Optimal Monitoring and Controlling of Invasive Species: The Case of Spotted Wing Drosophila in the United States

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The Case of Spotted Wing Drosophila in the United States[1]

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Abstract

Spotted wing drosophila (SWD) is an invasive pest with devastating effects on soft-skinned fruit crops. Due to zero tolerance of SWD infested fruit, current SWD management strategies usually focus on preventive broad-spectrum insecticide sprays. The industry is calling for management strategies that incorporate monitoring, an important SWD integrated pest management method, to reduce unnecessary applications of pesticide. However, most growers do not monitor because it is costly and traps do not provide perfect observation of the population size. To help inform optimal SWD monitoring and controlling decisions when only partial observation of the population size is possible, we first develop a Bayesian state-space model to represent the population dynamics of SWD. Based on the estimated parameters, we then introduce control variables to the population model and run simulations to evaluate the performance of alternative SWD management strategies. By doing so, our paper help extend the applicability of Bayesian state space modeling to decision making in invasive species management. We show that the economic impact of alternative SWD control strategies depends on the efficiency of monitoring traps, the action threshold selected (i.e. the number of SWD in traps that triggers insecticide applications), and the efficacy of the insecticide. Overall, we find that as the efficiency of monitoring improves, management strategies based on monitoring are superior to spray-only strategies. Our results also suggest that growers will choose higher action thresholds when monitoring traps are more efficient.

JEL codes: Q130, C63, D83

Keywords: Bayesian State-Space Model, Partial Observability, Integrated Pest Management, Invasive Species, Monitoring, Spotted Wing Drosophila

Introduction

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

In addition to a preference for commercial fruit crops, SWD exhibits a high reproductive capacity relative to other members of the species. Between 13 and 16 generations can be completed per year and a female can produce up to 350 eggs during its lifespan (Asplen et al. 2015). This high reproductive potential combined with a short generation time-cycle, results in rapid population growth and increased pest pressure during the critical crop-ripening period (Wiman et al. 2014).

The economic impacts resulting from SWD are a growing concern among businesses in the soft-skinned fruit sector. The female SWD has a unique serrated ovipositor which can puncture the skin of healthy fruit and lay its eggs inside. The visible physical damage caused by oviposition and internal larva feeding can cause considerable yield reduction (Goodhue et al. 2011). Controlling for SWD has also increased insecticide use and labor costs associated with pest management. In a 2015 winter survey of 436 fruit growers in the United States, respondents from 31 states estimated crop losses due to SWD at over $133 million, and increases in insecticide costs of between $100 and $300 per acre due to SWD (North Carolina State Cooperative Extension 2016). For small growers, the economic impact of SWD primarily came in the form of yield loss and management costs. For large commercial growers, however, economic impacts may also include rejection of shipments by buyers, who usually have zero tolerance for SWD infested fruit, particularly for the fresh produce market. Detection of infestation in a shipment, even if small, can result in complete rejection of the shipment (Burrack and Bhattarai 2015). Thus, the negative economic impact of SWD infestations can be substantial. Goodhue et al. (2011) assume a damage prevalence of 30% and estimate SWD annual damages of $500 million in fruit-producing regions across the western U.S. Likewise, North Carolina State Cooperative Extension (2016) estimates over $200 million annual losses due to SWD in eastern production regions of the U.S.

Due to the significant economic impact, current SWD management strategies tend to be very conservative, consisting mainly of preventive broad-spectrum insecticide sprays (Van Timmeren and Isaacs 2013; Wiman et al. 2014; Wise, VanWoerkom, and Isaacs 2015; Haye et al. 2016). However, these strategies may not be sustainable given the problems associated with overuse of insecticides in agriculture, including increased insecticide resistance, traces of insecticide in fruit that may render the product unmarketable, and adverse effects of insecticides on the health of both consumers and farm workers (Van Timmeren and Isaacs 2013). Moreover, growers are overspending on insecticide sprays if the applications exceed required amounts (Wise et al. 2014).

Therefore, the soft-skinned fruit industry is seeking alternative management strategies to reduce insecticide use.

Industry and research institutions are proposing alternative integrated pest management (IPM) methods to control SWD infestations and to reduce the negative impact caused by broad-spectrum insecticide applications. Current IPM methods include chemical control, monitoring, pruning, sanitation, and biological control. Among these methods, combining monitoring with insecticide applications is an important strategy which can give adequate early warning and avoid unnecessary sprays (Quarles 2015). There are two ways of incorporating monitoring in farm-level SWD management. The first is a monitor-to-initiate spray strategy, in which the grower initiates weekly monitoring at the beginning of the growing season, and starts spraying after the number of SWD caught by monitoring traps reaches or exceeds a predetermined threshold, and then continues weekly sprays for the remainder of the season while stopping monitoring activities. The second strategy is a monitor-to-guide spray strategy, in which the grower monitors weekly throughout the cropping season, and sprays only in weeks when the number of SWD caught by monitoring traps reaches or exceeds a predetermined threshold.

SWD control strategies that incorporate monitoring seem promising, but few growers have included monitoring in their SWD management plans (North Carolina State Extension Service 2016). Currently, monitoring of SWD activity is based on trapping methods available for other pests and for Drosophila species in general, i.e., attractants in baits and lure are not selective (Burrack et al. 2015). Identification requires using a magnifying glass to detect adult SWD. This makes it difficult and time consuming to distinguish SWD from other harmless Drosophila species in the field (Asplen et al. 2015). Thus, pest management relies on partially observed population density. Given the benefits and disadvantages of monitoring strategies, the research questions of this paper include: What strategies are likely to minimize damages due to SWD? What are the factors affecting the relative performance of monitoring strategies vs. insecticide spray-only strategies? An economic analysis addressing these critical questions is complex given the inability of growers to observe the true SWD population as well as the dynamic nature of SWD infestations.

To fill this gap in the literature, we developed a dynamic bioeconomic model of SWD control to identify the cost-minimizing SWD management strategy. We first develop a Bayesian state-space model to represent the population dynamics of SWD. Based on the estimated parameters, we then introduce control variables to the population model and run simulations to evaluate the performance of alternative SWD management strategies. We apply this model to the case of a blueberry grower making decisions to control SWD infestations during a single growing season. The objective function of the model is to minimize the sum of expected damages and management costs. Accordingly, the model takes into account: 1) the economic impacts accruing to SWD infestations; 2) the commercial value of the crop; 3) the alternative strategies available to monitor and control for SWD; and 4) the cost of each strategy.

Overall, we find that the economic impact of SWD control strategies depends on the efficiency of monitoring traps, the efficacy of insecticides, and the action threshold (i.e. the number of SWD caught in monitoring traps that trigger insecticide application). We first evaluate the performance of alternative SWD managing strategies based on the assumption that trapping efficiency is 0.1. This trapping efficiency is relatively low but is representative of the “status quo”. Our results show that including monitoring in SWD managing strategies can (1) help reduce unnecessary insecticide use; and (2) result in lower total costs than the spray-only strategy, when growers choose appropriate action thresholds. Although current trapping efficiency is low, strong national efforts have been made to design better traps and more selective lures to improve the efficiency of monitoring. To help understand how changes in trapping efficiency can affect economic impact due to SWD infestation, we also evaluate the performance of alternative SWD strategies under different trapping efficiencies. Our results indicate that as the efficiency of monitoring traps improves, management strategies which include monitoring are superior to the spray-only strategy. In particular, our results show that monitor-to-initiate spray strategy could be superior to the baseline spray-only strategy under all trapping efficiency levels, if the appropriate threshold to trigger spraying is chosen. Moreover, growers can choose higher action thresholds when monitoring efficiency increases. In addition, our sensitivity analysis shows that monitor-to-initiate spraying strategies have lower total costs than the monitor-to-guide spray strategies when insecticide efficacy is low. However, as insecticide efficacy improves, the more environmentally sustainable monitor-to-guide strategies are preferred. Our results are valuable for growers, extension specialists, and stakeholders to advance their SWD managing strategies. More importantly, our results have important policy implications: efforts to improve trapping efficiency can lead to more rational use of insecticides.

Literature Review

Since the detection of SWD in the U.S. in 2008, significant research has examined its biology (Cini, Ioriatti, and Anfora 2012; Pfeiffer, Leskey, and Burrack 2012; Burrack et al 2013; Asplen et al. 2015; Wang et al. 2016b) and has recommended alternative management strategies which include chemical control (Beers et al. 2011; Bruck et al. 2011; Van Timmeren and Isaacs 2013), monitoring and sampling (Lee et al. 2012; Burrack et al. 2015), and biological control (Wang et al. 2016a), among others. There are also a few studies analyzing the economic impact of SWD infestation (Bolda, Goodhue, and Zalom 2010; Goodhue et al. 2011). Although the biology and economic impact are relatively well understood, and alternative SWD management strategies have been recommended, ecological-economic or bioeconomic frameworks are needed to guide the optimization of SWD control and help prevent early insecticide resistance. Reducing the rate of pesticide resistance in SWD might be accomplished through monitoring and treatment within an IPM framework. The importance of monitoring has been recognized in invasive species detection and management (Epanchin-Niell et al. 2012; Berec et al. 2015) 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 employed for monitoring are not selective for SWD, making it difficult to differentiate SWD from other fruit flies.

Investigators in agricultural and resource economics have developed several frameworks to deal with partial observability. One such approach is modeling the management problem as a Partially Observed Markov Decision Process (POMDP) (Monahan 1982; Haight and Polasky 2010; MacLachlan, Springborn and Fackler 2016).

A POMDP is a generalization of the 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 in 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; MacLachlan, Springborn, and Fackler 2015). Following this approach, a decision-maker simultaneously manages and learns about the possible states of the population through learning-by-doing. AM 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). While incorporating learning-by-doing is an attractive feature, the AM approach is characterized by difficulties that have yet to be overcome. These difficulties include (1) the treatment of uncertainty over time, (2) the necessary assumption of stationarity of resource dynamics over the management time frame, and (3) 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 simultaneously address population uncertainty and partial observability. State-space models, which are most common in ecological research, are partitioned into an underlying process describing the transitions of the true states of the system (e.g., real SWD population) over time and an observed process (e.g., trapped SWD population) that links the observations of the system to the true states. Bayesian state-space modeling has been extensively used by ecologists to study fisheries (McAllister and Kirkwood, 1998; Millar and Meyer 2000; Lewy and Nielsen 2003), 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). Although Bayesian state space model can be used to estimate relatively complex population dynamics to address uncertainties in both the state process and the observation process, it has not been applied to solve decision making problems in invasive species management.

In this paper, we use the case of a SWD infestation to extend the applicability of Bayesian state space modeling to decision making in invasive species management. We do so by introducing control variables to a Bayesian state-space model and then run simulations to evaluate performance of alternative SWD control strategies. Our paper provides a Bayesian framework to optimally monitor and control an invasive species when the population size of the species can only be partially observed. Our model can be extended and applied to study other disease and pest management problems. In addition, our paper contributes to the literature on the control of the SWD by providing an economic analysis to evaluate optimal SWD managing strategies.

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 the estimated parameters, we then introduce control variables to the population model and run simulations to evaluate the performance of 10 alternative management strategies to control the population of SWD.

Population Dynamics

Generally, the quantities of interest (e.g., the population density of a species) in Bayesian state-space models are unknown and evolving over time. Observable variables provide only noisy information about the true population dynamics. State-space models typically consist of two equations which describe: (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* noise process 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 the 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 population growth rate, K is the carrying capacity of the population, 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 drawn 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 adult SWD being captured by monitoring traps.

Going forward, we use brackets to denote probability distributions. Letting $\theta_1 = (r, K, \sigma^2)$, 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) $[(N_1, \ldots, N_T), \theta_1] = [\theta_1] \times [N_1|\theta_1] \times \prod_{t=1}^{T}[N_{t+1}|N_t, \theta_1]$

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

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

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

A sample of the full joint posterior distribution in Equation (8) can be obtained from MCMC sampling using the OpenBUGS software, a commonly used software for performing Bayesian inference (Lunn et al. 2009). 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 individuals were monitored for 13 weeks in the 2014 growing season, starting from the fruit coloring stage, generally two weeks before harvest starts, and until the harvest ends.

[Insert figure 1 here]

Economic Model

In this section, we explain how we use the results from the population model to test the response of the SWD population levels under alternative management strategies. We develop an economic model for managing SWD infestation based on partial observation of the population level.

Our economic model describes the decision process of a blueberry farm manager controlling SWD infestations (figure 2). At the beginning of each period, nature decides the population level and SWD damage, the farm manager then chooses management actions. In each period, the manager makes two decisions. The first decision is whether to monitor the SWD population. We define a binary variable M_t to denote the monitoring decision ($M_t = 1$ if monitoring takes places and 0 otherwise). The second decision is whether to spray insecticide. 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 transition to the next period. Taking into account the effect of control actions, the population transition Equation (3) can be reformulated as:

(9) $N_{t+1} =$

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

where $Efficacy$ denotes the efficacy of the insecticide, which is measured by the percent reduction in SWD population.

[Insert figure 2 here]

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

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

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 that SWD only cause damage by reducing yields. Let p be the probability that blueberry fruit is damaged by a single SWD. The probability that the fruit is not damaged by SWD at period t is $(1-p)^{N_t}$ and the probability that fruit is 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 blueberries, and the probability of SWD damage (Equation 11).

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

Weekly relative yields (weekly yield as percentage of total yield) are shown in figure 3. These yields are approximated by a gamma distribution using data obtained from field observations (Gregory Loeb, personal communication, 2016).

[Insert figure 3 here]

Management costs are the sum of monitoring costs and spraying costs. A grower may have different management costs every week depending on the actual SWD population. For example, the grower could apply different dosages of insecticide every week, which leads to varying spraying costs. However, in reality growers usually follow manufacturers' recommendation to apply a single dosage of insecticide every week. Therefore, we assume a single level of monitoring and spraying costs. Management costs can be expressed as:

(12) $$Management\ Cost_t = Unit\ Spraying\ Material\ Cost \times S_t$$

$$+ \, Unit\ Spraying\ Labor\ Cost \times S_t$$

$$+ \, Unit\ Monitoring\ Material\ Cost \times M_t$$

$$+ \, Unit\ Monitoring\ Labor\ Cost \times M_t$$

We design and implement Monte Carlo experiments to evaluate 10 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 10 alternative strategies can be classified into four categories: no intervention, spray-only, monitor-to-initiate spray and monitor-to-guide spray (table 1). The farm manager does not take any control action under the no intervention strategy. The most commonly adopted management strategy by growers is spray-only; we therefore 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 to these two types of strategies as "initiate" strategies and "guide" strategies from here on. Interest in these strategy types stems from a desire to avoid unnecessary insecticide application. The difference between these two strategy types is that growers stop monitoring for SWD once they start insecticide sprays under initiate strategies; while under guide strategies, growers monitor SWD 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 strategies according to total cost during the season. The model parameters used to run simulations are shown in table 2. These parameters are based on the existing literature and on estimates from entomologists and extension personnel (Gregory Loeb and Juliet Carroll, personal communication, 2016).

[Insert table 1 here]

[Insert table 2 here]

Results & Discussion

In this section, we first present the parameter estimates governing population dynamics. We then show the performance of alternative SWD control strategies under different trapping efficiency levels. We also compare the performance of initiate strategies and guide strategies. We finally discuss the robustness of our results with respect to varying insecticide efficacy.

Population Dynamics

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 1.063, which is relatively high and indicates that the population size can grow very quickly without proper management. The posterior median of carrying capacity K is 2,878 flies per acre, indicating the maximum population size of SWD population on a representative one-acre blueberry farm in New York State.

[Insert table 3 here]

The model also provides estimates of the time series of the latent (unobserved) SWD population if the SWD infestation is not controlled (figure 4). 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 in 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, as most fruit has been already harvested.

[Insert figure 4 here]

Performance of Alternative Management Strategies

Simulations over 13 weeks were performed for management strategies 1-10 employing 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 no intervention strategy has the highest damage and total cost. Under this strategy, growers lose about 46% of the crop and are not able to make a positive profit because the yield loss is so high. The baseline spray-only strategy, which is also the most commonly used strategy, has the lowest damage cost. However, the spraying cost of the baseline strategy is the highest because growers are employing proactive calendar spray programs to prevent the SWD infestation. The initiate strategy has lower total cost than the baseline strategy if the threshold to trigger insecticide spray is $y_t = 1$ fly per acre and has the same total cost as the baseline strategy if the threshold $y_t = 3$ flies per acre is used. This is largely due to the reduction in insecticide applications. Although other initiate strategies using higher thresholds are more expensive than the baseline strategy, these strategies have lower spraying cost and are more environmentally sustainable. The guide strategies generate even lower spraying costs but higher damages. For example, when using $y_t = 10$ flies per acre as a threshold, the damage incurred under the guide strategy is $807, which is more than twice the damage incurred under the initiate strategy ($332).

[Insert table 4 here]

The results shown 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. Strong national efforts have been made to design better traps and more selective lures to improve the efficiency of monitoring. Trapping efficiency can significantly affect how effectively monitoring traps can capture SWD individuals and in turn affect the grower's spraying decisions and the choice of the action threshold. It is therefore very important to study how the relative performance of alternative SWD management strategies changes with respect to changes in trapping efficiency.

Initiate Strategies

Figure 5 shows the percentage change of the total costs of initiate strategies relative to the baseline spray-only strategy under different trapping efficiencies. We find that initiate strategies could be superior to the baseline spray-only strategy under all trapping efficiencies, if growers choose the optimal action threshold to initiate insecticide spray. For instance, the total cost of the initiate strategy is 1.0% lower than the cost of the baseline strategy when trapping efficiency is 0.1, 3.8% lower when trapping efficiency is 0.2, and more than 4% lower when trapping efficiency is equal to or higher than 0.3.

These results provide support for the industry's call for growers to adopt the initiate strategy rather than the spray-only strategy.

[Insert figure 5 here]

Our results also suggest that growers' selection of the threshold at which to initiate insecticide spray depend on the trapping efficiency. Growers should use lower thresholds when trapping efficiency is low and switch to higher thresholds as trapping efficiency improves. For example, when trapping efficiency is as low as 0.1, growers should choose the threshold $y_t = 1$ fly per acre for the initiate strategy to be slightly superior to the spray-only strategy (figure 5). Although the profit implications of initiate strategy with threshold $y_t = 1$ fly per acre and the spray-only strategy are practically the same, the former should be preferred given the risk of SWD developing resistance to insecticides. The best strategy is to initiate using the threshold $y_t = 3$ flies per acre when the trapping efficiency improves to 0.2. A threshold of $y_t = 5$ flies per acre should be chosen when the trapping efficiency is between 0.3 and 0.5. The threshold of $y_t = 10$ flies per acre should be selected when the trapping efficiency is 0.6 or more.

Our results provide support for efforts to improve trapping efficiency. More efficient traps will result in lower total costs. In addition, more efficient traps allow growers to use higher action thresholds to initiate insecticide sprays. However, the impact of trapping efficiency improvement on total cost differs depending on the threshold selected. When choosing a low threshold of $y_t = 1$ fly per acre, the relative total cost of the initiate strategy increases as trapping efficiency improves. Under higher thresholds, the total cost of the initiate strategy decreases first and then increases. These different patterns are largely due to trade-offs between spraying cost and damages. Lower thresholds and more efficient traps can result in insecticide sprays being triggered earlier, thus reducing damages but potentially increasing spraying costs. For each action threshold to initiate spraying, there is a certain trapping efficiency where the increases in spraying cost will dominate the decreases in damages beyond that trapping efficiency.

Guide Strategies

The results of guide strategies under different trapping efficiencies are shown in figure 6. As trapping efficiency improves, the patterns of the change in relative total cost of the guide strategies are similar to those of the initiate strategies. Nonetheless, unlike the initiate strategies which can be superior to the baseline spray-only strategy under all trapping efficiencies, guide strategies are lower cost than the baseline strategy only when trapping efficiency is above 0.2. When trapping efficiency is 0.1, the guide strategy with the lowest total cost is the one using the threshold of $y_t = 1$ fly per acre, but the total cost of this strategy is 3.4 percent higher than the baseline strategy. The optimal action threshold is $y_t = 3$ flies per acre when trapping efficiency is between 0.2 and 0.4. A threshold of $y_t = 5$ flies per acre is optimal when trapping efficiency is above 0.5. A threshold of $y_t = 10$ flies per acre is never optimal for the guide strategy.

[Insert figure 6 here]

Initiate Strategies vs. Guide Strategies

Although some growers have responded to the industry's call to use monitoring traps to inform their insecticide spray decisions, their choices between monitoring strategies have remained uninformed. Should growers only use monitoring traps to initiate insecticide spray or should they keep monitoring the SWD population levels and apply insecticide only if the trapped number of flies is above a certain action threshold? To answer this question, we compare the performance of these two types of management strategies. Detailed results are shown in figure 7.

[Insert figure 7 here]

The relative performance of the two types of monitoring strategies depends on the tradeoffs among damage costs, monitoring costs, and spraying costs. As trapping efficiency improves, insecticide application will be triggered earlier and this will lead to higher spraying costs and lower damages costs. This is true for both initiate strategies and guide strategies. However, for guide strategies, monitoring costs remain the same when trapping efficiency improves. But for initiate strategies, monitoring costs decrease as trapping efficiency improves because spraying triggered early also means early termination of monitor activities. The tradeoffs among the three components of costs also depend on the action threshold chosen by growers. When using a very low threshold ($y_t = 1$), the total cost of the guide strategy is higher than the total cost of the initiate strategy (figure 7-a). The major reason is that the monitoring cost of guide strategy is much higher than that of initiate strategy. When using a threshold of $y_t = 3$ flies per acre and when trapping efficiency is between 0.3 and 0.5 (figure 7-b), or when using a threshold of $y_t = 5$ flies per acre with trapping efficiency above 0.5 (figure 7-c), guide strategies yield lower total costs than initiate strategies. For the very high threshold of $y_t = 10$ flies per acre, the initiate strategy always performs better than guide strategy but the relative costs of these two strategies converge as trapping efficiency improves (figure 7-d).

Sensitivity Analysis against Insecticide Efficacy

Changing the insecticide efficacy can also change the relative performance of SWD managing strategies. A powerful insecticide can significantly reduce the SWD population such that growers can skip spraying during some periods with only a mild infestation following a high-efficacy spray. Conversely, if the efficacy of the insecticide is so low that growers need to spray every week to minimize damages due to SWD infestation, then growers should not include monitoring in their SWD managing strategies. As we can see in figure 8 and figure 9, when decreasing insecticide efficacy from 90% to 70%, both the initiate strategy and guide strategy perform worse than the baseline spray-only strategy, regardless of the trapping efficiency. Increasing the insecticide efficacy from 90% to 97%, on the other hand, helps reduce total costs of both initiate and guide strategies (figure 10 and figure 11). However, the magnitude of reduction in total cost depends on trapping efficiency. With trapping efficiency of 0.1, the total cost of using threshold of $y_t = 10$ flies per acre decreases greatly from 50.6% to 41.9% for the initiate strategy and from 155.4% to 101.6% for the guide strategy. With trapping efficiency of 0.9, the total cost of using $y_t = 10$ flies per acre decreases slightly from -4.6% to -4.8% for initiate strategies and from -4.4% to -8.9% for guide strategy.

[Insert figure 8 here]

[Insert figure 9 here]

[Insert figure 10 here]

[Insert figure 11 here]

Regarding the relative performance of initiate strategies and guide strategies, we find that guide strategies are more sensitive to changes in insecticide efficacy. With low insecticide efficacy of 70%, initiate strategies always perform better than the guide strategies (figure 12). When insecticide efficacy improves to 90% (figure 7), guide strategies start to show superiority under some combinations of trapping efficiency and threshold (i.e., trapping efficiency between 0.3 and 0.5 with the threshold of $y_t = 3$ flies per acre, and trapping efficiency greater than 0.5 with the threshold of $y_t = 5$ flies per acre). When insecticide efficacy further improves to 97%, the cost advantages of the guide strategy become even more compelling (figure 13). These results suggest that improvement in insecticide efficacy will result in the dominance of the guide strategy, which is more desirable environmentally.

[Insert figure 12 here]

[Insert figure 13 here]

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 account for uncertainties of SWD population dynamics in both the state transitioning process and the observation process. We then calibrated the model to evaluate the performance of 10 alternative management strategies which consist of different combinations of monitoring and spraying actions. We found that the economic impact of different SWD control strategies depends on the efficiency of monitoring traps, the action threshold selected, and the efficacy of the insecticide. Our results show that including monitoring of the SWD population can help reduce insecticide use. Moreover, strategies which include monitoring can be both economically and environmentally superior to the spray-only strategy, when an appropriate action threshold is chosen. Our sensitivity analysis indicates that initiate strategies perform better than guide strategies when insecticide efficacy is low. However, guide strategies are preferred if insecticide efficacy improves.

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. First, our model can be extended to examine a multi-year problem to account for possible SWD resistance due to insecticide overuse (Hueth and Regev 1974). For example, future research can model insecticide resistance as a "public bad" (Lazarus and Dixon 1984), and conversely, insecticide susceptibility as a "public good". Individual growers have no incentive to conserve SWD susceptibility since they cannot control the insecticide application decisions of their neighbors. Socially, it will likely be optimal for growers to collectively use less insecticide to conserve susceptibility over many years. Second, our model only uses SWD monitoring data from a single farm and ignores the fact that SWD moves freely through space. The probabilities of SWD being caught may depend on the location of the monitoring traps and therefore a single farm's data cannot provide coherent estimation of SWD population density (Royle and Young 2008). Future research should also account for SWD diffusion across regions and describe the SWD infestation within a "spatial-dynamic" problem (Epanchin-Niell and Wilen 2015; Atallah, Gómez, and Conrad 2017).

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Table 1. Alternative SWD Control/Management Strategies

Strategy	Description	Monitor	Spray
No Intervention			
1	Never monitor; Never spray	Never	Never
Baseline Strategy: Spray-only			
2	*Spray throughout the Season*	Never	Always
Monitor-to-initiate Spray Strategies			
3	Threshold=1 fly per acre	Sometimes	Sometimes
4	Threshold=3 flies per acre	Sometimes	Sometimes
5	Threshold=5 flies per acre	Sometimes	Sometimes
6	Threshold=10 flies per acre	Sometimes	Sometimes
Monitor-to-guide Spray Strategies			
7	Threshold=1 fly per acre	Always	Sometimes
8	Threshold=3 flies per acre	Always	Sometimes
9	Threshold=5 flies per acre	Always	Sometimes
10	Threshold=10 flies per acre	Always	Sometimes

Source: Author's definition of strategies based on extended discussion with extension specialists and industry stakeholders.

Table 2. Parameter Values Used to Calculate Economic Cost

Parameter	Value	Description	Sources
$Efficacy$	0.9	Proportion of SWD killed by insecticide	Provisional mortality rate suggested by Tanigoshi, Spitler and Gerdeman (2016)
p	0.001	Probability blueberry fruit damaged by one individual SWD	Calibrated based on a 50% yield loss if no control action taken
Baseline annual yield	5000	Baseline yield of blueberry (lb./acre)	Harrington and Good (2016)
Price	2.17	Pick your own (PYO) price ($/lb.)	Pritts and Hdidenreich (2016)
Unit spraying material cost	20.84	Material cost of applying insecticide ($/week/acre)	Calculated based on North Carolina State Cooperative Extension (2016) and personal communication with D. Welch, October 28, 2015
Unit spraying labor cost	11.11	Labor cost of applying insecticide ($/week/acre)	Calculated based on North Carolina State Cooperative Extension (2016) and personal communication with D. Welch, October 28, 2015
Unit monitoring material cost	9.3	Weekly cost for materials to set up monitoring traps and lures	J. Carroll, personal communication, April 5, 2016
Unit monitoring labor cost	6	Weekly labor cost to check monitoring traps	J. Carroll, personal communication, April 5, 2016

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

Parameter	Prior Distribution	Posterior Distributions of Key Parameters				
		Mean	Standard Deviation	2.5th Percentile	Median	97.5^{th} Percentile
r	~ *Uniform*(0.01, 10)	1.11	0.4583	0.3668	1.063	2.144
K	~ *Uniform*(100, 10000)	3290	1350	1832	2878	7236
σ^2	$\log(\sigma^2)$ ~ *Uniform*(-20, 20)	0.3544	0.3894	0.0678	0.2468	1.272

Source: Authors' estimations.

Table 4. Estimated Economic Costs of SWD Infestation under Various Management Strategies when Trap Efficiency is 0.1

Strategy	Description	Yield (lbs./acre)	Damage Cost($)	Monitoring Cost ($)	Spraying Cost($)	Total Cost($)	Profit ($/acre)
No SWD Infestation		/	5,000	/	/	/	2,220
No Intervention							
1	Never monitor; Never spray	2,684	5,026	0	0	5,026	-2,807
Baseline Strategy: Spray-only							
2	Spray throughout the season	4,984	35	0	383	419	1,801
Monitor-to-initiate Spray Strategies							
3	Threshold=1 fly per acre	4,983	38	35	341	415	1,805
4	Threshold=3 flies per acre	4,964	79	69	272	419	1,800
5	Threshold=5 flies per acre	4,935	142	82	243	468	1,752
6	Threshold=10 flies per acre	4,847	332	100	207	639	1,580
Monitor-to-guide Spray Strategies							
7	Threshold=1 fly per acre	4962	83	184	166	433	1,787
8	Threshold=3 flies per acre	4888	243	184	99	526	1,694
9	Threshold=5 flies per acre	4808	417	184	90	690	1,530
10	Threshold=10 flies per acre	4628	807	184	79	1,069	1,150

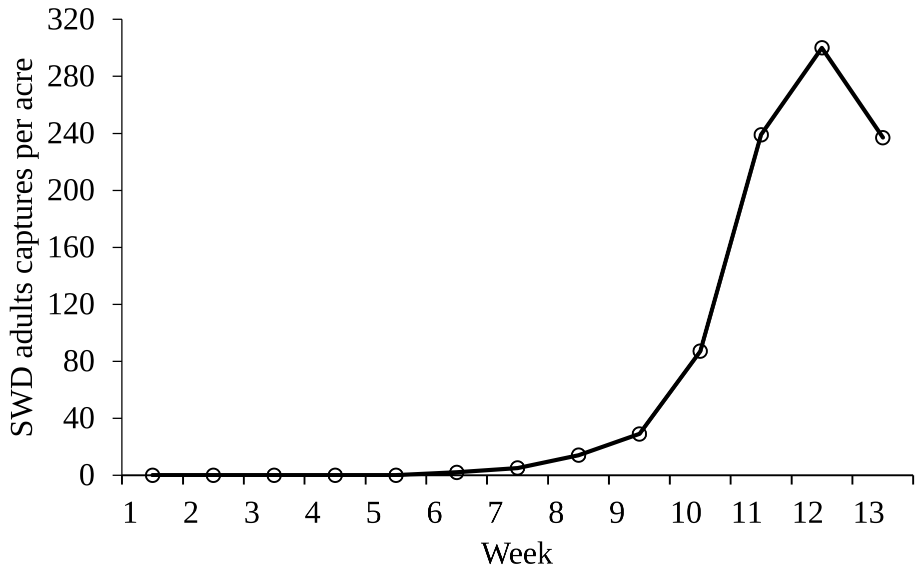


Figure 1. Weekly adult SWD trap captures

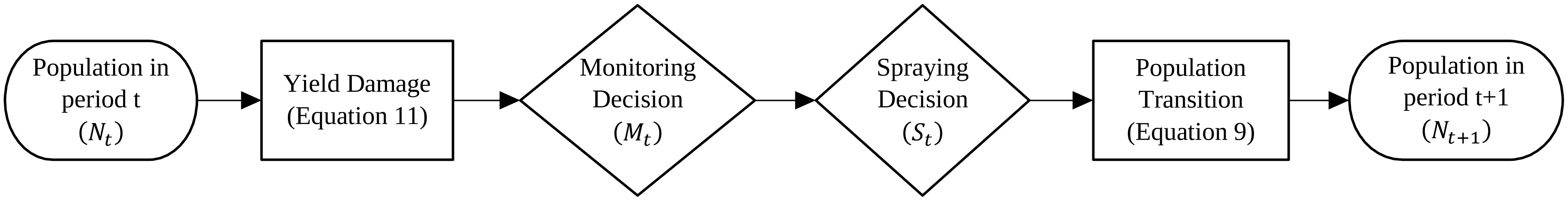


Figure 2. Decision process of controlling SWD infestation

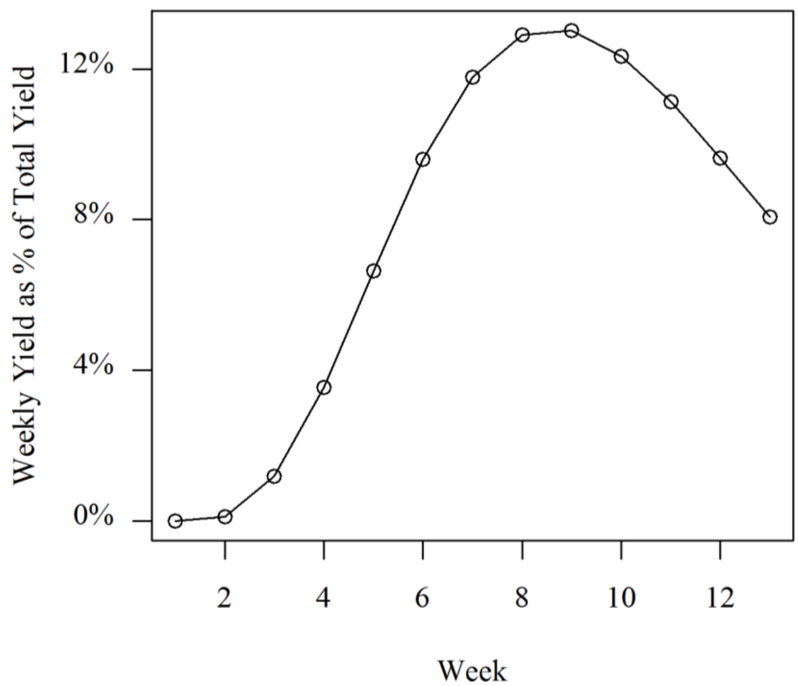


Figure 3. Blueberry weekly yield as percentage of total yield

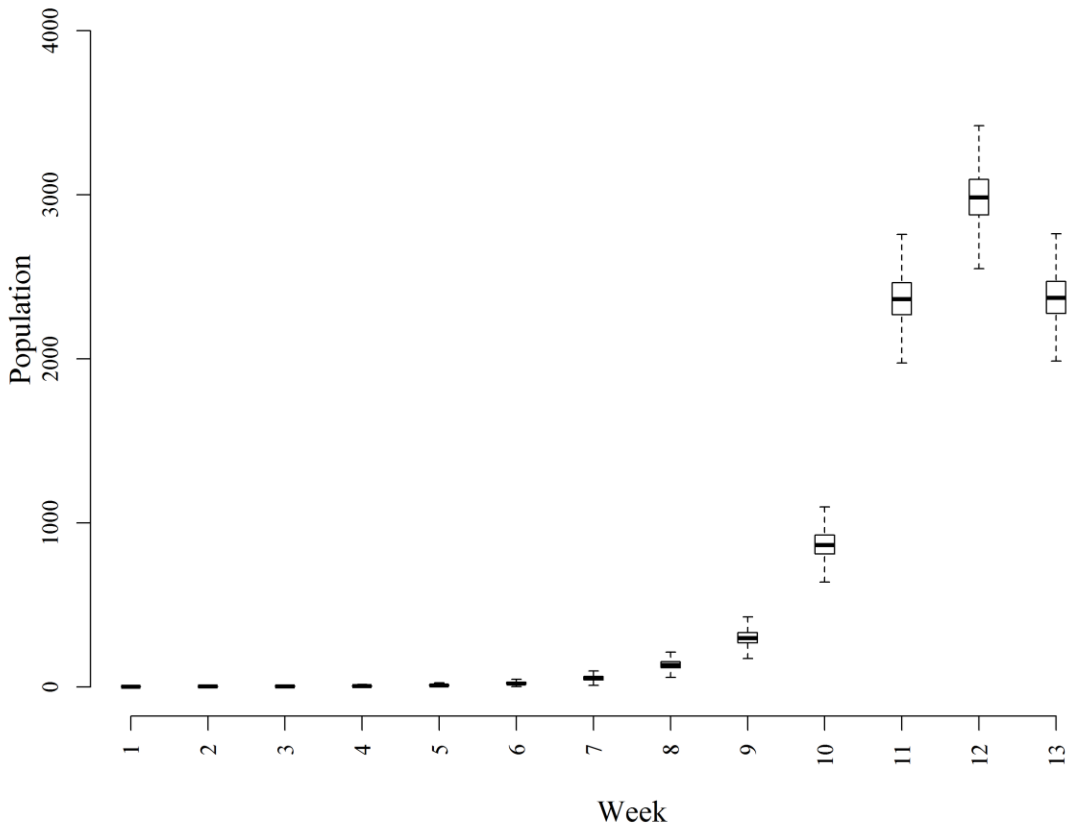


Figure 4. Marginal posterior distributions of the estimated SWD population size

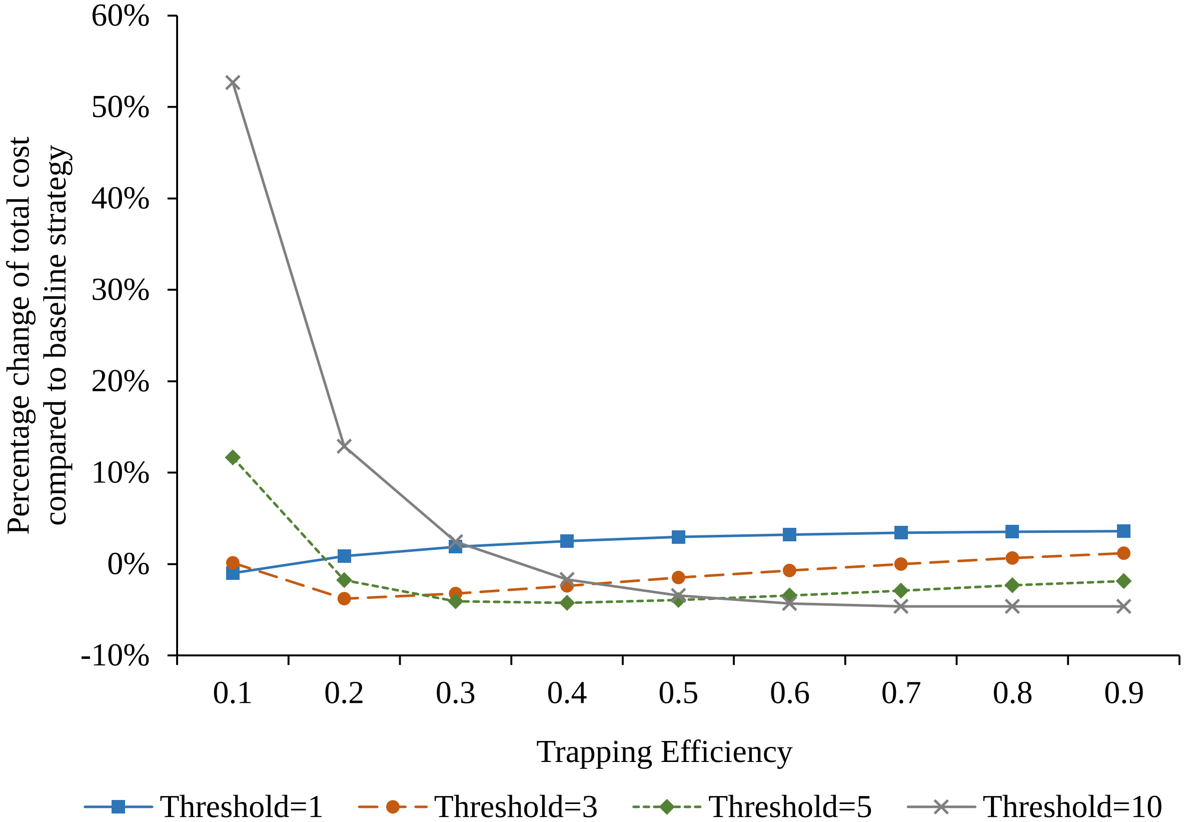


Figure 5. Relative total cost of monitor-to-initiate spray strategies vs. baseline spray-only strategy

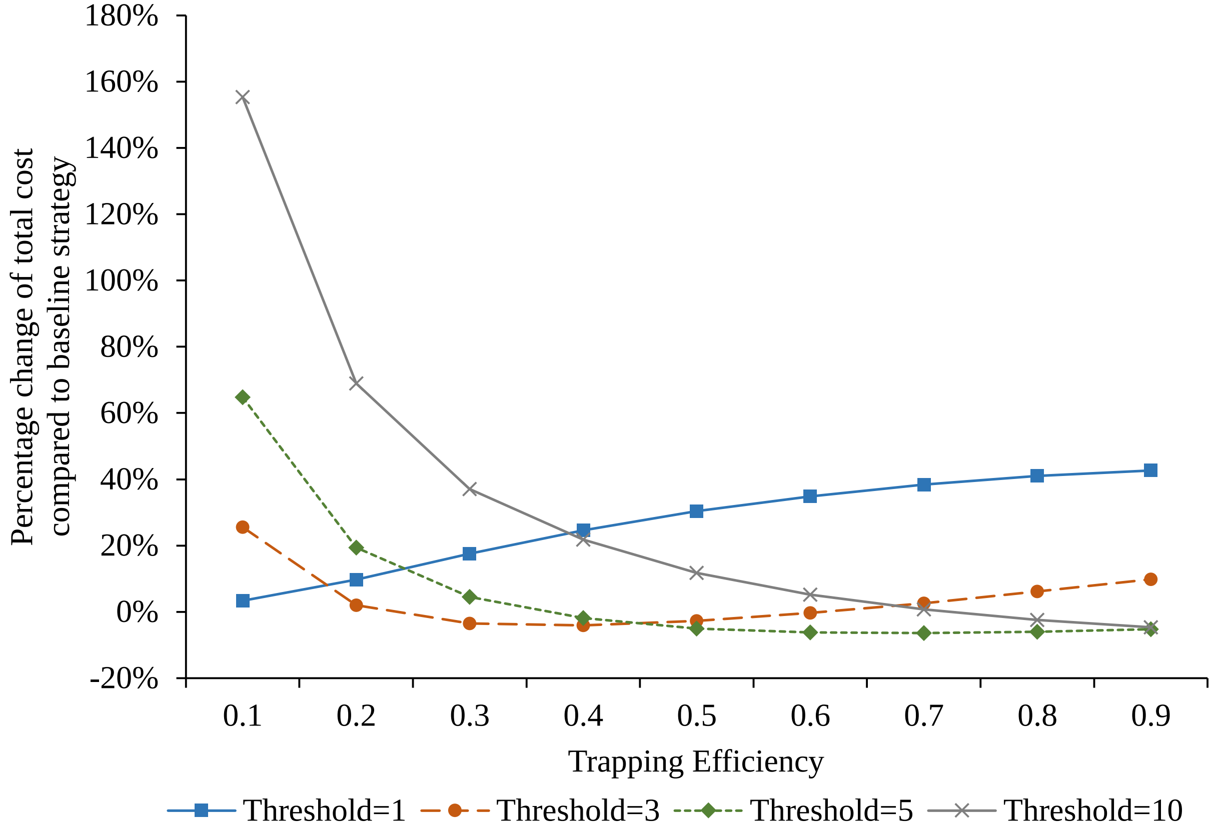
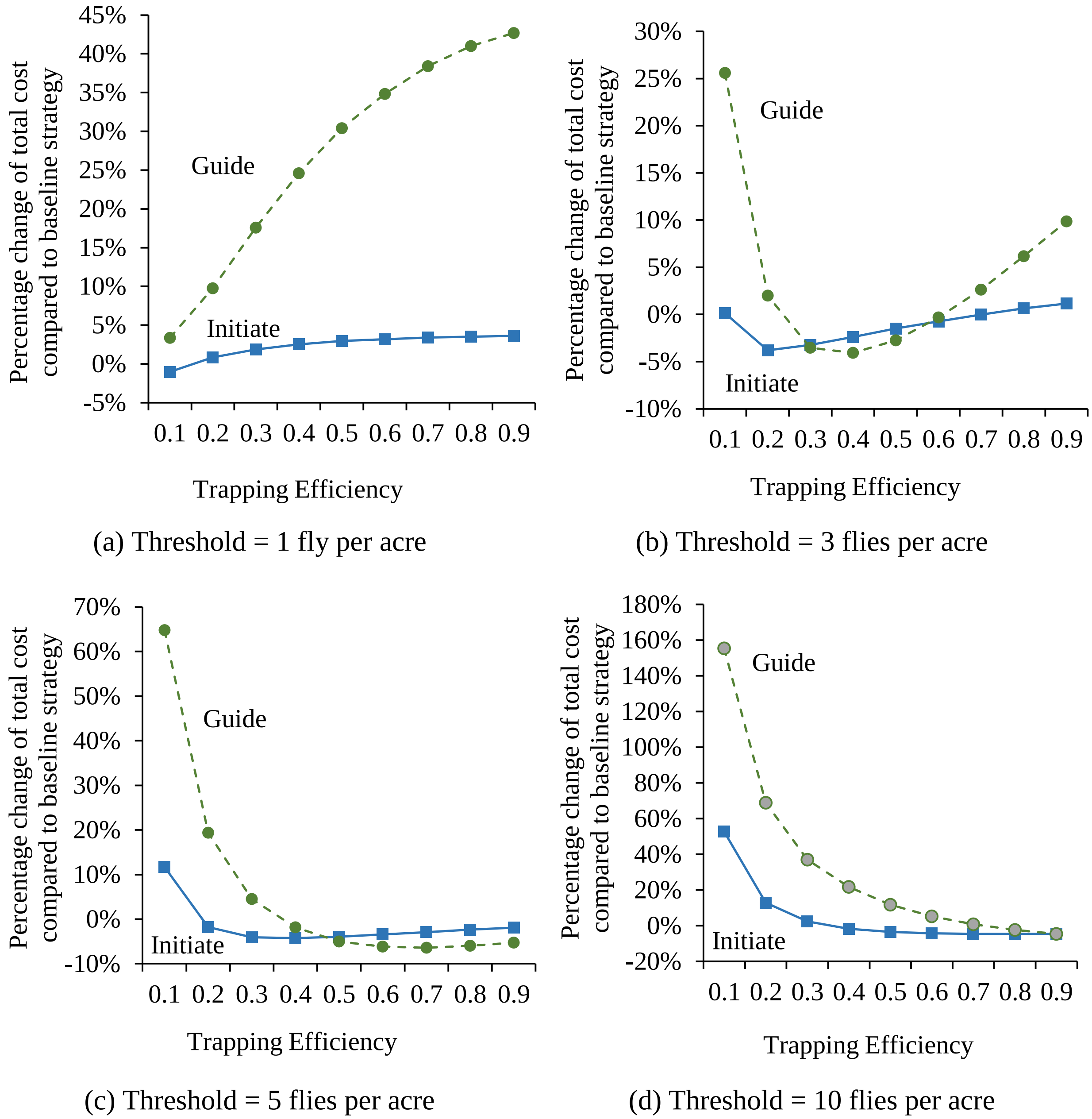


Figure 6. Relative total cost of monitor-to-guide spray strategies vs. baseline spray-only strategy



(a) Threshold = 1 fly per acre

(b) Threshold = 3 flies per acre

(c) Threshold = 5 flies per acre

(d) Threshold = 10 flies per acre

Figure 7. Monitor-to-initiate strategy vs. monitor-to-guide strategy

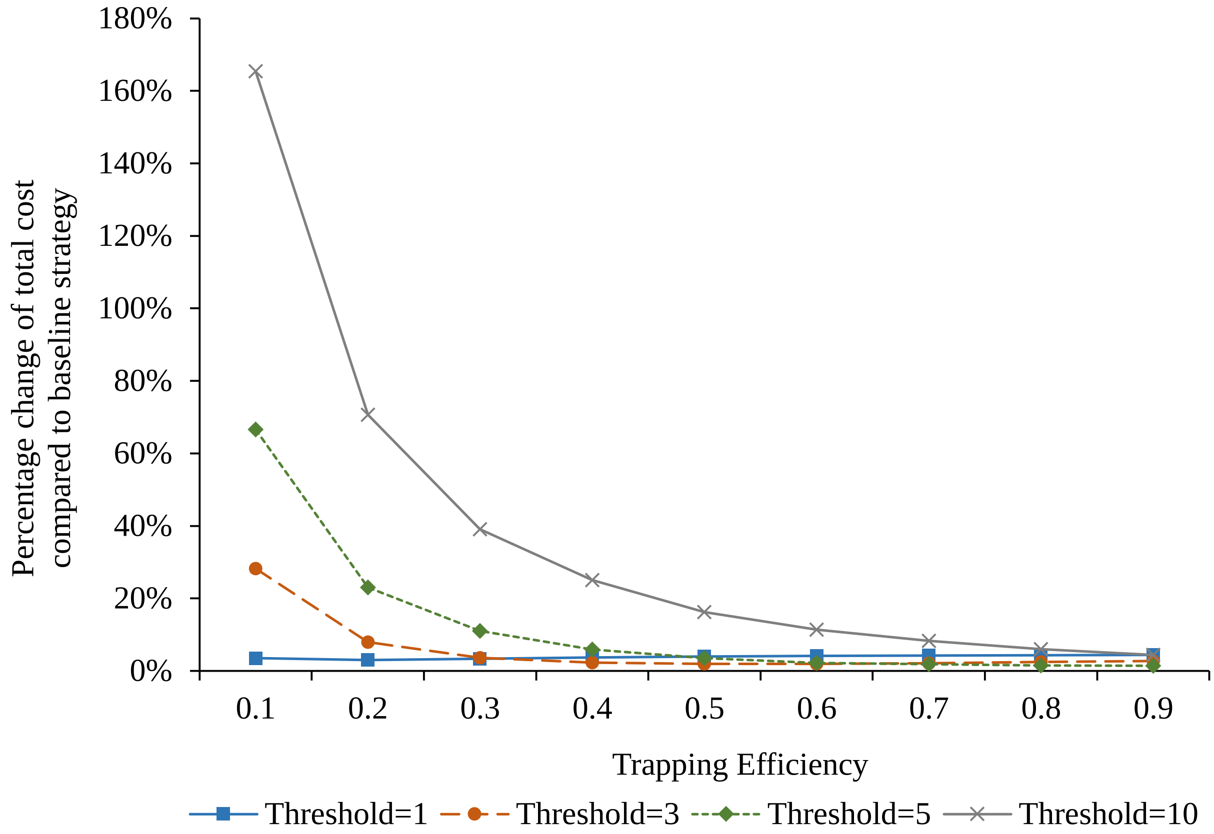


Figure 8. Relative total cost of monitor-to-initiate spray strategies using low efficacy (70%) insecticide

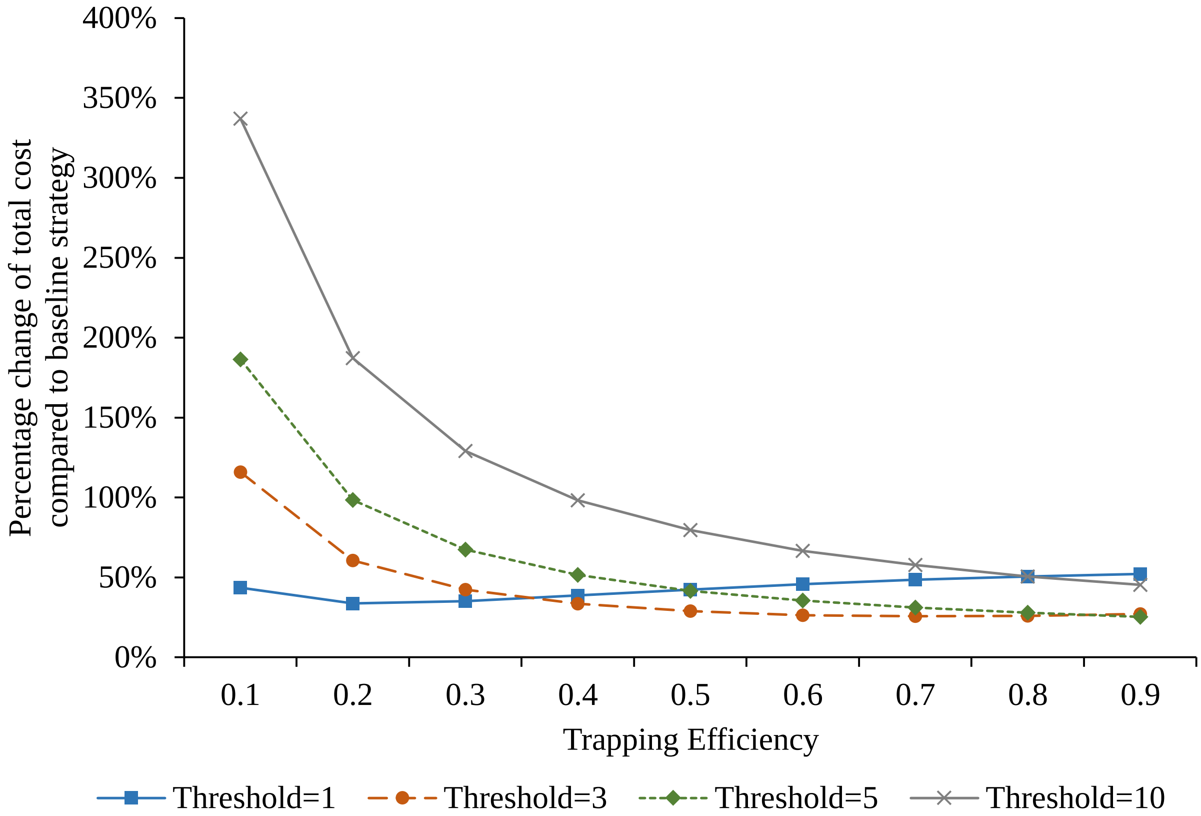


Figure 9. Relative total cost of monitor-to-guide spray strategies using low efficacy (70%) insecticide

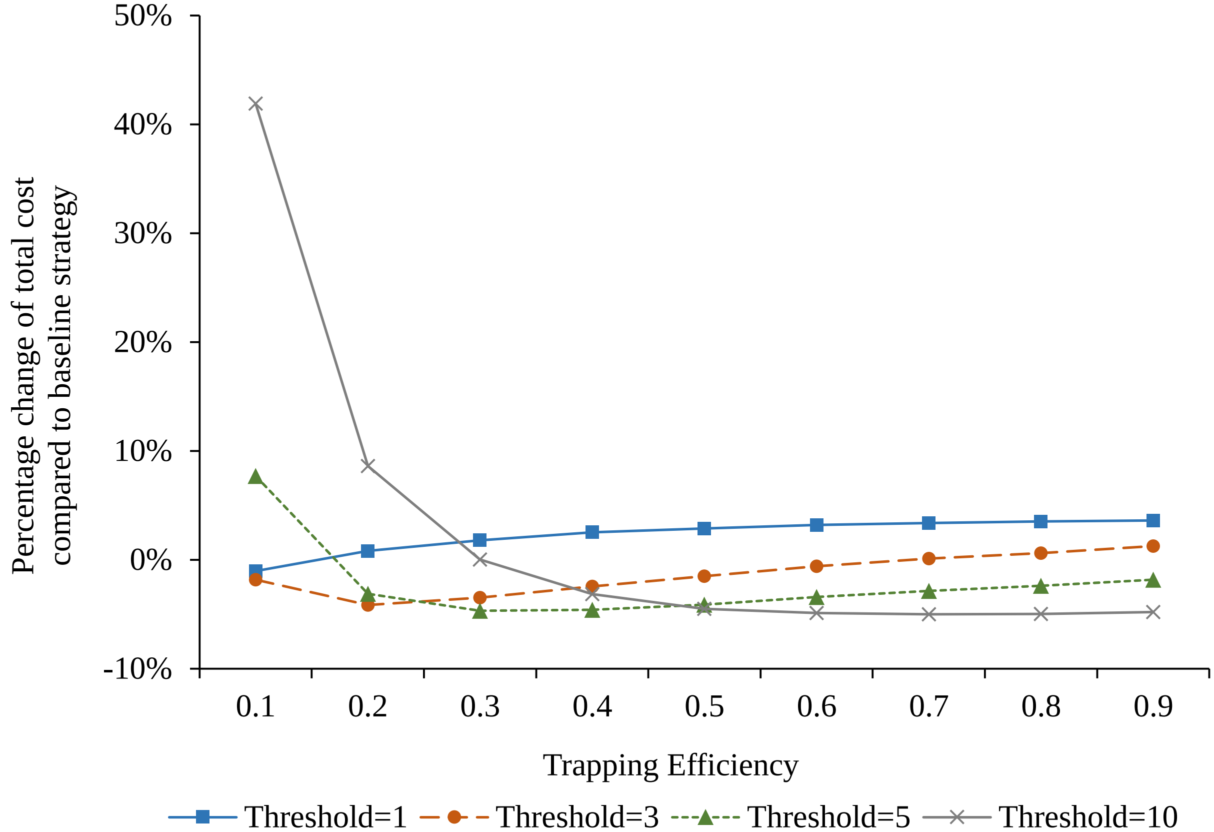


Figure 10. Relative total cost of monitor-to-initiate spray strategies using ultra-high efficacy (97%) insecticide

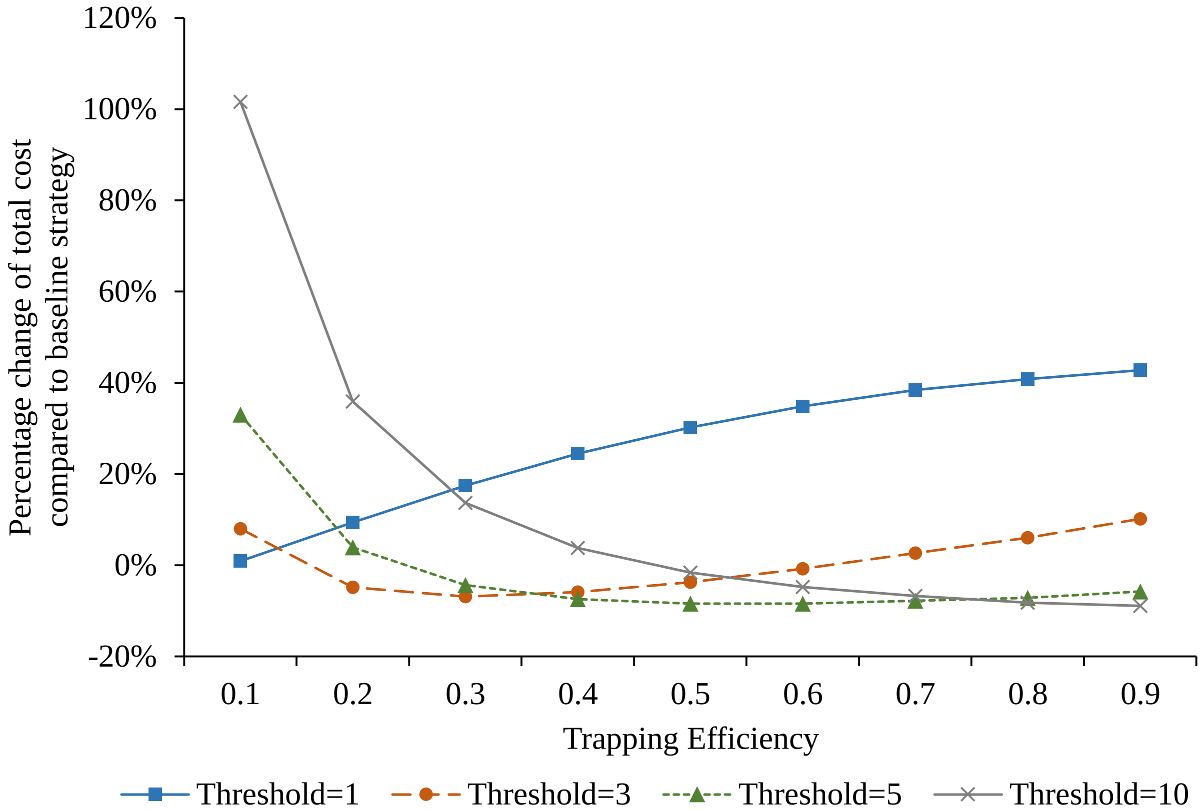
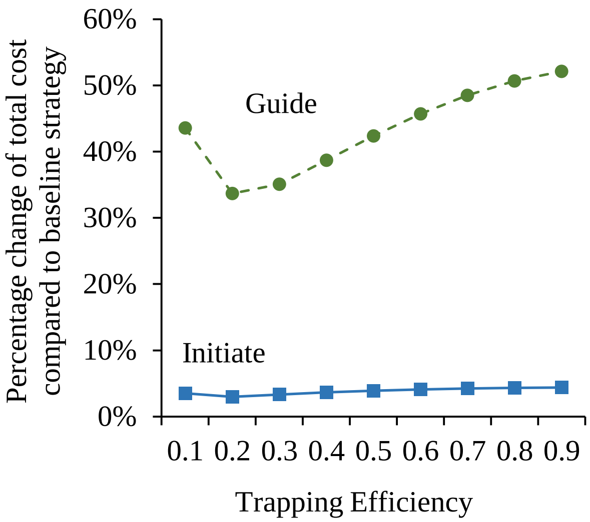
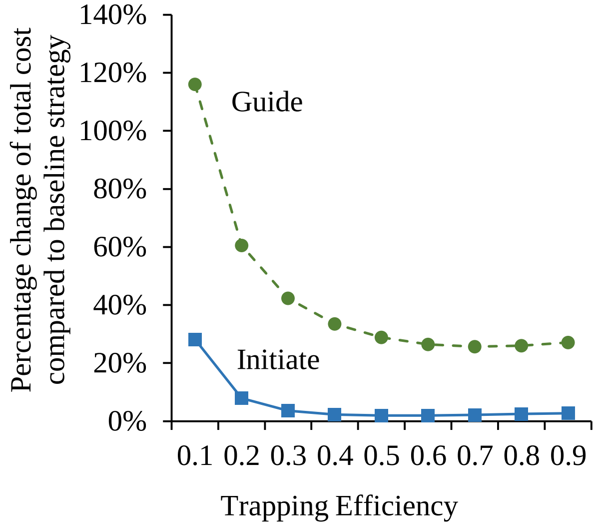


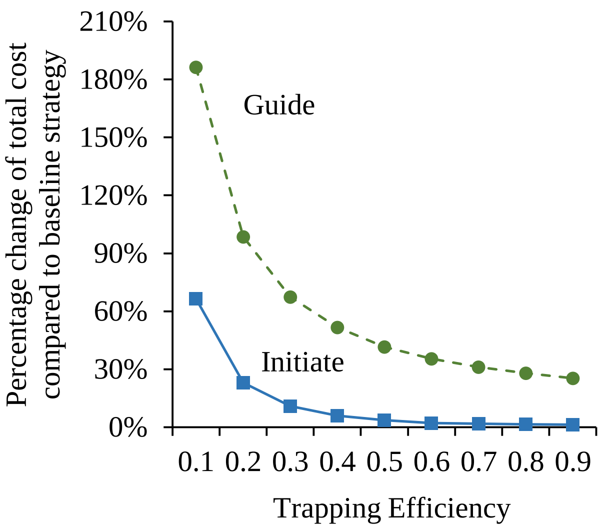
Figure 11. Relative total cost of monitor-to-guide spray strategies using ultra-high efficacy (97%) insecticide



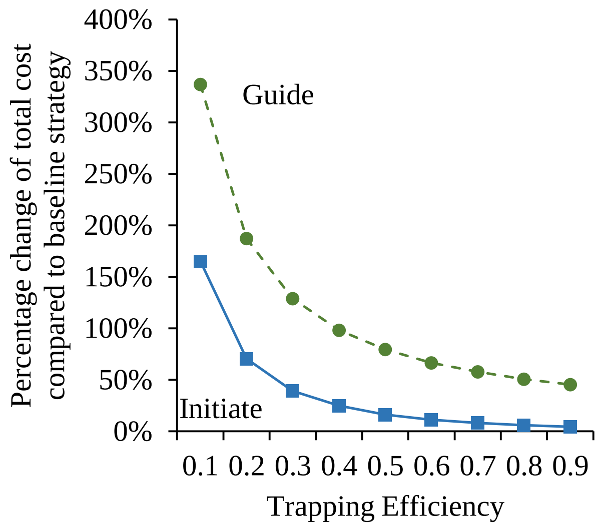
(a) Threshold = 1 fly per acre



(b) Threshold = 3 flies per acre



(c) Threshold = 5 flies per acre



(d) Threshold = 10 flies per acre

Figure 12. Monitor-to-initiate strategy vs. monitor-to-guide strategy: low efficacy insecticide (70%)

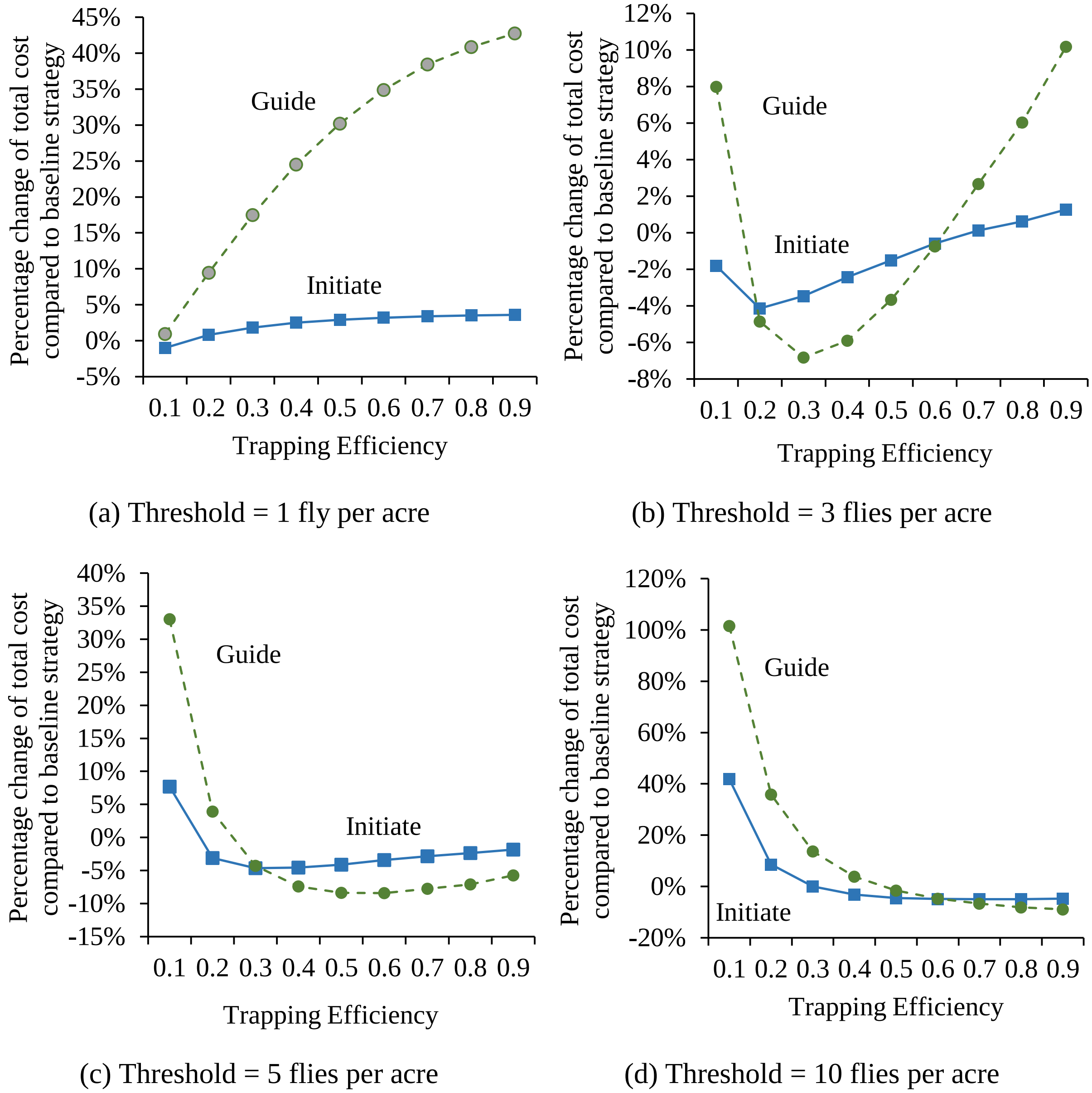


Figure 13. Monitor-to-initiate strategy vs. monitor-to-guide strategy: ultra-high efficacy insecticide (97%)