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Will Farmers adopt Remote Sensing for Soybean Aphid Management? An Economic Perspective.

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Abstract

This study examines the economic suitability of Unmanned Aerial Vehicles (UAVs) for scouting soybean aphids based on a plant-level spatiotemporal bioeconomic model of infestation. We find that UAV based scouting, although imprecise, generates optimal profit equivalent to manual scouting. But its greater tendency to detect false positives relative to manual scouting can also trigger frequent unnecessary treatments and dramatically reduce farmers' profits. Yet, UAV's commercial viability depends more on reducing its operating cost than improving its precision, once it has a tally threshold of 250 soybean aphids per plant.

1 Introduction

Globally, soybean is the largest source of animal protein and second largest source of vegetable oil. The U.S. is the world's largest soybean producer with an average value of over $40 billion produced on more than 80 million acres annually. The most important insect management challenge facing U.S. soybean farmers is the soybean aphid, an invasive pest that was first discovered in the U.S. in 2000. In Minnesota, soybean aphid has reduced the plant height, pod numbers, seed size and quality, and yield [65]. Soybean aphid is also a carrier of a number of plant viruses [14]. The growth rate of soybean aphid is known to be rapid in controlled environment i.e. under ideal conditions where population growth is not perturbed by the effects of weather or natural enemies.[1] Yield losses from this relatively new U.S. pest can reach 40% without management ([70], [46]). To meet this management challenge, farmers have primarily planted soybean seed treated with neonicotinoid insecticides and applied foliar pyrethroid insecticides ([38],[45]).

The profitability of aphid management using neonicotinoid seed treatments has been questioned because the efficacy of the systemic neonicotinoid insecticides declines over time limiting its control of later season aphids [27]. Soybean aphid populations from Minnesota and Iowa exhibited resistance ratios up by 40-fold for pyrethroids (i.e., bifenthrin and lambda-cyhalothrin) between 2015 and 2016. The reports of pyrethroids failing to control soybean aphid in the field were noted from Minnesota, Iowa, North Dakota, and South Dakota [45]. This questionable profitability combined with evidence of the negative impacts of neonicotinoid insecticides on pollinators has the U.S. Environmental Protection Agency debating restrictions on their use in soybean production ([24], [18], [23]). Regardless of the outcome of this debate, there is increasing pressure for soybean farmers to use more integrated pest management practices, which would include an increased reliance on foliar insecticides.

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[1] It is reported to double in 1.5 d in controlled environment [60]. However, the estimates of the soybean population growth from the field is known to be less than the theoretical intrinsic rate of growth [12]

The profitable and sustainable use of foliar insecticides requires application only when the aphid population has reached an economically significant level. To help soybean farmers better time their foliar applications, entomologists have developed and refined manual scouting protocols that randomly sample soybean plants in order to estimate the severity of aphid infestation. An insecticide application is triggered if the average number of aphids per plant exceeds the profit maximizing threshold (250 aphids per plant is the current recommendation) ([71],[33]). This protocol is repeated throughout the growing season as long as aphids are active. It is labor intensive and not very precise given the small number of plants that can be economically sampled, which helps to explain why grower have relied more on planting insecticide treated seed.

Recent research using unmanned aerial vehicles (UAVs) shows that they can detect the presence or absence of aphids above the recommended threshold in 1.5×2.5 meter grid cells within a soybean field. While these detection rates are not without error, this discovery raises the prospect of replacing manual scouting with UAV based scouting protocols that observe an entire field rather than a small sample from it. The technology is currently not yet advanced enough to provide precise estimates of the pests or diseases responsible for observed stress or the severity of infestation, advances in navigation and imaging hardware and software are making remote sensed scouting costs competitive with conventional scouting costs. As the costs of obtaining remotely sensed scouting information declines, an interesting question that arises is how precise does remote scouting information have to be before it is more profitable to use than conventional scouting? In this paper, we intend to explore these questions.

These objectives will be accomplished through the development of an agent based pest management model and the application of this model to soybean aphid management. In this model, individual plants are the agents. Each plant is initially and randomly endowed with an insect population (or is insect free). Each day the insect population on a plant grows and then a portion of it migrates to other plants. At the end of the growing season, cumulative insect infestation days is calculated and used to determine a plant's yield loss. Within this biological framework, various decision rules can be constructed for simulating treatments that reduce the plant's insect population. For this paper, two decision rules are considered. Both the decision rules are based on a weekly scouting regimen with whole field insecticide applications triggered when scouting detects an insect infestation that is severe enough to reduce expected profitability without the application. The first decision rule is manual scouting where an insecticide application is triggered when the average number of insects on a random sample of plants exceeds the treatment threshold. The second decision rule is UAV scouting where an insecticide application is triggered when the proportion of plants with a detectable (with error) aphid population exceeds the treatment proportion. For each of these decision rules, the expected net return to management exclusive of scouting costs, average number of insecticide applications, and average total insecticide use are calculated using Monte Carlo methods.

The key results of the paper are as follows. First, when we assume that the per hectare cost of scouting is the same for UAV and manual scouting, and that insecticide treatment following UAV scouting is triggered only if soybean aphid density is at least 250 aphids per plant, then the optimal expected profit based on UAV scouting is \$785.18 per hectare. Conversely, the optimal expected profit from manual scouting is \$785.3 per hectare. With manual scouting, treatment is suggested in third and fourth weeks since the arrival of soybean aphids once the optimal threshold of 275 aphids per plant is reached. In case of remote sensing, the field should be treated in the fourth week once 45% of its plants are infested with at least 250 aphids per plant. Second, while the two methods have very similar optimal profits, manual scouting is still a better option because it estimates infestation level more precisely. It is significantly better for farmers who do not experience soybean aphid infestation frequently or those who prefer treating their fields early in the season. Third, expected profit from UAV scouting does not vary much with its probabilities of type I and type II errors. When it goes from providing perfect information to no information at all, the optimal expected profit falls from \$785.18 to \$778.15 per hectare. Fourth, increase in cost of UAV based scouting causes a linear decline in its profitability with no affect on its economic threshold. Pederson *et al.* (2006, [67]) find UAV based weed scouting to be 80% as costly as the conventional scouting. Under such circumstances, remote sensing for surveying soybean aphid will result in an expected profit of \$796.02 per hectare which is a 1.4% more than the expected profit from manual scouting. If the cost of operating UAVs became negligible, then its expected profitability will rise to \$840 per hectare.

The paper is structured in the following way: Section 2 reviews the literature on soybean aphids scouting methods, the use of UAVs in agriculture and spatial bio-economic models which are used in studying plant diseases. Section 3 explains our spatial model of soybean aphid infestation using cellular automation with agent based models. We specify the biological processes ranging such as reproduction, migration, wing induction and death, which together form state transition rules in subsections 3.1.1, 3.1.2 and 3.1.3. Section 3.2 describes the pest management strategies available to the farmers and their profit maximization problem within the biological framework mentioned above. Our model is parametrized in section 4. We then elaborate how we simulated our model in section 5 and our results in section 6. Finally, section 7 concludes.

2 Literature Review

Integrated Pest Management (IPM) for soybean aphid uses repeated sampling throughout most of the growing season. In Minnesota, it is recommended to sample 20-30 random soybean plants from all over the field beginning late vegetative stage through reproductive stage R5 [44]. Farmers are also recommended treating their entire soybean field with foliar insecticides when aphid population exceeds 250 aphids per plant with 80% of plants infested and population are increasing [33]. This Economic Threshold (ET) of 250 soybean aphids per plant is estimated based on the theory of economic injury level (EIL) [70]. EIL is defined as the lowest pest population density that causes economic damage. ET is defined as the injury equivalency of a pest population corresponding to the latest possible date a given control tactic could be implemented to prevent injury from causing economic damage [68]. Ragsdale et al. (2007, [70]) estimate EIL ($\approx$ 674 aphids per plant) and ET ($\approx$ 273 aphids/plant) between R1 and R5 (assuming 4-d lag) based on 19 yield loss experiments conducted over a period of 3 years in six states. If left untreated, soybean aphid herbivory can cause yield loss exceeding 40% [70].

The ET of 250 aphids per plant is based on a static model and lacks a dynamically optimal decision guide when multiple treatments are needed [89]. Its recommendations can be suboptimal because of two reasons. First, since this model is static, it assumes that the marginal benefit of all treatments are independent and equal. But treating crops today affects how beneficial subsequent treatments will be later in the season. Decision making based on the static model, therefore, may overestimate the value added by a treatment and consequently recommend more than needed. Second, static models do not incorporate the cost of increasing pest resistance to insecticides on optimal control of a pest. Regev et al. (1974, [37]) show that when making treatment decisions, farmers only take into consideration the monetary cost of insecticides and not the increased user costs. User costs are increased future costs of controlling the pests as a result of the decision to apply chemicals today. If user costs are accounted for, it would result in the ET increasing during the course of the growing season rather than remaining fixed at a particular level as usually presented in entomological literature.

The recommended ET assumes that aphid population will reach EIL if not treated. But there are multiple biotic and abiotic factors such as deteriorating host plant quality, crowding, natural enemies and extreme weather which can prevent the escalation of population to EIL ([83], [43], [51]). In fact, soybean aphids are known to have a density dependent population [16]. Costamagna et al. (2008, [11]) proposes an exponential growth model with intrinsic growth rate decreasing linearly with time. They attribute the decreasing rate of growth to deteriorating plant phenology with time. Matis et al.(2009, [59]) on the other hand suggest a population model where density dependence is introduced via death rate being dependent on cumulative population.

Cantangui et al. (2006) [10] introduced stage-specific EILs and ETs for R2, R4 and R5 soybean development stages using the law of diminishing increment regression model and symmetric bell shaped and logistic growth models. They perform caged experiments in 2003 and 2004 for their study, which suggested leveling off of the yield loss with increasing soybean aphid numbers. This motivates using the regression model based on the law of diminishing increment. They argue that stage specific EILs can give the farmers enough lead time to decide which developmental stage of the plant is the most suitable time for them to treat for soybean aphid. For infestation starting at V5, the stage specific EILs are 3.5, 74.6 and 212.1 soybean aphids/plant at R2, R4 and R5 respectively assuming a field with yield potential of 3700 kg/ha, soybean market value of \$0.29/kg and control cost of \$24.7/ha. This study has been criticized because it bases EILs on caged plants which prevents the access of natural enemies to aphids and any aphid movement from or to the host plant.[2] As a result, the estimated EILs are likely lower than optimum, which can cause significant overtreatment facilitating the development of an insecticide resistant soybean aphid population.

Hodgson et al. (2004) [34] developed a binomial sequential sampling plan using field collected data in Minnesota from 2001 to 2003 and computer simulations of sampling effort. This binomial sequential sampling plan underlies speed scouting. Speed scouting is based on the mathematical relationship between proportion of plants infested, aphid density per plant and ET of 250 aphids/plant. Instead of taking whole plant counts, speed scouting introduces a tally threshold (40 aphids/plant) to declare plants as infested or not infested. As a result, only 11 plants are needed to make decision about treatment. Hodgson et al. (2007) [32] test the validity of speed scouting using commercial fields in Minnesota and replicated small field trials in Iowa, Michigan, Minnesota and Wisconsin. They conclude that 79% of the time speed scouting resulted in same recommendation as whole plant counting based on ET of 250 aphids/plant. However, speed scouting is a conservative plan and hence it consistently recommends insecticide use before ET is reached using whole plant count.

Alves et al. (2015, [1]) find that UAVs can also detect stress caused due to soybean aphids. In their experiment, soybean aphid decreased the near-infrared reflectance (NIR) and Normalized Difference Vegetation Index (NDVI) reflectance, which provide measure of plant health. However, similar changes in NIR and NDVI can be detected due to other types of stressors such as soybean cyst nematode and soybean sudden death syndrome ([29], [28], [6]). Marston et al. (2019, [57]) examine

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[2] Comment on “Soybean Aphid Population Dynamics, Soybean Yield Loss, and Development of Stage-Specific Economic Injury Levels” by M. A. Catangui, E. A. Beckendorf, and W. E. Riedell, Agron. J. 101:1080–1092 (2009)

combination of features (wavelengths) of a UAV which will improve its accuracy in detecting aphid pressure. They also use machine learning, in particular linear Support Vector Machine (SVM) models, to generate an actionable information from remote sensing data. They find that all wavelength combinations trained with SVM models were able to detect aphid pressure above and below ET of 250 aphids per plant with over 80% accuracy. However, the models were more accurate in identifying cases with aphids below ET than above ET.

Treatment strategies are based on imperfect monitoring of pest population. Fackler et al. ([20], [21]) discuss how such observational uncertainty can be addressed using an extended Partially Observable Markov Decision Processes (POMDP). In context of pest management, POMDP approach replaces the imperfect information on pest population with a probability distribution and actions are taken based on this distribution. These type of models are also capable of handling structural uncertainties which occur due to the imperfect knowledge of the underlying theory [87]. Haight and Polasky (2010, [25]) model the problem of monitoring and treating a site for an invasive species using POMDP with infestation level as a state variable. They find that quality and cost of monitoring changes the optimal management strategy. With costless and perfect monitoring, expected costs are 20–30% lower across the range of belief states relative to the expected costs without monitoring.

There is a large literature on control of pests by their natural enemies which suppresses pest population growth and has potential to mitigate pest control costs and crop yield loss. Zhang and Swinton (2009, [89]) exploit this predator-prey relationship in modelling managerial choices. Zhang and Swinton (2009) develop an intra-seasonal dynamic bioeconomic optimization model for insecticide based pest management that takes into account both the biological control effect of natural enemies on the pest population and the effects of pesticide on the level of natural pest control supplied. Thus, they introduce insecticide decisions using a natural enemy adjusted economic threshold. However, they do not take into account the relative voracity of natural enemies. Bahlai et al. (2013, [4]) develop a mechanistic dynamic tritrophic population and phenology model for soybean aphid, incorporating environmental cues, host plant cues and natural enemy dynamics. To standardize the impact of different predators, they introduce the concept of Natural Enemy Unit (NEU) which is defined as the number of natural enemies that kill 100 individual prey in 24 hours. Their results suggest that natural enemy abundance and host plant phenology are the most important factors affecting soybean aphid population. One of the major drawback of this study is that it is deterministic and non-spatial. Hallett et al. (2014, [26]) estimate a dynamic action threshold (DAT) in presence of natural enemies by introducing NEUs in the population growth model. In their model, an insecticide application was triggered only if natural enemy numbers were insufficient to suppress pest populations. DAT also provided equivalent yields to the conventional action threshold during field experiments and reduced the average number of pesticide applications.

Spatial bioeconomic models have become popular recently in studying plant diseases and infestation. Sanchirico et al. (2005, [75]) investigate how ignoring spatial distribution of bioeconomic models can lead to suboptimal results. Space can be incorporated in bioeconomic disease models using state transition probabilities based on location [72] and partial differential equations [36]. These models however assume spatial heterogeneity to be exogenous [77]. But this may not be true. The spread of pests or disease to a new plant mostly depend on whether its neighboring plants are infested or not. Agent based models (ABM) allow spatial heterogeneity to be determined endogenously. These models study population of heterogeneous autonomous agents. These agents make decisions based on simple rules by interacting with other agents and their environment [82]. Atallah et al. (2015, [3]) use ABM to investigate the profitability of different disease control strategies for grapevine leafroll disease. They model grapevine leafroll disease at plant level using cellular automata and find that spatial strategies targeting immediate neighbors of symptomatic vines are better than nonspatial strategies.

3 Bioeconomic Model

This section explains the bioeconomic model used in this paper. It has two subparts. The first part is about modeling infestation of soybean aphids in a field during a single growing season. To do this, we use cellular automaton (CA) model with ABM. Miller (2009, [62]) define CA as discrete spatio-temporal dynamic systems based on local rules. They are characterized by regular lattice of cells, all of which have a finite number of states. There are rules to govern the state transition of cells in every time period; a cell transitions into a new state based on its current state and the states of its neighbors according to the transition rules [82]. In our model, soybean field is represented by a grid and its cells are occupied by soybean plant agents. The state of a cell or a soybean plant is defined by the number and composition of its resident soybean aphid as well as its location. State transition of a cell is determined by pertinent biological processes of soybean aphids such as their reproduction, migration, wing induction and death. The second part of our model deals with profit maximizing pest management strategies for the farmer. We analyze pest management decisions based on manual scouting and aerial surveillance (UAVs).

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[3] Although each cell is characterized by 2-D (row, column), here we identify them by a single uniquely defined index i which is a linear combination of its row and column number.

3.1 Population Dynamics of Soybean Aphids

The soybean field is a two dimensional grid with M_1 rows and M_2 columns and consequently there are a total of $M_1 \times M_2$ cells. Grid cells are of equal size and are denoted by i where $i \in \{1, 2....M_1M_2\}$.[3] Each cell has a soybean plant situated at its center. Suppose the soybean plants in the field are homogeneous at any given time.

Consider a single soybean growing season. Soybean aphids enter the field at time t= 0. They are characterized by their morph j and age group l and so, are referred as soybean aphids $\{j, l\}$. Their morphs include alate (winged, w) and aptera (wingless, $\tilde{w}$) i.e. $j = \{w, \tilde{w}\}$. The age groups are nymph ($\tilde{a}$) and adult (a) i.e. $l = \{a, \tilde{a}\}$. We consider a soybean aphid to be nymph only on the day it is born; it becomes an adult next day onwards.[4] Let the population of aphids $\{j, l\}$ at time t in cell i be denoted by N_t^{ijl}. Therefore, total number of aphids in cell i, labeled N_t^i, equals $\sum_j \sum_l N_t^{ijl}$.[5] The state of a cell i at time t is given by vector $S(i|t)$ such that

$$S(i|t) = (N_t^{i\tilde{w}\tilde{a}}, N_t^{i\tilde{w}a}, N_t^{iw\tilde{a}}, N_t^{iwa}, i). \tag{1}$$

The average number of aphids per plant at time t, labeled N_t, equals $\dfrac{\sum_i N_t^i}{M_1M_2}$. The unit of time t is a day and it takes on integer values between $\{0, t_{max}\}$. In spring, aphids start migrating from buckthorn to soybean [71]. Suppose the initial aphid count migrating to soybean field is lognormally distributed with mean μ and standard error σ i.e.

$$N_0 \sim LogNormal(\mu, \sigma). \tag{2}$$

The migrants are all alate female adults [71]. Therefore, at time *t=0*, the state of any cell is $S(i|t = 0)= (0, 0, 0, N_0, i)$. Parameters μ and σ are derived from the mean and variance of N_0 in Appendix 1. The number of plants infested at the beginning is based on these parameters. The location of infested plants is random. Many species of aphids use visual cues [15] and show edge effects [40] when choosing their host plant. But, evidence on edge effects for soybean aphids is dubious ([78],[71]). There are no visual cues for aphids in our model since we assume homogeneity within plants. As a result, we assume their landing on soybean plant is random. Once in the field, soybean aphid may reproduce, grow wings, migrate and die. Each of these biological processes are affected by external factors such as temperature, photo-period and presence of natural enemies which are all assumed to be constant

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[4] Note that nymphs in soybean aphid literature is used to address all instar stages and therefore a nymphal stage may last 3-4 days [90]. In this paper, we do not track the age of aphids for computational simplicity and so we modify the meaning of the terms nymph and adult aphid.

[5] We suppress a superscript notation in a variable when the notational variable has been summed over.

unless stated otherwise.

3.1.1 Birth and Death

In section 2, we discuss that soybean aphid population is density dependent. This can be either due to bottom-up or top-down factors or a combination of the two. Some of these factors include decline in host plant quality, crowding and presence of natural enemies ([74],[16], [12],[22],[13],[60]). Costamagna et al. (2007, [11]) and Matis et al. (2009, [59]) propose two different models in soybean aphid literature which characterize density dependence adequately. The first one is an exponential growth model with decreasing rate of growth to capture bottom-up effects on soybean aphid abundance . The second growth model assume death rate to be a function of cumulative aphid density. In our model, we need to assess the nymph and adult aphid density in each grid cell. So, we use the second growth model to represent population dynamics of soybean aphids. The growth equation proposed by Matis et al. (2009) is

$$\frac{dX_t}{dt} = (\lambda - \delta F_t)X_t \tag{3}$$

where X_t and $F_t = \int X_t dt$ are the population and cumulative population density respectively at time t. λ and δF_t are the birth and death rate at time t respectively. Therefore, at any time t, total number of new births is λX_t while the number of deaths equal $\delta F_t X_t$. To apply this growth equation in our context, we discretize time i.e. $dt \to 1$. Then soybean aphid population in time $t+1$ for cell i is given by

$$N^i_{t+1} = (1 + \lambda - \delta F^i_t)N^i_t. \tag{4}$$

3.1.2 Dispersal

Aphids are mostly sedentary [40] because dispersal requires energy which may lower their chance of finding new hosts ([40], [81]).[6] However, they do move both long and short distance. Their propensity to move and the distance covered depend on their morphs. While aptera walk short distances and usually end up on neighboring plants ([2],[40]), alates can fly for miles given the right environmental conditions [66]. Aphid dispersal is also a function of their age. Older aphids are less likely to relocate [8]. Long distance movement, also called migration, is quite infrequent compared to the localized displacement ([40],[66],[55]). Short distance dispersals or the 'appetitive dispersals' are generally induced by factors such as worsening predator density at the host plants, host plant quality and crowding ([35],[74],[40]). In this paper, we only focus on the localized dispersal of aphids because it is the more

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[6] Flight not only lowers the longevity of alate aphids but also their fecundity and reproductive period[91].

important of the two types of movement in order to understand their infestation pattern in a field.

To simplify our model, we make the following assumptions about aphid dispersal. (1) Only adult aphids ($l = a$) can move between plants.[7] (2) No mortality occurs during dispersal. This is assumed because of the lack of estimates or data in the literature on death rate during displacement. (3) At any given time period t, soybean aphid can undertake only one interplant trip. (4) The percentage of aphids dispersing/emigrating from a plant at any time t will depend on its aphid density. Donaldson et al. (2007, [16]) regressed the percentage of aphids dispersing from their host plant on the host plant's aphid density and found a positive relationship between the two. But their finding was mostly driven by two outlier plants with aphid density above 4,000.[8] Emigration rates on majority plants did not show an overall increase with aphid density and was 4% for densities less than 4,000 soybean aphid per plant. Let E_t^{ijh} denote the percentage of aphid morph j which emigrate from cell i to h at time t. Then assumption 4 implies that the percentage of total aphid population emigrating from cell i, labeled E_t^i, is a function of N_t^i i.e.

$$\begin{aligned} E_t^i &= \frac{\sum_j N_t^{ij} \sum_h E_t^{ijh}}{N_t^i} \\ &= \varepsilon(N_t^i). \end{aligned} \tag{5}$$

Propensity to emigrate is different for the two morphs.[9] Apterous soybean aphids are inactive and generally do not move once they have settled in a desirable feeding location ([40]) unless instigated by external factors such as deteriorating host plant quality, presence of predators, crowding, wind and rainfall ([86], [61], [16], [8],[30],[48]). While apterous adults can only walk, winged adult aphids both walk and fly ([8],[54]). Lombaert et al. (2006, [54]) estimated the rate of dispersal for melon aphids to study the impact of their dispersal on their fitness. They found that the rate of walking was 2% and independent of aphid density. But, aerial dispersal was strongly density dependent and it happened in large numbers only when local crowding increased dramatically. Donaldson et al. [16], however found that for any given aphid density, the percentage of alates emigrating were at most 4%.

The destination cell h is determined based on the distance aphids can move. Alates can fly miles under right environmental conditions [66]. Zhang et al. (2008, [90]) show that more than 80% of

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[7] Remember that in our model, aphids become adults from the day after their birth. Therefore, they are capable of interplant movement when only a day old. In reality, aphids hardly move until fourth instar stage [8], which occurs 4 to 6 days after their birth.

[8] Donaldson et al. [16] state the two plants with final aphid density of 6,550 and 10,100 aphids exhibited 20% emigration rate

[9] Boiteau 1997 [8] studied the relative ability of apterous and alate morphs to disperse from one potato leaflet to another. As per this study, the percentage of buckthorn, potato and green peach wingless adult aphids relocating can be as high as 25%, 45% and 15% respectively depending on their age. On the other hand, these numbers for the winged adults of the respective species were 45%, 40% and 40%.

the young adult aphids (12- 72 hours after molting) flew over 0.5km using flight mill experiment.[10] Aptera aphids, on the other hand, avoid movement even under mechanical perturbations [48]. They generally do not walk beyond neighboring plants and therefore are not considered the main force behind enlarging the infection foci beyond the field ([39],[84]). We define the neighborhood of aphid type j at cell i, denoted by $\mathcal{N}(j|i)$, as the set of cells which it can migrate to from its host cell. Suppose that aphids always move to a new plant when migrating i.e.

$$h \in \mathcal{N}(j|i) - \{i\}. \tag{6}$$

In our model, $E_t^{ijh} > 0$ if and only if $h \in \mathcal{N}(j|i) - \{i\}$ for aphid j. As we have already discussed above, aphids to not have preference about their landing within their neighborhood. In other words, every cell h in the set $\mathcal{N}(j|i) - \{i\}$ is equally likely to be chosen as a destination by an emigrating aphid of type j.

3.1.3 Wing Induction

Various factors such as crowding, host plant quality, presence of natural enemies and photoperiod can induce wings in aphids ([50],[63],[76],[41],[73]). Wing induction in aphid can be postnatal or prenatal. Nymphs, in their early instar stages, may grow wings to escape any danger and find a more suitable host plant. On the other hand, if an aphid experience life threatening environmental conditions, she may pass on this information to its successors genetically. As a result, aphids develop wings prenatally. Prenatal wing induction can continue for multiple generations depending on the intensity of environmental factors experienced by their predecessor. This process is difficult to model given our computational limitations and we assume that wing induction is only postnatal.

We also assume that the factor driving postnatal wing induction is crowding.[11] The larger the population density at host plant, the more likely its nymphs are to develop into alates. Suppose the probability of aphids developing wings, $p(j = w|t, i)$, at t increases at a decreasing rate with population density N_t^i at host plant i [76]. Let this relationship be a logit function of the form

$$\ln\left[\frac{p(j = w|t, i)}{1 - p(j = w|t, i)}\right] = a_0 + a_1 N_t^i. \tag{7}$$

Based on the above biological processes, our model can estimate density of nymphs and adults aphids for both morphs $\forall i, j$ at any given time period. At time t, aphid population at cell i is given by

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[10] The older ones (> 72 hours after molting) showed reduced flight time, distance and speed. They also find 16-28°C to be the optimal temperature range for flight.

[11] In our model, soybean plant quality is uniform across all plants. Additionally, effect of natural enemies are not modeled explicitly. Hence, we focus on effect of crowding on wing induction.

$$N_t^i = \lambda N_{t-1}^i + (1 - E_t^i)(1 - \delta F_{t-1}^i)N_{t-1}^i + \sum_z E_t^{zi} N_t^z \tag{8}$$

such that $i \in \mathcal{N}(j|z) - \{z\}\ \forall j$. The state transition rules are explained for each morph and age group in Table 1. We now turn to modeling pest management strategies of farmers.

	Variable	Transition rule	References
1.	Nymphs	$N_t^{ij\tilde{a}} = \lambda N_{t-1}^i[I(j = w)p(j = w\|t, i)$	
		$+I(j = \tilde{w})(1 - p(j = w\|t, i))]$	(4),(7)
2.	Total Adults	$N_t^{ija} = N_t^{ija}(1 - E_t^{ij}) + \sum_z E_t^{zji} N_t^{zj}$	
	i. Indigenous Adults	$N_t^{ija} = (1 - \delta F_{t-1}^i)N_{t-1}^{ija}$	(4)
	ii. Emigrants	$N_t^{ija} E_t^{ij}$	(5)
	iii. Immigrants	$\sum_z E_t^{zji} N_t^{zj}$	(5), (6)
3.	Total aphid j	$N_t^{ij} = N_t^{ij\tilde{a}} + N_t^{ija}$	
4.	Total aphids	$N_t^i = N_t^{i\tilde{w}} + N_t^{iw}$	

Table 1: Transition rules for the state variables of cell i at time t

[1] Superscripts $\{i, j, l\}$ in N_t^{ijl} represent host cell location, morph and age group respectively. Therefore, $i \in \{1, 2, ..M_1M_2\}$, $j \in \{w, \tilde{w}\}$ and $l \in \{a, \tilde{a}\}$.

[2] $I(j = w)$ is an indicator variable which equals 1 if $j = w$ and 0 otherwise. On the other hand, $I(j = \tilde{w}) = 1 - I(j = w)$.

[3] Superscripts $\{i, j, h\}$ on variable E_t^{ijh} denote host cell i, morph j and destination cell h respectively. Cell h is within the neighborhood of cell i using Equation 6. Therefore, in 2(iii) and (iv), $i \in \mathcal{N}(j|z)\ \forall j$ and $i \neq z$.

3.2 Pest Management and Profit Maximization

Farmer's pest management strategy consists of two processes- scouting and insecticide treatment. Farmers scout weekly once the aphids arrive to assess aphid density in their field. They then treat the entire field if the infestation can cause economic damage. Let the farmers scouting technique be denoted by k.[12] There are two types of scouting technology.

1. Manual Scouting

2. Aerial Scouting

Manual scouting, $k = m$, includes weekly full plant count of aphids on 20-30 randomly sampled plants from the whole field. They will treat their field with insecticide if the observed aphid density

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[12] In the subsequent sections, we use terminologies 'pest management strategy' and 'scouting technique' interchangeably.

is at least ψ. The value of ψ is chosen such that it maximizes the expected profit of the farmer.[13] Aerial scouting ($k = u$), on the other hand, is scouting soybean aphids using UAVs. UAV technology today can detect pest population above a certain threshold, labeled ϕ. Farmers fly drones above their field and take snapshots. These images are color coded to distinguish areas of the field where pest population is above ϕ. Therefore, with drones for surveillance, farmers can find what proportion of their field has soybean aphid density at least equal to ϕ. Given this information, they will choose to treat their fields if the number of soybean plants with at least ϕ soybean aphids are greater than κ. As in manual scouting, the value of κ is also chosen such that it maximizes expected profit of the farmer. Note that ψ and κ are economic thresholds for manual scouting ($ET_m = \psi$) and aerial scouting ($ET_u = \kappa$) respectively. While both of them maximize farmer's expected profit for their respective scouting techniques, the unit of ψ is soybean aphid density per plant while that of κ is the number of plants.

Aphid density estimated based on both types of scouting technique are prone to error. When scouting manually, the error can result for two reasons. First, manual scouting is arduous and time consuming [9]. Consequently it is prone to human error and will depend on the individual who scouts. Second, it does not provide complete coverage of the field. In our paper, we model error in manual scouting due to the second reason only. Marston et al. (2019, [57]) report the performance of UAVs in detecting aphid pressure of 250 aphids per plant. They test it for various models with different combination of wavelengths, trained with SVM. They find that probability of type 2 error is 0.1 on average while that of type 1 error range between 0.2 and 0.4.

Let Y^P be the potential output of soybean per hectare of field, and P_y be the market price of the crop. Farmers know the arrival time of soybean aphids, $t=0$, with certainty. They scout and treat with insecticide if necessary in time period 's' s.t. $s=7t \; \forall \; 7t \in \{1, t_{max}\}$. In other words, farmers scout and can treat once a week. Let $L(N_0, I_s^k)$ represent the percentage yield loss due to soybean aphids, which depends on initial observed aphid infestation (N_0), and how often farmers choose to treat. This decision to treat at time s based on scouting technology k is represented by I_s^k. It equals 1 when treatment is done or 0 otherwise. Therefore, I_s^k is

$$I_s^m = \begin{cases} 0 & N_s < \psi \\ 1 & N_s \geq \psi \end{cases} \tag{9}$$

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[13] Currently, this threshold level is recommended to be 250 soybean aphids per plant.

when scouting is done manually and

$$I_s^u = \begin{cases} 0 & \sum_i I(N_s^i > \phi) < \kappa \\ 1 & \sum_i I(N_s^i > \phi) \geq \kappa \end{cases} \tag{10}$$

when using UAVs respectively where $I(N_s^i > \phi)$ is the indicator function which equals 1 if $N_s^i > \phi$ or 0 otherwise. I_s^k is a function of ET_k and spatial distribution of aphids in the field $\{N_s^1, N_s^2, ..., N_s^{M_1 M_2}\}$ at any time s and therefore can be written as $I_s^k(ET_k, N_s^1, N_s^2, ..., N_s^{M_1 M_2})$.[14] When the insecticide is sprayed aphid density of the field becomes $N_t(1-\theta)$ where θ is the efficacy of treatment. Hence, soybean aphid population at the beginning of the next day $s+1$ will equal

$$N_{s+1} = N_s[I_s^k(1-\theta) + (1 - I_s^k)] \quad \forall \quad \text{k, s=7t.} \tag{11}$$

Percentage yield loss due to soybean aphids increases at a decreasing rate with aphid density.[15] It converges asymptotically to a yield loss of 40% [70] - 50% [85] when aphid pressure is as high as 80,000 cumulative aphid-days (CAD). Soybean aphid literature mostly use a linear ([70],[56]) or concave functions such as a negative exponential [10] to express percentage yield loss as a function of aphid density. But, soybean aphid also has a damage boundary of 4,000 to 5,000 CAD [68]. As a result, there is negligible yield loss when aphid pressure is in the range of 4,000 to 5,000 CAD as shown by the linear loss function of Figure 1 ([70],[46]). Therefore we use a sigmoidal function to express the relation between soybean aphid density and percentage yield loss. Let the percentage yield loss function be

$$L(N_0, I_s^k) = \frac{\alpha_1}{\alpha_2 + e^{\{\alpha_3 CAD + \alpha_4\}}} \tag{12}$$

where CAD is Cumulative aphid-days (CAD). Cumulative aphid-days is a measure of aphid abundance over time [31]. When sampling is done weekly, CAD equals

$$CAD = \sum_s \left[\frac{N_{s-7} + N_s}{2}\right] \times 7. \tag{13}$$

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[14] I_s^m can also be written as a function of $\{N_s^1, N_s^2, ..., N_s^{M_1 M_2}\}$ because N_s is an unbiased estimate of mean aphid density of the field.

[15] Zilberman et al. (1986) [52] demonstrate the importance of correctly specifying the damage abatement processes in the estimation of production functions and input productivity. They show that the use of traditional specifications like Cobb-Douglas overestimate the productivity of damage control inputs and underestimate the productivity of other

In practice, CAD is computed based on the samples taken from the field rather than the true population N_s. But we use N_s $\forall$ s instead so that we can estimate the actual loss.

Soybean plants have also developed tolerance to soybean aphids and therefore can withstand insect feeding without incurring excessive yield losses. Prochaska et al. (2013, [69]) in their field trials found yield loss of 13% for soybean genotype KS4202 at a range of 35,000-50,000 CAD. Ragsdale et al. (2007, [70]), on the other hand, reported a much higher yield loss of 24-36% for the same range of aphid pressure. Moreover, Kucharik et al. (2016, [49]) found that at low aphid pressure (2,000 CAD) soybean plants had higher yield through a compensatory photosynthetic effect than plants which did not experience significant aphid pressure. In this paper, we assume no form of host plant resistance or tolerance to soybean aphids. We would, however, discuss the impact that any soybean aphid tolerance will have in our model.

Two types of costs are involved in pest management. First is the cost of monitoring or sampling pests to get estimates for the level of infestation. This cost is incurred every time the field is monitored and depends on the scouting method. Let the cost of scouting once equal C^k. Therefore the total cost of scouting in a season equals $C^k \times n(s)$ for a given method k where $n(s)$ is the number of times scouting is done. The other cost is that of treatment which includes expenditure on insecticide and its application. This expense equals the product of cost of a single spray, labeled C_I and number of times farmers decide to treat the field. Therefore for scouting method k, cost of treatment equals $C_I \times \sum_s I_s^k$. Farmers will also incur a fixed cost when purchasing UAVs which is not included in our analysis. This is because we analyze profitability of the two techniques in a single growing season. It may take a farmer multiple seasons to cover the cost of buying a drone. Hence, a profit analysis based on a single growing season will underestimate the profitability of UAV based scouting if the cost of purchase is included. Therefore, we assume that farmers have free access to UAVs.

Let the maximum expected profit of the farmers equal $E(\pi_k^*)$ if they adopt scouting technique k. The objective of a risk neutral farmer is then to choose scouting strategy k such that it maximizes their expected profit $E(\pi^*)$ i.e.

$$E(\pi^*) = max\{E(\pi_m^*), E(\pi_u^*|\phi)\}. \tag{14}$$

To solve Equation 14, we first need to solve for $E(\pi_k^*)$ $\forall$ k=m,u. This requires identifying the optimal ET for each scouting technique k, given the population dynamics of soybean aphid and the yield loss

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inputs. Traditional specifications also predict that the spread of resistance will lead to reduction in the use of a damage control agent. In contrast, the specification proposed in their paper captures the real phenomenon, i.e. the use of a damage control agent increases in response to resistance and that it will decrease only when resistance is so widespread that alternative measures are most cost effective.

function. The optimization problem to solve for optimal ET for method k can be stated as follows:

$$\begin{aligned}
E(\pi_k^*) &= \max_{ET_k \geq 0} E(\pi_k) \\
s.t.\ \pi_k &= PY^p(1 - L(N_0, I_s^k)) - C^k n(s) - C_I \sum_s I_s^k \\
Log(N_0) &\sim N(\mu, \sigma) \\
\sigma^2 &= 9.152 * \mu^{1.543} \\
N_t^i &= \lambda N_{t-1}^i + (1 - E_t^i)(1 - \delta F_{t-1}^i) N_{t-1}^i + \sum_z E_t^{zi} N_t^z \quad \forall \quad z \\
i &\in \mathcal{N}(j|z) - \{z\} \quad \forall j \\
E_t^i &= \varepsilon(N_t^i) \quad \forall i \\
\ln\left[\frac{p(j = w|t, i)}{1 - p(j = w|t, i)}\right] &= a_0 + a_1 N_t^i \quad \forall i \\
I_s^k(ET_k, N_s^1, N_s^2, ..., N_s^{M_1 M_2}) &\in \{0, 1\} \\
N_{s+1} &= N_s[I_s^k(1 - \theta) + (1 - I_s^k)] \quad \forall \quad k, s \\
CAD &= \sum_s \left[\frac{N_{s-7} + N_s}{2}\right] \times 7 \\
L(N_0, I_s^k) &= \frac{\alpha_1}{\alpha_2 + e^{\{\alpha_3 CAD + \alpha_4\}}} \\
s &= 7t \quad \forall \quad t > 0 \\
t &\in \{0, t_{max}\}
\end{aligned}$$

In the next section, we discuss the parametrization of our benchmark model. The discussion follows in the same order as in section 3.

4 Model Parametrization

Let there be 10 rows and columns in the field i.e. M_1=M_2=10. Therefore the field has a total of 100 grid cells/plants. The intra-row and inter-row space between plants are assumed to be 3 and 30 inches respectively [34]. The time of arrival of soybean aphids, t=0, corresponds to the V1-V4 growth stage of soybean [35] and t=t_{max} corresponds to the beginning of growth stage R5. This is because to control economic damage from soybean aphid, farmers should undertake measures at most by soybean growth stage R5 [89]; any cure or prevention after R5 has negligible impact on their profit. Therefore, t_{max} on average equals 50 [80].

Birth and Death

Matis et al. (2009, [59]) found that the analytical solution to Equation 3 is given by

$$N_t = 4N_{max}e^{-bt_{max}(t-T_{max})}[1+e^{-bt_{max}(t-T_{max})}]^{-2}$$

where N_{max}, T_{max} and b are the predicted size and time of the peak count (in days) and relative rate (per day) respectively. Observed field data can be used to estimate N_{max}, T_{max} and b which in turn gives λ and δ of Equation 3.[16] They estimated the parameters of Equation 3 based on caged experiments. But under a caged setting, environmental conditions are set artificially and at optimum which inflates population growth. For example, in Matis et al. (2009), the mean peak aphid density recorded was approximately 34,000 and 55,000 per plant for years 2004 and 2005 respectively. But Bannerman et al. (2017, [7]) report mean peak aphid density in open fields to range between 148-1,726.2 aphids per plant. In this paper, to find optimal pest management strategy of farmers, we need realistic population growth model. So, we choose parameter values accordingly: Let N_{max}, T_{max} and b be normally distributed with parameters 1000 ± 100, 36.29 ± 0.42 and 0.228 ± 0.23 respectively [47]. This implies that the birth rate λ on average equals 0.23 while the death rate parameter δ is 0.000013. Figure 2 shows a sample population generated using the above parameter values. Let N_0 equal 5 aphids per plant. Using equations in Appendix 1, $\{\mu, \sigma\}$ is then estimated to be $\{0.78, 1.19\}$.

Dispersal

Donaldson et al. (2007, [16]) estimate percentage of aphids which emigrate as a linear function of soybean aphid density. They find

$$E_t^i = \begin{cases} 1.35 + 0.00184N_t^i, & N_t^i > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

We assume Equation 5 equals Equation 15.[17] Emigrating population comprises of the alate as well as aptera adults. The probability of an alate emigrating is 4% [16] i.e. $E_t^{iw} = 0.04 \; \forall \; i$. Therefore, total number of alate emigrating from any cell i at time t is $E_t^{iw}N_t^{iw}$. Rest of the emigrants which equal $E_t^iN_t^i - E_t^{iw}N_t^{iw}$ are aptera adult aphids. The neighborhood of alates $\mathcal{N}(\tilde{w})$ has a radius of 0.5km [90]. Thus alate adults can move anywhere in the field.[18] Aptera aphids move very short distance especially when there are suitable hosts nearby [5]. They can move at a speed of 5-20cm per minute

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[16] According to Matis et al. (2009), $\lambda = \frac{b(d-1)}{d+1}$ and $\delta = \frac{b^2}{2N_{max}}$ where $d = e^{(bT_{max})}$.

[17] The authors do not report the error structure. We, therefore, to begin with assume this process to be definitive.

[18] The area of our field is 7,290 inch squared which equals 4.7×10^{-6} km^2.

or run 15-30cm per minute [66]. Hence, we assume their neighborhood $\mathcal{N}(w)$ has a radius of 10 inches only. This implies that aptera adults can move up to 3 adjacent plants within their row.

Wing Induction

Equation 7 is estimated based on the data from Hodgson et al. (2005, [35]) using a logit model with zero intercept. It equals

$$\ln\left[\frac{p(j=w|t)}{1-p(j=w|t)}\right] = 9.38\times 10^{-5}N_t + e_t$$

where the error term $e_t \sim N(0, 0.213)$. The constant term a_0 is assumed to be zero because wing induction does not happen when the population density on host plant is 0.

Pest Management and Profit Maximization

Potential yield Y^P and Price P of soybean are 4.04 ton/ha and \$220.46/ton [70]. In our model, as already mentioned before, farmers scout and may treat weekly. Since the window of treatment is 50 days ($\{0, t_{max}\}$), farmers scout (and may treat) 7 times i.e. n(s)=7. Every Insecticide treatment costs \$35.82/ha (C_I) [42] and has an effectiveness θ of 99% [89]. Johnson et al. (2009, [42]) also report cost of manual scouting to equal \$9.88/ha. We do not have information on the cost of remote sensing and hence, to begin with, we suppose both types of scouting methods monitor a field at the same cost of \$9.88/ha. This implies that per plant scouting is cheaper when using remote sensing. It is because while UAV scans all the plants, only 20-30 random plants from the field are scouted manually every time sampling is done. Suppose \$9.88/ha cost of monitoring is based on sampling 25 plants per hectare. Then manual scouting costs \$9.88/25 per plant and UAV scouting costs \$9.88/100 if the field has 100 plants in total.[19] The average cost of monitoring C^k per unit area and time is also assumed to be homogeneous of degree one in the size of soybean field. However, it may not be true. Matese et al. (2015, [58]) state that when field size increases from 5 to 50 hectares, the operating costs of UAVs increase by a factor of 2.66. On the other hand, when fields are scouted manually, the cost of labor may increase at a decreasing rate because of diminishing marginal returns.

We assume ϕ to be 250 soybean aphids per plant. This tally threshold is based on the current IPM recommended ET of 250 aphids per plant. The probability of type 1 and 2 error for UAV based scouting in detecting 250 aphids per plant is 0.3 and 0.1 respectively. These values are derived from Marston et al. (2019, [57]) and are based on SVM model with combination of wavelengths 780, 1,010 and 720 nm (Model 3).

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[19] This implies that when the field is monitored manually using 20 random plants, it costs \$7.9 per hectare.

Parameters of the yield loss function are chosen such that the damage threshold is $\approx$ 5,000 CAD and yield loss converges to 40% when aphid pressure reaches 80,000 CAD ([70], [46]). $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$ in Equation 12 equals $\{4, 10, 0.00013, 6\}$. Figure 2 compares our sigmoidal loss function to the linear loss function based on data from Ragsdale et al. 2007 ([70]). Table 2 puts together the definition of parameters used in our model, their values and references.

5 Simulating the model

The model is initialized at time *t=0* by introducing soybean aphid into the field. To do this, we find how many plants are expected to become infested given the distribution of N_0, and their location in the field. Then each of these cells are assigned aphid population based on Equation 2. Expected number of infested plants equal probability of infestation times the total number of plants in the field (=100). Probability of infestation is defined as the likelihood that $N_0 \geq 1$. We estimate it using a large sample of N_0's to ensure its unbiasedness. 25,000 samples of N_0 are drawn and fraction of cases where $N_0 \geq 1$ is determined; the probability that a plant will become infested equals this fraction by law of large numbers. Location of these plants is then determined by randomly drawing $\sum_i I(N_0^i \geq 1)$ grid cells i from a uniform distribution $U(1, 100)$; $I(N_0^i \geq 1)$ is an indicator function that equals 1 if $N_0^i \geq 1 \ \forall \ i$ and 0 otherwise. Next, each of these cells i are infested with N_0^i alate adults through random draws based on Equation 2. Each grid cell is also assigned values for n_{max}, T_{max} and b which determine their birth rate λ and death rate parameter δ.

At time $t > 0$, N_t^i is estimated using N_{t-1}^i and Equation 4 for every cell i. We then determine the composition of aphid population for each cell i using the transition rules stated in Table 1. Total number of emigrants $E_t^i N_t^i$ is calculated for each cell using Equation 15. Out of these emigrants, 4% are alates and rest are aptera adults. These aphids then disperse to cells randomly chosen from within their neighborhood. At each cell, net immigrants from all other cells are added to the existing aphids to get the total number of aphids post dispersal.

At the end of time period t, state vector $S(i|t)$ is known $\forall$ i. Scouting and treatment is done weekly. On $s = 7t$, 20 cells are randomly chosen from the field to scout manually and average aphid density is estimated. Insecticide treatment follows ($I_s^m = 1$) if observed density is greater than threshold ψ. On the other hand, when remote sensing is used, total number of cells i with $N_t^i > \phi$ is determined. If it is greater than κ, then $I_s^u = 1$. At $t = t_{max}$, cost of treatment ($C_I \sum_s I_s^k$), yield loss proportion $L(N_0, I_s^k)$) and cost of sampling ($C^k n(s)$) are estimated for $k = m, u$. Subsequently, the profit π_k is computed for each scouting strategy k given their respective threshold of spray.

The process explained above presents one full simulation of profit maximization problem based on parameters defined in section 4. We execute this model 50 times such that each iteration corresponds to a different draw of initial population N_0. This gives us 50 outcomes (e.g. profits, treatments and losses) for strategy k and its threshold of spray ET_k. The values of ET_u and ET_m are chosen with intervals of 5 and 25 respectively to keep it computationally light. The expected profit $E(\pi_k)$ is then the average of all 50 profit outcomes. ET_k^* is chosen as the optimal treatment threshold if and only if it gives the maximum expected profit $E(\pi_k^*)$. Once we have ET_m^* and ET_u^*, the optimal pest management strategy and expected profit are inferred using Equation 15 .

6 Results

We first discuss the case of no treatment. The parameter values $\{\mu, \sigma\}$ based on $m = 5$ results in a maximum yield loss of 6.5% if infestation is left untreated, irrespective of the scouting technique. This is equivalent to 15,817 CAD and results in expected profit of \$777.5 per hectare. To put it differently, farmers will end up with at least \$777.5 per hectare if they delay treatment by choosing high κ or ψ in hope of saving the cost of spraying.

Figures 3a and 3b show how expected profit changes with treatment thresholds for manual scouting (ψ) and UAV based scouting (κ) given that ϕ equals 250 aphids per plant. The tables below each figure gives the probability of insecticide spray at different sampling times, s. The optimal threshold of spray ψ^* equals 275 aphids per plant which gives an expected profit $E(\pi_m^*)$ of \$785.3 per hectare. When scouting manually, farmers choose to treat during $s = 3$ or 4 out of the 7 times. Chances of treatment during these time periods are 6% and 94% respectively. In case of remote sensing, it is optimal to treat the field with insecticide when 45 plants are infested with at least 250 aphids per plant. The optimal treatment threshold κ^* of 45 plants results in treating the field at $s = 4$ and an expected profit of \$785.18 per hectare. Time period $s = 4$ is the 4^{th} week since the beginning of infestation. Because in our model $t = 0$ coincides with V1-V4 stage, $s = 4$ corresponds to R2-R4 reproductive growth stage of soybean [64].

At their respective optimum, the two techniques have very similar profitability. But figures 3a and 3b suggest that overall manual scouting is a better option. $E(\pi_m)$ lies between \$750 and \$785 per hectare when soybean aphid pressure is in the range of 0 to 900 aphids per plant. On the contrary, $E(\pi_u|\phi = 250)$ has a minimum of approximately \$600 per hectare when κ equals 5 plants and a maximum of \$785 per hectare at κ=45. Scouting manually estimates aphid pressure more precisely than remote sensing. The economic performance of the two pest management techniques are similar if farmers delay treatment, or in other words, choose high threshold values. Delaying treatment can build up aphid pressure so much that after a point it is no longer useful because of two reasons. First, very high aphid density can lead to irreversible damage in plant quality and yield [79]. Second, density dependence kicks in once aphid pressure reaches n_{max} and causes reduction in infestation level naturally. Figures 4a and 4b show that at $\psi = 900$ aphids per plant and $\kappa = 100$ plants, percentage yield loss reaches its maximum 6.5% and there are no treatments recommended. As a result, expected profit $E(\pi_m)$ and $E(\pi_u)$ converge to profit under no treatment as shown in figure 3a and 3b. If they chose to treat early i.e. at low threshold, then manual scouting is significantly more profitable than remote sensing. It is because UAVs are prone to generating false positive outcomes which will cause unnecessary treatments even at low aphid pressure. The probability of type 2 error is 10% and therefore on average 10 out of 100 plants will be falsely reported to have at least 250 aphids. Consequently, at $\kappa = 5$ plants, farmers treat 6.6 times on average out of 7 as shown in figure 4b and reduce their yield loss to 0.97%. But any decision to treat early, say at $\psi = 25$ aphids per plant, based on observations from scouting manually result in 2 treatments in total only while reducing the yield loss to 1.03%.

Will improving precision enhance the profitability of UAVs as a scouting technique? Intuitively, expected profits and yield loss should be negatively related with both types of error rates because they comprise the quality of information received from remote sensing. Optimal threshold of treatment should increase when there is higher chance of getting false positives and vice versa. False positive outcomes are equivalent to overestimating aphid pressure. When it becomes more likely, the possibility of unnecessary treatments also increases which in turn will reduce their marginal benefit. As a result, treatment will be delayed in order to increase the marginal benefit of treatment. On the other hand, when type 1 error becomes more probable, treatment threshold should decrease. False negatives imply underestimating the aphid pressure in the field. As a result, the marginal benefit of treatments are high and so they should be conducted at lower threshold. Discerning the effect of probability of type 1 and 2 error on the number of treatments is more complicated. When quality of information goes down, yield loss will increase. This may encourage farmers to treat more times. However, increasing total the number of treatments may not always be needed. Treating early in the season may be enough to suppress the aphid pressure overall and trim yield loss.

To test our hypotheses, we perform sensitivity analysis of pest management decisions with respect to

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[20] UAVs being systematically right is as informative to farmers as if it is systematically wrong. These conditions are equivalent to when error rates ≤ 0.5 and ≥ 0.5 respectively.

type 1 and 2 error rates. We vary the probability of type 1 and 2 errors from 0 to 0.5 at an interval of 0.05 and estimate the optimal expected profit and treatment threshold for every pair of values.[20] The results are presented in detail in Appendix 7. Figures 6a and 6b show how isoprofit lines and treatment threshold vary with the likelihood of type 1 and 2 errors. The isoprofit lines have lower values when the probability of type 1 and type 2 error increased. The relationship between expected profit and these probabilities is negative on average but not in a strict sense. For instance, in Table 3, we see that the expected profit is at a maximum when probabilities of type 1 and type 2 errors are either 0 and 0.5 or 0.1 and 0.4 respectively. Under these conditions, the expected profit is \$785.23 per hectare which is \$0.05 greater than when UAV is 100% accurate. This marginal gain in profit is achieved by reducing yield loss. The gain in profit is also associated with change in treatment decision. Table 5 shows average number of treatments $E(I_s^u)\ \forall\ s$, given the probabilities of type 1 and 2 error. When remote sensing is 100% accurate, profit is maximized by always treating in the third week $s = 3$ at threshold of 45 plants. On the other hand, if UAVs never give false negative information but generate false positives with 0.5 probability, then the optimal strategy is to treat at a threshold of 75 plants 2% and 98% of the times during second and third week respectively. When false positive outcomes are generated 50% of the times, it is impossible to dissociate true case of infestation from the false ones. As a result, treating in 2^{nd} week, even if just 2% of the times, before treating in the 3^{rd} week curbs aphid pressure sufficiently. In this case, spreading the treatment over multiple periods here therefore gives the same results as extra treatments but at a lower cost.

The unmanned aerial systems are expected to become cheaper in near future ([67],[88],[17],[19]). Figure 5 demonstrates how the cost of monitoring by UAVs will affect their profitability in comparison to manual scouting. We fix the cost of manual scouting C_m at \$9.88 ha^{-1} and express the cost of remote sensing C_u as its fraction. Consequently, $E(\pi_m^*)$ is also fixed at \$785.27 ha^{-1} while $E(\pi_u^*)$ changes with C_u. The expected profit declines linearly with increase in cost of monitoring. It is because the cost of monitoring is independent of economic threshold ET_k. Therefore, any change in it only causes parallel shifts in iso-profit lines and subsequently the optimal expected profit; it does not alter optimal threshold ET_k and treatment decision $I_s^k\ \forall\ k, s$. With our current assumption of $C_u = C_m$, $E(\pi_u^*) \approx E(\pi_m^*)$. If the operating cost of UAVs became negligible (≈ 0), farmers expected profit would rise to \$840.1 ha^{-1} which is 1.07 times more than the optimal profit from manual scouting given its cost C_m. Pederson et al. (2006, [67]) estimated UAV based weed scouting to be 80% as costly as conventional scouting (€19.4 ha^{-1}). If this relationship holds for soybean aphids as well, then $E(\pi_u^*)$ will be \$796.02 ha^{-1}. This amounts to 1.014 times $E(\pi_m^*)$ (refer to the red dotted line in figure 5).

7 Conclusion

Soybean farmers have significantly increased their usage of neonicotinoid and foliar insecticides to control soybean aphid infestation. But in the recent years, such treatments are under dispute not only because of the growing resistance in soybean aphids but also due to their harmful effects on pollinators. That is why soybean farmers have been pressured to practice IPM. But many IPM practices, especially manual scouting, are extremely arduous and time consuming, thereby lowering the chances of farmers' adopting them. Since the advancement in remote sensing technology, researchers are exploring UAVs as an alternative for scouting pests including soybean aphids. In this paper, we explore how precise and cheap UAVs have to be to work as a viable scouting option for farmers.

We develop a plant-level bioeconomic model of soybean aphid infestation and control in a field. We analyze alternative scouting techniques which include the traditional manual scouting as well as UAV based surveillance. Our results can be summarized as follow: (i) When farmers treat optimally and on time, their expected profit is approximately \$785 per hectare for both scouting technologies. Yet, UAVs, on average, have greater downside risk than when scouting manually, particularly for farmers who prefer early precautionary treatments. UAVs are higher at risk of detecting false positives which can make farmers perform unnecessary treatments. Conversely, delaying the spray of insecticides may eventually damage the crops irreversibly, irrespective of the scouting method adopted. (ii) Currently, remote sensing technologies can diagnose an infestation level of 250 aphids per plant with almost 80% accuracy. We find that with a tally threshold of 250 aphids per plant, there is not much value added in making UAVs more precise. In fact, perfecting their accuracy at the tally threshold of 250 aphids per plant, can only add 1% to farmers' expected profitability than when they leave the infestation in their fields unchecked. (iii) But, if the cost of operating UAVs was lessened, farmers will readily adopt it as a scouting technique. A 20% reduction in its operating cost increases its expected profitability by 1.4%. Additionally, aerial surveillance of the field helps in identifying the hot spots and consequently treating only those areas. Selective treatments will not only be more cost-effective for farmers but also environmentally beneficial.

This paper is one of the early efforts to understand the economic viability of remote sensing technology in pest management and unfolds a plethora of research possibilities. To adequately model the benefits of aerial surveillance, we need to look at the scope of targeted treatments as discussed in the previous paragraph. Furthermore, the weakness of manual scouting (i.e., relatively small sample sizes) is a strength of UAV scouting and the weakness of UAV scouting (i.e., relatively large measurement error) is a strength of manual scouting. This brings us to another interesting question: Can UAV scouting profitability complement manual scouting rather than substitute for it?

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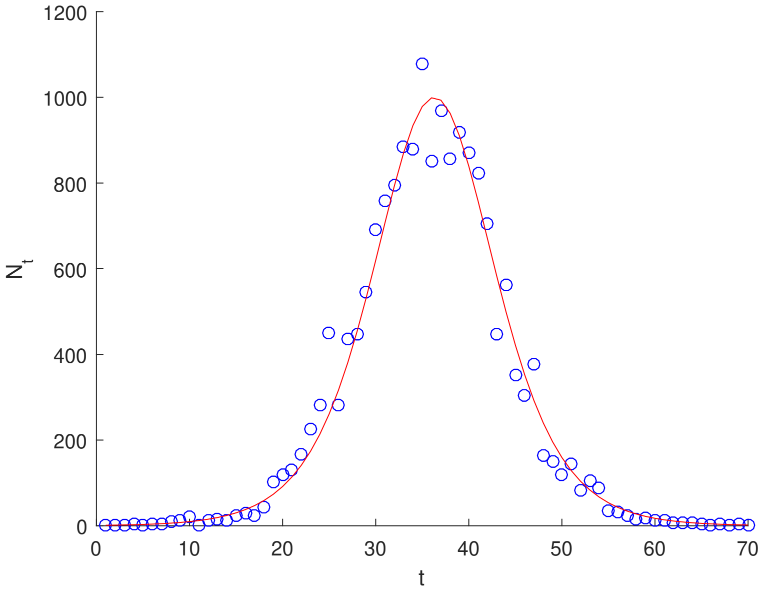


Figure 1: Population N_t as a function of t when $N_{max} \sim N(1000, 100)$, $T_{max} \sim N(36.29, 0.42)$ and $b \sim N(0.228, 0.23)$

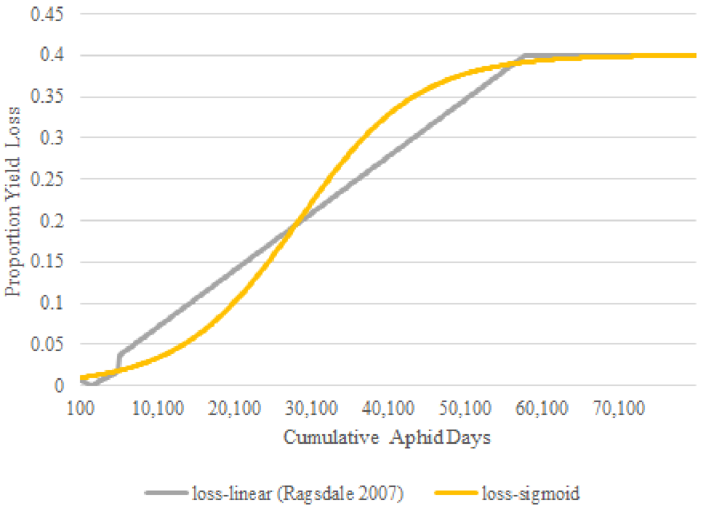
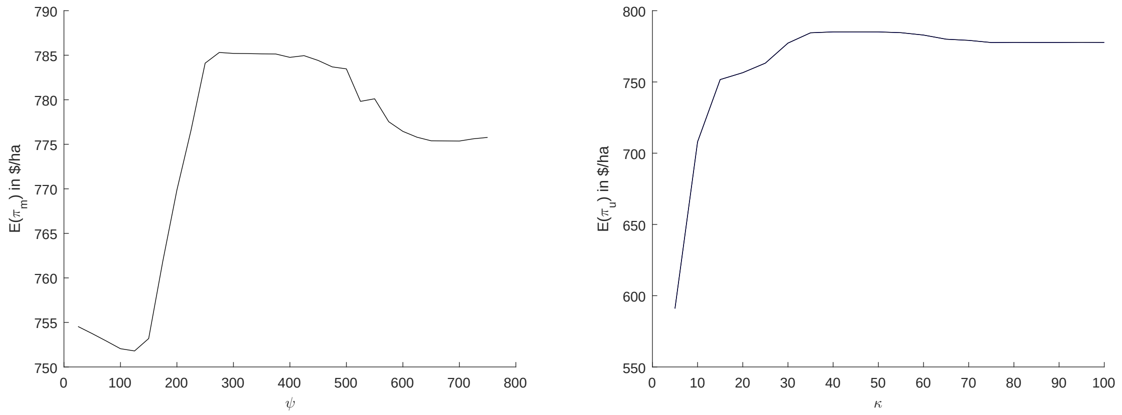


Figure 2: Fitted sigmoidal proportional yield loss function versus linear loss function



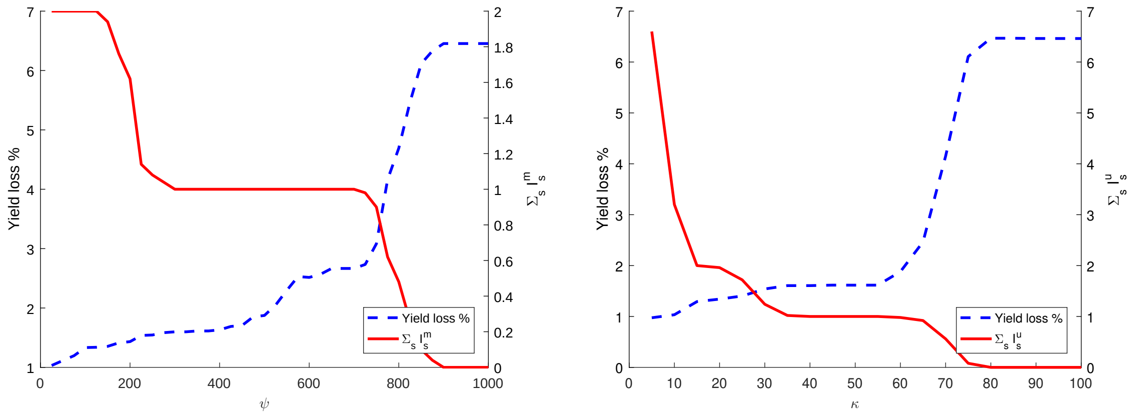
s	1	2	3	4	5	6	7
$E(I_s^m)$	0	0	0.06	0.94	0	0	0

(a) Manual Scouting

s	1	2	3	4	5	6	7
$E(I_s^u)$	0	0	0	1	0	0	0

(b) Remote Sensing

Figure 3: Expected profit in \$ per hectare using (a) Manual scouting and (b) Remote sensing given ϕ equals 250 aphids per plant



(a) Manual scouting

(b) Remote sensing

Figure 4: Percentage yield loss and total number of treatments as a function of economic thresholds (a) ψ for manual scouting and (b) κ for remote sensing given $\phi = 250$

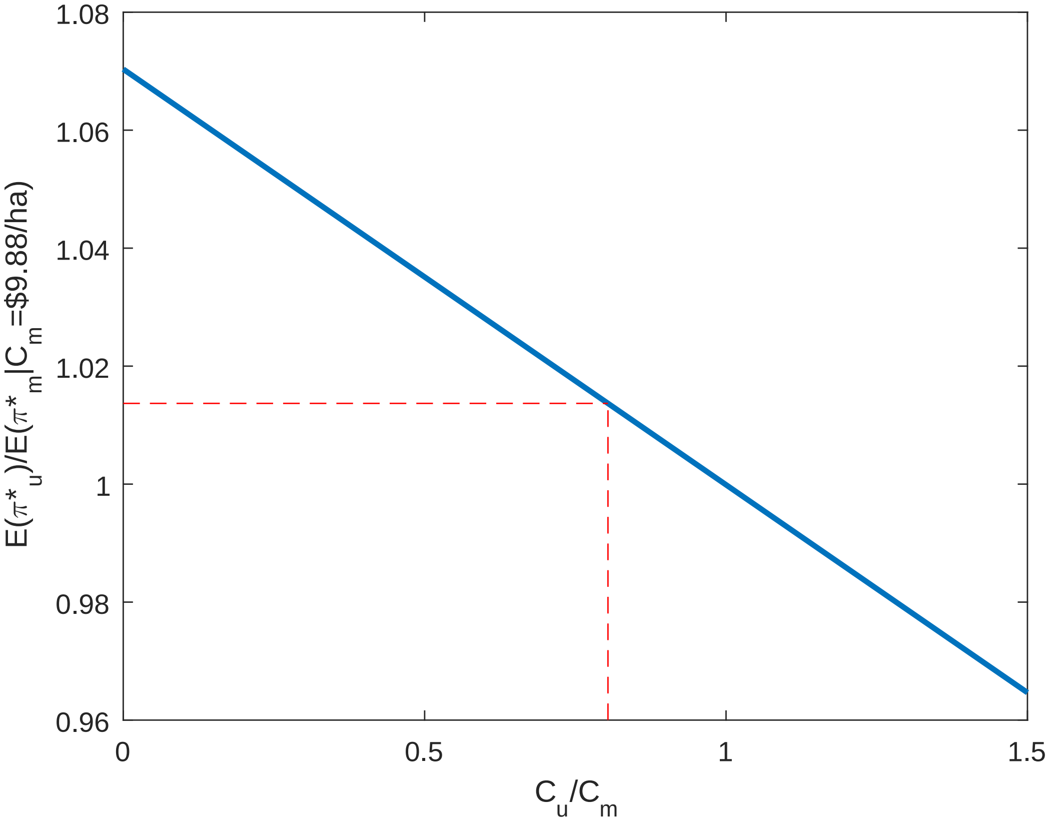
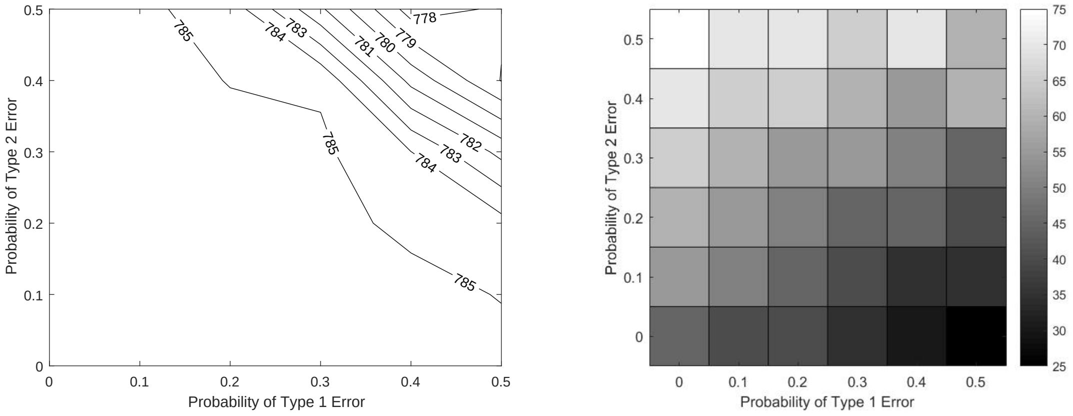


Figure 5: Relationship between the ratios of expected optimal profits $E(\pi_u^*)/E(\pi_m^*)$ and monitoring costs C_u/C_m when C_m is fixed at \$9.88 ha^{-1}.



(a)

(b)

Figure 6: (a) Isoprofit lines and (b) Optimal ET for UAV based scouting as a function of Probability of type 1 and 2 errors.

Parameter	Symbol	Value/Functional form	Reference
Maximum days	t_{max}	50	[64]
Rows & columns in field	M_1 & M_2	10	Assumption
Price of soybean	P	\$220.46/ton	[70]
Potential Output	Y_P	4.04 ton/ha	[70]
Cost of monitoring	C^k	\$9.88/ha $\forall\ k = m, u$	[42]
Treatment Cost	C_I	\$35.82/ha	[42]
Yield loss function parameters	α_1	4	[70]
	α_2	10	Assumption
	α_3	0.00013	"
	α_4	6	"
Efficacy of Insecticide	θ	0.99	[89]
Plants sampled during manual scouting		20	[64]
Mean of aphid count at t=0	m	5	Assumption
Variance of aphid count at t=0	ν	$9.152 \times m^{1.543}$	[34]
Birth and Death rate parameters	n_{max}	1,000±100	[47]
	T_{max}	36.29±0.42	"
	b	0.228±0.23	"
Radius of neighborhood of alates		0.5km	[90]
Radius of neighborhood of aptera		10 inches	Assumption
Probability that alate migrates at time t	E_t^{iw}	0.04 $\forall\ i$	[16]
Tally threshold of UAV	ϕ	250 aphids per plant	[57]

Table 2: Parameters and their values

Appendices

Appendix 1

To estimate $\{\mu, \sigma\}$, we use the mean m and variance ν of N_0. $\{\mu, \sigma\}$ are related to $\{m, \nu\}$ in the following way [53]:

$$\mu = log\left(\frac{m^2}{\sqrt{\nu + m^2}}\right) \tag{16a}$$

$$\sigma = \sqrt{log(\frac{\nu}{m^2+1})} \tag{16b}$$

In order to calculate ν, Taylor's power law is used. Taylor's power law relates the variance of the number of individuals of a species per unit area of habitat to the corresponding mean by a power law relationship. Hodgson et al. (2004, [34]) estimate the parameters of Taylor's power law equation for soybean aphid. Using their estimates, we know that

$$\nu = 9.15 \times m^{1.543}. \tag{17}$$

We estimate $\{\mu, \sigma\}$ using equations (16a),(16b) and (17).Note that for $\sigma > 0$, $m^2 + 1 > 9.5m^{1.5}$ using

(16a) , (16b) and Taylor's law.

Appendix 2

		Probability of Type 2 Error						
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**Average**
Probability of Type 1 Error	**0**	785.18	785.18	785.18	785.18	785.18	785.23	785.19
	0.1	785.18	785.18	785.18	785.18	785.23	785.19	785.19
	0.2	785.18	785.18	785.18	785.18	784.98	784.59	785.05
	0.3	785.18	785.18	785.18	785.18	784.85	781.18	784.46
	0.4	785.18	785.18	784.87	784.01	780.71	777.55	782.92
	0.5	785.18	784.97	784.35	781.71	777.96	778.15	782.05
	Average	785.18	785.15	784.99	784.41	783.15	781.98	784.14

Table 3: $E(\pi_u^*)$ as a function of probability of Type 1 and 2 Errors in \$ per hectare

		Probability of Type 2 Error					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Probability of Type 1 Error	**0**	0.016	0.016	0.016	0.016	0.016	0.016
	0.1	0.016	0.016	0.016	0.016	0.016	0.016
	0.2	0.016	0.016	0.016	0.016	0.016	0.017
	0.3	0.016	0.016	0.016	0.016	0.016	0.021
	0.4	0.016	0.016	0.016	0.017	0.022	0.064
	0.5	0.016	0.016	0.017	0.021	0.064	0.062

Table 4: % Yield loss as a function of probability of type 1 and 2 error

		Probability of Type 2 Error					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
Probability of Type 1 Error	**0**	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0.02,0.98,0,0,0]
	0.1	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0.02,0.98,0,0,0]	[0,0,0.04,0.96,0,0,0]
	0.2	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0.02,0.98,0,0,0]	[0,0,0.98,0.02,0,0,0]	[0,0,0.04,0.9,0.06,0,0]
	0.3	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0.02,0.98,0,0,0]	[0,0,0.02,0.94,0.04,0,0]	[0,0,0.6,0.38,0.02,0]
	0.4	[0,0,0,1,0,0,0]	[0,0,0,1,0,0,0]	[0,0,0,0.98,0.02,0,0]	[0,0,0.02,0.86,0.12,0,0]	[0,0,0.04,0.62,0.26,0.06,0]	[0,0,0,0.02,0,0,0]
	0.5	[0,0,0,1,0,0,0]	[0,0,0,0.98,0.02,0,0]	[0,0,0,0.92,0.08,0,0]	[0,0,0.02,0.64,0.3,0.02,0]	[0,0,0,0.02,0,0,0]	[0.02,0,0.02,0.02,0,0,0]

Table 5: Likelihood of treatment as a function of probability of type 1 and 2 errors in $ per hectare.

Each entry in the table is of the form $[E(I_1^u), ..., E(I_7^u)]$