population in twenty-one counties in New York state during growing seasons of conventional blueberry production from 2013 to 2022, we use Bayesian inference via Markov Chain Monte Carlo to estimate the posterior distribution of key parameters characterizing SWD population dynamics, including intrinsic growth rate, initial population rate, temperature effects, and pest migration effects. These parameters are then used to simulate SWD population dynamics for a representative blueberry grower in New York across 10,000 simulations. Then we evaluate the distribution of crop damage and total costs under various SWD management strategies. Our results indicate that the status quo strategy of weekly spraying remains the optimal strategy for profit-maximizing blueberry growers, offering the lowest expected total costs and the least variability in yield and total costs. While both improved (i.e., utilizing larva sampling) and traditional (i.e., utilizing adult trapping) monitoring-based spraying strategies result in higher expected total costs than the status quo approach, the risk level and expected total costs of the larva-sampling initiated spraying strategy show only a small difference compared to the status quo one. Policymakers could consider offering small incentives to cover this difference in expected total costs and encourage the adoption of improved IPM practices in New York state.

The research provides timely insights for stakeholders on optimal SWD management strategies, contributes to improving growers' welfare and sustainability, and sheds light on the field of bio-economics for pest management and the adoption of integrated pest management. Our work also adds to the limited economic analysis of SWD control and management. Based on these findings, policies offering monetary incentives for IPM adoption, such as Environmental Quality Incentives Programs, can encourage grower adoption of IPM strategies for controlling SWD infestations.

2. Literature Review

Economics of Spotted Wing Drosophila

Economic studies of spotted wing drosophila (SWD) can be broadly grouped into two categories: evaluation of economic impacts due to SWD damages; and comparison of economic performance with the adoption of different SWD management strategies. Researchers have estimated significant economic losses due to SWD damage in different regions within and among countries (De Ros et al. 2015; Knapp, Mazzi and Finger 2021; Yeh et al. 2020). Recently, attention has turned to the economic performance of SWD control management strategies, especially integrated pest management strategies, in a variety of crops and regions using tools such as cost-benefit analysis, economic modeling, and simulation (Farnsworth et al. 2017; Yeh et al. 2020; Fan et al. 2020).

Combining biology of invasive pest species and grower's economic behaviors, bioeconomic framework is appropriate to evaluate integrated pest management (IPM) strategies for controlling SWD infestation. Fan et al. (2020) is the first study that developed a Bayesian bioeconomic framework to assess economic performance of SWD management strategies and focused on conventional monitoring strategy: adult trapping. However, the adult trapping methods have been abandoned in some regions because of their inaccurate observation of true SWD infestation. Now entomologists show the fruit-sampling based strategy could provide information for more accurate and efficient observation of SWD (Van Timmeren, Davis and Isaacs 2021). A recent study also shows that incorporating fruit sampling and early harvest is more cost appealing than the status quo strategy for large organic growers in Oregon state (Yeh et al. 2023). This study employed a bioeconomic state-space approach, but did not consider spatial heterogeneity and local micro-environmental factors due to data availability.

Bioeconomic modelling for controlling invasive species

One challenging issue of research on controlling invasive species is imperfect observation of true population size, which limits manager's ability to effectively manage invasive species. Previous literature overcame this problem by constructing the problem as a partially observable Markov Decision Process (POMDP) (Fackler and Haight 2014; Haight and Polasky 2010). These studies assume the state is one of a small number of categories describing the population of the species. The POMDP framework provides a way to explicitly incorporate the value of a monitoring program and to determine the optimal control strategy by solving a dynamic optimization problem. Haight and Polasky (2010) model the problem of monitoring and treating a site for an invasive species using a state variable that takes on one of three values: no, moderate or severe infestation. In their model, the manager can do nothing or can treat, monitor, or both. (Fackler and Haight 2014) extended POMDP framework and showed how information content affects optimal monitoring strategies. This literature has been limited to highly simplified models with state and action spaces that are discrete and small. MacLachlan, Springborn and Fackler (2017) overcomes this problem and applies to continuous variables by extending POMDP framework with density projection. However, it works only if we assume exponential families of densities for parameters, which limits its applicability. When modelling pest population size as state variable, the standard distribution for count data is Poisson or binomial distribution, which are not in the exponential family.

Structural uncertainty is another challenge in modelling invasive species problem due to insufficient knowledge of underlying structure of population dynamics. While the basic POMDP framework is effective in addressing observational uncertainty, it is limited in handling structural uncertainty due to incomplete knowledge of the values of the state transition equations (Fackler and Haight 2014). There has been an extension to the POMDP framework that enables both structural uncertainty and observational uncertainty by encompassing both standard POMDPs and Adaptive Management (AM) (Fackler and Pacifici 2014). In this framework, newly collected information helps to resolve structural uncertainty, resulting in new estimates of unknown parameters.

The Bayesian state-space model is a novel research framework applied to controlling invasive species. State space models, as a special type of hierarchic model, offer a way to incorporate observational uncertainty, model uncertainty, and environmental stochasticity (Newman et al. 2014). Recently, (Fan et al. 2020) developed a Bayesian state-space framework for sustainable pest control and evaluated cost-effectiveness of SWD management strategies. In our research, we extended this bioeconomic model and used Bayesian inference via the Markov Chain Monte Carlo (MCMC) method to generate the posterior distribution of population model parameters. The Bayesian state-space framework solves observation uncertainty by decomposing an observed time series of counts into a state process component and an observation process component. The state-space model also takes into account structure uncertainty from modelling the function form of state process and observation process. Simulation methods such as MCMC are used to estimate the posterior distributions. Although time consuming, MCMC may be the only practical approach for estimating parameters, especially for hierarchical models with many random effects. Software packages such as JAGS make these methods readily available.

3. Method

3.1 Stage 1: Bayesian State-space model

We model SWD population dynamics by extending the state-space model proposed by Fan et al. (2020). State-space model is a special type of hierarchical model, which is common approach to model population dynamics in ecological research when the quantities of interest (e.g., the population density of a species) are unknown and evolving over time. State-space models typically consist of two equations that describe: (a) the state process that captures the stochastic dynamics of the unobserved state variables, and (b) the observation process that associates the data to the state variables, which may involve some observation noises. Observable variables provide partial but noisy information about the true population.

Our state-space model is specified as follows. At a given time step, the unobserved state variable (i.e., the true SWD population) includes three life stages: egg stage $N_{E,i,t}$, larva stage

$N_{L,i,t}$, and adult $N_{A,i,t}$. We assume that grower observes the population with accuracy rate α_{FS} for larvae from fruit sampling, and adult catch rate α_{AT} for adult SWD by using traps in the field. Equation (1) and (2) model grower's observation process, where $y_{A,i,t}$ is the SWD adult count data at the site i in period t and $y_{L,i,t}$ is the number of larvae observed by fruit sampling at the site i in period t.

$$\text{Adult via trapping: } y_{A,i,t} \sim \text{binomial}\left(N_{A,i,t}, \alpha_{AT}\right) \tag{1}$$

$$\text{Larva via fruit sampling: } y_{L,i,t} \sim \text{binomial}\left(N_{L,i,t}, \alpha_{FS}\right) \tag{2}$$

In this extended model, the initial adult population is explicitly modeled as a Poisson distribution with mean λ where $N_{A,i,1}$ is the adult population size at site i (for $i = 1, \dots, I$) in period 1 (Equation (3)). Poisson distribution is the standard distribution to model count data assuming that the mean and the variance are both λ. Modeling the initial population separately can help characterize the spatial variation in the data and reduce estimation bias by using spatially replicated count data. Equation (4) models the population size subsequent periods using the well-known growth function where $N_{i,t} = N_{i,t-1} * (r_t + 1)$. $N_{A,i,t}$ is the population at site i in period t (for $t = 2, \dots, T$). r_t is the net growth rate per period, where e^{r_N} is the intrinsic growth rate of adult population. The intrinsic growth rate measures the maximum rate at which a population can grow under ideal conditions. r_0 measures how temperature in each period affect the population growth of SWD adult. It is calculated by subtracting the death rate from the reproduction rate per generation time.

$$N_{A,i,1} \sim Poisson(\lambda) \tag{3}$$

$$N_{A,i,t} \sim Poisson\left(\left(N_{A,i,t-1} - y_{A,i,t-1}\right) * (r + 1) + Migr_t\right) \tag{4}$$

Where $\log(r_t) = r_N + r_0 * Temperature_t$ and $Migr_t = \sigma * yield_t$

$$\mathrm{r_t} = e^{r_n} * e^{r_T * Temperature_t}$$

For the birth subprocess, we assume Poisson distribution for new egg birth with the fertility rate ρ.

$$N_{E,i,t} \sim Possion(N_{A,i,t} * \rho) \qquad (5)$$

For the last subprocess, egg develops to larval inside fruit. During the growing season, it takes 3 days from egg to larval and the larval stage will keep around 5 to 7 days. Thus, the total time for egg transiting into larval stage will be 8 to 10 days and we assume the larva population at time $t + 1$ can be presented as:

$$N_{L,i,t} = N_{E,i,t-1} \qquad (6)$$

We also assume larva go through the binomial processes with survival probability ϕ_L:

$$N_{s,L,i,t} \sim \mathrm{binomial}(N_{L,i,t}, \phi_L) \qquad (7)$$

If grower sprays at time t, with the insecticide efficacy rate at k_i, where $k_i \in \{k_L, k_A\}$, the larva population $\widetilde{N}_{L,i,t}$ and adult population $\widetilde{N}_{A,i,t}$ at time t can be represented as:

$$\widetilde{N}_{L,i,t} = (1 - k_L) * N_{s,L,i,t} \qquad (8)$$

$$\widetilde{N}_{A,i,t} = (1 - k_A) * N_{A,i,t} \qquad (9)$$

We parametrize the model using values proposed from previous studies and summarize in Table 1. Each week is considered as one time step in the model. For survival probabilities, studies suggest that the possible range is above 80%, with larva having higher survival rate than adult. For transition between egg stage and larva stage, we assume it takes a week for egg to transit into larva. The fertility rate affects the shape of the population curve, with a value of 0.1 from previous studies.

Table 1. Parameter assumptions for the state-space model

Parameter	Notation	Value	Source
Time step	t	Week	Authors' assumption
Fertility rate	ρ	0.1	(Rendon et al. 2019)
Insecticide mortality rate for larva	k_L	0.6	(Fan et al. 2020 and Rendon, Mermer, L. J. Brewer, et al. 2019)
Insecticide mortality rate for adult	k_A	0.7	(Fan et al. 2020 and Rendon, Mermer, L. J. Brewer, et al. 2019)
Fruit sampling accuracy rate	α_L	0.9	Authors' assumption
Trap catch rate	α_A	0.0052	(Kirkpatrick, Gut and Miller 2018)
Survival probability of larva	ϕ_L	0.9	(Asplen et al. 2015; Rendon et al. 2019)

Note: All authors' assumptions were consulted with industry representatives and extension specialists.

The posterior distribution in above equations involves high-dimensional integrations that are very difficult to evaluate analytically. Some studies used likelihood-based methods for estimating the parameters of their model. Bayesian inference is an alternative to classical inference with several appealing features. First, it allows direct probability statements to be made about a hypothesis, given data. Secon, Bayesian method offers straightforward approaches for combining data from multiple sources or using existing estimates of parameters as prior distributions. Third, a common usage of state-space models is to predict future population size, and this is easily accomplished using Bayesian methods. (Hostetler and Chandler 2015). In this paper, we use Bayesian inference via the MCMC method to generate samples from the posterior distribution that will be further used to summarize statistics of parameters and the states.

3.1.1 Data

The observed *D. suzukii* adult data were collected from 21 counties in New York State for the growing season from 2013 to 2022 from Species Distribution Maps dataset. We treat each site at one growing season as a site, and we have a total of 63 sites based on our data. For each site, adult *D. suzukii* individuals were monitored for eight weeks when the fruit is ripe enough and harvest starts. We collected historical county-level temperature data from the Global Historical Climate Network (GHCN) database to test the effect of temperature, humidity, and rainfall on population dynamics.

We also collected data from a field experiment conducted at four representative farms in New York State during the 2021 and 2022 growing seasons. The experiment utilized dry traps and a salt-based sampling method to obtain adult counts and early stages (i.e., eggs and larvae) at four commercial farms. Each farm was treated as one site for one growing season, resulting in a total of eight sites. Following the estimation of the state-space model, we utilized this dataset to examine and validate our candidate model.

Figure 1 illustrates the average weekly yields, calculated as a percentage of total yield, based on weekly yield data collected from a representative grower in New York state during the growing season from 2016 to 2022. As complete yield data for the other 62 sites are not available, we assume that all sites have the same relative weekly yield distribution as depicted in figure 1.

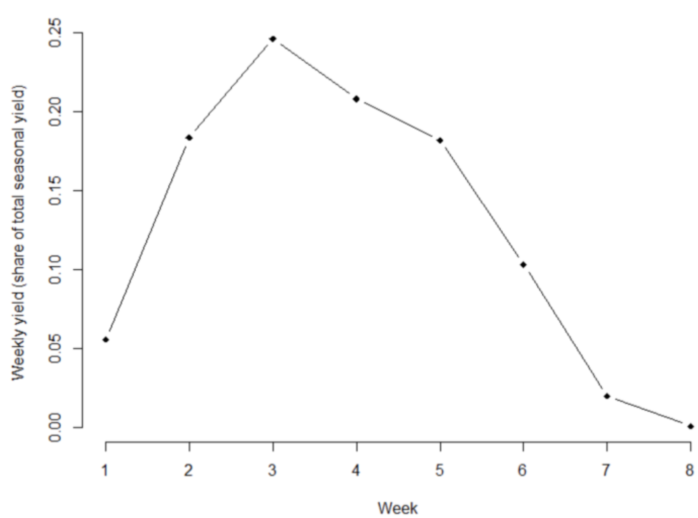

Figure 1: Weekly yield (share of total seasonal yield) of blueberry during harvesting season in New York state

3.2 Stage 2: An economic model

In this section, we explain how we use the posterior distributions of the parameters of the population model to simulate the response of the SWD population levels (i.e., eggs, larvae, and adults) under alternative SWD management strategies, which we rank using a cost-damage minimization framework.

Each period, the grower needs to choose monitoring decisions $M_{k,t}$. We define binary variables $M_{k,t}$ to denote monitoring decisions (e.g., $M_{L,t} = 1$ if grower monitors the activity of SWD by larva sampling, and $M_{A,t} = 1$ if grower monitors the activity of SWD by adult trapping and 0 otherwise). After the monitoring decision, the grower chooses whether to spray insecticide. Let S_t denote the spraying decision ($S_t = 1$ if the grower decides to spray at period and 0 otherwise) and Efficacy denotes the efficacy of the insecticide, which is measured as the percent reduction in SWD population. Note that the spraying decision may depend on the monitoring results. Following the spray decision, SWD with the population size $\widetilde{N_t}$ causes damage to fruits on the farm.

The grower's objective is to minimize the expected total cost, which is the sum of expected damages and management costs across time, by choosing the optimal SWD management strategy. The strategy δ is a rule that maps X_t into the grower's monitoring decision and spraying action for $t = 1, \dots, T$.

$$\min_{\delta} Total\ costs(\delta) = E\{\sum_{t=1}^{T} Damage_t\big(N_t(\delta)\big) + management\ costs(S_t(\delta) + M_{A,t}(\delta) + M_{L,t}(\delta))\} \tag{13}$$

We assume that damage depends on the population level after monitoring and spraying control actions and that SWD only causes damage by reducing marketable yields. Let d_L be the yield reduction rate per larva. d_L is calibrated based on a 50% yield loss if no control action is taken. The damage for period t is the product of weekly blueberry yields, the price of blueberries, the total larva counts and the probability of SWD damage.

$$Damage_t(\widetilde{N_t}) = yield_{pest\ free,t} * price * \widetilde{N}_{L,i,t} * d_L \quad (14)$$

Management costs are the sum of monitoring costs and spraying costs. Assuming that growers follow the manufacturers' recommended single dosage of insecticide every week, management costs can be expressed as:

$$Pest\ Management\ Costs_t = Unit\ Spraying\ cost * S_t + Unit\ MonitoringCost_A * M_{A,t} + Unit\ MonitoringCost_L * M_{L,t} \quad (15)$$

We run simulations over a growing season of two weeks to evaluate six different strategies (Table 2) for managing a SWD infestation in a one-acre representative blueberry farm. The grower does not take any control action under the no-intervention scenario. The most commonly adopted management strategy by growers is the calendar-based spray, which is weekly pesticide application in New York state; we choose this strategy as the baseline to compare outcomes of alternative strategies and evaluate its cost effectiveness and risk level. The rest of the strategies are monitoring-based IPM strategies. We assess the yield loss and economic performance of five monitoring-based control strategies. Strategy 2 and 4 are monitoring-initiated strategies, in which the grower initiates weekly monitoring at the beginning of the harvesting season employing adult trapping (Strategy 2) or larva sampling (Strategy 4), and starts spraying after the number of SWD caught reaches or exceeds a predetermined threshold, and then continues weekly sprays for the remainder of the season while stopping monitoring activities. Strategy 3 and 5 are monitoring guided strategies, in which the grower monitors weekly throughout the harvesting season and sprays only in weeks when the number of SWD (adult or larva) caught by adult trapping (Strategy 3) or larva sampling (Strategy 5) reaches or exceeds a predetermined threshold. Strategy 6 is adult-trapping initiated with sampling guided, in which the grower initiates adult monitoring by utilizing trapping at the beginning of the harvesting season, and starts weekly monitoring using larva sampling after the number of SWD adults caught by traps reaches or exceeds a predetermined threshold, and then sprays only in weeks when the number of SWD larva reaches or exceeds a predetermined threshold.

Table 2. *D. suzukii* control strategies: Definitions and Descriptions

Strategy (δ)	**Description**	**Monitor**	**Spray**
0. No intervention	Never monitor; Never spray	Never	Never
1. Weekly spraying	Spray throughout the season	Never	Always
2. Adult trapping-based spray: Monitor-to-initiate	Threshold =1 adult per acre	Sometimes	Sometimes
3. Adult trapping-based spray: Monitor-to-guide	Threshold =1 fly per acre	Always	Sometimes
4. Fruit sampling-based spray: Monitor-to-initiate	Threshold =1 larva per acre	Sometimes	Sometimes
5. Fruit sampling-based spray: Monitor-to-guide	Threshold =1 larva per acre	Always	Sometimes
6. Adult trapping initiated, and sampling guided	Threshold =1 fly/larva per acre	Always	Sometimes

We use the samples of the posterior distribution of the population model parameters generated by the MCMC estimation to simulate the economic performance of the strategies. For each strategy δ, we use the population dynamics, the population model parameters in the posterior distribution sample, and monitoring decisions, and spraying decisions described by δ to obtain simulated values of true SWD population and observed SWD counts for each period of the growing season. Environmental stochasticity, demographic stochasticity, and observational uncertainty are introduced during this simulation process, using Poisson distribution and binomial distribution described in equations (1) to (9). The total cost of each strategy is also calculated in the simulation process. The whole process is replicated for 10,000 samples of the posterior distribution and the total cost of each strategy is averaged. The total costs of strategies are ranked using the objective function, and the strategy with the lowest total cost is deemed the optimal strategy among the twelve strategies considered in this study.

The economic parameters that we used to calculate the total cost of each strategy are shown in table 3. Blueberry harvesting in New York typically starts in early July and ends in late August. For the costs related to blueberry production and SWD controls, the information is based on previous studies and consultation with industry representatives and extension specialists. We account for the extra monitoring costs incurred by using adult trapping and larva sampling strategies.

Table 3. Parameter values of a representative New York blueberry farm

Parameter	Value	Source
Pick-on-your-own Prices	$2.16 per lb.	Ag MRC (2021) https://www.agmrc.org/commodities-products/fruits/blueberries
Costs		
adult trapping cost	$10 per acre	Authors' assumption
fruit sampling cost	$17 per acre	Authors' assumption
Spraying cost (High efficacy insecticide)	$38	Calculation based on quotes from NY blueberry growers
Spraying cost (low efficacy insecticide)	$26	Calculation based on quotes from NY blueberry growers
Others		
Baseline annual pest-free yield	5,000 lbs. per acre	(Fan et al. 2020)
Harvest window	8 weeks (early July to late August)	Authors' assumption

Note: All authors' assumptions were consulted with industry representatives and extension specialists.

Results and Discussion

In this section, we first present the posterior distribution of estimated parameters from Bayesian state-space model. Then we show the economic performance of alternative SWD management strategies under the status quo insecticide efficacy and monitoring efficiency (including trap catch rate and fruit sampling accuracy rate). We then conduct sensitivity analyses to evaluate the performance of alternative SWD control strategies under various biological and economic parameters.

Posterior distribution of key parameters in Bayesian state-space model

Table 4. Descriptive statistics of the marginal posterior distributions of the key parameters

Parameter	Prior distribution	Posterior distributions of the key parameters					Convergence diagnostic
		Mean	SD	2.50%	50%	97.50%	R hat
λ	~*Uniform*(0,200)	59.35	1.806	55.83	59.3	62.9	1.00
r_N	~*Norm*(0, 0.01)	-2.69	0.178	-2.82	-2.72	-2.3	1.00
r_0	~*Norm*(0, 0.01)	0.03	0.002	0.02	0.029	0.032	1.01
δ	~*Uniform*(0, 50)	0.19	0.187	0.005	0.129	0.69	1.01

Table 4 summarizes the marginal posterior distributions of key parameters generated from the Bayesian state-space model. The mean SWD adult count in the initial period in each location, λ ,is around 59. We define the growth rate in subsequent periods using the equation $\mathrm{r_t} = e^{r_N} * e^{r_T * Temperature_t}$. The estimated average intrinsic growth rate of SWD adults, e^{r_N}, is around 0.068 with an average r_N of -2.69, falling within the established range of intrinsic growth rates for commercial blueberry in laboratory experiment (0.01-0.2). The parameters r_0 shows a 0.03 percentage change in SWD adult population growth rate with one-unit increase in temperature. Our result is consistent with previous studies on how SWD population changes with rising temperature (Tochen et al. 2014; Baser et al. 2015), which have shown a 0.033 percentage change in growth rate with a one-unit increase in temperature from 10-30°C.

The model provides estimates of the time series of the average latent (unobserved) SWD population if the SWD infestation is not controlled. In figures 2 and 3, we show the population dynamics of SWD (adult, egg, and larva) over one harvesting season for a one-acre representative farm across 10,000 simulations. We simulated the population dynamics using the MCMC posterior distributions of population model parameters and a baseline temperature in Onondaga, NY, during the 2022 harvesting season, where our representative farm is located.

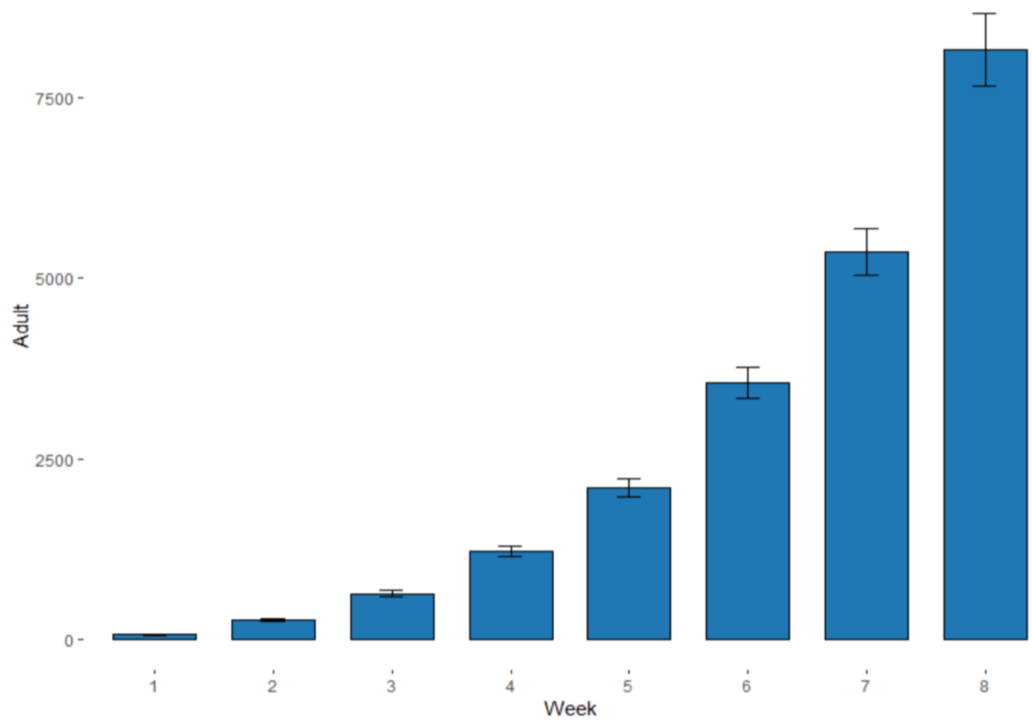

Figure 2: Simulated SWD adult population (mean and standard deviation) based on posterior distribution of model parameters

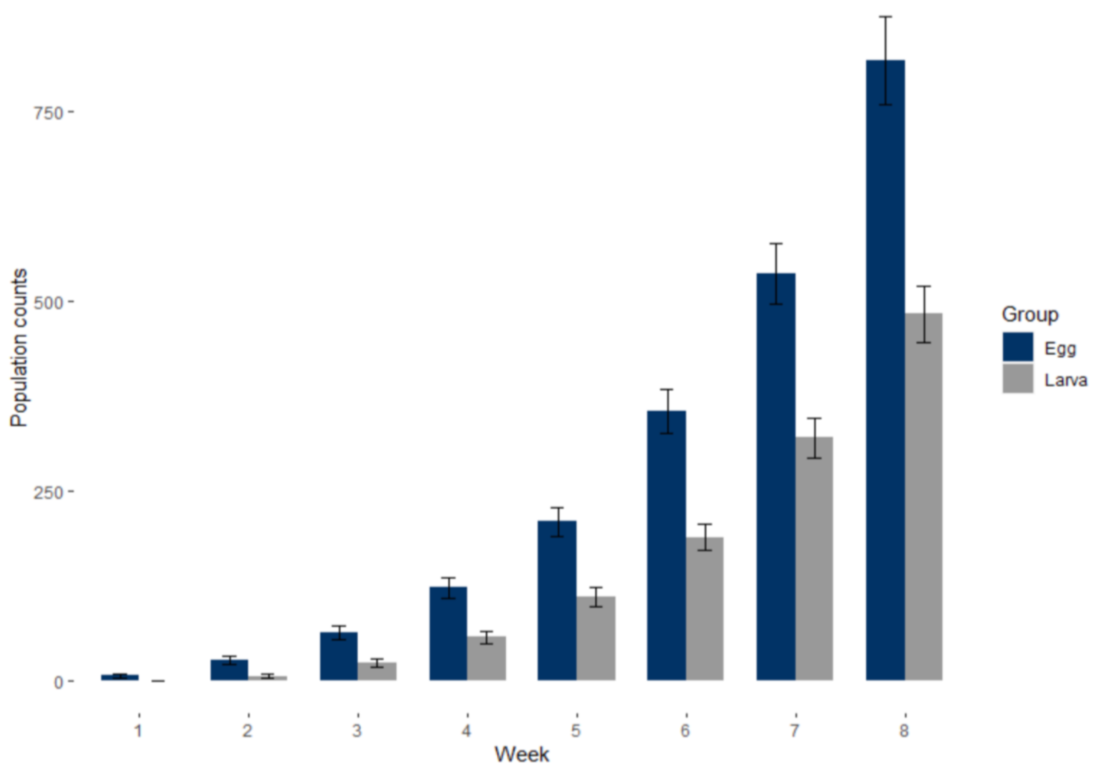

Figure 3: Simulated SWD egg and larva population (mean and standard deviation) based on posterior distribution of model parameters

Results under baseline insecticide efficacy and monitoring efficiency

We evaluate the economic outcomes for a representative blueberry farm in New York state over a harvesting season (early July to late August) based on the estimated distribution of true SWD population dynamics. Table 5 displays the main results under six SWD management strategies, assuming a baseline monitoring efficiency (i.e., a trapping efficiency of 0.0052 and sampling accuracy rate of 0.9) and insecticide efficacy (i.e., insecticide mortality of 0.7 for SWD adults and 0.6 for SWD larvae). We present the expected outcome and variability of yield, total costs (including damage costs, monitoring costs, and spraying costs), as well as total spraying and monitoring times for a calendar-based spraying strategy and five monitoring-based spraying strategies. Summarizing results over 10,000 simulations, we find that the status quo strategy adopted by most growers in New York, weekly spraying, still demonstrates its cost advantage, exhibiting the lowest expected total costs and the least risk among all SWD control strategies.

Table 5. Estimated average economic performance under various management strategies for a representative blueberry grower in New York State

Strategy	Yield	Total costs	Damage costs	Monitoring costs	Spraying costs	Total spraying	Total monitoring
Unit	(lbs./acre)						
No SWD infestation	5000	0	0	0	0	0	0
0. Never monitor, never spray	2,316.5 (208)	5,796.47 (455.3)	5,796.5 (455)	0	0	0	0
1. Weekly spray	4,814.4 (22)	608.91 (47.67)	400.9 (48)	0	208.00 (0)	8	0
2. Adult trapping-initiated spray	4735.5 (79)	741.05 (156.19)	571.38 (170.67)	23.96 (10.92)	145.71 (28.40)	5	3
3. Adult trapping-guided spray	4,640.5 (104)	972.95 (211.48)	776.52 (228.74)	80.00 (0)	116.43 (21.15)	4	8
4. Larva sampling-initiated spray	4,773.0 (25)	680.27 (53.57)	490.35 (53.68)	34.15 (1.57)	155.78 (2.40)	6	2
5. Larva sampling-guided spray	4,772.9 (25)	782.23 (52.82)	490.47 (53.07)	136.00 (0)	155.76 (2.48)	6	8
6. Adult trapping-initiated, and larva sampling-guided spray	4,736.4 (78)	833.79 (52.82)	569.39 (164.57)	119.32 (7.6)	145.07 (27.43)	6	8

Note: [1]Results are averaged over 10,000 simulations; [2] Uncertainty indicated by standard deviation of economic outcomes suggested by our model are reported in the parentheses.

The no-intervention scenario (Strategy 0) yields the highest expected total costs and risk level, as expected. Under this scenario, the grower experiences an average loss of about 54% of crop yield, consistent with our field observations. The calendar-based spraying strategy has the lowest expected total costs (around $609) among all SWD management strategies, offering the most certain net return. This strategy is also the most commonly adopted by berry growers in New York state due to its low total losses, driven by frequent pesticide applications and high expected crop yield compared to all monitoring-based control strategies. While monitoring-based strategies (both fruit sampling-based and trapping-based spraying) could reduce insecticide use 25% to 50% and are more environmentally sustainable, they do not perform as well economically as the status quo strategy. The reduced spraying costs from monitoring-based spraying do not offset the high monitoring costs, primarily labor costs. Notably, the improved monitoring-based strategy (i.e., larva-sampling initiated spraying), has lower total costs and more certain results than conventional trapping-based spraying, with total costs of $680 per acre, owing to improved monitoring accuracy of SWD population and fruit infestation with timely pesticide applications.

The distributions of yield and total costs with a random draw of SWD population dynamics over 10,000 simulations shows the risk levels associated with each SWD control strategy, as depicted in Figures 4 and 5. All monitoring-based strategies (S2-S6) shift the distribution of blueberry yields downward and increase yield variability (Figure 4). Both larva-sampling spraying and trapping-based spraying strategies increase the probability of achieving low yields and decrease the probability of achieving high yields. Notably, both initiated and guided larva-sampling strategies exhibit low yield variability and high expected yields, comparable to those of the status quo strategy.

We also assess the distribution of total costs for six SWD management strategies (Figure 5). Consistent with the yield distribution shown in Figure 4, all monitoring based IPM strategies shift the distribution of total costs upward, indicating higher costs and increased variability. Our results indicate that the sampling-initiated spraying strategy carries the least risk among all monitoring-based strategies, with an expected total cost difference of $71 compared to the status quo strategy (S1). In contrast, the conventional monitoring-based strategies (S2 and S3) utilizing adult trapping exhibit significantly higher variability in expected total costs than the improved larva-sampling spraying strategies (S4 and S5).

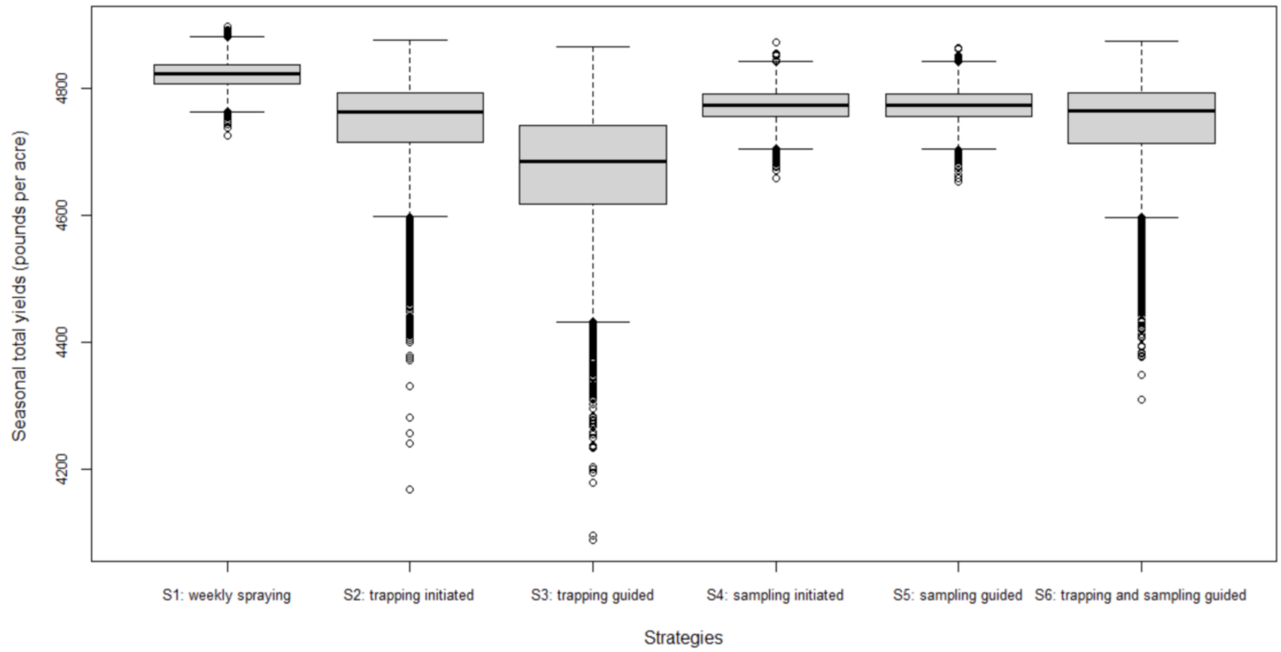

Figure 4: simulated distribution of yield with six SWD control strategies for a representative one-acre blueberry farm in New York state

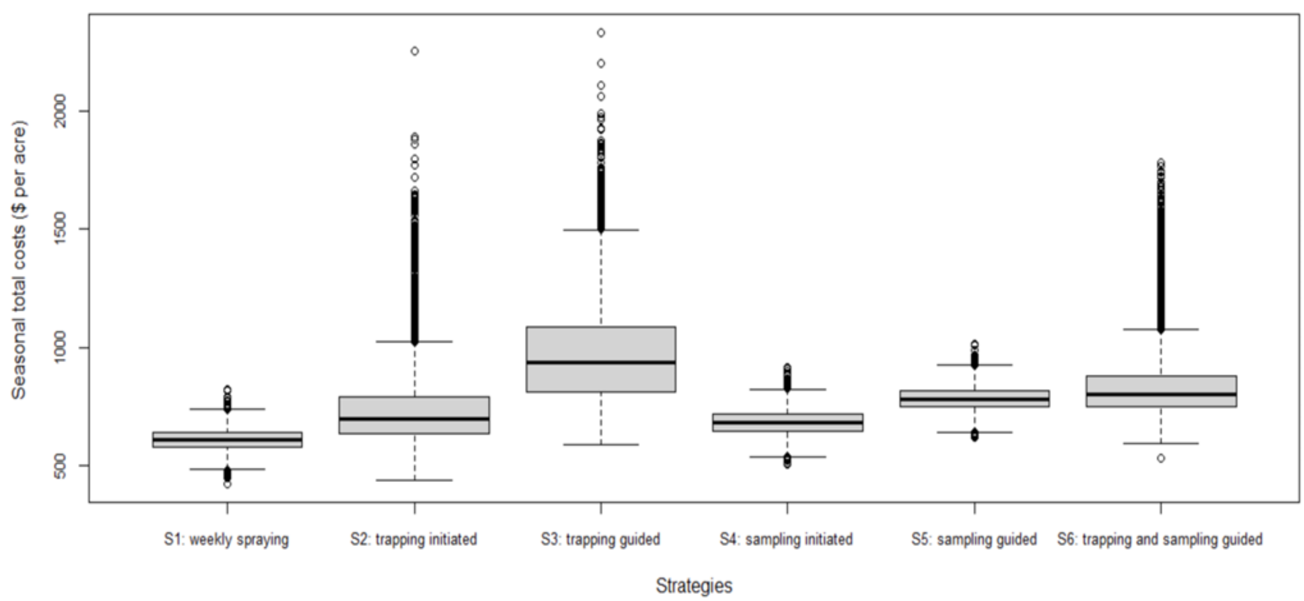

Figure 5: simulated distribution of total costs with six SWD control strategies for a representative one-acre blueberry farm in New York state

Sensitivity Analysis

Insecticide efficacy

Changing insecticide efficacy affects the economic performance of SWD management strategies. For example, excessive insecticide application can result in development of insecticide resistance and decreased efficacy. Our main results are based on a baseline insecticide efficacy of 70%. In this section, we explore how the economic performance of monitoring-based control strategies shifts with variations in insecticide efficacy due to resistance development and technological advancements.

Under high insecticide efficacy, both the calendar-based spray strategy and monitoring-based spray strategy show lower expected total costs and reduced variability in yield and total costs compared to the baseline efficacy scenario. In this context, larva sampling-initiated spraying emerges as the most cost-effective strategy, with only a $1 per acre difference in expected total costs compared to the calendar-based strategy. Conversely, under low insecticide efficacy, all adult-trapping and larva-sampling control strategies (including both initiated and guided strategies) become significantly more expensive compared to the baseline scenario. The status quo strategy remains the optimal cost-effective action, with monitoring-based control strategies costing around $300-500 more per acre than the status quo. These findings underscore that growers would be much more inclined to keep adopting the calendar-based spray strategy if insecticide efficacy decreases in the future due to overspray and resistance development.

Conclusion

In this paper, we extended a Bayesian state-space bioeconomic framework to assess the cost-effectiveness and risks associated with various invasive species management strategies, particularly when multiple integrated pest management (IPM) strategies are available to evaluate uncertain pest population and infestation levels. We applied this framework to the control of Spotted Wing Drosophila (SWD), a destructive invasive pest impacting the soft-skinned fruit industry. We conducted the economic evaluation of the status quo strategy, calendar-based spraying, and five monitoring-based IPM strategies, analyzing their yield and costs distributions under uncertainties in pest population. Additionally, we performed sensitivity analyses to examine the impact of changes in biological and economic parameters on the economic performance of alternative SWD control strategies.

The calendar-based spraying remains the most cost-effective and least risky SWD control strategy, with the lowest expected total costs, yield and costs variabilities compared to monitoring-based IPM strategies. However, it incurs high spraying costs due to frequent insecticide applications. The larva-sampling initiated and guided control strategies yield higher total costs and risk levels compared to the status quo control strategy. However, growers can save 25% in spraying costs by transitioning to larva-sampling guided control, albeit with slight increases in total costs. The larva-sampling spraying strategy offers more accurate population and infestation estimates than adult trapping but comes with increased monitoring and labor costs. Monitoring-based IPM strategies elevate total cost distributions and variabilities, yet, the sampling-initiated control strategy shows the least risky results among them, with an expected total costs difference of $71 compared to the status quo strategy. In contrast, conventional monitoring-based strategies utilizing adult trapping exhibit significantly higher expected total costs and greater variability than improved larva-sampling spraying strategies.

These findings suggest that policies offering monetary incentives for IPM adoption, such as Environmental Quality Incentives Programs, can encourage growers to adopt improved monitoring-based strategies for SWD control. Our results are valuable for the soft-skinned fruit industry, extension personnel, and other stakeholders interested in enhancing SWD management practices. Nonetheless, our modeling approach has several limitations that should be addressed in the future.

References

Asplen, M.K., G. Anfora, A. Biondi, D.-S. Choi, D. Chu, K.M. Daane, P. Gibert, A.P. Gutierrez, K.A. Hoelmer, W.D. Hutchison, R. Isaacs, Z.-L. Jiang, Z. Kárpáti, M.T. Kimura, M. Pascual, C.R. Philips, C. Plantamp, L. Ponti, G. Vétek, H. Vogt, V.M. Walton, Y. Yu, L. Zappalà, and N. Desneux. 2015. "Invasion biology of spotted wing Drosophila (Drosophila suzukii): a global perspective and future priorities." *Journal of Pest Science* 88(3):469–494.

Balew, S., E. Bulte, Z. Abro, and M. Kassie. 2023. "Incentivizing and nudging farmers to spread information: Experimental evidence from Ethiopia." *American Journal of Agricultural Economics* 105(3):994–1010.

Baser, N., M. Ouantar, O. Broutou, F. Lamaj, V. Verrastro, and F. Porcelli. 2015. "First finding of *Drosophila suzukii* (Matsumura) (Diptera: Drosophilidae) in Apulia, Italy, and its population dynamics throughout the year." *Fruits* 70(4):225–230.

Chalak, M., M. Polyakov, and D.J. Pannell. 2017. "Economics of Controlling Invasive Species: A Stochastic Optimization Model for a Spatial-dynamic Process." *American Journal of Agricultural Economics* 99(1):123–139.

Creissen, H.E., P.J. Jones, R.B. Tranter, R.D. Girling, S. Jess, F.J. Burnett, M. Gaffney, F.S. Thorne, and S. Kildea. 2019. "Measuring the unmeasurable? A method to quantify adoption of integrated pest management practices in temperate arable farming systems." *Pest Management Science* 75(12):3144–3152.

De Ros, G., S. Conci, T. Pantezzi, and G. Savini. 2015. "The economic impact of invasive pest Drosophila suzukii on berry production in the Province of Trento, Italy." *Journal of Berry Research* 5(2):89–96.

Deguine, J.-P., J.-N. Aubertot, R.J. Flor, F. Lescourret, K.A.G. Wyckhuys, and A. Ratnadass. 2021. "Integrated pest management: good intentions, hard realities. A review." *Agronomy for Sustainable Development* 41(3):38.

Emiljanowicz, L.M., G.D. Ryan, A. Langille, and J. Newman. 2014. "Development, Reproductive Output and Population Growth of the Fruit Fly Pest <I>Drosophila suzukii</I> (Diptera: Drosophilidae) on Artificial Diet." *Journal of Economic Entomology* 107(4):1392–1398.

Epanchin-Niell, R.S., and J.E. Wilen. 2012. "Optimal spatial control of biological invasions." *Journal of Environmental Economics and Management* 63(2):260–270.

Fackler, P., and K. Pacifici. 2014. "Addressing structural and observational uncertainty in resource management." *Journal of Environmental Management* 133:27–36.

Fackler, P.L., and R.G. Haight. 2014. "Monitoring as a partially observable decision problem." *Resource and Energy Economics* 37:226–241.

Fan, X., M.I. Gómez, S.S. Atallah, and J.M. Conrad. 2020. "A Bayesian State-Space Approach for Invasive Species Management: The Case of Spotted Wing Drosophila." *American Journal of Agricultural Economics* 102(4):1227–1244.

Farnsworth, D., K.A. Hamby, M. Bolda, R.E. Goodhue, J.C. Williams, and F.G. Zalom. 2017. "Economic analysis of revenue losses and control costs associated with the spotted wing drosophila, *Drosophila suzukii* (Matsumura), in the California raspberry industry: Economic analysis of spotted wing drosophila in California raspberries." *Pest Management Science* 73(6):1083–1090.

Grassi, A., A. Gottardello, D.T. Dalton, G. Tait, D. Rendon, C. Ioriatti, D. Gibeaut, M.V. Rossi Stacconi, and V.M. Walton. 2018. "Seasonal Reproductive Biology of Drosophila suzukii (Diptera: Drosophilidae) in Temperate Climates." *Environmental Entomology* 47(1):166–174.

Greene, C.R., R.A. Kramer, G.W. Norton, E.G. Rajotte, and M. Robert M. 1985. "An Economic Analysis of Soybean Integrated Pest Management." *American Journal of Agricultural Economics* 67(3):567–572.

Gress, B.E., and F.G. Zalom. 2019. "Identification and risk assessment of spinosad resistance in a California population of *Drosophila suzukii*." *Pest Management Science* 75(5):1270–1276.

Haight, R.G., and S. Polasky. 2010. "Optimal control of an invasive species with imperfect information about the level of infestation." *Resource and Energy Economics* 32(4):519–533.

Hostetler, J.A., and R.B. Chandler. 2015. "Improved state-space models for inference about spatial and temporal variation in abundance from count data." *Ecology* 96(6):1713–1723.

Kirkpatrick, D.M., L.J. Gut, and J.R. Miller. 2018. "Estimating Monitoring Trap Plume Reach and Trapping Area for Drosophila suzukii (Diptera: Drosophilidae) in Michigan Tart Cherry." *Journal of Economic Entomology* 111(3):1285–1289.

Knapp, L., D. Mazzi, and R. Finger. 2021. "The economic impact of *Drosophila suzukii* : perceived costs and revenue losses of SWISS cherry, plum and grape growers." *Pest Management Science* 77(2):978–1000.

Lane, D.E., T.J. Walker, and D.G. Grantham. 2023. "IPM Adoption and Impacts in the United States" B. Castro, ed. *Journal of Integrated Pest Management* 14(1):1.

MacLachlan, M.J., M.R. Springborn, and P.L. Fackler. 2017. "Learning about a Moving Target in Resource Management: Optimal Bayesian Disease Control." *American Journal of Agricultural Economics* 99(1):140–162.

Newman, K.B., S.T. Buckland, B.J.T. Morgan, R. King, D.L. Borchers, D.J. Cole, P. Besbeas, O. Gimenez, and L. Thomas. 2014. *Modelling Population Dynamics: Model Formulation, Fitting and Assessment using State-Space Methods*. New York, NY: Springer New York. Available at: http://link.springer.com/10.1007/978-1-4939-0977-3 [Accessed September 1, 2022].

Rasche, L., A. Dietl, N. Shakhramanyan, D. Pandey, and U.A. Schneider. 2016. "Increasing social welfare by taxing pesticide externalities in the Indian cotton sector: Increasing social welfare by taxing pesticide externalities in the Indian cotton sector." *Pest Management Science* 72(12):2303–2312.

Rendon, D., S. Mermer, L.J. Brewer, D. Dalton, C.B.D. Silva, J. Lee, R. Nieri, K. Park, F. Pfab, G. Tait, M. Rossi-Stacconi, N. Wiman, and V.M. Walton. 2019. "Cultural Control Strategies to Manage Spotted-wing Drosophila." SWD series #2 Oregon State University Extension Service. Available at: https://catalog.extension.oregonstate.edu/sites/catalog/files/project/pdf/em9262.pdf.

Sanchirico, J.N., and J.E. Wilen. 1999. “Bioeconomics of Spatial Exploitation in a Patchy Environment.” *Journal of Environmental Economics and Management* 37(2):129–150.

Tait, G., S. Mermer, D. Stockton, J. Lee, S. Avosani, A. Abrieux, G. Anfora, E. Beers, A. Biondi, H. Burrack, D. Cha, J.C. Chiu, M.-Y. Choi, K. Cloonan, C.M. Crava, K.M. Daane, D.T. Dalton, L. Diepenbrock, P. Fanning, F. Ganjisaffar, M.I. Gómez, L. Gut, A. Grassi, K. Hamby, K.A. Hoelmer, C. Ioriatti, R. Isaacs, J. Klick, L. Kraft, G. Loeb, M.V. Rossi-Stacconi, R. Nieri, F. Pfab, S. Puppato, D. Rendon, J. Renkema, C. Rodriguez-Saona, M. Rogers, F. Sassù, T. Schöneberg, M.J. Scott, M. Seagraves, A. Sial, S. Van Timmeren, A. Wallingford, X. Wang, D.A. Yeh, F.G. Zalom, and V.M. Walton. 2021. “*Drosophila suzukii* (Diptera: Drosophilidae): A Decade of Research Towards a Sustainable Integrated Pest Management Program.” *Journal of Economic Entomology* 114(5):1950–1974.

Tochen, S., D.T. Dalton, N. Wiman, C. Hamm, P.W. Shearer, and V.M. Walton. 2014. “Temperature-Related Development and Population Parameters for *Drosophila suzukii* (Diptera: Drosophilidae) on Cherry and Blueberry.” *Environmental Entomology* 43(2):501–510.

Van Timmeren, S., A.R. Davis, and R. Isaacs. 2021. “Optimization of a Larval Sampling Method for Monitoring *Drosophila suzukii* (Diptera: Drosophilidae) in Blueberries” C. Rodriguez-Saona, ed. *Journal of Economic Entomology* 114(4):1690–1700.

Van Timmeren, S., D. Mota-Sanchez, J.C. Wise, and R. Isaacs. 2018. “Baseline susceptibility of spotted wing Drosophila (*Drosophila suzukii*) to four key insecticide classes: Spotted wing Drosophila baseline susceptibility.” *Pest Management Science* 74(1):78–87.

Wang, Y., and R. Finger. 2023. “Pest prevention, risk, and risk management: The case of *Drosophila suzukii*.” *Journal of the Agricultural and Applied Economics Association* 2(1):98–113.

White, F.C., and M.E. Wetzstein. 1995. “Market Effects of Cotton Integrated Pest Management.” *American Journal of Agricultural Economics* 77(3):602–612.

Wyckhuys, K., F. Sanchez-Bayo, A. Aebi, M.B. Van Lexmond, J.-M. Bonmatin, D. Goulson, and E. Mitchell. 2021. “Stay true to integrated pest management” J. Sills, ed. *Science* 371(6525):133–133.

Yeh, D.A., B. Dai, M.I. Gómez, and V.M. Walton. 2023. “Does Monitoring Pests Pay Off? A Bioeconomic Assessment of *Drosophila suzukii* Controls.” *Pest Management Science*:ps.7801.

Yeh, D.A., F.A. Drummond, M.I. Gómez, and X. Fan. 2020. “The Economic Impacts and Management of Spotted Wing Drosophila (*Drosophila Suzukii*): The Case of Wild Blueberries in Maine.” *Journal of Economic Entomology* 113(3):1262–1269.

Appendix

1. MCMC Procedure

Going forward, we use brackets to denote probability distributions. Letting $\theta_1 = (\lambda, r_0, r_1, \delta)$ and assuming site independence, the stochastic transition defined in equation (4) can be written as $[N_{A,i,t} | N_{A,i.t-1}, \theta_1]$. Let $t = \{1, \dots, T\}$ denote the time series for which observations are available. Conditional on θ_1, the sequence of unknown states $\{N_{A,i,1}, \dots, N_{A,i,T}\}$ follows a first-order Markov chain. Using the transition kernel defined by equation (4), the joint prior distribution of θ_1 and $\{N_{A,i,1}, \dots, N_{A,i,T}\}$ can be formulated as:

$$\left[\{N_{A,i,1}, \dots, N_{A,i,T}\}, \theta_1\right] = [\theta_1] \times [N_{A,i,1}] \times \prod_{t=2}^{T} [N_{A,i,t} | N_{A,i,t-1}, \theta_1]$$

Assume these random variables are independent. Conditional on state $N_{A,i,t}$ and letting $\theta_2 = \alpha_{AT}$, the joint prior distribution of θ_2 and $\{y_{A,i,1}, y_{A,i,2}, \dots, y_{A,i,T}\}$ can be written as:

$$\left[\{y_{A,i,1}, y_{A,i,2}, \dots, y_{A,i,T}\}, \theta_2\right] = [\theta_2] \times \prod_{t=1}^{T} \left[y_{A,i,t} \middle| N_{A,i,t}, \theta_2\right] \times \left[\{N_{A,i,1}, \dots, N_{A,i,T}\}, \theta_1\right]$$

Combining the prior on the parameters $[\theta] = [\theta_1, \theta_2]$, and applying Bayes’ rule, the full posterior distribution of all unknowns can be decomposed as:

$$\left[\{N_{A,i,1}, \dots, N_{A,i,T}\}, \theta \middle| \{y_{A,i,1}, \dots, y_{A,i,T}\}\right] \propto [\theta] \times [N_{A,i,1}] \times \prod_{t=1}^{T} \left[y_{A,i,t} \middle| N_{A,i,t}, \theta_2\right] \times \prod_{t=2}^{T} [N_{A,i,t} | N_{A,i,t-1}, \theta_1]$$

2. Trace of posterior distribution of key populatio parameters