Can remote sensing improve the profitability and reduce the risk of integrated pest management for soybean aphid control?

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Selected Paper
AAEA Annual Meeting
Chicago, IL, July 30-August 1, 2017

Acknowledgements

The authors are grateful for the financial support provided for this research by the University of Minnesota's MnDRIVE Transdisciplinary Research initiative and the Minnesota Agricultural Experiment Station project MIN-14-134.

Introduction

Processed soybean is the largest source of protein feed for animals and second largest source of vegetable oil in the world.[1] It is the second most planted field crop in the United States after corn, with 83.7 million acres devoted to its production in 2016.[2] Soybean Aphid Aphis Glycines Matsumura (Hemiptera: Aphididae) is an invasive pest to North America that was first detected in Wisconsin in 2000 [1] and has since spread throughout the North Central Region [15]. In 2013, 31% of soybean growers reported soybean aphid as the most important threat to soybean production which is the largest insect threat reported for the crop [9]. This insect is a native pest in China and the rest of Asia, where it is seen to cause a yield loss in excess of 50% if plants are colonized in the early vegetative growth stage (Wang et al., 1994) [19]. In Minnesota, soybean aphids have caused a reduction in plant height, pod numbers, seed size and quality, and yield (Ostlie, 2001) [13]. Soybean aphid is also a carrier of a number of plant viruses (Davis et al, 2005) [3].

Soybean aphid is known to reproduce rapidly under favorable circumstances and its multiplication is highly unpredictable. McCornack et al. (2004) [12] report that under optimal temperature, their population can double in 1.5d (Julian days) thus making an efficient estimation of soybean aphid density especially important. Due to high variability in its population dynamics, crop consultants now scout on average 36% more soybean acreage than before 2000.[3] The arrival of soybean aphid in North America has also magnified the use of foliar insecticides in the North Central Region which was almost negligible before 2000 in order to prevent economic damage.[4] In 2013, half of all soybean farmers used insecticide treated seed, while under one-quarter applied foliar insecticides. However, the neonicotinoid insecticides used to treat seed are active against the non-target pollinators as well as aphids. Thus, an accurate and rapid sampling method will not only cut down on labor and application cost but also prevent environmental damage by avoiding unnecessary insecticide application.

Currently, integrated pest management practices (IPM) recommend to begin weekly sampling for aphids as soon as they are first noted on soybeans. Sampling consists of counting aphids on 20-30 randomly sampled plants across the whole field and uses 250 aphids per plant as the Economic Threshold (ET) which if surpassed on 80% of the sampled plants should lead to the spray of insecticides in the whole field. When counting aphids on a plant, farmers need to focus on underside of the leaves, and not count cast skins or confuse potato leafhoppers for aphids. As the vegetative stage ends, aphids move down the plant towards pods, stems and leaves lower in the canopy, so farmers should look at both sides of the leaf, stems and pods throughout the canopy for aphids. These recommendations are both complex and time consuming and have hindered adoption rates of soybean aphid IPM practices [16]. Alternatively, farmers who only partially adopt these complex IPM sampling recommendations are likely to make measurement errors in terms of the aphid numbers.[5] Current estimates for the economic threshold do not account for the possibility of such measurement error. In this paper, we estimate ET while accounting for the error in measurement. These

[1] http://www.ers.usda.gov/topics/crops/soybeans-oil-crops.aspx

[2] http://www.usda.gov/nass/PUBS/TODAYRPT/acrg0616.pdf

[3] E.W. Hodgson, unpublished data

[4] USDA-NASS. 1998. Agricultural Chemical Usage: 1997 Field Crops Summary. Pub. No. Ag Ch 1(98). USDA-NASS-Econ. Res. Serv. (ERS), Washington, DC.

[5] According to Hurley and Mitchell (2014) [8], for the foliar applications that did take place, 68.5% were based on scouting making them consistent with the principles of IPM while 25.2% were prophylactic or calendar based treatments that are inconsistent with IPM principles. 6.3% of the farmers used both.

new estimates of optimal threshold which are adjusted for quality of sampling will give farmers more insight into when to treat and hence raise their profits. It will also increase the profitability in long run since a more accurate knowledge of when to treat means avoiding unnecessary treatments which in turn will prevent the development of insecticide resistant pests.

Remote sensing technologies, such as with unmanned aerial vehicles (UAVs), offer an alternative to labor intensive field based scouting. Since a close examination of the whole plant is more convenient with manual scouting than with UAVs, it is expected to be more accurate for sampling plants. However, UAVs make it practical to scout an entire field rather than a sample of plants. This more complete field coverage is expected to be less costly than traditional manual scouting. A more complete field coverage also makes it practical to detect infestation in specific parts of the field thus making it possible for farmers to treat only infested areas rather than the entire field. By limiting treatments to only infested parts of the field, farmers will apply less insecticide which will reduce treatment costs and avoid unnecessary exposure to insecticide. While the technology is 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?

The objective of this research is to determine how measurement error, scouting costs, and treatment costs affect the profitability and risk of IPM for the soybean aphid. This objective is accomplished using a dynamic bioeconomic simulation model. The model is used to estimate the sensitivity of the optimal ET, expected profit, the standard deviation of profit, and frequency of insecticide applications to measurement error, scouting costs and insecticide application costs. The contribution of the research is two-fold. First, it provides a bioeconomic framework for assessing how the precision of scouting affects the profitability and risk of IPM practices. Second, its analysis identifies the facets of remote sensing technologies that are most important to develop if the goal is to use these technologies to improve the profitability and adoption on IPM for soybean aphid management.

Literature Review

Ragsdale et al. (2007) [17] estimated an economic threshold (ET) which is currently the primary recommendation for soybean aphid IPM in United States. The paper recommends this threshold based on the theory of economic injury level (EIL). In integrated pest management, the 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 [14]. The recommended ET is 250 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. Thus, when the soybean aphid population exceeds 250 per plant, soybean should be treated with foliar insecticide. If left untreated, soybean aphid herbivory can cause yield loss exceeding 40%.

IPM for soybean aphid uses repeated sampling throughout most of the growing season. It is recommended to start sampling for soybean aphid in the late vegetative stage and to continue through R5.[6] However, most of the papers focused on estimating ET or EIL's for soybean aphid do not take into account the dynamic nature of sampling and pesticide applications. This can lead to overuse of pesticides which can cause pests to develop resistance. Regev et al. (1974) [7] explain the effect of increasing pest resistance to insecticides on optimal control of a pest in a single pest-single crop pest management model. He shows that when making treatment decisions, farmers only take into consideration the monetary cost of insecticides and do not account for the increased user costs. These 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.

Cantangui et al. (2006) [2] 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 use field data from 2003 and 2004 for their study, which suggested that on an average the maximum possible yield loss due to soybean aphids is 75% at V5 and 48% at R2. This leveling off of the yield loss accompanied with increasing soybean aphid numbers is the reason for using 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. Their study shows that for soybean aphid infestation starting at V5, the stage specific EILs are 3.5, 74.6 and 212.1 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 not only prevents access of natural enemies to aphids, but also prevents any aphid movement from or to the host plant.[7] 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) [6] 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) [5] 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.

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)[20] and Hallett et al.(2014) [4] exploit this predator-prey relationship in modelling managerial choices. Zhang and Swinton (2009) develop an intra-seasonal dynamic

[6] http://www.extension.umn.edu/agriculture/soybean/pest/docs/soybean-aphid-scouting.pdf

[7] 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)

bio-economic 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. Hallett et al. (2014) takes this into consideration while estimating a dynamic action threshold by combining the impact of various natural enemies with exponential growth model.

Methodology

An important facet of IPM is to apply pesticides only when the expected damage from a pest infestation exceeds the cost of application. The literature about how best to make such a determination is extensive. For soybean aphid, as already discussed before, the current IPM practices requires a rigorous investigation of the whole field. Farmers should at least have 20-30 whole plant inspected per field for both nymph and adult aphid, and watch out for any aphid look-a-likes to avoid overestimating infestation. Such a protocol can provide farmers with precise information on the level of infestation in their fields, but they are also time-consuming and therefore lose precision if fewer plants are sampled or are not examined in as great detail as recommended. In order to avoid the inefficiency induced by the complexity of these processes, Hodgson et al. (2007) [5] proposed speed scouting which is less time consuming and costly. The use of UAVs promises to further reduce the time and cost of determining the level of infestation in a field, with some sacrifice in precision also likely. Therefore, we develop a model that focuses on estimating the optimal threshold for treating soybean aphid when the cost of monitoring, costs of insecticide applications, and precision of monitoring vary across alternative IPM protocols.

Let Y^P be the potential output of soybean per acre of field, and P be the market price of the crop. $L(x_1, I_1, .., I_T)$ represents the percentage yield loss attributable to aphid, which depends on initial aphid infestation (x_1) and when and how often a farmer chooses to treat soybean with a foliar insecticide. This decision to treat at time t is represented by I_t. It equals 1(0) when treatment should(should not) be done, i.e. when the observed aphid density (x_t^0) is greater (less) than an economic threshold (ET_t). In a growing season, soybean is most susceptible to damage by soybean aphids during R1 to R5 (Jameson-Jones, 2005).[8] Like Zhang and Swinton (2009) [20], we assume one spray per reproductive stage and that the predicted yield reached at R5 is carried on through to harvest. Hence, insecticide spray is meaningful only during R1-R4. Therefore, 't' which is the time of monitoring and spraying if needed, takes on values 1 to 4 to represent reproductive stages R1- R4 respectively. The time line for decision making is further detailed in Table 1.[9]

Two types of costs are involved in pest management. First is the cost of monitoring or sampling pests (C) to get estimates for the level of infestation. This cost is incurred each time the field is monitored. Hence, in our model, the total cost of monitoring is $4C$. The other cost is that of treatment which includes expenditure on insecticide and its application. This expense depends on number of times farmers decide to spray ($\sum_{t=1}^{4} I_t$). In this model, we assume that farmers apply insecticide to the whole field rather than just a portion whenever

[8] Jameson-Jones, S., 2005. Insect and Insect Management: Soybean Aphid. University of Minnesota Extension. http://www.soybeans.umn.edu/crop/insects/aphid/aphid.htm

[9] We assume no gap between the time of scouting and the time when treatment is done. In reality, however, these two actions are not simultaneous because of the time taken to prepare for treatment. This fact can be easily incorporated in the model by allowing population density to increase during this time gap. But, we ignore this detail here to keep the model simple.

t	Reproductive Stage	Action taken
1	R1(beginning flowering)	Scout/Spray
2	R2(full flowering)	Scout/Spray
3	R3(beginning pod)	Scout/Spray
4	R4(full pod)	Scout/Spray
-	R5(beginning seed)	Harvest

Table 1: Timeline

they decide to spray. As a result, total cost of treatment is $C_I \sum_{t=1}^{4} I_t$. This cost is expected to be positively related with ET assuming other factors remain unchanged. The higher the cost of treatment, the lower is the profit if threshold is low because a low ET would result in more frequent sprays. Therefore, the farmer will be willing to delay treatment and tolerate a higher threshold.

We assume that the farmer chooses ET to maximize her expected utility given the population dynamics of soybean aphid and the yield loss function. If they are risk neutral, then maximizing expected utility is equivalent to maximizing expected profit (π). Our optimization problem can be formally stated as:

$$\max_{ET_t \geq 0} E[U(\pi)]$$

$$s.t. \ \ \pi = PY^p(1 - L(x_1, I_1, .., I_T)) - T \times C - C_I(\sum_{t=1}^{T} I_t)$$

$$I_t = \begin{cases} 0 & x_t^0 < ET_t \\ 1 & x_t^0 \geq ET_t \end{cases} \tag{1}$$

$$x_t = g(x_1, r_1, .., r_{t-1}, I_1, I_2, .., I_{t-1}, \theta) \tag{2}$$

Equation 2 gives the population dynamics of soybean aphid. At any point in time t, the true aphid density x_t depends on an underlying initial aphid population (x_1), their natural growth rates in periods leading up to t ($r_1, .., r_{t-1}$), the efficacy of insecticide (θ) and number of treatments done before time t. The underlying or true aphid density is the central variable in pest management. While scouting, farmers try to estimate this variable as accurately as possible so that they can optimally decide whether to treat or not. However, because of error in sampling, what is actually observed (x_t^0) is different from the true aphid density (x_t). We assume a multiplicative relation between the observed and actual aphid density of the form:

$$x_t^0 = x_t e^{\eta_t} \quad \forall t \tag{3}$$

where e^{η_t} is the measurement error when scouting at time t. This error depends on the underlying sampling technique. As per our hypothesis, the higher the precision in sampling, the lower is e^{η_t}. We assume the measurement error to be log normally distributed s.t.

$$\eta_t | x_t \sim N(\mu_\eta, \sigma_\eta^2). \tag{4}$$

The distribution of error is assumed to be independent of time because it is mostly dependent on sampling technique which does not change over the growing season.

At any time t, x_t depends positively on the initial infestation in the field (x_1). The degree of initial infestation is a function of both external and internal factors such as humidity, temperature and the time when farmer starts scouting. Hence, we assume that the initial density (x_1) is exogenous and follows a normal distribution with mean μ_{x_1} and variance $\sigma^2_{x_1}$. The parameters along with their values are explained in table 2.

A negative exponential curve is used for expressing the relation between soybean aphid and percentage yield loss.[10] It is a well established fact that there is a maximum possible reduction in yield regardless of soybean aphid numbers during a growing season. Hence, this functional form captures the diminishing yield loss with increasing aphid density. The parameter α_1 in the percentage yield loss function (as shown in Table 2) is the upper asymptote and $e^{-\beta_1}$ is the ratio between any two consecutive increments in yield loss due to two consecutive increments in soybean aphid concentration units (Spillman, 1924) [18]. Here, we use Cumulative aphid days (CAD) as a unit of soybean aphid concentration.

In our model, although we allow for multiple treatments during a growing season and therefore use dynamic optimization for optimal decision making, we do not allow ET to vary with time.[11,12] Hence, the decision to treat, whenever and however many times it is made throughout the growing season, is always based on the same threshold level. Therefore,

$$ET_t = ET \quad \forall t. \tag{5}$$

This is done to simplify the complexity of pest management practices and make their adoption more likely.

Results

In this paper, we use a dynamic bioeconomic simulation model in order to estimate the optimal threshold. Our estimates depend on parameters $\mu_{x_1}, \sigma_{x_1}, \mu_\eta$ and σ_η for which we do not have good information. As a result, we start out by assuming them to be 100, 50, 1 and 0.25 respectively. We estimate the optimal ET to be 241 aphids/plant at which the expected profit and standard deviation of profits are \$796/ha and \$12.86/ha respectively. The probability of treatment is approximately 91% in t=2 which is the highest across all the time periods. Figure 1 summarises our results. It also shows how prophylactic treatment in all four time periods impacts profit; if the insecticides are sprayed at very low level of infestation, farmers can lose \$60/ha.

Our results are based on the assumption that farmers are risk neutral. We now discuss how a farmer's risk tolerance affects the optimal ET using the risk efficiency frontier plotted in Figure 2. This frontier illustrates a farmer's trade off between expected profit and the variability of profit as the ET ranges from 0 to 400 aphids/plant. The dashed line represents the frontier of this trade off. Any point off the frontier would mean a suboptimal profit for the

[10] Zilberman et al. (1986) [11] 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 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.

[11] Regev et al. (1974) argued that ET should increase during the course of the growing season to take into account the the effect of increasing pest resistance

[12] Other papers to have used dynamic framework for making optimal pest management decisions are Zhang

amount of risk taken. Given the risk frontier, we see that a highly risk averse farmer would prefer to operate at point A and thus treat her field at a threshold of 10 aphids/plant in order to avoid fluctuations in expected profit. On the other hand, a less risk averse farmer would be ready to tolerate higher risks to get more profit and thus operate at point B where she will treat her field at a higher threshold of 241 aphids/plant.

To assess the effect of uncertainty associated with the parameter values and assumptions, we perform sensitivity analysis on selected parameters. Figure 3 shows the impact of changes in monitoring precision and treatment costs on the optimal ET and expected profits. We expect the average profit to be increasing in precision of monitoring and decreasing in cost of treatment. Our sensitivity analysis results are in line with this prediction as can be seen in Figure 3 (iii) and (iv). We also expect that the variance of profit decreases with an increase in the accuracy of the monitoring technology. This is intuitive because a more precise sampling technique means better prediction of when to treat. With more accurate monitoring, farmers can tolerate higher threshold for treatment and avoid any unnecessary treatment cost which they would have incurred had there been large measurement error associated with sampling. Hence, while the variance of expected profit decreases in monitoring precision, ET increases with an increase in the accuracy of sampling technique as shown in Figure 3 (v) and (i) respectively. We also find that ET is positively related to the cost of treatment as depicted by Figure 3 (ii). A higher treatment cost implies increased marginal cost at all levels of infestation. We know that at a utility maximizing ET, marginal benefit from treatment equals marginal cost of treatment. Therefore, at the new optimal threshold, this increase in marginal cost should be met by an equal increase in marginal benefit. Keeping all else constant, this increase in marginal benefit comes from controlling damage due to greater infestation. Hence, the new ET is greater than the old one. As a result of spraying at a higher threshold which is not accompanied by any change in precision level, the variability in profits is expected to increase in cost of treatment. Figure 3 (vi) supports this claim.

The sensitivity analysis of expected profit with respect to monitoring precision and cost of treatment shows that it is more sensitive to the latter parameter. An increase in expected profit following a marginal rise in monitoring precision as shown in Figure 3 (iii) is much smaller than the rise in expected profit due to a marginal fall in cost of treatment as shown in Figure 3 (iv). Thus, although scouting using UAV may be less precise than manual scouting, it can still be a more profitable mode of sampling because of its ability to significantly reduce total cost of treatment by allowing detection and thus limiting treatment to only patches of infestation in the field rather than treating the entire field as in the case of manual scouting.

We also analyze how the change in level of precision and cost of treatment individually impacts the probability of treatment in different stages of growth. Figure 4 summarizes these results. As we already know, treatment happens more often in R2 (91%) than any other stages of growth. However, as monitoring becomes more inaccurate, the likelihood of treatment spreads out among all the growth stages. Therefore, an increase in the level of imprecision causes the probability of treatment to decrease in R2 and increase in rest of growth stages. The probability of treatment gets more concentrated in R2 with an increase in cost of monitoring. This is shown in Figure 4 (ii). When the cost of treatment is below \$ 18/ha, treatment always happens in R1. In this range of costs, the fields are sprayed at least twice on average. This fact is ascertained by the sum of probability of treatment across all time periods being greater than 2 at all levels of cost of treatment below \$18/ha. However, as this cost becomes greater than \$18/ha, treatment in a given season happens less than twice.

and Swinton (2009) and Hallett et al. (2014).

In this range of costs, the probability of treatment stagnates to an average of 91% in R2 and is less than 20% for rest of the reproductive stages considered here. This points out to another important question about whether high costs of treatment encourages prophylactic treatment in R2 and make monitoring unnecessary.

Conclusion

There are many factors which affect the profitability and risk of IPM for soybean aphid, such as measurement error in sampling, scouting costs, and treatment costs. Out of all these factors, IPM focuses the most on precision in sampling for achieving optimal pest management. It sketches out a lengthy sampling technique in order to estimate aphid density which guarantees high precision in predicting the level of infestation. However, the process is so complex and time consuming that it increases the likelihood of farmers not following it thoroughly and ironically ending up with inaccurate information about the level of infestation in their fields. This will reduce farmers' profits as they will not be able to correctly predict when their crop needs treatment. Hodgson et al. (2007) [5] proposes speed scouting as an alternative sampling technique. Their process is less time consuming and complex, but, it consistently recommends insecticide use before ET is reached using whole plant count. In this paper, we try to find out the role of these different factors in improving profitability and risk management for soybean aphid. We use dynamic bioeconomic simulation model to estimate the sensitivity of expected profit, optimal ET, variance of profit, and frequency of insecticide application to measurement error, scouting costs and treatment costs.

Given our assumptions, we estimate an optimal ET of 241 aphids/plant at which the expected profit and standard deviation of profits are $796/ha and $12.86/ha respectively. With an ET of 241 aphids per plant, nine years out of ten it is optimal to treat the field after the second of the four scoutings. Only once in six years the first, third or fourth scouting would also result in treatment during the cropping season. With such a predictable scouting outcome, it would not be surprising to see farmers using a once a year prophylactic application based on the crop's growth stage. We also find that optimal ET varies with the risk tolerance of farmers. A highly risk averse farmer chooses very low threshold for treatment in order to avoid fluctuations in her earning caused by unexpected levels of infestation. On the other hand, a less risk averse farmer would be ready to take risk and treat her field at high threshold in expectation of making larger profits.

Our findings show that expected profit is increasing in the precision of monitoring and decreasing in the cost of treatment. The variance of profit also decreases with improved precision of monitoring technology. We also find that the optimal threshold for treatment is increasing in accuracy of the monitoring technology. This is intuitive because a higher precision allows farmers to predict when economic damage can occur more accurately and thus tolerate higher ET so as to avoid unnecessary treatment cost which they could have incurred had the sampling technique been highly imprecise in detecting level of infestation. The ET is also increasing in the cost of treatment. A higher treatment cost increases the marginal cost for farmers at all levels of infestation. This should be matched by a higher marginal benefit in order to achieve optimal profit, since at optimal profit marginal cost always equals marginal benefit. Keeping all else constant, this increase in marginal benefit comes from controlling more damage due to greater infestation. This means that at higher cost of treatment, spraying should be done at higher threshold of infestation. Therefore, ET increases in cost of treatment.

Although profit is sensitive to both the level of monitoring precision and cost of treatment, we find that it is much more responsive to changes in the latter in comparison to the former variable. Hence, if a pest management protocol lowers the total cost of treatment by a large amount, it can be more profitable to the farmers even if it involves sacrificing the level of precision to some extent. The use of UAVs for monitoring offers such an option. Although, manual scouting is likely to be more accurate in sampling plants than using UAVs, the latter makes it practical to scout an entire field rather than just a sample of plants. As a result, UAVs can detect patches of infestation and allow spraying insecticides in only those infested areas rather than treating the whole field. Hence, despite expecting them to be less precise than manual scouting, we speculate that UAVs may turn out to be more profitable than traditional scouting because they can lower the cost of treatment extensively by limiting treatment to only infested patches.

One of the drawbacks of this paper include assumptions about parameters. We assume that the aphid density and measurement error associated with sampling are normally distributed with some mean and standard deviation. However, since this is still an incipient research, these assumptions are not yet corroborated by existing research. This leaves a scope for improvement where in future the model can be re-estimated based on more well researched parameters.

This paper points out another useful direction for research which is developing pest management models that include the possibility of treating only infested patches rather than the whole field. The ET of 250 aphids/plant is estimated based on an aphid density averaged across the entire field. IPM recommends treating the whole field if the estimated aphid density surpasses this threshold. However, with advancement in monitoring technology (such as use of UAVs), it is possible to detect infestation in specific parts of the field and to treat only those infested areas. This possibility brings forth a whole new puzzle of how the threshold for treatment will change with the amount of area infested along with the intensity of infestation. But, this question must be preceded by whether UAVs are at least as suitable technology for monitoring as manual scouting since they are expected to have lower precision than manual scouting. Hence, we first need to answer how precise the remote scouting information should be before it becomes at least as profitable to use than conventional scouting.

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Parameter	Symbol	Value/Functional form	Source
Price of soybean	P	\$220.46/ton	Ragsdale et al.,2007 [17]
Potential Output	Y_P	4.04 ton/ha	Ragsdale et al., 2007 [17]
Cost of monitoring	C	\$9.88/ha	Johnson et al., 2009 [10]
Treatment Cost	C_I	\$35.82/ha	Johnson et al., 2009 [10]
Yield loss function	$L(x_1, I_1, .., I_T)$	$L(x_1, I_1, .., I_T) = \alpha_1 \{1 - e^{-\beta_1 \sum_{i=1}^{T} \frac{(x_i + x_{i-1}) t_i}{2}}\}$	-
Efficacy of Insecticide	θ	0.99	Zhang & Swinton, 2009 [20]
Aphid growth rate at time t	r_t	5.29, 5.15, 2.35,1.13	
Average number of Aphid per plant at time t	x_t	$x_t = \begin{cases} x_1, & t = 1 \\ x_1 \prod_{i=1}^{t-1} (1 + r_i)(1 - \theta I_{i-1}), & T \geq t > 1 \end{cases}$	-
Mean Aphid density at t=1	μ_{x_1}	100	Assumption
S.e of Aphid density at t=1	σ_{x_1}	50	Assumption
Mean of log of measurement error at t=1	μ_{x_1}	1	Assumption
S.e of log of measurement error	σ_{η_t}	0.25	Assumption

Table 2: Definition of parameters and their values

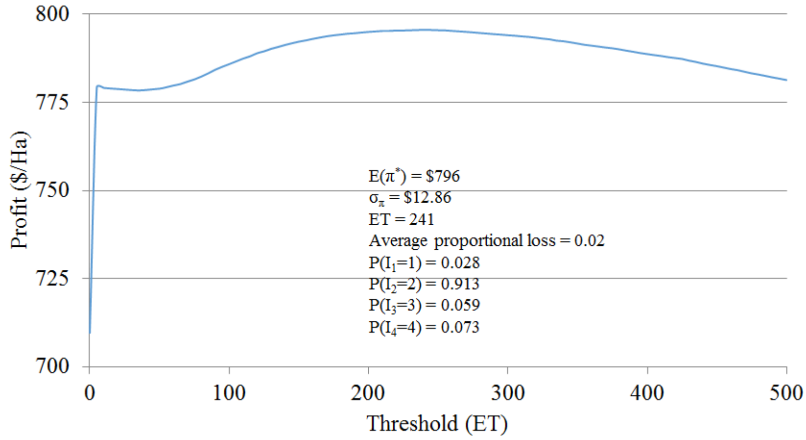


Figure 1: Expected profit by treatment threshold

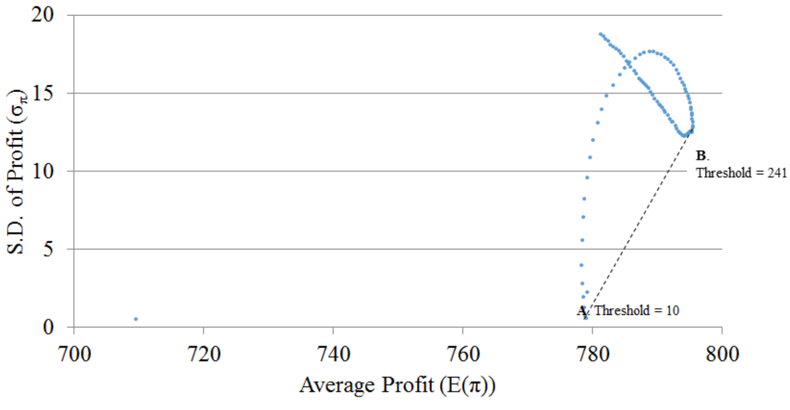


Figure 2: Risk Efficiency Frontier

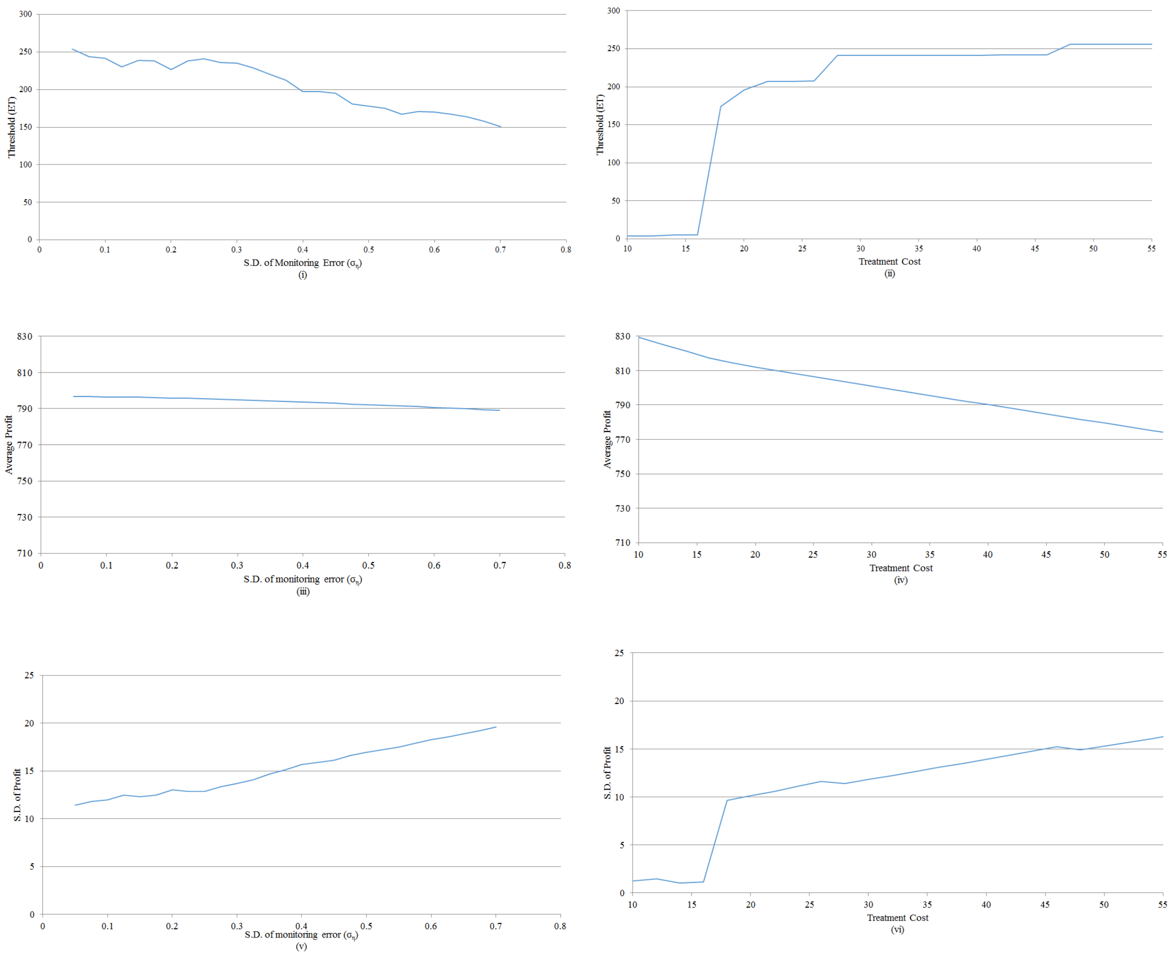
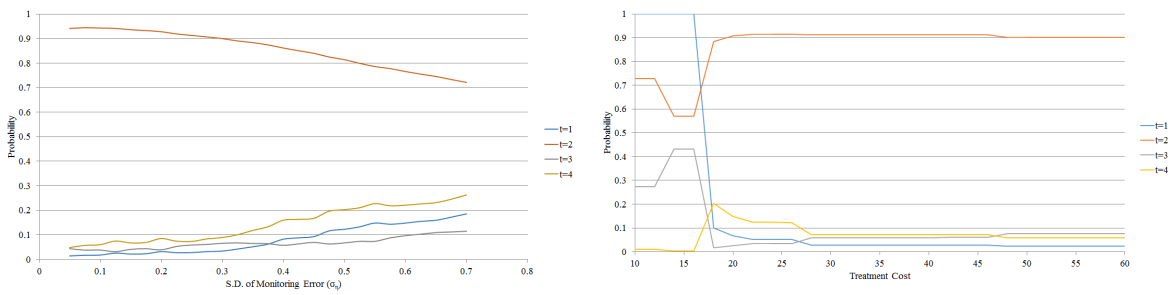


Figure 3: Sensitivity analysis with respect to monitoring precision and treatment cost



(i) (ii)

Figure 4: Sensitivity analysis of probability of treatment in different time periods with respect to monitoring precision and cost of treatment