

An agent-based model of insect resistance management and mitigation for Bt maize: A social science perspective

Yuji Saikai & Paul D. Mitchell

Abstract

It is natural to see insect resistance management as a complex system in which there are spatial-temporal interaction between many biological and social factors. Therefore, we build an agent-based model and conduct simulation experiments to provide insights into the complex system and inform policymakers of potential options. Specifically, we emphasize the significance of social factors, e.g. economic incentives and social network, which have been neglected in the literature. The results suggest that we are in a critical situation where the resistance to Bt crop is about to surge and immediate actions should be taken. In accordance with our intuitions, proactive measures such as refuge requirement and tax are more efficient in terms of economic surplus than reactive ones such as ban and spray.

Author Summary

While the evolution of insect population is certainly a biological phenomenon, in agricultural landscapes, it is intervened by human activities constituting a complex system of both biological and social factors. To analyze it, we build an agent-based model, which is a computer simulation model that can handle spatially and temporally interacting factors. The results suggest that we are in a critical situation where the resistance to Bt crop is about to surge and immediate actions should be taken. In accordance with our intuitions, proactive measures such as refuge requirement and tax seem more efficient in terms of economic surplus than reactive ones such as ban and spray.

1 Introduction

Globally, farmers have planted more than 2.3 billion hectares of genetically engineered crops since their commercial introduction in 1996, including a new maximum of 190 million hectares in 2017 [1]. Focusing on maize (*Zea mays*), the world's leading grain crop with annual production exceeding a billion metric tons, the United States, Brazil and Argentina together produced almost half of the world's maize in 2017 [2]. Bt maize – maize genetically engineered to produce *Bacillus thuringiensis* (Bt) toxins in plant tissues for insect control – accounted for more than 80% of the maize planted in each nation [1]. After more than two decades of commercial use of genetically engineered crops, insect resistance to Bt toxins continues to be a major concern around the world [3]. A high-dose/refuge resistance management strategy continues to be the primary policy for delaying resistance to these Bt toxins [4–6]. Nevertheless, field-evolved resistance to some of these Bt toxins has been documented for populations of western corn rootworm (*Diabrotica virgifera virgifera*) in the United States and various lepidopteran species in multiple locations [7].

The commercialization of Bt crops has generated a variety of research, including bioeconomic models integrating population genetics and pest ecology with farmer returns. Though this modeling contributed to the development of insect resistance management policies, little other work exists on the role of social factors in the evolution of insect resistance to commercialized toxins. Insect resistance to these toxins evolves in response to human management activities, activities driven by a variety of social factors that include not only economic considerations, but also sociological, psychological, cultural, and political considerations [8]. As a result, examining genetic and ecological processes in isolation from these broader social factors potentially misses key determinants of the evolution of insect resistance. Hence, a broader, complex systems model of insect resistance management that incorporates both biological and social processes can potentially provide new insights [9].

In the United States, the U.S. Environmental Protection Agency (EPA) required companies commercializing Bt crops to develop resistance mitigation plans as a condition for product registration. Once a resistant population has been officially documented according to the EPA process, these plans generally restrict the availability of the technology (Bt seed) in and around the region where the resistant population emerges. However, though resistant insect populations and field failures have been documented in the U.S. in the scientific literature [7,10], the official EPA process has not triggered implementation of these plans, with the EPA instead requiring a more generalized response by Bt crop registrants [11]. Nevertheless, little research exists that evaluates and compares these and other mitigation policies. Given the length of time that Bt crops have been in use in the U.S. and other nations, it seems likely that insect resistance will become an increasing problem for Bt crops, implying that more research on mitigation responses and strategies would be especially timely.

This paper has two goals. First, we develop an agent-based model of insect resistance to Bt maize that incorporates social factors in order to show that social factors can also play a key role in the evolution of insect resistance to Bt toxins in agricultural cropping systems. Second, we use this agent-based model to compare different mitigation policies in order to inform policy makers and other stakeholders of the types of programs that generate the largest economic benefits for mitigating resistance.

Agent-based modeling has become as a standard approach for studying complex systems and emergent behavior, including socio-ecological modeling of insect resistance management [12,13]. In agent-based models, an observed macroscopic phenomenon emerges as a result of interaction among heterogeneous agents in a dynamically evolving environment. Agents typically follow simple decision rules and influence each other either directly or indirectly through the environment, which itself evolves according to its own rules and agent actions. Due to these complex processes being explicitly modeled, it is best to simulate them in computer, which allows researchers to test a wide range of parameter values. In other words, agent-based models are laboratory experiments conducted in silico [13,14]. Despite the remaining challenges to overcome such as ad hoc assumptions and a lack of relevant data for validation [15–17], agent-based modeling can provide insights into complex systems, which would be difficult to study otherwise. Given the merits, applications of agent-based models to pest and resistance management in agricultural systems have been developed [18–20].

Although agent-based models can integrate many factors, they still face the fundamental tradeoff in modeling: fidelity to the phenomenon being examined and abstraction for ease of analysis and interpretation [13]. This paper focuses on deriving new insights into policy options for insect resistance management, particularly mitigation, and emphasizes the significance of social factors for questions relevant to policymakers [18]. As a result, the biological aspects of the model are simpler than other models focusing almost exclusively on biological processes [21–23], while the social components are richer than existing models that use individual-based modeling that incorporates social factors [24].

We extend the existing work [24] on insect resistance management for Bt crops by more fully leveraging the power of agent-based modeling. First, we explicitly model the local and dynamical influence of neighbors through social network on each individual farmer, rather than reducing it into static parameters, which is often the case in the existing literature. This addition changes how farmers make decisions regarding adoption of Bt maize into a hybrid process that mixes both individual profit considerations and a desire to mimic neighbors, which can better match observed aggregate adoption data. Second, we allow the additional cost of planting Bt seed to vary, because this cost influences adoption decisions and companies have reduced it to encourage farmers to continue to plant Bt maize [25]. With this pricing flexibility, we calibrate the farmer decision model using historical data that reflects these decreasing prices, and then can examine the impact of tax on Bt seed as a policy option for mitigating resistance.

For this analysis, we parameterize the bioeconomic model for European corn borer (*Ostrinia nubilalis*) in maize production and calibrate the social model using historical Bt maize adoption data for the state of Wisconsin. Through the calibration process, we emphasize the significant role that a social factor – the local influence of neighbors via social networks [26] – can play in the evolution of insect resistance. Using the calibrated model, we then simulate a number of mitigation policies implemented both over the entire landscape and around the local areas where resistance develops. In particular, we consider combinations of increased refuge requirement, ban on the use of Bt maize, areawide use of additional insecticide to control the pest, and a tax on the sale of Bt seed. To access relative performance of each policy, we use economic surplus as a monetary measure of the social value generated by the use of Bt maize and conduct sensitivity analysis of key parameters to explore the robustness of the model.

2 Model

2.1 Grid space

The model is spatially explicit with 30×70 grid space, representing the cropland in Wisconsin (150×350 km²). Approximately 44% of the landscape is dedicated to corn production [27]. The following figure depicts a typical model landscape, which is in the condition of 90% Bt adoption and 51% resistance allele frequency.

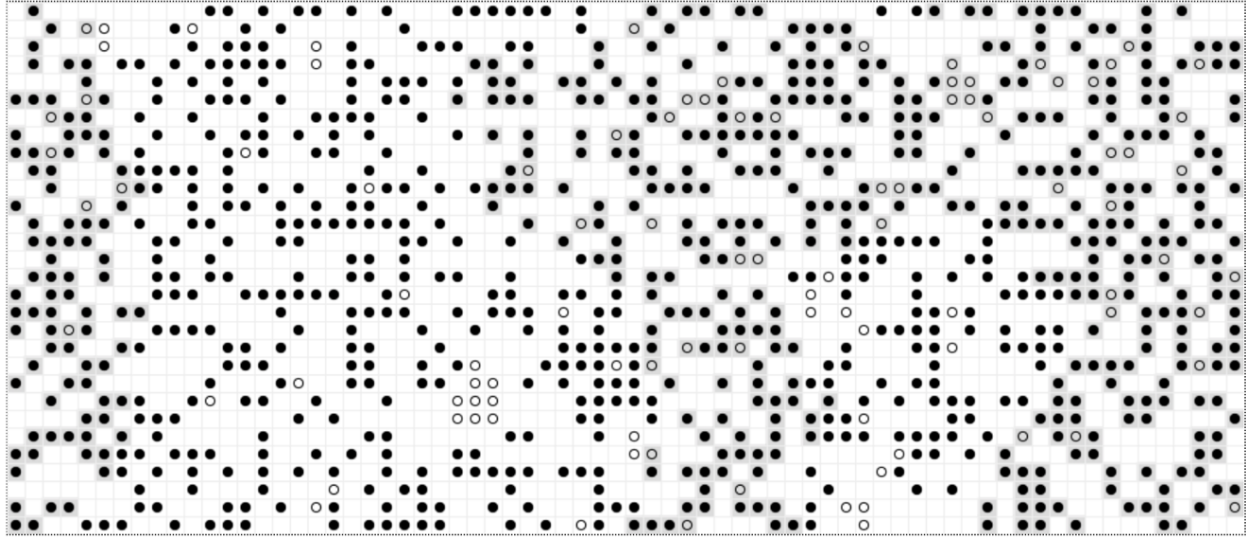


Figure 1. Typical model landscape

A circle (○) represents a farmer who plants the conventional seed, whereas a filled circle (●) represents a farmer who adopts Bt seed. Light-gray background (■) indicates that an individual cell has over 50% resistance allele frequency, which Tabashnik [28] uses as a criterion for resistance development. To avoid boundary effects, the space is configured as a torus; top cells wrap to the corresponding bottom cells, and so do left-most cells to the right-most cells. In other words, the model space is assumed to be a part of a larger area with the same dynamics happening [23].

2.2 Insect module

One of the key building blocks of the model is the population dynamics of the European corn borer (*Ostrinia nubilalis*), which has been a major pest in corn production, and its response to Bt seed usage. The pest population-genetics model uses discrete time steps corresponding to distinct pest generations and consistent with the seasonality of many types of crop production. Although *O. nubilalis* has two or more generations per year in most of the U.S. [29], we simplify the model to one discrete time step per year that aggregates population dynamics across the two generations. Hutchison et al. [30] used a comparable empirical approach to estimate annual population growth rates for *O. nubilalis* using annual observations of second-generation adult population densities in Minnesota and Wisconsin.

Following Mitchell & Onstad [31], we assume three genotypes with respect to resistance to Bt toxin. Specifically, there are two alleles, *R* (resistance) and *S* (susceptible), constituting three genotypes, *RR*, *SS*, and *RS*, whose survival rates are 1, 0, and 0.18 respectively. Without human

intervention, the population of European corn borer oscillates over approximately seven years [32] due largely to the entomopathogenic parasite, *Nosema pyrausta* [33]. In addition, the observation in Wisconsin over 1944-1995 shows that on average the peak and trough of the oscillation are about respectively 1.2 and 0.2 larvae per plant. Thus, we approximate the dynamics by a lagged logistic growth model:

$$Y_{t+1} = rY_t \left(1 - \frac{Y_{t-1}}{K}\right),$$

where r is the growth rate and K is the carrying capacity. We figure out that $r = 2.15$ and $K = 1.4$ generate reasonable approximation. While this oscillation independently takes place at each cell, each population and genotype composition are mixed across overlapping local neighborhoods due to the dispersal.

At each period, mating takes place among three genotypes and results in a new mix of them. We assume random mating and use the following calculation. Let α_t , β_t , and γ_t denote respectively the frequencies of three genotypes at period t , i.e. $\alpha_t = \%RR_t$, $\beta_t = \%SS_t$, and $\gamma_t = \%RS_t$. Then, assuming the Hardy-Weinberg equilibrium, the genotype frequencies evolve as follows:

$$\begin{aligned}\alpha_{t+1} &= \alpha_t^2 + \alpha_t\gamma_t + 0.25\gamma_t^2, \\ \beta_{t+1} &= \beta_t^2 + \beta_t\gamma_t + 0.25\gamma_t^2, \\ \gamma_{t+1} &= 1 - \alpha_{t+1} - \beta_{t+1}.\end{aligned}$$

Insects are assumed to disperse uniformly within the dispersal radius and land on some corn fields (i.e. not onto empty cells and die). Regarding the dispersal distance, the literature has mixed evidence due to a wide range of observations, e.g. differences between spring & summer, male & female, and pre- & post-mating. While they could fly 50km [34], in most cases dispersal takes place within 20km [35,36]. In our model, to reduce the computational requirement, we set 15km or 3 cells as the dispersal radius.

2.3 Farmer module

The decision each farmer makes is whether to plant Bt or conventional corn at each season. In reality, it is likely determined by a number of factors, and some proposed a complex empirical model [37]. Utilizing an agent-based model with suitable random components, however, we take a different approach to modeling a complex phenomenon and avoid explicitly enumerating them, because complexity can emerge not only from complex factors but also from simple ones [14]. On the one hand, profitability based on expert knowledge is surely major components in commercial farming. On the other, farmers are strongly influenced by their own first-hand experience and local environment [26]. Therefore, we model the decision process as a hybrid of profit maximization and local imitation.

First, the profit-based component is specified by the following switching function [24]:

$$\Pr(\text{switch}) = \begin{cases} 1 - \exp[\beta(\pi_A - \pi_C)], & \text{if } \pi_A > \pi_C \\ 0, & \text{otherwise} \end{cases}.$$

The function determines the probability of switching from the current choice to the alternative one based on how much the alternative choice is relatively more profitable $\pi_A - \pi_C$ than the current choice. The details of profit calculation are found in Appendices. We make the switching decision “soft” due to our ignorance of other individual factors. It is applied to both cases where the current choice is Bt and the conventional. Parameter β captures the responsiveness to profitability; the higher β , the more likely to use a profitable alternative. Notice that the exponential utility function exhibits a constant absolute risk aversion of a farmer, which is commonly used in the empirical analysis [38,39]. While Milne et al. [24] use an regression estimate $\beta = 0.0055$, our model is quite different from such statistical models, and so we calibrate β against the Bt seed adoption data in Wisconsin.

Next, we model the local component using social network. Diffusion of innovations is a social phenomenon to which network analysis has been widely applied [40,41]. In particular, the adoption of hybrid seed corn in Iowa is one of the classic studies of the kind [42]. We distinguish being informed of the new technology and its adoption and focus on modeling the latter process because of the relative ease of obtaining information in the era of the Internet. It seems that local environment such as neighboring farmers is mainly responsible for adoption decision [26,42]. In addition, geographical proximity is a natural approach to defining a local network of each farmer. Therefore, we assume that each farmer is connected to the other farmers who reside in the neighborhood square. The size of the square is determined by “radius” r . For example, the following figure shows a size-2 neighborhood where the farmer (\times) is at the center and there are nine neighbors (\circ and \bullet).

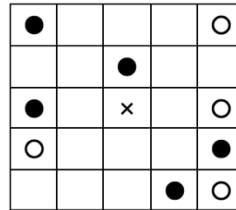


Figure 2. Typical neighborhood of size 2

Those neighbors themselves have their own neighborhoods, and each connection is assumed to be undirected. So, local networks are tightly overlapped. Notice that a size- n neighborhood can involve minimum 0 or maximum $4n(n + 1)$ neighbors. Since we assume each farmer is a representative agent of the region he operates, we consider that $n = 3$, which gives rise to the maximum 48 neighbors, is too many for a single farmer to base his decisions on. At the same time, we do not have any knowledge about the network size distribution. Thus, we randomly assign a neighborhood size to each farmer under the uniform distribution over $\{0, 1, 2\}$.

Given the profit-based component and the local network component, we assume that each farmer makes a seed choice at each season as follows:

- With probability q , he bases his decision on profits using the switching function,
- Otherwise, follows the majority choice of the neighbors at the previous period. In the example above, if the farmer (\times) follows the majority, he plants Bt seed next season because more Bt adopters (\bullet) in the neighborhood at the previous season.

If a farmer has no neighbors, he always uses the switching function. In addition to β , q is the other calibration parameters.

Lastly, a refuge policy is often implemented in the way so-called “refuge in a bag” [43]. In our model, $r\%$ refuge requirement has two effects. First, the effective seed fee is $(100 - r)\%$ of the scheduled price at that period. Second, the effective survival rate of each genotype is calculated as the weighted average: $0.01r + (1 - 0.01r)s$, where s is the original rate. We assume that, by default, 5% of requirement is already in place, and later in section 2.1 increased levels of requirement are examined.

2.4 Running the model

Each run of the model begins with the initialization of the model, including randomly placing farmers across the landscape. Since the corn fields occupy roughly 44% of the total farmland in Wisconsin, which is represented by 30×70 cells, the total number of farmers is approximately $0.44 \times 30 \times 70 = 924$. After the initialization, the run proceeds period by period; a period corresponds to a growing season or year in the real world. Before introducing farmers into the model, we run only the insect module for 11 periods, which corresponds to the pre-Bt periods and helps stabilize the model’s biological dynamics. Thereafter, each period involves the following processes in order.

1. Update the pest population of each cell simultaneously:
 - i. Bt toxin effects (reduction of the population according to the survival rates of three genotypes),
 - ii. reproduction (population change due to the other biological factors),
 - iii. mating (change in genotype composition),
 - iv. dispersion (local re-mixing of population).
2. All the farmers make planting decisions simultaneously.

2.5 Calibration

We use the adoption data in Wisconsin to calibrate the model. The calibration method is to minimize the sample average of the mean squared errors (MSEs). Specifically, in each run, we calculate MSE, which is the mean squared deviation of the model’s Bt adoption rate from the actual data. Then, since each run is a random realization, we take the sample average of MSEs from all the runs. This is the quantity to minimize. There are two calibration parameters, β and q , as described in section 2.3. To highlight the significance of the local network, we first calibrate the model only with the profit-based component and see how much the hybrid model performs better. We conduct this experiment by fixing $q = 1$ and calibrating only β ; the fixed $q = 1$ means that, in making planting decisions, all farmers ignore neighbors and simply follow the switching function all the time. We consider that coarse fitting suffices due to avoiding both over-fitting and excessive computational requirement, and so use grid search with increment 0.0002 for β and 0.1 for q .

For the case only with the profit-based component, averaging over 500 runs with arbitrary random seeds #201-700, we obtain the optimal $\beta = 0.0023$. Notice that the difference from $\beta = 0.0055$ in [24]; indeed, the model with $\beta = 0.0055$ behaves very poorly. In contrast, for the hybrid model with the same set of random seeds, we obtain the optimal $\beta = 0.0039$ and $q = 0.2$. The following figure plots three series, from which it is easy to see the superior fitting of the hybrid model. In particular, $q = 0.2$ has a remarkable implication that, 80% of times, those who have neighbors blindly follow the majority choice in the neighborhood.

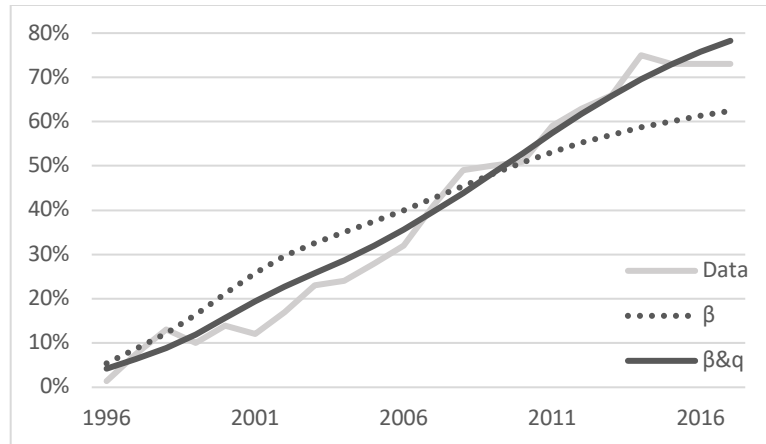


Figure 3. Superior fitting of the hybrid model

3 Results

3.1 Baseline results

The baseline results are obtained by running the calibrated model 1,000 times (with seeds #1001-2000) and averaging each series over the iterations. The following figure plots the baseline results: insect population, Bt seed adoption rate, and R-allele frequency.

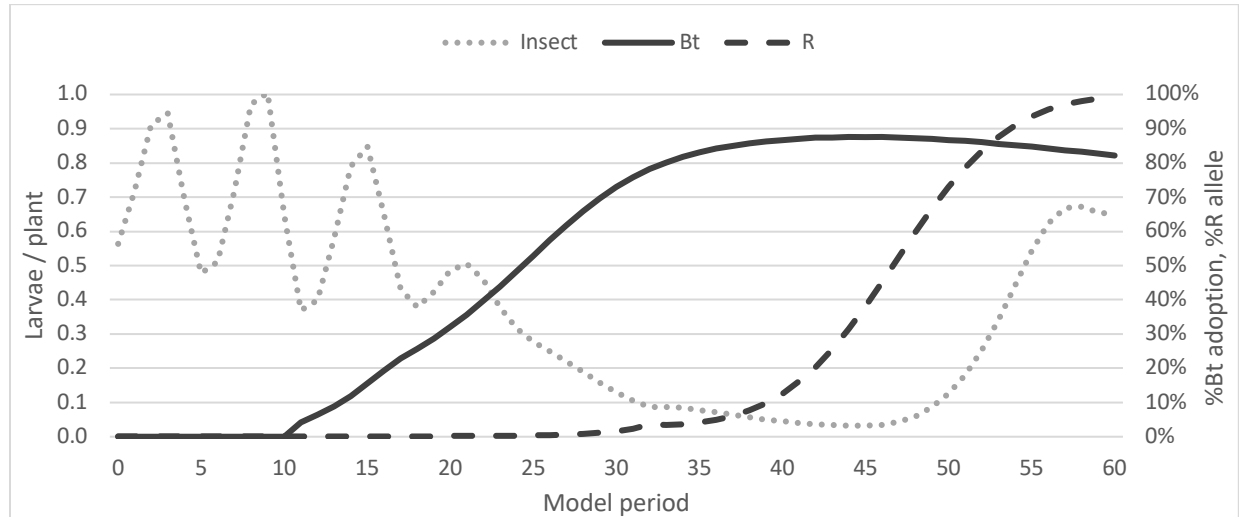


Figure 4. Baseline results

Note that the model period goes from 0 to 60, where 11-32 corresponds to year 1996-2017 respectively. Despite the current low level of R-allele frequency at period 33 (year 2018), the model indicates that, if we do not take any measure, it is about to surge and will reach a resistance level of 50% within 15 years.

To highlight the difference created by the social network, the following figure shows the result of the same simulation runs under the model only with the profit-based component (i.e. $\beta = 0.0023$ and $q = 1$). The most noticeable feature is the lower adoption rate almost over all the periods. This is an intuitive result because farmers are more profit-sensitive and therefore, as the technology becomes inefficacious due to the resistance, they opt for non-Bt seeds. As a consequence of the lower usage of the technology, the R-allele frequency reaches the resistance level ($>50\%$) at period 49, which is slower than the baseline case (period 47).

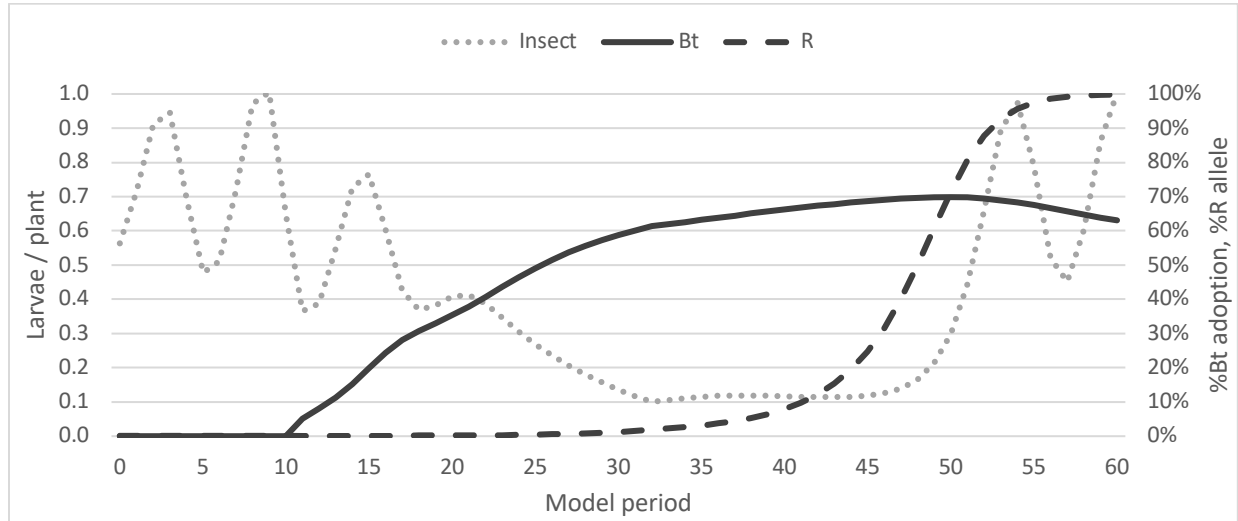


Figure 5. Results without social network effect

3.2 Policy experiment

Having developed the model, we now implement potential policies of interest and analyze their effects. Strongly influenced by the biological studies, in practice, refuge requirement is the most common measure. In contrast, due to the significance of social aspects and the complexity created by the interaction of biological and social factors, we experiment combinations of three types of policies: increased refuge requirement, remediation of local resistance development, and tax on the Bt fee. While the first two directly regulate the use of Bt, the last one adjusts the farmers' economic incentives and indirectly deter the use of Bt. Increased refuge requirement is a policy that forces every farmer to use a higher proportion of the conventional seed. The U.S. Environmental Protection Agency requires 20-50% of refuge for susceptible European corn borer [30]. We increase the requirement from the standard 5% to either 20% or 50%. Next, remediation can take two forms: ban on the Bt use and insecticide spray to reduce resistant genotypes before dispersing. The ban is imposed within a radius from the cell where the resistance is observed. We consider two radii: one same as the radius of insect dispersal (3 cells) and the other twice as large (6 cells). It is in a sense 100% refuge requirement but applied locally and dynamically imposed and lifted according to the situation at the previous period. Insecticide spray takes place immediately in the period of resistance. In terms of coverage, we consider both only the cell of resistance and the neighborhood of 3-cell radius. We assume 100% compliance, 80% efficacy rate, and \$32/ha cost. As above, the resistance is declared when R-allele frequency becomes above 50%, and the timing of detection is assumed to be between Bt toxin effects and reproduction/dispersal processes. Finally, a tax policy increases the Bt seed fee by 25% or 50%. In total, these options create 81 possible combinations of policy:

$$\begin{aligned}
& \times | \{5\%, 20\%, 50\% \} | \\
& \times | \{ \text{None}, \text{Ban}(r=3), \text{Ban}(r=6) \} | \\
& \times | \{ \text{None}, \text{Spray}(r=0), \text{Spray}(r=3) \} | \\
& \times | \{0\%, 25\%, 50\% \} | \\
& = 81
\end{aligned}$$

where $|\cdot|$ denotes the size of the set. Each policy scenario is implemented immediately after the calibration phase (i.e. at period 33). Finally, to access relative superiority of each policy, we use social surplus as a performance metric, which is approximated by the sum of farmer profits and technology fees collected by the seed company divided by the total number of farmers. We assume that collected taxes are added to the surplus, while costs of spraying are subtracted from the farmer's profit. For each policy combination, we examine a surplus over 25 different lengths of planning horizon starting from period 33 up to period 57.

In a similar way to the baseline simulation, for each policy, we run the calibrated model 500 times (with seeds #7001-7500) and average series of surplus over the iterations. Identifying an optimal policy for each length of future periods, it turns out that the optimal policies concentrate on four combinations as shown in the following table.

Table 1. Optimal policies over different planning horizons

#	Refuge	Ban	(radius)	Spray	(radius)	Tax	Optimal horizon
1	5%	No	—	No	—	0%	1-15
2	20%	No	—	No	—	0%	16-22
3	20%	No	—	No	—	25%	23
4	20%	No	—	No	—	50%	24-25

Furthermore, there is very little difference among #2, #3, and #4 policies. Therefore, in terms of maximizing the surplus, the model suggests that in the long term 20% refuge requirement is optimal, whereas in the short or medium term no extra intervention is optimal. Also, due to the little impact on surplus, tax may be used for re-distributional purposes without reducing the long-term surplus.

In addition to maximizing surplus, it is also interesting to see how ban and spray policies perform, because there may be different performance criteria for choosing policies other than surplus maximization. The following figure plots per period surplus under four policies against the number of periods in the future to account. Note that, for ease of illustration, cumulative surplus over each length of future periods is divided by the corresponding length, which makes per period surplus. Notice also that Refuge 20% and Refuge 20%, Spray, Tax 50% policies become active immediately and therefore the surplus drops at planning horizon of 1, whereas Baseline and Ban do not influence the farmers at that period. First of all, as mentioned above, the baseline (i.e. no intervention) is optimal over 1-15 lengths and 20% refuge requirement is optimal for 16-25 lengths. Second, ban (with radius 3) seems considerably suboptimal due to the lost revenue for the seed company. Lastly, spray with radius 0 combined with refuge and tax have comparable performance in the long term.

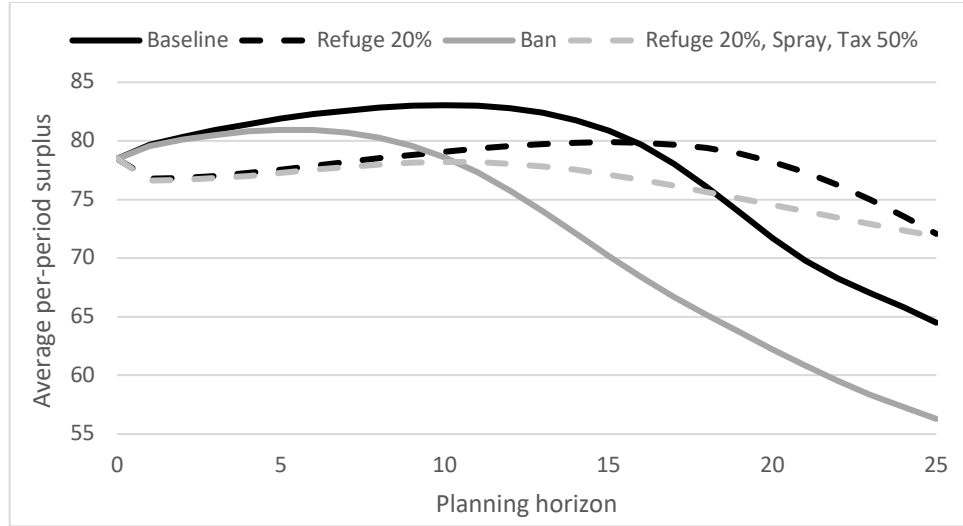


Figure 6. Per period surplus under four policies.

To reiterate the significance of social network effect, we also run the same simulation of the model only with the profit-based component (i.e. $\beta = 0.0023$ and $q = 1$). The result is remarkably different from the policy analysis under the baseline calibration with social network. Without social network effects, refuge requirement is little favored, and ban becomes optimal in the long term; the recommended policies are considerably different.

Table 2. Optimal policies under the model without social network effects

#	Refuge	Ban	(radius)	Spray	(radius)	Tax	Optimal horizon
1	5%	No	—	No	—	0%	1-18
2	5%	No	—	No	—	25%	19
3	5%	Yes	3	No	—	0%	20-21
4	5%	Yes	3	No	—	25%	22-25

To investigate how the social benefits of Bt seed are distributed among farmers, company, and tax, we define the farmer benefit to be profit under the actual seed choice minus (hypothetical) profit under non-Bt seed. Note that if a farmer indeed uses non-Bt seed, the farmer benefit is equal to 0. Specifically, we look into the benefit shares under three policies: baseline, 20% refuge, and 20% refuge + 50% tax. The following figure presents the benefit shares under the baseline. As seen, the benefits are shared almost equally.

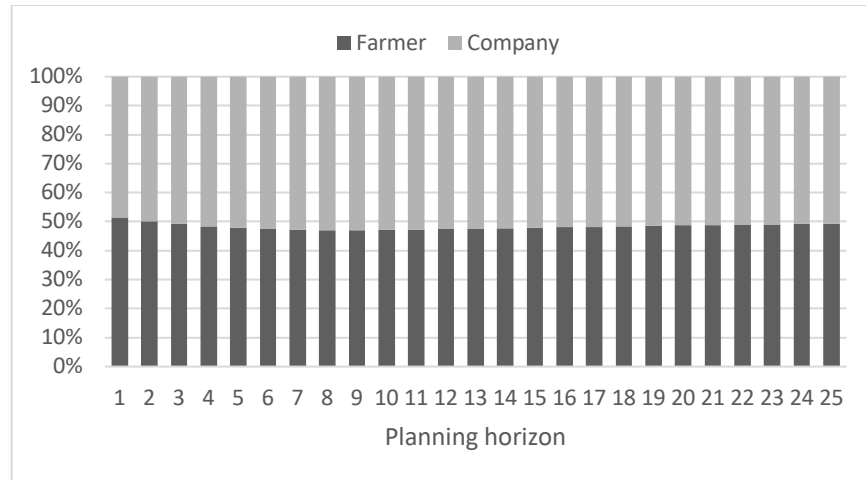


Figure 7. Baseline benefit shares

Next, under 20% refuge requirement, the farmer's share decreases uniformly over all the future period. Despite the increased total surplus in the long term, this may socially or politically become an issue.

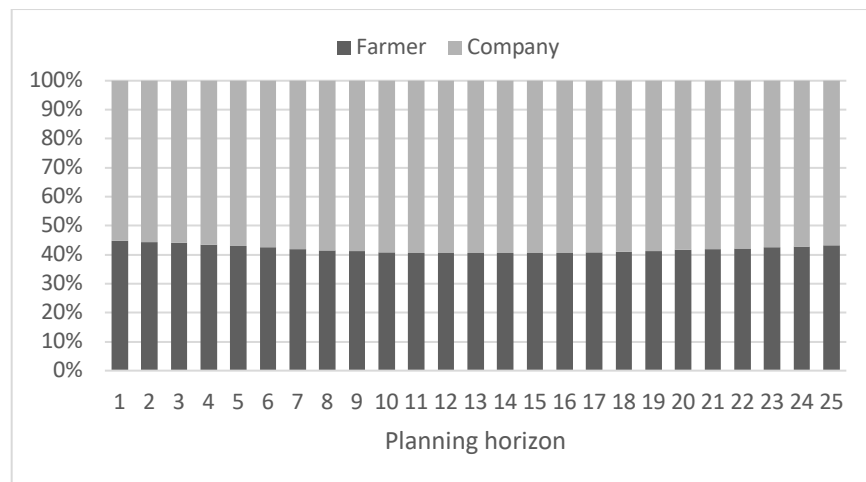


Figure 8. Benefit shares under 20% Refuge

One way to address the issue, policy makers could use tax without reducing the surplus. As the following figure shows, tax could redistribute the social benefit and raise the farmer's share back to 50% or even higher.

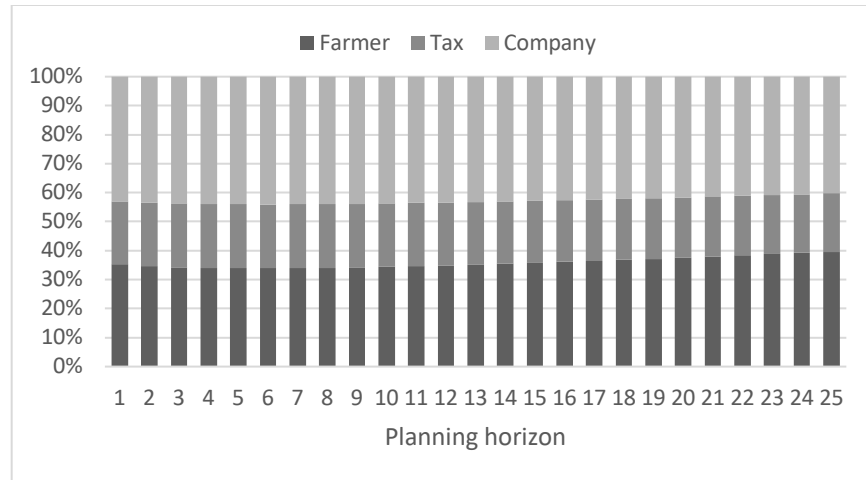


Figure 9. Benefit shares under 20% refuge + 50% tax

Finally, the following figures plot the dynamics of Bt adoption rate and R-allele frequency over the planning horizons under baseline, 20% refuge, 50% tax, and ban ($r=3$) policies. The simulations are run with the same set of random seeds as used in the baseline results (seeds #1001-2000). Notice that the Bt adoption rate for Ban is plotted in a different range. Given the two figures, it is easy to see that the ban policy has the fundamentally different effects on farmers behavior and thereby insect resistance development.

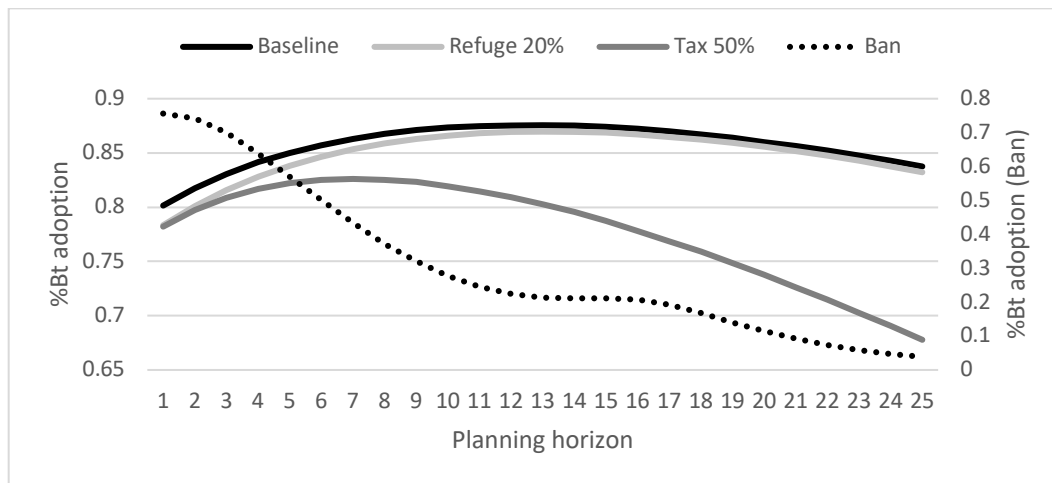


Figure 10. Bt adoption rate prediction under four policies

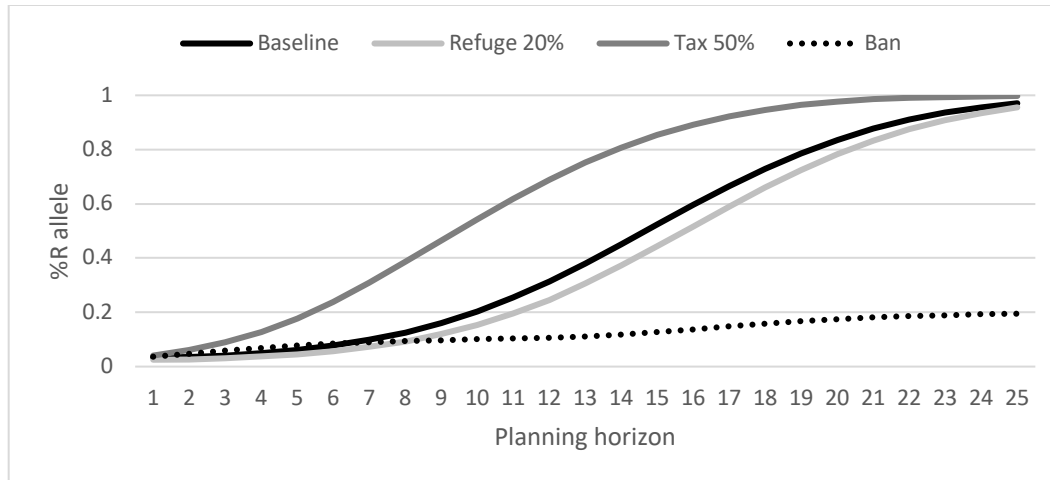


Figure 11. *R*-allele frequency prediction under four policies

4 Conclusion

We have constructed an agent-based model, which incorporates both biological and social factors, and conducted the policy experiments. The baseline result underlines the need to take immediate actions, and the policy experiments in particular suggest that proactive measures such as refuge requirement and tax will likely be more efficient in terms of economic benefit than reactive ones such as ban and spray.

We have used, as a performance metric, an economic surplus, which is the sum of farmer's profit and seed company's extra revenue. In reality, however, environmental damage is a big concern to policymakers when it comes to agricultural chemicals and alternative methods for pest management. Therefore, reduction in environmental impact relative to the conventional pesticide should be part of the performance metric. Specifically, since pest control with Bt seed is considered to have less impact, its use increases the social benefit. Although in general such an additional performance factor makes the system even more complex, with agent-based models, the policy analysis will be no more difficult than re-defining the performance metric and running simulations again.

For future work, as a general challenge in agent-based modeling, we should collect data for validation. In terms of extending the model, social network has potentials for capturing crucial mechanisms as many social scientists are interested in. For example, when remediation policies are implemented, farmers do not necessarily comply with the orders. Instead, just as making seed choice decisions, they may follow neighbors' reactions. Finally, if the research objective is to achieve greater prediction accuracy, in principle, a straightforward approach is to build a richer model with more parameter values estimated instead of assumed. Since agent-based models are highly modularized, it will be relatively easy to add sub-models from various domains such as entomology, ecology, and social sciences. But, we do not believe that merely constructing complex larger models will lead to greater prediction because of overfitting and a lack of data for even more parameters to estimate, especially social data. Consequently, modeling decisions will likely remain the challenge, where such choices are often more art than science.

5 References

1. ISAAA. Global Status of Commercialized Biotech/GM Crops in 2017: Biotech Crop Adoption Surges as Economic Benefits Accumulate in 22 Years. Ithaca, NY: ISAAA; 2017. (ISAAA Brief). Report No.: 53.
2. USDA. World Agricultural Supply and Demand Estimates [Internet]. Washington, DC; 2018. (WASDE). Report No.: 581. Available from: <https://www.usda.gov/oce/commodity/wasde/>
3. Tabashnik BE. ABCs of Insect Resistance to Bt. PLOS Genet. 2015 Nov 19;11(11):e1005646.
4. Huang F, Andow DA, Buschman LL. Success of the high-dose/refuge resistance management strategy after 15 years of Bt crop use in North America. Entomol Exp Appl. 2011 Jul 1;140(1):1–16.
5. Pardo-López L, Soberón M, Bravo A. *Bacillus thuringiensis* insecticidal three-domain Cry toxins: mode of action, insect resistance and consequences for crop protection. FEMS Microbiol Rev. 2013 Jan 1;37(1):3–22.
6. Tabashnik BE, Brévault T, Carrière Y. Insect resistance to Bt crops: lessons from the first billion acres. Nat Biotechnol. 2013 Jun;31(6):510–21.
7. Gassmann AJ, Petzold-Maxwell JL, Keweshan RS, Dunbar MW. Field-Evolved Resistance to Bt Maize by Western Corn Rootworm. PLOS ONE. 2011 Jul 29;6(7):e22629.
8. Hurley TM, Mitchell PD. Insect Resistance Management: Adoption and Compliance. In: Onstad DW, editor. Insect Resistance Management. 2nd ed. San Diego: Academic Press; 2014. p. 421–51.
9. Rebaudo F, Dangles O. An agent-based modeling framework for integrated pest management dissemination programs. Environ Model Softw. 2013 Jul 1;45:141–9.
10. Gassmann AJ, Petzold-Maxwell JL, Clifton EH, Dunbar MW, Hoffmann AM, Ingber DA, et al. Field-evolved resistance by western corn rootworm to multiple *Bacillus thuringiensis* toxins in transgenic maize. Proc Natl Acad Sci. 2014;201317179.
11. Andow DA, Pueppke SG, Schaafsma AW, Gassmann AJ, Sappington TW, Meinke LJ, et al. Early Detection and Mitigation of Resistance to Bt Maize by Western Corn Rootworm (Coleoptera: Chrysomelidae). J Econ Entomol. 2016 Feb 1;109(1):1–12.
12. Miller JH, Page SE. Complex adaptive systems: An introduction to computational models of social life. Princeton university press; 2009.

13. Peck SL. Simulation as experiment: a philosophical reassessment for biological modeling. *Trends Ecol Evol.* 2004 Oct 1;19(10):530–4.
14. Epstein JM. *Generative social science: Studies in agent-based computational modeling.* Princeton University Press; 2006.
15. Durlauf SN. Complexity, economics, and public policy. *Polit Philos Econ.* 2012 Feb 1;11(1):45–75.
16. Filatova T, Verburg PH, Parker DC, Stannard CA. Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environ Model Softw.* 2013 Jul 1;45:1–7.
17. Feola G, Binder CR. Towards an improved understanding of farmers' behaviour: The integrative agent-centred (IAC) framework. *Ecol Econ.* 2010 Oct 15;69(12):2323–33.
18. Renton M. Shifting focus from the population to the individual as a way forward in understanding, predicting and managing the complexities of evolution of resistance to pesticides. *Pest Manag Sci.* 2013;69(2):171–5.
19. Renton M, Busi R, Neve P, Thornby D, Vila-Aiub M. Herbicide resistance modelling: past, present and future. *Pest Manag Sci.* 2014;70(9):1394–404.
20. Gay P-E, Lecoq M, Piou C. Improving preventive locust management: insights from a multi-agent model. *Pest Manag Sci.* 2017;74(1):46–58.
21. Ives AR, Paull C, Hulthen A, Downes S, Andow DA, Haygood R, et al. Spatio-Temporal Variation in Landscape Composition May Speed Resistance Evolution of Pests to Bt Crops. *PLOS ONE.* 2017 Jan 3;12(1):e0169167.
22. Onstad DW, Meinke LJ. Modeling Evolution of *Diabrotica Virgifera Virgifera* (Coleoptera: Chrysomelidae) to Transgenic Corn with Two Insecticidal Traits. *J Econ Entomol.* 2010 May 31;103(3):849–60.
23. Storer NP. A spatially explicit model simulating western corn rootworm (Coleoptera: Chrysomelidae) adaptation to insect-resistant maize. *J Econ Entomol.* 2003;96(5):1530–1547.
24. Milne AE, Bell JR, Hutchison WD, van den Bosch F, Mitchell PD, Crowder D, et al. The effect of farmers' decisions on pest control with Bt crops: a billion dollar game of strategy. *PLOS Comput Biol.* 2015;11(12).
25. Shi G, Chavas J, Stiegert K. An Analysis of the Pricing of Traits in the U.S. Corn Seed Market. *Am J Agric Econ.* 2010 Oct 1;92(5):1324–38.
26. Kaup BZ. The reflexive producer: The influence of farmer knowledge upon the use of Bt corn. *Rural Sociol.* 2008;73(1):62.

27. USDA. Census of agriculture [Internet]. 2012. Available from: <https://www.agcensus.usda.gov/Publications/2012/>
28. Tabashnik BE. Delaying insect resistance to transgenic crops. *Proc Natl Acad Sci*. 2008 Dec 9;105(49):19029–30.
29. Mason CE, Rice ME, Calvin DD, Van Duyn JW, Showers WB, Hutchison WD, et al. European Corn Borer Ecology and Management. Iowa State University; 1996. (North Central Regional Extension Publication). Report No.: 327.
30. Hutchison WD, Burkness EC, Mitchell PD, Moon RD, Leslie TW, Fleischer SJ, et al. Areawide Suppression of European Corn Borer with Bt Maize Reaps Savings to Non-Bt Maize Growers. *Science*. 2010 Oct 8;330(6001):222–5.
31. Mitchell PD, Onstad DW. Effect of extended diapause on evolution of resistance to transgenic *Bacillus thuringiensis* corn by northern corn rootworm (Coleoptera: Chrysomelidae). *J Econ Entomol*. 2005;98(6):2220–2234.
32. Onstad DW, Maddox JV. Modeling the effects of the microsporidium, *Nosema pyrausta*, on the population dynamics of the insect, *Ostrinia nubilalis*. *J Invertebr Pathol*. 1989;53(3):410–21.
33. Bell JR, Burkness EC, Milne AE, Onstad DW, Abrahamson M, Hamilton KL, et al. Putting the brakes on a cycle: bottom-up effects damp cycle amplitude: Managing epidemic persistence. *Ecol Lett*. 2012 Apr;15(4):310–8.
34. Showers WB, Hellmich RL, Derrick-Robinson ME, Hendrix WH. Aggregation and dispersal behavior of marked and released European corn borer (Lepidoptera: Crambidae) adults. *Environ Entomol*. 2001;30(4):700–10.
35. Dorhout DL, Sappington TW, Lewis LC, Rice ME. Flight behaviour of European corn borer infected with *Nosema pyrausta*. *J Appl Entomol*. 2011;135(1–2):25–37.
36. Dorhout DL, Sappington TW, Rice ME. Evidence for obligate migratory flight behavior in young European corn borer (Lepidoptera: Crambidae) females. *Environ Entomol*. 2008;37(5):1280–90.
37. Useche P, Barham BL, Foltz JD. Integrating Technology Traits and Producer Heterogeneity: A Mixed-Multinomial Model of Genetically Modified Corn Adoption. *Am J Agric Econ*. 2009 May 1;91(2):444–61.
38. Chavas J-P. Risk analysis in theory and practice. Academic Press; 2004.
39. Mitchell PD, Hutchison WD. Decision making and economic risk in IPM. In: Radcliffe EB, Cancelado RE, Hutchison WD, editors. *Integrated Pest Management: Concepts, Tactics, Strategies and Case Studies* [Internet]. Cambridge: Cambridge University Press; 2008. p. 33–

50. Available from: <https://www.cambridge.org/core/books/integrated-pest-management/decision-making-and-economic-risk-in-ipm/1B17130CD5A60148EA1057C0B1ECE4AF>
40. Easley D, Kleinberg J. Networks, crowds, and markets: Reasoning about a highly connected world. Cambridge University Press; 2010.
41. Jackson MO. Social and economic networks. Vol. 3. Princeton university press; 2010.
42. Ryan B, Gross NC. The diffusion of hybrid seed corn in two Iowa communities. Rural Sociol. 1943;8(1):15.
43. Hodgson E. Refuge in a Bag is Here: Explaining the Simplified Refuge [Internet]. 2010 [cited 2018 Jul 18]. Available from: <https://crops.extension.iastate.edu/cropnews/2010/06/refuge-bag-here-explaining-simplified-refuge>
44. Mitchell P, Riedell W. Stochastic dynamic population model for northern corn rootworm (Coleoptera: Chrysomelidae). J Econ Entomol. 2001;94(3):599–608.
45. Hurley TM, Mitchell PD, Rice ME. Risk and the value of Bt corn. Am J Agric Econ. 2004;86(2):345–358.
46. USDA. Commodity Costs and Returns [Internet]. 2016 [cited 2016 Oct 28]. Available from: <http://www.ers.usda.gov/data-products/commodity-costs-and-returns/commodity-costs-and-returns/#Recent Costs and Returns: Corn>
47. USDA. Adoption of Genetically Engineered Crops in the U.S. [Internet]. 2017. Available from: <http://www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-us.aspx>

6 Appendices

6.1 Key parameters

Table 3. Key parameters

Grid dimension	30×70
Proportion of corn field in the total cropped land	44%
Survival rates of <i>RR</i> , <i>SS</i> , <i>RS</i> genotypes	(1, 0.01, 0.18)
Growth rate of insect population (<i>r</i>)	2.15
Carrying capacity of insect population (<i>K</i>)	1.2
Insect dispersal distance	15km
Neighborhood size distribution over {0, 1, 2}	Uniform

6.2 Sensitivity analysis

We conduct sensitivity analysis by changing the parameters whose chosen values may be seen naive or ad hoc. Specifically, we perturb each parameter either by $\pm 10\%$ (similar to [44]) or to some meaningful value and re-calibrate the model using the same set of random seeds (#201-700). The model sensitivity to each parameter is examined by looking at the calibration parameters β and q , and relative changes in cumulative surplus over the first 10 years after the calibration phase (i.e. period 33-42) and R-allele frequency at period 47 (the period when the baseline model develops resistance by reaching 52% of R-allele frequency). These simulations are run with the same set of random seeds (#1001-2000) as used for the baseline. The following table presents the result, where we see overall robustness and consistency of the model.

Table 4. Sensitivity analysis

Parameter	Change	β	q	SP	%R
RS survival rate	+10%	0.0039	0.2	0%	31%
	-10%	0.0039	0.2	0%	-34%
Growth rate of insect population	+10%	0.0033	0.5	-2%	57%
	-10%	0.0039	0.2	1%	-52%
Carrying capacity of insect population	+10%	0.0035	0.2	-2%	-12%
	-10%	0.0041	0.2	0%	-5%
Insect dispersal distance	20km	0.0039	0.2	0%	4%
	10km	0.0035	0.3	0%	14%
Grid dimension	40×93	0.0037	0.3	0%	9%
	20×47	0.0033	0.5	1%	22%
Neighborhood size distribution	(.25, .5, .25)	0.0043	0.3	-2%	-21%
Technology fees	+10%	0.0041	0.2	0%	-3%
	-10%	0.0037	0.2	0%	1%

6.3 Yield, profits, and benefit of Bt

Similar to [24], we fix the potential yield (i.e. no pest damage) at 10 t/ha and the price at \$100/t. The damage is field-specific and assumed to be a function of the pest population (x). In particular, we adopt the yield loss function from [45]:

$$Loss = 0.021\mu^{\frac{2\alpha-1}{\alpha^2}} \left(\frac{1}{\sigma^2 + \mu^2} \right)^{\frac{\alpha-1}{2\alpha^2}},$$

where $\alpha = \frac{1}{0.58} \approx 1.72$, $\mu = 2.56x + 5.65\sqrt{x}$, and $\sigma = 3.4 + 1.73x$.

To compute the expected costs, using the data for the heartland region [46], we first obtain the average cost-revenue ratio and then multiply it by the potential revenue (\$1,000). According to the data, over the last six years, the average revenue and costs are \$740/acre and \$672/acre respectively. Thus, the ratio is $672/740 = 0.91$, and we use $0.91 \times \$1,000 = \910 for every farmer at every period. In addition, if a farmer plants Bt seeds, he incurs an extra technology fee based on the following data in Wisconsin.

Year	96 - 03	04	05	06	07	08	09	10
Fee	17.49	17.45	17.04	15.78	13.75	11.41	9.18	7.27

Since the data is available only up to 2010, we assume the same price of \$7.27 at the subsequent periods. Finally, if $y\%$ of refuge is required, we use the effective fee, $(1 - 0.01y) \times \text{Fee}$, in profit calculation. Combining all together, the profit of each farmer at each period is calculated as follows:

$$\text{Profit} = \$100 \times 10(1 - \text{Loss}) - 910 - \text{Effective Fee} .$$

We define the benefit of Bt to be the actual profit minus the profit under non-Bt seed:

$$\text{Benefit} = \$100 \times 10(\text{Loss}_{\text{non}} - \text{Loss}_{\text{actual}}) - \text{Effective Fee} .$$

As readily seen, if the actual choice is non-Bt seed, the benefit is 0 due to $\text{Loss}_{\text{non}} = \text{Loss}_{\text{actual}}$ and $\text{Effective Fee} = 0$.

6.4 Adoption rates data

The following figure plots the adoption rates of Bt seeds in Wisconsin from 1996 to 2017 (22 data points), where each adoption rate is the sum of the number for "Insect-resistant (Bt) only" and the number for "Stacked gene varieties" [47].

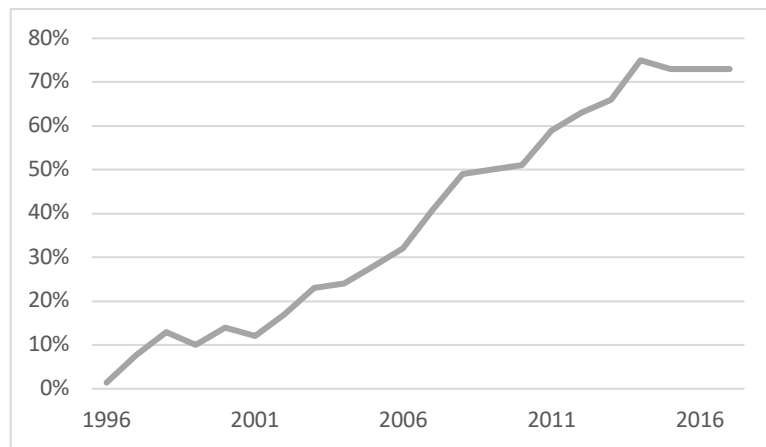


Figure 12. Bt seed adoption rates in Wisconsin

6.5 Confidence intervals of baseline Bt adoption rates

The next figure adds to the Bt adoption rates 5th and 95th percentiles for each period. With 1,000 iterations, we can be reasonably confident in the prediction.

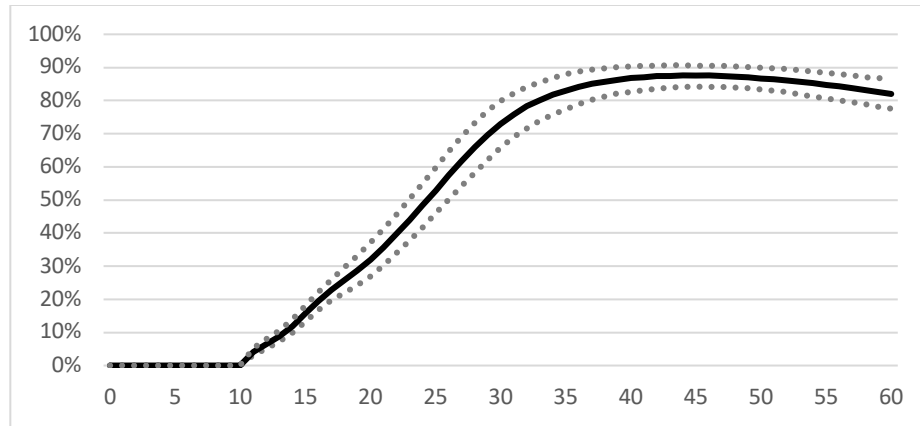


Figure 13. Bt adoption rates with confidence intervals

6.6 Python codes

<https://github.com/ysaikai/BTABM>