Spatially Explicit Dynamically Optimal Provision of Ecosystem Services: An Application to Biological Control of Soybean Aphid[1]

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Abstract

Grass conservation plantings (CP) are regularly installed as filter strips to supply water quality benefits and provide wildlife habitat, but these CPs also provide other agroecosystem services, including pest control which may reduce the need for insecticide spraying. This research extends previous work (Zhang and Swinton, 2009), by developing a multi-year space-time optimization problem as a dynamic bioeconomic model. The suggested model is applied to the problem of controlling Soybean Aphids in Newton County, Indiana. The previous literature is expanded in four major ways: the objective function is formulated as the social planner's problem to reflect externalities, stochastic arrival of Soybean Aphids and appearance of natural enemies over space, spatially-explicit composition of the natural habitat network, and spatial heterogeneity of land cover properties. The empirical results show that natural enemies can provide suppression of Soybean Aphid and this reduces spraying frequencies. Installation of CPs increases the flow of ecosystems services across the landscape by providing habitat for beneficial natural enemies that prey upon the soybean aphid and other crop pests.

Key words: Space-Time Optimization, Ecosystem Services, Conservation Planting,
Soybean Aphid, Biocontrol

JEL Codes: Q57, C61

I. Introduction

Agricultural pests pose a persistent risk to crop yields and pest management can contribute significantly to costs of production. According to Pimentel et al. (2005), $13.5 billion in losses occur from crop pests annually and total annual pest control expenses are approximately $120 billion in the US. The most prevalent means of pest control in modern agriculture is the use of pesticides. However, pesticides remain a source of much debate about environmental pollution and food safety issues. An alternative method of pest control relies on natural enemies to control crop pests and requires farmers to provide habitat for these beneficial insects on their land. Two types of conservation plantings (CP) adjacent to crop fields that can provide habitat are considered in this study; low diversity filter strips containing cool season grasses (NRCS CP-21) and moderate diversity wildlife buffers containing both native warm season grasses and flowering plants (NRCS CP-33). As a natural or semi-natural habitat, CPs and agricultural landscapes are capable of providing many ecosystem services to society that are not exchanged in markets but have value to people. As noted by Zhang and Swinton (2009), natural enemies supply an important ecosystem service by suppressing pest population growth that has the potential to mitigate pest control costs and crop yield loss in agricultural ecosystems.

In the Midwestern US, an economically significant pest in soybean fields is Soybean Aphid (*Aphis glycines Matsumura*), which is an invasive exotic species that originated in Asia. In the US, this pest was first observed in Wisconsin in 2000 and has spread across the Midwestern US, the Great Plains states and southern Canada (Venette and Ragsdale, 2004). Soybean Aphid can adversely impact critical plant physiological processes associated with soybean yield and seed composition. Soybean Aphid feeding injury can reduce soybean photosynthetic rates by up to 50% in infested leaflets (Catangui et al., 2009). Feeding injury affects biological pathways for restoring chlorophyll to a low energy, light receptive stage (Macedo et al., 2003). Riedell et al. (2009) shows that Soybean Aphid are capable of reducing total nodule volume of a plant by 34%, nodule leghemoglobin content by 31%, plant nitrogen fixation rate by 80%, and shoot ureide No concentration by 20%. Considering its ability to reproduce quickly, controlling this pest remains crucial for soybean producers.

Smith and Pike (2002) indicated that Soybean Aphid is among the three key pest drivers of insecticide use in the North Central region. Soybean Aphid is a relatively new threat to soybean production and its equilibrium with the soybean agroecosystem has not yet been established. In some areas 30-50% of fields have been sprayed to control aphids. Using data from NASS (2007), Zhang and Swinton (2009) report that 42% of soybean acreage in Michigan and 30% in Minnesota were sprayed during the 2005 growing season, compared with less than 1% in the North Central region before Soybean Aphid arrived. Suppression of Soybean Aphid population by natural enemies (insects that prey upon Soybean Aphid) is also reported as an effective way of control this pest (Landis et al., 2004; Costamagna and Landis, 2006; Costamana et al., 2008). Total economic benefit of natural enemies is valued at $4.5 billion annually in the US (Losey and Vaughan, 2006) and Zhang and Swinton (2009) show that natural enemies can reduce spray frequencies effectively. Bianchi et al. (2006) and Gardiner et al. (2009) mention that natural enemy populations are supported by complex landscapes with a high proportion of natural or semi-natural vegetation. Koh et al. (2013)[2] found that habitat connectivity and spatial network are critical aspect of natural enemy abundance.

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[2] Koh et al. (2013) is one of results from the same project which this study is involved. As a part of it, the field data was collected and this paper uses the same data set with Koh et al. (2013).

Based on the previous results, conservation plantings (CP) adjacent to crop fields that can provide habitat for natural enemies could be an effective way to reduce spraying and to take advantage of agroecosystem services in crop fields. Because installing new CPs has a cost, finding economically optimal locations to install CPs could avoid costly spraying by using natural enemies to control crop pests. The economic threshold approach pioneered by Stern et al. (1959) and Pedigo et al. (1986) provides an approach to incorporate this problem into an economic decision model. By extending the Natural Enemy-adjusted Economic Threshold (NEET) suggested by Zhang and Swinton (2009), this paper develops a multi-year space-time optimization model to find CP locations in the landscape that efficiently suppress crop pests. The suggested model is a multi-year spatio-temporal extension of Zhang and Swinton's (2009) single farmer profit maximization model covering one soybean planting season without considering spillover benefits that result from natural enemy habitat on other farmers' land as well as protected natural areas. The model is applied to Soybean Aphid control in Newton County, Indiana. For parameter estimation, the field data collected by the Holland Landscape Ecology Laboratory (http://www.entm.purdue.edu/landscapeecology/) at Purdue University during the 2011 soybean season is used.

The remainder of the paper begins with reviewing Zhang and Swinton's (2009) model and extending it to cover the multi-year space-time optimization problem. Detailed model specifications and parameter estimations follows in the next section. After discussing initial values and simulation designs briefly, results, conclusion and future research steps are discussed.

II. Bioeconomic Models of Pest Management

2.1. Economic Threshold Model of Pest Control

Though natural science studies of population dynamics of Soybean Aphid and its natural enemies have grown since this pest first appeared in the U.S. in 2000, it has not been studied much by economists. Two exceptions are recent studies that examine optimal pest management of Soybean Aphid at the farm-level (Zhang and Swinton 2009; Zhang et al. 2010). Zhang and Swinton (2009) derived a natural enemy-adjusted economic threshold (NEET) for spraying insecticide and solved the individual farmer's profit maximization problem in a single year, determining the optimal timing of pesticide applications as a function of natural enemy levels and expected yield damage. Zhang et al. (2010) investigated economically optimal spatial habitat management at the farm scale, assuming a small homogeneous spatial domain, where investments in habitat for natural enemies increase the supply of pest control ecosystem services, potentially reducing the need to spray. Since the final model which this study suggests is a space-time extension of Zhang and Swinton's (2009) objective function that includes habitat investment and the pesticide spraying decision, we start by describing their single season model. Assume that a single farmer wants to maximize profit from soybean production for a single soybean season. Then, the control variable, timing of spraying (x_t) can be determined by the following optimization problem.

$$\max_{x_t}\left[p\cdot y_T-\sum_{t=1}^{T-2}c(x_t)\right] \tag{1}$$

$$\text{s.t.: } y_{t+1}=f(y_t,A_t) \qquad \text{and} \qquad y_1=y^0,\ \mathrm{t}=1,\cdots,\mathrm{T}-1$$

$$A_{t+1}=g(x_t,A_t,E_t) \qquad \mathrm{t}=1,\cdots,\mathrm{T}-2$$

$$E_{t+1}=h(x_t,A_t,E_t) \qquad \mathrm{t}=1,\cdots,\mathrm{T}-3$$

The objective function presents profit from soybean: revenue (soybean price $p \times$ soybean harvest y_T) minus total cost of controlling Soybean Aphid ($\sum_{t=1}^{T-2} c(x_t)$). The state variable y_t denotes the yield potential at time t which captures changes in yield potential as a result of plant damage due to pest injury, A_t presents population density of Soybean Aphid at the time period t, and E_t indicates population of Natural Enemies at the time period t. The optimization problem (1) includes interaction between spraying and predator-prey population dynamics, where natural enemies prey upon Soybean Aphid which feeds on soybean affecting yield. The solution of the problem is the optimal timing of spraying, where the time steps are the reproductive stages, from R1 to R5, of the soybean plants[3]. Thus, the sequential decision process undertaken determines the timing of spraying for Soybean Aphids over the course of the growing season.

In extending the problem structure in equation (1) to the space-time problem at the landscape scale, several additional considerations must be taken into account to find the optimal conservation planting locations. The farm scale spatial analysis in Zhang, et al. (2010) focused on the provision of on-farm habitat for natural enemies, finding that it was not privately optimal to invest in habitat management for natural enemies unless the use of pesticides was not an option (i.e. organic farming). The spatial scope of the previous work does not take into account the influence of nearby habitat on other farms or natural areas or the connectivity of natural enemy habitat at the landscape scale. Landscape composition is an important determinant of distribution of pests and their natural enemies (Bianchi et al. (2006); Gardiner et al. (2009); Meehan et al. (2012)). Spatial heterogeneity makes the landscape scale problem more

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[3] Soybean growth stages are mainly classified as two stages: Vegetation and Reproduction stage. Zhang and Swinton's (2009) model, equation (1) assumes that Soybean Aphid damages are limited to Reproductive stage from R1 to R5. Detailed soybean growth stage can be referred at Purdue Soybean Station (http://www.agry.purdue.edu/ext/soybean/).

complicated because the choice of optimal CP locations depends upon the location-specific benefits and costs of CP installation.

2.2. A Multiyear Space-Time Economic Threshold Model

This study includes spatial and temporal dynamics to extend Zhang and Swinton's (2009) model in several important ways. First, our model examines public net benefits from making spatially explicit investments in conservation grass plantings at the regional scale given economic constraints and predator(natural enemy)-prey(aphid) dynamics. All locations in the spatial domain surrounding prairie remnants, large tracts of core prairie, and restoration grasslands at Kankakee Sands nature preserve in northwestern Indiana are nodes on a grid where crops or habitat for natural enemies can be grown. Individual nodes are part of a network, such that planting a CP in a specific node may act as a bridge connecting several patches of habitat for natural enemies. The decision to invest in on-farm habitat considers more than a single farm. Second, this is a multi-year problem with stochastic arrival (day of year) of Soybean Aphids. In an aphid year, when arrival occurs—which month relative to when optimal breeding temperature (20°-30℃) is reached—can be important in determining when or if the economic threshold for spraying is triggered. Third, spatial location of arrival in aphid years is also stochastic. Initial arrival of Soybean Aphid follows a random point process such as Poisson or Cox process and their population can be interpreted as population density. Natural enemies, however, are living in natural areas (wooded areas, prairie, stream corridors) or grass plantings before moving into crop fields to chase prey following arrival. For example, a representative predator, lady bugs, can fly

2.5 km a day or longer, defining the spatial extent of the influence of semi-natural habitat for natural enemies of Soybean Aphid (Koh et al. 2013) in this study.

The proposed model for the spatially-explicit dynamic optimization problem is given in (2). The space and time indices in the problem are: k is a year for $k = 1, \cdots, K$; t is a reproductive stage within a single crop year from R1(t=1) to R5 (t=5) and harvest occurs at time T; s is location of soybean fields, $s = 1, \cdots, S$, and l is location of CPs, $l = 1, \cdots, L$.

$$\underset{CP_{k,s}x_{k,s,t}}{\text{Argmax}} \sum_{k=1}^{K} \left[\sum_{s=1}^{S} \left(p_k \cdot y_{Tk,s} - c_1(CP_{k,l}) - \sum_{t=1}^{T-2} c_2\left(x_{k,s,t}\right) \right) \right] \tag{2}$$

$$\text{s.t.: } y_{k,s,t+1} = f(y_{k,s,t}, A_{k,s,t}) \quad \text{and} \quad y_{k,s,1} = y^0_{k,s}, \ \mathrm{t} = 1, \cdots, \mathrm{T} - 1$$

$$A_{k,s,t+1} = g(x_{k,s,t}, A_{k,s,t}, E_{k,s,t}) \qquad \mathrm{t} = 1, \cdots, \mathrm{T} - 2$$

$$E_{k,s,t+1} = h(x_{k,s,t+1}, A_{k,s,t}, E_{k,s,t}, CP_{k,l}) \qquad \mathrm{t} = 1, \cdots, \mathrm{T} - 3$$

The difference between the decision rules in optimization problem (2) compared to equation (1) can be seen in the Figure 1.

[Figure 1 about here]

The Figure 1 shows a decision process in a soybean field *s* for the season *k*. Installation of CPs is determined each year at the beginning of the growing season. Once a CP is installed, it continues for the rest of the years in the planning horizon. Since this is multi-year problem, the timing of CP installation is determined by inter-temporal pest control effectiveness while the effects of spraying are limited to a single year. Installation of a CP makes new habitat for natural enemies that influence landscape-scale habitat connectivity and the spatial network. This process is depicted in the second row of Figure 1 and is not present in problem (1). Adding a new CP is another control variable in this optimization problem. Thus, there are two decision variables in (2), $CP_{k,s}$ and $x_{k,s,t}$. The cost functions defined in the problem are now two separate functions; one is installation cost of a CP, c_1, and the other is cost spraying, c_2. Because CP only directly affects to the population dynamics of natural enemies, the CP variable is included in the natural enemy equation of motion. The installation of the CP indirectly influences aphids via natural enemies.

The specified model of the optimization problem (2) is shown in the below.

$$\underset{CP_{k,s}x_{k,s,t}}{\text{Argmax}} \sum_{k=1}^{K} \left[\sum_{s1,s2}^{S1,S2} \tau^{k-1} \left(p_1 \cdot y_{Tk,s} - c_1(CP_{k,l}) - \sum_{t=1}^{T-2} c_2\left(x_{k,s,t}\right) \right) \right] \tag{3}$$

Subject to:

$$y_{k,s,t+1} = y_{k,s,t} \left(1 - \frac{\text{ŋ}_t \cdot A_{k,s,t}}{1 + \text{ŋ}_t \cdot A_{k,s,t}} \right) \qquad \text{t} = 1, \cdots, 5, \text{T}$$

$$A_{k,s,t+1} = (1 + ng_t)\left(A_{k,s,t} - \text{ƙ} \cdot x_{k,s,t} \cdot A_{k,s,t}\right) - pr(E_{k,s,t} - \text{ƙ} \cdot x_{k,s,t} \cdot E_{k,s,t}) \qquad \text{t} = 1,2,3,4$$

$$E_{k,s,t+1} = \beta_1 A_{k,s,t+1} + \beta_2 A_{k,s,t+1}^2 + \beta_3 E_{k,s,t}\left(1 - \text{ƙ} \cdot x_{k,s,t}\right) + \beta_4 N_{k,s} \qquad \text{t} = 1,2,3$$

where

ŋ_t: proportion of yield lost per unit of pest density

ng_t: net growth rate of Soybean Aphid population in the absence of predation

ƙ : mortality rates of insecticide application

pr : aggregate predation rate per natural enemy unit

$\tau = \frac{1}{1+r}$: discount factor given annual discount rate, *r*, according to the Producer Price Index

$N_{k,s}$: proportion of natural area influencing natural enemies at soybean field *s* for in year *k*

In the problem (3), discrete time discounting is included based on the Producer Price Index (PPI). Since the majority of soybean producers are planting soybeans and corn in alternate years, field indices have a biennial form. The notation *s1* is used for growing seasons of odd years and *s2* is used for growing seasons of even years. The most crucial part in the problem is the natural enemy equation. As seen in the Figure 1, installation of CP affects natural enemy abundance. It is, however, hard to empirically map CP effects to the population of natural enemies directly. In this study, installation of a CP is assumed to increase the proportion of natural area (N) within 2.5 km of the soybean field centroid where it is installed, based on Koh et al. (2013). The functional form of natural enemy equation of motion is chosen as the best fit model among several competing models estimated from empirical data. The details are explained in the next section.

III. Parameter Estimation

This section describes the process followed to parameterize the optimization problem (3). Some parameters are estimated from field measurement data (Newton County, Indiana) collected by the Holland Landscape Ecology Lab at Purdue and some parameters come from the previous literature. All parameters are summarized in Table 1 and details are described in the following sections.

[Table 1 about here]

3.1. Population Dynamics of Soybean Aphid

In the Soybean Aphid equation in (3), three parameters are required to be estimated: net growth rate of Soybean Aphid population in the absence of predation (ng_t), the mortality rate of insecticide used to control aphids (ƙ), and aggregate predation rate per natural enemy unit (pr). To get realistic ng_t, a reliable repeated exclusion experiment, where natural enemies are excluded from soybean plants that aphids are allowed to feed on, is required. From abundant field experiment data comparing exclusion and treatments where aphid predation is allowed, Costamagna et al. (2007) found that a linear decreasing growth model has the best fit for explaining natural growth of the Soybean Aphid population. The discrete daily growth model can be written as:

$$A_{d+1} = A_0 \cdot \exp(d \cdot (r_{max} \cdot (1 - a \cdot d/2))) \tag{4}$$

where d is the number of days since the first day that aphids arrived and r_{max} is value of the intrinsic rate of increase at the d=0. The parameter a denotes the decrease of linear decreasing rate per unit of time as the host plant advances through the phenological stages. The equation (4) describes a symmetrical bell-shaped population curve with the peak at $d = 1/a$. The relative rate of increase is largest at $d = 0$, and decreases linearly in time. Its slope becomes zero at $d = 1/a$, which is the time of the population peak, and becomes more and more negative as time passes. The population returns to a value of A_0 at $d = 2/a$, at which time the relative rate of change is $-r_{max}$ (Costamagna et al., 2007). From the Costamagna et al. (2007), natural growth of population of Soybean Aphid can be simulated with $r_{max} = 0.395$ and $a = 0.022$. In our simulation, however, these values make population growth too fast to explain our data. We adopt Zhang and Swinton's (2009) parameter, $r_{max} = 0.28$ and $a = 0.02$ and apply them to the median length of soybean growth stages in Indiana.[4] The simulated growth rates, using equation (4), of Soybean Aphid over each growth stage are shown in Figure 2.

[Figure 2 about here]

Zhang and Swinton's (2009) net Soybean Aphid population growth rate per stage in the absence of natural suppression is assumed and given by:

$$ng_t = \left(\frac{\hat{A}_{t+1}}{\hat{A}_t}\right) - 1 \tag{5}$$

where $\hat{A}_t$ is the mean of Soybean Aphid population for each growth stage depicted by the dotted line in Figure 2.

The mortality rate from insecticide (ƙ) is assumed as 0.99 and aggregate predation rate per natural enemy unit (pr) is calculated as 35 aphids/day/E in Zhang and Swinton (2009).

3.2. Population Dynamics of Natural Enemies

Population dynamics are modeled using the well-known Lotka-Volterra prey-predator equation that was adopted previously by Zhang and Swinton (2009). This is modified to incorporate the effect of installation of CPs on abundance of natural enemies. A general form is given by:

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[4] The median length of each growth stage is reported in Table 4. The details of this can be found in Casteel's work http://www.agry.purdue.edu/ext/soybean/Arrivals/2011_0707SOYReproDev.pdf (Accessed at April 4, 2013)

$$E_{k,s,t+1} = h(x_{k,s,t+1}, A_{k,s,t}, A_{k,s,t+1}, E_{k,s,t}, CP_{k,s}) \tag{6}$$

Many different functional forms linking the variables in equation (6) are possible. In this study, we assume a quadratic relationship between the Soybean Aphid and natural enemy populations. Before estimating parameters, we need to address a missing observation problem in the field measurement data. The field measurement data for Soybean Aphid density is collected from individual plants enclosed in exclusion cages and using sweep nets for the population of natural enemies. A total of 28 (=15 CP sites + 13 control sites without CPs) patches are irregularly collected to take observations for the 2011 growing season. Because the year 2011 is not an aphid year, Soybean Aphids appeared late in the growing season (R5 stage) and natural enemies are observed throughout the growing season, starting earlier than Soybean Aphids. Thus, only R5 and later growing stage data can be used to estimated equation (6).

From 28 observation values at the R5 stage, 4 missing values for Soybean Aphid and 3 missing values for natural enemies are realized. The field measurement data is geostatistical data which collected at a certain geographical locations. To fill out missing data, spatial prediction method can be adopted. The semivariogram which is a scatter plot of geographical distance and distance of observations (which is the absolute value of differences of two observations) called semivariance is generally used to see spatial correlation between observations. Figure 3 shows the semivariogram of Soybean Aphid at R5 stage in the field data. Since all semivariogram of Soybean Aphid and natural enemies at R5 and R6 stages are shown to be similar , other semivariograms are not attached. If scatter dots are clustering at the shorter distance, this implies that similar values are getting together on closer spatial position. Thus, Figure 3 means that there is no spatial correlation between observations and missing values in the data were replaced with the sample mean of each stage.

[Figure 3 about here]

Simple Ordinary Least Squares (OLS) is used to estimate marginal effects of each variable. Table 2 shows the estimation results of competing models considered. From the lowest AIC/BIC and expected direction of sign, Model 43 is selected as the best fit and its form is the one shown in equation (3). The best functional form could be getting all estimates for each stage as simultaneous equations. Data availability and late appearance of Soybean Aphid for 2011 makes this estimation approach infeasible. Given data limitations, it is assumed that the results in Table 2 are applicable across all growth stages and thus, the regression coefficients in equation (6) are not indexed by reproductive stage t. Spatial Econometrics techniques are also considered but the estimation results are not statistically reliable given the limited number of observations and a single time period. This may be because distances between the data collecting patches are too far to have spatial correlation.

3.3. Other Parameters

To get price parameters in the optimization problem (3), we need to specify the initial year. This is because all of the price parameters will be discounted to the initial time period at the rate r. Considering the fact that the field data was collected in 2011, prices for the year 2011 are assumed to apply to the entire planning horizon. The discount rate used is from the Producer

Price Index (PPI) from the Bureau of Labor Statistics[5]. From Table 4 in the next section, it is clear that the soybean reproductive stage ends around the beginning of September for each year. Thus, the 12 months unadjusted September PPI based on the September 2010-2011 period of 6.9% is used for the parameter r. The USDA NASS reported soybean price (p_1) in Newton County, Indiana in 2011 was $12.50/bu. The cost of grass filter strip CP installation is based on the Natural Resource Conservation Service (NRCS)[6] estimate of $618.63 per acre. The cost of spraying to control aphids is calculated following Song et al. (2006). Total treatment cost of spraying ($12/ac) consists of insecticides cost ($7/ac), scouting ($2/ac), and labor cost for spraying ($3/ac) (Zhang and Swinton, 2009.)

IV. Empirical Study Area and Simulation Design

The social planner's optimization problem in (3) is applied to Newton County, Indiana. Based on the 2011 Crop Data Layer (CDL)[7], the study area can be represented as Figure 4 and land cover properties are summarized in Table 3.

[Figure 4 about here]

[Table 3 about here]

Figure 4 includes Newton County and the 2.5 km buffer around each grid point inside the county that is influenced by and has an influence on the amount of natural enemies as described above.

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[5] Producer Price Index is released as monthly base by the Bureau of Labor Statistics. http://www.bls.gov/ppi/

[6] Details of cost item can be referred at http://efotg.sc.egov.usda.gov/treemenuFS.aspx

[7] The whole US Crop Data Layer is available at http://nassgeodata.gmu.edu/CropScape/

From the 2011 CDL of the whole US, we captured the interested geographical boundaries and it originally provides a raster type map which contains 2,248,254 cells with (30 m by 30 m) resolution. We merged the raster file to a polygon format which contains 84,108 polygons. Land cover in the CDL was reclassified as 11 different categories summarized in Table 3. The actual location of existing CP21 and CP33 grassland planting polygons are added along with the 15 study sites where the field measurement data were collected are represented in Figure 4. By polygon definition, 6,501 soybean fields and 7,132 corn fields are recognized in Newton County in 2011. Considering crops rotation in soybean and corn, we assume that 6,501 soybean fields for odd year spatial domain as s_1 and 7,132 corn fields for even year spatial domain as s_2.

To make our example tractable and realistic, we create a scenario based upon actual soybean production and aphid arrival data in Newton County, using data from the years 2002-2011. Table 4 includes aphid year history and soybean production in Newton County for incorporating into the simulation scenario in order to verify that spraying occurs in years when there was significant aphid pressure.

[Table 4 about here]

Using the median duration of each stage in Indiana, the reproductive stages for 10 years are determined. From USDA NASS database, the inferred reproductive stages[8] are shown in Table 4. While the simulation is based on specific years, the simulation depicts a forward-looking 10 year planning horizon represented as $k = 1, \cdots, 10$. The first day of initial arrival for each year will be

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[8] Using definition of R1 stage, the first day of the week reported as being R1 status by USDA NASS is used to determine the initial date of the R1 stage. The other stages are calculated with the median duration of each stage in Indiana.

tracked from the Purdue Entomology Extension newsletter.[9] By fixing the time domain based on Table 4 and the spatial domain from Figure 4, we reduce uncertainties due to variation in the length of the growing season and landuse.

This optimization problem still includes two stochastic terms. One is random arrival of Soybean Aphid and the other is random appearance of natural enemies. Soybean Aphid arrivals in the Midwestern US begins when the temperature reaches 20℃ and aphids are transported through westerlies. Depending upon when temperature goes up and how many Soybean Aphids are delivered by westerlies, aphid and non-aphid years are determined. An aphi year being one in which sufficient aphid pressure exists that economic spraying thresholds are triggered. As shown in Table 4, there were three aphid years in Indiana during the 2002-2011 period. In 2003 and 2007, especially serious damages from Soybean Aphid was recorded, and both years had notably less production. Thus, incorporating random arrival of Soybean Aphid is one important issue, as there remains no good way to forecast an aphid year before it happens. Various point processes could potentially be used (Cressie and Wikle, 2011) to simulate random arrival of Soybean Aphid as a space-time point process. We assume random arrivals follow a homogeneous Poisson process according to:

$$A_{k,s,0} \sim Poisson\ (\lambda^0) \tag{7}$$

where $A_{1,s,0}$ is arrival of Soybean Aphid and λ^0 is intensity. Intensity $\lambda^0$is the expected number of arrivals before reproductive stages. To simplify the generating process and to avoid explosion of population density at an early stage, it is assumed that $\lambda^0 = 1$. The expected number of observations on the first day in the field measurement data is also close to one.

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[9] Newsletter by the Purdue Entomology Extension is weekly online published report about crops and pests in Indiana. http://extension.entm.purdue.edu/pestcrop/

As shown in Table 4, Soybean Aphid arrived earlier in the growing season in some years while in other years it did not. The optimization problem, equation (3) considers only reproductive stages R1 to R5. Thus, different arrival date of Soybean Aphid at each year makes different initial distribution of Soybean Aphid before R1 stage which is not captured by equation (3). Thus, population dynamics of Soybean Aphid at vegetation stages before the reproductive stages must be simulated as an initial condition. Since the field measurement data was collected with predation by natural enemies and spraying, we can estimate equation (4) as a population dynamics equation of Soybean Aphid with predation and spraying. Because of inclusion of predation and spraying, we can reduce dynamics of natural enemies and spraying in this stage. Nonlinear least squares estimation of equation (4) yields the results in Table 5.

[Table 5 about here.]

For simulation of the initial distribution of Soybean Aphid, random Poisson process of equation (7) is implemented first for all soybean fields at each year. The estimated parameters from Table 5 are used in growth equation (4) to simulated each day and the cumulative summation over time before R1 stage is calculated.

Appearance of natural enemies is assumed to be random following a uniform distribution as:

$$E_{k,s,0} \sim U(0, C) \tag{8}$$

where *C* is a constant. Zhang and Swinton (2009) assumed that the maximum *C* is four and the field data also shows that the maximum natural enemies in the earlier stages are approximately four. Thus, we choose *C*=4 as baseline simulation.

Dynamic optimization generally can be solved by Hamilton-Jacobi-Bellman (HJB) equation. The dynamic problem in (3), however, includes discrete arguments: binary decision for installation of CPs and the binary decision to spray. Thus, gradient-based approaches are not suitable for this type of problem. Zhang and Swinton (2009) used numerical calculation based on a set of optimal control paths which finds the solutions after calculating all of the possible combinations of control variables. We adopt this approach to solve our optimization problem in (3). Figure 5 shows the process used to find solutions.

[Figure 5 about here]

Because of the stochastic terms random arrival of Soybean Aphid and appearance of natural enemies, we need to evaluate control paths repeatedly for various scenarios with different initial distribution of Soybean Aphid and natural enemies. Let's assume that we have *M* different initial distributions from stochastic arrival of Soybean Aphid and appearance of natural enemies. Depending on scenarios, different numbers of feasible control paths will be defined. Assume that we are trying to find the optimal CP locations among *L* numbers of CP candidates in a certain scenario. Additionally, just suppose that we are considering installing CPs at the first year and only consider spraying during the R1 to R4 growing stages each year. Then we need to calculate $2^L \times 2^4$ (paths for CP installation by paths for spray timing) different control paths for 6,743 odd year fields and 7,516 even year fields for a 10 horizon length. If we want to install CPs in different years we will have more control paths. And then, we can calculate the profits from all of the feasible paths. The CPs and spray timing that achieves maximum profit will be a solution of that scenario and they will be saved into solution groups. After repeating this process M times, we can determine the CP locations that convey the highest discounted net benefits based on which one show up more times in the solutions.

Even though the optimal control path approach is feasible in description, calculating all of possible control paths can be extremely computationally expensive. For example, if we consider 100 fields as CP candidates and intend to install optimal CPs at the first year, we need to calculate a total of $2^{100} \times 2^{4} = 2.02 \times 10^{31}$ control paths and this is generally infeasible. To make our problem tractable, we have to reduce control paths into feasible numbers. We first reduce spatial domain for CP candidates as shown in Table 6.

[Table 6 about here]

From 6,743 soybean fields and 7,516 corn fields in 2011 CDL, polygons with an area smaller than 5 ha are removed from the choice set. Since installing CPs increases the proportion of natural area, candidate locations would have less proportion of nature. Thus, we further reduce the number of candidate locations for CP installation by only considering those sites in the lowest Quartile based on the proportion of the polygon’s total area that is natural area that provides potential habitat for natural enemies. All polygons outside the Newton County boundary are eliminated. The fields with CPs already installed are also removed. This leaves 86 soybean fields and 82 corn fields and contiguous fields are merged into a single polygon using a clustering technique. This leaves 10 final CP candidates. The length of an installed candidate CP is assumed to be the longest diagonal path across an individual polygon and is 15 feet wide based on the Indiana filter strip conservation planting rule.

Table 7 shows an illustrative example of the optimization problem (3) for a scenario.

[Table 7 about here]

In Table 7, all simulation results are incorporating areal changes of soybean fields. As shown in Table 4, the trend over the last 10 years has been toward fewer planted soybean areas. Thus, all planted areas in the simulation are weighted by ratio of planted areas in Table 4 from soybean and corn fields in the 2011 CDL. This scaling method helps simulations to incorporate changes of planted area even though a fixed spatial domain is assumed. Four major points can be made from the simulation results.

First, aphid and non-aphid years based on arrival length seem to be well incorporated in the model. The baseline simulation shows that spray frequencies are different across aphid and non-aphid years, with no spraying for aphids taking place in non-aphid years. Second, natural enemies are having the effect of suppressing Soybean Aphid in soybean fields. This can be seen by comparing the spray counts in the baseline and “less natural enemy” scenarios modeled. The Less Natural Enemy simulation is simulated lower level appearance of natural enemies at the initial stage denoted by the upper bound of uniform distribution. These simulation results indicate how more natural enemies can reduce spraying frequencies, leading to higher production and profit. Third, CP can provide semi-natural habitat for natural enemies and it contributes to attract natural enemies to soybean fields. After simulation, one CP location is chosen as the optimal location and it reduces spray counts. Thus, it explains that installation CP makes agroecosystem services more effective. Finally, net benefit from CP installation can be higher than spray. In case of CP Installation, the profit shows the highest values. Thus, installation of CPs can be an economically better way to control Soybean Aphid instead of spraying. Considering other opportunity costs of spraying, this result supports that CPs are economically beneficial as well as eco-friendly.

V. Conclusion and Future Steps

Installation of conservation planting (CP) in the farm landscape is considered as a strategy to decrease required spraying for Soybean Aphid that relies on agroecosystem services. Extending Zhang and Swinton (2009) and Zhang, et al (2010), this study formulates and solves a multi-year space-time optimization problem. Soybean Aphid control in Newton County, Indiana is explored as a case study for testing the suggested model. Our model extends the previous literature is XXX key ways.

First, our model examines public net benefits from making spatially explicit investments in conservation grass plantings at the regional scale given economic constraints and predator(natural enemy)-prey(aphid) dynamics. All locations in the spatial domain surrounding a nature preserve in northwestern Indiana composed of remnant and restoration prairie are nodes on a grid where crops or habitat for natural enemies can be grown. Individual nodes are part of a network, such that planting a CP in a specific node may act as a bridge connecting several patches of habitat for natural enemies. The decision to invest in on-farm habitat considers social net benefits rather just a single farm. Second, this is a multi-year problem with stochastic arrival (day of year) of Soybean Aphids. Third, spatial location of arrival in aphid years is also stochastic Finally, the spatial heterogeneity issues are partly improved by considering a spatial domain larger than a single farm. Even though all habitat is assumed to be of homogeneous quality, different classifications of land properties are applied and size of soybean field can create different chances of soybean arrivals as well as different benefits and costs from investing in habitat for natural enemies.

The preliminary simulation results show how biological control ecosystem services are provided by natural enemies that suppress Soybean Aphids and a CP can provide semi-natural habitat for natural enemies and it contributes to attract natural enemies to soybean fields. This means that installation CP makes agroecosystem services more effective and net benefit from CP installation can be higher than spray. Thus, installation of CPs can be an economically better way to control Soybean Aphid instead of spraying.

Since this study is still ongoing process, a general process to rigorously test validity of the suggested model is still underway. The following future steps for analysis are planned: ranking CP candidate locations based on repeated stochastic simulation and alternative modeling scenarios; more extensive validation using observed data from 2011; and extensive sensitivity analysis of simulation parameters.

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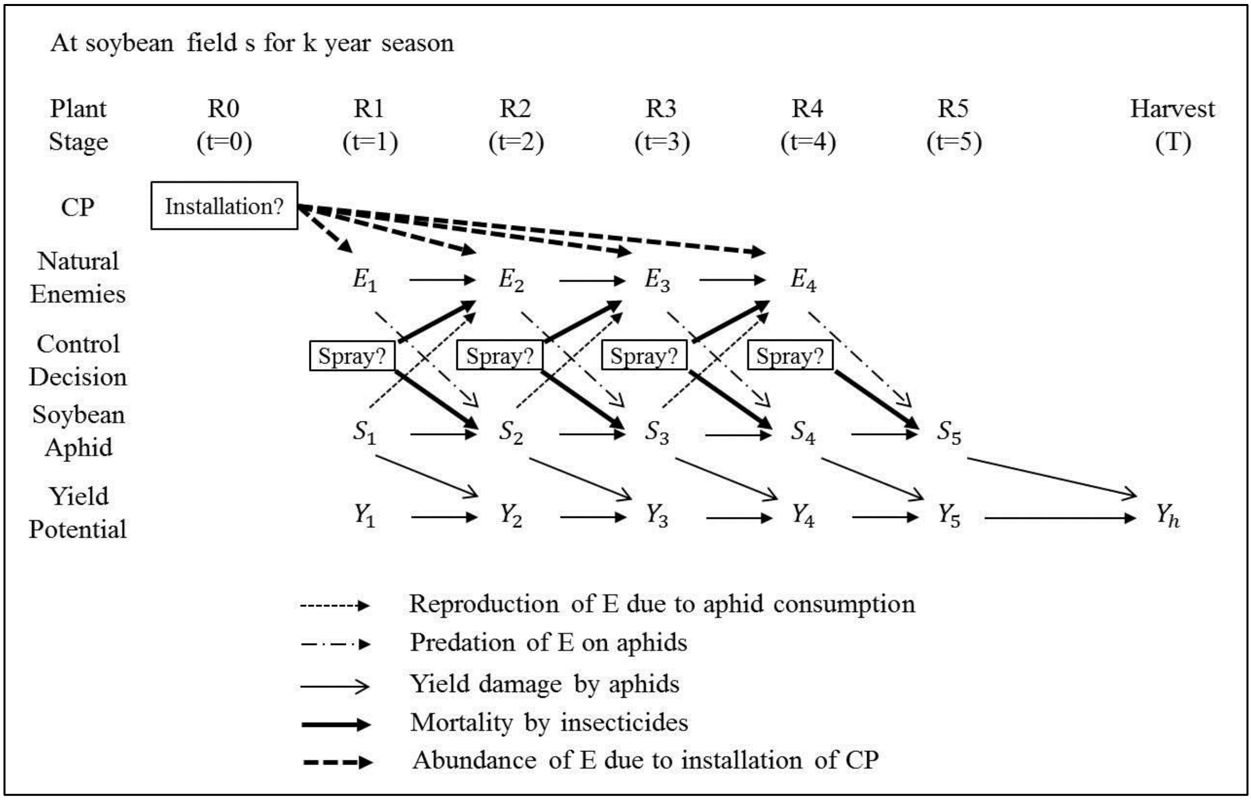

Figure 1. Dynamics of the Suggested Multi-year Space-Time Optimization Model

Note: This figure is an conceptual extension of Fig. 1 in Zhang and Swinton (2009, p. 1317.).

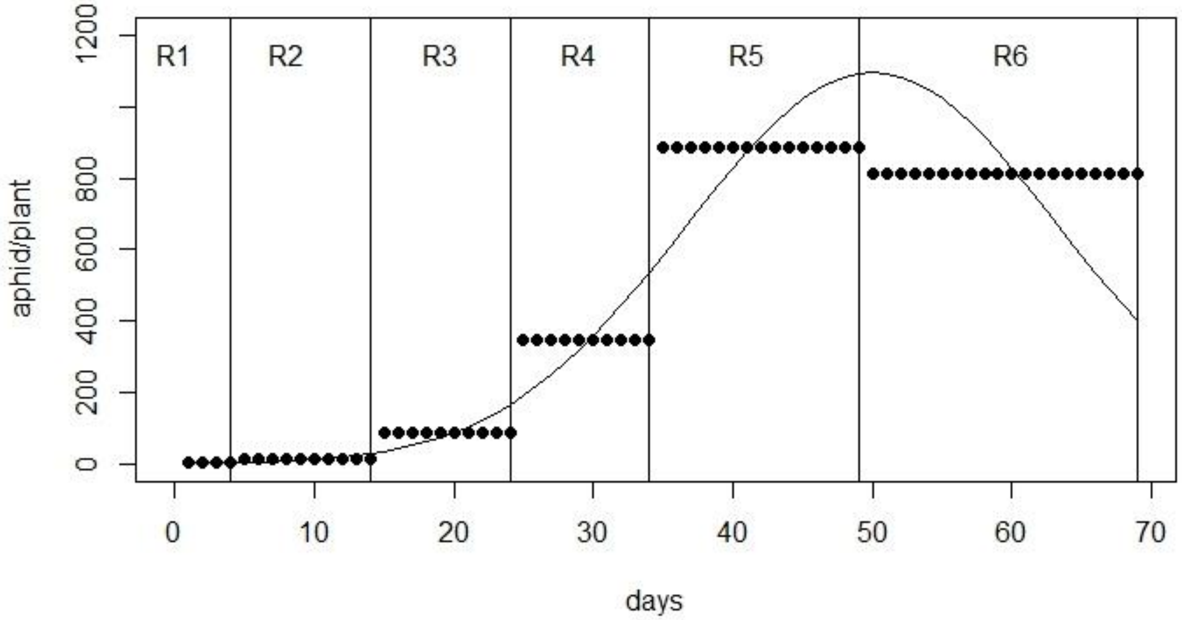

Figure 2. Natural Growth of Soybean Aphid Population with $r_{max} = 0.28$ and a $= 0.02$

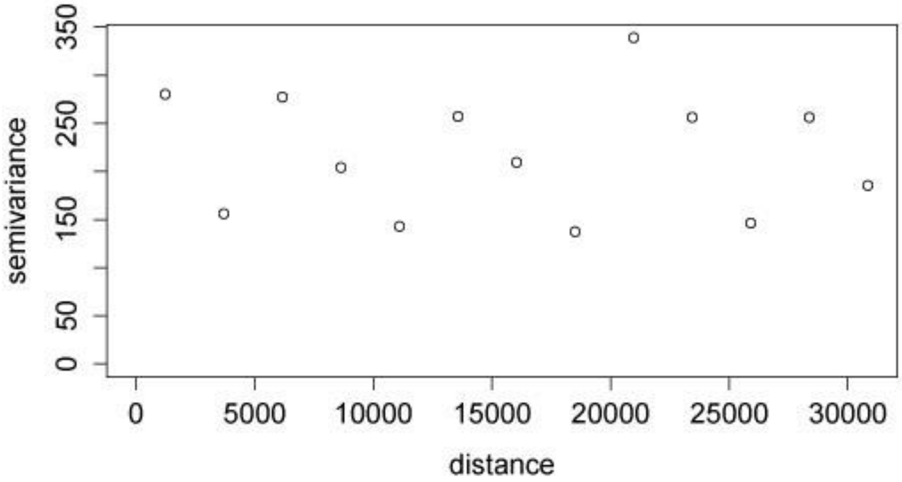

Figure 3. Semivariogram for R5 stage of Soybean Aphid.

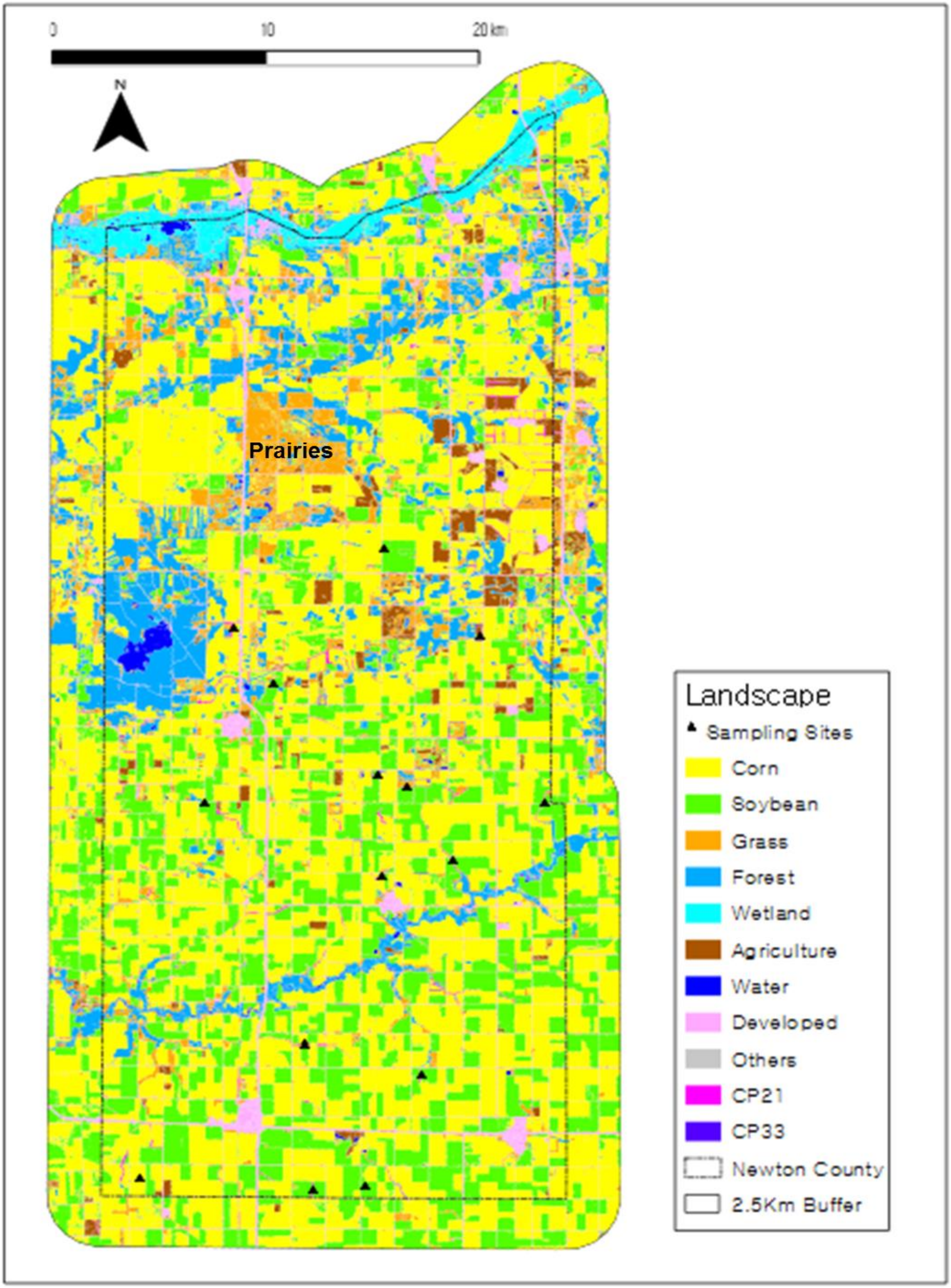

Figure 4. Study Area: Newton County, IN based on the 2011 Crop Data Layer

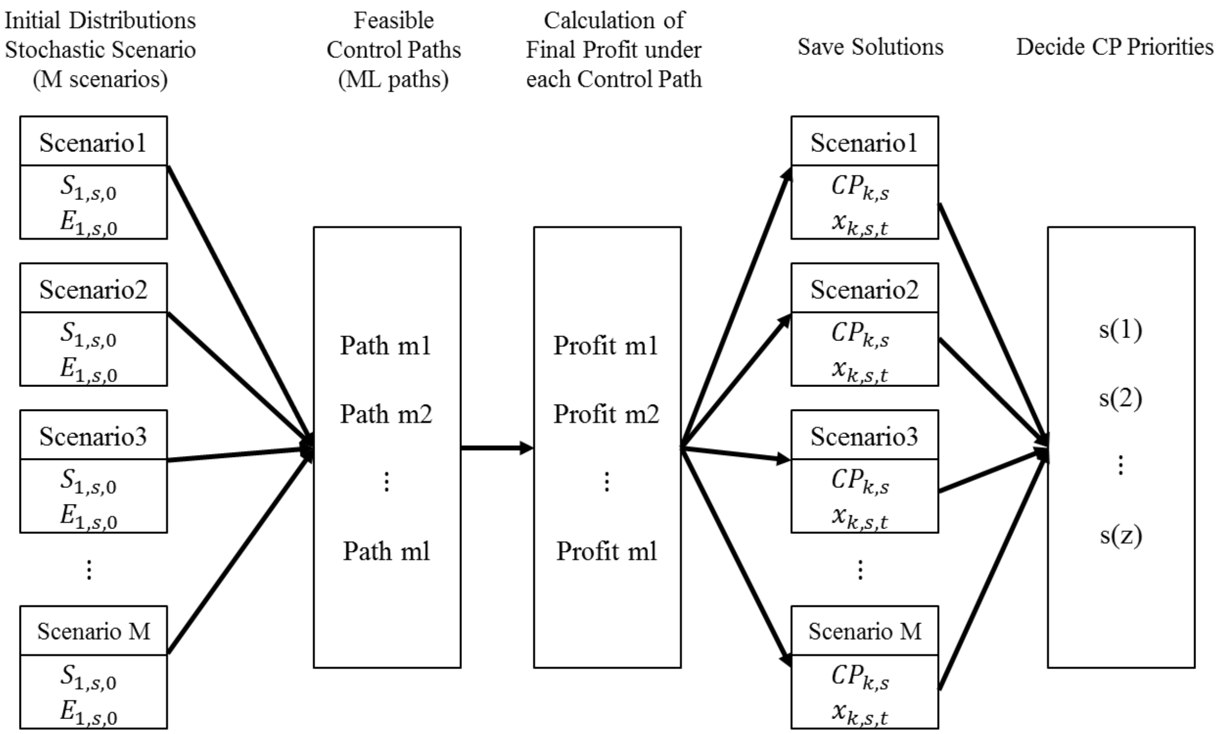

Figure 5. Solution Process: Control Path Approach

Table 1. Summary of Parameters

Parameter	Value	Meaning	Source
ng_t	$ng_1 = 5.4367$	net growth rate of Soybean Aphid population in the absence of predation	Calculated using Costamagna et al. (2007) and Zhang and Swinton (2009)
	$ng_2 = 5.7073$		
	$ng_3 = 2.9170$		
	$ng_4 = 1.5454$		
pr	35aphids/day/E	aggregate predation rate per natural enemy unit	Zhang and Swinton (2009)
ƙ	0.99	mortality rate of insecticide	Zhang and Swinton (2009)
β_i	$\beta_1 = 0.2558$	Coefficient of $A_{k,s,t+1}$	OLS estimates from the field data
	$\beta_2 = -0.002$	Coefficient of $A_{k,s,t+1}^2$	
	$\beta_3 = 0.0786$	Coefficient of $E_{k,s,t}$	
	$\beta_4 = 1.4086$	Coefficient of N_k	
$ŋ_i$	$ŋ_1 = 0.0002$	Proportion of yield lost per unit of pest density for each stage	Zhang and Swinton (2009)
	$ŋ_2 = 0.0002$		
	$ŋ_3 = 0.0003$		
	$ŋ_4 = 0.0001$		
	$ŋ_5 = 0.0002$		
r	0.069	Producer Price Index (PPI)	Bureau of Labor Statistics
p_1	\$12.5/bu	Initial Soybean Price	USDA NASS
$c_1(CP_{1,s})$	\$618.63/ac	Cost of CP installation	NRCS
$c_2(x_{1,s,t})$	\$12/ac	Cost of spray	Song et al. (2006)

Table 2. Estimation Results of Competing Models for Natural Enemies' Population.

rstage6&7	Model11				Model12				Model13				Model14				Model15				Model16			
N=56	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.		p-val	s.e.
Intercept	28.6744		***	10.3276	28.8626		***	10.3032	23.4824		**	10.5246	39.6974		***	12.1712	33.2014		**	12.8043	31.5899		**	12.6970
$A_{k,s,t}$	-0.0336	-0.1524		0.0316	-0.4434	-2.0130		0.3664	-0.4279	-1.9427	*	0.2227	-0.0365	-0.1658		0.0311	-0.3681	-1.6709		0.2258	0.2014	0.9145		0.4425
$A_{k,s,t}^2$									0.0003	1.7499	*	0.0002					0.0002	1.4737		0.0002	0.0006	3.7706	*	0.0003
$E_{k,s,t}$	-0.0138	-0.0092		0.2140	-0.0061	-0.0040		0.2135	0.2077	0.1380		0.2434	-0.9258	-0.6153		0.5328	-0.5636	-0.3746		0.6349	-0.7653	-0.5087		0.6418
$E_{k,s,t}^2$													0.0105	0.6473		0.0064	0.0085	0.5226		0.0064	0.0139	0.8575	*	0.0073
$A_{k,s,t} \times E_{k,s,t}$					0.0052	1.8594		0.0046													-0.0137	-4.9391		0.0092
$N_{k,s}$	1.0277	0.2401	*	0.0811	1.2127	0.2833	**	0.0483	1.4835	0.3466	**	0.6207	1.0861	0.2537	*	0.5695	1.4588	0.3408	**	0.6166	1.5959	0.3728	**	0.6161
R2	0.0715				0.0939				0.1262				0.1183				0.1554				0.1920			
AIC	411.557				412.189				410.152				410.660				410.252				409.770			
BIC	414.160				415.150				413.113				413.621				413.663				413.729			
rstage6&7	Model21				Model22				Model23				Model24				Model25				Model26			
N=56	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.
$A_{k,s,t}$	-0.0486	-0.1592		0.0330	-0.4419	-1.4485		0.3897	-0.5751	-1.8851	**	0.2207	-0.0478	-0.1566		0.0337	-0.5749	-1.8847	**	0.2228	0.0871	0.2854		0.4624
$A_{k,s,t}^2$									0.0004	1.6681	**	0.0002					0.0004	1.6708	**	0.0002	0.0008	3.4966	**	0.0003
$E_{k,s,t}$	0.3389	0.2517	*	0.1827	0.3486	0.2589	*	0.1829	0.5508	0.4091	***	0.1958	0.4095	0.3041		0.4669	0.6392	0.4748		0.4572	0.3421	0.2541		0.4857
$E_{k,s,t}^2$													-0.0010	-0.0502		0.0058	-0.0012	-0.0627		0.0055	0.0055	0.2919		0.0069
$A_{k,s,t} \times E_{k,s,t}$					0.0045	1.2784		0.0049													-0.0157	-4.0431		0.0097
$N_{k,s}$	2.0103	0.5378	***	0.4846	2.1940	0.5870	***	0.5174	2.3839	0.6378	***	0.4893	1.9706	0.5272	***	0.5453	2.3350	0.6247	***	0.5439	2.4431	0.6536	***	0.5394
R2	0.4743				0.4845				0.5271				0.4746				0.5275				0.5513			
AIC	417.298				418.204				413.368				419.269				415.317				414.432			
BIC	419.631				420.808				415.971				421.873				418.278				417.843			
rstage6&7	Model31				Model32				Model33				Model34				Model35				Model36			
N=56	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.		p-val	s.e.
Intercept	28.7812		***	10.0918					26.7217		**	10.0534	38.7475		***	12.1096	35.1672		**	12.3738				
$A_{k,s,t+1}$	0.0470	0.2171		0.0289					0.2100	0.9691	*	0.1100	0.0433	0.2001		0.0287	0.1802	0.8319		0.1126				
$A_{k,s,t+1}^2$									-0.0001	-0.7734		0.0001					-0.0001	-0.6465		0.0001				
$E_{k,s,t}$	-0.0975	-0.0648		0.1987					-0.1945	-0.1293		0.2062	-0.9039	-0.6008		0.5882	-0.8347	-0.5548		0.5875				
$E_{k,s,t}^2$													0.0092	0.5686		0.0063	0.0075	0.4626		0.0064				
$A_{k,s,t} \times E_{k,s,t}$																								
$N_{k,s}$	0.8136	0.1901		0.5716					0.5982	0.1397		0.5815	0.8699	0.2032	*	0.5668	0.6794	0.1587		0.5837				
R2	0.0973								0.1371				0.1183				0.1598							
AIC	409.977								409.453				409.700				409.958							
BIC	412.580								412.414				412.661				413.369							
rstage6&7	Model41				Model42				Model43				Model44				Model45				Model46			
N=56	Coeff.	STB	p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.		p-val	s.e.	Coeff.	STB	p-val	s.e.	Coeff.		p-val	s.e.	Coeff.	STB	p-val	s.e.
$A_{k,s,t+1}$	0.0559	0.1974	*	0.0306					0.2558	0.9033	**	0.1148	0.0561	0.1979	*	0.0308	0.2624	0.9266	**	0.1161				
$A_{k,s,t+1}^2$									-0.0002	-0.6777	*	0.0001					-0.0002	-0.6994	*	0.0001				
$E_{k,s,t}$	0.2238	0.1684		0.1736					0.0786	0.0584		0.1888	0.3965	0.2945		0.4615	0.3191	0.2370		0.4532				
$E_{k,s,t}^2$													-0.0023	-0.1186		0.0057	-0.0033	-0.1713		0.0056				
$A_{k,s,t} \times E_{k,s,t}$																								
$N_{k,s}$	1.7570	0.4701	***	0.4965					1.4086	0.3769	***	0.5232	1.6634	0.4450	***	0.5531	1.2621	0.3377	**	0.5832				
R2	0.4853								0.5156				0.4868				0.5188							
AIC	416.115								414.718				417.945				416.344							
BIC	418.448								417.322				420.549				419.306							

* p<0.10 ** p <0.05 *** p<0.01

The buffer size of $N_{k,s}$ is 2.5 Km.

Table 3. Description of Landuse in Year 2011 based on the USDA Crop Data Layer (CDL)

Class	Class ID	CDL Field ID
Corn Field	1	1 Corn
Soybean Field	2	5 Soybean
Grass	3	59 Sod/Grass Seed, 60 Switchgrass, 171 Grassland Herbaceous, 181 Pasture/Hey
Forest	4	58 Clover/Wildflowers, 70 Christmas Trees, 141 Deciduous Forest, 142 Evergreen Forest, 143 Mixed Forest
Wetland	5	190 Woody Wetlands, 195 Herbaceous Wetlands
Agriculture	6	4 Sorghum, 12 Sweet Corn, 13 Pop or Orn Corn, 14 Mint, 24 Winter Wheat, 26 Dbl Crop WinWht/Soybeans, 27 Rye, 28 Oats, 36 Alfalfa, 37 Other Hay/non Alfalfa, 43 Potatoes, 44 Other Crops, 49 Onions, 57 Herbs, 61 Fallow/Idle Corpland, 216 Peppers, 219 Greens, 221 Stawberries, 225 Dbl Crop WinWht/Corn, 241 Dbl Crop Corn/Soybeans, 242 Blueberries
Water	7	111 Open Water
Developed	8	121 Developed/Open Space, 122 Developed/Low Intensity 123 Developed/Med Intensity, 124 Developed/High Intensity
Others	9	0 Unidentified, 131 Barren
CP21	10	Polygons from Koh et al. (2013)
CP33	11	Polygons from Koh et al. (2013)

Table 4. Observed Duration of Soybean Reproductive Stage in Indiana for 10 years, 2002 - 2011

Stage[a]	R1		R2		R3		R4		R5		R6		First Observed Soybean Aphid[b]	Aphid (O) / Non-Aphid (X) Year[b]	Planted Area (ac)[a]	Soybean Production (1,000 bu)[a]
Median Duration	4		10		10		10		15		20					
	begins	ends	begins	ends	begins	ends	begins	ends	begins	ends	begins	ends				
2011	6/27/2011	6/30/2011	7/1/2011	7/10/2011	7/11/2011	7/20/2011	7/21/2011	7/30/2011	7/31/2011	8/14/2011	8/15/2011	9/3/2011	7/29/2011	X	61.6	3004
2010	6/21/2010	6/24/2010	6/25/2010	7/4/2010	7/5/2010	7/14/2010	7/15/2010	7/24/2010	7/25/2010	8/8/2010	8/9/2010	8/28/2010	7/23/2010	X	64.5	3254
2009	6/30/2009	7/3/2009	7/4/2009	7/13/2009	7/14/2009	7/23/2009	7/24/2009	8/2/2009	8/3/2009	8/17/2009	8/18/2009	9/6/2009	6/12/2009	X	67.3	3266.6
2008	6/22/2008	6/25/2008	6/26/2008	7/5/2008	7/6/2008	7/15/2008	7/16/2008	7/25/2008	7/26/2008	8/9/2008	8/10/2008	8/29/2008	6/13/2008	X	66.4	3397.3
2007	6/25/2007	6/28/2007	6/29/2007	7/8/2007	7/9/2007	7/18/2007	7/19/2007	7/28/2007	7/29/2007	8/12/2007	8/13/2007	9/1/2007	5/23/2007	O	56.8	2857.5
2006	7/3/2006	7/6/2006	7/7/2006	7/16/2006	7/17/2006	7/26/2006	7/27/2006	8/5/2006	8/6/2006	8/20/2006	8/21/2006	9/9/2006	6/6/2006	X	76.2	3748.2
2005	6/20/2005	6/23/2005	6/24/2005	7/3/2005	7/4/2005	7/13/2005	7/14/2005	7/23/2005	7/24/2005	8/7/2005	8/8/2005	8/27/2005	5/26/2005	O	72.5	3564.7
2004	6/21/2004	6/24/2004	6/25/2004	7/4/2004	7/5/2004	7/14/2004	7/15/2004	7/24/2004	7/25/2004	8/8/2004	8/9/2004	8/28/2004	6/11/2004	X	73.4	3783.4
2003	7/1/2003	7/4/2003	7/5/2003	7/14/2003	7/15/2003	7/24/2003	7/25/2003	8/3/2003	8/4/2003	8/18/2003	8/19/2003	9/7/2003	6/11/2003	O	76.8	2447.4
2002	6/24/2002	6/27/2002	6/28/2002	7/7/2002	7/8/2002	7/17/2002	7/18/2002	7/27/2002	7/28/2002	8/11/2002	8/12/2002	8/31/2002	6/18/2002	X	77.8	3875.6

[a] USDA NASS, 2002-2011

[b] Purdue Entomology Extension weekly online newsletter, http://extension.entm.purdue.edu/pestcrop/

Table 5. Estimation Result of Daily Soybean Population Dynamics Equation (4) with Predation and Spraying

Variable	Coefficient	Approx. S.E.	95% Confidence Intervals	
r_{max}	0.1906	0.0675	0.0568	0.3245
a	0.0498	0.0136	0.0228	0.0769
N.	118			
F	4.26*			

Table 6. Geographical Filtering Process

Filter	Field			
CDL Polygons	Soybean		Corn	
	6,743 Polygons		7,516 Polygons	
Area > 5ha ($50,000m^2$)	Quantile	Area (m^2)	Quantile	Area (m^2)
	100% Max	3,437,100	100% Max	15,705,900
	99%	907,200	99%	1,782,900
	95%	184,500	95%	207,900
	90%	24,300	90%	22,500
	75% Q3	2,700	75% Q3	2,700
	50% Median	900	50% Median	900
	25% Q1	900	25% Q1	900
	10%	900	10%	900
	5%	900	5%	900
	1%	900	1%	900
	0% Min	900	0% Min	900
	574 Polygons left		603 Polygons left	
Proportion of Nature < Q1	Quantile	Proportion of N	Quantile	Proportion of N
	100% Max	0.82343350	100% Max	0.76123857
	99%	0.67571848	99%	0.61444212
	95%	0.44917467	95%	0.49449370
	90%	0.39653405	90%	0.43483937
	75% Q3	0.23862101	75% Q3	0.31533588
	50% Median	0.12476123	50% Median	0.17010670
	25% Q1	0.05133461	25% Q1	0.05762064
	10%	0.03391568	10%	0.03610192
	5%	0.02552874	5%	0.02900308
	1%	0.01343848	1%	0.01332340
	0% Min	0.00768729	0% Min	0.00698812
	144 Polygons left		150 Polygons left	
Out of Newton County	132 Polygons left		128 Polygons left	
CP installed	86 Polygons left		82 Polygons left	
Clustering	10 Polygons left			

Table 7. Simulation Result

	Baseline Simulation (E ~ U(0,4))			
Year		Profit ($)	Production (bu)	Spray Counts
1	Non-Aphid Year	39,216,924	3,137,354	0
2	Aphid Year	33,223,827	2,911,849	4,365
3	Non-Aphid Year	31,815,014	2,908,557	0
4	Aphid Year	27,317,573	2,790,949	12,942
5	Aphid Year	26,936,982	2,967,937	14,496
6	Aphid Year	18,779,346	2,222,437	19,672
7	Non-Aphid Year	22,159,463	2,645,547	0
8	Aphid Year	19,678,232	2,539,906	1,813
9	Non-Aphid Year	19,206,993	2,620,421	0
10	Non-Aphid Year	17,157,607	2,502,339	0
	Total	$255,491,963	27,247,293 bu	18.71%

	Less Natural Enemy (E~U(0,1))			
Year		Profit ($)	Production (bu)	Spray Counts
1	Non-Aphid Year	38,986,625	3,118,930	0
2	Aphid Year	33,072,985	2,911,596	6,180
3	Non-Aphid Year	31,487,562	2,878,621	0
4	Aphid Year	27,361,858	2,809,300	15,024
5	Aphid Year	27,047,101	2,991,861	16,179
6	Aphid Year	18,782,910	2,224,509	20,791
7	Non-Aphid Year	21,940,788	2,619,440	0
8	Aphid Year	19,536,901	2,533,795	2,922
9	Non-Aphid Year	19,206,993	2,620,421	0
10	Non-Aphid Year	17,157,607	2,502,339	0
	Total	$254,581,330	27,210,811 bu	21.42%

	CP Installation			
Year		Profit ($)	Production (bu)	Spray Counts
1	Non-Aphid Year	39,216,924	3,137,354	0
2	Aphid Year	33,238,195	2,913,706	4,359
3	Non-Aphid Year	31,815,014	2,908,557	0
4	Aphid Year	27,324,547	2,791,608	12,933
5	Aphid Year	26,936,987	2,967,937	14,496
6	Aphid Year	18,779,345	2,222,436	19,669
7	Non-Aphid Year	21,159,463	2,645,547	0
8	Aphid Year	19,683,722	2,540,606	1,878
9	Non-Aphid Year	19,206,993	2,620,421	0
10	Non-Aphid Year	17,157,607	2,502,339	0
	Total	$255,518,796	27,247,293 bu	18.70%