Beyond the Threshold: The Economics of Information in Pest Management *

Hyewon Lee, David Hennessy

August 2025

Abstract

The paper constructs a dynamic decision model with endogenous information acquisition, specifically tailored to pest management under uncertainty, to understand the farmer's decision-making on the optimal scouting and spraying. By explicitly modeling scouting—a factor often overlooked in the existing literature—the paper highlights its pivotal role in shaping pest control decisions. The paper also revisits the canonical Economic Threshold (ET) and Economic Injury Level (EIL) concepts and shows how imperfect information and scouting costs shift the threshold. Based on the real-time decision-making model, the study calibrates and sketches plausible policy schemes and compares the private vs. social optimal decisions. Calibration shows (1) the private optimum is one well-timed spray without scouting, (2) farmers choose to scout only when the cost is trivial, (3) technology improvement combined with free scouting can lead to no pesticide use; and (4) internalizing the social cost of pesticide use yields 'never spray' as socially optimal.

1 Introduction

Soybeans are a cornerstone of agricultural output in the U.S. and globally, but their production faces numerous challenges, including pest infestations that can markedly reduce yields. Among these, the soybean aphid has emerged as a significant threat and has rapidly become a major pest in soybean production since its first identification in North America in 2000. Native to Asia, this invasive pest can cause yield losses of up to 40% under severe infestations (Ragsdale et al., 2007),

*Acknowledgements: I am deeply grateful to Dr. Erin Hodgson for data and insights on soybean-aphid biology, and Drs. Donghyuk Kim, Sergio H. Lence, and Quinn Weninger for helpful feedback and discussions. All remaining errors are our own.

making its management a critical priority for soybean farmers. Prior research also indicates that controlling the soybean aphid early is economically efficient (Kim et al., 2008).

Entomologists have established practical guidelines to aid farmers in pest management: the Economic Injury Level (EIL) and the Economic Threshold (ET). EIL is the lowest population density that will cause economic damage, and ET is the density at which control measures should be determined to prevent an increasing pest population from reaching the EIL (Stern et al., 1959). Specifically for soybean aphids, pesticide application is recommended only when populations reach approximately 250 aphids per plant, with 80% of plants infested and aphid populations actively increasing (Ragsdale et al., 2007). This threshold is a fundamental ground rule of Integrated Pest Management (IPM) for soybean production, aiming to minimize crop loss and pesticide use. Regularly monitoring aphid populations and acting when they reach the economic threshold is essential, since soybean aphid densities can exhibit high inter-annual and intra-seasonal variation. Figure 1 shows the soybean aphid population trend across multiple locations in Northern Iowa (Sutherland, Nashua, Kanawha) from 2014 to 2024. Observations are collected weekly during the growing season, and no treatment was applied. The red and blue dashed lines are drawn for the ET and EIL of soybean aphids, respectively. The graph clearly illustrates that aphid populations fluctuate unpredictably.

While conventional ET rules offer the advantage of being simple and practically straightforward, the simplicity can become a limitation considering the complexities of the real world. Uncertainties in pest population dynamics, stochastic environmental conditions, and frictions in acquiring timely and accurate field-level information complicate the farmer's ability to assess whether the threshold has been met. This is the critical problem, as misjudging pest pressure can lead to substantial losses: untreated infestations can devastate yields, while unnecessary pesticide applications increase private costs and harm the environment. In this regard, scouting is a key strategy for acquiring reliable pest pressure information. It is the prevalent practice among farmers and a core tool for IPM. Scouting helps reduce uncertainty about pest populations by getting field-level information, and farmers can detect when pest densities approach the economic threshold. This additional information helps farmers to refine their beliefs about the infestation level, aligning their spraying decisions more closely with actual field conditions.

While scouting is a crucial tool, the existing threshold rule framework does not accommodate scouting explicitly in the threshold model. The traditional ET model presumes a known pest population level, which, in practice, is often inferred through scouting activities. However, scouting is not a free action. It entails explicit costs, whether from hiring professionals or dedicating their time to field inspections. As such, scouting should be viewed as an investment in better information and must be undertaken with careful consideration of its costs and benefits. Moreover, it is important to recognize that scouting itself does not yield perfect information. The reliability

and precision of pest pressure estimates from scouting can vary significantly depending on the method. Manual scouting by farmers may offer only coarse or localized snapshots of pest densities. In contrast, professional consultants may provide accurate assessments, but at a higher cost. Emerging technologies, such as drone-based surveillance and image recognition tools via apps, provide better information at relatively lower cost. Thus, the heterogeneous and imperfect scouting information, along with its economic costs, must be incorporated into threshold-based decision frameworks.

Moreover, despite the central role of scouting in IPM, actual on-farm adoption often falls short of these guidelines. Extension programs for soybean aphid management frequently advise weekly field inspections or even more frequent checks during periods of rapid pest growth. However, not all the farms do the active scouting (Czapar et al., 1995; Hammond et al., 2006). This divergence between recommended practice and actual behavior underscores the importance of incorporating scouting into economic threshold models and farmer's decision-making models.

This paper investigates the critical, yet often overlooked, economics of information in agricultural pest management. Farmers face a constant trade-off: the cost of scouting for pests versus the risk of spraying too much, too little, too early, or too late. To explore this, we move beyond static models and develop a dynamic framework that endogenizes both the scouting and spraying decisions under uncertainty, allowing us to quantify the precise worth of scouting information and its impact on optimal pest control strategies. This analysis is crucial in the context of agriculture's growing environmental footprint, where reducing chemical inputs while ensuring farm profitability has become a key policy challenge. By simulating the effects of policy levers like scouting subsidies and pesticide taxes, our model provides clear insights into how policy can steer pest management toward practices that are both more profitable for farmers and healthier for the environment.

To contextualize our research questions, we situate our work within the existing literature on economic thresholds, scouting, and stochastic pest dynamics. The concept of the economic threshold was introduced in entomology, but it has also been extensively studied from an economics perspective. Headley (1972) and Hall and Norgaard (1973) cast pest control as a static decision rule, equating marginal damage and control cost under average conditions. While later extensions allowed for biological and price uncertainty (Moffitt et al., 1984; Moffitt, 1986), for instance, showing that risk aversion or stochastic pest pressures tend to raise the optimal spray threshold, these seminal models assumed perfect, cost-free information about pest levels. Recognizing this limitation, Stefanou et al. (1986) introduced an important advance by endogenizing scouting in the decision process. In their framework, a farmer chooses not only whether to spray but also whether (and how intensively) to sample pest populations, acknowledging that better information can improve the spray decision. The authors calibrate the model to the cotton-Lygus

bug system in the San Joaquin Valley of California and show that investing in scouting has a positive value only under conditions such as the crop having at least average strength with the grower's high expectation on pest population, and high accuracy on scouting. Otherwise, the expected value of scouting information is not greater than the scouting cost. This finding highlights the idea that economic thresholds are not simply biological constants but are influenced by the decision-maker's information set. However, their approach fixes the scouting quality, treats pest population dynamics in a simplified form, and collapses the time horizon into two decision stages when they calibrate the cotton-lygus example.

Parallel research brought dynamic optimization and real options analysis into pest management, focusing on the optimal timing of control under uncertainty. Saphores (2000) is a seminal contribution that framed the static ET as a state-dependent trigger in a stochastic optimal control model following a geometric Brownian motion process. The pest population follows a noisy growth process, and waiting for more information has explicit value: when future pest growth is highly unpredictable, the optimal threshold for action rises (spray is delayed) to avoid needless treatment if the infestation might not materialize. His calibrated application to European red mites in apple orchards illustrates that an optimal stochastic threshold policy could significantly reduce pesticide use by an estimated 20–30% compared to following a naïve deterministic threshold rule. Building on this, several studies have applied a stochastic dynamic framework with a real options approach to related topics (Saphores and Shogren, 2005; Mbah et al., 2010). It is important to note, however, that most of the literature assumes the farmer can observe the pest density continuously and perfectly (no measurement error) and focuses only on the timing of a single spray. There is no explicit role for imperfect information or repeated scouting in the framework – the uncertainty is in pest biology, not in pest observation. Despite the limitation, the real options approach is a major step in dynamic threshold modeling, highlighting the value of flexibility and timing under uncertainty.

Recent research has enhanced dynamic pest management models by incorporating various sources of uncertainty and complexity. Studies have shown that spatial dynamics (Atallah et al., 2015; Chalak et al., 2017) and realistic pest growth assumptions (Dangerfield et al., 2018) significantly affect optimal control strategies. Overall, these findings highlight the value of adaptive, information-responsive thresholds under uncertainty.

Despite these advances, there remains a gap in fully integrating imperfect information and learning into dynamic threshold models. In light of these gaps, this study develops a unified modeling framework that endogenizes the imperfect and costly scouting decision alongside the spraying decision in an uncertain, sequential setting. In this approach, the farmer updates beliefs about pest density based on scouting reports and optimally chooses, at each decision point, whether to incur scouting costs and whether to apply control, given the current information and

remaining season. This integrated model of dynamic pest management with scouting captures the two-way interaction between information and action: better information (via scouting) can prevent needless sprays or avert costly infestations, but it must be worth the scouting expense. By jointly optimizing scouting and spraying over time, the framework quantifies the value of scouting information in economic terms and shows how optimal economic thresholds adjust when the decision-maker faces uncertainty about pest levels and can only learn through costly monitoring.

This study is organized as follows. First, we review the traditional approach to EIL and ET, focusing on scouting and information uncertainty. Next, we develop a real-time decision model of the scouting and spraying decisions. Based on the models, we provide the calibration, introduce policy levers, and discuss simulation results. Lastly, we conclude with future work intentions.

2 A New Approach to EIL and ET

In this section, we re-derive the canonical action threshold of pesticide application and see how uncertainty and scouting as an investment change the threshold. Based on the scientific approach by Ragsdale et al. (2007), the section accepts established premises and seeks to redefine the framework by explicitly integrating a scouting component and uncertain growth of the pest infestation into their model. Through a detailed review and modification of existing approaches, the following section aims to present a robust and theoretically grounded model.

From the perspective of conventional methodologies, scouting has not been treated as a discretionary decision variable, but rather as a necessary step for identifying the target population. As such, in this section, scouting is treated as a given, rather than a variable subject to optimization. However, departing from prior work, we explicitly incorporate the cost implications of scouting into our analysis.

2.1 Recovery of the Baseline EIL and ET

The practical guideline for soybean management, an ET of 250 aphids per plant, is derived in Ragsdale et al. (2007), using linear regression, data fitting, and the sum of a geometric series. This entomology approach to EIL and ET starts with setting up the population growth model of soybean aphids. The population of soybean aphids, N_t, grows over time following the exponential growth model, $N_t = N_0 \cdot e^{rt}$ where N_0 is the initial population and e^r is the average growth rate. The growth rate is fixed to $r \approx 0.127$ ($e^r \approx 1.14$, 14% growth per day). The growth rate was gained from field data[1]. Ragsdale et al. (2007) defines the treatment window as the interval spanning

[1] 19 location-years of field data were used, including Iowa, Minnesota, Nebraska, North Dakota, and Wisconsin in 2003, 2004, and 2005.

from when aphid infestation reaches 80% of plants to the point of maximum aphid density and estimates the growth rate from the treatment window.

Then, the model identified the damage coefficient from pests by estimating the yield loss at the Cumulative Aphids Days (CAD) level (equation 1). CAD quantifies the total aphid pressure over a period of time, reflecting both how numerous the aphids were and how long they persisted. CAD is calculated via the trapezoidal rule, letting N_i be the aphid count at day t_i, $\text{CAD} = \sum_{i=1}^{n-1} \frac{N_i+N_{i+1}}{2} \times (t_{i+1} - t_i)$. The authors assumed that the regression is a well-estimated regression because it identifies the intercept as nearly 100%. The CAD coefficient β_1 is estimated as -0.0688 per 10,000 CAD, which indicates the yield was reduced by 6.88% for every 10,000 aphid-days accumulated. The coefficient of CAD was mainly used to derive the threshold level of pesticide application.

$$1 - \text{Yield loss (\%)} = \beta_0 + \beta_1 \cdot \text{CAD} + \varepsilon \tag{1}$$

The model computed the gain threshold (GT), an economically tolerable yield loss. GT is defined as follows:

$$\text{GT}(\%) = \frac{C}{V \cdot Y} \cdot 100 \tag{2}$$

where C is the pesticide application cost (\$/ha), V is the market value of soybean (\$/ton), Y is the yield potential (tons/ha). Hence, if the yield loss is greater than GT, it indicates the cost of damage is greater than the cost of control.

The EIL in terms of CAD was obtained using equation (1) and (2). When GT is divided by the coefficient $|\beta_1|$, the outcome is realized as the threshold for economic injury level in terms of CAD.

$$\text{EIL(CAD)} = \frac{\beta_0 - (1 - \text{GT})}{|\beta_1|} \approx \frac{\text{GT}}{|\beta_1|} \tag{3}$$

The value derived in equation (3) is algebraically equivalent to the sum of a geometric series according to the authors' assumption that the population growth follows the exponential growth model, as the CAD represents a cumulative quantity. Equating the two expressions is the final step to derive the EIL in terms of aphid density (population). Starting from a nontrivial population a, λ is the daily growth rate, and the last term of the sequence is the EIL in terms of the aphid population. The corresponding ET is shown with lead time t from ET to EIL level.

$$\text{EIL(CAD)} = \frac{\text{GT}}{|\beta_1|} = a + a\lambda + a\lambda^2 + \cdots + \underbrace{a\lambda^{n-1}}_{N_{\text{EIL}}} \tag{4}$$

$$N_{\text{EIL}} = \frac{\text{EIL}\,(\text{CAD})\,(\lambda - 1) + a}{\lambda},\ N_{\text{ET}} = \frac{N_{\text{EIL}}}{\lambda^t} \tag{5}$$

2.2 Limitations of the Traditional Approach

The ET estimate advanced in Ragsdale et al. (2007) is derived under four critical simplifications. First, it ignores the cost of scouting and assumes perfect, costless observation of pest populations. Second, it treats aphid population dynamics as deterministic, overlooking biological and environmental uncertainty. In reality, farmers choose actions ex ante while facing multiple layers of uncertainty. For example, pest growth depends on many factors: the climate conditions, such as temperature or moisture, the abundance of host plants or natural enemies, farming practices, etc. Aphids begin to settle on the crops, and their population soars whenever the time and location allow favorable climate conditions for aphids. However, it is also feasible that natural enemies such as lady beetles help control soybean aphid outbreaks so that the population growth is slower than expected. Hence, farmers encounter uncertainty every time that they cannot be sure of the subsequent population growth. Although farmers may develop informed expectations about pest growth based on experience and environmental cues, such expectations are often imprecise and insufficient without additional field information. Within such a stochastic environment, a single deterministic ET figure can be ambiguous, offer limited decision-making value, or even reduce expected profit.

Third, the model treats the spray decision as a static, one-time threshold rather than a dynamic and sequential decision process. This contrasts sharply with how pest management decisions are made in practice. In reality, farmers do not make decisions in isolation at a single point in time but instead observe, reassess, and act in a sequential and adaptive manner as new information becomes available. The static framework ignores this temporal flexibility and can result in suboptimal decisions, particularly when the economic consequences of acting too early (wasting resources) or too late (suffering avoidable yield loss) are significant. Lastly and most importantly, the model does not maximize the farmer's profit. Although farmers ultimately undertake pest management to maximize their own economic returns, the existing framework does not consider the profit maximization rule in the model, relying on biological thresholds instead.

In addition, it is necessary to note that the variables in ET fluctuate: Crop prices and production costs change over time. Figures 2 and 3 display the yearly trend in prices and fees. Figure 2 shows the spraying costs (materials not included) and scouting costs by the methods. Notably, the costs vary throughout the year and differ by the equipment choices. Figure 3 shows the soybean market price received by farmers, which has a marked fluctuation. These variables are crucial in calculating the gain threshold, which is the critical point for the economic damage (loss). Hence, a single fixed threshold may yield different consequences for different farmers.

The following subsection revisits and extends the conventional EIL and ET framework by incorporating two critical refinements: scouting as an explicit economic activity and uncertainty

in pest population dynamics. These modifications generate a more realistic threshold that better reflects the real-world decision-making environment faced by farmers. More importantly, numerical illustrations reveal not only how threshold values shift, but also how highly sensitive they are to assumptions about costs, monitoring frequency, and population growth volatility. This sensitivity underscores a key insight that a simple, fixed numeric threshold is unlikely to be optimal under realistic conditions.

However, the third and fourth limitation of the traditional approach—its static, one-shot treatment of pesticide application decisions without economic optimization—remains unresolved within this framework. Capturing those limitations requires a fundamentally different modeling approach: one that treats both scouting and spraying as endogenous and sequential decisions under uncertainty to maximize the grower's profit. Section 3.1 develops such a dynamic model, building on the refinements introduced in the current subsection. This model addresses the shortcomings of the static threshold paradigm and provides normative insights into optimal timing, information acquisition, and treatment strategies under uncertainty.

2.3 An Extension of the Baseline EIL and ET

As scouting is pivotal in successful pest management and the farmer has to pay the cost to reveal his field's pest infestation level, the gain threshold (GT) should include the scouting cost, S. Scouting shifts the gain threshold upward compared to the equation (2).

$$\hat{\text{GT}}(\%) = \frac{C + \mathbf{S}}{V \cdot Y} \cdot 100 \tag{6}$$

According to the Historical Iowa Farm Custom Rate Survey from Iowa State University Extension and Outreach (Plastina and Johanns, 2024) and Asbridge (2005), scouting costs vary from \$3.5 to \$7.6 per acre during 2004 and 2005 (aligning with Ragsdale et al. (2007)'s base year). Including scouting cost increases the gain threshold by about 1.2-2.8%, yielding a higher EIL and ET level.

Subsequently, the aphid population follows a stochastic growth process. To simplify the argument, consider the population growth as either high or low, with binary growth factors: $G_h = e^{r_h}$ and $G_\ell = e^{r_\ell}$.

$$N_{t+1} = N_t \cdot R_t, \text{ where } R_t \in \{G_\ell, G_h\} \tag{7}$$

From equations (6) and (3), a new economic injury level in CAD, $\hat{\text{EIL}}\,(\text{CAD})$, can be derived. As the farmer needs to figure out the growth path before it actually happens to identify the spraying threshold, let's assume the growth factor is realized with a certain probability, $\text{P}\,(R_t = G_\ell) = \rho$. The farmer uses the expected growth rate to calculate the ET. Due to the convexity of the growth function, the expected growth rate is the weighted geometric mean of the pest growth factors,

capturing multiplicative uncertainty in pest population dynamics. Hence, the expected growth rate is $\bar{G} = G_\ell^\rho G_h^{1-\rho}$. Thus, the corresponding EIL and ET are derived following the traditional approach.

$$\hat{N}_{\text{EIL}} = \frac{\hat{\text{EIL}}\,(\text{CAD})\left(\bar{G}-1\right)+a}{\bar{G}}, \quad N_{\text{ET}} = \frac{\hat{N}_{\text{EIL}}}{\bar{G}^t} \tag{8}$$

2.4 Numerical Illustration

Based on the canonical derivation and the extension introduced so far, we demonstrate the numerical illustration and see how the thresholds shift. In Table 1, the first column (1) is the replication result of the traditional approach. In Ragsdale et al. (2007), the authors ran every plausible combination of four yield potential levels (30, 40, 50, 60 bu/ac), three soybean prices (5.5, 6.00, 6.50 $/bu), and three spraying cost scenarios (6.64, 9.92, 13.33 $/ac). From 36 scenarios, the mean value of EIL(CAD) was 5,563, and the mean EIL(aphids) was 674. The mean ET with a 7-day lead time was 273 ($t = 7$), as the entomologists assume the farmer needs 7 days to be prepared for pesticide application and take action in a practical sense. Hence, the ET was established to be 250 aphids per plant for practical purposes. Because the original dataset is unavailable and minor rounding and model-fit errors remain, our calculated result differs slightly; still, the resulting ET is effectively unchanged.

Using the same scenario from (1), column (2) adds the scouting cost to the gain threshold (equation (6)). The scouting cost is fixed as 7.6$ per acre (Asbridge, 2005). Higher GT yields higher EIL and ET levels. GT increased by about 76% due to scouting, and in turn, it yields about a 79% higher action threshold.

Column (3) adds uncertainty about the population growth. For the exercise, suppose the arithmetic mean of G_ℓ and G_h is the same as the growth rate from Ragsdale et al. (2007). G_ℓ is approximately 1.02 and G_h is about 1.26, and each state is equally likely, $\rho = 0.5$. The corresponding $\bar{G}$ is approximately 1.13, while the EIL level and ET level become slightly lower because of the uncertainty added. Column (4) assumes that the high growth factor is more likely to be realized. It shows that when ρ is 0.3 and the following action threshold is lower than in case (3).

Column (5) reports ET under the assumption of daily scouting with immediate decision-making based on the most up-to-date field information. In contrast to the thresholds calibrated in the mid-2000s, our analysis uses recent field estimates: the low and high pest growth rates are set at $G_\ell = 1.004$ and $G_h = 1.02$, respectively[2]. We run 36 scenarios with three costs (13.22, 16.22, 19.22 $ per acre), three market values (11.5, 12, 12.5 $ per bushel), and four yield poten-

[2]The growth rate is derived from the field experiment data from Soybean Research Laboratory (Iowa State University).

tials (50, 60, 70, 80 bushels per acre). The scouting cost is $6.1 per acre. Due to the combination of slow pest growth, the estimated EIL and ET levels are considerably lower than in canonical values. Hence, a small population increment becomes economically significant quickly. In such a setting, even modest pest presence becomes economically actionable because pest populations rise slowly, and the marginal economic impact of a small increase can be meaningful. As a result, the model recommends spraying at relatively low aphid densities. This scenario might seem counterintuitive, as spraying at significantly low levels can reduce beneficial natural enemies, promote resistance, and not yield meaningful incremental protection of crop value (Ragsdale et al., 2007). A low threshold also happens because spraying is not a choice variable, but mandatory. The conceptual framework we introduce in the next section treats spraying as a choice variable, and the agent decides based on the consideration of the all-season discounted profit. In that way, a suitable threshold would be obtained.

Column (6) and (7) shows the case when the farmer does weekly scouting. According to University Extension programs for soybean crop management, the experts recommend weekly scouting. Based on the ideal routine, the threshold derivation changes as the time frame in the traditional approach is daily (see the Appendix A). Also, the scouting costs decrease due to less scouting frequency ($6.64 according to Asbridge (2005)), and the expected growth rate is much higher. When the monitoring interval lengthens from day to week, the growth rate over that period rises sharply, and its pest population observed in a single scouting jump accordingly. Hence, the economic threshold has to fall steeply as the following time period's population will be much higher —the opportunity cost of waiting (cost of delay) becomes much higher. The threshold is indeed significantly lower.

3 Conceptual Framework

3.1 Dynamic Model

In this section, we develop a framework of decision-making under uncertainty with learning by scouting, dynamic multi-period optimization, and economic trade-offs in pest management decisions. Unlike traditional ET, which suggests spraying whenever pest densities cross a predetermined threshold based on long-term expected conditions, our model allows the farmer to adaptively respond to newly acquired information about pest growth each time.

The basic model environment assumes that the soybean aphid grows stochastically. A decision-maker who grows soybeans in the US encounters sequential choices to manage his field from soybean aphid infestation. At the start of each time period, the corresponding true pest population of soybean aphid is developed. However, the grower can not detect all the pests in his fields and does not have perfect information on the pest population and CAD. At the start of each period t,

based on the prior information, the farmer can (i) *scout* to acquire information about the current infestation and then (ii) *spray* the pesticide. He aims to maximize his expected payoff by balancing the certain costs of his actions with the potential losses from pest damage and yield benefits. If the grower scouts, he decides whether to spray the pesticide based on his updated information from scouting. If the grower does not scout, he makes the spraying decision based on his prior. A farmer makes these sets of actions every week until the harvest.

Biology. The pest population growth follows a weekly binomial tree following the Jarrow-Rudd Model (Jarrow and Rudd, 1983). The Jarrow-Rudd approach is a discrete-time, risk-neutral approximation of the Geometric Brownian Motion (GBM) process. The approach converges to GBM in the limit when the time step goes to zero. The model assumes equal probability of up and down movements ($p_{up} = \frac{1}{2}$), where the up (u) and down (d) factors are chosen to match the mean and variance of the GBM. For a one-week time step, the Jarrow-Rudd up and down multipliers are constructed as follows,

$$u = e^{\left(\mu - \frac{1}{2}\sigma^2\right) + \sigma}, \; d = e^{\left(\mu - \frac{1}{2}\sigma^2\right) - \sigma} \tag{9}$$

where μ is the biological mean growth rate of the pest population and σ reflects the environmental or stochastic volatility in growth due to weather, predator pressure, etc. The expected log growth rate is $\mu - \frac{1}{2}\sigma^2$ with the variance of σ^2. Hence, the population at the start of time t, N_t^{pre}, is as follows:

$$N_t^{\text{pre}} = N_{t-1} \times \begin{cases} u, \text{ with probability } p_{up} \\ d, \text{ with probability } 1 - p_{up}. \end{cases} \tag{10}$$

Farmer's control: pesticide application. As a farmer makes a sequential decision by deciding whether to scout and then spray, backward induction is a standard approach to derive the optimal strategy and payoff. Hence, it starts from the decision node on whether to spray the pesticide. The binary decision variable is $A_t \in \{0, 1\}$. If the farmer chooses to spray ($A_t = 1$), the pesticide kills a fraction of the current pest population, $\rho \in (0, 1)$. If no pesticide is applied, the pest population remains unchanged in that step. Hence, the population after all the decisions at time t can be written as:

$$N_t = (1 - \rho A_t)\, N_t^{\text{pre}}, \tag{11}$$

and N_t is carried to the next period $t + 1$ with growing factors.

Pest Damage accumulation. Field damage is accumulated via CAD, following the definition of CAD on a weekly basis.

$$\text{CAD}_t = \text{CAD}_{t-1} + \frac{1}{2}\left(N_{t-1} + N_t\right) \times 7 \tag{12}$$

Since CAD is inherently cumulative, the decision maker's final payoff—accounting for pest damage—is determined by the CAD level at the final time period T.

Scouting. At each time step, the farmer decides whether or not to scout and gather the information. The binary decision variable is $S_t \in \{0, 1\}$. If he decides to scout ($S_t = 1$), the agent receives a signal Z_t depending on the quality of the scouting technology. Let the instrument's reliability be captured by the binary variable $\zeta \sim$ bernoulli $(1 - q_t)$ where $q \in (0, 1]$ denotes the probability that the instrument delivers a perfect signal at time t. The observed signal can be written as:

$$Z_t = (1 - \zeta_t) N_t^{\text{pre}} + \zeta_t \tilde{N}_t, \text{ where } \tilde{N}_t = N_t^{\text{pre}} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}\left(0, \tau_t^2\right) \tag{13}$$

In short, the scouting reads out the pest population perfectly with probability q_t with the observation $Z_t = N_t^{\text{pre}}$. With the probability $1-q_t$, the scouting gives a noisy read-out $Z_t = N_t^{\text{pre}} + \varepsilon_t$ with normal error and time dependent variance τ_t^2. The farmer forms an expectation of the pre-spray pest population conditional on whether scouting is performed. These expectations are subsequently used to evaluate the expected payoff from scouting and not scouting, which guides the farmer's decision.

When scouting is chosen, the posterior mean of N_t^{pre} is

$$\mathbf{E}\left[N_t^{\text{pre}} \mid Z_t\right] = \frac{\mathcal{L}_u(Z_t) n_{u,t} + \mathcal{L}_d(Z_t) n_{d,t}}{\mathcal{L}_u(Z_t) + \mathcal{L}_d(Z_t)} \tag{14}$$

where $\mathcal{L}_s\left(Z_t\right)$ is the likelihood of observing the scouting signal Z_t when the true population is $n_{s,t}$ for $s \in \{u, d\}$. The likelihood combines the case of a perfect read-out and a noisy read-out as

$$\mathcal{L}_s\left(Z_t\right) = q_t \delta\left(Z_t - n_{s,t}\right) + (1 - q_t) \frac{1}{\tau_t \sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{Z_t - n_{s,t}}{\tau_t}\right)^2\right]. \tag{15}$$

where $\delta\left(\cdot\right)$ is the Dirac delta function indicating the perfect signal. Without scouting, the farmer keeps the prior expectation,

$$\mathbf{E}\left[N_t^{\text{pre}}\right] = \bar{n} = \frac{\left(n_{u,t} + n_{d,t}\right)}{2} \tag{16}$$

These conditional expectations are the key inputs in comparing the expected net benefit of scouting against the expected net benefit of not scouting at time t.

The quality of the signal improves through repeated scouting, a form of learning-by-doing. When the agent scouts, two things happen: (i) the quality of the instrument improves, and (ii) the noise in the measurement is reduced. Mathematically,

$$q_{t+1} = q_t + \eta\,(1 - q_t)\,,\ \tau_{t+1}^2 = \frac{\tau_t^2}{1+\kappa} \tag{17}$$

where $\eta > 0$ and $\kappa > 0$ are learning parameters governing the rate of improvement in signal quality and precision, respectively. If the farmer does not scout, the variables remain unchanged: $q_{t+1} = q_t, \tau_{t+1}^2 = \tau_t^2$. The setup captures a trade-off between the current cost or benefit of scouting and the future value of improved signal quality.

Per-period cash flow. The farmer makes the decision for scouting and spraying every week, and those actions incur costs if he decides to do. Scouting cost for week t is c_{sc} and spray cost is c_{sp}. At $t = T$, the farmer harvests and receives the yield revenue. The corresponding cash flow is $P\bar{y}\,(1 - \alpha \cdot \text{CAD}_T)$ where P is the soybean market price, $\bar{y}$ is the yield potential, α is the damage coefficient from pest infestation (equivalent to $|\beta_1|$ in Section 2).

Bellman recursion. Denote $x_t = N_{t-1}, \text{CAD}_{t-1}, q_t, \tau_t^2$,

$$V_t\,(x_t) = \max_{S_t,\,A_t} \left\{-c_{\text{sc}} S_t - c_{\text{sp}} A_t + \beta \mathbb{E}\left[V_{t+1}\,(x_{t+1})\,|x_t, S_t, A_t\right]\right\}, \quad V_T\,(x_T) = P\bar{y}\,(1 - \alpha \cdot \text{CAD}_T)\,. \tag{18}$$

Starting from the final week and moving backwards, the Bellman recursion evaluates the best action at each state and time. The recursion considers the immediate reward plus the expected future value if the system transitions optimally thereafter. By iterating backward week by week, it determines the optimal action (scout or spray) for every possible state in each week.

Time Horizon. For the time horizon, the critical soybean aphid management window typically begins in mid to late June and continues until the early R6 growth stage (when pods are filled with green seeds), which usually extends into mid to late August in most Midwest regions. Intensive management after the window has no gain since yield loss from aphids after this stage is minimal, and insecticide applications are not likely to provide economic benefit. Hence, the time frame would be approximately 8-10 weeks.

3.2 One-Time Decision

To align with the threshold-based intuition from the traditional ET model and understand how the farmer chooses the action in our new framework, we examine a simplified case where the farmer only makes a one-time choice for his pest management. The farmer gets his final payoff right after his action. We omit the subscript t for brevity. The biological prior in a one-shot decision is simply a one-period binomial tree with exactly two possible outcomes. The initial population starts from N_0, and it grows into $N^{\text{pre}} = n_u = N_0 u$ or $N^{\text{pre}} = n_d = N_0 d$. Either outcome happens with equal probability.

Spraying decision. If he decides not to spray the pesticide, the end-of-week density will

be N^{pre}. On the contrary, if the farmer sprays, the end-of-week density becomes $(1-\rho)N^{\text{pre}}$. Spraying decision yields the CAD level as follows,

$$\begin{aligned} \text{CAD}_{\text{spray}} &= \frac{N_0 + N^{\text{pre}}}{2} \times 7 \qquad \text{(spraying)} \\ \text{CAD}_{\text{nospray}} &= \frac{N_0 + (1-\rho)N^{\text{pre}}}{2} \times 7 \qquad \text{(not spraying)} \end{aligned} \tag{19}$$

Thus, CAD saved by spraying is $\text{CAD}_{\text{spray}} - \text{CAD}_{\text{nospray}} = \frac{7}{2}\rho N^{\text{pre}}$. The farmer will compare the costs and benefits of his action based on the amount of damage avoided through the action.

If the farmer sprays, given information set $\mathcal{I}$, the gain from spraying is the realized monetary value from the saved CAD via applying the pesticide, and he has to pay the spraying cost, c_{sp}. Denote $B(\mathcal{I})$ as the payoff from spraying. If there were a scouting choice, he observes Z and the payoff from spraying is $B(Z)$. If there were no scouting, he would keep his prior, and the payoff is $B(\emptyset)$.

The spraying threshold is as follows:

$$B(\mathcal{I}) = P\bar{y}\alpha\rho\frac{7}{2}\mathbf{E}\left[N^{\text{pre}}|\mathcal{I}\right] - c_{\text{sp}} \geq 0$$

or

$$k\mathbf{E}\left[N^{\text{pre}}|\mathcal{I}\right] \geq c_{\text{sp}}, \text{ where } k = \frac{7}{2}P\bar{y}\alpha\rho \tag{20}$$

and $\mathbf{E}\left[N^{\text{pre}}|\mathcal{I}\right]$ is the posterior mean of N^{pre} depending on the scouting choice. For concise notation, denote k as the set of parameters that scale the marginal damage from the pest.

For the spraying threshold, let Z^* be the point where $B(Z) = 0$. The cut-off point of observation Z^* indicates the spraying threshold. The equality $B(Z^*) = 0$ is equivalent to

$$\mathbf{E}\left[N^{\text{pre}}|Z^*\right] = \frac{c_{\text{sp}}}{k}. \tag{21}$$

As the posterior mean is strictly increasing in Z (see Appendix B for proof), the cut-off point rises as spraying cost increases. However, if k increases, the threshold falls.

Scouting decision. For a scouting decision, the expected payoff with scouting is

$$\begin{aligned} \Pi^{\text{Scout}} &= -c_{\text{sc}} + \int_{-\infty}^{\infty} \max\{0, B(z)\} g(z)\, dz \\ &= -c_{\text{sc}} + \int_{Z^*}^{\infty} B(z)\, g(z)\, dz \end{aligned} \tag{22}$$

where $g(z)$ is the marginal density of the signal ($g(z) = \frac{1}{2}\mathcal{L}_u(z) + \frac{1}{2}\mathcal{L}_d(z)$). The last equality

holds because $B(z)$ is increasing in z. The expected payoff without scouting is

$$\Pi^{\text{noScout}} = \max\{0, B(\emptyset)\}. \tag{23}$$

Scouting is worthwhile only if $\Pi^{\text{Scout}} > \Pi^{\text{noScout}}$ and the threshold is

$$\int_{Z^*}^{\infty} B(z)\, g(z)\, dz \geq c_{\text{sc}} + \max\{0, B(\emptyset)\}. \tag{24}$$

The scouting threshold indicates that the value of information from scouting is non-zero. In this regard, the value of information (VOI) is

$$\text{VOI} = \Pi^{\text{Scout}} - \Pi^{\text{noScout}} = \int_{Z^*}^{\infty} B(z)\, g(z)\, dz - \left[c_{\text{sc}} + \max\{0, B(\emptyset)\}\right], \tag{25}$$

and the scouting is worthwhile only if VOI ≥ 0.

The structure of the VOI and the scouting threshold are contingent on the payoff from spraying under prior information, especially with regard to spraying cost. VOI can be written as the function of c_{sp}:

$$\text{VOI}\left(c_{\text{sp}}\right) = \int_{Z^*(c)}^{\infty} \left[k\mu(z) - c_{\text{sp}}\right] g(z)\, dz - c_{\text{sc}} - \max\left\{0, k\mathbf{E}\left[N^{\text{pre}}\right] - c_{\text{sp}}\right\} \tag{26}$$

where $\mu(z) = \mathbf{E}\left[N^{\text{pre}} | Z = z\right]$ and $Z^*(c)$ solves $k\mu(Z^*) - c_{\text{sp}} = 0$. By Leibniz's rule, the derivative of the first integral term with respect to the spraying cost is $-\text{Pr}\left(Z > Z^*\left(c_{\text{sp}}\right)\right)$. Hence, the first derivative of the VOI with respect to spraying cost is as follows:

$$\frac{d\text{VOI}}{dc_{\text{sp}}} = \begin{cases} -\text{Pr}\left(Z > Z^*\right) + 1 & \text{if } c_{\text{sp}} < k\mathbf{E}\left[N^{\text{pre}}\right], \\ -\text{Pr}\left(Z > Z^*\right) & \text{if } c_{\text{sp}} > k\mathbf{E}\left[N^{\text{pre}}\right]. \end{cases} \tag{27}$$

When spraying is profitable under prior information ($c_{\text{sp}} < k\mathbf{E}\left[N^{\text{pre}}\right]$), VOI increases, and it gets the maximum at $c_{\text{sp}} = k\mathbf{E}\left[N^{\text{pre}}\right]$, and then decreases when the spraying is not profitable without scouting. Therefore, VOI exhibits an inverted-U shape in c_{sp}. Since higher spraying costs simultaneously reduce the farmer's profit and raise the action cut-off Z^*, the value of scouting first increases, while spraying remains marginally profitable, and then declines once spraying is no longer attractive under prior information. Apart from spraying cost, when spraying is not profitable under prior information, RHS of the equation (24) is fixed to c_{sc}, so that any parameter that stretches $B(z)$ upward or steepens it, such as higher q, lower τ, larger difference in pest population, higher damage scaling parameters, monotonically increases VOI.

4 Calibration

4.1 Baseline Model

In this section, we calibrate the model we introduced and experiment with the various hypothetical scenarios. Table 2 lists baseline parameter choices. The baseline model parameters were primarily selected based on the latest data available (as of 2025) and aligned with real field status. Spraying cost is the summation of spraying cost from Plastina and Johanns (2024) and the material cost calculated from the data of Kynetic USA, a research company that collects agriculture-related survey data. The damage coefficient α is obtained from the traditional ET model. $\rho = 0.95$ indicates a single spray knocks down 95% of current aphids, and it is consistent with pyrethroid/neonicotinoid performance under good coverage. In the dynamic model, initial aphid density N_0 is set to 2, which is non-trivial. To make the population growth in the model align with reality, we put a biological cap on the population of aphids at 2,000, which is the largest value from the recent data of population (see Figure 1).

4.2 Alternative Scenarios

Based on the baseline model, we simulate several scenarios that include counterfactual policies, technology development, and environmental scenario to gauge the impact on farmers' decisions. The scenarios considered in our simulations are not merely hypothetical constructs; they reflect plausible developments that could realistically unfold under certain conditions. In the following sections, we discuss the scenarios' plausibility and compare the simulation results to analyze how outcomes vary across different settings.

Taxes on Pesticide Use. Although taxes on pesticide use are limited due to political and technical challenges, it is theoretically plausible. Many European countries, including Denmark, Norway, Sweden, and France, impose taxes on pesticide use in each country's way (Böcker and Finger, 2016). In the US, California has a system called "mill assessment," a fee levied on the first sale of registered pesticide products sold for use in the state based on mills, one-tenth of a cent per dollar of sales. The rate is set in regulation by the Department of Pesticide Regulation (DPR)[3]. This fiscal instrument exemplifies a user-fee approach to internalizing the regulatory costs of environmentally harmful products.

Subsidies on Scouting. There is limited direct evidence of large-scale government subsidy programs specifically targeting field scouting services. However, the government and extension

[3]Before, the rate levied was 21 mills ($0.021) per dollar of sales for all sales of registered pesticides for use. From July 1, 2024, to June 30, 2025, inclusive, the rate was 24.5 mills ($0.0245) per dollar of sales. The rate is scheduled with slight annual increases through 2027. For the specific rate and information, see California Department of Pesticide Regulation (2024).

programs often promote IPM, which relies heavily on field scouting to inform pest control decisions. Various research grants, extension programs, technical assistance, training, and cost-share programs for IPM adoption can indirectly subsidize scouting activities. For example, the Environmental Protection Agency (EPA) awards Pesticide Environmental Stewardship Program (PESP) grants to organizations to promote the use of IPM in agriculture to minimize the chemical risks and environmental damage. Also, the National Institute of Food and Agriculture (NIFA) regularly funds IPM initiatives. There are regional and state-level programs as well, such as the North Central IPM Center, funded by the USDA, which financially supports projects to expand scouting and its tools.

Technology Development. In line with the aforementioned programs, many of these initiatives also support the development of technologies that enhance scouting activities, scouting faster, cheaper, and more objectively. The technology now extends beyond classic sweep nets and sticky traps; it encompasses drones and high-resolution cameras, remote-sensing constellations, and in-field IoT sensor grids-tools that bring precision and speed to field scouting. Since effective implementation of IPM depends on timely and accurate field information, every marginal improvement in measurement technology amplifies downstream gains in spray precision, yield stability, and input-cost elasticity. From an economic standpoint, these technologies compress the marginal cost of information and can shift the optimum spray threshold upward, sometimes eliminating a spray outright.

Private vs. Social Optimal Decision. It is widely known and evident that pesticide use causes a variety of negative externalities, including the loss of beneficial insects through non-target effects, declines in biodiversity (e.g., fewer pollinators and birds), and broader environmental degradation, as well as human health risks from exposure to toxic residues (Deynze et al., 2024; Harper and Zilberman, 1992; Li et al., 2020; Purece et al., 2024; Sexton et al., 2007). According to Bourguet and Guillemaud (2016), estimates of the hidden social costs of pesticide use vary tremendously across different studies. For instance, one comprehensive analysis by Pimentel and Burgess (2014) attempts to quantify the environmental and social costs of pesticide use in U.S. agriculture. They estimate a total external cost on the order of $10 billion per year, broken down into categories of damage as public health impacts[4] ($1.14 billion per year), bird losses ($2.2 billion per year), groundwater contamination ($2.0 billion per year), loss of natural enemies ($520 million per year), crop losses due to pesticide use ($1.4 billion per year), pollination losses (honeybee & wild bee, $334 million per year), pesticide resistance ($1.5 billion per year), fishery losses ($100 million per year), and government costs for pesticide regulation/monitoring ($470

[4]Public health effects include acute poisonings, carcinogenic threats, and other chronic effects, such as neurological effects, respiratory effects, estrogenic effects, reproductive effects, and pesticide residues in food. The authors stress that the negative health effects are more severe in children than in adults.

million per year). This estimate illustrates that the societal costs of pesticides are substantial, even by a conservative method. Notably, other research finds widely differing values: Bourguet and Guillemaud (2016) reports that published estimates of pesticide externalities range from as low as $5.4 million in some contexts to as high as $13.6 billion. In their updated evaluation, U.S. hidden costs alone were posited to reach about $39.5 billion per year by the early 1990s. This broad range underscores the uncertainty and context-specific nature of quantifying pesticide externalities, but it unequivocally shows that the true cost of pesticide dependence is far greater than the private cost paid by farmers.

Because farmers do not internalize the external costs, they may overuse pesticides from society's perspective. In fact, a farmer's individually optimal pest control strategy can be socially suboptimal. Over time, reliance on chemical controls can become entrenched due to short-term incentives and historical practice, leading to a form of technological "lock-in" (Cowan and Gunby, 1996). For example, even if IPM or other alternatives might yield better long-run outcomes, the presence of positive feedbacks such as immediate effectiveness of chemicals, familiarity, or pest resurgence cycles, keeps farmers using pesticides by default. This path dependence means the agricultural sector can get stuck in an equilibrium of heavy pesticide use, even when this trajectory is inferior to safer and sustainable strategies in the long run. The outcome is a socially suboptimal equilibrium where the marginal private benefits of spraying are outweighed by the external costs imposed on society.

Among the pesticides used in soybean production, those applied for soybean aphid control tend to have higher environmental and health impacts. Table 3 shows the Environmental Impact Quotient (EIQ) of common pesticide active ingredients. The EIQ is a composite index that measures potential risk to farm workers, consumers, and the ecology. Notably, insecticides targeted at soybean aphids score higher on this index than many other pesticides used in general soybean farming. For example, lambda-cyhalothrin, a pyrethroid insecticide, has an ecological impact rating more than twice as high as that of many standard soybean herbicides or fungicides. Likewise, chlorpyrifos, an organophosphate insecticide formerly used for aphid control, and other aphid-targeting chemicals stand out for their high EIQ values. In short, the tools used to handle the soybean aphid problem are relatively dirty from an environmental standpoint, compounding the concern over their widespread use.

These potent insecticides also pose significant human health risks. Farmers and agricultural workers face occupational exposure, and rural communities can be affected via drift and residue in food and water. Acute poisoning can cause symptoms such as nausea, vomiting, and headaches, while chronic low-level exposure has been linked to more severe outcomes. For instance, epidemiological studies have found that exposure to pyrethroid insecticides correlates with higher risks of attention deficit hyperactivity disorder (ADHD) even at low exposure levels (Purece et al.,

2024). Organophosphates and pyrethroids are also suspected to have carcinogenic or endocrine-disrupting properties. Chlorpyrifos, for example, has been shown to act as an estrogenic endocrine disruptor, interfering with hormonal systems. Such chemicals can impair neurological development and reproductive health. The health burden of these effects often only becomes apparent in the long term, representing yet another hidden cost of heavy pesticide use.

Environmental harm and pest resistance are additional spillover problems created by overreliance on pesticides. When a highly effective tool like a pyrethroid is repeatedly used, it exerts strong selection pressure on the pest population. Over time, the pest can evolve resistance, rendering the insecticide less effective. Recent field studies have documented that by the late 2010s, scrutiny of a few soybean aphid populations in the Upper Midwest confirmed that pyrethroid resistance has emerged (Hanson et al., 2017). Figure 4 shows the pyrethroid use trend from 1988 to 2022. Panel (a), total pyrethroid use in soybean production, shows trips on soybeans surged in the mid-2000s, immediately after the soybean aphid's arrival, and they have remained high ever since. Panel (b), focusing specifically on pyrethroids applied for aphid control, shows a notable upward trend (albeit with some year-to-year fluctuations). This pattern implies that many growers responded to the aphid infestations by leaning heavily on pyrethroid sprays. However, the long-run consequence has been accelerated resistance development. As resistance rises, the efficacy of pyrethroids declines, which can push farmers to use more or switch to other insecticides that may be even more toxic or more costly. This vicious cycle can be added to the externalities. Thus, what seems privately optimal to the farmer can create dynamic externalities, reducing future pest control options and increasing future costs for society.

When all these spillover effects are accounted for, it becomes clear that the privately optimal pesticide use regime is not socially optimal. The farmer's private cost of spraying is only a part of the true cost. In our framework, we denote c_{sp}^{s} as the social cost of a pesticide application, which is higher than the farmer's private cost c_{sp}. Incorporating c_{sp}^{s} into the decision model will likely shift the solution toward reduced pesticide use – intuitively, if each spray costs more to society then fewer sprays will be justified. This has important policy implications: it suggests that interventions may be warranted to internalize the external costs and realign the farmers' incentives with the social optimum.

To calibrate the social cost of spraying in our model, we draw on the literature estimates discussed above. Notably, studies indicate that the external costs of pesticides can be on the same order of magnitude as the direct costs of pesticides themselves. For example, U.S. farmers spend roughly $10 billion per year on pesticides, and the environmental and health damages from pesticide use have likewise been estimated at around $9–10 billion annually (Pimentel, 2005). In other words, every dollar in private pesticide expenditure may impose approximately another dollar in external costs. To reflect this, we assume that the total cost of an insecticide application is about

double the out-of-pocket cost. This calibration is a conservative representation of externalities, and we acknowledge that in some cases the ratio could be higher. However, using a multiplier of two provides a reasonable baseline that is supported by empirical studies and ensures that the parameter is calibrated carefully to reflect substantial, but plausible, external costs.

Parameter Choices. The taxes on pesticide scenario increases spraying costs by 10% ($c_{\text{sp}} = \$12.87$), capturing regulatory disincentives for pesticide use. The scouting subsidy scenario reduces the cost of monitoring aphid populations to zero ($c_{\text{sc}} = \$0$), simulating public support for early information acquisition. The Technology improvement scenario assumes enhanced scouting effectiveness, with higher initial quality, lower signal noise, and faster learning rates ($q0 = 0.85$, $\tau = 20$, $\eta = 0.2$, $\kappa = 0.6$). The social cost scenario internalizes externalities from pesticide use by adding a per-acre social cost to spraying ($c^s_{\text{sp}} = \$11.7$). The scouting subsidy and technology improvement scenario combines these two interventions to assess potential synergy effects.

4.3 Result

One-Time Decision. Based on the thresholds derived from the one-time decision scheme, we identify the scouting and spraying mechanism for a nuanced understanding. For the pest population set up, suppose $N_0 = 120$ and the growth factors are $\mu = 0.6$ and $\sigma = 0.5$. In this case, $n_u \approx 282$ and $n_d \approx 155$, of which the high outcome is close to the canonical ET threshold. The blue line in Figure 5 presents the one-time VOI curves for the baseline model. Under the current data, the farmer does not choose to scout as the VOI has a negative value. For the spraying decision, the farmer never sprays the pesticide as $B(\mathcal{I}) < 0$ in any case according to equation (20). Figure 6 shows the VOI and scouting decision under the one-time decision scheme, and it clearly shows that the VOI curve has almost no notable shift from the baseline under the tax policy (panel (a)). The scouting subsidy (panel (b)) generates the largest upward shift, turning VOI positive at spray costs above around \$3/acre. The subsidy is set to cover all the scouting costs, and the result shows that the farmer scouts only when the scouting does not incur any costs. Incorporating a social cost of spraying (panel (c)) modestly raises VOI but does not make scouting positive at very low spray costs. The technology improvement scenario (panel (d)) has a similar impact as social cost inclusion. In all cases, VOI peaks near \$3/acre and then declines, forming a tent-shape, indicating the range where additional information is most valuable to the grower. In all cases, the agent sprays anyway as the benefit of spraying in any case yields positive values.

Dynamic Model. Figure 7 shows the results of the dynamic decision-making model. Each figure plots the mean path from a Monte-Carlo simulation (120 times), a random example path, 95% confidence interval, and the actions chosen from the example path. According to panel (a),

a decision maker does not scout and directly spray once at the early stage of the time frame in the baseline model. Imposing taxes on pesticide use or technology advances does not alter the farmer's choice in general (Figure 7b and Figure 8a). However, when scouting becomes free, nearly weekly scouting is implemented, and the spraying decision is delayed (Figure 7c).

Figure 8b shows the case when scouting becomes free and its quality is enhanced. In this case, the farmer scouts heavily during the earlier weeks. However, the grower does not spray the pesticide to control the pest infestation. It can be inferred that the higher scouting quality confirms that the pest infestation level is not severe enough, or rather, not profitable enough to apply the pesticide.

Figure 8c shows the notable result. The scenario shows that socially optimal decisions diverge from private optima when significant negative externalities are priced in. Doubling the spraying cost to approximate external damages removes spraying from the optimal plan under baseline biological parameters. Now, the cost is too high for a certain action. In this case, the population explodes, but the farmer decides that the cost of spraying, including the externalities, is a lot higher than the damage from not managing the pest infestation. The result implies that a calibrated Pigouvian tax must be carefully sized if biological or stewardship constraints (e.g., resistance, natural-enemy conservation) are to be respected.

Figure 9 shows the VOI in the dynamic model over the time horizon. The VOI here is calculated by subtracting the expected value without scouting from the expected value with scouting and the scouting cost. The baseline result shows that the VOI has a flat line at exactly the scouting cost. It means that the farmer does not scout unless the scouting is free. As in Figure 7 and 8, the farmer scouts only when the scouting incurs no cost, and it is shown in Figure 9 as the positive VOI values. Comparing the Figure 9e with 9d, better signals push the scouting window earlier because improved signals resolve the uncertainty faster.

To summarize the findings from the calibration, first, the baseline privately optimal plan is a single early spray with no scouting. Second, the most important incentive for farmers to scout is the cost. Reducing the cost of scouting to zero creates a short window with positive VOI, leading to frequent early-season scouting and delayed treatment. Third, improving signal accuracy without lowering its cost does not change behavior, but pairing better signals with a subsidy shifts the useful-to-scout window earlier and can avert spraying altogether. Fourth, including externalities of pesticides requires the farmer to endure the damage from the pest.

We also have simulated different key exogenous factors for the simulation. Higher price assumes an increase in crop market value by 10% ($P = \$13.2$), higher volatility represents greater uncertainty in aphid population growth ($\sigma = 0.7$), and higher damage reflects more severe yield losses from aphid infestation ($\alpha = 0.0000136$). However, those parameters did not substantively affect farmer decision-making. The results are shown in Appendix C.

5 Conclusion

This study integrates costly, imperfect scouting into a stochastic dynamic model of pest management and analyzes the economic value of scouting as an information acquisition strategy under uncertainty. By revisiting the traditional spraying threshold, the paper also emphasizes the role of scouting and the inherent uncertainty of pest management. Analytical derivations and calibrated simulations show that when scouting is expensive relative to expected damage, farmers forego information. Lowering that cost via subsidies has the largest leverage on behavior. Besides, accounting for external costs can justify no-spray equilibria.

The paper has a few limitations. First, the framework ignores spatial spill-overs, multiple pests, and beneficial insect dynamics; these omissions may bias the estimated benefits of precision scouting. Second, farmers' risk preferences are held neutral. Risk-averse growers may value early scouting differently. Third, key biological and economic parameters, such as growth factors and price and cost parameters, are treated as known and fixed, although they are uncertain and heterogeneous across firms in reality. Addressing these limitations will sharpen economic guidance for sustainable pest management. Additionally, incorporating the concept of dose of pesticide in the framework and evaluating dynamic policy instruments such as time-varying taxes or performance-based subsidies that account for seasonal variation in externalities and information needs would deepen the nuanced understanding of farmers' decision-making on pest management.

Figures

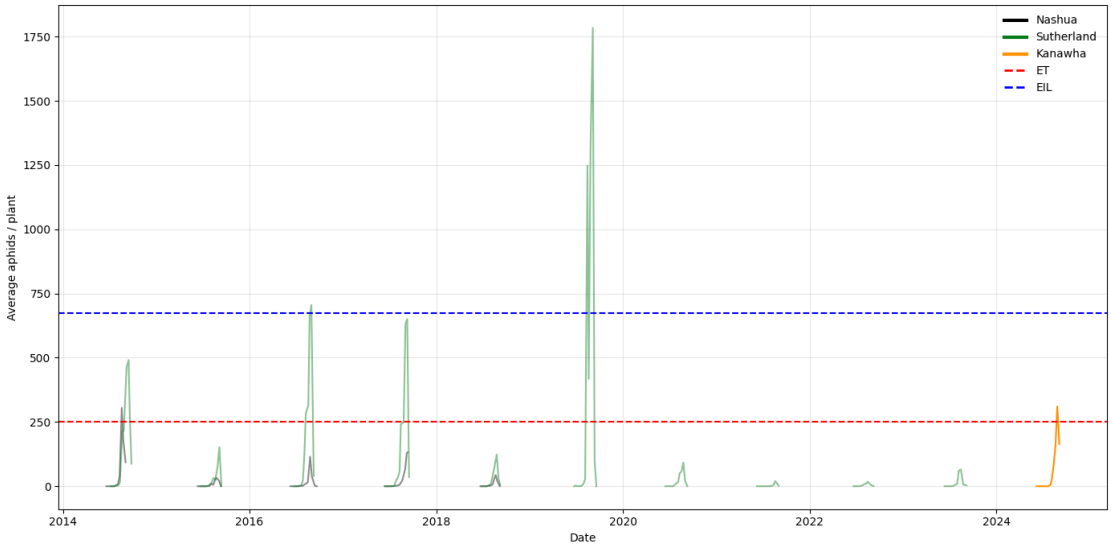


Figure 1 Soybean aphid Population Trend

Source: Soybean Research Laboratory (Iowa State University)

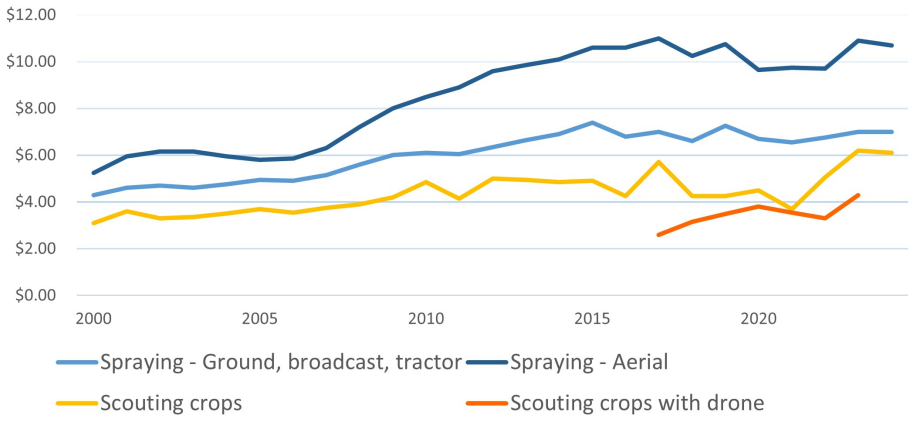


Figure 2 Spraying and Scouting Costs on Soybean Production ($ per acre)

Source: Historical Iowa Farm Custom Rate Survey (Iowa State University Extension and Outreach)

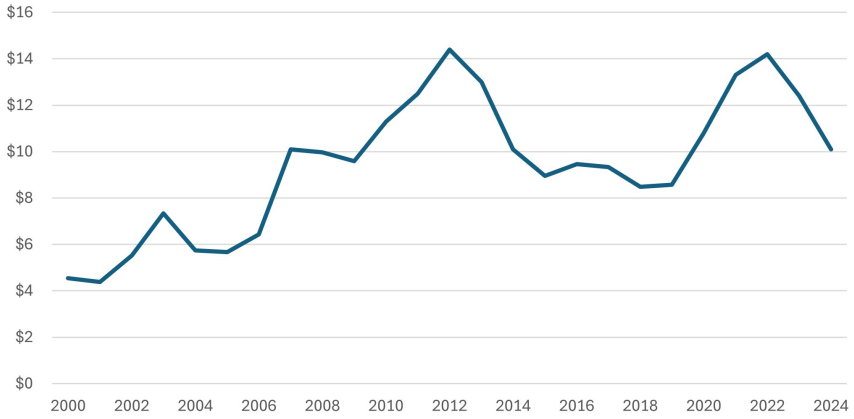
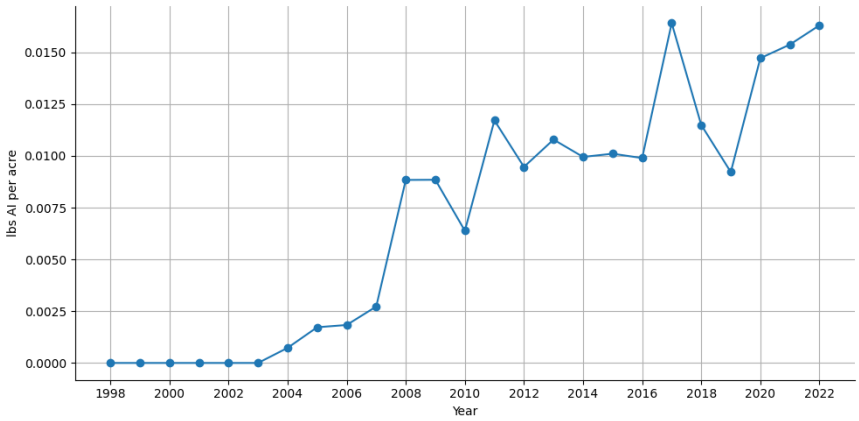
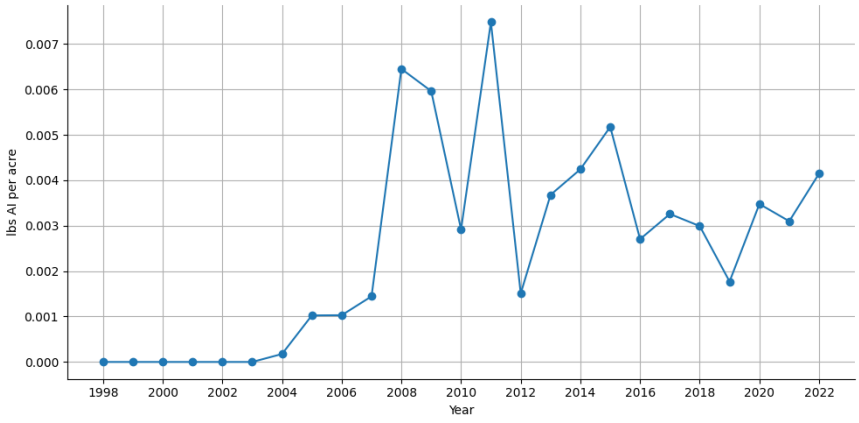


Figure 3 Soybean Price ($ per bushel)

Source: USDA-NASS



(a) Pyrethroid use on soybean production



(b) Pyrethroid use to control aphids

Figure 4 Pyrethroid Use (Active Ingredient lbs per acre)

Source: Kynetic USA

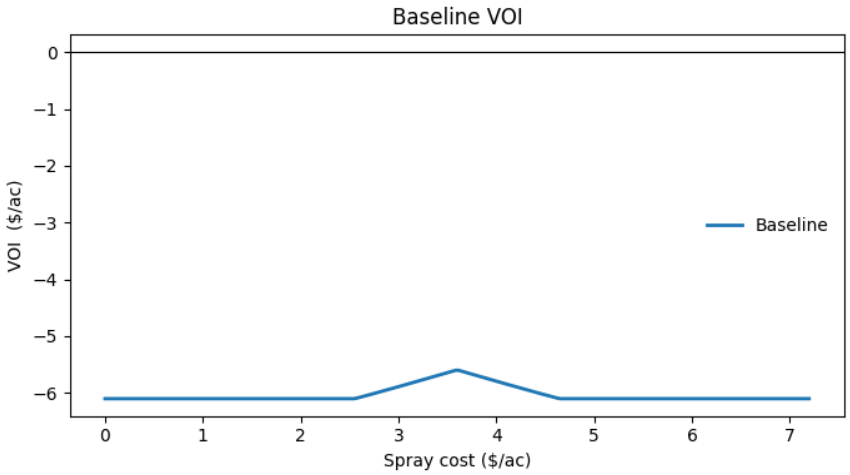
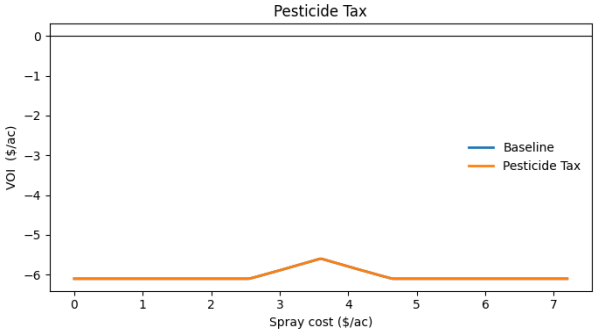
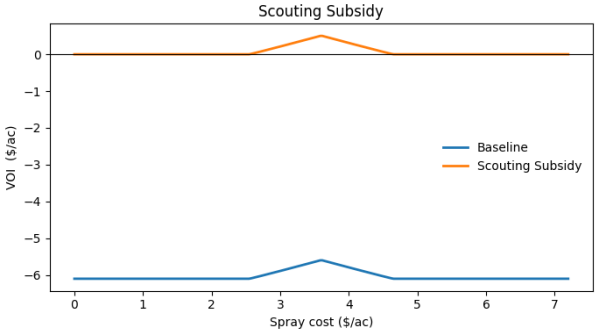


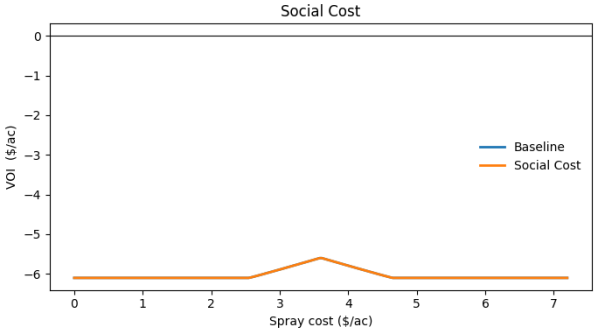
Figure 5 Value of Information (VOI) Under One-Time Decision Model (Baseline)



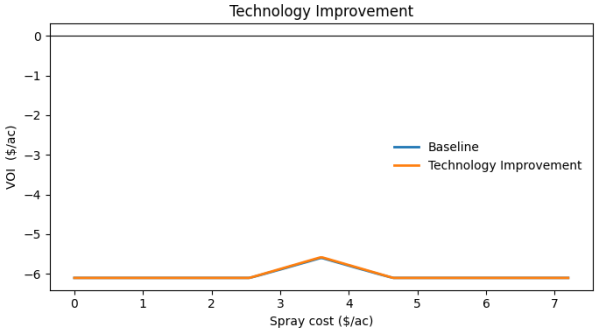
(a) Pesticide Tax



(b) Scouting Subsidy

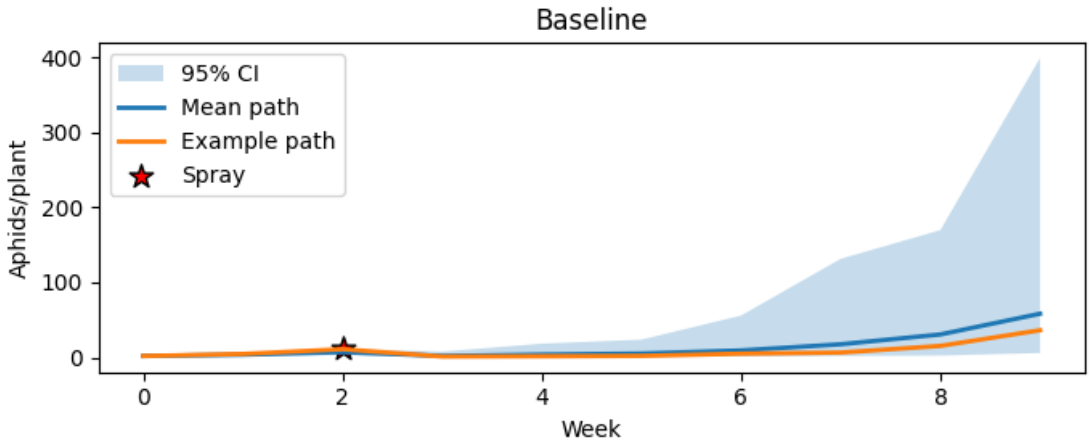


(c) Social Cost

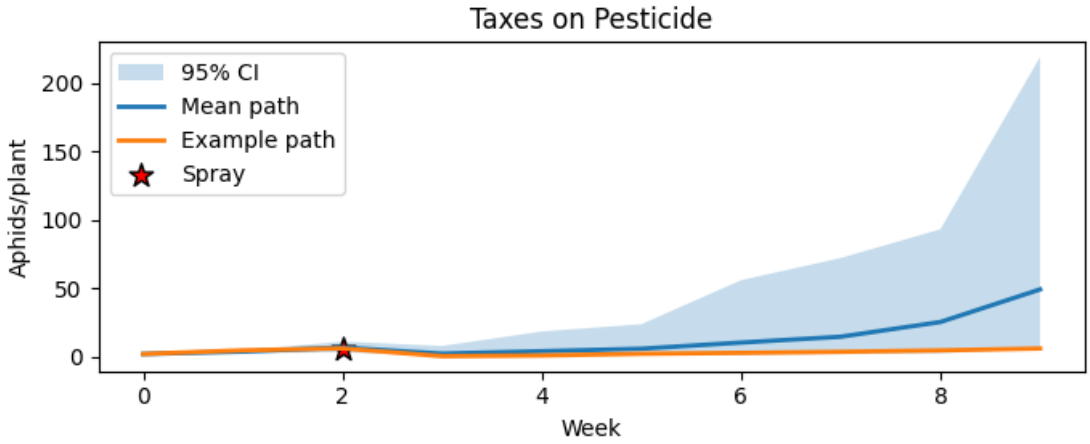


(d) Technology Improvement

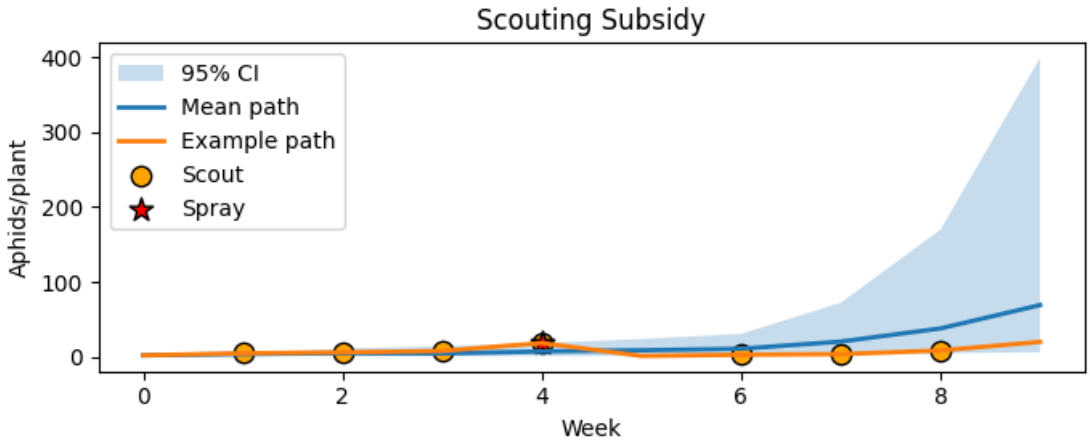
Figure 6 Value of Information (VOI) Under One-Time Decision Model (Alternative scenarios)



(a) Baseline

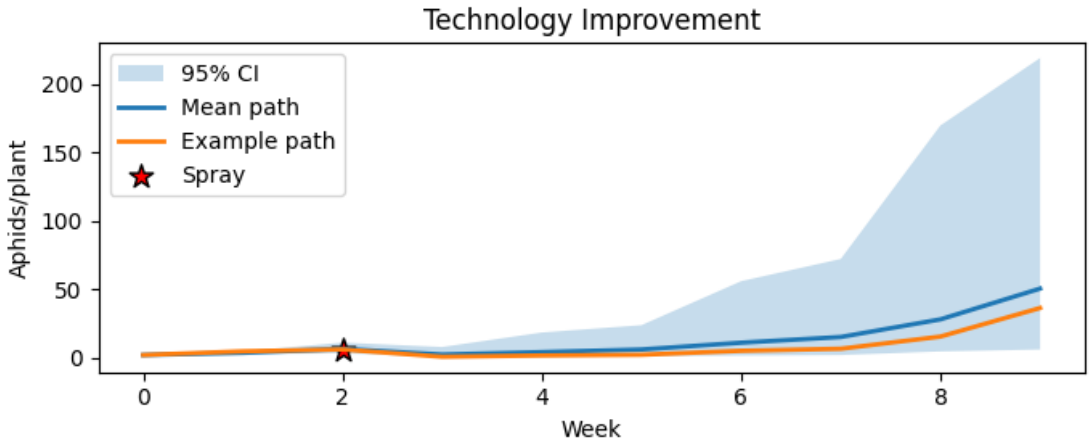


(b) Taxes on Pesticide

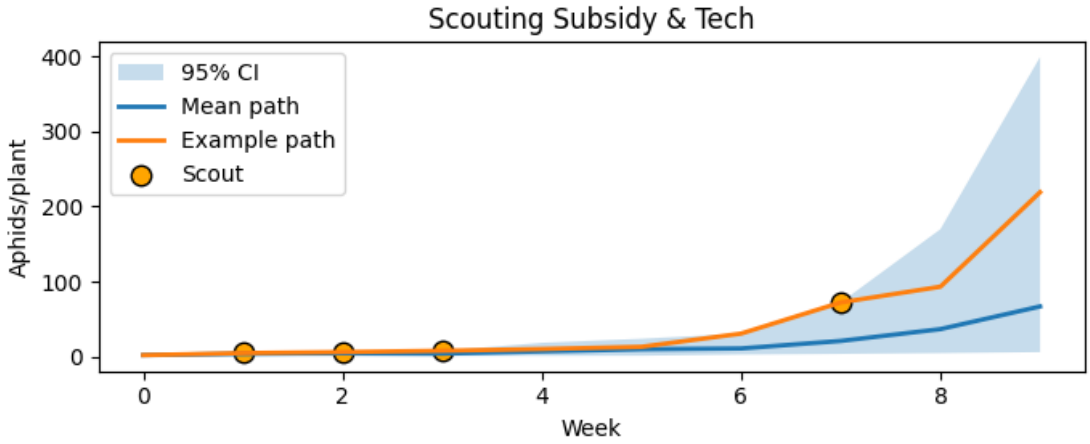


(c) Scouting Subsidy

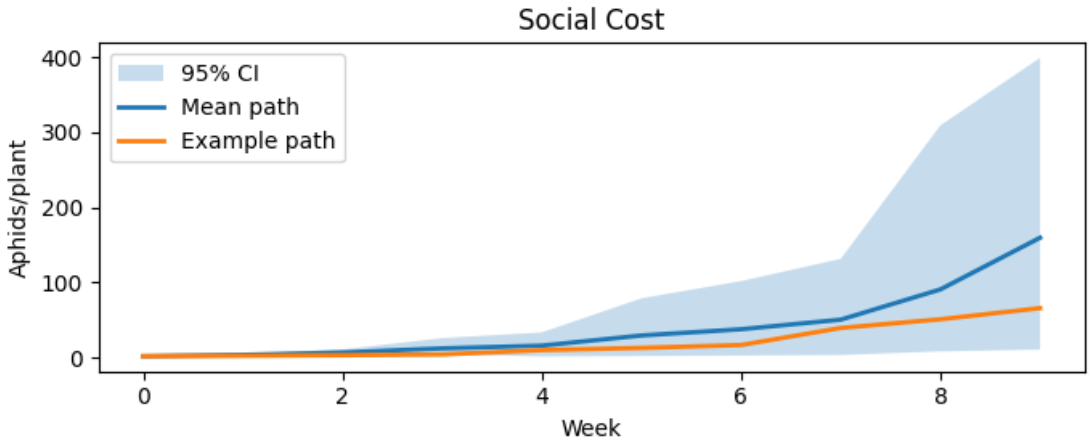
Figure 7 Simulated Trajectories Under Scenarios



(a) Technology Improvement

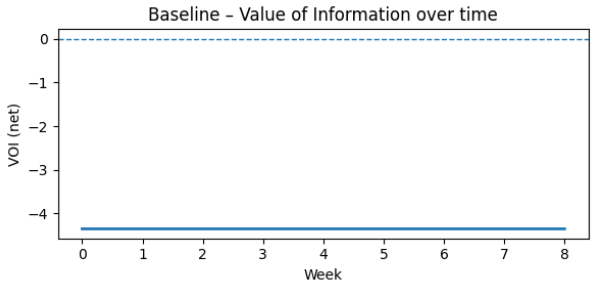


(b) Scouting Subsidy and Technology Improvement

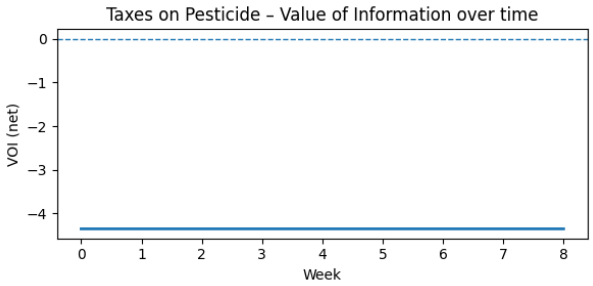


(c) Social Cost

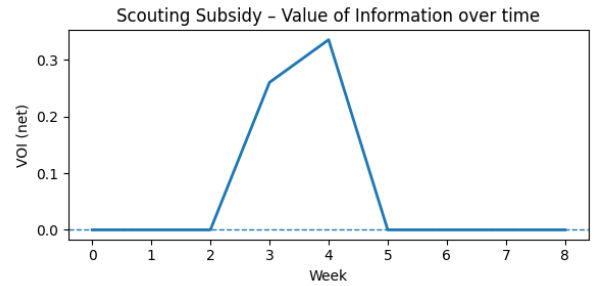
Figure 8 Simulated Trajectories Under Scenarios (continued)



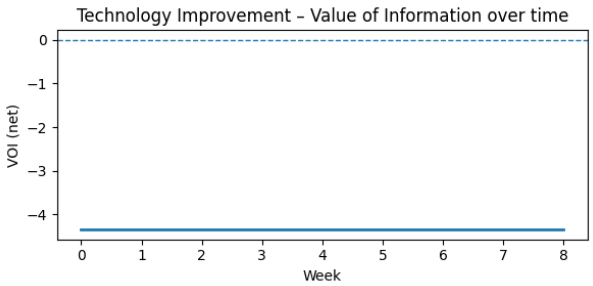
(a) Baseline



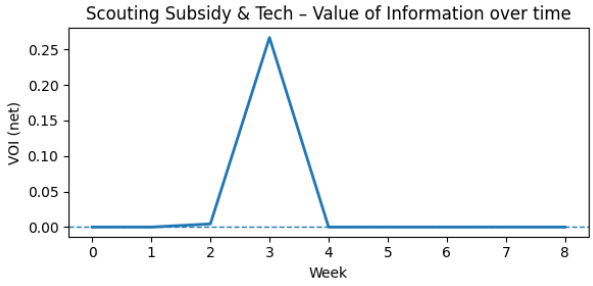
(b) Taxes on Pesticide



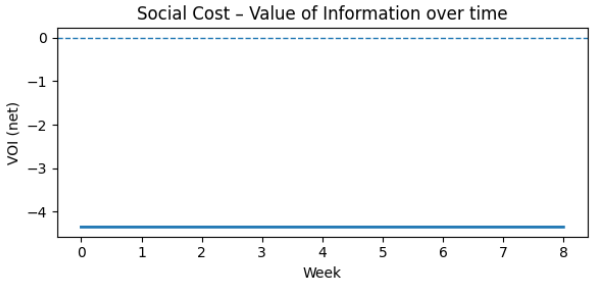
(c) Scouting Subsidy



(d) Technology Improvement



(e) Scouting Subsidy and Technology Advance



(f) Social Cost

Figure 9 Value of Information (VOI) Under Dynamic Model

Tables

Table 1 Numerical Example of EIL and ET

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Scouting	No	Yes	Yes	Yes	Yes	Yes	Yes
Uncertainty	No	No	Yes	Yes	Yes	Yes	Yes
ρ	-	-	0.5	0.3	0.5	0.5	0.3
Time Frame	Daily	Daily	Daily	Daily	Daily	Weekly	Weekly
G (or $\bar{G}$)	1.14	1.14	1.13	1.18	1.01	2.41	3.24
GT (%)	3.96	6.98	6.98	6.98	3	6.6	6.6
EIL(CAD)	5,541	9,934	9,934	9,934	4,072	9,321	9,321
N_{EIL}	662	1,186	1,172	1,534	67	457	435
N_{ET}	272	487.4	487.1	474	59	190	134

Table 2 Baseline Model Parameters

Parameter	Value	Description	Source
P	12	Market price ($/bu)	USDA–NASS
$\bar{y}$	60	Yield potential (bu/acre)	Soybean Research Lab. (ISU)
c_{sp}	11.7	Spray cost ($/acre)	Plastina and Johanns (2024), Kynetic USA
c_{sc}	6.1	Scouting cost ($/acre)	Plastina and Johanns (2024)
α	6.88×10^{-6}	Yield-loss coefficient per CAD	Ragsdale et al. (2007)
ρ	0.95	Pesticide kill fraction	
q	0.7	Scouting quality	
τ_0	40.0	Initial signal noise SD	
μ	0.60	Mean weekly aphid growth rate	
σ	0.30	Growth volatility	
η	0.10	Reliability learning rate	
κ	0.50	Precision learning rate	
β	0.99	Weekly discount factor	
Weeks	9	Management horizon (weeks)	

Table 3 EIQ of Pesticide in Soybean Production

Active Ingredient	Farm Worker	Consumer	Ecological	Final EIQ
For Overall Soybean Production				
Glyphosate	80.00	12.00	32.00	41.33
2,4-D	60.00	9.00	22.00	30.33
Chlorimuron-ethyl	64.00	13.00	31.50	36.17
Sulfentrazone	80.00	24.00	49.00	51.00
For Aphid Control				
Cyhalothrin	120.00	16.00	88.00	74.67
Chlorpyrifos	105.00	19.50	137.00	87.17
Thiamethoxam	28.00	19.00	56.00	34.33
Fludioxonil	72.00	19.00	74.00	55.00

Source: Kynetic USA, Eshenaur et al. (2020)

Note: Within each grouping, active ingredients are listed in descending order of their usage.

Appendix

A Weekly Scouting

If the farmer scouts weekly, the whole procedure is the same, but equations (4) and (5) are modified with weekly growth rate G_w. Also, $\frac{7}{2}(G_w+1)$ is multiplied for each population term as our time framework is in a weekly manner, but the CAD is cumulative aphids *days*. $\frac{7}{2}(G_w+1)$ is derived from the definition of CAD, $\text{CAD} = \sum_{t=0}^{n-1} \frac{N_t+N_{t+1}}{2} \times 7 = \sum_{t=0}^{n-1} \frac{N_t(1+G_w)}{2} \times 7 = \sum_{t=0}^{n-1} N_t \cdot \frac{7}{2}(G_w+1)$.

$$\begin{aligned} \text{EIL}(\text{CAD})_w &= \frac{7}{2}(G_w+1)\left(a + a\cdot G_w \cdots + aG_w^{m-1}\right) \\ &= \frac{7}{2}(G_w+1)\cdot a\frac{G_w^m-1}{G_w-1} \end{aligned} \tag{28}$$

where m is the number of week from an initial week when the CAD is at the EIL level. In this way, the weekly EIL and ET are modified. The economic threshold should be divided by G_w^1, assuming seven days (a week) of lead time.

$$\begin{cases} \mathbb{E}\left[N_{(w)\text{EIL}}\right] = aG_w^{m-1} = \dfrac{2\cdot\text{EIL}(\text{CAD})_w(G_w-1)+7a(G_w+1)}{7G_w(G_w+1)} \\ \mathbb{E}[N_{(w)\text{ET}}] = \dfrac{\mathbb{E}\left[N_{(w)\text{EIL}}\right]}{G_w} \end{cases} \tag{29}$$

B Monotonicity of the posterior mean

To prove that the posterior mean $\mathbf{E}\left[N^{\text{pre}}|Z\right]$ is strictly increasing in Z,

$$\begin{aligned} \mathbf{E}\left[N^{\text{pre}}|Z\right] =& \frac{\mathcal{L}_u(Z)\,n_u + \mathcal{L}_d(Z)\,n_d}{\mathcal{L}_u(Z)+\mathcal{L}_d(Z)} = w(Z)\,n_u + (1-w(Z))\,n_d \\ =& n_d + w(Z)\,(n_u-n_d), \quad \text{where} \quad w(Z) = \frac{\mathcal{L}_u(Z)}{\mathcal{L}_u(Z)+\mathcal{L}_d(Z)}, \end{aligned} \tag{30}$$

$w(Z)$ is the posterior probability of the state 'up' and we only need to show that $w(Z)$ is increasing in Z. To show that, define $R(Z) = \frac{\mathcal{L}_u}{\mathcal{L}_d}$. If the case is perfect read-out points, At $Z = n_u$, $R(Z) = +\infty$ and at $Z = n_d$, $R(Z) = 0$. Between the point masses ($Z \neq n_u, n_d$),

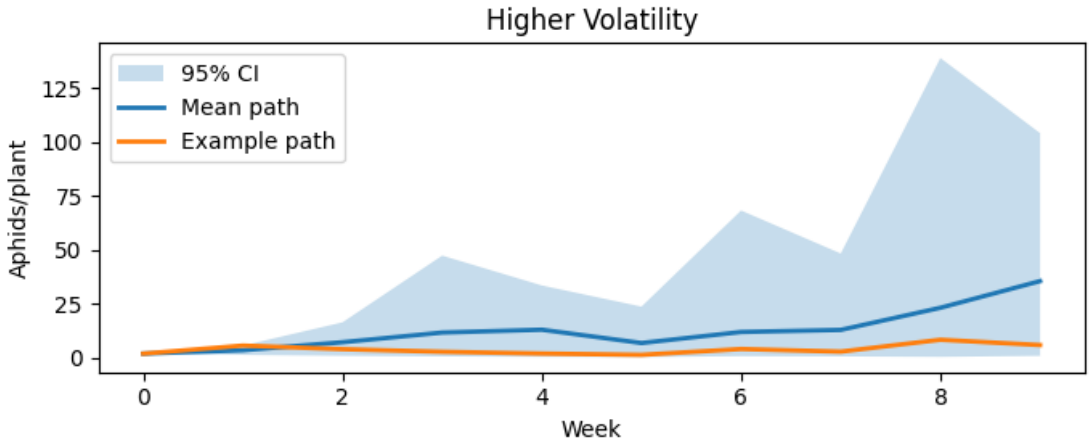
$$
\begin{aligned}
R(Z) &= \frac{(1-q)\frac{1}{\tau\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{Z-n_u}{\tau}\right)^2\right]}{(1-q)\frac{1}{\tau\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{Z-n_d}{\tau}\right)^2\right]} \\
&= \exp\left[\frac{2Z(n_u-n_d)+n_d^2-n_u^2}{2\tau^2}\right]
\end{aligned} \tag{31}
$$

Differentiating with respect to Z,

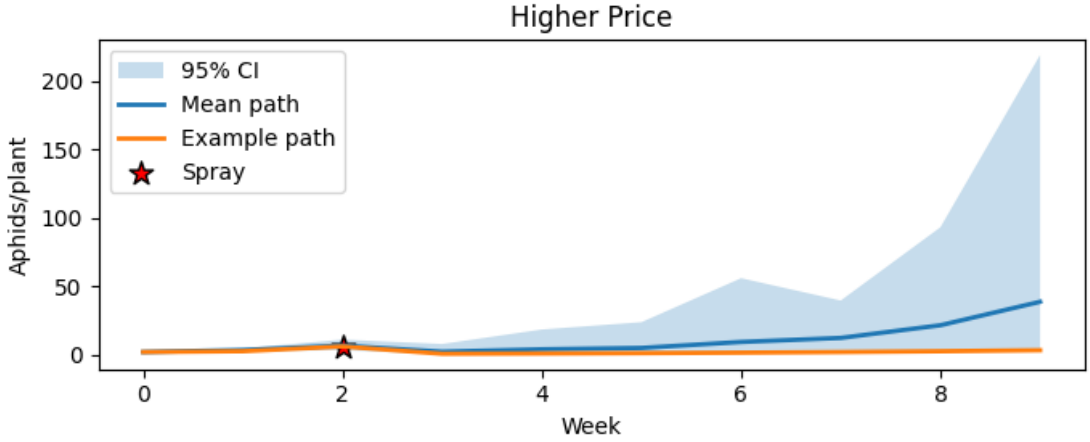
$$
\frac{dR\left(Z\right)}{dZ} = R\left(Z\right)\frac{n_u-n_d}{\tau^2} > 0 \tag{32}
$$

because $n_u > n_d$ always holds. Therefore, $R\left(Z\right)$ is strictly increasing between n_u and n_d, and jumps from 0 at $Z = n_d$ to $+\infty$ at $Z = n_u$. Overall, $R\left(Z\right)$ is monotonically increasing. As, $w\left(Z\right)$ can be written as $w\left(Z\right) = \frac{R(Z)}{1+R(Z)}$, $w\left(Z\right)$ is also increasing in Z, and thus the posterior mean $\mathbf{E}\left[N^{\text{pre}}|Z\right]$ is strictly increasing in Z.

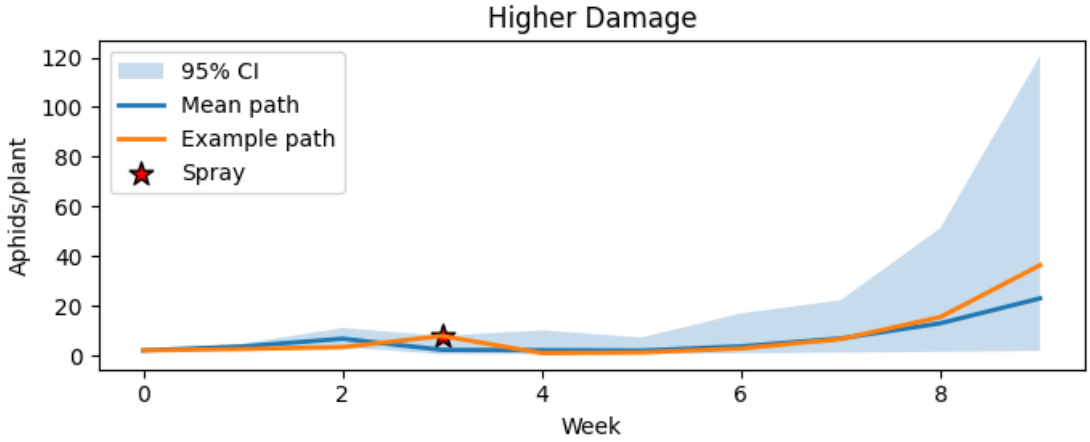
C Calibration Results



(a) Higher Volatility ($\sigma = 0.7$)



(b) Higher Market Price ($P = \$13.2$)



(c) Higher Damage ($\alpha = 13.7610^6$)

Figure 10 Simulated Trajectories Under Alternative Scenarios

References

Asbridge, David, "What Do Ag Professionals Charge for Their Services?," *Doane Agricultural Services Co.*, February 2005.

Atallah, Shady S., Miguel I. Gómez, Jon M. Conrad, and Jan P. Nyrop, "A Plant-Level, Spatial, Bioeconomic Model of Plant Disease Diffusion and Control: Grapevine Leafroll Disease," *American Journal of Agricultural Economics*, 2015, *97* (1), 199–218. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/aau032.

Bourguet, Denis and Thomas Guillemaud, "The Hidden and External Costs of Pesticide Use," in Eric Lichtfouse, ed., *Sustainable Agriculture Reviews: Volume 19*, Cham: Springer International Publishing, 2016, pp. 35–120.

Böcker, Thomas and Robert Finger, "European Pesticide Tax Schemes in Comparison: An Analysis of Experiences and Developments," *Sustainability*, April 2016, *8* (4), 378. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

California Department of Pesticide Regulation, "Text of Proposed Regulation: Mill Assessment Collection – Section 6386 Amendment," 2024.

Chalak, Morteza, Maksym Polyakov, and David J. Pannell, "Economics of Controlling Invasive Species: A Stochastic Optimization Model for a Spatial-dynamic Process," *American Journal of Agricultural Economics*, 2017, *99* (1), 123–139. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/aaw043.

Cowan, Robin and Philip Gunby, "Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies," *The Economic Journal*, 1996, *106* (436), 521–542. Publisher: [Royal Economic Society, Wiley].

Czapar, G. F., M. P. Curry, and M. E. Gray, "Survey of Integrated Pest Management Practices in Central Illinois," *Journal of Production Agriculture*, 1995, *8* (4), 483–486. _eprint: https://acsess.onlinelibrary.wiley.com/doi/pdf/10.2134/jpa1995.0483.

Dangerfield, C. E., A. E. Whalley, N. Hanley, and C. A. Gilligan, "What a Difference a Stochastic Process Makes: Epidemiological-Based Real Options Models of Optimal Treatment of Disease," *Environmental and Resource Economics*, July 2018, *70* (3), 691–711.

Deynze, Braeden Van, Scott M. Swinton, David A. Hennessy, Nick M. Haddad, and Leslie Ries, "Insecticides, more than herbicides, land use, and climate, are associated with declines

in butterfly species richness and abundance in the American Midwest," May 2024. Pages: 2022.07.29.502042 Section: New Results.

Eshenaur, B., J. Grant, J. Kovach, C. Petzoldt, J. Degni, and J. Tette, "Environmental Impact Quotient: "A Method to Measure the Environmental Impact of Pesticides."," `https://cals.cornell.edu/new-york-state-integrated-pest-management/risk-assessment/eiq` 2020. New York State Integrated Pest Management Program, Cornell Cooperative Extension, Cornell University. First published 1992; updated through 2020.

Hall, Darwin C. and Richard B. Norgaard, "On the Timing and Application of Pesticides," *American Journal of Agricultural Economics*, 1973, *55* (2), 198–201.

Hammond, Clarissa M., Edward C. Luschei, Chris M. Boerboom, and Pete J. Nowak, "Adoption of Integrated Pest Management Tactics by Wisconsin Farmers1," *Weed Technology*, July 2006, *20* (3), 756–767. Publisher: Weed Science Society of America.

Hanson, Anthony A, James Menger-Anderson, Celia Silverstein, Bruce D Potter, Ian V MacRae, Erin W Hodgson, and Robert L Koch, "Evidence for Soybean Aphid (Hemiptera: Aphididae) Resistance to Pyrethroid Insecticides in the Upper Midwestern United States," *Journal of Economic Entomology*, October 2017, *110* (5), 2235–2246.

Harper, Carolyn R. and David Zilberman, "Pesticides and Worker Safety," *American Journal of Agricultural Economics*, 1992, *74* (1), 68–78. Publisher: [Agricultural & Applied Economics Association, Oxford University Press].

Headley, J. C., "Defining the Economic Threshold," in "Pest Control: Strategies for the Future," Washington, D.C.: National Academy of Sciences, 1972, pp. 100–108.

Jarrow, Robert A. and Andrew Rudd, *Option Pricing*, Dow Jones-Irwin, 1983.

Kim, C. S., Glenn Schaible, Lynn Garrett, Ruben Lubowski, and Donna Lee, "Economic Impacts of the U. S. Soybean Aphid Infestation: A Multi-Regional Competitive Dynamic Analysis," *Agricultural and Resource Economics Review*, October 2008, *37* (2), 227–242.

Li, Yijia, Ruiqing Miao, and Madhu Khanna, "Neonicotinoids and decline in bird biodiversity in the United States," *Nature Sustainability*, December 2020, *3* (12), 1027–1035. Publisher: Nature Publishing Group.

Mbah, Martial L. Ndeffo, Graeme A. Forster, Justus H. Wesseler, and Christopher A. Gilligan, "Economically optimal timing for crop disease control under uncertainty: an options approach," *Journal of The Royal Society Interface*, April 2010, *7* (51), 1421–1428. Publisher: Royal Society.

Moffitt, L. Joe, "Risk-Efficient Thresholds for Pest Control Decisions," *Journal of Agricultural Economics*, 1986, *37* (1), 69–75. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1477-9552.1986.tb00318.x.

_ **, Darwin C. Hall, and Craig D. Osteen**, "Economic Thresholds Under Uncertainty with Application to Corn Nematode Management," *Journal of Agricultural and Applied Economics*, December 1984, *16* (2), 151–158.

Pimentel, David, "'Environmental and Economic Costs of the Application of Pesticides Primarily in the United States'," *Environment, Development and Sustainability*, June 2005, *7* (2), 229–252.

_ **and Michael Burgess**, "Environmental and Economic Costs of the Application of Pesticides Primarily in the United States," in David Pimentel and Rajinder Peshin, eds., *Integrated Pest Management: Pesticide Problems, Vol.3*, Dordrecht: Springer Netherlands, 2014, pp. 47–71.

Plastina, Alejandro and Ann M. Johanns, "Historical Iowa Farm Custom Rate Survey," `https://www.extension.iastate.edu/agdm/crops/html/a3-12.html` April 2024. File A3-12. Revised April 2024.

Purece, Anthony, Sofie Theresa Thomsen, Dietrich Plass, Anastasia Spyropoulou, Kyriaki Machera, Philippe Palmont, Amélie Crépet, Rafiqa Benchrih, Brecht Devleesschauwer, Nina Wieland, Paul Scheepers, Deepika Deepika, Vikas Kumar, Gerardo Sanchez, Jos Bessems, Dario Piselli, and Jurgen Buekers, "A preliminary estimate of the environmental burden of disease associated with exposure to pyrethroid insecticides and ADHD in Europe based on human biomonitoring," *Environmental Health*, October 2024, *23* (1), 91.

Ragsdale, D. W., B. P. McCornack, R. C. Venette, B. D. Potter, I. V. MacRae, E. W. Hodgson, M. E. O'Neal, K. D. Johnson, R. J. O'Neil, C. D. DiFonzo, T. E. Hunt, P. A. Glogoza, and E. M. Cullen, "Economic threshold for soybean aphid (Hemiptera: Aphididae)," *Journal of Economic Entomology*, August 2007, *100* (4), 1258–1267.

Saphores, Jean-Daniel M., "The Economic Threshold with a Stochastic Pest Population: A Real Options Approach," *American Journal of Agricultural Economics*, 2000, *82* (3), 541–555.

— **and Jason F. Shogren**, "Managing exotic pests under uncertainty: optimal control actions and bioeconomic investigations," *Ecological Economics*, February 2005, *52* (3), 327–339.

Sexton, Steven E., Zhen Lei, and David Zilberman, "The Economics of Pesticides and Pest Control," *International Review of Environmental and Resource Economics*, September 2007, *1* (3), 271–326.

Stefanou, Spiro E., Marc Mangel, and James E. Wilen, "Information in Agricultural Pest Control," *Journal of Agricultural Economics*, 1986, *37* (1), 77–88.

Stern, V., R. Smith, R. van den Bosch, and K. Hagen, "The integration of chemical and biological control of the spotted alfalfa aphid: The integrated control concept," *Hilgardia*, October 1959, *29* (2), 81–101. Publisher: University of California, Agriculture and Natural Resources.