A Farm-level Bioeconomic Model of Invasive Species Management: The Case of Spotted Wing Drosophila in Maine

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Abstract

Spotted wing drosophila (SWD) is one of the most severe pest issues for the U.S. berry production in recent years. In this study, we develop a novel bioeconomic model to identify optimal control strategies of SWD for a representative wild blueberry farm in Maine. The proposed bioeconomic model incorporates both ecological and economic aspects of the issue and considers two of the SWD life-stages (larva and adult population). We use field data from 2012 to 2017 to estimate the key parameters of SWD population dynamics. The estimated population parameters are then combined with a farm-level dynamic optimization problem with a finite-horizon spanning the crop production cycle. The results of the model indicate optimal spraying schedule and harvest timing that maximize the entire stream of expected payoffs, considering the stochasticity from SWD infestation and the population dynamics. Our preliminary results suggest the economic value of early harvesting in the wild blueberry production as well as adopting mixed strategies of early harvest and pesticide application to minimize the costs of controlling for SWD.

1. Introduction

Spotted wing drosophila (SWD) or *Drosophila suzukii*, is a pest of soft-skinned fruits that is native to East Asia. The unique serrated ovipositor allows female SWD to lay eggs under the ripening or unripe fruit skin and causes direct damages to fruit (Asplen et al. 2015). SWD has expanded to much of the United States (U.S.) since 2008, which results in large pest management costs in berry production, and the national crop loss due to SWD was estimated at $718 million annually (Bolda, Goodhue and Zalom 2010; Walsh et al. 2011). Domestic growers usually take a proactive approach to protect their crops from SWD infestation. The dominant SWD control strategy is to apply intensive chemical insecticide treatments through the growing season. However, the resulting high costs and environmental concerns have urged the industries and researchers to evaluate alternative pest management strategies (Farnsworth et al. 2017).

In this study, we focus on the case of wild (lowbush) blueberry in Maine and use a novel bioeconomic modeling approach to identify optimal SWD control strategies. SWD was first found in Maine in 2011 and has become one of the most severe pest concerns for growers in the state (Drummond et al. 2018). Most growers have increased the frequency of chemical insecticide applications to prevent SWD infestation, while some also consider employing other cultural controls to avoid SWD infestation, such as harvest earlier in the season. Given the climate of the region, SWD appears to be a mid to late season pest for Maine growers. Therefore, harvesting earlier can potentially avoid late season high pest pressure. However, the tradeoff for early harvesting is that growers may have revenue loss from unripe fruit that is not harvested (Drummond et al. 2018).

In order to evaluate the SWD-targeted management tactics and the resulting welfare changes in the case of wild blueberry production in Maine, we construct a bioeconomic model which includes two components: (1) a population dynamic model of the pest, and (2) a grower's seasonal dynamic optimization model. In the field of bioeconomic research, previous literature emphasizes the importance of including the ecological aspects into economic modeling (Conrad and Smith 2012; Kling et al. 2016). Specifically, in the area of invasive species management, bioeconomic models which incorporate population dynamics of the studied species can inform the optimal resource allocation and suggest effective controls to minimize long-term damages (Epanchin-Niell 2017). While the approach of bioeconomic modeling can provide valuable insights on invasive species control, most studies use spatio-temporal optimization model that does not take into account the age structures of the studied species (Atallah et al. 2015). However, for the case of pest insects on crop production such as SWD, the grower's economic outcome is mostly contingent upon larval infestation rather than the adult population. The nature of issue emphasizes the need for considering the age structure of the studied pest when constructing the bioeconomic model. To the best of our knowledge, Büyüktahtakın et al. (2015) is the only study that develops a bioeconomic model that considers the age structure of the studied species. However, it is hard to generalize the model developed for an invasive legume plant to pest issues such as SWD. Therefore, the proposed bioeconomic model in this study that incorporates the age structure of the pest extends the literature of bioeconomic modeling for pest management issues. Furthermore, the ecological estimates of SWD population dynamics are used to infer the stochasticity in grower's decision model which suggest the best control options to optimize the seasonal production outcomes. The model presented here not only provides timely information for growers under different infestation scenarios but also be extended to other research on invasive pest management.

2. The bioeconomic model

The bioeconomic model proposed in this study consists two parts: (1) an ecological model to estimate the population dynamics of SWD, and (2) an economic model, which is the grower's dynamic optimization problem to evaluate the optimal farm-level control strategy. The solution of the grower's optimization problem is based on the estimated SWD population parameters from the ecological model. Specifically, the estimates of the ecological parameters are used to simulate the transition probabilities in the grower's optimization model. The two models are linked as depicted by Figure 1 and described in the following sections (2.1 and 2.2). The proposed bioeconomic model for SWD considers two major age structures of the pest, namely larva and adult stages, and was calibrated with six years of field monitoring data. Both models are specified under a finite time horizon and use week as the discrete time step. The time period in the models includes a total of 13 weeks as the wild blueberries are generally susceptible to SWD infestation between July and September.

[Insert Figure 1: Model Coupling]

2.1. The ecological model: SWD population dynamics

The main purpose of the ecological model is to infer the transition of SWD population in the economic model to solve for the grower's expected profit maximization problem. Given that we can only observe the partial population from field data but not the true SWD population in the field, we employ a state-space modeling approach to estimate the SWD population parameters. Under the state-space modeling framework, there are two processes included: the state process and the observation process. In our case, the state process represents the underlying unobservable SWD population dynamics in the field. We breakdown the state process into a sequence of stochastic subprocesses to link the population dynamics of larva and adult (Newman et al. 2014). Using Bayesian inference, we specify the binomial distribution as the observation processes with assumed accuracies for adult SWD trap and larval testing. The population parameters estimated in the model include survival probability, fertility rate, level of external migration, etc. The detailed specification of the ecological model is included in the appendix.

The field data were obtained from 92 lowbush blueberry fields in Maine with SWD larva and adult observation from 2012 to 2017. Adult SWD population was monitored with sticky traps in the field, while larva was observed using fruit sampling (see Drummond, Ballamn and Collins (2019) for details on the data collection). We employ Markov Chain Monte Carlo (MCMC) sampling to obtain the posterior distribution for each population parameter using the Bayesian inference software, JAGS[1]. In order to jointly analyze data from multiple farms, the underlying assumption is that the population of each farm is independent of the other nearby farms and follows the same assumed state process (King et al. 2009).

2.2. The economic model: farm-level grower's dynamic optimization

The proposed economic model is a finite-horizon stochastic dynamic optimization problem adopted from the problem of investment under uncertainty (Dixit and Pindyck 1994). At each week, the grower makes decisions on whether to spray insecticide to control SWD or whether to harvest to receive 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. The choice variable ($\mathrm{c_t}$) is the tuple of the choice of harvesting (h_t) and choice of spraying (s_t), which take one of the three possible values.

$$\mathrm{c_t} \equiv (\mathrm{h_t}, \mathrm{s_t}) \in \{(1,0), (0,0), (0,1)\}$$

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 regulated

[1] http://mcmc-jags.sourceforge.net/

maximum pesticides residue levels allowed. The state variable is the tuple of observed counts of larva ($y_{1,t}$) and observed count of adult SWD ($y_{2,t}$) at time *t*. Based on field data, the assumed range of larva and adult population are integer units from 0 to 50 and from 0 to 30, respectively. Thus, the state variable tuple has the grid size of 1,581 combinations.

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:

$$\begin{aligned} \mathrm{V_t}(\mathrm{y_{1,t}}, \mathrm{y_{2,t}}) = \quad & \max_{h_t, s_t} \ \mathrm{h_t} \cdot \mathrm{\pi_t} + (1 - h_t)(1 - s_t) \cdot \beta \cdot \mathrm{E}\big(\mathrm{V_{t+1}}(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}}) \big| \mathrm{s_t} = 0\big) \\ & \quad + (1 - h_t) s_t \cdot \beta \cdot \big(\mathrm{E}\big(\mathrm{V_{t+1}}(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}}) \big| \mathrm{s_t} = 1\big) - spraycost\big) \\ = \quad & \max \ \{ \mathrm{\pi_t}, \ \ \beta \cdot \mathrm{E}\big(\mathrm{V_{t+1}}(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}}) \big| \mathrm{s_t} = 0\big), \\ & \quad \beta \cdot \mathrm{E}\big(\mathrm{V_{t+1}}(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}}) \big| \mathrm{s_t} = 1\big) - spraycost \ \} \end{aligned} \tag{1}$$

where $\mathrm{\pi}_t = \mathrm{E}\big(yield_t \cdot p_t \cdot (1 - \mathrm{loss_t}) \big| \mathrm{y_{1,t}}, \mathrm{\mu}_p\big)$. $\mathrm{V_t}(\mathrm{y_{1,t}}, \mathrm{y_{2,t}})$ denotes the value function at time *t* given the level of state variable tuple $(\mathrm{y_{1,t}}, \mathrm{y_{2,t}})$ and represents the present discounted value of the entire stream of payoffs conditional on choosing optimally in the remaining time periods in the future. $\mathrm{E}(\mathrm{V_{t+1}}(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}}))$ indicates the expected continuation value, which is the value of waiting to harvest conditional on the stochastic population transition from the current state $(\mathrm{y_{1,t}}, \mathrm{y_{2,t}})$ to the next state $(\mathrm{y_{1,t+1}}, \mathrm{y_{2,t+1}})$. The per period payoff function ($\mathrm{\pi}_t$) is the expected revenue defined as the product of expected yield, expected price given the mean price ($\mathrm{\mu}_p$), and the percentage losses in production due to infestation ($\mathrm{loss_t}$). Thus, the value function suggests the maximal value among all three possible choices and is different at each time period (indexed by *t*). The transition function from one state at time *t* to the other state at *t+1* is calculated using the estimated ecological population parameters from the previous section. For each state variable tuple $(y_{1,t}, y_{2,t})$, we employ 10 repetitions to calculate the transition probability of one given state tuple at time *t* to another state tuple at time *t+1*. If the resulting state tuple is larger than the assumed grid range, we group the frequency of state tuple as the maximal available levels.

The values of key model parameters are selected from the actual context of wild blueberries in Maine. The grower is assumed to be a price taker and only knows the mean price (μ_p) which is assumed to be $0.26 per lb. We assume an annual discount rate of 0.9 and calculate the weekly discount factor (β) accordingly. The yield at time *t* ($yield_t$) is the product of the crop ripeness at *t* and the assumed yield of a healthy field at 4,000 lbs per acres. The cost of spraying ($spraycost$) is fixed at $40 per acre. The percentage production loss (loss_t) is calculated based on the level of infestation from the observed larva ($y_{1,t}$). The production loss 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. We assume that a grower must harvest regardless of the level of the state variable at the final week. Thus, the value function can be solved by backward iterations.

[Insert Table 1: Assumed production loss based on observed larval infestation]

3. Preliminary results

The preliminary results consist of the optimal choice trajectories and the corresponding final payoffs at harvest for four scenarios (Table 2). Each scenario differs in terms of the tuple of initial states (i.e. the observed population size during the first period). For scenario 1-3, we assume zero initial larva population, which is generally the case when most fruits are yet to develop at the beginning of the season. For scenario 1, the initial adult population is zero. The optimal trajectory is to not spray throughout the first seven weeks and harvest at week eight.

Since the ecological model of population dynamics include a component of external migration, the zero initial population in scenario 1 does not mean grower faces no chance of SWD throughout the season but a lower probability of transiting into the states with high population levels in the later weeks.

Scenario 2 and 3 both start with no larval infestation but with 5 and 15 initial adult population. The results show that the optimal harvest timings are different accordingly, where scenario 3 is better off harvest one period earlier than scenario 2. In scenario 3, the optimal choice is to not spray in the first week, spray in weeks 2-3, then harvest at week 4 when the fruit ripeness at 79.8%. Compared to scenario 2, although the optimal management in scenario 3 suggests a fewer total count of spraying than the optimal management in scenario 2, scenario 3 has a lower payoff relative to scenario 2. This suggests that scenario 3 has a large unripe crop loss from harvesting a period earlier and possible higher infestation loss. For scenario 4, we assume a positive number of the initially observed larva and the same initial adult population at 15 as scenario 3. The result of scenario 4 suggests that the optimal strategy consists of spraying after week 2 and a later harvest timing when the initial larva population is positive, which is somewhat counterintuitive. However, it may be because the profit loss from larger risk of infestation can be partially compensated by the higher fruit ripeness. Comparing all scenarios, the payoffs at harvest decline when the initial population increases.

[Insert Table 2. Optimal trajectories starting from different initial states]

4. Sensitivity analysis

Two sensitivity analyses are performed: higher spraying costs (an increase from $40 to $100 per acre) and higher blueberry market price (an increase from $0.26 to $1 per lb.). Preliminary results of the sensitivity analyses are summarized in Table 3-4 with the same scenarios on the initial population size. For scenario 1, the optimal management option is the same regardless of spraying costs or blueberry market price. However, the optimal trajectories are different for scenario 2-4 under higher spraying cost or market price. When the spraying cost is higher, the optimal harvest timing in both scenario 2 and scenario 3 is a week earlier than original. Furthermore, spraying is no longer an optimal choice in scenario 3-4 at any given week before harvesting. For scenario 4, the harvest timing also shifts forward from week 8 to week 4.

In contrast, for the case of facing a higher blueberry market price (Table 4), scenario 2-4 shows a delay in optimal harvest timing and the optimal management options indicate more insecticide applications than the original results. The different optimal management results for the case of the higher blueberry price might be due to the fact that higher price prioritizes the importance of harvesting at a higher fruit ripeness level and may thus offset the spray costs, which are relatively low. In addition, sensitivity analyses provide relevant welfare implications. For the case of higher spray costs, it mimics the cases of growers who face a more regulated marketing channel regarding production practices. For example, if the growers are exporting to Japan, the regulation allows for fewer SWD-targeted insecticides compared to the U.S., and the acceptable insecticide options are generally more expensive. Comparing to the baseline results, the corresponding payoffs reduces more than one third for scenario 2-4 when the spraying cost is higher.

[Insert Table 3 and Table 4. Sensitivity analyses]

5. **Preliminary conclusion and future work**

In this paper, we develop a novel bioeconomic modeling approach for controlling SWD in the case of wild blueberry production in Maine. The proposed bioeconomic model is stochastic given the uncertainty faced by growers regarding the SWD population dynamics. The model is also dynamic because SWD population and infestation levels vary over time and are affected by the previous spraying decisions implemented by the grower. As the current industry relying heavily on chemical insecticide application to control SWD infestation, our preliminary results highlight the economic benefits of choosing mixed control strategies and the importance of harvest timing for wild blueberry production. The preliminary results also suggest that monitoring systems for both adult flies and larvae have high economic value since growers can manage the field accordingly. Our next step is to perform robustness checks on the ecological model and add in weather data to more accurately infer the transition probabilities between the population states. We also plan to modify the production loss function, since some growers face buyer's rejection of all production even when a small portion of infestation is detected.

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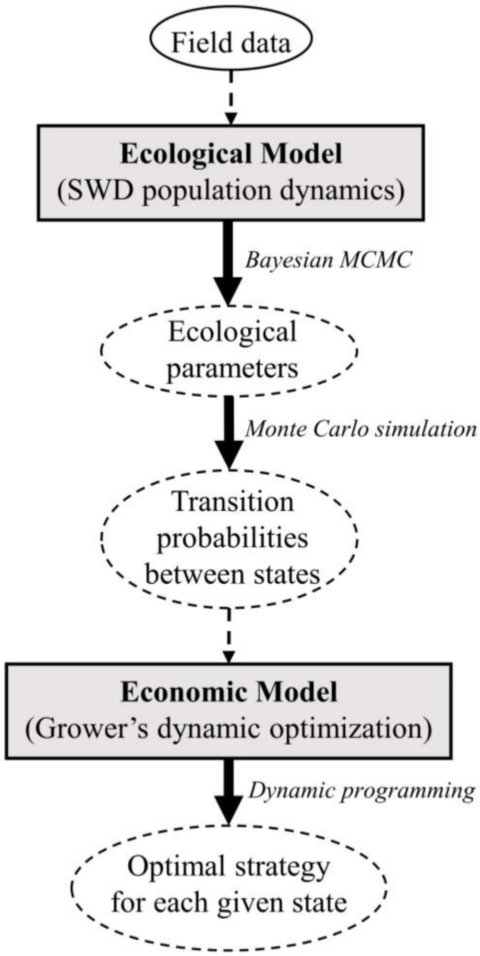

Figure 1. Model Coupling

Table 1. Assumed production loss based on observed larval infestation

Observed larval infestation	Percentage of production loss
Less than 0.3%	0%
Between 0.3% and 1%	10%
Between 1% and 5%	30%
Between 5% and 10%	50%
More than 10%	80%

Table 2. Optimal trajectories starting from different initial states

		Initial states on observed larva (y1) and adult (y2) population			
		Scenario 1: (y1, y2) = (0,0)	Scenario 2: (y1, y2) = (0,5)	Scenario 3: (y1, y2) = (0,15)	Scenario 4: (y1, y2) = (5,15)
Week	Fruit Ripeness	Optimal Choice	Optimal Choice	Optimal Choice	Optimal Choice
1	12.29%	No spray	Spray	No spray	No spray
2	29.90%	No spray	Spray	Spray	Spray
3	56.49%	No spray	Spray	Spray	Spray
4	79.80%	No spray	Spray	Harvest	Spray
5	92.32%	No spray	Harvest	-	Spray
6	97.34%	No spray	-	-	Spray
7	99.11%	No spray	-	-	Spray
8	99.71%	Harvest	-	-	Harvest
9 and beyond	99.90%	-	-	-	-
Payoff at harvest ($/acre)		$1,037	$960	$830	$726

Table 3. Sensitivity analysis (higher spray costs): optimal trajectories starting from different initial states

		Initial states on observed larva (y1) and adult (y2) population			
		Scenario 1: (y1, y2) = (0,0)	Scenario 2: (y1, y2) = (0,5)	Scenario 3: (y1, y2) = (0,15)	Scenario 4: (y1, y2) = (5,15)
Week	Fruit Ripeness	Optimal Choice	Optimal Choice	Optimal Choice	Optimal Choice
1	12.29%	No spray	Spray	No spray	No spray
2	29.90%	No spray	Spray	No spray	No spray
3	56.49%	No spray	Spray	Harvest	No spray
4	79.80%	No spray	Harvest	-	Harvest
5	92.32%	No spray	-	-	-
6	97.34%	No spray	-	-	-
7	99.11%	No spray	-	-	-
8	99.71%	Harvest	-	-	-
9 and beyond	99.90%	-	-	-	-
Payoff at harvest ($/acre)		$1,037	$830	$587	$581

Table 4. Sensitivity analysis (higher blueberry market price): optimal trajectories starting from different initial states

		Initial states on observed larva (y1) and adult (y2) population			
		Scenario 1: (y1, y2) = (0,0)	Scenario 2: (y1, y2) = (0,5)	Scenario 3: (y1, y2) = (0,15)	Scenario 4: (y1, y2) = (5,15)
Week	Fruit Ripeness	Optimal Choice	Optimal Choice	Optimal Choice	Optimal Choice
1	12.29%	No spray	Spray	Spray	No spray
2	29.90%	No spray	Spray	Spray	Spray
3	56.49%	No spray	Spray	Spray	Spray
4	79.80%	No spray	Spray	Spray	Spray
5	92.32%	No spray	Spray	Harvest	Spray
6	97.34%	No spray	Harvest	-	Spray
7	99.11%	No spray	-	-	Spray
8	99.71%	Harvest	-	-	Spray
9	99.90%	-	-	-	Spray
10 and beyond	99.97%	-	-	-	Harvest
Payoff at harvest ($/acre)		$3,988	$3,894	$3,693	$2,799

Appendix: Ecological model specifications

The model is modified from Newman et al. (2014). The notations are as follow. The life stage is denoted as j, which is either larva(L) or adult(A). In the state process, there are a sequence of sub-processes, i, occurred at each time step: survival, transition, birth, spray, and movement. $N_{j,t}$ denotes the population of life stage j at the end of time t (after all sub-processes occurred). Intermediate variable, $u_{i,j,t}$, is the population of sub-process i and life stage state j after time t.

The population parameters to be estimated include survival probability (ϕ_L, ϕ_A), transition probability (π), fertility rate (ρ), initial population at the first period t_0 ($N_{L,0}$ and $N_{A,0}$) and the level of migration from external sources (ω). The sequence of sub-processes is modeled in the following order.

1. Survival ($i = S$)
$$\begin{cases} \text{larva:} & u_{s,L,t} \sim binomial(N_{L,t-1}, \phi_L) \\ \text{adult:} & u_{s,A,t} \sim binomial(N_{A,t-1}, \phi_A) \end{cases}$$
2. Transition ($i = R$)
$$\begin{cases} \text{larva:} & u_{r,L,t} \sim binomial(u_{s,L,t}, 1-\pi) \\ \text{adult:} & u_{r,A,t} = u_{s,A,t} + u_{s,L,t} - u_{r,L,t} \end{cases}$$
3. Birth ($i = B$)
$$\begin{cases} \text{larva:} & u_{b,L,t} = u_{r,L,t} + b_t \\ & \text{where newborn } b_t \sim Poisson(u_{r,A,t} * \rho * fr\bar{u}it) \\ \text{adult:} & u_{b,A,t} = u_{r,A,t} \end{cases}$$
4. Migration (M_t) and spray ($spr_t \in \{0, 1\}$)
$$\begin{cases} \text{larva:} & N_{L,t} \equiv (1 - spr_t) \cdot u_{b,L,t} + spr_t \cdot u_{b,L,t} \cdot (1 - \bar{\kappa}_L) \\ \text{adult:} & N_{A,t} \equiv (1 - spr_t) \cdot u_{b,A,t} + spr_t \cdot u_{b,A,t} \cdot (1 - \bar{\kappa}_A) + M_t \cdot fr\bar{u}it \\ & \text{where migration } M_t \sim Poisson(\omega) \end{cases}$$

We assume fixed insecticide efficacy (in percentage term) as $\bar{\kappa}_L = 0.8$, $\bar{\kappa}_A = 0.4$ for larva and adult, respectively. Migration depends on the availability of fruit, where $fr\bar{u}it$ is an index of fruit ripeness in percentage depends on Julian date (Drummond et al. 2019) as:

$$fr\bar{u}it = 100/(1 + exp(30.903 - 0.159 * JulianDate))$$

The observation process is assumed to be the binomial distribution with assumed accuracy as $\bar{\alpha}_L = 0.3$ for larval testing and $\bar{\alpha}_A = 0.1$ for adult trapping.

$$\begin{cases} \text{larva:} & y_{L,t} \sim binomial(N_{L,t}, \bar{\alpha}_L) \\ \text{adult:} & y_{A,t} \sim binomial(N_{A,t}, \bar{\alpha}_A) \end{cases}$$