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Optimal Monitoring and Controlling of Invasive Species:

The Case of Spotted Wing Drosophila in the United States

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Optimal Monitoring and Controlling of Invasive Species:
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Abstract

Spotted wing drosophila (SWD) is an invasive pest having a devastating effect on soft-skinned fruits such as blueberries, raspberries, blackberries, strawberries, and cherries. Due to zero tolerance of SWD infested fruit in both fresh and frozen markets, current SWD management strategies consist mainly of preventive broad-spectrum insecticide sprays. Extension services across the United States are calling for management strategies that incorporate monitoring to reduce unnecessary insecticide sprays. Nonetheless, little is known about the economic benefits of these management strategies over the broad-spectrum insecticide sprays. In this paper, we develop a dynamic bioeconomic model to identify the cost-minimizing mix of SWD management strategies. We employ Bayesian methods in a dynamic simulation setting to evaluate the economic outcomes of alternative strategies involving insecticide sprays and monitoring combinations. We apply this model to a blueberry farmer making decisions to control SWD infestation. We find that the economic impacts of different SWD control strategies depend on the efficacy of the insecticide applied, the efficiency of monitoring traps, and also the action threshold selected. Overall, as the efficiency of monitoring traps improves, the management strategies which include monitoring are superior to the spray-only strategy. Also, growers can choose more liberal action thresholds when using monitoring traps with higher efficiency. In addition, monitor-to-initiate spray strategies perform better than the monitor-to-guide spray strategies in general.

1. Introduction

Spotted wing drosophila (SWD, *Drosophila suzukii*), native to eastern Asia, is a devastating pest of soft-skinned fruits and has rapidly expanded its global range in the past decade to include the United States (U.S.), Mexico, Europe, Canada and South America (Walsh et al. 2011; Cini et al. 2012; Depra et al. 2014). While most Drosophila species are considered harmless or nuisance pests (e.g. one species is attracted to spoiled and overripe fruit), SWD exhibits a strong preference for ripe or ripening fruit that has market value (Asplen et al. 2015; Cini et al. 2012). The crops most significantly affected by SWD include blueberries, blackberries, raspberries, strawberries, and cherries. These crops are highly valued in the market, at nearly $4.5 billion annually (USDA NASS 2013) and grown on over 40,000 farms (USDA Census of Agriculture 2012) in the United States alone.

In addition to its preference for commercial fruit crops, SWD exhibits a formidable reproductive capacity relative to other members of the species. It is able to complete between 13 and 16 generations per year and a female can produce up to 350 eggs during its lifespan (Asplen et al. 2015; Burrack et al. 2015). This high reproductive potential combined with a short generation time results in rapid population growth, and increasing pest pressures during the crop-ripening period (Wiman et al. 2014). Moreover, it is difficult to distinguish SWD from other harmless Drosophila species in the field. Perfect identification requires a magnifying glass and that SWD reaches adulthood (Asplen et al. 2015). Thus, pest management relies primarily on imperfect observation of the population density – often with the help of monitoring traps.

Economic damages due to SWD are a growing concern among businesses in the soft-skin fruit sector. In most cases, buyers have zero tolerance for SWD infested fruit, particularly for the fresh market and for whole frozen products. Detection of infestation in a shipment, even if small,

can results in complete rejection of the product (Burrack and Bhattarai 2015). Economic impacts of SWD are substantial. Goodhue et al. (2011) estimate SWD annual damages of $500 million in fruit producing regions of Western U.S. assuming 30% damages. Likewise, NC State Cooperative Extension (2016) estimate over $200 annual losses due to SWD in Eastern production regions of the U.S. Controlling for SWD has also increased insecticide use and labor associated with management. In a 2015 winter survey of 436 fruit growers in the United States, respondents from 31 states reported crop losses due to SWD estimated at over $133 million and increases in insecticide costs of between $100 and $300 per acre (NC State Cooperative Extension 2016).

Current SWD management strategies tend to be very conservative, consisting mainly of preventative broad-spectrum insecticide sprays (Haye et al. 2016; Wise et al. 2015; Wiman et al. 2014; Van Timmeren and Isaacs 2013). Current strategies may not be sustainable, given problems associated with overuse of insecticide in agriculture, including insecticide resistance, traces of insecticide in fruit that may render product unmarketable (mainly in international markets), and adverse effects of both consumers and farm workers, among others (Van Timmeren and Isaacs 2013). Moreover, farmers may be overspending in insecticide sprays as the current applications are in excess of what is really needed (Wise et al. 2014). The industry needs alternative management strategies that contribute to the reduction of insecticide use.

One possible alternative to preventative broad-spectrum insecticide sprays consists of strategies that combine monitoring with insecticide applications. Nevertheless, very few growers include monitoring in their SWD management strategies (NC State Extension Service 2016). Extension services across the U.S. are calling for two primary ways to incorporate monitoring in farm-level SWD management. One is called monitor-to-initiate spray strategy, in which the

farmer starts weekly monitoring at the beginning of the cropping season, starts sprays after the number of SWD caught by traps reaches a predetermined threshold; and subsequently continues weekly sprays while stops monitoring. The other is called monitor-to-guide spray strategy, in which the farmer monitors weekly throughout the cropping season, sprays weekly if the number of SWD caught by traps reaches a predetermined threshold, and does not spray if the number of flies caught is smaller than the threshold.

SWD control strategies that incorporate monitoring are promising, yet little is known about the economic benefits of these strategies over preventative broad-spectrum insecticide sprays. Relevant questions include: What strategies are likely to minimize losses due to SWD? And what threshold (i.e. number of SWD caught in traps) should be employed, so that monitoring strategies are superior to insecticide spay-only strategies? An economic analysis addressing these critical questions is complex given the inability of farmers to observe the true SWD population as well as the dynamic nature of SWD infestations.

To fill this gap in the literature, we develop a dynamic bioeconomic model of SWD control to identify the cost-minimizing SWD management strategy. We employ Bayesian methods in a dynamic simulation setting to evaluate the economic outcomes of alternative strategies involving insecticide spray and monitoring combinations. We apply this model to a blueberry farmer making decisions to control SWD infestations. The objective function of the model is to minimize the sum of expected damages and management costs. To do this, the model takes into account: 1) the economic losses accruing to SWD infestation; 2) the value of the crop; 3) the alternative strategies available to monitor and control for SWD; and 4) the cost of strategies to control and monitor for SWD.

We find that the economic impacts of control strategies depend on the efficacy of insecticides, the efficiency of monitoring traps, and the action threshold (i.e. number of SWD caught in traps). Spray-only strategies minimize total costs when the efficiency of monitoring traps is low. In contrast, monitor-to-initiate strategies tend to minimize SWD losses when using more efficient monitoring traps and high efficacy insecticide. Overall, monitor-to-initiate spray strategies performs better than monitor-to-guide spray strategies. Only when using relative conservative action thresholds, spraying high efficacy insecticide, and using relatively efficient monitoring traps, monitor-to-guide spray strategy have lower total cost than monitor-to-initiate spray strategy.

2. Literature Review

Since the detection of SWD in the U.S. in 2008, significant research have been undertaken to study the invasion biology of the pest (Cini et al. 2012; Pfeiffer et al. 2012; Burrack et al 2013; Asplen 2015; Wang et al. 2016) and document its economic impacts (Bolda et al. 2009; Goodhue et al. 2011). Building on recent knowledge on the pest biology, one of the key research areas identified is the study of cost-effective management strategies. Such research would build on recently developed temperature-dependent pest population models to inform decision making in an integrated pest management (IPM) framework (Asplen 2015; Wiman et al. 2014). Given the zero tolerance for SWD infested fruit in both fresh and frozen markets, current management strategies consist mostly of proactive insecticides applications (Beers et al. 2011). There are limited effective insecticide options for managing SWD and insecticide resistance is expected to become a major issue unless its use is optimized (Haye et al. 2016). Such optimization would

rely on a mix of chemical (i.e., pesticide use), cultural (e.g., monitoring), and biological (e.g., natural enemies) control strategies (Haye et al. 2016).

Recent economic impact studies estimate reduction in revenues of 20% and 37% on strawberry and raspberry farms, respectively, if SWD is not controlled (Goodhue et al. 2011). Although this economic impact is well understood, there is a lack of ecological-economic or bioeconomic frameworks that can guide the optimization of SWD control while preventing insecticide resistance through the integration of monitoring and treatment within an IPM framework. The importance of monitoring has been recognized in invasive species detection and management (Berec et al. 2015; Epanchin-Niell et al. 2012) and natural resource management (White 2000) when the true state of the system can only be partially observed. In the case of SWD, the current available attractants are not selective for SWD, making it very difficult to differentiate SWD from other fruit flies. Researchers have developed several frameworks to deal with the partial observability problem. One such approach is modelling the management problem as a partially observed Markov decision process (POMDP) (Monahan 1982; Haight and Polasky 2010). A POMDP is a generalization of a Markov decision process which allows modeling the uncertainty in the state of the underlying Markov process (Monahan 1980). Applications of POMDP include invasive species control (Moore 2008; Haight and Polasky 2010), endangered species management (Tomberlin 2010), decision making by fishermen (Lane 1989), and survey and management of cryptic threatened species (Chadès et al 2008). One of the advantages of POMDP is that it embeds the complexity of imperfect state information into a decision making framework. However, because of its computational complexity, this method has the drawback of handling only small state-spaces and representing simplistic problems (Fackler and Haight 2014).

Adaptive decision-making or adaptive management (AM) is another approach that is appropriate to model a partially observed population (White 2000; Williams 2011). According to this approach, a resource manager simultaneously manages and learns about the states of the population through the process of management. Adaptive management applications include wetlands management (Williams 2011), invasive species control (Moore 2008), pest management and weed control (Shea et al. 2002), habitat restoration (McCarthy and Possingham 2007), and harvest management (Hauser and Possingham 2008, Moore et al 2008). Despite its attractive feature of incorporating learning by doing, the adaptive management approach is characterized by key emerging difficulties that are yet to be overcome. These include, among others, the treatment of uncertainty over time; the necessary assumption of stationarity of resource dynamics over the management time frame; and the choice of a spatial scale that is consistent with both the decision-making and the ecological processes (Williams and Brown 2016).

Bayesian state-space modeling offers an alternative framework to address population uncertainty and partial observability. State-space models, most common in ecological research, are partitioned into an underlying process (e.g., real SWD population) describing the transitions of the true states of the system over time and an observed process (e.g., trapped SWD population) that links the observations of the system to the true states. The models are then fitted using a Bayesian data augmentation approach (King 2012). Bayesian state-space modeling has been extensively used among ecologists to study fisheries (Lewy and Nielsen 2003; McAllister and Kirkwood, 1998; Millar and Meyer 2000), conservation (Chaloupka and Balazs 2007), harvest regulation (Walters 1975; Trenkel, elston and Buckland 2000), animal invasion (Hooten et al. 2007), and animal movements (Jonsen, Flemming, and Myers 2005), among other study systems.

Although Bayesian state space models are known for being able to address uncertainties in both state process and observation process, and for their flexibility in modelling complex population dynamics, they do not provide a framework for identifying optimal management policies. In this paper, we use the case of SWD to extend the applicability of Bayesian state space modeling to decision making. We do so by combining a Bayesian state-space model of SWD infestations with simulations of alternative SWD control strategies currently recommended for an IPM approach.

3. Model

In this section, we first develop a Bayesian state-space model to represent the population dynamics of SWD. We estimate parameters of the population dynamics model using a Bayesian Markov Chain Monte Carlo (MCMC) approach. Based on these estimated parameters, we then run simulations to evaluate the performance of 19 alternative management strategies when efforts are being made to control the population of SWD.

3.1 Population Dynamics

Bayesian state-space models have been applied to many ecological problems to describe the population dynamics of different systems. Generally, the quantities of interests (e.g., the population density of a species) are unknown and evolving over time. Observable variables provide only noisy information about the true population dynamics. State-space models generally consist of two equations which describing: 1) the state process that captures the stochastic dynamics of the unobserved state variables, and 2) the observation process that associates the data at hand to the state variables, which may involve some observation noise. Mathematically:

(1) $N_{t+1} = f(N_t, \theta_1, \epsilon_t)$, the state process, and

(2) $y_t = g(N_t, \theta_2, \omega_t)$, the observation process.

The state process (Equation 1) describes the population dynamics, where N_t is a hidden (not observed) state variable (i.e., population size) at period t, θ_1 is a vector of parameters, and ϵ_t is an *iid* process noise which captures the stochastic dynamics of N_t. The observation process (Equation 2) relates the observation (data) at hand y_t (e.g., abundance index, or observed number of captured individuals) to the state variable N_t through an observation function involving parameters θ_2 and some *iid* observation noise ω_t.

We employ a classical Schaefer (logistic) population function (Equation 3) and assume that population at each period is not affected by the number of SWD caught in monitoring traps, yielding:

(3) $N_{t+1} = \left[N_t + r \times N_t \times \left(1 - \frac{N_t}{K}\right)\right] \times e^{\epsilon_{t+1}}$

where r is the intrinsic growth rate, K is the carrying capacity, ϵ_{t+1} is a normally distributed $N(0,\ \sigma^2)$ random term representing environmental noise (e.g., rain, temperature, humidity, etc.).

We assume that the fate of each individual SWD facing a trap (i.e. being captured or escaping) is ruled by the same *Bernoulli* mechanism. Then, the number of captures can be thought of as a binomial sampling from the population. We define the likelihood of y_t conditional on N_t as:

(4) $y_t \sim Binomial(N_t,\ \pi)$

where π is the trapping efficiency, defined as the probability of an individual being captured by monitoring traps.

From here on, we use brackets to denote probability distributions. Let $\theta_1 = (r, K, \sigma^2)$, the stochastic transition defined in Equation 3 can be written as:

(5) $[N_{t+1} | N_t, \theta_1]$

Let $t = [1, \dots, T]$ denote the time series for which observations are available. Conditional on θ_1, the sequence of unknown states $(N_1, \dots, N_T)$ follows a first-order Markov chain. Assuming an initial value for N_1 and using the transition kernel defined by Equation 5, the prior distribution can be formulated as:

(6) $[(N_1, \dots, N_T), \theta_1] = [\theta_1] \times [N_1|\theta_1] \times \prod_{t=1}^{T}[N_{t+1}|N_t, \theta_1]$

Conditional on state N_t and parameter $\theta_2 = \pi$, the likelihood of y_t can be factorized as:

(7) $[(y_1, \dots, y_T), \theta_2] = \prod_{t=1}^{T}[y_t|N_t, \theta_2]$

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:

(8) $[(N_1, \dots, N_T), \theta|(y_1, \dots, y_T)] \propto [\theta] \times [N_1] \times \prod_{t=1}^{T}[N_{t+1}|N_t, \theta_1] \times \prod_{t=1}^{T}[y_t|N_t, \theta_2]$

A sample of the full joint posterior distribution in equation (8) can be easily obtained from MCMC sampling using the OpenBUGS software. The trap data used for the MCMC estimation are presented in figure 1. These data were obtained from a blueberry farm located in western New York State. Adult SWD were monitored for 13 weeks in the 2014 growing season, starting from fruit coloring stage, generally two weeks before harvest started, and until the harvest ended.

[Insert figure 1 here]

3.2 Economic Model

In this section, we explain how the results from the population model can be used to test the response of the SWD population levels under different management strategies. We develop an economic model of managing SWD infestation based on noise observation of the population level.

Our economic model describes the decision process of a blueberry farm manager controlling SWD infestations. At the beginning of each period, nature decides the population level and damage of SWD, the farm manager then chooses management actions. At each period, the manager needs to make two decisions. The first decision is whether to monitor for SWD population or not. We define a binary variable M_t to denote the monitoring decision ($M_t = 1$ if monitoring takes places and 0 otherwise). The other decision is whether to apply insecticide or not. Let S_t denote the spraying decision (S_t =1 if the farm manger decides to spray at period t and 0 otherwise). Note that the spraying decision may depend on the monitoring results. Following the management actions, the state of the infestation may change and will transit to the next period. Taking into account the effect of control actions, the population transition equation (3) can be reformulated as:

$$(9)\ N_{t+1} = \begin{cases} \left[(1 - Efficacy) \times N_t + r \times (1 - Efficacy) \times N_t \times \left(1 - \frac{N_t}{K}\right)\right] \times e^{\epsilon_{t+1}}, \text{if } S_t = 1 \\ \left[N_t + r \times N_t \times \left(1 - \frac{N_t}{K}\right)\right] \times e^{\epsilon_{t+1}}, \text{otherwise} \end{cases}$$

where $Efficacy$ denotes the efficacy of the insecticide applied, which can take two values $Efficacy_{\text{hi}}$ and $Efficacy_{low}$.

The objective of the farm manager is to minimize the expected total cost across time, by choosing an optimal SWD management strategy (δ). The difference between alternative management strategies falls into the two abovementioned control decisions at each period. We formulate the optimal SWD control problem as follows:

$$(10)\ \min_{\delta} Total\ Cost(\delta) = \mathbb{E}\{\sum_{t=1}^{T} Damage_t\ (N_t(\delta)) + Management\ Cost_t(S_t(\delta) + M_t(\delta))\}$$

where $\mathbb{E}$ is the expectation operator over the random quantities due to the stochastic nature of the dynamic system. At each period t, the manager faces two types of costs: damages and

management costs. We assume that damages depend on the population level at the start of each period and SWD only cause damage by reducing yields. Let p be the probability that blueberry fruits are damaged by one individual SWD. The probability that fruits are not damaged by any SWD at period t is $(1-p)^{N_t}$ and the probability that fruits are damaged by SWD of population size N_t is $1-(1-p)^{N_t}$. The damage for period t is thus the product of weekly blueberry yields, the price of blueberry, and the probability of SWD damage (Equation 11). The weekly relative yields (weekly blueberry yield as percentage of total yield) are shown in figure 2. These yields are approximated by a gamma distribution using yield data obtained from field observations (Gregory Loeb, personal communication, 2016).

[Insert figure 2 here]

(11) $Damage_t\ (N_t) = Baseline\ Annual\ Yield \times Weekly\ Relative\ Yield_t \times Price \times [1-(1-p)^{N_t}]$

Management costs are the sum of monitoring costs and spraying costs. Although management costs may depend on the level of SWD population, for simplicity we assume a single level of monitoring and spraying costs. Management costs can be expressed as:

(12) $$\begin{aligned} Management\ Cost_t = {} & Unit\ Spraying\ Material\ Cost \times S_t \\ & + Unit\ Spraying\ Labor\ Cost \times S_t \\ & + Unit\ Monitoring\ Material\ Cost \times M_t \\ & + Unit\ Monitoring\ Labor\ Cost \times M_t \end{aligned}$$

We design and implement Monte Carlo experiments to evaluate 19 different strategies for managing a SWD infestation in a one acre blueberry farm. Each experiment consists of 10,000 simulation runs, over a growing season of 13 weeks (the period between fruit coloring and harvest). The 19 alternative strategies can be classified into four categories: laissez-faire, spray

throughout the season, monitor-to-initiate spray and monitor-to-guide spray (table 1). The farm manager does not take any control action under the laissez-faire strategy. The most commonly adopted management strategy by growers to prevent SWD infestation is applying insecticide throughout the season. We choose this strategy as the baseline to compare outcomes of alternative strategies. Two additional types of sustainable strategies recommended by research and extension professionals are monitor-to-initiate spray strategies and monitor-to-guide spray strategies. For simplicity, we will refer these two types of strategies as initiate strategies and guide strategies from here on. The interest on these strategy types lien on the ability to avoid unnecessary insecticide sprays. The difference between these two strategy types is that growers stop monitoring for SWD activities once they start insecticide sprays under the initiate strategies; while under the guide strategies, growers monitor SWD activity throughout the season and only spray if the number of trapped SWD reaches a predetermined threshold. To find the optimal SWD control strategy, we run simulations using the objective function (Equation 10) to rank them according to total cost. The model parameters used to run simulations are shown in table 2. These parameters are based on existing literature and estimates from entomologists and extension personnel (Gregory Loeb and Juliet Carroll, personal communication, 2016).

[Insert table 1 here]

[Insert table 2 here]

4. Results & Discussion

We find that the economic impacts of different SWD control strategies depend on the efficiency of monitoring traps, the efficacy of the insecticide applied, and also the action threshold selected. When employing monitoring traps with very low efficiency, the baseline spray-only strategy

performs better than most initiate and guide strategies. Nonetheless, as the efficiency of monitoring traps improves, initiate strategies not only result in lower total costs but also require less insecticide sprays. However, our results suggest that using high efficacy insecticides is necessary for initiate strategies to be superior to baseline spray-only strategy. In addition, we find that conservative thresholds are preferred when the trapping efficiency is low and liberal thresholds should be chosen with more efficient traps. Finally, our results suggest that initiate strategies perform better than guide strategies in most cases.

4.1 Population Dynamics Results

The prior distributions and main statistics of the marginal posterior distributions of the key parameters used in the Bayesian state-space population model are shown in table 3. The weekly intrinsic growth rate r, the per capita rate of population growth, is 1.115, which is relatively high and indicates that the population size can grow very fast without proper management. The posterior median of carrying capacity K is 2,887 files per acre, indicating the maximum population size of SWD the studied farm can sustain.

[Insert table 3 here]

The model also provides estimates of the time series of the latent (unobserved) SWD population size (figure 3). The time series of the population size exhibits the typical S-shape of logistic growth curves. From week 1 to 11, the population quickly grows to more than 2,000 flies per acre. Starting from week 11, the population grows at a relatively slower rate and reaches its maximum around 3,000 flies per acre in week 12. The population size then decreases in week 13 to around 2,400 flies per acre.

[Insert figure 3 here]

4.2 Performance of Alternative Management Strategies

Simulations over 13 weeks were performed given the management strategies 1-19 and the parameter values described above. Table 4 shows the main results when we assume a trapping efficiency of 0.1, which is consistent with the traps currently used by growers. The laissez-faire (no action) strategy has the highest damage and total cost. Under this strategy, growers lose about 45% of the crop. The baseline strategies, which are also the most commonly used strategies, have the lowest damage and total cost. However, the spraying costs of baseline strategies are the highest because growers are employing proactive calendar spray programs to prevent SWD infestation. When applying high efficacy insecticide, the initiate strategies have lower total costs than the baseline strategy if the threshold to trigger insecticide spray is 1 and 3 flies per acre. This is largely due to the reduction in insecticide applications. Although other initiate strategies of using either higher thresholds or low efficacy insecticide are more expensive than baseline strategies, these strategies have lower spraying cost and are more environmentally sustainable. The guide strategies generate even lower spraying costs but higher damages. For example, the damage of guide strategy when using 10 flies per acre as a threshold and a low efficacy insecticide is $1214, which is almost twice the damage of initiate strategy ($644).

[Insert table 4]

The results showed in table 4 are based on the assumption that trapping efficiency is 0.1. This trapping efficiency is relatively low because the currently available lure/attractants are not selective for SWD, thus making it difficult to differentiate SWD from other harmless fruit flies. Researchers are making efforts to improve the selectivity of the traps. Should the efficiency of traps improve in the future, initiate strategies and guide strategies may be superior to the baseline strategies.

4.2.1 Initiate Strategies

Figure 4 shows the costs of initiate strategies using high efficacy insecticide relative to the baseline spray strategy. We find that most initiate strategies have lower costs than the baseline strategy. For example, the percentage changes of total costs are below 0% when using threshold of 5 flies per acre, except when trapping efficiency is 0.1. The optimal action threshold changes with trapping efficiency. When the trapping efficiency is as low as 0.1, threshold 1 is optimal. The optimal threshold is 3 when the trapping efficiency is 0.2 and 5 when trapping efficiency is between 0.3 and 0.5. The liberal threshold of 10 flies per acre is the best when trapping efficiency is improved to be equal to or higher than 0.6.

[Insert figure 4 here]

The results of using low efficacy insecticide are shown in figure 5. It is interesting to note that the percentage changes in total costs are all above 0% in this case, which indicates that the baseline strategy is superior to all initiate strategies when the insecticide efficacy is low. This suggest that using high efficacy insecticides is necessary when employing initiate strategies. Otherwise, it is always more economical to just spray throughout the season.

[Insert figure 5 here]

4.2.2 Guide Strategies

The results of guide strategies when using high efficacy insecticide are shown in figure 6. The figure indicates that a guide strategy is superior to the baseline only when using a threshold of 3 flies per acre and when trapping efficiency is between 0.3 and 0.6. Depending on the threshold selected, the impact of efficiency improvement on total cost differs. There is a trade-off between damages and spraying costs. More efficient traps result in insecticide sprays being triggered

earlier, thus reducing damages and potentially increasing spraying costs. When using conservative thresholds, increases in spraying cost dominate the decreases in damage and vice versa.

[Insert figure 6 here]

Similarly to the initiate strategies, if low efficacy insecticides are used, then baseline strategies are superior to all guide strategies (figure 7). We find similar trade-offs between damages and spraying cost for guide strategies when using high efficacy insecticides.

[Insert figure 7 here]

4.2.3 Initiate Strategies vs. Guide Strategies

Although many growers have used monitoring traps to inform their insecticide spray decisions, it is not clear to them which monitor strategy is better. Should growers only use monitoring traps to initiate insecticide spray or should they keep monitoring SWD population level and apply insecticide only if trapped number of flies is above certain action threshold? To answer this question, we compare the performance of these two types of management strategies. Detailed results are shown in figures 8-11. Overall, initiate strategies perform better than guide strategies. Only when using a threshold of 3 flies per acre, spraying high efficacy insecticide, and trapping efficiency is between 0.3 and 0.5, guide strategies yield lower total costs than initiate strategies (figure 8-a).

[Insert figure 8 here]

When using a very conservative threshold (1 fly per acre), the total cost of guide strategies is higher than the cost of initiate strategies, regardless the efficacy of the insecticide used (figure 8). The reason is that the monitoring cost of guide strategies is much higher than the monitoring

cost of initiate strategies. We note that, when using a high efficacy insecticide, the total cost of both initiate strategies and guide strategies increases as the efficiency of SWD traps improves. However, the cost of guide strategies increase at a higher rate than initiate strategies. When using more efficient traps, the guide strategy triggers more frequent insecticide sprays, resulting in higher spraying costs. When using low efficacy insecticides, the cost of initiate strategies is not very sensitive to the efficiency of traps used. The cost of guide strategy decreases first and then increases as the trapping efficiency improves. When the trapping efficiency increases from 0.1 to 0.2, the decrease in cost are mainly due to decreases in crop damages. These suggest that when using very conservative thresholds, efforts to improve trapping efficiency are beneficial only when trapping efficiency increases from 0.1 to 0.2. Using traps with efficiency greater than 0.2 results in higher total costs.

Figure 9 compares costs of initiate and guide strategies for a threshold of 3 flies per acre. The costs of both initiate and guide strategies when using high efficacy insecticides decrease first and then gradually increase as the trapping efficiency improves. The cost of guide strategies is more sensitive to changes in trapping efficiency than the cost of initiate strategies. For trapping efficiency between 0.3 and 0.5, a guide strategy generates lower total costs than an initiate strategy. The outcome of using low efficacy insecticides is different than when using high efficacy insecticides. Both guide and initiate strategies exhibit similar patterns as efficiency of monitoring traps increases. Improvement in trapping efficiency decreases the cost of both strategies.

[Insert figure 9 here]

The results of using more liberal thresholds of 5 and 10 flies per acre are very similar to the results of the threshold of 3 flies per acre with a low efficacy insecticide (figure 10 and 11).

The rationale behind the similarities is the same as above. The only difference is that, when using thresholds of 5 and 10 flies per acre with high efficacy insecticide, the initiate strategy performs better than the baseline strategy when using more efficient traps whereas the guide strategy always performs worse.

[Insert figure 10 here]

[Insert figure 11 here]

5. Conclusion

In this paper, we developed a dynamic bioeconomic model to identify cost-minimizing SWD management strategies. We employed a Bayesian state-space model to simultaneously take into account uncertainties of SWD population dynamics in both the state transitioning process and the observation process. We then used estimated parameters to evaluate the performance of 19 alternative management strategies which consist of different combinations of monitoring and spraying actions. We find that the economic impacts of different SWD control strategies depend on the efficacy of the insecticide applied, the efficiency of monitoring traps, and also the action threshold selected. Our results show that including monitoring in SWD management strategies can help reduce insecticide sprays. Moreover, these strategies can be both economically and environmentally superior to the spray-only strategies, when using more efficient traps.

Our findings are valuable to fruit growers, extension personnel and other stakeholders in advancing their SWD management practices. Nevertheless, our model has several limitations that should be addressed in future research. For example, in our model the sequence of control actions in each management strategy is predetermined. Future research should extend our model to solve for optimal control actions in each period. In addition, when modelling population dynamics, we only used data from adult monitoring traps. Including data obtained from fruit

sampling to detect SWD larvae will improve the accuracy of SWD population estimation. Also, our model considers SWD control in a single farm. Future research should include spatial features such as SWD diffusion across regions or externalities caused by SWD from neighboring infested farms. Finally, we considered SWD infestation of one growing season only. Our model can be extended to examine a multi-year problem to take into account possible resistance developed due to insecticide overuse.

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Table 1. Alternative SWD Control/Management Strategies

Strategy	Description	Monitor	Spray
Laissez-faire (No Actions)			
1	Never monitor; Never spray	Never	Never
Baseline Strategies: Spray throughout the Season			
2	Spray using high efficacy insecticide	Never	Always
3	Spray using low efficacy insecticide	Never	Always
Monitor-to-initiate Spray Strategies			
4	Threshold=1; High efficacy insecticide	Sometimes	Sometimes
5	Threshold=1; Low efficacy insecticide	Sometimes	Sometimes
6	Threshold=3; High efficacy insecticide	Sometimes	Sometimes
7	Threshold=3; Low efficacy insecticide	Sometimes	Sometimes
8	Threshold=5; High efficacy insecticide	Sometimes	Sometimes
9	Threshold=5; Low efficacy insecticide	Sometimes	Sometimes
10	Threshold=10; High efficacy insecticide	Sometimes	Sometimes
11	Threshold=10; Low efficacy insecticide	Sometimes	Sometimes
Monitor-to-guide Spray Strategies			
12	Threshold=1; High efficacy insecticide	Always	Sometimes
13	Threshold=1; Low efficacy insecticide	Always	Sometimes
14	Threshold=3; High efficacy insecticide	Always	Sometimes
15	Threshold=3; Low efficacy insecticide	Always	Sometimes
16	Threshold=5; High efficacy insecticide	Always	Sometimes
17	Threshold=5; Low efficacy insecticide	Always	Sometimes
18	Threshold=10; High efficacy insecticide	Always	Sometimes
19	Threshold=10; Low efficacy insecticide	Always	Sometimes

Table 2. Parameter Values Used to Calculate Economic Cost

Parameter	Value	Description
$Efficacy_{hi}$	0.9	Proportion of SWD killed by insecticide of high efficacy
$Efficacy_{low}$	0.8	Proportion of SWD killed by insecticide of low efficacy
p	0.001	Probability blueberry fruit damaged by one individual SWD fly
Baseline annual yield	5000	Baseline yield of blueberry, unit: lb/acre
Price	$2.17	Pick your own (PYO) price, 2012 blueberry pricing survey
Unit spraying material cost	20.84	Weekly material cost of spraying high efficacy pesticide
Unit spraying labor cost	11.11	Weekly labor cost of spraying high efficacy pesticide
Spraying relative cost	0.8	Cost for low efficacy insecticide as % of hi efficacy insecticide
Unit monitoring material cost	9.3	Weekly cost for monitoring traps and lures
Unit monitoring labor cost	6	Weekly labor cost to check monitoring traps

Table 3. Main Statistics of the Marginal Posterior Distributions of the Key Parameters

Parameter	Prior Distribution	Posterior distributions of key parameters				
		Mean	Sd	2.5% pct.	Median	97.5% pct.
r	$\sim$ *Uniform*(0.01, 20)	1.115	0.4823	0.3697	1.065	2.153
K	$\sim$ *Uniform*(100, 10000)	3316	1388	1846	2887	7480
σ^2	$\log(\sigma^2) \sim$ *Uniform*(-20, 20)	0.3555	0.4126	0.0669	0.2467	1.306

Table 4. Estimated Economic Costs of SWD Infestation under Various Management Strategies

Strategy	Description	Monitoring Cost	Spraying Cost	Damage Cost	Total Cost
Laissez-faire (No Actions)					
1	Never monitor; Never spray	0	0	5015	5015
Baseline Strategies: spray throughout the season					
2	Spray using high efficacy insecticide	0	383	35	419
3	Spray using low efficacy insecticide	0	307	39	345
Monitor-to-initiate Spray Strategies					
4	Threshold=1; High efficacy insecticide	36	341	38	415
5	Threshold=1; Low efficacy insecticide	35	273	49	358
6	Threshold=3; High efficacy insecticide	69	272	78	418
7	Threshold=3; Low efficacy insecticide	69	218	155	441
8	Threshold=5; High efficacy insecticide	82	243	141	466
9	Threshold=5; Low efficacy insecticide	83	194	297	574
10	Threshold=10; High efficacy insecticide	99	208	329	636
11	Threshold=10; Low efficacy insecticide	99	166	644	910
Monitor-to-guide Spray Strategies					
12	Threshold=1; High efficacy insecticide	184	166	83	432
13	Threshold=1; Low efficacy insecticide	184	168	144	496
14	Threshold=3; High efficacy insecticide	184	99	244	526
15	Threshold=3; Low efficacy insecticide	184	133	427	743
16	Threshold=5; High efficacy insecticide	184	89	418	690
17	Threshold=5; Low efficacy insecticide	184	120	683	987
18	Threshold=10; High efficacy insecticide	184	78	813	1075
19	Threshold=10; Low efficacy insecticide	184	105	1214	1503

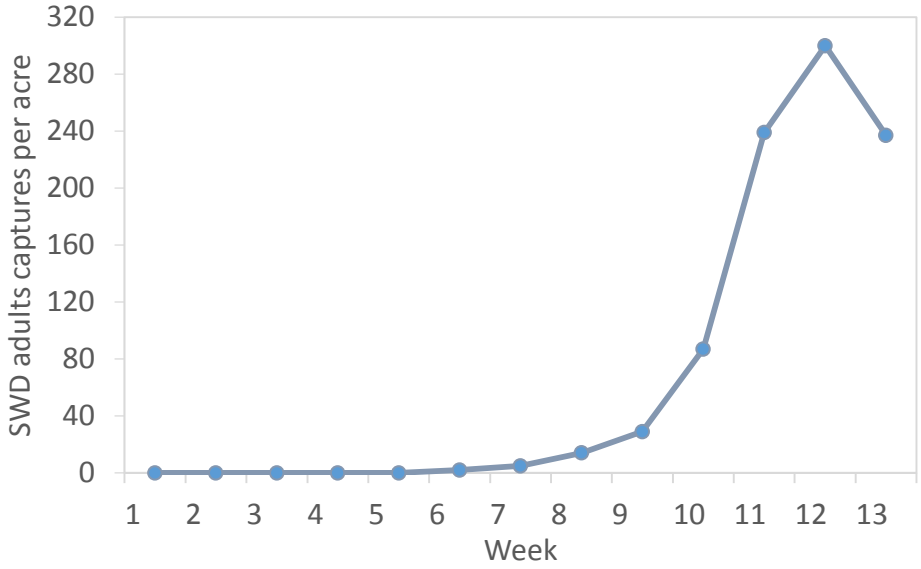


Figure 1. Weekly adult SWD trap captures

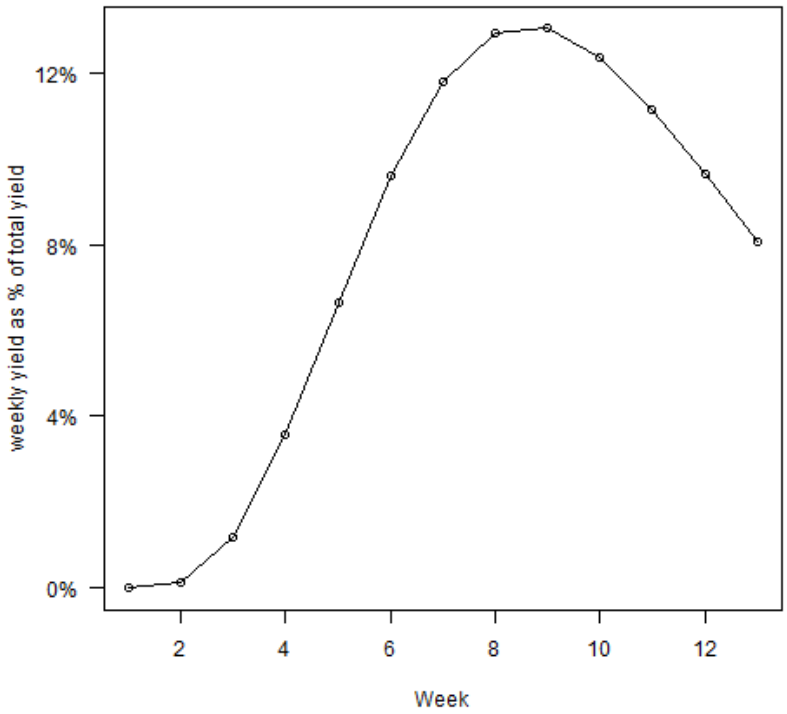


Figure 2. Blueberry weekly yield as percentage of total yield

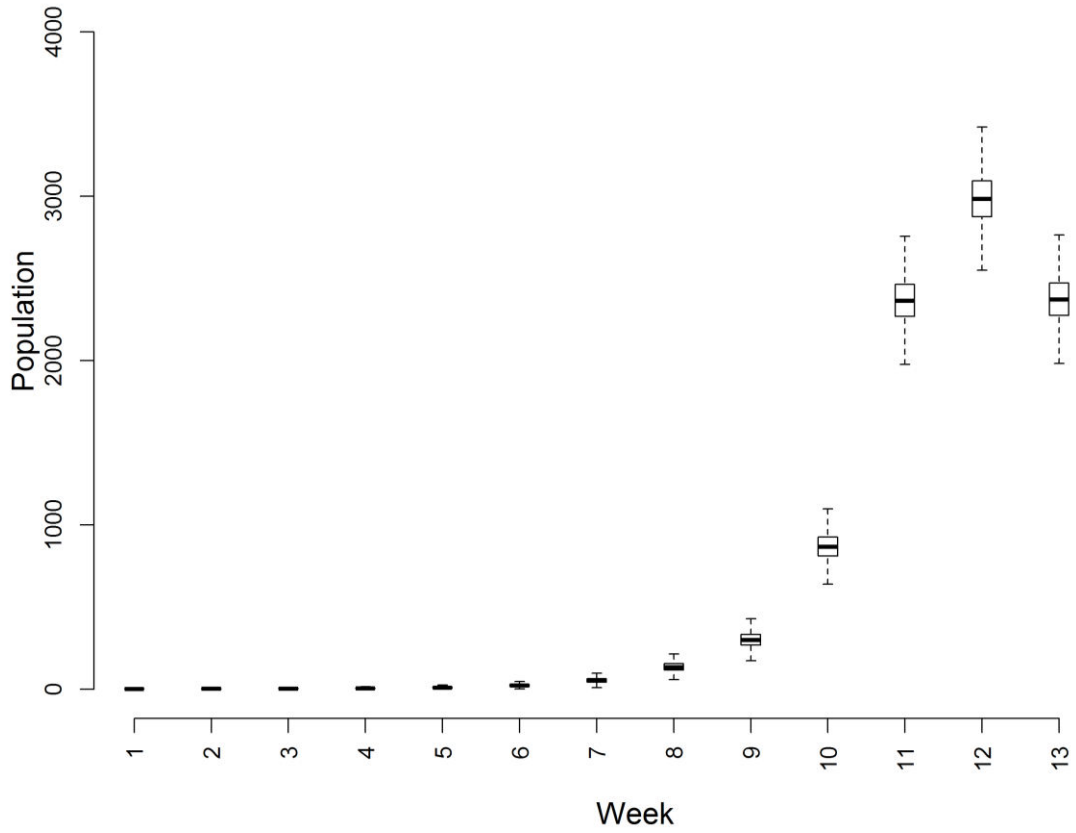


Figure 3. Marginal posterior distributions of the estimated SWD population size

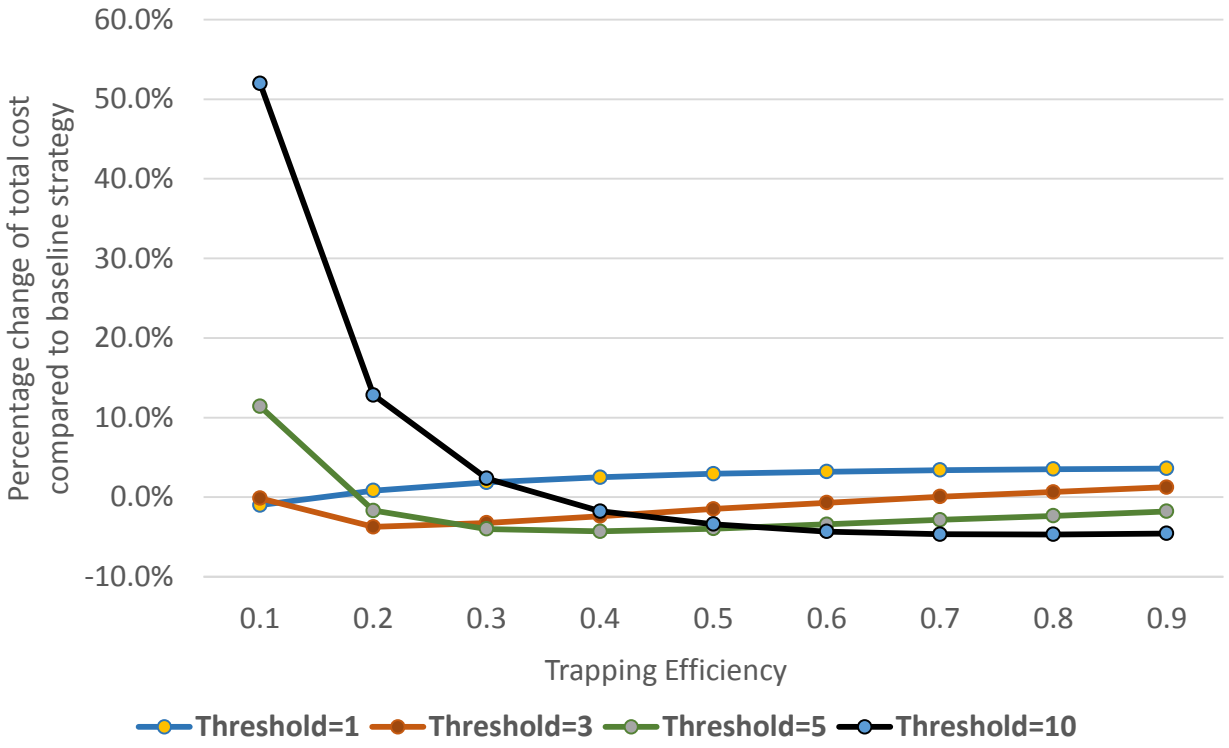


Figure 4. Relative total cost of monitor-to-initiate spray strategies using high efficacy insecticide

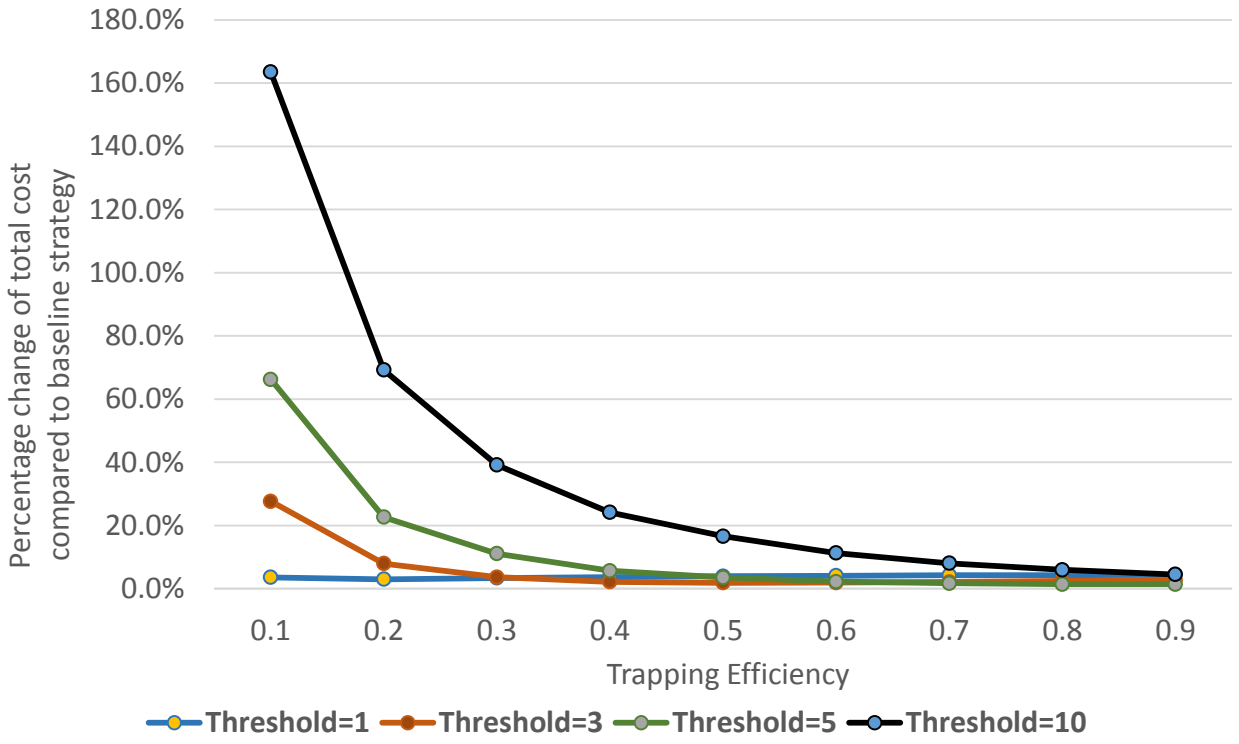


Figure 5. Relative total cost of monitor-to-initiate spray strategies using low efficacy insecticide

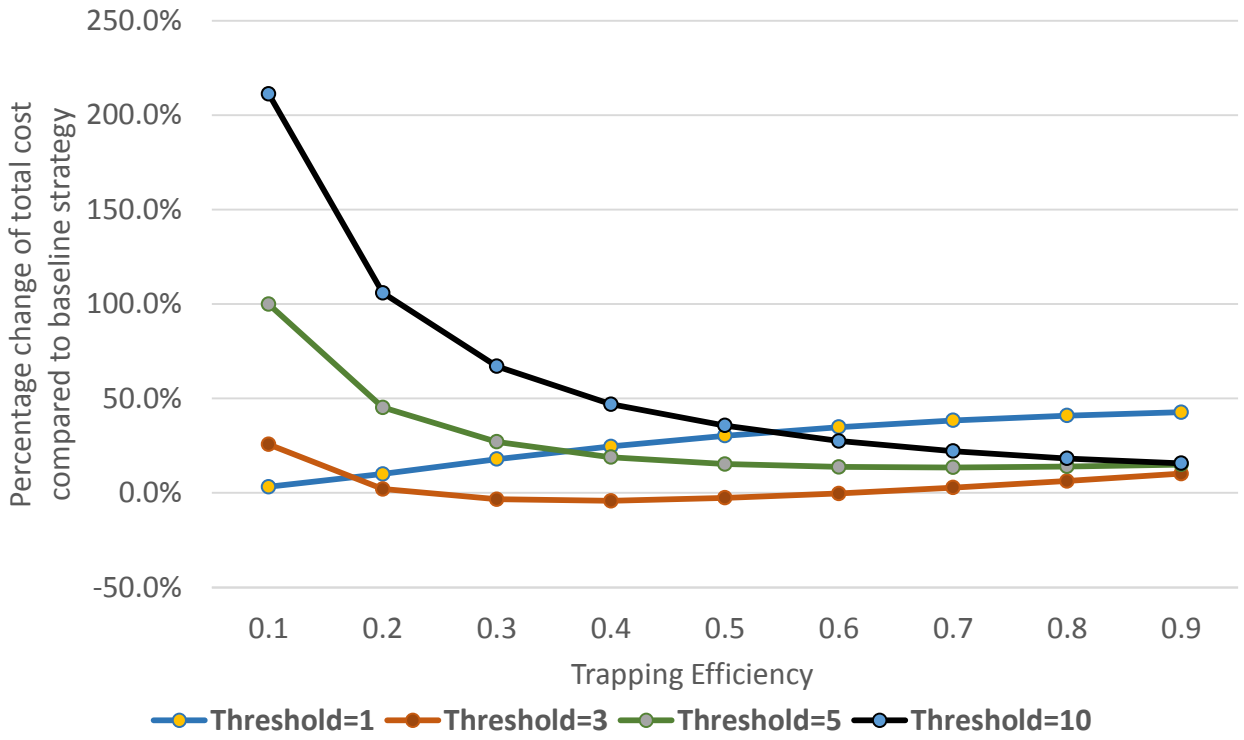


Figure 6. Relative total cost of monitor-to-guide spray strategies using high efficacy insecticide

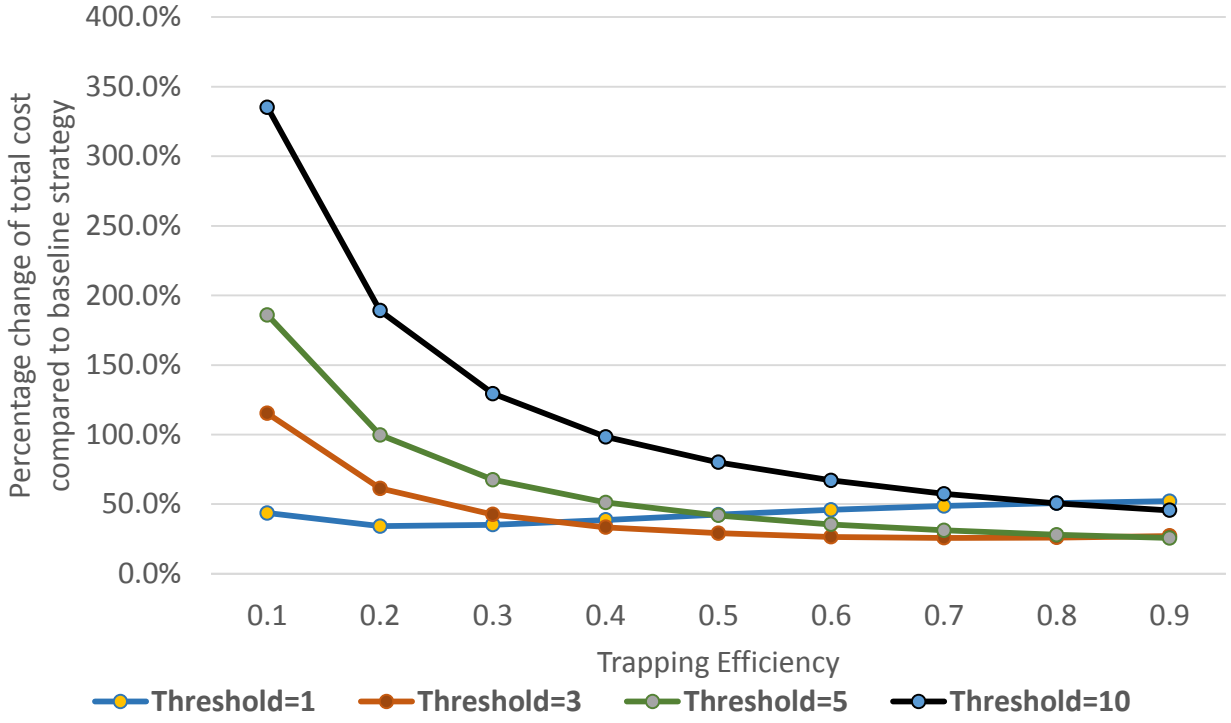
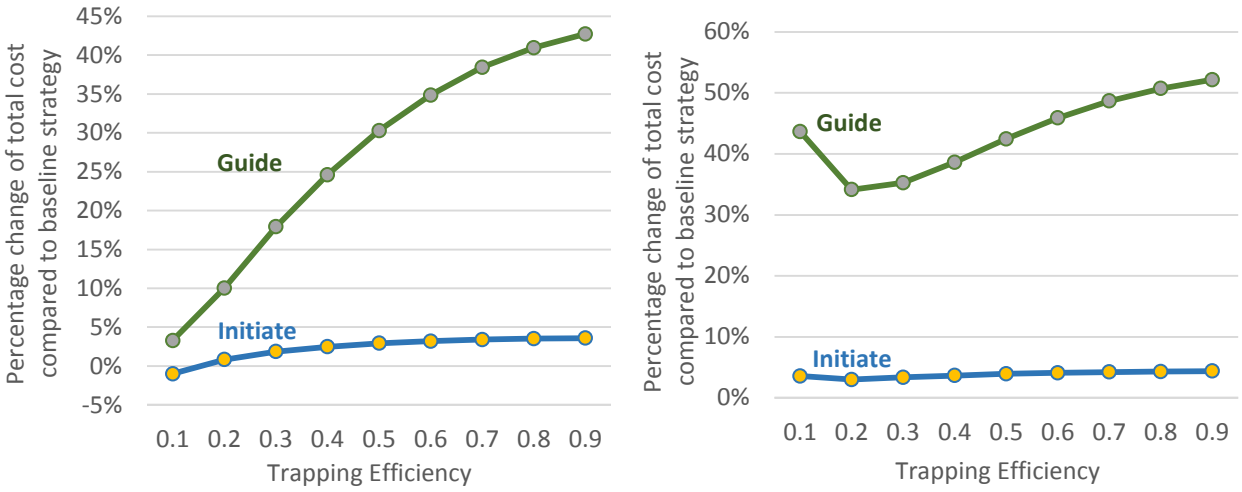
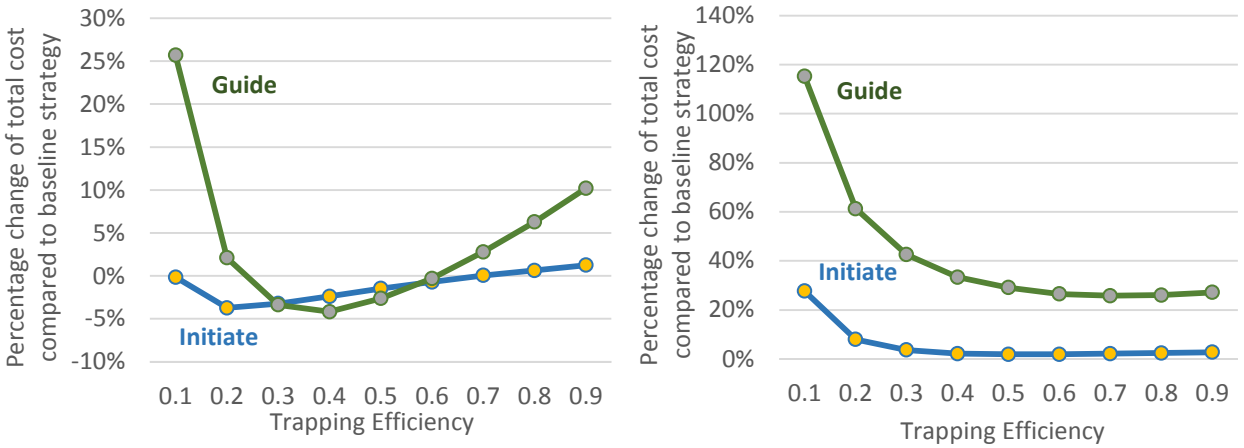


Figure 7. Relative total cost of monitor-to-guide spray strategies using low efficacy insecticide



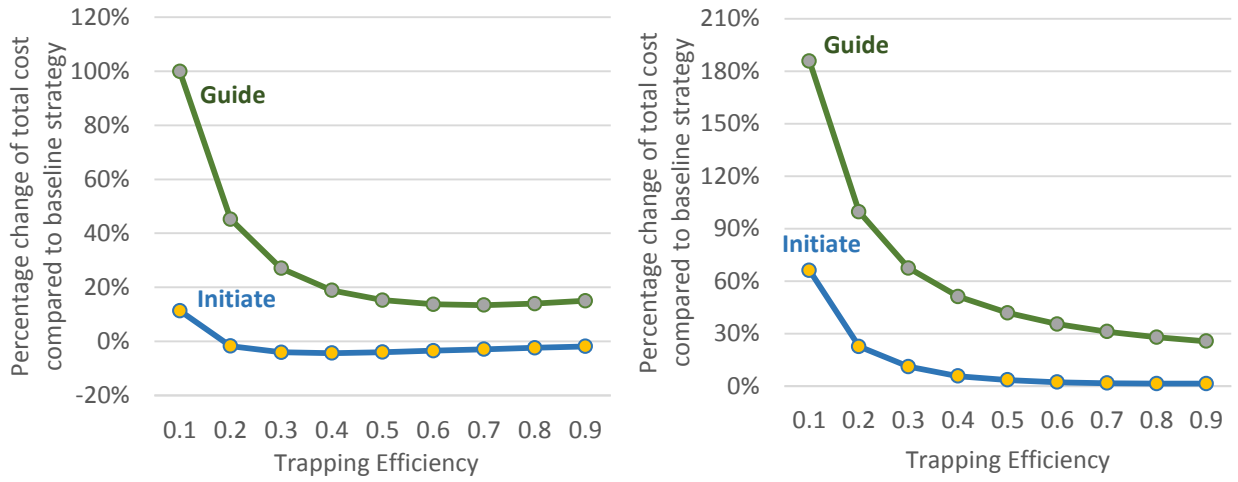
(a) High Efficacy Insecticide (b) Low Efficacy Insecticide

Figure 8. Monitor-to-initiate strategy vs. monitor-to-guide strategy: threshold =1



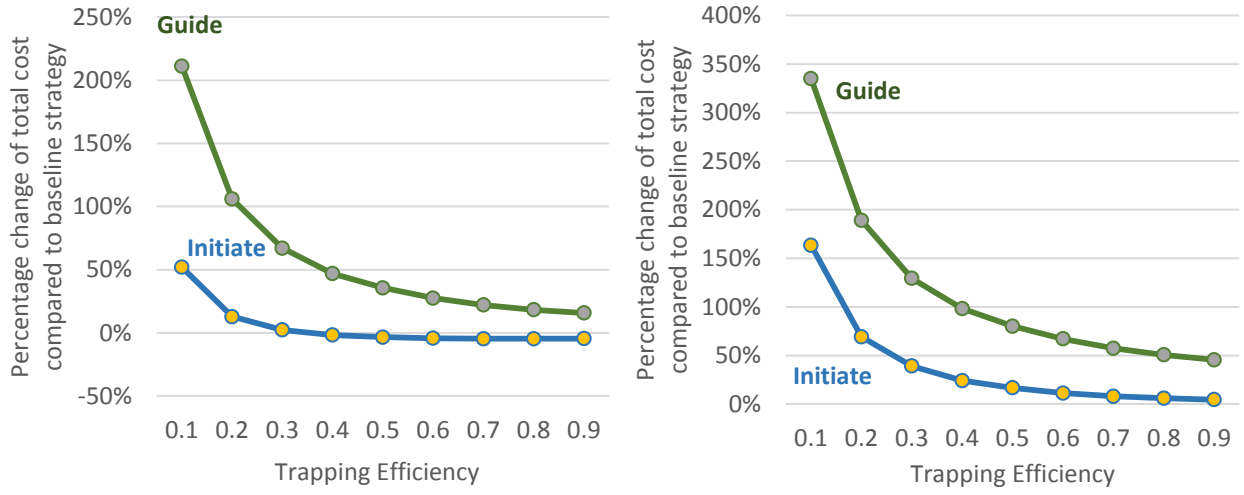
(a) High Efficacy Insecticide (b) Low Efficacy Insecticide

Figure 9. Monitor-to-initiate strategy vs. monitor-to-guide strategy: threshold =3



(a) High Efficacy Insecticide (b) Low Efficacy Insecticide

Figure 10. Monitor-to-initiate strategy vs. monitor-to-guide strategy: threshold =5



(a) High Efficacy Insecticide

(b) Low Efficacy Insecticide

Figure 11. Monitor-to-initiate strategy vs. monitor-to-guide strategy: threshold =10