Pesticide Resistance, Population Dynamics, and Invasive Species Management

Contractor and Cooperator Report No. 43
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By Gregory J. McKee, Colin A. Carter, James A. Chalfant, Rachael E. Goodhue, and Frank G. Zalom

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Keywords: Invasive species, strawberries, greenhouse whitefly, pyriproxyfen, population dynamics, spatial externalities, pesticide use restrictions, data gathering, optimal management, simulation

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Table of Contents

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Executive Summary

In agriculture, invasive species represent a unique challenge for public policymakers and economists analyzing optimal pest control policies. To accurately evaluate policies involving invasive species, economic models must describe the inter-temporal features of producer responses to invader biology, seasonal changes in demand, and the policies themselves. Responses to externalities from pest control, such as pesticide resistance or pest movement, complicate finding the optimal policy and must be accounted for. This dynamic bioeconomic simulation model represents the biological, economic, and regulatory features of managing the effects of a specific invasion: the late 1990s invasion of California strawberries by the greenhouse whitefly, *Trialeurodes vaporariorum*, and the pesticide use restrictions imposed by California regulators to manage pesticide resistance.

Research questions

The model answers three specific research questions:

1. What is the cost of the pesticide use restrictions to strawberry growers, in terms of reduced profits?
2. Under what conditions would this short run cost be less than the gains due to the reduction in the speed of the development of pesticide resistance in the greenhouse whitefly over the long run?

3. How does the timing of whitefly migration affect optimal private and regional management strategies? Under what conditions will voluntary cooperation render a central regulatory authority unnecessary?

Background

The greenhouse whitefly invasion of California strawberries was first documented in the mid-1990s in Ventura County. The invasion was later observed in the Watsonville/Salinas strawberry-growing region in Monterey and Santa Cruz counties. The greenhouse whitefly has been called a "resident invader" of commercial strawberries. Although greenhouse whiteflies were common in coastal California prior to that time, strawberries had not been previously recorded as a host.

Use restrictions associated with pesticides registered for application against the whitefly on commercial strawberries create a complex management problem. Chemicals registered for use against the whitefly on strawberries in the mid-1990s proved ineffective. This resulted in an explosion of the whitefly population in 2001 and 2002, requiring quick identification and registration of new pesticides. Two chemicals with different modes of action were registered in 2003: imidacloprid (marketed as Admire©) and pyriproxyfen (an insect growth regulator marketed as Esteem©). Compared with all other previously registered pesticides, both products provide relatively effective, long-term control of the greenhouse whitefly in commercial strawberry fields.

These pesticides are used at different points in the season to manage the whitefly population. Admire© is registered for application from planting to no fewer than 14 days before harvest begins. Since marketable yields are typically available weekly, and spoil quickly if left on the plants, the 14-day interval is too long for treatments to be commercially viable during the strawberry harvest season. Esteem©, however, requires only a 2-day post-application interval. Other restrictions do constrain its application. The maximum number of applications allowed per season is 2. The first application must be made as soon as adult whiteflies appear.

Methods

There are three model components. The two biological components include a model of the population dynamics of the greenhouse whitefly and a model of the effect of the whitefly population on strawberry yields. The population model pairs information from scientific literature regarding the lifecycle of the greenhouse whitefly with field trial data regarding population and temperature to construct a calibrated simulation model of the greenhouse whitefly population. The effects of different pesticide treatment regimes on the greenhouse whitefly population are simulated using the population model. The population-yield component uses field trial data on greenhouse whitefly populations and strawberry yields to estimate the damage function. The economic component of the model captures the grower's objective of maximizing profits from strawberry production subject to the biological constraints of the agricultural system, market prices, and constraints imposed by government regulation.

The analysis compares the ability of the structural calibrated simulation model of whitefly population dynamics to replicate the observed Watsonville whitefly population sample to the ability of a reduced-form autoregressive econometric model. In this case, the calibrated simulation model performs better. This finding is not a general one. The relative performance of the methodologies will be dependent on the data and other information available in each specific case.

There is a tradeoff involved in choosing between these modeling approaches. The autoregressive model uses statistical techniques and historical data on the pest population to predict the future population. It is a simple approach and requires limited information on the pest population. This may be an attractive option for policymakers in the case of a biological invasion, since limited data will still permit rapid policy analysis. Such a model, however, may omit important biological factors if no statistical data are available. On the other hand, a simulation model can incorporate data obtained outside a statistically valid scientific experiment. For example, it can integrate results from studies of the pest in similar environments with results from experiments regarding the current invasion. The conclusions that result, however, depend on how biological and economic relationships are specified, whether obtained from outside sources or assumed.

The calibrated simulation model identifies the most striking feature of the population dynamic of the whitefly: the changing rate at which the whitefly population develops over the course of the growing season. Accounting for this variability changes the timing of pesticide applications compared to the timing obtained from a reduced-form model that assumes a uniform rate. Though the simulation model is still constrained by data, it describes more accurately the feedback between grower management decisions and the biological interaction between the invader and host plants than the autoregressive model does. This improvement is important for two reasons. First, it allows policymakers to better anticipate the effect of proposed regulations on grower behavior. Second, it makes more accurate statements about the magnitude of the costs and benefits of various policies, which could lead to different conclusions about the efficacy of policies across the two models.

Results: Cost of Pesticide Use Restrictions

The effects on single-season grower profits for the following three use restrictions on the pesticide pyriproxyfen are examined:

1. A limit of no more than 2 applications per season;
2. A requirement to apply another pesticide (imidacloprid) at planting in order to use pyriproxyfen; and
3. A requirement that the first application of pyriproxyfen be made as soon as adult whiteflies are observed.

The restriction to 2 or fewer applications of pyriproxyfen always reduced profits when only a single season is modeled. Applying imidaclopid at planting always increased profits. Furthermore, the requirement to use imidacloprid at planting does not partially offset the cost of the restriction to 2 or fewer applications of pyriproxyfen per season. Instead, a third application of pyriproxyfen and imidacloprid are complements, so the cost of the 2-application limit per grower is larger when imidacloprid is applied at planting. Timing the first application of pyriproxyfen reduced profits.

Tables 1 and 2 report the change in profit for the treatments analyzed in the Watsonville and Oxnard regions, respectively. The “fully regulated” treatment program is defined as an application of imidacloprid at planting, an application of pyriproxyfen on the first day with nonzero adult whitefly populations, and a second application of pyriproxyfen on the optimal date, given the date of the first application.

Results: Cost-Benefit Analysis of Slowing Resistance Development

When the long-run benefit of slowing the development of resistance to pyriproxyfen in the greenhouse whitefly is compared to the reduction in profits due to the use regulations, there are some conditions under which the use regulations increase long-run profits.

As the kill rate increases, or if the resistant whitefly population is not regularly diluted through migration, then fewer applications each season are profit-maximizing because resistance increases more rapidly as the number of pyriproxyfen applications per season increases. The requirement to use imidacloprid with pyriproxyfen always results in greater profits over the long term than using pyriproxyfen alone does. The results also show that the requirement to use imidacloprid does not eliminate the cost of the restriction to 2 or fewer pyriproxyfen treatments. Tables 3 and 4 report the combination of parameters for which 2 treatments per season are more profitable than 3 for Watsonville and Oxnard, respectively.

To have a sense of which scenario is the most relevant to actual field conditions, we compare them with the observations made by Bi, Toscano, and Ballmer (2002). Observed kill rates were between 40-73 percent for adult whiteflies and 51-100 percent for nymph whiteflies. Actual field conditions over the 6-year horizon may, therefore, fall along the middle columns of these tables. In this analysis, the initial values of the factors determining the development of resistance establish the policy choice. Nevertheless, as time passes, the optimal treatment program may actually move across the boundary between the 3- toward the 2-application program as resistance increases, if it does so faster than anticipated in this model. Hence, it is important to know about pyriproxyfen resistance in the regional population, before deciding whether 3 applications are sustainable or whether the limit of 2 applications per season should remain as a use restriction.

Results: Voluntary Coordination

The bioeconomic model assesses the influence of whitefly migration timing, market conditions, and pesticide regulations on optimal private and regional invasive species management strategies. Limiting the number of applications of pyriproxyfen per year will not substitute for coordination among growers when seeking to control the greenhouse whitefly. Regardless of whether 2 or 3 applications per year are allowed, greater profits can be obtained through coordination.

It is not always necessary to create a central agency for controlling the economic effects of invasive species. This finding is consistent with the emergence of the Whitefly Action Committee, a voluntary group who collects and disseminates information about the greenhouse whitefly and whitefly control methods in the Oxnard area.

There are two reasons that information exchange may emerge voluntarily in the strawberry/whitefly case. First, coordination can be beneficial to strawberry growers producing in fields adjacent to ones with alternative host crops that generate populations of migrating adult whiteflies at certain times of the year. Because adult whiteflies migrate across fields, the management decisions of one grower affect other growers in the area. If strawberry growers use information regarding the harvesting of adjacent crops (and hence the expected whitefly immigration dates) to adjust pryiproxyfen application timing, profits may increase relative to the case when information is not shared. This suggests that if growers operating adjacent fields did not provide information for free, strawberry growers may be willing to pay for information in order to make optimally timed pesticide applications. A second condition favoring voluntary coordination is that the net benefits from free-riding on the coordination efforts of others are small to growers of whitefly host crops, and may even be negative.

Free-riders benefit from reduced whitefly populations as other growers share and utilize information about the timing of adult whitefly population migrations, while not sharing similar information with adjacent growers of host crops themselves. The benefits to free-riding include the alternative use of resources that would be required to cover the cost of sharing information among growers. The result, however, is that the neighbor will not make optimally timed pyriproxyfen applications, leading to a larger-than-optimal whitefly population at the end of the season. Other things equal, this results in a larger adult population migrating back into the free-riding grower’s field at a future date, leading to foregone yields and increased control costs. When these costs exceed that of coordination, the net benefits to free-riding are negative. The estimated costs of sharing crop information become negligible, enhancing the likelihood of voluntary coordination.

Conclusion

This study demonstrates the importance of considering both economic and biological features of invasive species management when developing environmental policies, even when limited data are available, and develops a methodology for doing so. The long-run goal of any invasive species management policy should be to maximize total economic benefits. This study advances the ability of government agencies to conduct regulatory impact analyses for invasive species in agricultural systems by providing an economic and biological framework to model invasive species management. The analysis provides a method for identifying and quantifying the benefits and costs associated with pesticide use policies created to preserve the effectiveness of chemical pesticides after the arrival of an invasive species in an agricultural system. Consequently, it could be utilized by policymakers involved in the pesticide registration process or in post-registration use regulation. In the case of California, the Department of Pesticide Regulation undertakes these tasks.

For Additional Information

The following publications report findings from this cooperative agreement:

Goodhue, Rachael E., and Gregory J. McKee. "Designing and Implementing Invasive Species Prevention, Eradication, and Control Policies: Economics, Biology and Uncertainty," *Choices*, 21(3):129-132, third quarter, 2006.

McKee, Gregory J. *Pesticide Resistance, Population Dynamics, and Invasive Species Management*, Ph.D. dissertation, University of California-Davis, Department of Agricultural and Resource Economics, 2006.

McKee, Gregory J., Colin A. Carter, James A. Chalfant, and Rachael E. Goodhue. "Bioeconomic Modeling of Greenhouse Whiteflies in California Strawberries," *Choices*, 21(3):143-146, third quarter, 2006.

McKee, Gregory J., Rachael E. Goodhue, Frank A. Zalom, Colin A. Carter, and James A. Chalfant. "Population Dynamics and the Economics of Invasive Species Management: The Greenhouse Whitefly in California-grown Strawberries," *Journal of Environmental Management*, at press.

McKee, Gregory J., Frank G. Zalom, and Rachael E. Goodhue. "Management and Yield Impact of the Greenhouse Whitefly (*Trialeurodes vaporariorum*) on California Strawberries," *HortScience*, 42(2):280-284, April 2007.

Table 1. Simulated increase in per-acre profits relative to untreated control, Watsonville

Treatment	Increase in profits
Imidacloprid not applied	
No Pyriproxyfen (untreated)	$0
Optimally timed Pyriproxyfen applications	
1 application	$2,000
2 applications	$3,100
3 applications	$4,100
Imidacloprid applied	
No Pyriproxyfen	$2,900
Optimally timed Pyriproxyfen applications	
1 application	$5,200
2 applications	$8,200
3 applications	$9,500
Fully regulated	$7,400
Simulated profits from an untreated field	$36,200

Table 2. Simulated increase in per-acre profits relative to untreated control, Oxnard

Treatment	Increase in profits
Imidacloprid not applied	
No Pyriproxyfen (untreated)	$0
Optimally timed Pyriproxyfen applications	
1 application	$8,900
2 applications	$16,000
3 applications	$24,000
Imidacloprid applied	
No Pyriproxyfen	$5,700
Optimally timed Pyriproxyfen applications	
1 application	$13,400
2 applications	$19,800
3 applications	$26,000
Fully regulated	$23,200
Simulated profits from an untreated field	$36,100

Table 3. Six-season optimal number of Pyriproxyfen treatments with an application of Imidacloprid, Watsonville

Natural decline in resistance	Kill rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%									
10%							**2 treatments optimal**		
20%									
30%									
40%									
50%			**3 treatments optimal**						
60%									
70%									
80%									
90%									
100%									

Table 4. Six-season optimal number of Pyriproxyfen treatments with an application of Imidacloprid, Oxnard

	Kill rate								
Natural decline in resistance	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
0%									
10%									
20%									
30%									
40%							**2 treatments optimal**		
50%		**3 treatments optimal**							
60%									
70%									
80%									
90%									
100%									

1. Introduction and Objectives: Agricultural Production, Invasive Species, Externalities, and Environmental Policy

1.1 The Role of Time and Space in Invasive Species Management Policy

In agriculture, invasive species represent a unique challenge for public policymakers and for economists analyzing pest control policies (Sumner, 2003). If a species has only recently become established, then the understanding of its interactions with other plants or animals in the ecosystem, responses by producers, and appropriate controls—all fundamental to designing effective policies—is limited at best (Eiswerth and van Kooten, 2002; USDA-APHIS, 2000). In addition, finding the optimal policy is complicated, as externalities from chemical use and the development of pesticide resistance must be taken into account (Hurley, Babcock, and Hellmich, 2001; Hyde et al., 2000).

Efficient policymaking in connection with a newly arrived invader is challenging because of unforeseeable changes associated with that invasion (Horan, et al., 2002). The difficulty associated with anticipating and adjusting to changes in the relationships among species in agricultural systems is the key difference between managing an invasive species and a more typical, native pest. The native pest control problem involves a generally stable relationship between an agricultural system and a resident pest. In this case, organisms may have adapted to each other’s presence, methods of control are also understood, and decision-makers can anticipate the economic and environmental effects of that pest and its interactions with the environment. In contrast, the consequences of a newly arrived invasive pest are not always foreseeable (Eiswerth and Johnson 2002;

Knowler and Barbier, 2000). When an invasive pest population is first established, relationships between species change, and no approved chemical controls may be available. When these changes occur in an agricultural system, they affect production. Thus, the dearth of information about these changes affects the ability of a grower to respond to an invasive species in agriculture. Furthermore, the appropriate policy response is harder to determine, given the unpredictability of growers' responses to the invader.

The biological relationship between the invader and a host crop influences the economic impact of an invasive species. A new biological interaction increases the potential for catastrophic agricultural losses relative to native agricultural pests (Perrings, Williamson, and Dalmazzone, 2000). For instance, a newly invasive species may have no natural enemies when it enters a particular crop system. If the invasive population is not controlled, the result may be severe damage or even total crop failure.

The choices growers make also affect the economic impact of the invasion. In general, the abundance and location of suitable host habitat directly influence development of an invasive population. In agriculture, these factors are determined by grower decisions: when and what to plant, how long to leave the plants in the ground, and pest-management decisions. These decisions influence both current damages and the size of the invader's future population, which then affects future plantings. Economic choices therefore affect both the likelihood that the new interaction will persist and the ultimate economic damages caused by the invasion.

Incentives for managing the economic impact of an invasion change over time. For example, changes in the invading population's growth rate or in the value of agricultural output may determine what approach to control is optimal—inaction, well-timed chemical applications to manage the population, or even intensive efforts to eradicate the invader. Clearly, there is a complicated, dynamic relationship between an invasive pest, its host, and its management.

When biological invasions affect more than one field in a region, externalities are likely to be present but unaccounted for in an individual grower's pest management decisions. Private management decisions may not be the ones that are socially optimal, and regional coordination may be necessary to control the invasion (Bhat, Huffaker, and Lenhart, 1993). Four types of externalities typically result from chemical applications. First, environmental quality may be degraded by certain types of pesticides. For instance, the Montreal Protocol, an agreement among 183 countries designed to phase out the production and consumption of compounds that deplete ozone in the stratosphere, is a reaction to such externalities. Second, exposure of both farmworkers and the general public to harmful effects from chemical applications can result in adverse health effects.

A third externality associated with pest-management decisions is emphasized in this study—the development of pesticide resistance. The potential for resistance complicates the single-grower's management problem. Pesticide resistance develops in insect populations through multiple applications of chemicals with the same mode of action. The term *mode of action* refers to the sequence of events that describe the effect of the pesticide on the insect, from absorption until its death. If resistance develops over successive generations of surviving insects, this becomes an intertemporal externality: each generation is less susceptible to the chemical through the propagation of genes favoring survival. This issue is analyzed in Chapter Six.

The final externality, also emphasized in this study, is related to the spatial relationship among growers. When pests are mobile, the benefits from reducing pest populations extend to neighboring growers as migrations occur between fields. Spatial externalities—externalities resulting from diffusion—are a complicating factor even in the absence of dynamic considerations such as resistance. A regional approach to pest control may be preferable any time one grower's actions affect the pest population on another grower's field. This is discussed in Chapter Seven.

1.2 Pesticide Resistance as a Management Externality

The potential for catastrophic losses from invasive species makes the long-term preservation of susceptibility to pesticides important. Preserving susceptibility, however, can be difficult, particularly when a pest invasion persists for more than one season. The use of chemical pesticides in agriculture is regulated to prevent overuse at both the state and federal level. In part, these concerns about overuse are based on concerns over pesticide resistance. For example, discussions with regulators, industry participants, and scientists indicate that, at least in California, regulators will approve the use of only one new chemical with the same mode of action at a time. When interviewed, a government regulator asserted that this is done to preserve the susceptibility of the pest to the new chemical (Inouye, 2005). Industry members and researchers confirmed that regulators made this statement to them as well (Benchwick, 2005; Ishida, 2005; Zalom, 2005). This suggests that the government considers it worse to approve two chemicals with the same mode of action than waiting to approve a second one with a different mode of action in the future. This is because resistance does not just depend on the mode of action, but also how intensively it is used. Despite these regulations, the immediate need for the new chemical and inexperience with its use can result in ill-timed applications, which tend to increase the number of applications made and further promotes resistance.

Widespread use of traditional organophosphate pesticides, for example, has led to their decreased effectiveness due to the development of pesticide resistance in many insects (Metcalfe et al., 2002). New families of chemical pesticides have been developed to replace them. As these newer pesticides have been introduced, policies have been implemented to delay the development of resistance. One example is the regulations for chemicals called “insect growth regulators” (IGRs), which were registered for use in Arizona cotton in 1996. The registration included two regulations designed to delay the development of resistance: restrictions on the number of applications per year and requirements to use alternative chemicals in conjunction with them (Dennehy et al., 1997). The former slows the development of resistance, while the latter reduces the number of resistant pests that survive by using a chemical with a different mode of action. These policies have helped to delay the development of resistance to IGRs. Similar restrictions have since appeared on IGR labels for other crops.[1]

1.3 Pest Migrations as a Diffusion Externality

When pests are mobile, the benefits from pest control are not all captured by the grower who undertakes control. This spatial externality suggests that growers may under-

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[1] The EPA label for the IGR “Esteem 0.86 EC” lists several crop-pest combinations approved for use. Special use instructions, explicitly stating the goal of managing insecticide resistance through the use of alternative chemicals and application limits, appear at the end of the label for each crop. Additional crop-pest combinations also appear on supplemental labels with similar instructions. Similar restrictions appear on the label for buprofezin, another IGR.

invest in pest control, and that social welfare may increase by organizing pest control on a regional basis. There may also be ways that government policy can mimic a regional outcome. For instance, input subsidies could increase their use to a socially optimal level.

The type of organization required, or the preferred policy, will depend on the benefits and costs associated with coordinated pest management. In some cases, voluntary coordination is sufficient, while in others, a central authority may be needed to enforce control activities. The identification of the benefits and costs of each type of organization will be needed in order to create the most economically efficient regional management policy.

1.4 Optimizing Returns Under Dynamic Production Constraints and Environmental Policy

The overall goal of this study is to develop a theoretical and empirical approach that allows policymakers to formulate environmental policies that best respond to invasive species. This approach will facilitate an empirical assessment of the effects of such regulations on the welfare of affected economic agents and on the efficacy of control of the pest. It also will suggest the types of information that would be most valuable for improving the economic efficiency of regulations as the invasion persists.

To create economically efficient environmental policies, an understanding of a grower's profit-maximizing response to the effects of the invader is required. This is best done by modeling the mechanics of the biological and economic changes caused by an invasive pest, coupled with an economic model of grower behavior. The theoretical and empirical approach presented in this study allows an economic assessment of the effects of environmental policies on the welfare of agricultural producers by completing three interrelated objectives.

First, we assess how the optimal timing of a grower's pest control applications is affected by pest biology, market prices, and government regulations. Policies designed to delay the development of resistance to a specific pesticide may reduce single-season profits, from the perspective of an individual grower, but may extend the useful life of the chemical and possibly increase profits over the longer term. To evaluate the effects of such policies, growers' responses to specific use restrictions must be incorporated into any analysis of the restrictions' benefits and costs.

To examine the effects of use restrictions on a single grower, we compare the profits obtained from a pesticide application program that conforms to established use restrictions with the profits obtained from a profit-maximizing program that does not include these restrictions. Comparisons of the effects of the restrictions on grower behavior are made for both a single season and over multiple seasons. The effect of these regulations on the welfare of other growers, consumers, pesticide producers, and society is ignored in this part of the analysis.

Second, we analyze how use restrictions delay the development of pesticide resistance. This is particularly important for invasive species, because invaders may persist for several generations. Also, since few chemical controls may be available, pesticide effectiveness must be maintained. Every combination of use restrictions has a unique effect on the development of resistance, but this effect can be known only by understanding the impact of the restrictions on grower behavior. We examine the efficiency of a range of policy choices by modeling grower responses across various pesticide application frequencies, efficacies, and pest migration effects, and we assess how these decisions might affect the development of pesticide resistance over several growing seasons. This allows a determination of the long-run benefits from restricting chemical use.

Third, we analyze the factors that affect successful management of an invasive pest when control is more effective on a regional level than on a field-by-field basis. Although the first two objectives can be addressed by modeling a single representative grower and field, our third research objective requires us to introduce issues of space and multiple growers. When pests are mobile, it is important to contrast an individual grower's management decisions with the approach that a centrally coordinated control program would take. Factors affecting the need to approach pest management on a regional level include the role of spatial relationships among growers in promoting the spread of an invader and the contribution of each grower to the increase in local pesticide resistance.

We complete these three objectives in the context of the recent arrival of the greenhouse whitefly in strawberries grown in coastal California. We evaluate a set of use restrictions for a pesticide that was recently registered for control of the greenhouse whitefly on strawberries, the IGR pyriproxyfen (Esteem©). The use restrictions were designed primarily to reduce the development of pesticide resistance in the greenhouse whitefly. They limit the total number of applications of Esteem© within a season, restrict the timing of those applications, and require that Esteem© be used in combination with a chemical that has a different mode of action, imidacloprid (Admire©), which is used only at planting time.

To achieve our first research objective of characterizing the optimal timing of applications from a grower's point of view, we develop a model that represents the important biological, economic, and regulatory features of managing the effects of a greenhouse whitefly infestation. The two biological components of this model are a model of the population dynamics of the greenhouse whitefly and a model of the effect of the whitefly on strawberry yields. Detailed scientific data are used to construct each of the biological components. The economic component of the model captures the grower's objective of maximizing profits from strawberry production subject to the biological constraints of the agricultural system, market prices, and constraints imposed by government regulation. This model is used to determine optimal dates for treatment with Esteem© within a single season and the relationship between current-season whitefly control decisions and the future size of the whitefly population.

To complete our second objective, the bioeconomic model just described is combined with a simple model of pesticide resistance development in the whitefly population. The precise mechanics of the development of Esteem© resistance by the greenhouse whitefly are unknown. The available scientific literature suggests, however, that the share of Esteem©-resistant whiteflies in the population depends on three factors: the initial endowment of resistance in the whitefly population, migration of susceptible whiteflies between strawberry fields, and the percentage of susceptible whiteflies killed by each Esteem© application, also termed the "kill rate." Ideally, a model of whitefly resistance to Esteem© would incorporate data on the extent to which resistance to

Esteem© currently exists in the whitefly population, and how it may develop over time. Such genetic information is not available. Instead, we base our conclusions on how grower behavior affects development of pesticide resistance by conducting a sensitivity analysis over a range of values for those three factors.

Completing the third objective involves adapting the bioeconomic model to include additional information on whitefly population movements between fields. This conceptual framework assesses the influence of the timing of whitefly migrations, market conditions, and pesticide regulations on optimal strategies for regional invasive species management. We examine how privately optimal whitefly management choices compare to regional management.

Overall, our study demonstrates the importance of considering both economic and biological features of invasive species management when developing environmental policies, even when limited data are available. The long-run goal of any invasive species management policy should be to maximize total economic benefits. This study advances the ability of government agencies to conduct regulatory impact analyses for invasive species in agricultural systems, by providing an economic and biological framework within which to model invasive species management. In particular, our analysis provides a method for identifying and quantifying the types of benefits and costs associated with pesticide use policies created to preserve the effectiveness of chemical pesticides after the arrival of an invasive species in an agricultural system.

The remainder of the study proceeds as follows. In Chapter Two, we discuss previous economic literature that has modeled the problem of invasive and native pest control and management of pesticide resistance, and discuss the contribution of our study to the existing literature. In Chapter Three, we discuss important features of the greenhouse whitefly invasion in California strawberries that have affected the biological and economic path of the invasion. In Chapter Four, data used to create the bioeconomic model are discussed, as well as the components of the bioeconomic model. In Chapter Five, we present an analysis of the effect of the Esteem© use restrictions on greenhouse whitefly management for the single-season case. The effectiveness of these use restrictions in preventing resistance is discussed in Chapter Six, which extends the analysis to multiple seasons. In Chapter Seven, we consider the externalities associated with pest management at the regional level. Chapter Eight presents concluding remarks.

2. Literature Review: Related Literature on Invasive Species Management and the Role of Bioeconomic Modeling in Invasive Species Management Policy Analysis

Heightened awareness of the role played by economic activities in the establishment and spread of invasive species has generated concern over their potentially catastrophic effects on agriculture (Zhao, Wahl, and Diaz, 2004; Sumner, 2003; Perrings, Williamson, and Dalmazzone, 2000). Areas of significance for invasive species policy include international agricultural trade, with its potential to transport foreign organisms worldwide; a better understanding of the effect of economic activities on ecosystems; and increased ability to identify and control organism pathways such as ports of entry. These have all focused policymaking on the connection between economic activity and the spread of invasive species (for example see U.S. Department of Agriculture (USDA), Animal and Plant Health Inspection Service, 2000). Economic activity encompasses many factors affecting invasive species, beyond the role of trade in providing a means for their migration. The crops grown in particular areas and the broad menu of available pest management practices are critical determinants of the success of an invasion. Understanding the characteristics of invasive pest populations, their impacts on agriculture, and how these are influenced by human behavior is therefore critical for developing efficient management policies.

The study of management of invasive species is relatively new, although many studies are available on the costs associated with individual invasions in agriculture. Simberloff (1996) lists the costs of several invasions, including $50 billion in accumulated costs since the 1890s from the invasion of the boll weevil from Mexico into U.S. cotton, $110 million in losses in 1990 alone for the invasion of leafy spurge in rangelands in the western U.S., and hundreds of millions in annual costs for managing hydrilla and hyacinth on U.S. waterways. However, as Perrings (2000) notes, development of a general theory describing invasive species has received little attention from economists. This chapter focuses on areas that appear to be lacking in this newly developing body of literature.

Both grower decisions and changes in biological relationships ultimately affect invasive-pest management policy. Hence, policy design must consider and incorporate these factors. Few studies in the pest management and invasive species literatures, however, combine relevant economic, biological, and regulatory features of invasive-pest management in a realistic simulation framework that can be used to asses the economic efficiency of regulations. These studies that have done so form the context of our work.

The main focus of our study is to understand how regulations affect grower decisions. The studies discussed in this chapter thus provide the context for our research. Section 2.1 introduces static and dynamic models of growers' pest-management decisions.

When pests are mobile, the interactions between biology and human behavior are more complex, because one grower's decisions affect other growers in the region. It is important to understand the different outcomes that can result from an individual grower's approach to management of an invasive species, and how they compare to the approach that a centrally coordinated control program would take in creating an effective management policy. Section 2.2 therefore generalizes the single-grower models and presents selected theoretical and methodological concepts associated with modeling regional pest management.

2.1 Models of Pest Management

To better understand how economic agents affected by a biological invasion might act in managing it, one must consider relevant models of decision-making. A common way to model a grower's pest-management decisions is to link management choices to pest population levels and their associated impacts on the value of the affected crop. Such models can be used to characterize the pesticide-management decisions the grower will make.

A grower's decision model could include explicit expressions for both biological and market conditions. For example, Moffitt et al. (1984) incorporated descriptions of pest biology and crop yield and used these to simultaneously determine the optimal pest population and control intensity. In their model, the grower's objective is assumed to be maximization of per acre profits from production when managing pests:

$$\max_{z} \pi(z) = p(A - aNe^{-bz}) - rz - F, \text{subject to } a \geq 0\,, \tag{2.1}$$

where π is net returns of pest management per acre, p is the crop price, A is the yield per acre with no damage, a is the damage-per-pest-unit, and N is the pre-treatment pest population per acre. The variable z represents the per acre pest management input, r is its cost per unit, and F is the total fixed costs of pest management per acre. The negative exponential function represents the assumed relationship between pest management inputs and the kill rate. For b>0, this specification implies that increases in the pest-management input reduce the pest population at a decreasing rate; for example, as the population size decreases, it becomes harder to kill the marginal pest. The choice of the amount of management input is made so as to maximize profits. Notice that, in this model, all other decisions are assumed to have been made prior to observing the pest population, and none are adjusted at the time z is chosen.

Since pest-management decisions affect the development of pest populations both when management inputs are applied and in future periods, a model of how pest-control efforts affect population dynamics is needed. Harper et al. (1994) modeled the population dynamics of the rice stink bug in their development of dynamic economic thresholds for single-field management. These thresholds represent the pest population density that produces marginal damages equal to the marginal cost of preventing that damage, but also reflect information about changes in rate of yield production and prices, as well as the dynamic nature of pest populations. The revenue that growers receive for rice is a function of yield, rice quality, and market conditions. Harper et al. accounted for the effect of the stink-bug infestation on profits due to reductions in yields and in rice quality, by modeling changes in damage potential over time associated with the pest's physical development. The decision rules calculated through the relatively complex dynamic model produced higher net returns than did the static model. The biological information needed to calculate these decision rules was easy to obtain; the authors recognized that total damage could be estimated based on the size of the adult stink bug population, which is easy to count. Characterizing the conditions that will hold for an optimal pest management program will be useful in management of the whitefly. Currently, growers use physical "rules of thumb" based on size of the whitefly population to identify the threshold for pesticide use.

The importance of accounting for how management decisions affect the population dynamics of a targeted pest also was demonstrated in Wu (2001). He modeled weed-growth dynamics in a decision model and contrasted the returns from optimal management with returns from the decision rules derived from a static model. He showed that, since the multi-season effects of the weed seed bank are ignored by the static decision rule, lower returns to weed management result. The dynamic model accounts for the fact that the size of future weed infestations depends on the size of the current pest population and on herbicide efficacy. This result pertains to the strawberry/whitefly case because the size of today's adult whitefly population determines the size of the future adult whitefly population by reproduction, and the extent to which pesticide resistance within the population influences the rate at which resistance develops to new chemical applications.

Although the approaches taken in these studies are useful for analyzing how growers may act when facing a pest invasion, the models do not explicitly incorporate the effects of human behavior on the novel biological relationships created by a biological invasion. When modeling a pest management problem, it is important to account for feedback between human behavior and the persistence of the invasive pest population, as well as the population dynamics of the pest and relevant spatial relationships.

Methods used for economic analysis in the invasive species literature are designed to describe how novel interactions between organisms affect the state of an agricultural system. This literature has produced studies of both short- and long-term invasive species management, which we will adapt to our particular agricultural example. One contribution to this developing literature is Knowler and Barbier (2000). The authors modeled the relationship between the sizes of the anchovy and jellyfish populations. Although control costs were not discussed, the authors analyzed how to measure the costs associated with biological invasions when the native species is a valuable harvested commodity, and focused on a permanent reduction in the growth rate of the native species caused by competition with the invader. The question of management was not considered. They estimated the cost of this reduction by comparing discounted steady-state profits before and after the invasion, and used this model to measure the impact of invasion by a species of comb jelly on the anchovy fishery in the Black Sea.

Eiswerth and Johnson (2002) contributed to the methods used to analyze invasive species management by demonstrating how biological factors affect optimal management of an invasive species. They used an optimal control model to describe the relationship between an invader and its ecosystem and the optimal management of an invasive species stock after establishment. They solved for an optimal path for the level of management. Their work emphasizes that invasive management analysis must be site-specific, since "the rates of invasive growth and difficulties of invasive species management and ecosystem restoration differ spatially, even for any one particular invader." Site-specific effects can occur when, for example, a particular region is more favorable for the invader because more food is available or the environment is more suitable for its reproduction.

Our study further develops the methods used in these studies to measure the economic impact of invasive species. Our first contribution is to demonstrate the importance of considering the short- and long-term economic impacts of regulations such as limits on the number of chemical applications within a season. Investigations in this area add to the invasive species literature by modeling the decision-making process for using newly registered pesticides. For instance, because of the newly developed interaction between the greenhouse whitefly and strawberries, new registrations on pesticides were required to authorize them for use against the whitefly in strawberries. All previously registered pesticides were ineffective, due to resistance or other reasons. Although an extended process of research and risk assessment typically is required before a new pesticide can be registered for use on a given crop or pest, this requirement can be relaxed, in some cases, by obtaining an emergency pesticide registration. However, the potential benefits from quick registration can be negated by use restrictions that are not set optimally.

Our main contribution is to analyze the short- and long-term economic impacts of regulations on grower behavior in an empirical setting. This is done by incorporating the main regulatory and economic determinants of a grower’s decision, as well as the external effects of the decision. Inclusion of externalities also contributes to the pest management literature since, although pesticide resistance is discussed in that literature (Hurley, Babcock, and Hellmich, 2001; Hyde et al., 2000), to the best of our knowledge, this study is the first study to recognize the importance of pesticide resistance in designing invasive-pest management policy.

An important economic feature of our analysis is assessing how regular commodity price cycles, over the course of a growing season, affect grower decisions within the constraints of pesticide regulations. The principal form of whitefly damage to strawberries is reduced marketable yields. Presumably, growers are more concerned with preserving marketable yields when prices are high. This will determine their optimal timing for applications of chemicals, and may not necessarily correspond to what would be optimal from the perspective of pest control alone. If policy makers fail to understand how price cycles and changes in marketable yield loss affect strawberry production decisions, they will not correctly predict the effects of regulations on grower behavior.

Our second contribution is to expand the point made by Eiswerth and Johnson (2002) by making broader methodological points about the value of using limited biological information in modeling invasive species management. Very different conclusions about the impacts of policies can be drawn, depending on the quality of the biological and behavioral models. In this study, we show that the principal features of the biology and behavior in the new system must be modeled as accurately as possible, even when information is limited. Overly simplified assumptions about the new biology of the system, for example, can lead to results that do not accurately represent how the new interaction works.

Similarly, our study contributes to the entomology literature by modeling the newly formed relationship between strawberries and greenhouse whiteflies. Though permanently established in strawberry-growing regions, whitefly populations in a given strawberry field fluctuate according to a periodic cycle rather than being a slowly growing stock. They start at very low numbers per leaf and, in the absence of control measures, quickly grow to economically damaging levels within a season. Understanding this population growth cycle is fundamental to determining the optimal timing of pest management inputs.

2.2 Regional Pest Management

The temporal rather than spatial emphasis of studies by Eiswerth and Johnson

(2002), Wu (2001), Knowler and Barbier (2000), and Harper et al. (1994) means that they do not discuss the externalities that result from pest mobility. This is an especially relevant and complex consideration when growers of multiple commodities are involved, since management of invasive pests in each commodity involves different incentives at different times. This is the case, for instance, in the Oxnard, California area, where several crops, including strawberries, are whitefly hosts at various times of year.

The regional aspects of biological invasions are important to consider in deciding whether and how to intervene through policy. Regional control efforts may be voluntary or carried out through local government authorities. Carlson and Wetzstein (1993) described factors that may require mandatory participation in regional pest-management efforts in an affected area. The key point from their work that is relevant to this study is that, when an individual grower does not take into account the welfare of adjacent growers, mandatory participation in regional control may be necessary, regardless of any differences in management incentives across growers. This is the case with invaders whose host habitat is seasonal, where beneficiaries of control efforts at specific points in time differ from those who must undertake control efforts. For example, the greenhouse whitefly follows a regular pattern of movement from crop to crop. At each point in the whitefly's seasonal selection of habitat, adjacent growers of different crops have different incentives for control efforts.

A famous example of a successful regional management of an invasive species in which all growers were required to participate is the Boll Weevil Eradication Program. The boll weevil, which infested cotton across the southern United States, arrived from Mexico in the late 19th century. Beginning in the late 1970s, a program was initiated to eradicate the boll weevil from cotton acreage in Virginia and North Carolina. This program was later expanded to other southeastern states, Arizona, and California. Dumas and Goodhue (1999) found that this program was successful in Virginia, North Carolina, and Georgia since it ultimately increased cotton acreage in affected areas. This increase occurred in two phases. The first, or eradication, phase tended to decrease cotton acreage due to high per-acre program costs. Depending on location, this phase took several years to complete. The second, or maintenance, phase of the program tended to increase cotton acreage in the area because of increased yields and decreased pesticide costs. The authors demonstrated that the full benefits of a regional invasive pest management program may not become completely apparent for several years after its commencement, and that failure to differentiate between program phases can lead to an underestimate of long-run program benefits.

Feder and Regev (1975) demonstrated that decentralized pest-control decisions made by individual agents trying to control an area-wide stock of pests may lead to an inefficient allocation of pest-management resources. They concluded that "externalities inherent in the decentralized solution lead to myopic decision rules [for pest control] that are not optimal" for society; in contrast, centralized controls may incorporate "the population dynamics and environmental effects", optimally accounting for the common property nature of a regional pest population (Feder and Regev, 1975).

In addition to the temporal determinants of an optimal policy, the element of space cannot be overlooked, as discussed in Chapter One. Though explicitly combining elements of space and time is not a trivial problem, Hof (1998) and Bhat, Huffaker, and

Lenhart (1993) offer two examples of the theoretical considerations necessary for creating a spatiotemporal model of optimal pest management.

Hof (1998) developed an optimization model with both temporal and spatial dimensions. Its objective was to assign a location for pest extermination over time, given the initial location of the pests, their population growth, and dispersal. Hof's model considered *N* discrete points of space, called cells, and discrete points in time. Each cell was a point in space from which pests could be released, and each point in time, $t = 1, \ldots,$ T, was considered as an occasion in which pests could be released. A matrix of coefficients, g_{nh}, represents the flow of a portion of the population from any cell *n* into another cell, *h*, at a given point in time. With S_{ht} representing the population in any cell *h* at time *t* and r_n the rate of population growth per period within cell *n*, the population within each cell at any time period is

$$S_{ht} = \sum_{n} g_{nh}\left[(1 + r_n)S_{n(t-1)}\right],\ t = 1, \ldots, \mathrm{T} \quad \forall h. \tag{2.2}$$

$$S_{n0} = \textit{Initial population} \quad \forall n \in 1, \ldots, \mathrm{N}$$

Management efforts were measured in Hof's model by measuring the fraction of the pest population exterminated in cell h, a_h, multiplied by the amount of management effort per pest, *Y*, in cell *h* per unit of time *t*. Thus, management is related to the exterminated pest population. Equation (2.2) was then modified in (2.3) to show a reduction in the pest population through cell-specific actions:

$$S_{ht} + a_h Y_{ht} = \sum_{n} g_{nh}\left[(1 + r_n)S_{n(t-1)}\right],\ \mathrm{t} = 1, \ldots, \mathrm{T} \quad \forall h. \tag{2.3}$$

Hof's model included an equation for restrictions on pest management resources, which is appropriate for the strawberry/whitefly case, as discussed previously. The optimization model then was to select Y_{ht}, the management-induced pest mortality in cell h at time t to minimize

$$\sum_{t=1}^{T}\sum_{n} S_{ht} \qquad (2.4)$$

subject to

$$S_{ht} + \alpha_h Y_{ht} : \sum_{n} g_{nh}\left[(1+r_n)S_{n(t-1)}\right],\ \text{t = 1, …, T} \quad \forall h\,.$$

$$\sum_{h} Y_{ht} \leq K_t \quad \text{t = 1, …, T}$$

Hof solved this model numerically.

Hof's method can be used to model elements of the strawberry/whitefly case. First, the whitefly tends to move at specific times. As mentioned, this occurs when a new crop is planted in a nearby field or when a currently infested field is disturbed, such as by harvesting. This can be represented by considering each field as a single "cell." Second, there are constraints on the use of the pesticide Esteem© as a post-plant insecticide, corresponding to limits on K_t, the use restrictions. Finally, the regional population is controlled by optimally selecting the path of management-induced whitefly mortality so that profits are increased for all growers in the region.

Hof's model, however, is inadequate to capture the effect of biological invasions on agricultural production decisions. The model considers only the size of the population.

Producers, on the other hand, have profit maximization as their objective, which involves measuring output, market prices, and management costs.

The methodology used by Bhat, Huffaker, and Lenhart (1993) to develop a spatio-temporal model of wild beaver control provides concepts useful for consideration in our study. They studied beavers in rural New York, where they are native pests. Beavers cause losses to land owners by destroying trees either directly, through dam building, or indirectly through flooding. Since not all of the land on which timber grows is owned by a single person, there is the potential for regional control to achieve a better outcome that what is achieved by each individual landowner. Bhat, Huffaker, and Lenhart's modeling approach assumed that all the landowners in the area have an interest in controlling beaver damage and that they agree to utilize a public agency to administer the area-wide control policy via a cost-sharing mechanism. The solution of their model is an expression that can be interpreted as equalizing the marginal flow of current and future losses and the net discounted value of beaver stock (in terms of damage prevention).

Hof (1998) and Bhat, Huffaker, and Lenhart (1993) contribute to modeling spatiotemporal optimality. Neither, however, incorporated market conditions as a constraint on collective behavior. In contrast with these examples, all of the agricultural producers affected by greenhouse whitefly populations face a whitefly damage function and the economic cost of that damage, which changes over time. Thus, in this study we combine temporal influences with important spatial features to illustrate why a grower cannot operate in isolation, providing a more comprehensive analysis of responses to a biological invasion than the current focus of the invasive species literature on the importance of dynamics alone.

3. An Empirical Application - The Effect of the Greenhouse Whitefly on California Strawberry Production

In this chapter, we will discuss the major attributes of the greenhouse whitefly invasion of California strawberries, and the importance of this case to agriculture. This invasion was first noticed in the mid-1990s in Ventura County. The invasion was later observed in the Watsonville/Salinas strawberry-growing region in Monterey and Santa Cruz Counties in California. Though greenhouse whiteflies were common in coastal California prior to that time, strawberries had not been recorded as a host. This invasion has three economic and biological characteristics that make it a particularly interesting case.

First, restrictions associated with pesticides registered for use against the whitefly create a complex management problem. Chemicals that were already registered for use against the whitefly on strawberries proved ineffective upon its establishment. This resulted in a sudden explosion of the whitefly population in strawberries in 2001 and 2002, and required quick identification and registration of new pesticides. Consequently, two chemicals with different modes of action were registered for use against greenhouse whiteflies on strawberries in 2003: imidacloprid (Admire©) and pyriproxyfen (Esteem©). In contrast with all other previously registered pesticides, both of these provide relatively effective, long-term control of the greenhouse whitefly in commercial strawberry fields.

These new pesticides are used at different points in the season to manage the whitefly population. Admire© is registered for application only from planting to a minimum of 14 days before fruit harvest begins. This is because of a 14-day post-application interval required for the concentration of Admire© in the plants to decrease to a level that makes the fruit safe for human consumption. Since marketable yields are typically available weekly, and spoil quickly if left on the plants, the 14-day interval is too long for Admire© treatments to be commercially viable during the strawberry harvest season. Esteem©, on the other hand, has a different mode of action than Admire©, and requires only a two-day post-application interval. This allows it to be applied at any time during the life of the crop. Other restrictions, however, do constrain the application of Esteem©. These limit the maximum number of applications that can be made during the season and specify the timing of the first application. This means that the management choices for strawberry growers using Esteem© are the number and timing of Esteem© applications during the season.

The second factor that makes this an interesting case is that the greenhouse whitefly's life cycle can be modeled plausibly with a single season of data. The life span of a whitefly is very short—on the order of several weeks. Modeling of the population dynamics of an invasive species is more difficult when there are fewer generations per growing season, or when a single generation survives for multiple seasons. This is because not enough information can be gathered to ascertain the determinants of population growth in a short period of time. With multiple generations in a season, it is possible to estimate important parameters using data from a relatively short time period. The estimated model can then be used for sensitivity analysis, and to guide data collection efforts for other invasive species by identifying key parameters associated with the rate of population development and how these are affected by economic activities.

Finally, the greenhouse whitefly has been an economic problem for strawberry growers in two geographically separate regions of California: the Watsonville/Salinas region (Monterey and Santa Cruz Counties) and the Oxnard region (Ventura County). Growers in these two areas face distinctly different economic conditions related to the time and length of their respective harvest seasons. The differences in these conditions create different host cycles and whitefly population dynamics, which then lead to differences in decisions concerning whitefly management.

To document the importance of these conditions, we describe the primary features of the California strawberry industry in section 3.1. In section 3.2, we discuss the greenhouse whitefly, its development, and its interaction with strawberry plants. In section 3.3, we describe how the economic decisions made by growers in the two regions affect the population dynamics of the greenhouse whitefly. Finally, in section 3.4, we discuss how chemical controls are used to manage the greenhouse whitefly in strawberries.

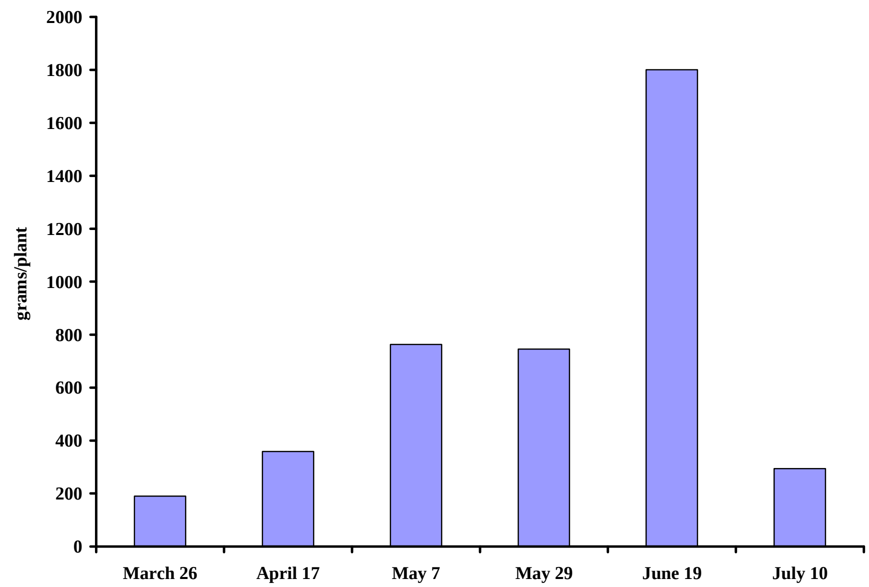
3.1 The California Strawberry Industry

Strawberries are an economically important crop in California. Total revenue from California strawberries currently exceeds $1 billion per year, making them the eighth most valuable crop in California in 2004. California accounts for nearly 90% of U.S. fresh strawberry production (USDA-NASS, 2004). This is due to both greater acreage and a longer growing season than other states. Florida, the next largest producer, accounts for a little less than 10% of U.S. fresh strawberry production. Of the 1.84 billion pounds of strawberries produced in California in 2003, about 75% were sold as fresh and 25% were sold for the frozen and processed market (CASS, 2004).

Strawberries are grown commercially in five geographically distinct regions along the California coast. From south to north, these are the San Diego area, Orange County, the Oxnard plains in Ventura County, the Santa Maria Valley, and the Watsonville/Salinas area. The proximity of these areas to the coast creates an ideal climate for strawberry production, as warm days and cool nights prevail much of the year. These coastal growing areas are also favorable habitats for the greenhouse whitefly.

Strawberries are produced at various rates during the life of the plant. Strawberry plants begin by producing relatively slowly. Figure 3.1 shows typical yields for the Camarosa variety grown in Watsonville. Production in that region peaks in June. As shown in Figure 3.1, the average yield per plant on June 19 was 241% larger than that of May 29. The rate of production decreases thereafter. The harvest on July 10, for example, was 16% of that on June 19.

Figure 3.1. Average Sample Yields (g/plant) by Date for Watsonville, 2003



Source: Zalom, unpublished data, 2003

Variations in climate across California’s strawberry growing regions allow production of strawberries at partially overlapping times of year. Early warm temperatures in southern California allow harvesting of summer-planted strawberries in September through December, and fall-planted berries to begin in late December and January, matching Florida’s harvest season. The harvest of fresh-market strawberries in the state then moves north, ending in the Watsonville/Salinas region, which accounts for most of California’s production. The range of climates and available plant cultivars allows strawberry production somewhere in California virtually year round, as harvesting ends in the Oxnard area around April or May and continues in Watsonville/Salinas until late November or early December.

Strawberry production decisions are affected by input costs. Although strawberries are perennials biologically, they are produced commercially as annuals in California. Two factors make it attractive to remove the plants after one season. First, there is a progressive decline in strawberry quality, especially in berry size, within and across seasons as the plants age. Second, the buildup of insect pests, weeds, and soil pathogens tends to reduce plant yields in second-year plants. Hence, most growers prepare for new planting annually. These preparations include fumigation, field preparation, and the cost of labor and plants for transplanting. These preparations are costly. Cash costs during the first three months, when most field preparation activities take place, average a little more than 17% of total cash costs per acre for the entire season (Bolda, Tourte, Klonsky, and De Moura, 2004).

The combination of the progression of strawberry harvest northward along the coast, and the decline in strawberry yield and quality over time, affects how each region participates in the strawberry market over the course of the year. Strawberries are sold to two markets: first to the fresh market, and then to the relatively low-valued processed market. Each region starts by producing fruit for the fresh market, dominating that market until the next region begins to produce. At this point in time, the first region has fruit of relatively poor quality, compared with more northerly regions, so fruit from the first region is then sold to the processed market. For example, the fresh-market harvest from fall-planted fields ends around April or May for Oxnard, at which time berries are sold to the processed market. In contrast, since the Watsonville/Salinas is the northernmost production region, harvest for the fresh market lasts as late as December, sales to the relatively lower-priced processed market never exceeding 10% of production. The strawberries in the processed market are mostly sold as frozen strawberries, but are also used as inputs for frozen foods and other products.

Occasionally, growers in the Watsonville area leave the plants in the field for longer than one season. In some cases, the plants remain through two full seasons, about 22 months, which saves the costs associated with field preparation for the second season. Other growers, who have had relatively poor sales or wish to harvest late- or second-season fruit, may choose to leave their plants in the ground for two or three months longer than a full season, followed by a regular rotation period for the field with another crops such as fava beans or vegetables. As a whole, such activities are becoming less common in the Watsonville area, because growers of single-year fields are increasingly critical of growers of second-year fields for two reasons. First, these fields have a higher incidence of plant disease, which is carried by the whitefly and other insects into nearby first-year plantings. Second, the second-year plantings harbor larger pest populations, including the whitefly, than is the case in single-season fields. These pests then may migrate into first-year fields (Bolda, 2004). The number of acres of plants left in the ground for more than a season has declined by 36%—from 1,476 acres in 1999 to 949 acres in 2004 (California Strawberry Commission, 2005).

The market price for fresh strawberries within and across growing regions varies over the course of the year. During the period when there are fewer strawberries harvested (between October and January), a pound of fresh strawberries has historically sold at wholesale for more than $1.00 and occasionally more than $2.00 (USDA-FNMS). During the middle of the year, between March and September, the fresh wholesale price is typically around $0.50 per pound.[2]

This cycle of high prices in the fresh market at the beginning and end of the year and low prices mid-year is driven by several factors. First, fresh strawberries are highly perishable. Since they cannot be stored, the current price represents demand and harvest conditions at the time. Second, yields from any given field start small (a few hundred grams/plant of fruit each month), peak (exceeding 1 kilogram/plant of fruit each month), and then decline again. A third reason for lower prices in the middle of the season is the increased availability of substitute fruits such as grapes and cherries. Fourth, the increase in the supply of fresh strawberries relative to early in the year, which occurs as southern growing regions are steadily harvesting and northern regions are coming into full production. Total California production typically peaks in June (see Figure 3.2 below), a time when all the regions are producing fruit and areas like Watsonville are at maximum production. This cycle is an important temporal element to consider when identifying an

[2] These averages are based on sales data between 1988 and 2002.

optimal whitefly management strategy, because the value of the crop—and hence, incentives for pest control—changes from month to month.

To take advantage of the relatively higher wholesale prices for fresh strawberries at the beginning and end of the year, strawberry growers throughout the state, especially in the Oxnard area, have altered their cropping cycles to include a summer planting. These plants are harvested primarily between September and December, unlike the bulk of the traditional fall plantings, which are harvested statewide between February and September. Statewide, summer-planted acreage expanded by 188% between 1998 and 2004, increasing from 1,208 to 3,480 acres, or from about 5% to 11% of statewide acreage (California Strawberry Commission, 2005). Oxnard-area growers who summer plant are, in effect, responding to the relatively higher late-season prices in the Watsonville area.

The increase in total acres of summer plantings has made interactions between the growing regions more complex. Summer-planted berries from the Oxnard area now compete with late-season berries from Watsonville that were planted the previous fall. This phenomenon, like breeding programs emphasizing early-season production, has been driven by the traditionally higher prices received between October and January, when substitute fruits are fewer and less plentiful.

The increase in summer-planted acreage has changed the relative contributions of growing regions to statewide production. To see the impact of the summer plantings, divide the calendar year into stages that roughly correspond with the timing of the introduction of substitute fruits throughout the year, following Carter et al., 2005: Stage we – January through Easter; Stage I –Easter through Mother’s Day; Stage II – Mother’s

Day through July Fourth; Stage IV – July Fourth through Labor Day; Stage V – from after Labor Day through the end of the year.

The effect of the increase in plantings on the contribution of the Oxnard and Watsonville growing regions to total state revenue is shown in Table 3.1. Between 1995 and 1998, the Oxnard area made no measurable contribution to state revenues from strawberries between Labor Day and the end of the year (Stage V), while the Watsonville area produced about 95% of the state's fresh strawberry revenues during that production stage. At this time of year, and in Stage I, harvests from summer plantings dominate sales to the fresh market. Since summer plantings are concentrated in the Oxnard area, the increase in these plantings has changed the contribution of this growing region to total production statewide. Comparing the 1995-1998 and 1999-2004 periods, the Oxnard area increased from producing 0% to 38% of the state's fresh strawberry revenues during Stage V, while Watsonville's share declined from 95% to less than 60%, despite increased acreage in the region during the 1999-2004 period.

Table 3.1. Regional Strawberry Production Revenues as a Percentage of California Revenues, by Stage

Oxnard					
	Stage I	**Stage II**	**Stage III**	**Stage IV**	**Stage V**
1995-1998	57%	37%	6%	0%	0%
1999-2004	63%	40%	5%	0%	38%

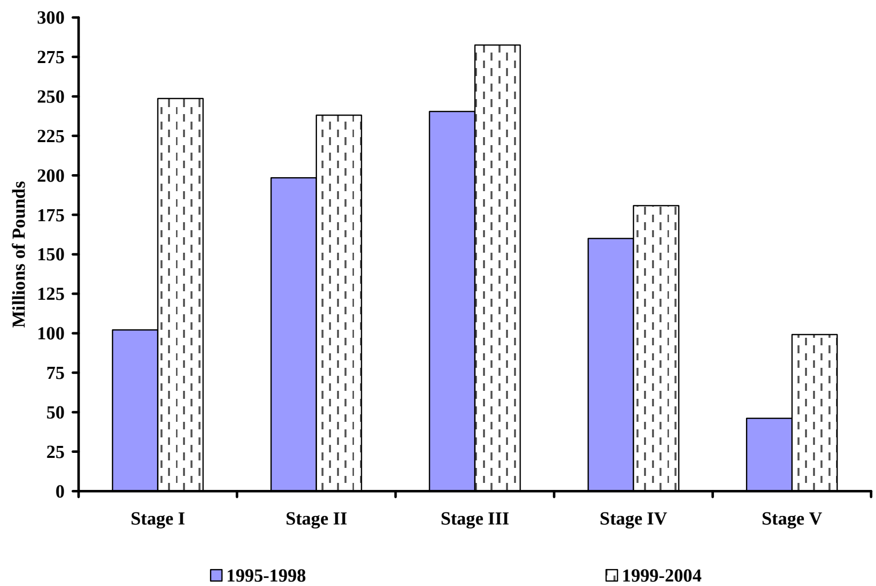
Watsonville					
	Stage I	**Stage II**	**Stage III**	**Stage IV**	**Stage V**
1995-1998	3%	24%	76%	93%	95%
1999-2004	4%	27%	77%	92%	59%

Sources: Stages adapted from Carter et al., 2005; volumes and prices from USDA Agricultural Marketing Service, 1995–2004.

Total fresh strawberry production in each stage also increased between the 1995–

98 and 1999–04 periods. Partly because of the increase in summer-planted acreage, the increase in production is not distributed uniformly throughout the year. This can be seen graphically in Figure 3.2, which illustrates aggregate statewide fresh strawberry volumes for the two periods.

Figure 3.2. Aggregate Statewide Fresh Strawberry Volume, by Stage: 1995–1998 and 1999–2004



Sources: Stages from Carter et al., 2005; volumes from Agricultural Marketing Service, USDA 1995–2004.

3.2 *The Greenhouse Whitefly: Trialeurodes Vaporariorum*

Since the whitefly is common to the coastal region and had not previously used strawberries as a host, we might term it a "resident invader" of strawberries. The largest populations observed after the invasion were in the Oxnard growing region in 2000–01. A smaller outbreak occurred in the Watsonville region in 2002–03. The addition of a summer strawberry crop, the practice of leaving plantings in the ground for more than a season, and perhaps, as some experts suggest, genetic changes in the greenhouse whitefly have contributed to whitefly infestations in these regions.

The greenhouse whitefly damages strawberry plants by feeding on the nutrients in the plants' sap, which results in yield losses (Byrne, Bellows, and Parrella, 1990). Entomologists have conducted field analyses to determine the yield loss. Losses in affected fields range from 5% in the Watsonville area (Zalom, unpublished data) to 20-25% in the Oxnard area (California Strawberry Commission, 2003).

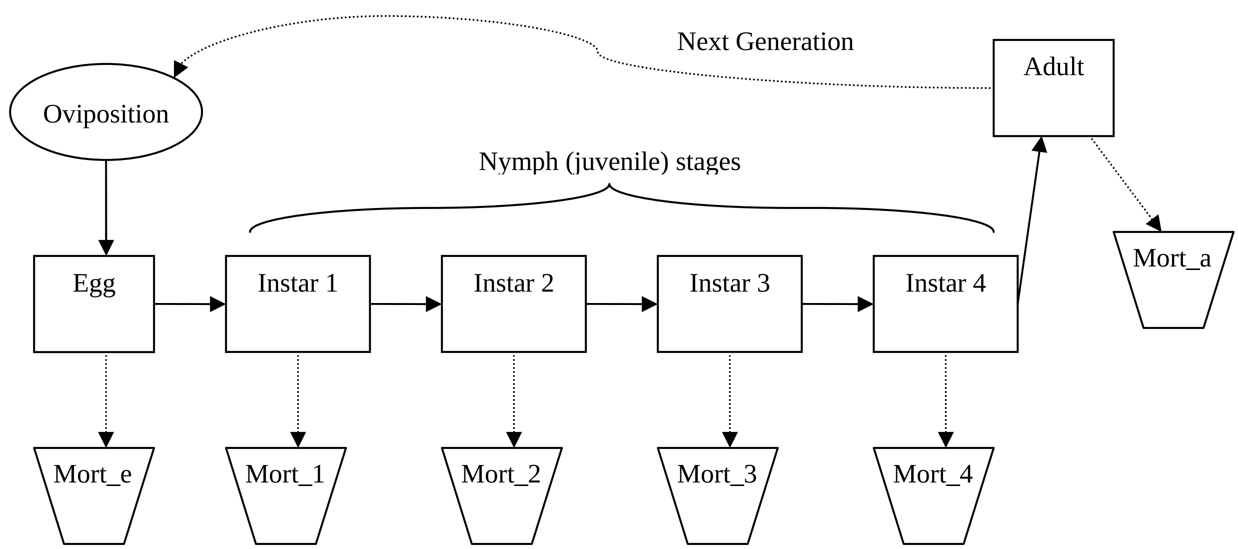
Better understanding of how and when the greenhouse whitefly damages strawberry plants requires an understanding of the fly's physical development. Many organisms, including the greenhouse whitefly, cannot regulate their internal temperature. Their rates of physical development depend on the amount of heat in the environment.

Phenology is the study of the timing of recurring biological phases. Phenology models can be used to predict the rate and timing of the whitefly's physical development.[3] These models describe the total amount of heat to which the whitefly must be exposed in order to mature. Each degree of heat during a twenty-four hour period, above a minimum temperature that must be met for development to occur, is called a degree-day (°D). The minimum temperature required for an organism to proceed in its development is referred to as the thermal threshold or lower development threshold. For the greenhouse whitefly, the thermal threshold is 48ºF (8.7ºC) (Osborne, 1982). When the temperature falls below this level, no physiological development occurs, although the whitefly does not necessarily die. Whitefly eggs, for example, can survive temperatures as low as 34ºF for several days (Hulspas-Jordaan and van Lenteren, 1989).

[3] See ucipm.ucdavis.edu/weather/ddphenology.html for a more complete discussion of phenology models.

The physiological development of the greenhouse whitefly consists of a series of life stages (Byrne and Bellows, 1991; Byrne, Bellows, Parrella, 1990). These stages are illustrated in Figure 3.3. The first stage is as an egg, which is the result of oviposition, or, the process of laying eggs. The second through fifth stages are called instars, which is defined as a stage in the life of an arthropod (such as the greenhouse whitefly) between each molt (the process of shedding the exoskeleton). The four instar stages are collectively referred to as the nymph part of the life cycle. The final stage is as an adult. With the exception of eggs, all of these stages cause damage to strawberry plants feeding on plant nutrients. Each stage is accompanied by a natural rate of mortality: in Figure 3.3, mort_e refers to the natural frequency of egg mortality, mort_1, 2, 3, and 4 refer to the mortality of the first, second, third, and fourth instars, and mort_a refers to the natural frequency of adult whitefly mortality. Each of these rates of mortality is discussed briefly below, and in more detail in Chapter Four.

Figure 3.3. Representative Diagram of Greenhouse Whitefly Physical Development



Mort_* = mortality of given life stage
Adapted from Hulspas-Jordaan and van Lenteren (1989)

Table 3.2 lists the cumulative amount of environmental heat, measured in degree-days (°D), required by the whitefly to reach each stage in its life cycle in degrees Fahrenheit.[4] For simplicity, the model aggregates the instar stages into a single nymph stage.

Table 3.2. Development Time in Cumulative Degree-days (°D) for the Greenhouse Whitefly, in Degrees Fahrenheit

Life Stage	Development Time (°D)
Egg	221.2
Nymph	464.0
Egg to Adult	685.3

Source: Osborne (1982)

The first stage of the whitefly's life is as an egg laid by the adult female whitefly. An adult female whitefly can lay hundreds of eggs during its lifetime, and can lay 0 to about 15 per day, depending on temperature. This process, called oviposition, typically occurs on the undersides of host plant leaves. Because the rate of physiological development depends on the amount of heat available, the amount of time it takes for an egg to hatch depends on the time of year. In the Watsonville area, it can take as long as 20 days for eggs laid in late January and early February, and as little as seven or eight days for eggs laid in the late summer months. In the Oxnard area, the time ranges from 19 to 20 days for eggs laid in early January to as little as six or seven days in the mid- and late summer months.

The four life stages following hatching of the egg are called the first, second, third, and fourth instars. The four instar stages differ from each other only in the size of

[4] To validate Osborne's development times, we compare them with the results of an alternative model suggested by Hulspas-Jordaan and van Lenteren (1989). The authors estimated a series of quadratic equations that regress development time for each stage of the whitefly life cycle on daily temperature based on data obtained in controlled experiments. We compare the development times from both models during parts of the year in Watsonville when the thermal threshold was exceeded (late May – early October 2003). The development times estimated by the two models for this period are comparable.

the growing nymph, and are collectively are referred to as the nymph part of the life cycle. In its early hours of life, the first instar crawls around on the leaf upon which it emerged, settles, and then inserts its mouthparts into the leaf and begins feeding on the nutrients in the fluids of the plant. The nymph whitefly will remain there during all four of the instar phases. In the Watsonville area, the amount of time the whitefly spends as a nymph varies from 35 to 38 days for eggs laid in late January and early February to as little as 16 or 17 days for eggs laid in the late summer. In the Oxnard area, the nymph stages range from 35 to 38 days for eggs laid in early to mid-January to as little as 14 to 15 days for eggs laid in early July through mid-August. At the close of the nymph stage, the mature adult whitefly emerges, now with wings, allowing it to fly from one location to another.

The most favorable temperature range for the whitefly's physiological development is between 64°F and 81°F (van Lenteren and Noldus, 1990). Average outdoor high temperatures in the Oxnard area range from the low to mid 60s (December–April) to the mid 70s (July–September). The average low temperatures range from the low to mid 40s (December–February) to the upper 50s (June–September). Slightly lower temperatures prevail in the Watsonville area. The average high temperatures range from the low 50s to mid 70s (December-April) to low 60s to mid 70s (July-September). The average low temperatures range from the low 30s to low 50s (December-February) to the upper 40s and mid 50s (June-September). Consequently, because the minimum temperature or thermal threshold for whitefly physiological development is almost always met, conditions are favorable for whitefly development in these areas practically year-round.

Environmental conditions, plant nutrient availability, whitefly reproduction rates, and whitefly mortality interact to determine whitefly population development. Observations of whitefly development in the Watsonville area in 2002–03 showed distinct population peaks, after the initial adult whitefly immigration, in March and in May. Observations and anecdotal evidence from the Oxnard area in 2000 and 2001 indicate that the adult whitefly population in fall-planted strawberries there peaks in November, February, and April (Bi, Toscano, and Ballmer, 2002a).

Short generation times, especially during warmer periods of the year, result in multiple generations of greenhouse whiteflies being present on the leaves simultaneously. As a result, whitefly populations can develop rapidly in commercial strawberry fields. When a grower understands the relationship between temperature and development of the whiteflies, he can make better-informed decisions about when to apply chemical pesticides to maximize profits than when these decisions are made based on market conditions alone.

3.3 Effect of Economic Decisions on Population Dynamics

The economic decisions made by growers in both the Oxnard and Watsonville strawberry growing regions affect the population dynamics in the region. In both locations, growers have made management choices that have filled a gap in the greenhouse whitefly host crop cycle. The effect has been to provide a steady means of whitefly population growth.

Many crops in the Oxnard area are viable hosts, including tomatoes, lima beans, and celery in addition to strawberries. When any of these plants are in the ground simultaneously in a strawberry growing region, newer crops typically offer a more attractive food source for adult whiteflies, which whiteflies can identify through their sense of plant color, an indicator of the level of nutrients in the plant's leaves. Short migrations of a few hundred yards from field to field are common when a preferred food source is identified. Hence, decisions about which crops to plant determine the movement and development of the whitefly population.

The introduction of summer-planted strawberries in the Oxnard area created a preferred food source for the whitefly that did not previously exist. The proximity of the summer strawberry plants to other infested hosts allowed adult whiteflies to move into the summer strawberry crop after the other host plants were removed. These whiteflies, in turn, moved into the fall-planted strawberries that were started in September and October. The rise of summer plantings thus contributed to a new host cycle that allows the greenhouse whitefly population to grow and spread more rapidly than it otherwise could have.

Similarly, responses by growers in the Watsonville area to input prices also have affected the population dynamics of the greenhouse whitefly. Strawberry plants are the whitefly's predominant cultivated host in the Watsonville area, where some plantings are left in the ground for more than one season. Leaving the plants in the ground extends the host cycle by providing added time for whitefly populations to develop in the field. These additional whiteflies then migrate to newly planted fields. Such migrations have been particularly large when new plantings have been made adjacent to a second-year field (Bolda, 2004; Zalom, 2004).

3.4 Chemical Control of the Greenhouse Whitefly

Cultural and biological control techniques alone have not been effective against outdoor infestations of the greenhouse whitefly in strawberries (Toscano and Zalom, 2003; Phillips, Rodgers, and Malone, 1999). Chemical pesticides, therefore, are an important part of an effective whitefly control program. The greenhouse whitefly reproduces rapidly and tends to live on the underside of leaves, making it a difficult pest to manage effectively with chemicals. Heavy use of older pesticides, such as organophosphates, on greenhouse whitefly populations on other crops, including greenhouse and ornamental plants, has fostered their resistance to those chemicals. This has increased the need for and value of innovations in chemical control.

A new chemical registered in 2003, pyriproxyfen, marketed by the Valent Corporation as Esteem©, is relatively effective on whiteflies. Esteem©, an insect growth regulator, works principally by killing the eggs and nymph whiteflies on the strawberry plant; it has a limited direct effect on the adults (Ishaaya, De Cock, and Degheele, 1994). Field observations of strawberries indicate that a single Esteem© application reduces the adult and first and second instar populations for up to one month, and the third and fourth instar populations for up to nine weeks (Bi, Toscano, and Ballmer, 2002b and 2002c). Both the number and timing of applications of Esteem© are restricted by use regulations created by the California Department of Pesticide Regulation. In addition to managing the use of Esteem©, these regulations are intended to encourage the development of alternatives to Esteem© and to prevent growers from depleting the susceptibility of whiteflies to it.

Admire©, another chemical, is also relatively effective on whiteflies, and has a different mode of action than Esteem©. It is applied directly to the planting hole when the strawberry plants are set in the ground, or is distributed through the drip line. It is primarily effective against adult greenhouse whiteflies, and the effect of a single application lasts up to eight weeks (Bi, Toscano, and Ballmer, 2002b).

Resistance to pyriproxyfen has been observed in other species of whitefly. Specifically, *Bemisia tabaci* in Europe and Israel has shown resistance to pesticides that use pyriproxyfen as the active ingredient. Although recorded incidences of resistance to this and other chemicals appear to be increasing (Denholm and Horowitz, 2000), there is no evidence of development of significant resistance to pyriproxyfen by the greenhouse whitefly in California.

As noted earlier, restrictions on the use of Esteem© described on the label are designed to delay the development of greenhouse whitefly resistance to it.[5] Similar use restrictions exist for pyriproxyfen and other active ingredients in pesticides applied to other crops, so analyzing the impact of these restrictions on management of invasive species in agriculture is useful for any situation in which resistance management is a policy objective.

[5] The EPA label for Esteem lists several crops for which applications are limited to once or twice a year. This can be found at http://www.cdms.net/manuf/1prod.asp?pd=3737&lc=0.

4. An Interdisciplinary Model of Dynamic Invasive Species Management

This chapter develops a bioeconomic model that can be used to evaluate the costs and benefits associated with environmental regulations. We use this model to evaluate the economic efficiency of environmental regulations pertaining to invasive species management in agriculture. In particular, we assess the efficiency of use regulations for the pesticide Esteem©, which is registered for control of the greenhouse whitefly on strawberries. To account for interactions between grower decisions and the population dynamics of the greenhouse whitefly, a dynamic framework is used. The model combines the essential economic, biological, and regulatory features of the interaction between the greenhouse whitefly and strawberry production.

The data used to form the bioeconomic model are discussed in section 4.1. Field-level scientific data were gathered for the biological components of the analysis. These data describe the development of the greenhouse whitefly population on strawberries, suggest mortality and reproduction rates for the whitefly, and provide evidence concerning the efficacy of Esteem© and other chemical treatments against the whitefly. These data also describe the effect of whitefly feeding on strawberry yields. In section 4.2, we discuss how the data from the field experiment justify the focus of this study on the Esteem© use restrictions.

After the discussion of the data, we present the biological components of the model. In section 4.3, we develop our simulation model of whitefly population growth on strawberry plants. Its primary usefulness is to aid decision-makers in understanding the likely effects of alternative whitefly management decisions on the size of the future whitefly population. After describing how the model was constructed, we discuss how the model was calibrated to the observed sample and then use the model to simulate the development of two other whitefly populations.

In section 4.4, we present the second biological component, a model of the effect of whiteflies on strawberry yields. Finally, in section 4.5, we present an economic model of strawberry grower decision-making during a whitefly infestation. The grower is assumed to maximize profits from strawberry production, subject to constraints given by the biological components of the model, as well as the three use restrictions pertaining to Esteem© selected for analysis. These components are used to determine profit-maximizing choices concerning Esteem©, with and without these restrictions, to evaluate the effect of the restrictions on growers' profits.

Since both grower behavior and the biological changes associated with invasive species populations affect the economic impact of invasions, models of production decisions must incorporate the principal behavioral and biological features of the new invasion. The need for these components demonstrates the general importance of linking biological models to economic models of producer response, to analyze the impact of invasive species on agriculture.

4.1 Data Description and Methods

In this section, we discuss the methods used to collect the data analyzed in this study. First, we discuss a field experiment used to record observations of a greenhouse whitefly invasion in a commercial strawberry field. We then discuss how the data concerning the impact of whitefly feeding on strawberry yields were gathered. Finally, we discuss the relevant economic data.

4.1.1 Field Experiment Design

Biological data in this study were collected by Dr. Frank Zalom. He selected a site west of Watsonville, in Santa Cruz County, California, to which Camarosa variety strawberries were transplanted in November 2002. This study site is located across a paved road and downwind, based on prevailing winds, from an infested field in which strawberries had been planted in 2001 and not yet removed. Zalom observed the efficacy of various chemical treatments, sampled the greenhouse whitefly population, and measured the effect of the greenhouse whitefly population on strawberry yields.

To establish the efficacy of various pesticides against the greenhouse whitefly on strawberries, three replicates each of ten treatments and two replicates of an eleventh were organized into plots of 30 plants, placed randomly within the study area.[6] In total, 32 replicates were observed. The replicates were planted within standard 50-meter rows of plants within the field. Each row contained three or four experimental plots. Approximately 30 plants were placed in each plot, and the treatments were applied to all of the plants in each respective plot. These new plantings at the site chosen for study were immediately infested by migrating adult whiteflies. The chemicals used in this experiment and their application dates are listed in Table 4.1.

[6] The placement for treatment seven, Admire© on 12/2/02 through a drip line, was not randomized within the study area. Because this was the only treatment applied through the drip line it was necessary to place it at the end of the row, otherwise the pesticide would have contaminated the other plants.

Table 4.1: Treatments Used in the Strawberry Field Experiment, Watsonville, CA, 2002–03

Treatment Number	Description and Application Dates
1	Untreated Control
2	Admire© 11/12/02, Esteem© 3/26/03
3	Admire© 11/12/02
4	Untreated Control
5	Esteem© 3/19/03
6	Malathion 3/19/03
7	Admire© 12/2/02 (drip)
8	Admire© 12/13/02
9	Malathion and Danitol 3/19/03
10	Admire© 2/27/03
11	Mineral oil 1/30/03, 3/19/03

All treatments were tested for efficacy against the whitefly. The observations from two chemical treatments, Esteem© and Admire©, are the focus of this study. These, and all other chemicals listed in Table 4.1, were applied at their label rates. The combined treatment of Esteem© and Admire©, treatment two (Table 4.1), is more effective than the other treatments. Other treatments, however, are reasonable alternatives for use against the whitefly. Hence, using Malathion, for example, is preferable to doing nothing at all and would be a good alternative after the allowed number of Esteem© applications is reached. For purposes of this analysis, the observations from these other chemical treatments were used only to gather additional data about the relationship between the whitefly population size and associated strawberry yields.

Applications of Admire© were made (1) in the planting hole on November 12 (treatments 2 and 3), (2) in the drip line on December 2 (treatment 7), (3) by injection at the base of each plant on December 13 and February 27 (treatments 8 and 10). Esteem©

was applied (4) to the foliage on March 19 and 26 (treatments 2 and 5) using a sprayer at the volume of 200 gallons/acre.

4.1.2 Whitefly Population Data Gathering Procedure

Populations of whitefly eggs, nymphs, and adults were observed in each of the 32 experimental plots. Observations for egg and nymph populations were recorded from January 7, 2003, to July 3, 2003, at roughly three-week intervals. Whitefly nymphs and eggs were sampled by selecting and excising three leaves at random from the center row of plants in each plot, placing the leaves into plastic zip-lock bags, and transporting them to the laboratory where egg and nymph densities were determined under a microscope. In addition to the dates on which egg and nymph data were recorded, observations for whitefly adults were made on December 4, 13, and 24, 2002. The leaf-turn method was used to sample a single, fully-expanded leaf selected at random from three plants in each plot, to determine the size of the adult whitefly population (Naranjo and Flint, 1995).[7]

Multiple generations of whiteflies were observed at the sample site. The first adult whiteflies were migrants from the older, heavily infested field nearby, and entered the site after the strawberries were planted in November, 2002. Eggs deposited by the migrants matured into nymphs and then into adults in late winter, resulting in a peak in the adult whitefly population in late March and early April, 2003. The next generation of whiteflies matured into adults in mid-May. See Figures 4.1, 4.2, and 4.3, which show the

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[7] Three leaves was considered sufficient to estimate the size of the egg, nymph, and adult whitefly populations on a given plant. The California IPM website (http://www.ipm.ucdavis.edu/PMG/r734301011.html) suggests scouting for insects by inspecting twenty leaves in a quarter of any size strawberry field. The field experiment described above occupied less than one quarter of the field, but 96 plants were inspected, or one plant in ten. Zalom (2005) describes this as a relatively intensive sampling procedure for a field experiment of this size.

average populations of eggs, nymphs, and adult whiteflies at the site during the study period.

Figure 4.1. Average Egg Counts per Leaf Observed in an Untreated Watsonville Commercial Strawberry Field (2002–03)

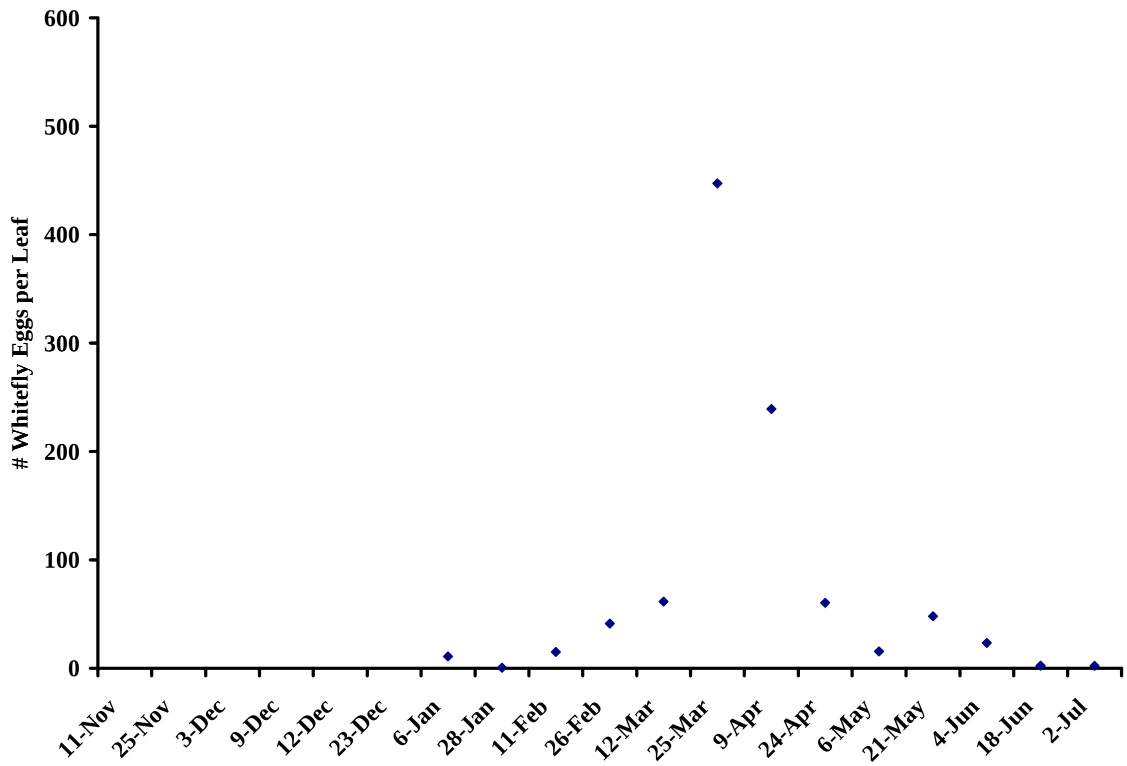


Figure 4.2. Average Nymph Counts per Leaf Observed in an Untreated Watsonville Commercial Strawberry Field (2002–03)

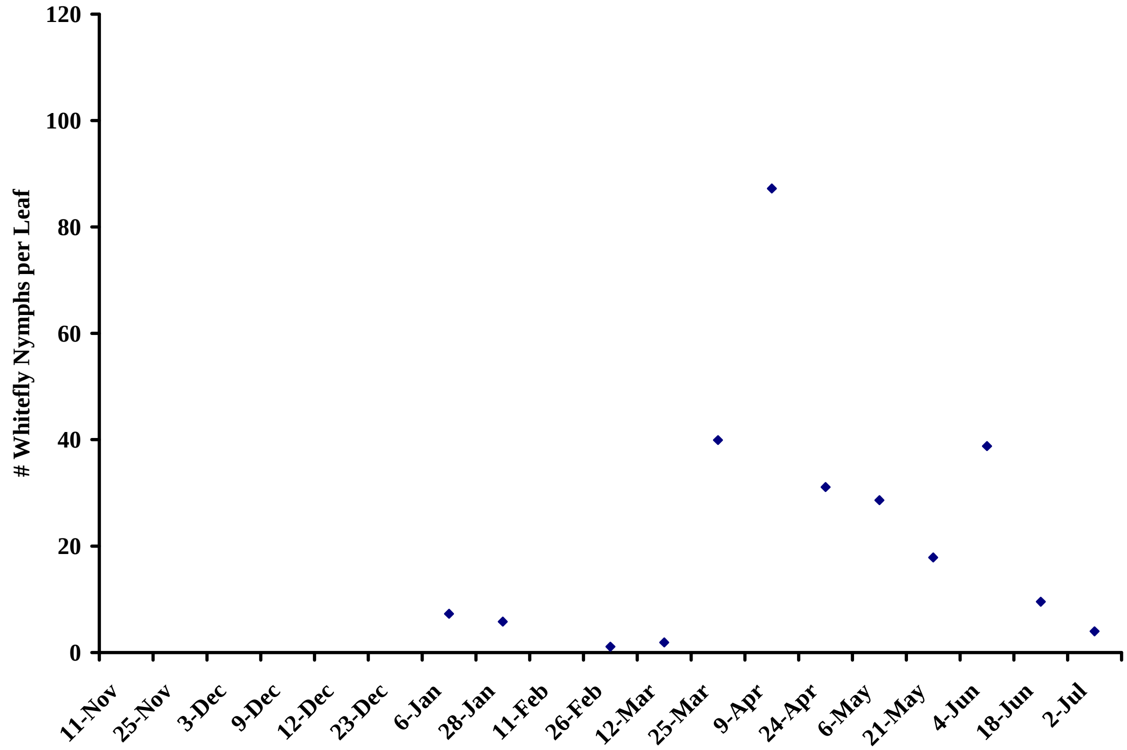
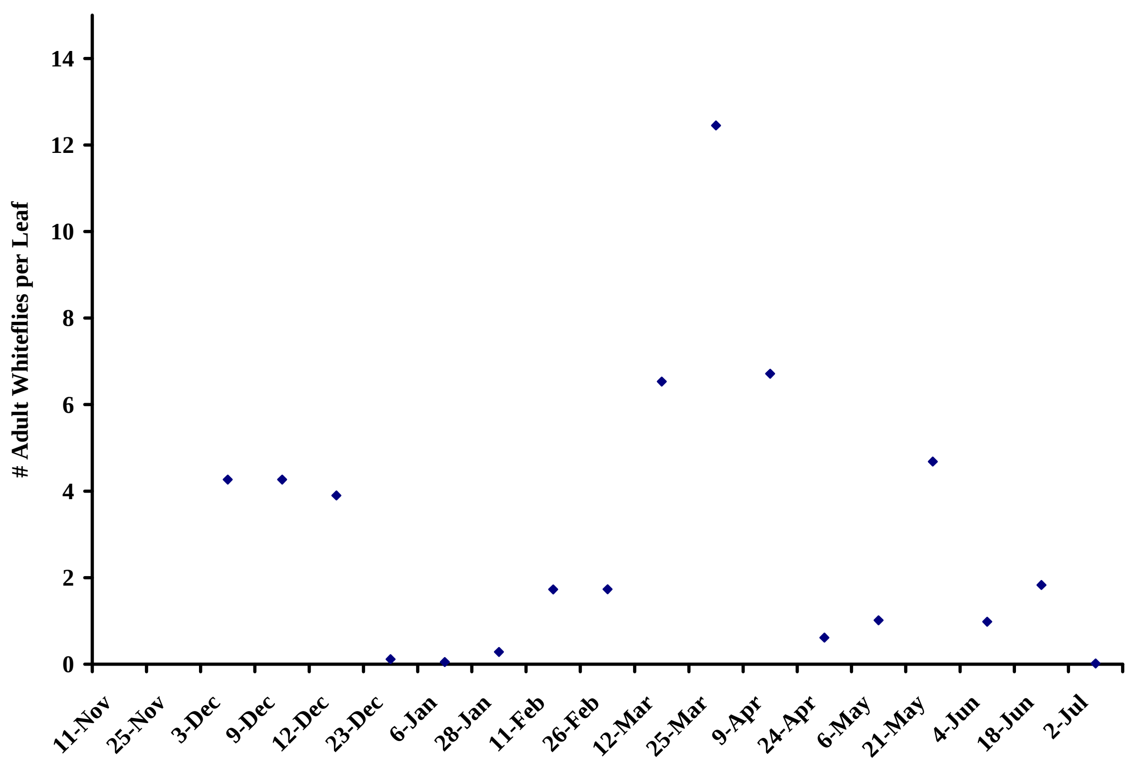


Figure 4.3. Average Adult Counts per Leaf Observed in an Untreated Watsonville Commercial Strawberry Field (2002–03)



To describe the size of the whitefly population on the strawberry plants over time, we utilize a measure called “whitefly-days,” WF_t, where t represents a week in the life of the strawberry plant. This measure is based on the previously established concept of mite-days (Allen, 1976) commonly used in the entomological literature (for examples, see Hall and Simms (2003), and Alston (2002)).

To calculate the number of whitefly-days, let A_t represent the number of adult whiteflies observed on a leaf on the sample date t and let n equal the number of weeks between samples. Then the average number of whitefly-days in any period of n weeks between two observations is estimated by the following equation:

$$WF_t = [n] \text{ x } [7/2] \text{ x } [A_t + A_{t-n}],\ n=1, \ldots, 52.$$

In order for this measure to be accurate when the data used to calculate the number of whitefly days are sampled once every three weeks, the population must be constant throughout the entire time between samples. The adult population changes daily if adult whiteflies move among leaves, nymphs mature into adults, or when mature adults die. Since only the endpoints of the time period between samples are observed, error is introduced into the measure. Hence, more frequent observations of adult whiteflies will allow a more accurate measure of the size of the whitefly population over time by accounting for changes in the density of the population over time. In order to remain at the same weekly observation frequency in our analysis as the economic data described below, we will select adult population estimates, created by the simulation developed in this chapter, at weekly intervals to calculate the number of whitefly days.

4.1.3 Data Collection Procedure for Data on Strawberry Yields

Strawberry yields were measured by observing the number of potential fruits, (flowers, green, and red berries) and the average weight of marketable fruit (mature red berries). To economize on observation effort and expense, observations were made every three weeks, which approximates the time required for a strawberry to mature from an open flower to a ripe fruit. Data were gathered on seven dates: March 6, March 26, April 17, May 7, May 29, June 19, and July 10. March 6 corresponded to the first harvest by the grower, and July 10 the last harvest prior to removing the plants. Sampling was done by counting the total number of potentially marketable fruit (flowers, green and red berries) from 10 plants in the center row of each plot and weighing five representative (actually marketable) red fruit to determine the average weight per marketable berry at each sampling date. The yield in grams per plant was estimated by multiplying the average number of fruit per plant by the realized average marketable berry weight on the subsequent sampling date. Consequently, only six yield observations ultimately resulted from these measurements.[8]

To convert these data into weekly periods, weekly data on marketable and unmarketable strawberry yields[9] from an unrelated but simultaneous research experiment nearby are used as a reference for the weekly distribution of yields. This field was not infested by whiteflies. Hence, we assume that whitefly feeding did not affect the weekly distribution of yields during the productive period of an infested plant, though the total

[8] Although sampling only five berries per plant is a source of sampling error, Zalom asserts that the sampling intensity for this procedure is sufficient. 320 plants were sampled for total berry count, and 160 berries were measured on each date.
[9] No data are available on the change in distribution of marketable and unmarketable fruit as a result of whitefly feeding. We assume this is unchanged from a non-infested field.

length of the period may change; we only assume that the total magnitude of yields during the time it produced is affected.

This conversion is done by, first, aggregating the yield data from this unrelated research into three-week periods that corresponded with the three-week periods in our study. Next, we calculate the distribution of those weekly yields as a share of the aggregate for each week in each three-week period. Then, assuming that the study field followed the same pattern as the weekly yield distributions, we multiply the observed tri-weekly yields from the study field by the corresponding weekly shares calculated from the unrelated research field. Finally, we multiply these weekly yields by the same proportion of marketable to total yields as in the unrelated research experiment, leaving us with weekly marketable yields.

4.1.4 Strawberry Price and Volume Data Collection Procedure

We obtained data describing strawberry market prices and whitefly control costs. Fresh strawberry prices and volumes for 1999–2003 came from daily regional wholesale price reports published by the Agricultural Market News Service of the USDA. The prices are aggregated into weekly averages by region, and the volumes are aggregated into weekly totals. The weekly regional volumes and prices for frozen strawberries for the same period came from the California Processing Strawberry Advisory Board. Total weekly regional prices and volumes of fresh and processed strawberries were then used to create a weekly, volume-weighted average price per pound for each region. Prices were deflated using the CPI for all items for all urban consumers. These average prices should be reasonably good measures of the price expected by growers, since none of the five years had particular or unusual price patterns that would have a misleading influence on the calculation of an average or expected price. The deflated prices were then averaged to calculate a weekly average real price so as to smooth out any year-specific market conditions, leaving a representative price for the analysis.

Costs for Esteem© and Admire© treatments were obtained from discussions with pest control advisors and UC Cooperative Extension agents in whitefly-affected regions. Labor costs for applying these chemicals are omitted from the analysis, because the applications are typically made in conjunction with other regularly scheduled applications (Benchwick, 2005; Ishida, 2005). Hence, the analysis will not reflect the actual profits from strawberry production, but will retain sufficient information to model decisions concerning the use and timing of Esteem© and Admire©.

4.2 Comparing the Efficacy of Selected Treatments

The "whitefly-days" measure can be used to compare the efficacy of the various chemical treatments against the greenhouse whitefly. Table 4.2 indicates the total observed number of adult whitefly-days for each experimental treatment for the period between January 29 and June 5, 2003. This period was selected because strawberry plants produce most of their fruit during that time. In addition, most of the effect of chemical treatments on the whitefly population and subsequent yields can be observed within this period because of the specific mode of action of the selected chemicals and the entire time their effects persist occur within this period. These data suggest that controlling the whitefly population before it begins to grow rapidly may be important; without treatment, eggs produced by adult whiteflies that invade the field will result in the late winter/spring outbreak of nymphs and adults shown in Figures 4.3 and 4.4.

Table 4.2. Cumulative Observed Adult Whitefly-Days, January 29 – June 5, 2003

Treatment	Mean $\pm$ SE[10]
Untreated	501.47 $\pm$ 74.16
Admire© @ planting	123.65 $\pm$ 34.09
Admire© @ planting + Esteem© 3/19	102.1 $\pm$ 4.3
Admire© @ 12/2	275.82 $\pm$ 21.93
Esteem© @ 3/19	399.52 $\pm$ 129
Malathion + Danitol @ 3/19	280.02 $\pm$ 66.76
Malathion @ 3/19	296.24 $\pm$ 32.19

Mean whitefly-days for each treatment group are compared to the untreated control by t-tests.
All means except Esteem© @ 3/19 are significantly different from untreated control at P<0.05 by t-tests.[11]

The data in Table 4.2[12] also show that, in treatments where Admire© was applied at planting, there were significantly fewer whitefly-days than in the untreated controls. In particular, the combined treatment of Admire© applied at planting followed by Esteem© on March 19 provides the highest level of whitefly population control. For this reason, the combined Admire© and Esteem© treatment is the focus of this study.

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[10] The standard errors were calculated as $\frac{s}{\sqrt{n}}$, where *s* is standard deviation of the three observations, and *n* is number of observations (three, except in the case of the untreated observations, which was six).

[11] The t-distribution is assumed to be a good approximation for this case. The *t*-tests were calculated using the difference in means test: $t_0^* = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$, where $\overline{x}_1$ and $\overline{x}_2$ are the sample means of the first and second groups of observations, s_1^2 and s_2^2 are the sample variances for each group, and n_1 and n_2 are the number of observations in each group, with the critical value selected at the 95% level with n-1 degrees of freedom.

[12] The data from treatments other than those using Admire or Esteem are only used to estimate the relationship between whitefly-days and strawberry yields. The data from the Malathion and Malathion/Danitol treatments are presented because the cumulative observed whitefly-days were the lowest for any treatment not using Admire or Esteem, and are intended to allow the reader to judge that the Admire/Esteem treatment can be considered the most effective among all observed treatments.

4.3 A Model of the Population Dynamics of the Greenhouse Whitefly

Different dates for Esteem© applications affect the development of the whitefly population, and hence profits, differently. One way to evaluate the effect of alternative treatment dates is to conduct controlled scientific experiments of pesticide efficacy for all possible application dates. Unfortunately, this would require a substantial amount of costly data collection.

A less costly alternative is to use a mathematical simulation. Simulations have an important advantage over field research, in that they allow evaluation of the effects of changes in key variables, such as chemical application dates, without additional field trials. If such a model can be created and calibrated for the interaction between the greenhouse whitefly and strawberries, gaps in our understanding can be filled.

To that end, we created a parameterized model of the development of a greenhouse whitefly population on a typical strawberry plant leaf. The selection of parameters affecting the rate of whitefly population development was influenced by the work of Hulspas-Jordaan and van Lenteren (1989), who modeled the population dynamics of the greenhouse whitefly on tomatoes in controlled conditions. However, strawberry plants are a new host plant for the greenhouse whitefly, very little is known about their relationship, and our model suggests factors that affect the interaction between the strawberry plant and greenhouse whitefly in ways that are not yet understood and require future study, such as the effect of changes in plant physiology on whitefly population development and the importance of weather patterns for whitefly mortality.

The data used to estimate the parameter values in this model were collected on a common strawberry variety, Camarosa. In the 2003-4 growing season, this represented at least 31% of statewide planted acreage, and was the most common commercial variety at the time.[13] We feel comfortable, therefore, using this model as a representative case for greenhouse whitefly infestations of strawberries.

The main function of this model is to simulate the timing and size of whitefly population peaks by replicating the observed life cycle of the greenhouse whitefly in a commercial strawberry field. The model applies the degree-day technique to estimate whitefly physiological development, as described in Section 3.2. This allows us to model the length of time any cohort of whiteflies is at the egg or nymph stage. The adult whitefly, has been observed to live as long as 30 days, which is assumed to be the maximum life span. Once the fly's physical development rate is known, we adjust the sizes of the daily whitefly egg, nymph, and adult cohorts over time by assigning values for greenhouse whitefly reproduction and mortality rates, the life span of adult whiteflies, and pesticide efficacy. Values for these parameters are selected such that the timing of the simulated flow of eggs, nymphs, and adults through time replicates the observations at each sample date listed in section 4.1.

The model is also used to simulate the effect of Esteem© on the whitefly population. The effect of alternative Esteem© application dates on whitefly population development is assessed by mathematically representing their effect in the model. All three populations are modeled because Esteem© affects each population differently. Therefore, the effect of alternative application dates has to be assessed on the simultaneous development of the egg, nymph, and adult populations.

[13] In 2004, 31.1% of statewide acreage (9,832 of 31,639) was planted with Camarosa, the most common short-day variety. Ventana is the second most popular at 8.8% of statewide acreage (2,777). Various proprietary varieties represented 30.8% of the statewide total acreage in 2004 (9,756) (California Strawberry Commission, 2004).

The parameter values used in the model are based on data collected from the experiment described in section 4.1, and are comparable to greenhouse whitefly reproduction, mortality, and pesticide efficacy rates published in the entomological literature (Bi, Toscano, and Ballmer, 2000b, c; Hulspas-Jordaan and van Lenteren, 1989). The model developed in sections 4.3.1.1 - 4.3.1.5 is based on the data collected from the untreated plots from the experiment described in section 4.1. This model is then modified to include the effects of Admire© and/or Esteem© treatments, using parameter estimates based on the data collected from the Admire© (Treatment 3) and Esteem© (Treatment 5) plots. The combined Admire©/Esteem© treatment is modeled by combining the parameters estimated from the Admire©-alone and Esteem©-alone models, and compared with the observed data from the observed Admire©/Esteem© treatment combination (Treatment 2). All parameters are treated as deterministic.

In section 4.3.1, we describe the mechanics of the model design, its principal parameters, and methods for selecting values. In section 4.3.2, we discuss the calibration of the model. In section 4.3.3, we calibrate the model for two additional cases to confirm its reliability by using it to model the development of other whitefly populations.

4.3.1 Whitefly Simulation Model Methodology

Whiteflies are a pest in many agricultural crops (Byrne, Bellows, and Parrella, 1990). Approximately a dozen species of whitefly are economic pests in agriculture, with their most prominent effect being a reduction in harvestable yields. This effect occurs in three ways: whiteflies reduce the level of nutrients carried in the plant by feeding on its sap, reducing total yields; they directly contaminate yields through production of honeydew, excrement produced by the whitefly, which can reduce marketable yields by rendering the fruit aesthetically unappealing; and they serve as vectors for plant viruses, which may also reduce total yields. Understanding how the whitefly population develops on the host plant informs a grower about the rate at which this damage may occur. From a practical standpoint, therefore, a simulation model can help us know more about the interaction between whiteflies and the strawberry plants.

As explained in Chapter Three, the physiological development of greenhouse whiteflies can be described as a sequence of life stages. The amount of time needed for physiological development depends on the amount of heat available, which is measured in degree-days. Since the life cycle of a whitefly can start on any day, the first step of the model is to calculate the degree-days for all possible oviposition dates.

To calculate the time required for physiological development, we obtained daily minimum and maximum temperature data from the Watsonville weather station operated by the National Climactic Data Center. We entered these data into a degree-day calculator found at http://www.ipm.ucdavis.edu/WEATHER/ddretrieve.html.[14] The calculator reported the daily number of degree-days for the study period of November 2002 through July 2003.

We calculate the development time for daily cohorts of whitefly egg, nymph, and adult populations. Eggs laid on a given day are considered a single cohort. The calendar date of maturity for the daily cohort at each life stage is found by calculating the date by

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[14] Since temperature changes throughout the day, several different methods are used to calculate degree-days, each giving different weights to the minimum and maximum daily temperature. We use the single-sine method, the most commonly used method in California agriculture (University of California Integrated Pest Management Program, 2005). The single-sine method assumes the daily minimum and maximum temperature form a pattern of temperature change over the course of a 24-hour period that can be represented as a sine wave. This method assumes that the temperature curve is symmetric around the maximum daily temperature. The number of degree-days is estimated by calculating the difference between the area under the sine curve and under the minimum temperature threshold, which was 48ºF in this case (Osborne, 1982).

which a sufficient number of degree-days, as listed in Table 3.2, are accumulated. Once that date is calculated, we can state when a particular cohort of whitefly eggs will mature into a new nymph cohort, and then into an adult cohort. Once the development time is known, the size of the cohorts is adjusted as it advances from one life stage to the next to reflect observed data. Cohort size can change through reproduction (oviposition) or mortality. This is represented in the model by assigning mortality and oviposition rates. For instance, the first cohort of eggs laid by the adult whiteflies that immigrate into the field at planting is adjusted based on hypothesized oviposition rates on the dates the adult whiteflies were observed. As these mature into nymphs, the size of the new cohort is reduced, through assigning a mortality rate, to reflect observed data.

The mortality rate represents the percentage of the daily cohort of eggs or nymphs that dies before advancing to the next life stage, or the percentage of adult whiteflies that dies before the end of the assigned life span. For simplicity, the rate of mortality is held constant for an entire week within a given stage of the whitefly life cycle, but is allowed to change across weeks. Mortality is assumed to occur on the date that the cohort advances to the next life stage, before any yield loss is realized at the next stage. Mortality rates are assigned for eggs, nymphs, and adults, together with a limit on adult longevity, modeled as 100% adult whitefly mortality after a selected number of days.

The oviposition rate determines the size of the egg cohort. We selected a combination of mortality and oviposition parameter values that replicate observed changes in the size of the cohort at each life stage. In making this selection, we tried to remain consistent with how factors external to the whitefly, such as weather or plant nutrient levels, affect the parameter values. These values compare with published data.

For instance, Hulspas-Jordaan and van Lenteren (1989) documented average daily oviposition rates between 0.96 and 8.4 eggs per female adult whitefly per day. Values in this model range from almost zero to almost seven per female per day.

4.3.1.1 Determinants of Whitefly Mortality

There are four primary determinants of whitefly mortality. The first is its life stage. Eggs are typically least affected by changes external to the whitefly, at least in controlled indoor conditions relative to nymphs and adults (Hulspas-Jordaan and van Lenteren, 1989). We will assume that this also holds true for outdoor conditions. Nymphs and adults tend to have relatively higher mortality rates. Naranjo, Cañas, and Ellsworth (2004) observed that the mortality rate for nymph and adult sweet potato whiteflies (*Bemisia tabaci*) can even approach 100% in outdoor conditions.

Mortality rates within each life stage differ across time, due to ambient temperature, precipitation, and the condition of the host plant. Whitefly mortality is highest at extremely low or high ambient temperatures for all life stages. Hulspas-Jordaan and van Lenteren (1989) cite numerous articles that describe the effect of various temperature ranges on whitefly mortality at all life stages. They observed that whitefly mortality is lowest, in general, between 77°F and 86°F.

Precipitation seems to affect whitefly mortality, although the effect of rainfall on whitefly mortality has not been verified experimentally. Strawberry growers and pest control advisors in the affected growing regions report that extended periods of rainfall, and even sprinkler irrigation, can reduce adult and nymph whitefly populations by inundating them (Benchwick, 2005; Ishida, 2005; Martinez, 2004). It also is possible that predation or the number of entomopathogens[15] on or near the plants could increase during times of rain (Zalom, 2005).

The condition of the host plant also affects whitefly mortality. Bi, Toscano, and Ballmer (2002a) and Zalom (2004) concluded, based on field experiments, that host plant quality—as related to changes in the rate of plant growth—is a factor in whitefly population dynamics. For example, they observed that adult whitefly populations on host plants decline when the plant's growth rate slows. Malone (2005) indicated that a relationship exists between regular cycles of high and low nutrient levels in strawberry plants and insect mortality. When nutrient levels are low, mortality for insects other than the whitefly has been observed to be relatively high. Although this relationship between plant nutrient levels and the greenhouse whitefly mortality has not been verified experimentally, in the next two paragraphs we discuss evidence that it exists.

The physiological condition of the plant creates a nutrient cycle, which affects the level of nutrients available to the whitefly for consumption. The cycle can be characterized by two levels of nutrients supplied by the strawberry plant. In the first part of the cycle, the plant uses these nutrients to generate vegetation. In the Oxnard and Watsonville growing regions, this occurs when the young plants grow vigorously in late winter and early spring. When the plant produces vegetation, relatively high levels of nutrients are present in the sap, which, in turn, provide a relatively good source of nutrients to the whitefly. In the second part of the cycle, the plant uses nutrients to generate fruit. At that time, the flow of nutrients through the plant is reduced, thereby

[15] Entomopathogens are bacteria, fungi, viruses, and nematodes that cause disease in other insects.

reducing the amount of food available to the whitefly. The cycle repeats in late summer, after the peak rate of fruit production has occurred (Malone, 2005; Zalom, 2005).

The host-plant nutrition cycle appears to affect the mortality of whiteflies on strawberries. As shown in Figures 4.3 and 4.4, the observed adult and nymph populations increased rapidly beginning in late March. The number of eggs observed between January and March and the number of degree-days during this time created conditions that should have allowed this sudden increase in the number of adults and nymphs to continue through May. Instead, populations declined suddenly, even though several egg cohorts should have advanced to the nymph stage by this time. This decline is correlated with the time strawberry plants in the Watsonville area begin to produce fruit, with the fruit production rate peaking in June. A possible explanation for this change in mortality is that the amount of nutrients available to the whitefly population suddenly changed, increasing the mortality of the nymphs and adults relative to the period when the plants partition nutrient resources to favor vegetative growth in January and February. This explanation has not been verified experimentally, though it is consistent with field observations and what is known about both the strawberry plant life cycle and the development of the greenhouse whitefly.

4.3.1.2 Whitefly Egg Mortality

No previous studies have been conducted to determine greenhouse whitefly egg mortality rates in strawberries in outdoor conditions. Research cited by Hulspas-Jordaan and van Lenteren (1989) suggested that egg mortality is uniformly low across temperatures in controlled settings. We assumed a mortality rate of 10% for all months in the simulation (October 2002 – July 2003) as a baseline. The baseline egg mortality was changed only in late March to early April, based on the assumption that the decline in plant nutrition levels influenced oviposition rates, resulting in relatively less viable eggs. Although this theory has not been confirmed experimentally, it parallels anecdotal observations by Zalom (2005) that insect populations decline as strawberry plants shift between vegetative and fruiting cycles.

4.3.1.3 Whitefly Nymph Mortality

No previous studies have examined greenhouse whitefly nymph mortality on strawberries in outdoor conditions. We initially set nymph mortality rates based on controlled indoor observations of whiteflies on other plants, as cited by Hulspas-Jordaan and van Lenteren (1989). These proved to be too low to correspond with the observed outdoor population. This was not unexpected, as very high mortalities are possible in outdoor conditions, due to variations in temperature, precipitation, and plant conditions. A study of outdoor mortality rates for the egg and nymph stages of the sweet potato whitefly, *Bemisia tabaci*, indicated that rates between 99% (for broccoli) and 66% (for spring cantaloupe) were possible (Naranjo, Cañas, and Ellsworth, 2004). The simple average mortality for nymphs in the simulation (December–July) is about 66%, with a baseline of 50%.

To assign greenhouse whitefly nymph mortality rates on outdoor strawberries, we follow the approach of Hulspas-Jordaan and van Lenteren (1989) and keep nymph mortality rates independent of temperature. Mortality parameters are assigned for each week in the simulation and calibrated to observed population levels. Table 4.3 provides the weekly mortality rates assigned in the simulation. Again, these represent the average mortality of a week's worth of nymph whitefly cohorts that mature into that stage during the week.

Table 4.3. Weekly Nymph Mortality Rates Used in the Simulation Model

Date	% Mortality	Date	% Mortality
11/16/02	**0.7**	4/5/03	**0.9**
11/23/02	**0.7**	4/12/03	**0.7**
11/30/02	**0.5**	4/19/03	**0.5**
12/7/02	**0.7**	4/26/03	**0.9**
12/14/02	**0.7**	5/3/03	**0.95**
12/21/02	**0.7**	5/10/03	**0.7**
12/28/02	**0.9**	5/17/03	**0.7**
1/4/03	**0.3**	5/24/03	**0.7**
1/11/03	**0.5**	5/31/03	**0.7**
1/18/03	**0.2**	6/7/03	**0.95**
1/25/03	**0.1**	6/14/03	**0.95**
2/1/03	**0.1**	6/21/03	**0.95**
2/8/03	**0.1**	6/28/03	**0.95**
2/15/03	**0.1**	7/5/03	**0.95**
2/22/03	**0.9**	7/12/03	**0.5**
3/1/03	**0.9**	7/19/03	**0.5**
3/8/03	**0.9**	7/26/03	**0.5**
3/15/03	**0.8**	8/2/03	**0.5**
3/22/03	**0.8**	8/9/03	**0.5**
3/29/03	**0.9**	8/16/03	**0.5**

The values used in Table 4.3 can be explained in terms of changes in weather and plant nutrient conditions. We increase the whitefly nymph mortality rates during rainy periods observed in November, December, and early January, when precipitation exceeding two inches fell within several days. In addition, 2.25 inches of rain were recorded in the Watsonville area between April 26 and May 4. Between mid-January and mid-February, precipitation was relatively low and temperatures were not extreme. Thus, we assume that whitefly nymph mortality was relatively low in that period.

Plant conditions changed between March and June. As mentioned previously, this period corresponds with the time when Camarosa strawberry plants in the Watsonville area commence fruit production (March) and when they produce the most berries per plant (June). The effect of these changes can be seen by the relatively large nymph population observed in early March that would have developed into adults by late April but did not, as seen in Figure 4.3. As stated, the declining leaf nutrients are assumed to have reduced the overall health of whiteflies. Note, however, that rainfall also occurred during this period. Although it is difficult to determine precisely whether most of the change in the nymph mortality rate is due to changes in plant nutrient levels or rainfall, it is most likely due to changes in nutrient levels. This hypothesis is supported by the observation that the increase in nymph mortality appeared to start in early April, when there was little rain, suggesting that something other than weather increased the mortality rate.

In the summer, when the plant and weather conditions became favorable again, we reduce the whitefly nymph mortality rate to between 40% and 50% of the cohort dying before the adult stage. At this time, weekly fruit production was 25% or less of its peak, so leaf nutrient levels had likely increased again. In addition, little rain occurred at this time and the ambient temperature was optimal for whitefly development.

4.3.1.4 Adult Whitefly Life Span and Mortality

Adult whitefly longevity and mortality parameters have different effects on the model. The principal difference is the effect on the total number of eggs a cohort of adults can produce. A longer life span increases the total number of eggs a cohort can produce, while the mortality rate reduces the number of adults laying eggs and thus reduces the number of eggs produced.

No studies exist that indicate the longevity of adult whiteflies in outdoor strawberry field conditions. Research cited by Hulspas-Jordaan and van Lenteren (1989) conducted in controlled indoor settings showed that the flies' life span is temperature-dependent. Longevity increases from 10 days at 50ºF to a maximum of 50 days at about 68ºF, followed by a decline at warmer temperatures. A baseline life span of 30 days is used for each week in this model. Adjustments are made to the base life span based on changes in weather and plant nutrition levels. We assume that higher rainfall and declining leaf nutrient levels both decrease the longevity and increase the mortality of the adult whitefly. We make this assumption based on the same reasoning as for whitefly nymph mortality. Accordingly, we reduce the life span to 25 days based on rainfall during February and to 20 days between May and August based on reduced strawberry-plant nutrition levels during the April–June fruiting period. Similarly, we assume that nymphs surviving this period would mature into cohorts of less healthy adults later on.

In addition to a longevity parameter, we assign an adult whitefly mortality rate. This represents the assumption that not all adult whiteflies live for the full baseline life span of 30 days. We assign a baseline mortality rate of 10%, which means that we assume that 10% of a daily cohort of new adult whiteflies die before the end of the maximum 30-day life span.

As in the case of whitefly nymphs, we adjust adult whitefly mortality rates for changes in weather and available plant nutrition. In particular, we assign mortality rates of 50% for adult whiteflies during rainy periods in November, December, and early January; we assign relatively low mortality rates for late January through mid-March when little rainfall was observed, and then increased the mortality to between 80% and 90% from late March through the mid-summer to accompany the effects of declining plant nutrition.

4.3.1.5 Determinants of Oviposition Rate

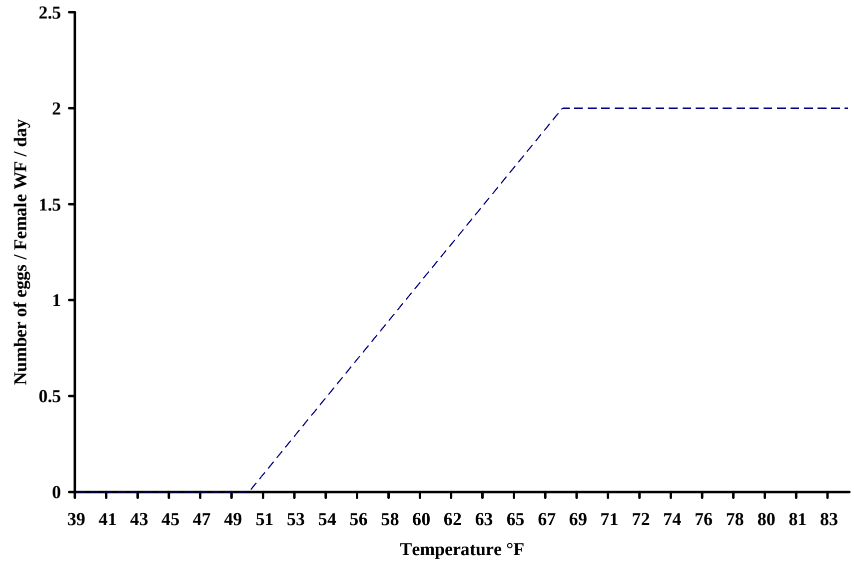
The oviposition rate is defined as the number of eggs laid (oviposition) per female per day. Hulspas-Jordaan and van Lenteren (1989) observed that the greenhouse whitefly's oviposition rate is affected by at least three factors—plant variety, temperature, and whitefly age. In this analysis, the plant variety is constant and its effect on oviposition rate is ignored.

The effect of temperature on greenhouse whitefly oviposition rates on other plants was studied by Hulspas-Jordaan and van Lenteren (1989). Their review of previous research on oviposition rates in controlled environments found oviposition rates on tomatoes of between 0.12 (at 50ºF for 24 hours) and 3.39 (during a 24-hour change in temperature from 68ºF to 95ºF) eggs per female per day.[16] Higher average oviposition rates were observed on other host plants such as eggplant in other controlled experiments.

The effect of temperature on oviposition rates is included in the simulation. The data in Hulspas-Jordaan and van Lenteren's Figure 9 are used as a benchmark. The values from Hulspas-Jordaan and van Lenteren's Figure 9 are shown in the dotted line in Figure 4.4. These values subsequently are adjusted so that the flow of cohorts from eggs into nymphs and from nymphs into adults is calibrated to match the observed flow across time. In the end, most daily oviposition rates range between one and two per female per day across the range of temperatures. In section 4.3.2, we discuss how the calibrated relationship between oviposition rate and temperature compare *ex post* with the observations of Hulspas-Jordaan and van Lenteren (1989).

[16] The ratio of female to male adult whiteflies was fixed at 1:1 throughout the simulation.

Figure 4.4. Baseline Oviposition Rates Used in the Simulation Model



Adapted from Hulspas-Jordaan and van Lenteren (1989)

In addition to the relationship of oviposition rate to temperature, Hulspas-Jordaan and van Lenteren (1989) observed that the oviposition rate varies with the age of the flies. The authors indicated that the rate is limited during the first few days of the flies' adulthood but then increases quickly during a few day period. The rate remains steady during most of their lives until declining slightly over a few day period as they approach the end of their life span. Because data are lacking, the relationship is not explicitly modeled in the simulation, but the *ex post* appearance of this relationship in the simulation results is used as a means of validating the model and is discussed in section 4.3.2 with other validation procedures.

Oviposition rates are assigned over the course of the simulation based on the benchmark rates, initial population age, temperature, and male-to-female ratio. Most of November is modeled as below the baseline oviposition rate. The age of the adults migrating into the field could not be determined, but the age of the adults and nymphs that emerged from their eggs was. By assuming a total daily population averaging about 2.5 adult whiteflies per leaf prior to the first observation on December 4, taking the mortality parameters and observed temperatures as given, we calculate the number of eggs and the possible timing of their oviposition required for the observed number of nymphs and adults to appear when they did. The oviposition rate that predicted the observed population changes is lower than the baseline, about 1.00 eggs/female/day, in contrast with 1.86 eggs/female/day assigned for temperatures around 58ºF, the average temperature over this period. One possible explanation for the lower rate is that a relatively old adult whitefly population migrated into the experimental plot at planting time; Hulspas-Jordaan and van Lenteren (1989) stated that the oviposition rate of adult whiteflies decreases at the end of their life span. Alternatively, the assumption of 2.5 adults per leaf migrating onto the plants may be too high for this period.

A sudden increase in oviposition rate occurred in mid- to late March (Figure 4.1). To accommodate this unexplainable increase, we increased the oviposition rate, relative to values just previous to these, to an average of 4.5 eggs per day per female between March 15 and March 31. The average daily temperature during this period was 56°F, to which we originally had assigned a value of 1.7 eggs per day per female.

For late May to the end of June, we find that the oviposition rate that calibrates the model best for this period is low relative to the baseline—an average of 0.2 eggs per female per day. We originally assigned a value of about 2.3 eggs per day per female at the temperatures observed during this period. Since the population was relatively young at this time and temperatures were relatively high, one explanation is that reduced plant nutrient levels diminished the reproductive ability of adult whiteflies during this period.

This would constitute a fourth factor affecting oviposition rate that Hulspas-Jordaan and van Lenteren did not mention. This relationship has not been confirmed by scientific experiment for the greenhouse whitefly on strawberries, but to the best of our knowledge no evidence exists that contradicts it.

4.3.1.6 Carrying Capacity

Since the surface area and available nutrients of a strawberry plant leaf are finite, we assume that a maximum number of nymphs and adults could fit on a leaf on any particular day. This maximum is the carrying capacity of the leaf. Although the leaf increases in size as it grows, for convenience we assume that the carrying capacity remains constant throughout the season. The carrying capacity of nymphs per day was set at 150 per leaf. The carrying capacity of adults per day was set at 50 per leaf. These numbers were selected based on the highest observed number of nymphs and adults within the samples observed in the study field. No carrying capacity for eggs is assigned since they occupy very little space and do not consume plant nutrients.

The assigned carrying capacities are achieved only in late September in the simulation, after the time the plants in the study field are removed, making a comparison with observed data impossible. It is relevant to extend the simulation this far because the period coincides with the time when many strawberry plants are typically removed in the Watsonville area. Such a large simulated adult whitefly population in September suggests that whitefly populations grow rapidly during this time. If the plants remained in fields longer and if plant nutrient levels remained constant, the whitefly population would continue to build and the affected field would become a reservoir of adult whiteflies that could migrate into newly planted fields. Whether or not these conditions hold at the end of the season, the results reinforce the importance of understanding the physiological development of the whitefly when making pest-management decisions.

4.3.2 Verifying the Model Calibration

Verifying the model's calibration allows the user to have some confidence that it represents observed conditions in the field experiment. In this subsection, we describe the criteria used to verify calibration of the model. In general, we find that the model satisfactory in the sense that it is sufficiently calibrated to predict the timing and approximate size of whitefly population peaks so that they compare with observed data.

The model was calibrated to replicate observed whitefly egg, nymph, and adult populations. As mentioned, this was done by calculating the rate of whitefly physiological development and assigning the mortality, oviposition, and carrying capacity parameter values to the different treatment conditions observed in the study field.

Development of the whitefly population represents an accumulation of cohorts within a given life stage, with individual cohorts progressing from one life stage to another. It is a complex problem to adjust the rates of flow of eggs to nymphs and then to adults, which subsequently reproduce at rates corresponding to the observed populations. The goal of the calibration is to accurately predict the timing of the population peaks, and, since whitefly-days are measured in terms of the adult whitefly population, to predict adult populations within approximately one adult of the observed adult population over the course of the simulation. Although other combinations may work—each providing a different description of whitefly population dynamics—this model provides a plausible representation of the flow of eggs, nymphs, and adults through time.

In the following, we verify calibration of the simulator for whitefly populations observed in three treatment plots. These are (1) untreated plots, (2) plots treated with Esteem© only, and (3) plots on which Admire© is applied at planting. In each case, we discuss the results of the calibration by assessing the model's ability to predict population peaks and by comparing the number of observed whitefly-days with the number predicted by the simulator.

Case 1: Untreated

Figures 4.5–4.7 show that simulated numbers of eggs, nymphs, and adults compare with the corresponding whitefly populations observed in the study field in 2002–03. The parameters for mortality, oviposition, and carrying capacity used in the model were used as a benchmark for the other two simulations to follow.

Figure 4.5. Observed and Simulated Average Whitefly Egg Populations per Leaf on Untreated Plants

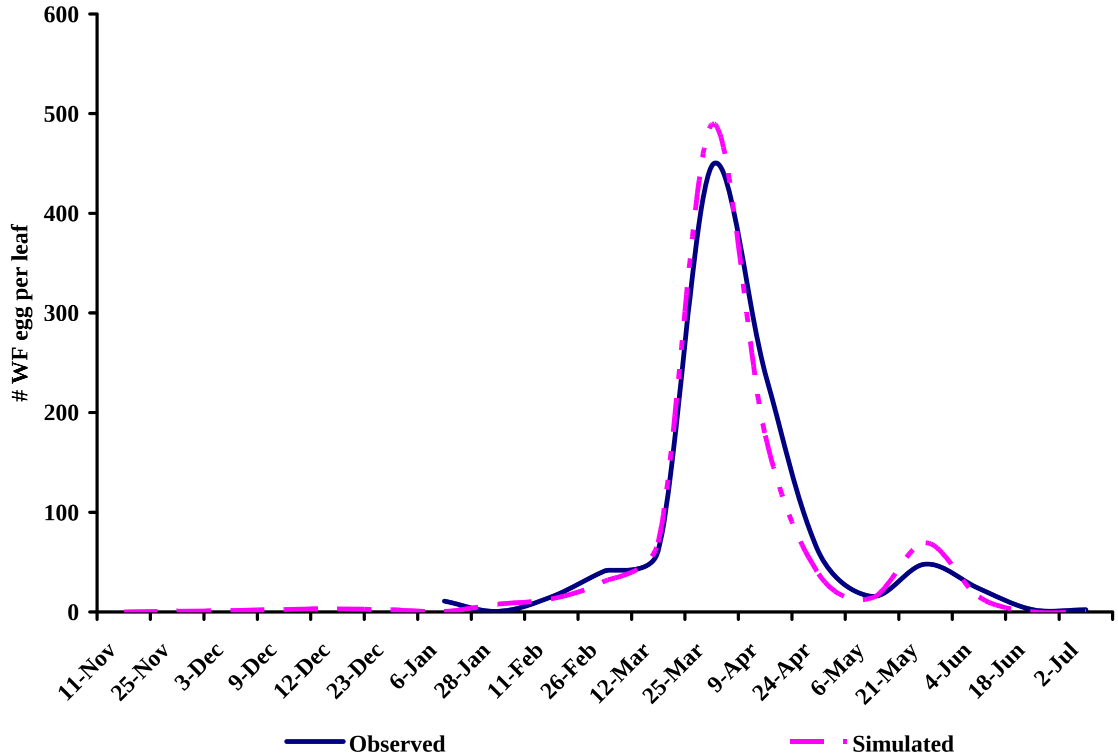


Figure 4.6. Observed and Simulated Average Whitefly Nymph Populations per Leaf on Untreated Plants

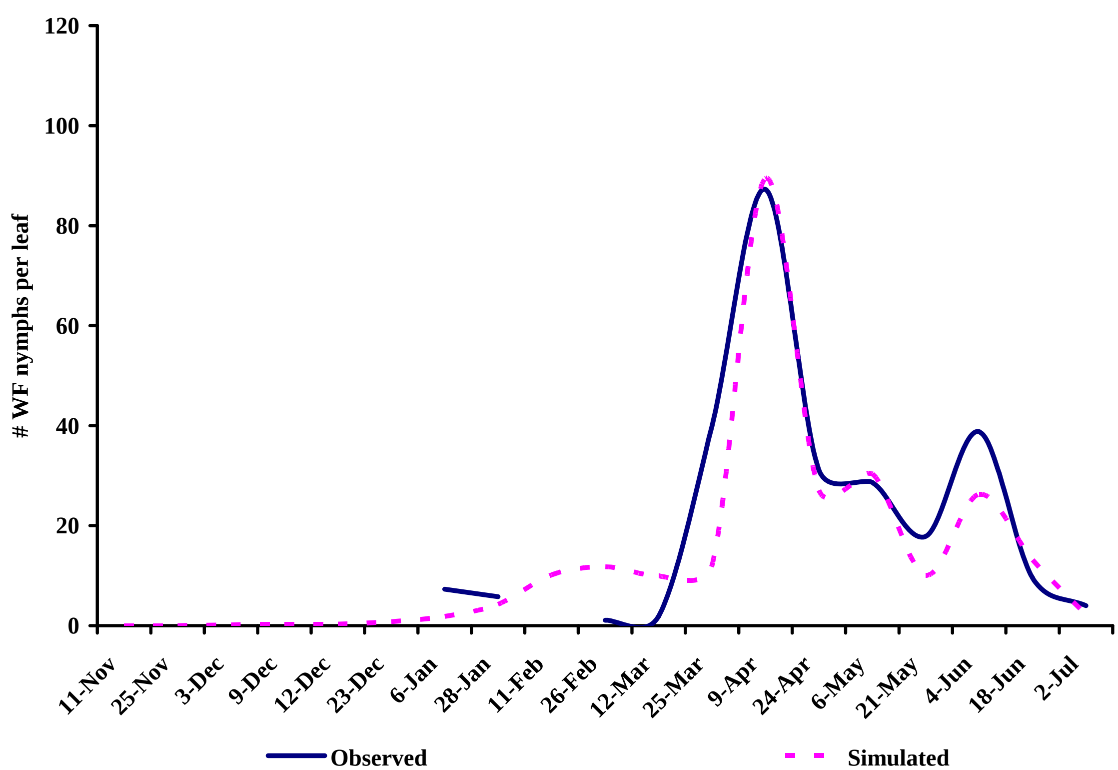
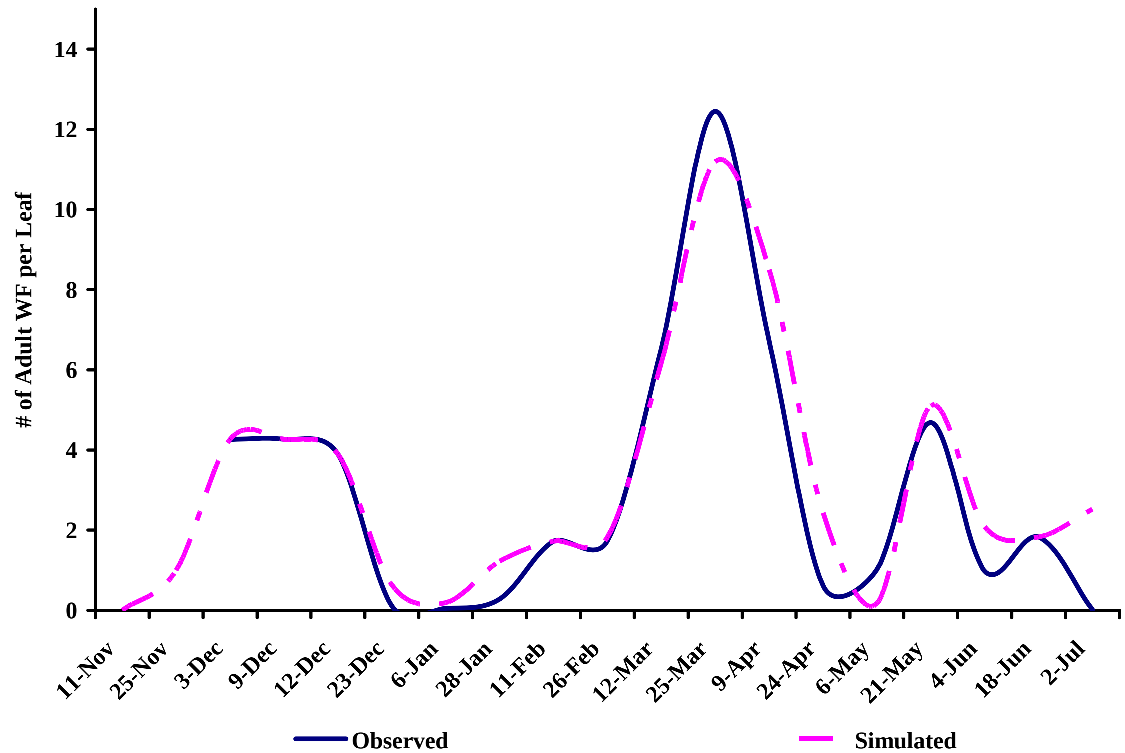


Figure 4.7. Observed and Simulated Adult Whitefly Populations per Leaf on Untreated Plants

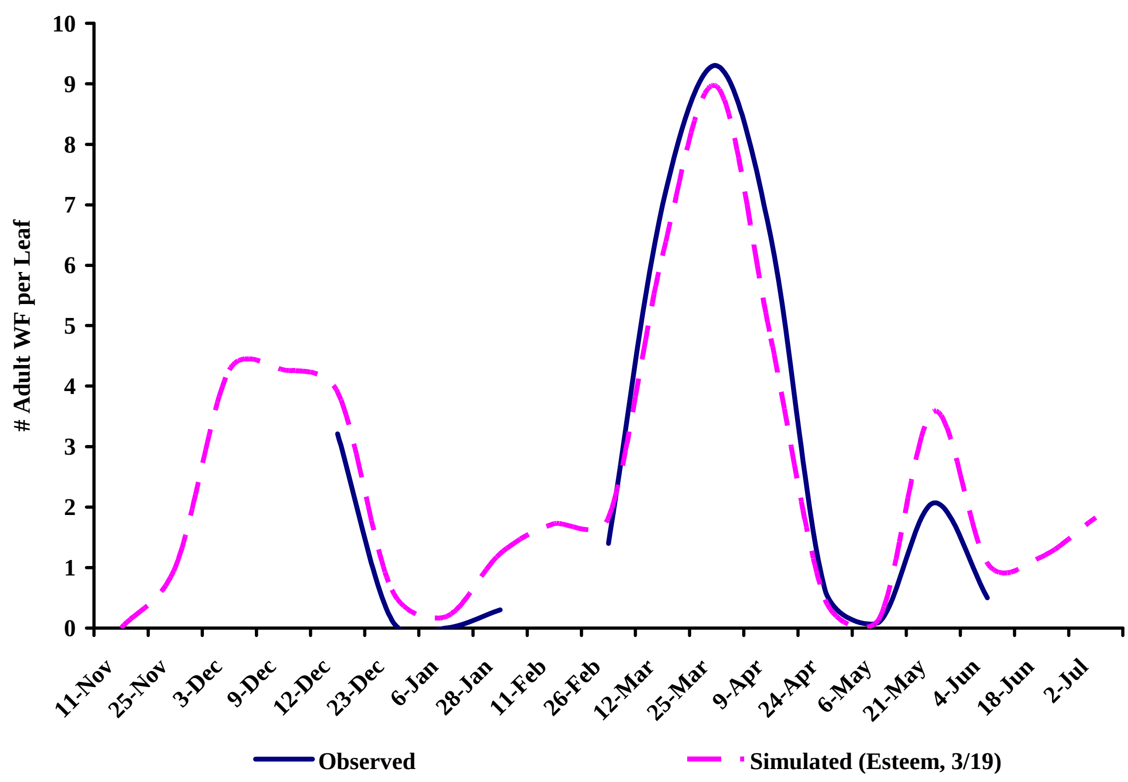


As mentioned, we apply two criteria for calibration when constructing the simulator. First, we verify that the shape of the curve representing the population size of each life stage is duplicated. That the model does so is seen in the figures. Second, to obtain the same number of cumulative whitefly-days in the simulation as in the actual observations, we try to obtain an absolute number of simulated adults within one adult of the observed population on the observation dates. There were 505 observed cumulative whitefly-days observed between January 6 and June 4. The simulation predicted 564 cumulative whitefly-days over the same period, a difference of 12%. This difference, as well as others in subsequent models discussed in this chapter, may be accounted for by unobserved determinants of whitefly population growth, which are unaccounted for in this model.

Case 2: Esteem© Alone

As demonstrated in section 4.1, the combination of Esteem© and Admire© currently forms the most cost-effective chemical management program for the greenhouse whitefly on strawberries. To develop the model that combines the effect of these two chemicals, we first adapt the base model to include the application of Esteem© alone and then compare the predicted population development with the observed population data collected in treatment 5 of the study field. The simulated and actual adult whitefly populations for this case are shown in Figure 4.8.

Figure 4.8. Observed and Simulated Average Adult Populations per Leaf with Esteem© Treatment on March 19, 2003



The parameters used in the simulation model previously described are adjusted to accommodate the effect of the Esteem© treatment. Specifically, we assume 30%

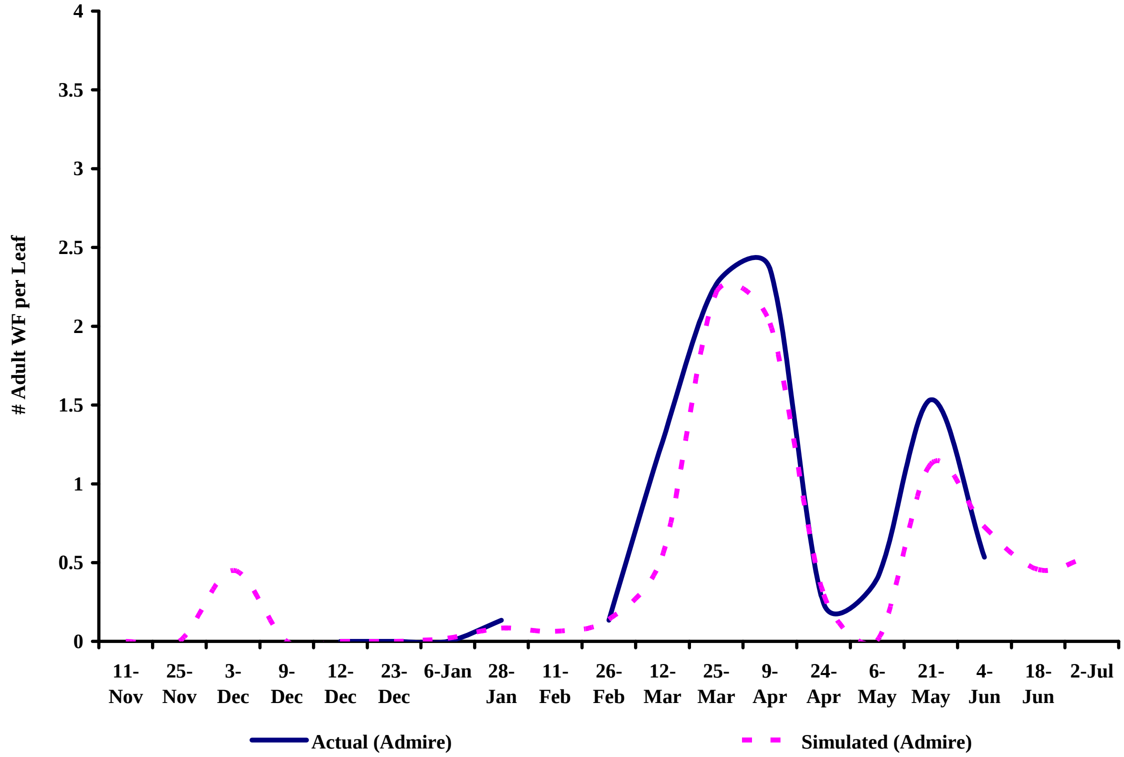
mortality for the total egg population present on the treatment date, 85% nymph mortality for the total nymph population on the treatment date, and 15% mortality for the total adult population on the treatment date. These values are based on finding a combination of parameter values associated with the application of Esteem© alone that produced simulated populations of eggs, nymphs, and adults most like the observed ones. Additional support for these parameters is found in trials done under field conditions to assess Esteem© efficacy on nymphs and adults. These were conducted by Bi, Toscano, and Ballmer (2002b,c), who found mortality rates similar to those used in the simulation.

As in the untreated model, the Esteem©-only model is calibrated so that it predicts the timing of the peaks in the adult whitefly population. It also predicts the size of the population within one adult of the actual observation on any date. Between January 6 and June 4 there were 403 actual cumulative whitefly-days observed. The simulator predicted 421 cumulative whitefly-days for the same period, about a 5% difference.

Case 3: Admire© at Planting

Lastly, we simulate the effect of the Admire© treatment alone on whitefly population development. In this simulation, we assume that Admire© was efficacious for about eight weeks after planting, based on information in Bi, Toscano, and Ballmer (2002b). We assume 70% mortality for the first day of any cohort of adult whiteflies and 100% mortality after seven days. Because Admire© is not effective on eggs and nymphs, all other parameter values are kept constant relative to the untreated simulation discussed previously.

Figure 4.9. Observed and Simulated Average Adult Populations per Leaf with an Admire© Treatment on November 12, 2002



The parameter values used to model the effect of the Admire© application on the whitefly population are comparable to those in a separate field trial by Bi, Toscano, and Ballmer (2002b). Those field experiments were done in Oxnard on fall plantings of commercial strawberries. They observed an adult mortality rate that was 31% to 61% higher than the control population starting at three weeks after treatment and lasting until six weeks post-treatment. Observations made by these same authors on summer plants showed larger decreases in adult greenhouse whitefly populations one to eight weeks after treatment than those observed on fall plants. The untreated and Admire©-treated plots had similar populations because of cold weather from week nine to twelve, which may have suppressed the efficacy of Admire©. In week thirteen, the adult population in the Admire©-treated plots fell below the untreated control population and remained at

40% to 66% fewer adults than in the untreated control plots through the end of the season.

The adult whitefly population in the Admire©-only simulation is shown in Figure 4.9. It predicts the timing of the population peaks obtained in treatment 3 in the field experiment but is less accurate than the Esteem© simulation in terms of predicting population size. There were 125 observed cumulative whitefly-days between January 6 and June 4. The simulator predicted 100 cumulative whitefly-days during the same period, a 25% difference.

4.3.3 Validating the Model

The parameterized model of whitefly population dynamics calibrated to each treatment is a simplified representation of the complex interaction between strawberry plants and greenhouse whiteflies. To know whether the model can provide reliable information about how alternative pesticide application dates affect development of the population, it is important to assess its reliability. The process of assessing the reliability of a model is called validation.

Validating the parameterized whitefly population model answers the question "Does this model predict the development of whitefly populations on strawberries?" This involves verifying the ability of the method used to develop this model to replicate other observations. The method used to predict development of the whitefly population is, first, to calculate the time needed for physical development across life stages and, second, to adjust the mortality and oviposition rates based on precipitation data, anticipated plant condition, and adult whitefly ages.

In this section, we validate the simulation model against three other observed greenhouse whitefly populations. First, we combine the Esteem©- and Admire©-only simulations to replicate the experimental plots on which Admire© was applied at planting, followed by an application of Esteem© on March 26, 2003, treatment 2. Second, we recalibrate the simulation model to replicate development of another population of greenhouse whiteflies observed in the Oxnard area between February and April, 2000. We find that the model successfully predicted the timing of whitefly population peaks in both of these cases. The final method of validation was to assess the model's ability to predict the relationships between oviposition and temperature and oviposition and age from the data reported by Hulspas-Jordaan and van Lenteren (1989), based on observations of greenhouse whitefly populations on tomatoes, raised in controlled settings.

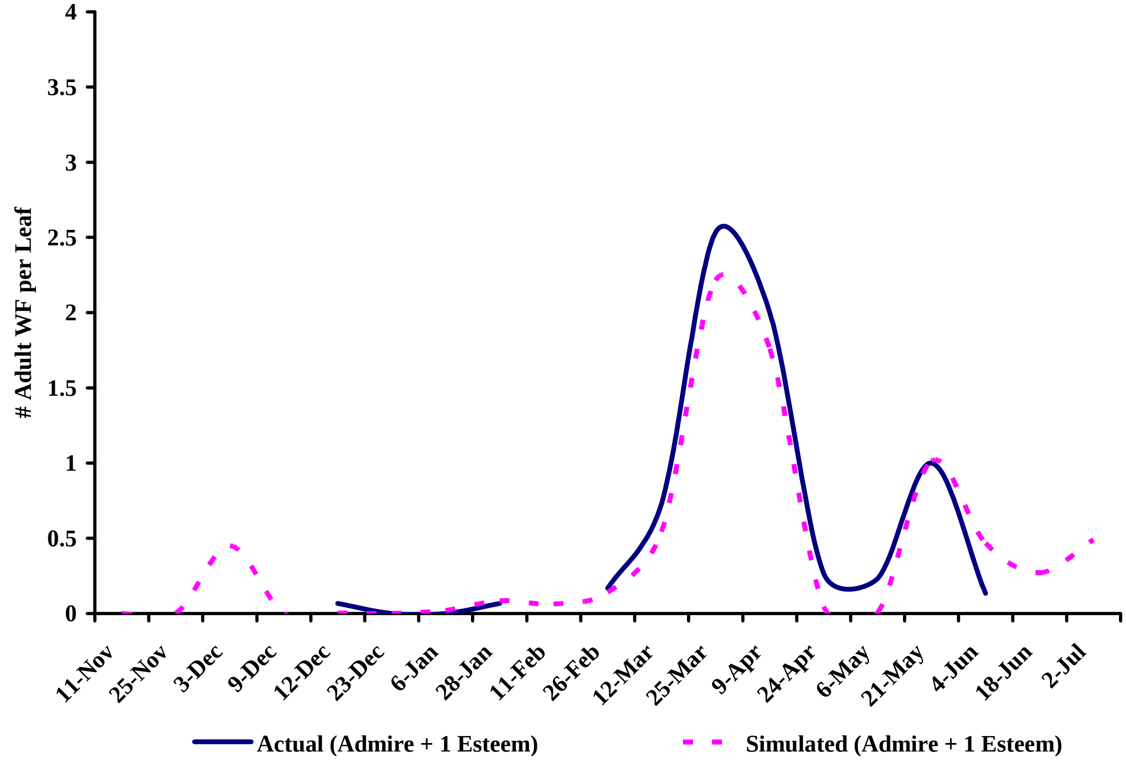
4.3.3.1 Validating the Model's Ability to Predict the Whitefly Population for the Admire©/Esteem© Treatment Combination

We simulate the effects of applying Admire© and Esteem© by combining the two parameterized Admire© and Esteem© application effects described in the previous two cases. Having calibrated this model, we can analyze the effect of alternate application dates for Esteem© used with Admire© on the population dynamics of the whitefly and thus on the profits available from strawberry production.

As before, all other parameter values are kept constant relative to the baseline model. The timing of the population peaks is accurately modeled. There were 103 cumulative whitefly-days observed between January 6 and June 4; 89 cumulative whitefly-days were predicted during the same period, a 14% difference (Figure 4.10).

Figure 4.10. Observed and Simulated Adult Populations with an Admire©

Treatment (November 12, 2002) and an Esteem© Treatment (March 26, 2003)



4.3.3.2 Validating the Model's Ability to Predict the Dynamics of a Whitefly Population in Oxnard, CA

Validating the model by replicating the development of an observed whitefly population in the Oxnard area is an appropriate test for two reasons. First, as previously noted, winter temperatures in Oxnard are warmer than in the Watsonville area. As a result, individual whiteflies mature faster in Oxnard than in Watsonville. This difference provides a good way to test the ability of the model to predict the timing of population peaks.

The second reason is that there is a difference between the timing and frequency of the whitefly population sampling period in the Oxnard and Watsonville areas. Observations in the Watsonville area for the whitefly adult population commenced within a few weeks of planting, and the egg and nymph population observations began a few weeks later. This means that, with the exception of the initial migration of adult whiteflies, all of the adult population peaks in the Watsonville field trial were observed. In contrast, assuming fall plantings were done in Oxnard in the middle of September 2000, about two months earlier than is typical for Watsonville, observations for the populations of whitefly eggs, nymphs, and adults in Oxnard commenced approximately 18 weeks after planting, on February 1. This would have allowed sufficient time for population peaks to occur prior to the start of sampling. Since early observed populations depend on presample populations, this difference provides a good way to test the model's ability to predict the occurrence of population peaks.

The data used for this analysis are observations of an Oxnard whitefly population in a commercial strawberry field published by Bi, Toscano, and Ballmer (2002a). Neither Admire© nor Esteem© was used to manage the whitefly populations in this field. The authors observed the egg, nymph, and adult whitefly populations at weekly intervals in three fall-planted commercial strawberry fields in Oxnard between February 1 and April 19, 2001. The fields were located in multifield regions of relatively high, moderate, and low whitefly populations with one field from each region selected for observation. Based on Oxnard area commercial practices we assume these were planted on September 15, 2000. Although the only field used to validate the model has a relatively high whitefly population, since we have found no evidence that the mechanics of whitefly population growth are affected by the population size, we anticipate that the model replicates the development of the moderate and low whitely population regions observed by the authors.

The procedures used to measure the adult whitefly population were the same as those used in the Watsonville field; however, the procedure used to measure the eggs and nymphs was different. Instead of counting all the eggs and nymphs on the entire leaf, only the eggs and nymphs within a 4.5cm^2 disk were considered. Since the model is designed based on leaf populations, the observations from Oxnard are converted into leaf-level populations. To determine the appropriate conversion factor, the surface area of 10 randomly selected, fully expanded strawberry leaves is measured. Average surface area is determined to be 35.5 cm^2. Assuming a uniform distribution of eggs and nymphs on the leaf, the egg and nymph observations reported by Bi, Toscano, and Ballmer (2000a) are multiplied by 7.89.

The method used to replicate the observed populations is the same as that used for the Watsonville data. Using temperature data from a weather station located in Oxnard, the number of degree-days was calculated for every day in the life of the field. This allowed us to model the date on which daily cohorts of whiteflies would mature to each life stage.

The second step in this method is to adjust the base mortality and oviposition parameters as a function of precipitation, plant condition, and adult whitefly age. Fall plantings are made in September in the Oxnard area and in November in Watsonville. The difference in planting dates exposes their respective whitefly populations to different amounts of heat over time. The difference in dates considered and in temperatures observed made it impossible to simply apply the same sequence of mortality and oviposition parameters used for the Watsonville-based model. The mortality rates are adjusted based on temperatures and precipitation as in the Watsonville-based model. For instance, mortality rates are increased on occasions when more than two inches of rain fell within a three-day period. The same baseline relationship between oviposition and temperature is used and adjusted as in the previous model. Finally, to account for the observed emigration of the adult whitefly population to an adjacent lima bean field in June, which became a preferred food source at that point, we set the adult mortality rate at 100% after June 1.

Figures 4.11–4.13 show the observed and simulated egg, nymph, and adult whitefly populations for the Oxnard case.

Figure 4.11. Observed and Simulated Whitefly Egg Populations per Leaf for Oxnard, 2001

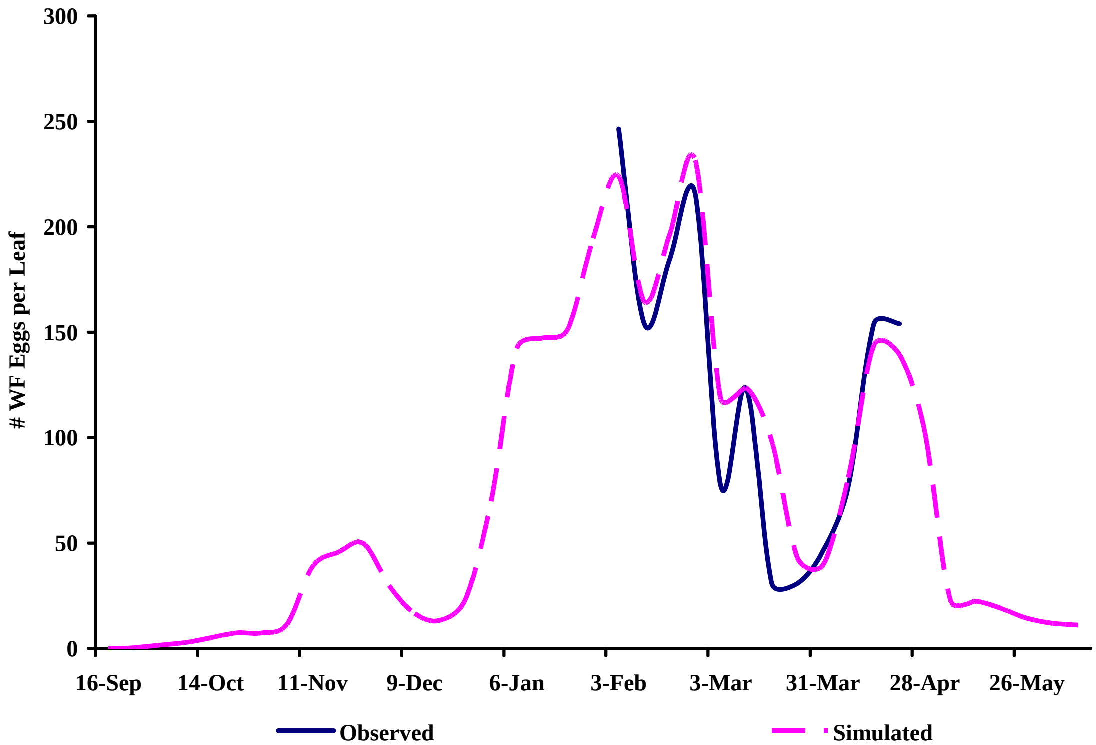


Figure 4.12. Observed and Simulated Whitefly Nymph Populations per Leaf for Oxnard, 2001

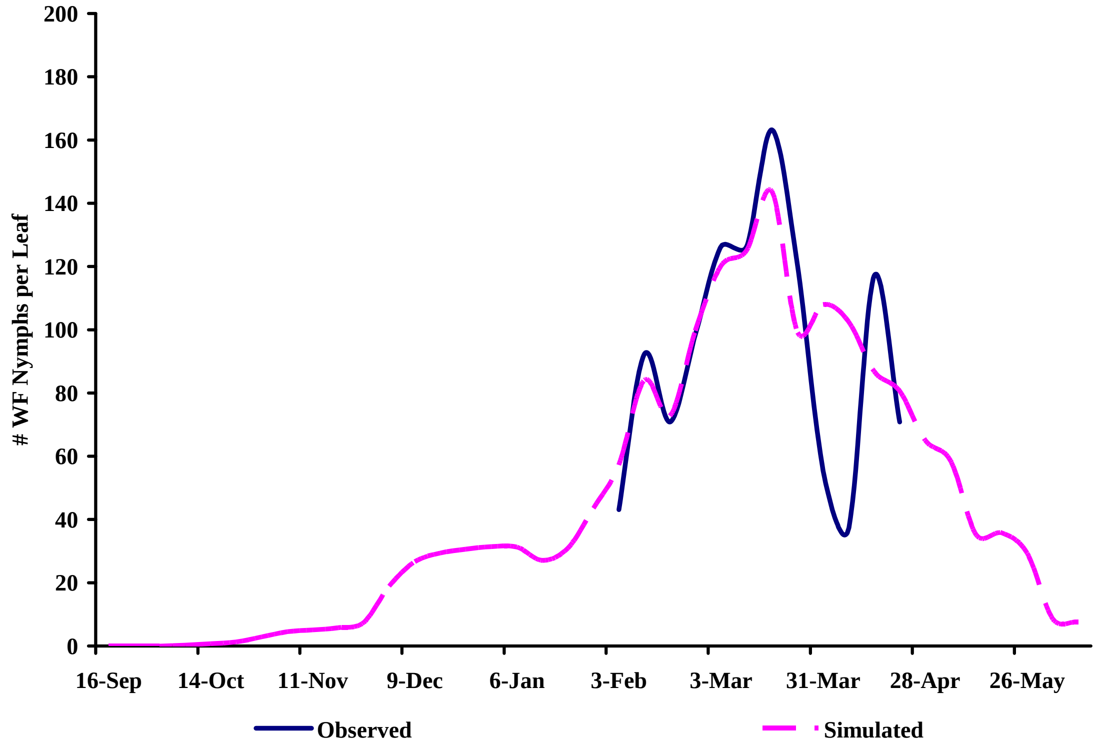
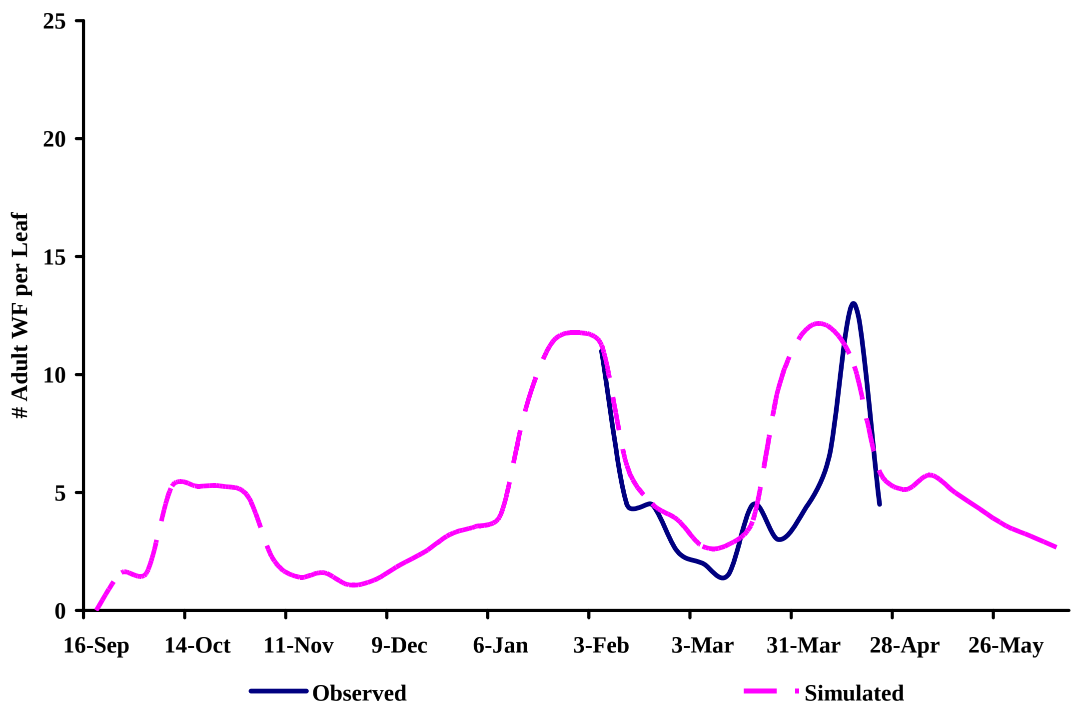


Figure 4.13. Observed and Simulated Adult Whitefly Populations per Leaf for Oxnard, 2001



As in the previous model, we apply two criteria to verify calibration of the simulator. First, we verify that the overall shape of the curve for each life stage is duplicated. That the model does this satisfactorily is shown in the figures. Note that the observations commence with a decline in the adult population. The model predicts that this is a decline after a peak in January and February. The model also predicts a peak soon after planting, based on the assumption that adult whiteflies infested the field upon planting and commenced oviposition. Enough degree-days were observed in this period to allow the eggs to mature and become adults within a month. The existence of both of these unobserved peaks was confirmed by a scientist familiar with the infestation, although no data are available (Zalom, 2005).

Second, we try to obtain an absolute number in the simulated adult population as close as possible to the observed one (within approximately one adult of the actual observation). There were 267 actual whitefly-days observed between February 1 and April 19. The simulation predicted 391**,** a difference of 46%. This surplus occurs during a period of overpredictions by the model between mid-March and mid-April. We have not been able to determine the reasons why this is the case.

The results from the Oxnard whitefly population model and the combined Admire© and Esteem© model demonstrate that the method of calculating the physical development time and adjusting the mortality and oviposition rates based on conditions external to the whitefly accurately predict the timing of whitefly population development and its size. This provides assurance that the model’s approach is valid.

4.3.3.3 Validating the Model's Ability to Predict Relationships between Oviposition, Temperature, and Age

Our first validation method assessed the model's ability to replicate the timing and size of greenhouse whitefly population peaks. The second method compares the *ex post* relationship between oviposition and age temperature with the positive relationship between temperature and oviposition and the relationship between age and oviposition observed by Hulspas-Jordaan and van Lenteren (1989), who describe oviposition as relatively limited during the first few days of the flies' adulthood but then increasing quickly and remaining steady until a few days before their deaths. This is done for both the Watsonville and the Oxnard models. The analysis of the presence of these relationships in the model is inconclusive.

The comparison of the ex post and published relationship between oviposition and age or temperature is a relevant validation technique because we do not impose the relationship between temperature and oviposition expressed in Figure 9 of Hulspas-Jordaan and van Lenteren (1989) and shown in Figure 4.4 for our model. The values displayed in Figure 4.4 were used as initial values but were adjusted as described to calibrate the model to the observed sample. In the end, the relationship between temperature and oviposition actually used in the simulation could have looked very different from the relationship displayed in Figure 4.4. This difference allows us to observe *ex post* whether the general relationship between temperature and oviposition in the simulation corresponded in general with the conclusions of Hulspas-Jordaan and van Lenteren. The ordered pairs of temperatures and daily oviposition rates for the Watsonville and Oxnard greenhouse whitefly simulations are shown in Figures 4.14 and 4.15, respectively.

Figure 4.14. Daily Relationship between Whitefly Oviposition and Temperature – Simulated Watsonville Population

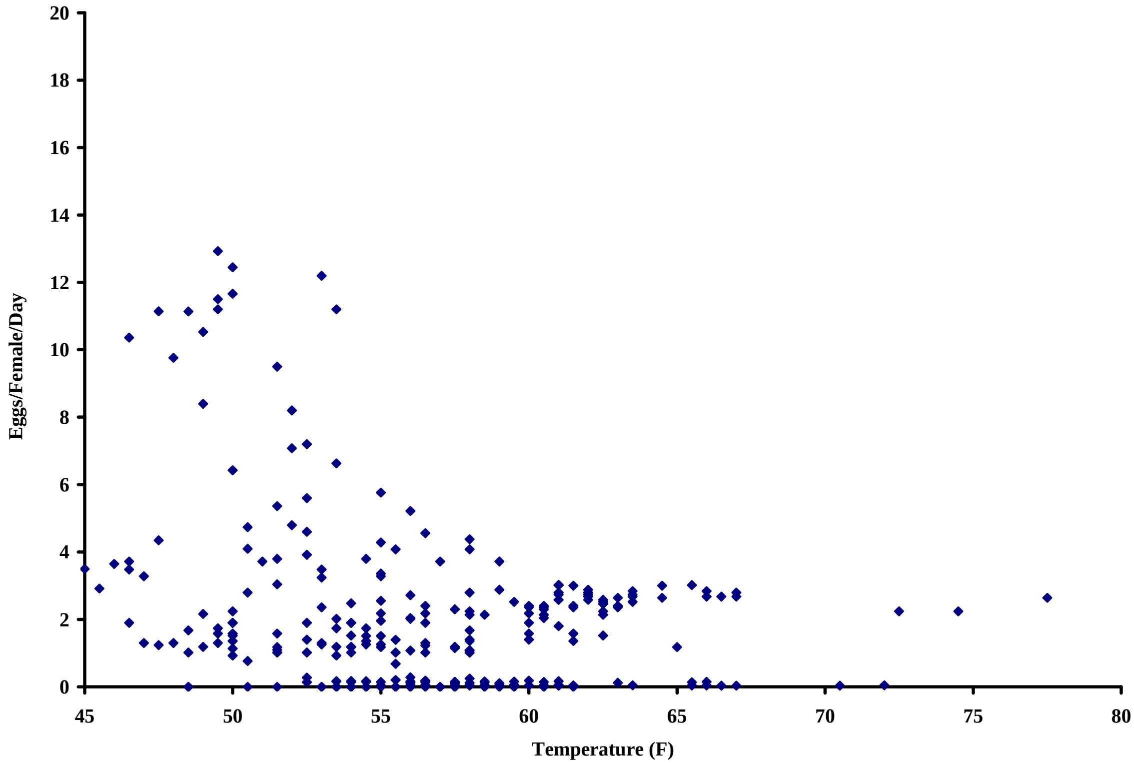


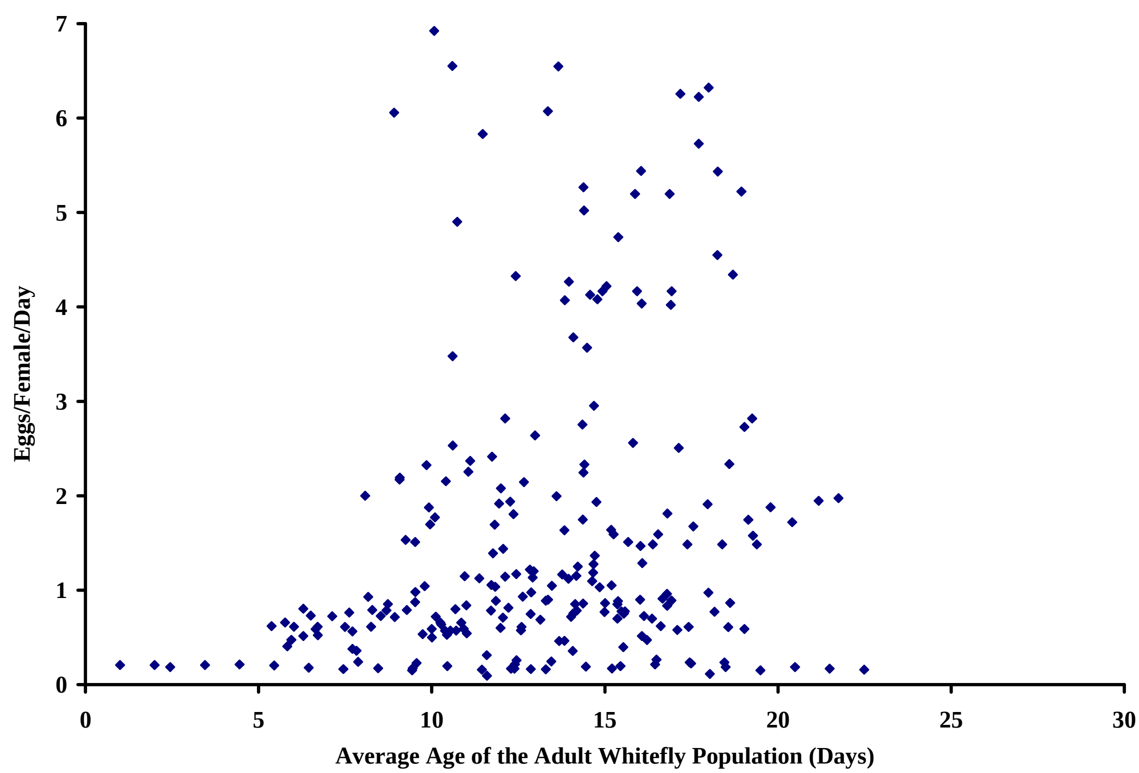
Figure 4.14 shows that no single oviposition rate held for any temperature. One possible explanation for this is the role of age as a determinant of oviposition rates. For example, we assign an oviposition rate of 6.5 eggs per day when the average adult whitefly age is 9.3 days in mid-March and the average daily temperature is 61.5ºF. In contrast, we assign an oviposition rate of 0.02 eggs per day when the adult whitefly population is 13.1 days old on average in mid-June and the average temperature is 56.5ºF.[17] Another possibility is the effect of plant nutrition cycles on whitefly fertility.

A statistical analysis of whether a relationship between temperature and oviposition rate exists in the simulation leaves the question of whether this was observed in the simulation unresolved for both the Watsonville and Oxnard models. A linear

[17] Note, however, that the adult whitefly population also could have been suffering from reduced plant nutrient levels at this time.

regression on the data in Figure 4.15 shows a negative and significant relationship between temperature (in ºF) and oviposition rate. The regression is eggs/female/day = intercept + β temperature. The intercept is 7.766, and the coefficient on temperature is -0.093 with a Student's *t* score of -4.949. The F-score for the regression is 24.494 with 335 degrees of freedom. The result for the Oxnard model is also negative, but insignificant: the intercept is 4.883, the coefficient on temperature is -0.133 with a Student's *t* score of -1.022. The F-score for the regression is 1.044, with 271 degrees of freedom. Although these two combined results suggest a negative relationship between oviposition and temperature, further analysis is not done because of a lack of scientific data and theory about the relationship between temperature and whitefly oviposition rates on strawberries.

Figure 4.15. Daily Relationship between Whitefly Oviposition and Temperature – Simulated Oxnard Population



The relationship between age and oviposition rate suggested by Hulspas-Jordaan and van Lenteren (1989) also could be observed for the Watsonville (Figure 4.16) and Oxnard (Figure 4.17) models after assigning the parameter values. Most of the oviposition rates lie between one and two eggs per female per day, as they suggest, with several outliers in the five- to 20-day age range. This roughly supports the statements made by Hulspas-Jordaan and van Lenteren (1989) that egg production increases with age up to a point, remains steady for almost the entire life span of the adult whitefly, and then declines close to the end of its life.

A statistical analysis of this question, however, leaves the question of the presence of this relationship unresolved. A linear regression on the data for the Watsonville model, in Figure 4.16, showed a negative but insignificant relationship between age and oviposition rate, which supports a flat relationship between age and oviposition. The regression is eggs/female/day = intercept + β age. The intercept is 2.610, and the coefficient on age is -0.023 with a Student’s *t* score of -0.901. The F-score for the regression is 0.812 with 335 degrees of freedom, making the regression model insignificant. In contrast, the Oxnard model exhibits a positive and significant relationship between oviposition and age: the intercept is -4.021, and the coefficient on age is 0.551, with a Student’s *t* score of 4.913. The F-score for the regression is 24.142 with 258 degrees of freedom.

Figure 4.16. Correlation of Whitefly Eggs per Day and Average Adult Population Age – Simulated Watsonville Population

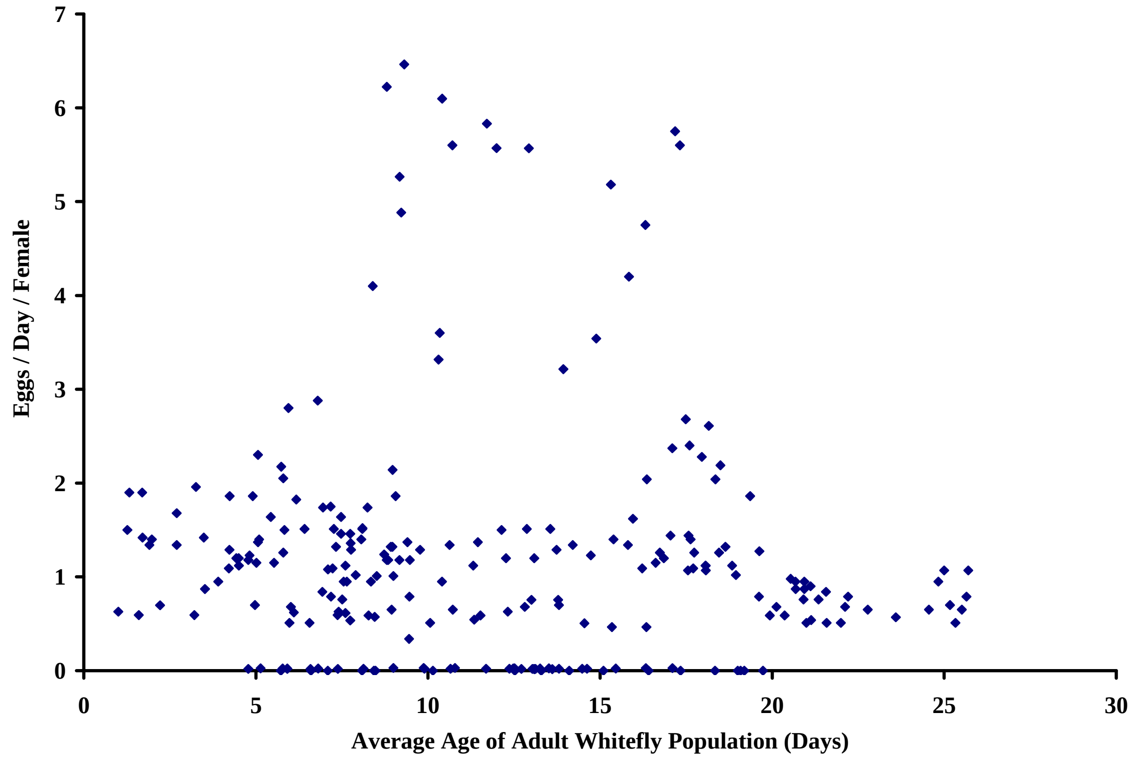
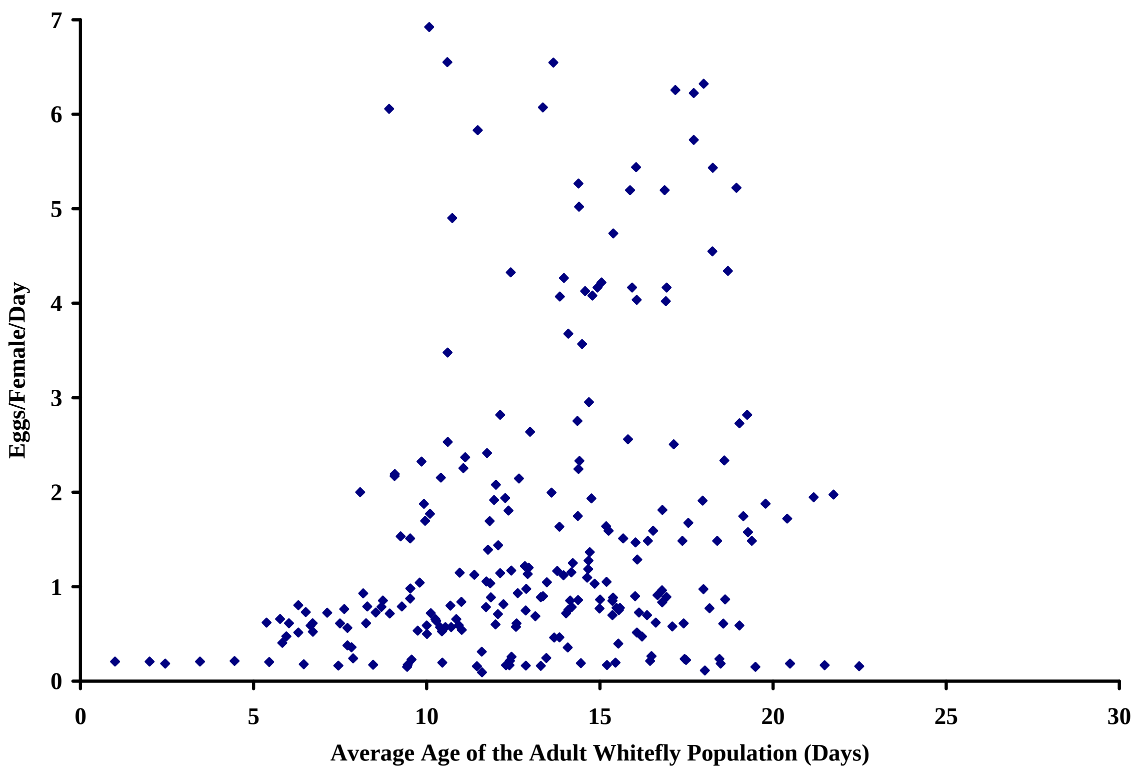


Figure 4.17. Correlation of Whitefly Eggs per Day and Average Adult Population Age – Simulated Oxnard Population



While the inconclusive results fail to completely validate the ability of the model to detect the desired relationships between age and temperature with oviposition frequencies, the results do show that such a relationship could be determined with sufficient observations on the oviposition rate of greenhouse whiteflies on strawberries in outdoor conditions.

These three sets of results show that, while the conceptual design of the model replicates the development of observed whitefly populations, the estimates are sensitive to the oviposition and mortality parameter values used. These represent difficulties associated with a lack of detailed data about these two parameters. The first source of sensitivity is assumptions about the age, quantity, and rate of arrival of migrating adult whiteflies at the beginning of the season. For example, underestimating the size of the group of migrating adult whiteflies may overstate the oviposition rate needed to produce the number of adults observed in early spring. Similarly, the true age and arrival time[18] affect the rate of oviposition by determining the amount of time available for and rate of oviposition. The impact of these components can be mitigated in the future by improved measurement of the size, age, and arrival time of migrating whitefly populations.

The second source of sensitivity is assumptions about mortality parameters. The true relationship of weather, strawberry plant physiology, and whitefly mortality is unknown. We select a set of mortality parameters that best replicates observed data based on the observations in the available data. These parameters are likely sensitive to

[18] Arrival time can be determined through frequent observation. For practical purposes, if adult whiteflies are present in the area and temperatures are high enough for flight and oviposition, one can assume that arrival occurred within a few days of planting (Zalom, 2005).

weather, since they correlate with periods of rain and cold and vary with the physiology of the plant.

Third, assumptions about oviposition rate affect the results. Since scientific observations (Hulspas-Jordaan and van Lenteren, 1989) indicate that the average age of the adult population affects the number of eggs laid per day, any factor that affects the age distribution of the population also will affect the oviposition rate.

There are other factors that affect development of the whitefly population that are not explicitly contained in this model—in particular, the presence of a nutrient cycle in strawberry plants and the effect of changes in strawberry plant nutrients on whitefly mortality. Evidence presented in this study suggests that these relationships exist. Together, these sources of sensitivity make it difficult to be certain that any simulation of alternative scenarios is a true representation of actual field conditions.

Despite these sensitivities, the model calibration and validation techniques demonstrate that the approach described here can be used to model the population development of the greenhouse whitefly population on strawberries in both the Oxnard and Watsonville area. By outlining the steps and data needed for similar insects, it also provides a more general approach for modeling the population development of invasive pests. The process used in developing the model also identified a sequence of data requirements that could enhance understanding about the relationship between greenhouse whiteflies and strawberry plants, which is valuable to both the commercial strawberry industry and to policymakers. By extension, the process used here to model development of an invasive population could be used to identify the data most necessary for predicting the effects of regulation on that development.

4.4 Analysis of Effect of Whitefly Feeding on Strawberry Yields

In this section, we discuss the second biological component of the model, estimation of the effect of greenhouse whitefly feeding on marketable strawberry yields.[19] This effect is calculated using the yield and whitefly population data discussed in section 4.1. Several assumptions about the interactions among strawberry plants, greenhouse whiteflies, and chemical treatments are made to simplify the analysis. We assume that the strawberry plant is equally vulnerable to whitefly damage at any point in its life cycle. We assume that the effect of whitefly feeding on yields begins as soon as the adult whitefly begins feeding. We abstract from any possible direct feedback relationship between the health of the plant and the size of the whitefly population—in other words, the health of the plant is assumed to be unaffected by whitefly feeding—due to a complete lack of scientific data on the nature of this relationship, let alone on the magnitude of the effects, by which to estimate it. We assume that Esteem© and Admire© have no harmful effects on the plant itself.

While the precise mechanics of the interaction between whitefly feeding and strawberry yields are unknown, it is apparent that strawberry yields are adversely affected by the whitefly (Toscano and Zalom, 2003; Udayagiri, Zalom, and Toscano, 2000). Although we assume that whitefly feeding affects yields as soon as feeding begins, and that marketable strawberries take approximately three weeks to mature, we hypothesize that an appropriate way to model the effect of whitefly feeding is to assume that feeding in week t affects yields available the next week. This is observed through a reduction in

[19] For convenience, the effect of the whitefly population on strawberry yields is measured only as a function of the number of adult whitefly-days. Regression analysis of strawberry yields on whitefly nymph and adult populations indicated that the equation was statistically significant but the individual coefficients were not.

the incremental contribution from total yields each harvest.[20]

To test this hypothesis, we estimate a simple econometric model in which the dependent variable is weekly strawberry harvest, y_t, where t denotes the number of weeks since planting. Two coefficients are used to test our hypothesis: the cumulative number of adult whitefly-days since the last harvest, $\sum_{j=j-1}^{t} WF_j$,[21] and an interaction term multiplying the aggregate number of whitefly-days since the last harvest and the number of weeks since planting, $\left(\sum_{j=j-1}^{t} WF_j\right)t$. This second term measures whether adult whitefly feeding affects the yields at different rates over time. For instance, does adult whitefly feeding cause more damage if it occurs later in the season?

Other variables capture features of the sample data. As noted in section 4.1, observations from chemical treatments other than Admire© and Esteem© are used only to gather additional data about the relationship between the whitefly population's size and resulting yields. Dummy variables (δ_i) are used to control for differences in yield effects between all the treatments listed in Table 4.1. We account for the time required for the strawberry plants' growth by including a time trend that counts the number of weeks since planting occurred. The sudden increase in yields in June is accounted for with a dummy variable on observations in June, δ_{June}. We also include a quadratic time term in the model to reflect the sudden changes in the rate of yields produced. An error term, ε_t ,

[20] This is done because of the limited amount of data available from the commercial field experiment described in section 4.1 on the relationship between whitefly feeding and yields. A regression on the size of marketable berries and whitefly feeding one, two, and three weeks prior to harvest was done, but no statistically significant results were obtained.
[21] In the case of the first harvest, the number of whiteflies during the previous week was used.

is used to represent any other unobserved characteristics of the relationship between whitefly feeding and strawberry yields. We assume that the error is normally distributed with a zero mean and constant variance. No other data are available for other variables that are typically used to explain harvestable yields, such as soil nutrient levels. However, since all the data were gathered in approximately 7,600 square feet (approximately 47 feet by 164 feet), or 1/6 of an acre, of the same commercial field during a single season, substantial differences are not likely.

Since no theoretical framework exists in the entomology literature or elsewhere to suggest the mathematical relationship between whitefly feeding and strawberry yields, we use the simplest statistical models that represent the data reasonably well. A specification test (Box and Cox, 1964) indicates that the log-linear models we use represent the data more accurately than linear models.

We estimate the following model using ordinary least squares.

$$Y_t = \sum_{i=1}^{11} \delta_i + t + t^2 + \beta_1 \sum_{j=j-1}^{t} WF_j + \beta_2 \left(\sum_{j=j-1}^{t} WF_j \right) t + \delta_{June} + \varepsilon \,. \tag{4.1}$$

Table 4.4 reports our findings regarding whether whitefly feeding between two consecutive harvests tends to reduce the subsequent harvest. We found that feeding between harvests increases yield losses as time passes, as demonstrated by the negative coefficient for the whitefly-days/weeks since planting interaction variable. We also found that the sudden increase in yield production in June was significant, as were the dummy variables for each treatment.

Table 4.4. Parameter Estimates for the Empirical Model of the Effect of Incremental Adult Whitefly Feeding on Incremental Strawberry Harvests, Watsonville, 2002–03

Dependent Variable: ln(Incremental Harvest, g/plant)

		Coefficient			**Coefficient**
Weeks Since Planting	t	4.854	Dummy: Esteem© 3/19/03	δ_5	84.200
	s.e.	(1.148)		*s.e.*	(30.500)
(Weeks Since Planting)^2	t^2	-0.051	Dummy: Malathion/Danitol 3/19/03	δ_6	84.161
	s.e.	(0.090)		*s.e.*	(30.510)
ln(Incremental Whitefly-Days)	WF_t	52.016	Dummy: Admire© (drip) 12/2/02	δ_7	84.016
	s.e.	(16.480)		*s.e.*	(30.510)
[ln(Incremental Whitefly-Days)] x (Weeks Since Planting)	$(WF_t)t$	-52.070	Dummy: Admire© 12/13/02	δ_8	84.264
	s.e.	(16.480)		*s.e.*	(30.510)
Dummy: Untreated Control	δ_1	84.183	Dummy: Malathion 3/19/03	δ_9	84.346
	s.e.	(30.510)		*s.e.*	(30.490)
Dummy: Admire© and Esteem© Treatment	δ_2	84.267	Dummy: Admire© 2/27/03	δ_{10}	84.364
	s.e.	(30.500)		*s.e.*	(30.500)
Dummy: Admire© at Planting	δ_3	84.260	Dummy: Mineral Oil 1/30/03 & 3/19/03	δ_{11}	84.220
	s.e.	(30.490)		*s.e.*	(30.510)
Dummy: Second Untreated Control	δ_4	84.361	June Dummy	δ_{june}	1.203
	s.e.	(30.510)		*s.e.*	(0.067)

Standard errors appear in parentheses.

N = 182

Adjusted R^2 = 0.8736

All coefficients significant at the 5% level.

The hypothesis of autocorrelation is rejected.

The coefficient on the whitefly-day-weeks cross-term $(WF_t)t$ is that strawberry yield decreases at an increasing rate. This occurs as time passes, t, and as the number of whitefly-days increases, WF_t. These interpretations are supported by the relatively early declines in yield that were actually observed by the grower in the commercial field adjacent to the study plots.

4.5 A Bioeconomic Model of Growers' Invasive Pest Management Decisions

To understand how economic agents might act in order to manage a biological invasion while constrained by regulation, we must implement a decision-making model. In this section, we develop a simple model of grower behavior for managing a greenhouse whitefly invasion at the single-field level. It illustrates the type of decision-making models used when investigating the pest-management decisions of agricultural producers.

We make several assumptions to simplify the analysis. First, we assume that the grower maximizes profits from a representative field infested with greenhouse whiteflies. Next, we assume that the grower acts independently of all other growers; he considers the effects of whiteflies only on his own field. The grower does not coordinate with neighboring growers in any way regardless of whether neighboring fields are infested. We assume that there are constant returns to scale and analyze returns for each treatment scenario on a per-acre basis. We scale up our biological model from the plant level to the acre level and assume the field is uniformly infested with whiteflies. Finally, although yields and harvest costs are directly influenced by the use of pesticides because the number of higher-quality berries harvested per unit of time increases when they are applied, we ignore this effect due to a lack of data.

The grower chooses the timing of Esteem© treatments to maximize:

$$\sum_{t=1}^{T} \pi_t = \sum_{t=1}^{T} (\mathrm{p_t})\mathrm{Y_t}\left(\mathrm{WF_t}\left(\sum_{\mathrm{k=1}}^{\mathrm{t}} \mathrm{E_{i,k}}\right)\right) - \mathrm{C_e}\ ,\ t \in [1, T] \tag{4.2}$$

$$\text{subject to } 0 \leq \mathrm{Y_t}\left(\mathrm{WF_t}\left(\sum_{\mathrm{k=1}}^{\mathrm{t}} \mathrm{E_{i,k}}\right)\right) \leq g\ ,\ i \in \{0,1,2\},\ t \in [1, T] \tag{4.3}$$

$$0 \le \sum_{t=1}^{T} \mathrm{E}_{\mathrm{i,t}} \le 2, \forall\, t \qquad (4.4)$$

$$0 \le \sum_{k=t}^{t+4} \mathrm{E}_{\mathrm{i,k}} \le 1, \forall\, t \qquad (4.5)$$

$$\sum_{k=1}^{t} \mathrm{W}F_{\mathrm{k}} - WF_t = 0 \Rightarrow \sum_{k=1}^{t} \mathrm{E}_{1,t} = 1 \qquad (4.6)$$

$$WF_t \ge 0, \forall\, t \qquad (4.7)$$

where π_t refers to profits net of treatment and other expenses in week *t*, *T* is the last week the plants remain in the ground, and p_t is the weighted average weekly regional wholesale fresh and processed strawberry price. The total number and the timing of Esteem© treatments in week *t* is expressed in $\mathrm{E}_{\mathrm{i,t}}$, which is the i^{th} Esteem© application in the season in week *t* at the label rate and $\sum_{k=1}^{t} \mathrm{E}_{i,t}$ is the cumulative number of applications within week *t*. Finally, C_e is the per-acre cost of Esteem©. The model constraints are the following: the weekly yield of the infested field cannot exceed that of a field that is not infested, *g* (Eq. 4.3); at most, two Esteem© applications can be made on the same acre per season (Eq. 4.4); applications must be made at least 30 days (four weeks) apart (Eq. 4.5); if no adult whiteflies are observed previous to the current week (after January 1) but are observed for the first time in week *t*, then $i = 1$ in week *t* (Eq. 4.6); and the number of whitefly-days can never be negative (Eq. 4.7). Equations (4.3) and (4.7) represent the biological features of the model. Equations (4.4), (4.5), and (4.6) represent the constraints imposed by the restrictions on use of Esteem©.[22]

The single-field whitefly management model uses the parametric simulation of the number of whitefly-days for any week *t*, the strawberry yield for any week *t* as a function of the number of whiteflies, and the regulatory constraints selected for analysis. The model is evaluated by deriving the optimal treatment date for one or more Esteem© treatments by finding the week in which maximum profits are obtained from the strawberry yield. At the optimum, profits for a grower from strawberry production when the field is infested by greenhouse whiteflies are $\sum_{t=1}^{T} \pi_t^* = \sum_{t=1}^{T} (\mathrm{p}_t)\mathrm{Y}_t\left(\mathrm{WF}_t\left(\sum_{k=1}^{t} \mathrm{E}_{i^*,k^*}\right)\right) - \mathrm{C}_e$ where the number, *i*, and timing, *k*, of Esteem© treatments maximize profits.[23]

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[22] Several other regulations are found on the label for Esteem, which has been granted an emergency registration annually since 2002. These include:

Method of Application: Ground (only)

Dosage: Use 10 fluid ounces of product (30 grams active ingredient (a.i.) per acre. Do not exceed a maximum of 60 grams of a.i. per acre per season. *This requirement parallels the total allowable dosage in the two applications.*

Dilution Rate: Apply in 100 to 400 gallons of water per acre.

Restricted Entry Interval (REI): 12 hours

Preharvest Interval (PHI): 2 days

Other Requirements: A. A maximum of 20,000 acres may be treated. *This is not likely to be binding for a single grower since it applies to strawberry acreage alone, which exceeded 30,000 acres in 2004.*

B. In order to protect federally listed threatened and endangered species from potentially harmful exposure to pyriproxyfen, users shall ascertain whether there are any listed species which could be exposed through their use of this product. If uncertain whether there are any listed species in a particular area, users shall contact the local county agricultural commissioner's office to determine whether a currently occupied habitat for any listed species is located on or adjacent to the property to be treated with pyriproxyfen. To protect federally listed species, users shall follow the use limitations in the "Endangered Interim Measures for Use of Pesticides" bulletin for insecticides that pertain to pyriproxyfen.

C. U.S.EPA has established a time-limited tolerance for residues of the insecticide pyriproxyfen, 2-[1-methyl-2-(4-phenoxyphenoxy) ethoxypyridine], in or on strawberry at 0.30 ppm.

D. Crop Rotation - Do not plant any crop other than those with registered pyriproxyfen uses in treated area sooner than 30 days after last application.

These other regulations were not analyzed because of the lack of relevant scientific data.

[23] The required dosage is fixed. The amount of chemical applied per acre is not a choice variable.

To verify that a nonzero profit maximum occurs, we calculate whether an Esteem© treatment would be made in the Watsonville area. Assuming 20,000 plants per acre,[24] a 100% marketable yield, and an average price (weighted by the price for weekly fresh and processed strawberry volumes per region) of $0.39/pound in the Watsonville area, an increase in yield of only six more grams of strawberries per plant (total yields exceed 4,000 grams on average) relative to the yield from an untreated field is needed to generate positive profits. The grower can obtain a harvest that is sufficient to offset the application costs by making a single Esteem© application as late as mid-June. Since earlier treatments reduce the whitefly population even more, as will be shown, the optimal timing and number of Esteem© applications for the season can be found.

The bioeconomic model is first used in Chapter Five to analyze decisions over a single season, the most common length of time a strawberry crop is left in the ground. Since the generation time of greenhouse whiteflies is so short, a single season is sufficient to study the effect of Esteem© use regulations on the maximum profits available from strawberry production. The use restrictions, however, are designed to prevent pesticide resistance, which develops over several seasons. Hence the model is adapted in Chapter Six to analyze the economic efficiency of the use restrictions in preventing resistance development.

[24] This represents the standard number of plants per acre as estimated by the spacing of plants found at the UC Experiment Station in Watsonville. Since the spacing between plants at the experiment station and commercial fields is the same, this total is consistent with the number of plants in commercial strawberry fields during the study.

5. A Single-Season Dynamic Model of Invasive Species Management

In this chapter, we employ the bioeconomic model described in Chapter Four to estimate the costs and benefits associated with policy restrictions that affect management of the greenhouse whitefly in strawberries. This analysis illustrates a more general approach to evaluation of invasive species management questions. We assess how pesticide use restrictions interact with pest biology and agricultural production decisions to affect the optimal timing of pesticide applications and resulting profits. In sections 5.1 through 5.5, we obtain the costs and benefits of the pesticide use restrictions for strawberry production in the Watsonville area by simulating the profits that result from alternative numbers, defined as *i* in Chapter Four, and timings, *t*, of Esteem© applications with or without an application of Admire©. In section 5.6, the costs and benefits for the same restrictions are obtained for the Oxnard growing region using the same method as for the Watsonville area. In section 5.7, we consider how the Esteem© use restrictions affect interseason migration of adult whiteflies. To emphasize the benefit of accurately modeling the biological and economic features of the new interaction between the invasive and host species, in section 5.8 we compare the results obtained from using the temperature-based whitefly population model used in sections 5.1 through 5.5 with an autoregressive model. The results show that the added information improves the ability of the bioeconomic model to analyze the management problem relative to a simple but reasonable autoregressive model of whitefly population development. Section 5.8 extracts general lessons for modeling invasive species management based on the observations in this chapter.

5.1 Optimal Single-Spray Esteem© Treatment Program

To determine the effect of the Esteem© use restrictions on strawberry production behavior and associated profits, we compute the optimal timing for one-, two-, and three-treatment control programs. The results of these calculations show how the restriction to two or fewer applications affects strawberry production decisions. If only one or two applications are optimal, then that use restriction is not binding. We report our results in terms of the increase in profits relative to an untreated acre.

To determine the optimal timing for a one-treatment control program, we used the numerical simulation model of the greenhouse whitefly population to compute the effect of a single application of Esteem© on the whitefly population and profit for every week in the season. As shown in section 4.4, the size of the whitefly population affects total strawberry yields through the amount of damage it causes to the plant. Profit, therefore, is determined by the magnitude and timing of the strawberry yield increase resulting from an application of Esteem©, which reduces the whitefly population. We identified the optimal timing of the application by combining results of the population, yield, and economic model to determine the week when the estimated return to the simulated Esteem© application is greatest. We limit the set of application dates for the Watsonville model to February 1 and beyond, because prevailing cold temperatures in the area reduce the efficacy of Esteem© prior to that date.

The whitefly population model indicates that the population of adult whiteflies increases relatively rapidly during the beginning of March, since many nymphs born earlier in the winter are maturing into adults. The population on March 4, the last day prior to the recommended treatment, is about 3.4 adults per leaf. By making the optimally timed single application early in March, the population spike that was observed in the field experiment is suppressed, preventing the associated yield losses.

A single application during the week of March 5 generates the largest simulated increase in profit relative to the untreated plot. Using the five-year average weekly strawberry price calculated in Chapter Four, these profits were approximately $2,000/acre, or about 6% of average gross returns from strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004).[25] We estimate that the optimally times Esteem© treated plant yields about 4,700 grams for the season ending September 1, an increase in cumulative yields of about 300 grams, relative to an untreated plant which yields about 4,400 grams.

Our analysis consistently shows that treatments in winter and spring (February through May) increase profits the most since these suppress the population spikes observed in the field in late March and mid-May. The effect of the treatments is complemented by declining leaf nutrient levels that occur before the most productive fruiting period begins in June. As mentioned in Chapter Four, whitefly mortality rates increase when plant nutrient levels decrease. The combined effects of Esteem© applications in winter and early spring, and decreases in leaf nutrients add between $1,200 (February 10) and $2,000 (March 5) in profit per acre during the season relative to an untreated acre. A single Esteem© treatment made in late spring, May, adds about $1,800 in profit.

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[25] An untreated acre was estimated to produce about $36,200. This is higher than the $35,475 reported by Bolda, Tourte, Klonsky and De Moura (2004) as average gross returns from an uninfested field. (Bolda, Tourte, Klonsky and De Moura create this average based on a standardized grower). The difference can be attributed to two factors: error in the simulation model and above-average returns to the grower who provided acreage for the test plots in this sample.

By contrast, applications made between June and September fail to control the early rise in the whitefly population and allow the accompanying yield loss to persist over a longer period. This means that the amount of yield that potentially could be recovered is smaller in these later months than it would be earlier in the spring, and no yield is recovered before this time. In addition, since a larger overall population has developed, and pesticide applications kill only a percentage of the population, a larger residual population remains after any Esteem© application made during those months. This results in greater yield losses than would be experienced if applications were made earlier in the season, when the initial target population is smaller.

The simulation suggests that timing of the two experimental treatments in the field study on March 19 (treatment 2) and March 26 (treatment 5) is later than optimal. When the March 19 spray was conducted, the sample population was between seven and nine adult whiteflies per leaf, and profits are estimated to be approximately $700 less than would have been generated by a single, optimally timed application. The total profits are roughly $1,300 more than the untreated plot, which represents about 4% of average gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). The increase in yield corresponding to the $1,300 is 200 grams per plant, or 4,600 grams per plant with treatment over the season compared to a yield of 4,400 from an untreated plant. Similar results hold for the March 29 application.

We next analyze whether the annual trend in strawberry prices discussed in section 3.1 affects Esteem© application timing. We perform two tests. First, we replace the five-year average weekly strawberry prices with the simple average price per pound, calculated from the five-year average weekly prices. We then calculate the profit-maximizing treatment time, and then compare it with the profit-maximizing timing calculated using the actual price cycle. We expect this test to determine whether the high prices for early yields is the reason why early March is the optimal time for a single application.

The optimal treatment time, in this case, is around the week of March 5, the same result as when the price cycle is included. Profits increase by about $100 relative to the case in which the price cycle is used. Thus, the optimal application date does not change when the price cycle is removed. This suggests that the effect of whitefly population development early in the season is more important for increasing profits than the availability of larger weekly harvests later in the season, such as in June.

To see whether the population development timing is more important than the price cycle, we perform a second test. In this test we replace the prices observed during March through May with the prices observed between June and October—in effect, reversing the price cycle for the Watsonville area. We would expect that if the optimal timing responds to higher prices, rather than the timing of the whitefly population development, that the optimal date would be made later so as to take immediate advantage of the higher prices later in the season.

Even with this test, however, the optimal treatment timing does not change. The relatively large whitefly population that would be allowed to develop early in the spring causes so much yield loss throughout the rest of the season that the imposed higher price at the end of the season is not adequate to make up for waiting. In this sense the early application behaves like an investment in the yields for the rest of the season.

These two tests show that the dynamics of the whitefly population cycle in

Watsonville are an important factor in selecting an optimal treatment date and that the role of strawberry prices is to change the absolute level of profits from applications made on the optimal date, not the date itself.

5.2 Economic Impact of Restriction to Two or Fewer Esteem© Applications

In this section, we examine the economic impact of the restriction to two Esteem© applications per acre per season. To do this, we evaluate the profitability of optimally timed two- and three-application programs, and compare them to profits from an optimal single-application program. If profits are greatest with three applications, then the use restriction is costly to growers. Because no field trials have been conducted to measure the impact of two or three Esteem© applications during the same season, the results of this analysis cannot be verified by existing data from an actual experimental treatment program. Consequently, it should be viewed as a representation of the potential effect of multiple Esteem© treatments on the whitefly population and subsequent yields in an infested plant.[26]

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[26] Pesticide-use reporting data from Monterey and Santa Cruz Counties show that at least two growers in Santa Cruz County and at least three in Monterey County applied Esteem twice on a total of approximately 150 affected acres (California Department of Pesticide Regulation, 2004). To get a sense for the share of affected acres this represents, approximately six to ten "large" growers were heavily affected by the whitefly in 2002–03, accounting for approximately 1,000 acres of strawberry plantings (Bolda, 2004). Assuming 100% of this acreage was infested, these acres represent about 10% of total 2003 acreage planted in the Watsonville area. The 150 acres treated twice represent 15% of the affected area or 1.5% of planted acreage.

The fact that only 15% of the affected acres were treated twice does not preclude the usefulness of a third application. The UC extension agent in those counties indicated that, ignoring the possible development of pesticide resistance, "a third application of Esteem . . . would most certainly be used for whitefly control, as it is superior in control of [the greenhouse whitefly compared to] many other pesticides" (Bolda, 2004).

Suboptimal application timings also could explain the small number of growers who made two applications of Esteem, and can be attributed to ignorance of whitefly population dynamics. Pest control advisors and growers described by Zalom and a representative of Bayer Chemical in the Oxnard area (Zalom, 2005; Ishida, 2005) fail to recognize the contribution of overwintering whitefly eggs to development of the spring

5.2.1 Optimal Times for Two Esteem© Applications

Optimal application timing for a two-application program is around the weeks of February 1 for the first profit-maximizing treatment and March 5 for the second. This program increases profits almost $3,100 per acre relative to an untreated field, or by about 9% of gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). These treatment dates are particularly profitable because Esteem© is principally effective on eggs and nymphs, and much of the population is comprised of overwintering eggs in early February and nymphs in early March. Treatments on these dates reduce these populations, and thus the number of potential new adults.

These results indicate that a second application is economically justified. The incremental increase in profit from an optimally timed second Esteem© treatment is approximately $1,200 per acre, relative to an optimally timed single treatment. This is smaller than the $1,300 incremental increase from a single application alone. The smaller incremental increase in profits from the second application is due relatively smaller reduction in the whitefly population as compared with the first application.

5.2.2 Optimal Times for Three Esteem© Applications

Having established that a second Esteem© treatment is economically justified, we examine whether the restriction to two or fewer treatments is a binding constraint on

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and summer whitefly population. More than half of the single-application treatment programs done in 2003 in Monterey and Santa Cruz Counties were done in May and June. Assuming all acres were infested at planting, they occurred much later than the optimal date. If the first application is made on June 1, then the simulation shows that a second application only just breaks even with application costs when done 30 days later and would not even be profitable if done after that. If the first application is done later than June 1, the results are no better. Increased understanding of whitefly population dynamics by growers and pest control advisors may make two applications of Esteem more common.

strawberry producer behavior. To do so, we use the simulation model to identify the timing of a set of three treatments that provides the highest estimated contribution to total strawberry profits.

The optimally timed program includes applications during the weeks of February 4, March 12, and May 5. This treatment program adds a total of nearly $4,100 per acre in profit relative to untreated plants, or about 11% of gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). The estimated incremental profit of the third treatment is approximately $900 relative to an optimally timed two-treatment program. This program shows that a strategy of making treatments in mid-winter and early spring, followed by a third treatment once the whitefly population starts to rebuild, allows the grower to obtain the most profits from strawberry production given the economic and biological constraints on the decision, though the regulatory constraint is binding for such a program. Simulations show that making a third application after this time would allow the population to build to a level that will remain larger through the remainder of the season than it would if treatments are optimally timed. Any earlier set of applications are less effective because of reduced Esteem© efficacy at colder temperatures and because sufficient time passes after the treatments for the population to rebuild to higher levels.

5.3 Esteem© used with Admire©

In this section, we discuss the combined effect of the first and second Esteem© use restrictions—the limit to two applications and the requirement to use Esteem© in combination with an application of Admire© within ten days of planting.[27] These requirements are motivated by the Department of Pesticide Regulation's informally stated objective to require that Esteem© be used in combination with Admire©, another previously registered pesticide with a different mode of action, so that development of pesticide resistance can be delayed.[28] In addition to having a different mode of action, Admire© is primarily effective on adult whiteflies, while Esteem© is most effective against whitefly nymphs in outdoor conditions.

Analyzing the joint effect of the Admire©-Esteem© requirement and the restriction to two applications of Esteem© is important for two reasons. First, we will be able to determine whether the combination requirement creates any costs; in other words, does requiring the use of Admire© with Esteem© reduce profits? Second, it allows us to determine whether the restriction to two applications of Esteem© is still inefficient given the Admire©-Esteem© requirement. To study whether the requirement to use Admire© with Esteem© is economically justified, we measure the profit first from an application of Admire© alone. We then calculate the joint effect of the restrictions by measuring the profit from one, two, and three applications of Esteem© after an application of Admire©.

5.3.1 Economic Impact of Requirement to Use Admire©

In this section, we estimate the incremental effect of an application of Admire© on the development of the whitefly population and profits from strawberry production. We conduct a simulation of the effect that an application of Admire© has on the

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[27] We analyze the requirement to use Admire as part of the analysis of the combined requirement.
[28] This objective was stated by the person that the Department of Pesticide Regulation (DPR) listed as a contact for the Esteem emergency registration label, John Inouye. Mr. Inouye indicated that no official documentation exists establishing this objective; rather, it represents the DPR's "in-house" objective to prevent the development of resistance to new pesticides by encouraging rotations with alternative pesticides and development of integrated pest-management techniques (Inouye, 2004, 2005).

whitefly's population dynamics and its associated profits. The parameter values used in the simulation are based on the field experiment data presented in section 3.1 and on Admire© efficacy data found in the entomological literature (Bi, Toscano, and Ballmer, 2002b).

In the simulation, an application of Admire© is made at planting. The increase in profit from this application, relative to an untreated acre, is about $2,900 per acre, or about 8% of gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). Hence, using Admire© is economically justified in the absence of using Esteem©.

5.3.2 Admire© with a Single Application of Esteem©

We conduct a simulation in which both Admire© and Esteem© are used to control the whitefly population. In the simulation, an application of Admire© is made at planting, followed by one application of Esteem©. As described in section 4.2, this combination of chemicals suppresses the whitefly population more than Esteem© alone does.

The optimal timing of a single application of Esteem© when done with Admire© is around the week of February 19, which is earlier than the single, optimally timed treatment of Esteem© is made without an application of Admire©. The simulation indicates that there are approximately 0.11 adults per strawberry leaf at this time, or about one adult for every ten leaves.

The earlier optimal time for the Esteem© treatment can best be explained by the fact that Admire© kills adults soon after their arrival on the plant, which changes the subsequent population dynamics for the season relative to the case in which only Esteem© is used. The Admire© application kills the adults after a short period of contact, reducing the amount of time the recently immigrated adults have to lay eggs, thus reducing the size of the future population. The model calculates that, under a combination treatment, it is best to treat a smaller population earlier and then let it grow rather than wait until it grows first as in the Esteem©-only case.

We compare the profits for a combined Admire© and single Esteem© treatment with the profits from a single-treatment, Esteem©-only program. Total profits for the combined program are about \$5,200 more than for an untreated acre. This represents about 15% of gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). The incremental benefit of a single optimally timed Esteem© treatment, when combined with Admire©, is \$3,300 per acre, which than the \$2,000 incremental benefit from a single optimally timed treatment Esteem© alone. Hence, the requirement to use Admire© with Esteem© is economically sensible when considered independently of the two-use restriction.

The estimation of profits from the combined treatment shows that Admire© and Esteem© work as complements to suppress the whitefly population. Complementarity occurs because the profits of the combined treatment are greater than the sum of the profits from using each treatment alone: \$5,200 > \$2,000 + \$2,900, as shown in Table 5.1.

Table 5.1. Simulated Increase in per-Acre Profits: Admire© and One Esteem© Treatment Relative to Untreated, Watsonville

		Admire© Used: Yes	Admire© Used: No
Esteem© Used Once	Yes	$5,200	$2,000
	No	$2,900	$0

5.3.3 Admire© with Multiple Applications of Esteem©

To estimate the joint effect on grower behavior of the restriction to two Esteem© applications per acre per season and the requirement to use Admire© within ten days of planting, we identify optimal timing for two and three applications of Esteem©. To do so, we simulate the increased profit from two and three applications of Esteem© when Admire© is applied at planting. A program with Admire© and two optimally timed applications of Esteem© calls for the Esteem© treatments to occur during the weeks of February 12 and March 14. Both of these timings are about one week later than the optimal program for two Esteem© applications done without Admire©. This delay is related to the delay in the rate of whitefly population development occasioned by the prompt control of the immigrating adult whitefly population by Admire© at planting.

The simulation model indicates that the average adult whitefly population per leaf prior to these treatments is 0.06 (February 11) and 0.11 (March 13). This program generates an incremental increase in profit of about $2,600 per acre relative to the profits from a field treated with Admire© and a single, optimally timed Esteem© treatment (February 19). Total profits are about $8,200 per acre more than those from an untreated acre of strawberry plants, or about 22% of returns net of application costs (Bolda, Tourte, Klonsky and De Moura, 2004). Table 5.2 shows that Admire© and two Esteem©

applications are complements in whitefly population control: $8,200 > $3,100 + $2,900.

Table 5.2. Simulated Increase in per-Acre Profits: Admire© and Two Esteem© Treatments Relative to Untreated, Watsonville

		Admire© Used	
		Yes	**No**
Esteem© Used Twice	**Yes**	$8,200	$3,100
	No	$2,900	$0

A program with Admire© and three optimally timed applications of Esteem© calls for the Esteem© treatments to occur during the weeks of February 4, March 12, and May 5—dates identical to those for the three-treatment, Esteem©-only program. We interpret this result to mean that, despite the delay in whitefly population development caused by the application of Admire© at planting, the value of waiting to make any of the three Esteem© applications, relative to the Esteem©-only program, is zero. The simulation model indicates that the average adult whitefly population per leaf prior to these treatments is 0.07 (February 3), 0.08 (March 11), and 0.01 (May 4). The incremental profits of a third application are about $1,700 more per acre than those from a program of two optimally timed applications of Esteem© after an application of Admire©. Total profits are about $9,500 per acre more than those from an untreated acre of strawberry plants, or about 27% of average gross returns net of application costs (Bolda, Tourte, Klonsky and De Moura, 2004). This indicates that Admire© and three Esteem© applications are complements in whitefly control: $9,500 > $4,100 + $2,900.

Table 5.3. Simulated Increase in per-Acre Profits: Admire© and Three Esteem© Treatments Relative to Untreated, Watsonville

		Admire© Used: Yes	Admire© Used: No
Esteem© Used Three Times	Yes	$9,500	$4,100
	No	$2,900	$0

The results of this simulation show that the limit to two or fewer applications of Esteem© per acre per season combined with requiring the use of Admire© imposes a short-term economic cost, just as it did in the case without an Admire© treatment. Hence, requiring use of Admire© at planting does not mitigate the cost of this restriction. In fact, because the complementarity between Admire© and Esteem© increases the incremental profit of a third Esteem© application, these costs are increased.

5.4 Economic Impact of Application Timing Requirement

In this section, we discuss the economic impact of the third Esteem© use restriction—the requirement to apply Esteem© "as soon as adult whitefly appear." As shown in Equation (5) in section 4.5, we interpret this to mean that an application of Esteem© should be made on the date the first adult whitefly emerges from an egg laid in the field as opposed to the date on which the first adult settles in the field, which could occur at transplanting.

This requirement is vague and difficult to use in selecting a precise point in time for an application of Esteem©. In practical terms, it is difficult to identify the date when the first adults emerge from eggs laid in the field. This lack of specificity can lead to a wide range of interpretations of the application date by pest control advisors (PCAs), which will affect grower profits. In this context, simulation models can suggest when to start scouting for adult flies by predicting the first date an adult whitefly will appear from eggs laid in the field the previous fall.

Since pesticide treatments tend to eliminate only a percentage of the target population, the rationale behind this use restriction is preventing development of a large population before making an Esteem© application. This is an important pest-management principle: eliminating a portion of the population while it is small means there will be fewer individuals left after the treatment to cause economic harm.

To assess the sensitivity of grower profits to various treatment timings, we utilize the results of the simulations done for each week in the season to obtain the optimal timing of one or more Esteem© applications. According to the simulation, the week the first adults emerged from eggs laid at planting is January 4, resulting in an adult whitefly population of 0.12 per leaf. As previously indicated, prevailing cold temperatures at the time would render Esteem© much less able to affect whitefly physiology. Therefore, the earliest an application of Esteem© could be considered is the week of February 1 when the adult whitefly population was about 1.7 adults per leaf. An application at this time increases simulated profits by about $800 relative to an untreated acre, or about 2% of average gross returns to strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). In contrast, the optimal single treatment the week of March 5 when the population is 3.4 adults per leaf results in increased profits of about $2,000 per acre, or about 6% of average gross returns. In addition to generating a smaller increase in profit, an application the week of February 1 leads to a larger adult whitefly population; for example, there are almost two more adults per leaf on September 1 after a

February 1 application than after a March 5 application. Hence, growers in the Watsonville area are constrained by the timing restriction when a single Esteem© application is made. Previous analysis shows that growers also are constrained by this requirement when two applications are made—the first profit-maximizing application is done the week of February 11, not February 1. Finally, growers in the Watsonville area are essentially unconstrained by this restriction when three applications are made since the first profit-maximizing application is done the week of February 4.

5.5 Economic Analysis of the Combination of the Three Restrictions

In this section, we explore the benefits and costs associated with the combination of all three Esteem© use restrictions on whitefly population management within a single season and single field. We compare the profits from when the grower complies with all three use restrictions to when he chooses the optimal Admire©/three-Esteem© treatment program described in section 5.3.3. The results show that greater profits are available from strawberry production when the optimal Admire©/three-Esteem© treatment program is used than when a program complying with all three use restrictions is employed. Although profits from the all the simulations described in this and previous subsections are listed in Table 5.4, the last two totals are the only ones discussed in the discussion that follows.

Table 5.4. Simulated Increase in per-Acre Profits from Esteem© Treatments, after an Application of Admire©, Relative to Untreated, Watsonville

Treatment	Increase in Profits
No Esteem©	$2,900
Esteem© Used Once	$5,200
Esteem© Used Twice	$8,200
Esteem© Used Three Times	$9,500
Fully Regulated – Esteem© Used Twice	$7,400

The "fully regulated" treatment program is defined as an application of Admire© at planting, an application of Esteem© on February 1 (the first day with nonzero adult whitefly populations "appear" when it is consistently warm enough that Esteem©'s efficacy is unaffected by cold), and a second application of Esteem© on March 8 (the optimal date, given the date of the first application). This program results in increased profits of about $7,400 relative to an untreated acre, or about 21% of average gross returns from strawberry production in the Watsonville area (Bolda, Tourte, Klonsky and De Moura, 2004). In comparison, the optimal three-treatment program that is comprised of an application of Admire© at planting and applications of Esteem© during the weeks of February 4, March 12, and May 5, which increased total profits by $9,500, or about 27% of average gross returns net of application costs (Bolda, Tourte, Klonsky and De Moura, 2004).

These results show that the combination of the three Esteem© use restrictions impose a short-term cost on strawberry production. The restriction to two applications per season results in lower profits, decreasing from $9,500 to $8,200. When this is combined with the restriction to make the first application when adult whiteflies appear, profits are increased by $7,400 instead of $9,500. The requirement to use Admire©, however, imposes no additional economic cost given the existence of the other two use restrictions.

The difference in increased profits between the optimal Admire©/three-Esteem© treatment program, $9,500, and the fully regulated program, $7,400, is $2,100 per acre of infested strawberries. Since the scientific and economic information used to perform this analysis is available to policymakers, $2,100 represents a lower bound on the cost that the use restrictions impose on strawberry production in the short-term. The costs could be greater because of the effect of suboptimal timing of treatment applications on the size of the whitefly population at the end of the season, as discussed in section 5.7. To the extent that the adult whitefly population is larger than the one that would result from the Admire©/three-Esteem© treatment program, the costs of control and of foregone yields will be greater in subsequent seasons due to larger populations of migrating adult whiteflies.

This analysis demonstrates that the essential biological, economic, and regulatory features of the grower's profit-maximizing problem must be modeled in order to create regulations that best respond to biological invasions. As stated in section 1.1, designing the appropriate policy for managing invasive species is difficult given the unpredictability of grower responses to a biological invasion. We have also shown that a model that uses all available information to inform the policy maker about the optimal management response to invaders, given alternative policies, will improve the ability of policy makers to create regulations that are economically efficient. In this study such an approach required information on the factors affecting greenhouse whitefly population development, a measure of its damage to yields, a model of grower decision making, a model of various management activities, and a way to illustrate the feedback among these components over time. In subsequent chapters we demonstrate the need to explicitly include long-term analyses of these feedbacks, and the effect of spatial relationships among growers on their optimal invasive pest management decisions.

5.6 Economic Analysis of Esteem© Use Restrictions in the Oxnard Growing Region

To this point, our analysis has focused on the costs and benefits of the Esteem© use restrictions on optimal greenhouse whitefly management by growers in the Watsonville growing region. To determine the extent to which these costs and benefits are related to region-specific prices and biological conditions, we now analyze the optimal grower response to the Esteem© use restrictions in the Oxnard growing region using the same method: deriving the optimal treatment timing for one, two, and three Esteem© applications with and without Admire© and comparing the maximum profits available both when the grower observes all of the Esteem© use restrictions and when the restrictions are relaxed.[29]

5.6.1 Results

The optimal timing for a single Esteem© application in the Oxnard growing region is the week of January 6. In contrast to the Watsonville region, the relatively warmer temperatures in the Oxnard area make an application feasible at this time. Profits are estimated to increase by approximately $8,900 relative to an untreated acre, or about

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[29] Since no plant-level data are available on the effect of the whitefly population's size on strawberry yields in the Oxnard region, we use the same regression coefficients estimated for the yields-whitefly relationship in the Watsonville region. These are adjusted so that the observed average yields per acre from uninfested fields in the Oxnard region are obtained. This set of coefficients is held constant for all simulations.
The effect of the reduced availability of data is to increase uncertainty in the model—the distribution of the missing data is unknown. This makes the estimated profits and yields less accurate. However, the results from the whitefly population model generate information about the ordinal relationship between various management responses to regulation, which is sufficient to suggest how the use restrictions affect Oxnard growers' behavior.

25% of average gross returns from strawberry production in the Oxnard area (Daugovish, Takele, Klonsky, and De Moura, 2004).[30] At this time, the adult whitefly population is 3.2 adults per leaf and is approaching a peak. Yields increase from about 4,500 g/plant to about 4,800 g/plant.

Optimal application timing for a two-application program is around the weeks of November 1 and the week of January 6. Profits are estimated to increase by approximately $16,000 relative to an untreated acre, or by about 44% of average gross returns from an acre of strawberry production in the Oxnard area (Daugovish, Takele, Klonsky, and De Moura, 2004). The adult populations at these times are 4.4 and 0.9 adults per leaf, respectively.

Optimal timing for three applications of Esteem© is the weeks of November 12, December 12, and January 12. This treatment regime increases profits by about $24,000 per acre relative to an untreated acre, or by about 67% of average gross returns from strawberry production in the Oxnard area (Daugovish, Takele, Klonsky, and De Moura, 2004). The populations of whiteflies on these dates are 0.82, 0.18, and 0.37 adults per leaf, respectively.

Since three optimally timed applications generate higher profits than two, the

[30] Average total gross returns to strawberry production are $36,089 per acre in Ventura County (Daugovish, Takele, Klonsky and De Moura, 2004). (We assume the fields used to construct this statistic are not infested with greenhouse whiteflies.) The simulated profits from an untreated field using the model are estimated at $75,000/acre. This represents the difference between the published gross returns and the profits estimated in the model for all simulations.

The difference comes from two sources. First, since no data are available to measure the effect of whiteflies on yields in the Oxnard area, the coefficients used in the strawberry yield regression model are from the Watsonville data. The yields for all chemically treated acres are much larger than in the Watsonville model, and are probably over-predicted.

Another source of the difference is the assumption on the size of the marketable share of yields in the Oxnard area. Data from an unrelated research experiment in the Oxnard area provided data on the weekly distribution of marketable and unmarketable fruit. Our interpretation of the data indicates 80% of the yield was marketable. To obtain profits similar to those reported by Daugovish, Takele, Klonsky and De Moura, a 40% marketable share is required, which is similar to the 47.6% ratio used for Watsonville. At a 40% share, profits of $37,400 result for an untreated acre.

three-application limit is binding for growers in the Oxnard area, as in the Watsonville area. Notice that the increased profits reported in these Esteem©-only simulations are too large to represent actual profits; they do suggest, however, that increased profits relative to an untreated acre are available as more applications are made.

We find that the requirement to combine Esteem© treatments with Admire© also makes economic sense for Oxnard growers. The increased profit from an application of Admire© alone at planting is estimated to be about $5,700 relative to an untreated acre. An optimally timed Esteem© application would be done the week of November 3, as opposed to the week of January 6. The application is done earlier because this maintains the relatively lower whitefly population fostered by the Admire© application throughout the season. This results in an incremental profit increase of $13,400 per acre relative to an untreated acre.

When combined with Admire©, a program of two optimally timed Esteem© applications would be done the weeks of November 1 and January 13. The first application is done at the same time as in the two-application Esteem©-only program, but the second is about one week later, caused by a delay in the development of the nymph whitefly population caused by the Admire© application. This program increases total profits by $19,800 more than an untreated acre.

A program of applying Admire© and making three optimally timed Esteem© applications would have the Esteem© applications done the weeks of November 1, December 30, and January 29. The first application is about two weeks earlier relative to the three-treatment Esteem©-only program, and the second and third applications are each about two weeks later. The first application is made earlier to take advantage of the relatively smaller population caused by the Admire© application. Using Admire© makes it possible to wait two additional weeks for the two other treatments. This program increases total profits by $26,000 more than an untreated acre.

The incremental increases in profits from these programs are 37%, 55%, and 72% of average gross returns from strawberry production in the Oxnard area (Daugovish, Takele, Klonsky and De Moura, 2004). As in the Esteem©-only programs, these profit increases are too large to represent actual values for profits available from the treatment programs. They do suggest, however, that more applications during a single season increase profits.

The timing of the three applications in the Admire©/three-Esteem© treatment program places them closer to planting and much closer together than in the Watsonville area. The November 1 application occurs about six weeks after the assumed September 15 planting date. In contrast, the first Esteem© application in the Watsonville area occurs on February 4, almost three months after planting. The Oxnard Esteem© applications occur at approximately 30-day intervals while the Watsonville Esteem© applications are six to seven weeks apart. This difference in timing reflects the role of climate in each region in determining optimal management decisions. Temperatures in the Oxnard area are higher overall than in the Watsonville area, and increase earlier in the production season. This creates conditions for faster and more intensive whitefly population development in the Oxnard area than in the Watsonville area. The relatively lower temperatures in the Watsonville area cause whitefly populations to grow more slowly, so spreading out the applications is optimal for growers.

As we did for the Watsonville area, we analyze the effects of the annual pattern of strawberry prices on the timing of Esteem© applications in the Oxnard area. We replace the weekly strawberry prices with the seasonal average price per pound. The optimal treatment time for this case, remains the week of January 6. The date does not change because an application early in the season is so important for reducing the whitefly population, and the price cycle only affects the level of profits, not the optimal timing of Esteem© applications.

Finally, we examine whether the use restriction that requires an application as soon as adults appear is a binding constraint on Oxnard-area grower profits. Given that the week of January 6 is the optimal time for a single application and that adult whiteflies first appeared on November 5 in the model (assuming planting and infestation on September 15), the timing requirement is a binding constraint on grower behavior in the absence of the other use restrictions. The timing requirement is not binding, however, when two or three Esteem© applications are made, regardless of whether Admire© is used.

As in the Watsonville area, the combination of all three use restrictions imposes a short-term cost on Oxnard-area strawberry producers. Applying Admire© at planting and making the required Esteem© applications during the weeks of November 5 and January 12 maximizes profits at $23,200 per acre. This figure is less than the profits generated by a combination of Admire© and three optimally timed Esteem© applications, which generate profits of $31,600 per acre. Hence, the Esteem© use restrictions create costs for growers in both the Oxnard and the Watsonville growing regions. However, based on the marketable yield share used in this analysis discussed in footnote six, the cost for producers in the Oxnard area is probably overstated by about a factor of two.

5.6.2 Alternative Whitefly Infestation Dates

Sprinkler irrigation can affect the date on which adult whiteflies arrive and start laying eggs in the newly planted field. This occurs because when the immigrating population is small, the irrigation inundates most of the adult whiteflies, preventing the population from getting established. We consider how different infestation dates affect optimal timing of Esteem© applications in the Oxnard area. The Watsonville area is not discussed because the qualitative results are the same.

We test the effect of the immigration date on the optimal timing of Esteem© treatments and corresponding profit levels. Instead of using September 15 as the whitefly immigration date, we assume the whiteflies arrive and commenced oviposition on November 1, which coincides with the end of sprinkler irrigation in an Oxnard-area field. A single optimally timed Esteem© application the week of December 30,[31] given an application of Admire© at planting, generates about $4,500 more in profits than an untreated acre, or about 13% of average gross returns from strawberry production in Ventura County (Daugovish, Takele, Klonsky and De Moura, 2004). Two optimally timed Esteem© applications with Admire© occur during the weeks of November 3 and December 23 and generate about $9,100 in additional profits relative to an untreated acre, or about 25% of average gross returns from strawberry production in Ventura County (Daugovish, Takele, Klonsky and De Moura, 2004). Finally, given an Admire© application, three Esteem© applications done the weeks of November 8, January 6, and February 6 generate about $14,700 in additional profit relative to an untreated acre, or 41% of average gross returns from strawberry production in Ventura County (Daugovish, Takele, Klonsky and De Moura, 2004).

We observed three effects from changes in the immigration date. First, profits from optimally timed chemical treatments are smaller than the applications made with the earlier infestation date. This occurs because the number of residual adult whiteflies tends to be higher in simulations with a later immigration date when all else is equal, causing

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[31] The vagueness of the timing requirement makes it difficult to interpret. In this case, it is optimal to make an Esteem application soon after adult whiteflies migrate into the field, which occurs before adults appear from eggs laid within the field. If the requirement means that no Esteem application should be made before adult whiteflies emerge from eggs laid within the field, then an application soon after the immigration of adult whiteflies would violate this requirement. In that case, the timing requirement would be binding for Oxnard area producers.

greater reductions in yields over the entire season. For example, when three optimally timed applications are made with a September 15 infestation, there are 0.7 adults on October 31, 0.17 adults on December 29, and 0.03 adults on January 28. By contrast, when three optimally timed applications are made with a November 1 immigration, there are 1.60 adults on November 7, 2.04 adults on January 5, and 0.40 adults on February 5. This occurs because immigrating whiteflies that arrive after irrigation ceases are relatively unaffected by the Admire© application performed within ten days of planting, which dissipates by that time. If, on the other hand, the immigration happens at planting, most of the adult population is controlled by the Admire© application. If correct, this analysis shows that, all else being equal, later applications of Admire© in irrigated fields may be more effective in controlling the whitefly population.[32]

The second effect of the change in immigration date is that the optimal timing for the treatments changes only for the single-treatment program; the single optimal Esteem© treatment now occurs at the end of December instead of the beginning of November, due to the delay in the development of the whitefly population caused by the later immigration date and the relatively slower population development associated with the cooler temperatures at this time. The optimal timing of two and three treatments remains essentially unchanged. In the original model, which assumes infestation at planting, the Admire© application kills the migrating adults and is followed by an application of Esteem©. The model with the later infestation date assumes that the migration occurs just as the Admire© application dissipates from the plant. It becomes optimal that the adult population be treated quickly with Esteem©. Hence, the timings

[32] Harvest typically begins in early January in the Oxnard area. Given the required 14-day postharvest interval for Admire, no application of Admire can be made later than about December 15 in the Oxnard area without affecting the harvest.

coincide.

The last observation we make from the change in the immigration date is that, after the effect of the market price cycle affects only the level of profits for the optimal application dates and not the dates themselves. This is the same result as in the original Oxnard and Watsonville models.

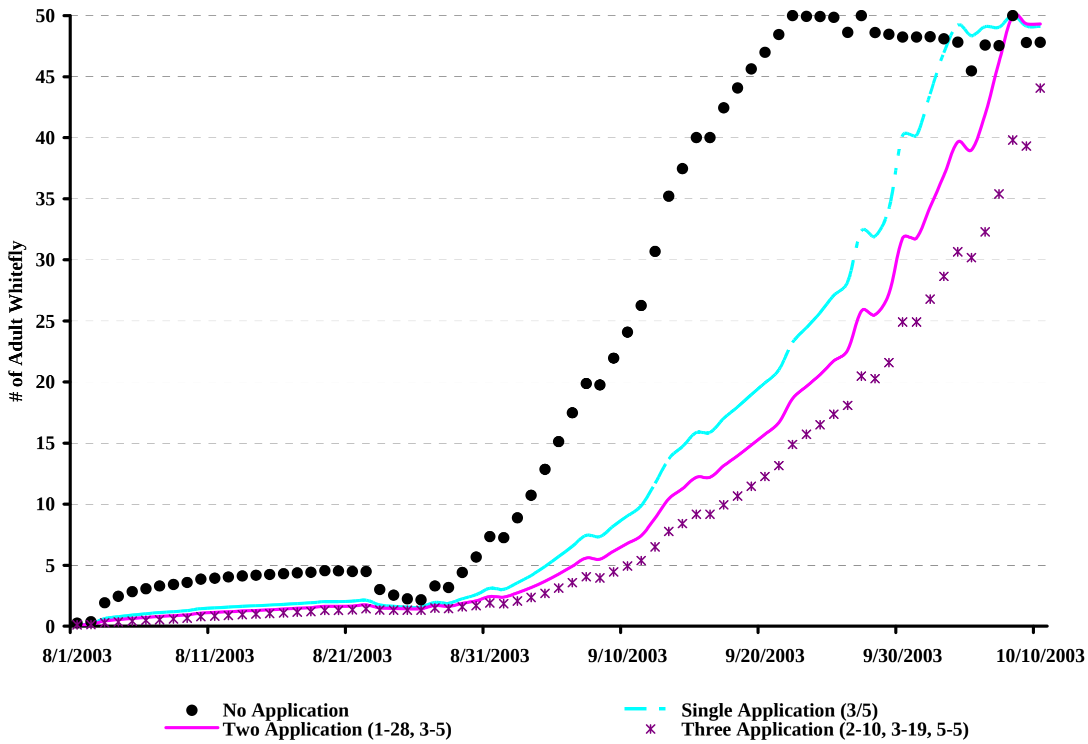
5.7 Effect of Current Whitefly Management on Future Plantings

To this point, our analysis has focused on the impacts of biological, economic, and selected use restrictions on grower behavior and returns within a single season. Because in many cases invasive species persist for more than a single growing season, it is important to analyze the effect of the Esteem© use restrictions over time. One way to account for the impact of the use restrictions over multiple seasons is to consider the effect of various Esteem© treatment programs on the size of the whitefly population near the time of the next strawberry planting. This is important for two reasons. First, the single-season analysis calculates that optimal application dates occur relatively early in the season. Growers may hypothesize that better inter-seasonal control could be achieved by making treatments near the end of the season. If that were the case, a grower's privately optimal decisions might change depending on the time horizon considered. Perhaps a later Esteem© treatment would make the season-ending adult whitefly population smaller. Second, the spatial and temporal organization of strawberry production in the Watsonville and Oxnard areas is conducive to cross-season effects. As mentioned in section 3.1, adult whiteflies migrate to newly planted fields from old plantings that are still in the ground in adjacent fields.

Based on the single-season results, adult whitefly populations are the largest on untreated plants at any point in time prior to when the leaf achieves its carrying capacity for adults. We conduct a simulation for the Watsonville area that compares the date the adult whitefly population reaches the model's carrying capacity of 50 per leaf when zero, one, two, or three optimally timed Esteem© applications are used during the season (Figure 5.1). As seen in the figure, an untreated field reaches carrying capacity around September 20. Waiting to make the first Esteem© application at this date would require reducing a larger population than that found in a field that has already received one or more applications. In contrast, a field that receives three simulated treatments reaches carrying capacity on October 16, 24 days later than the untreated field. The whitefly population on the untreated plants reached carrying capacity first because of the larger population in August relative to the treated plants. The simulation also indicates that the adult whitefly population grows more rapidly on untreated plants at this time than on treated plants. For example, the adult whitefly doubles in early September[33] from about 10 to about 20 adult whiteflies in six days. In contrast, the population doubles in about ten days for plants that receive one, two, or three optimally timed treatments.

[33] This is the earliest point at which a strawberry grower would consider removing plants. It also is not uncommon to leave plants in the field through September. If a short period exists during which no new plantings are available, the whitefly can survive on weed hosts until strawberries are once again planted.

Figure 5.1. Simulated Late-Season Adult Whitefly Population by Number of Optimally Timed Esteem© Treatments



These differences can affect profitability in the current season because the interval of 24 days allows for additional harvests prior to removing the plants from the field while generating a whitefly population no larger than the one found in an untreated acre. This presents a trade-off for the grower. On one hand the grower can obtain more marketable fruit, and the associated profits from additional harvests. On the other hand, the grower could remove the old plants before the start of the 24-day period, reducing whitefly management costs and foregone yields in subsequent seasons for adjacent fields.

5.8 General Lessons for Modeling Invasive Pests

In this section, we discuss four decisions that analysts must make when examining invasive species policy alternatives, and lessons regarding these decisions identified in this study. First, in section 5.8.1 we show why the essential biological and economic features of the interaction between the grower's decisions and the invasive pest should be included even when limited information is available regarding these features. Second, in section 5.8.2 we summarize why the results of this chapter demonstrate that the effect of regulation on grower behavior cannot be overlooked when assessing the efficiency of invasive species policies. Third, in section 5.8.3 we use the analysis in this chapter to demonstrate that policies regulating invasive species management in agriculture must be ranked on a site-specific or region-specific basis. Finally, in section 5.8.4 we briefly discuss the importance of analyzing the costs and benefits of regulation in both the short and the long term.

5.8.1 Using Limited Information in Modeling

Empirical bioeconomic models, which include information on biological relationships, economic relationships, and interactions between them, are a useful tool for policymakers addressing an invasive species problem (Eiswerth and Johnson, 2002; Knowler and Barbier, 2000). The usual concerns apply when evaluating invasive species policy using estimates or predictions based on data collected in the absence of invaders—care must be taken in interpreting data summarizing producer and market behavior, because policy decisions affect management decisions.

To illustrate this general point, we evaluate two alternative methods for modeling whitefly population dynamics: a reduced-form autoregressive econometric model and a structural, calibrated simulation model. The reduced-form autoregressive model uses statistical techniques and historical data on the pest population to predict the future population. It is a simple approach and requires limited information on the pest population. This may be an attractive option for policy makers in the case of a biological invasion, since limited data will still permit rapid policy analysis. Such a model, however, may omit important biological factors, such as variations in the population growth rate over time, if no statistical data are available. The model's effectiveness is also dependent on the validity of the imposed statistical assumptions.

On the other hand, a simulation model can incorporate data obtained outside a statistically valid scientific experiment. For example, it can integrate results from studies of the pest in similar environments with results from experiments regarding the current invasion. However, the conclusions that result depend on how biological and economic relationships are specified, whether obtained from outside sources or assumed.

Our analysis of the greenhouse whitefly/strawberry case identifies the most striking feature of the population dynamic of the whitefly: the changing rate at which the whitefly population develops over the course of the growing season. Since the amount of heat available in the environment regulates the rate at which the whitefly matures, whitefly development and reproduction are slowest during the coolest parts of the growing season and fastest during the spring and summer months. Accounting for this change in the rate of population development changes the timing of pesticide applications compared to a model that assumes a uniform rate. To demonstrate the importance of the information gained by understanding the influence of temperature on the greenhouse whitefly, we contrast the parameterized simulation model previously described with an autoregressive model of whitefly population dynamics that does not require the information and assumptions regarding the lifecycle and whitefly physical development that the temperature-based simulation does.

The autoregressive and the temperature-based simulation models can be contrasted by evaluating them both and selecting the model best able to replicate the observed Watsonville whitefly population sample. The results of this section show that the simulation model that utilizes all available information about the invasive species is preferable to an autoregressive model requiring the least amount of data possible, in terms of data collection effort. In this case, the value of the information outweighs the benefit of any statistical analysis in constructing the model. In order to obtain an assessment of the value of the added data, we compare the optimal decisions predicted by each model.

The simulation model uses readily available data and phenology models about the effect of the environment on pest biology to estimate the economic harm the pest causes. The added information makes it more accurate than the autoregressive model which only uses data on whitefly population levels.[34] Though the simulation model is still constrained by data, it has a better ability to describe the feedback between grower management decisions and the biological interaction between the invader and host plants than the autoregressive model. This improvement is important for two reasons. First, it allows policy makers to better anticipate the effect of proposed regulations on grower behavior. Second, it makes more accurate statements about the magnitude of the costs and benefits of various policies, which could lead to different conclusions about the efficacy of policies across the two models.

To determine the ability of an autoregressive model to predict the size of the adult

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[34] The effect of temperature, for example, is not explicitly included in the model. It is implicitly included through its effect on the development of the adult whitefly population. This is a complex relationship, and including only a single variable for it in a lagged-variable model with an autoregressive component would be insufficient to accurately depict the effect of temperature.

population, we estimate a pair of autoregressive models. In both models we assume the size of the adult population in week *t* can be predicted by the number of eggs *k* weeks ago, allowing a grower to use egg population counts as a determinant of management input use. The first uses only data regarding actual tri-weekly observations of eggs and adults in samples from the untreated plots (treatments 1 and 4), with the whitefly egg population first observed in Watsonville on January 6, 2003. In February 2003 the first significant number of adults is observed, a lag of five weeks. This model has the form

$$adults_t = \alpha + \beta_1 eggs_{t-0} + \beta_2 eggs_{t-3} + \beta_3 eggs_{t-6} + \beta_4 eggs_{t-9} + \beta_5 eggs_{t-12} + \varepsilon, \qquad (5.1)$$

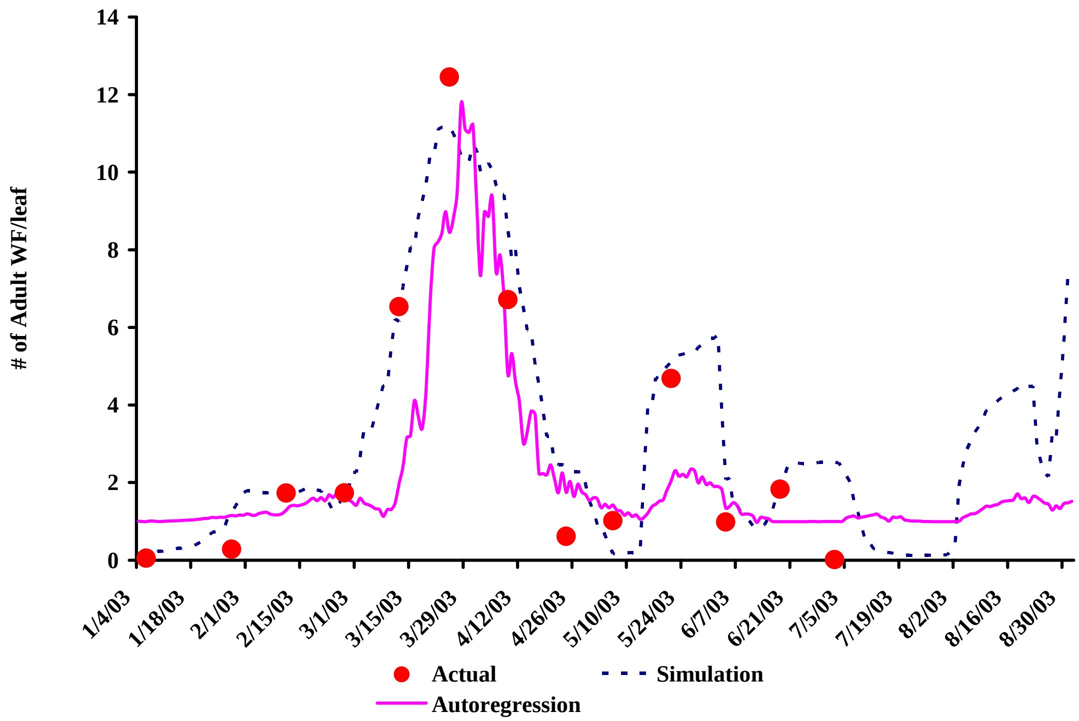
where $eggs_{t-k}$ is the number of eggs on the date (t) of the observation, k is the lagged number of weeks, and ε is an error term assumed to be distributed N(0,1). None of the lagged dependent variables in Equation (5.1) is significant. This result held for alternative numbers of lags. These results can be attributed to the small amount of data available—13 observations.

To increase the amount of data, we use the simulated egg and adult counts provided by the model. For practical purposes, using these data requires assuming that daily counts of eggs can be obtained for estimating autoregressive models. The simulated data contain simulated populations of eggs and adults for every day between November 11, 2002, and September 1, 2003. The simulated data are comparable to the observed sample. This model has the following form:

$$adults_t = \alpha + \beta_1 eggs_{t-1} + \beta_2 eggs_{t-2} + \beta_3 eggs_{t-3} + \beta_4 eggs_{t-4} + \beta_5 eggs_{t-5} + \varepsilon. \qquad (5.2)$$

Five lags are chosen because the average time needed to mature from egg to adult in the observed sample is 40 days or just over five weeks. The lags for the first, second, and third weeks are significant. The hypothesis of no autocorrelation cannot be rejected. The estimated coefficients for this model generate an estimated daily adult population series that can be compared with the simulated series and actual data series (Figure 5.2). If the autoregressive model reflects the biology of the whitefly population as fully as the simulation model, then these series should be comparable. If they are not, this indicates that information is lost or unmeasured in using the data.

Figure 5.2. Simulated and Estimated Adult Whitefly Population in Strawberry Plants for a Simulated Commercial Strawberry Field, Watsonville, CA (2002-03)



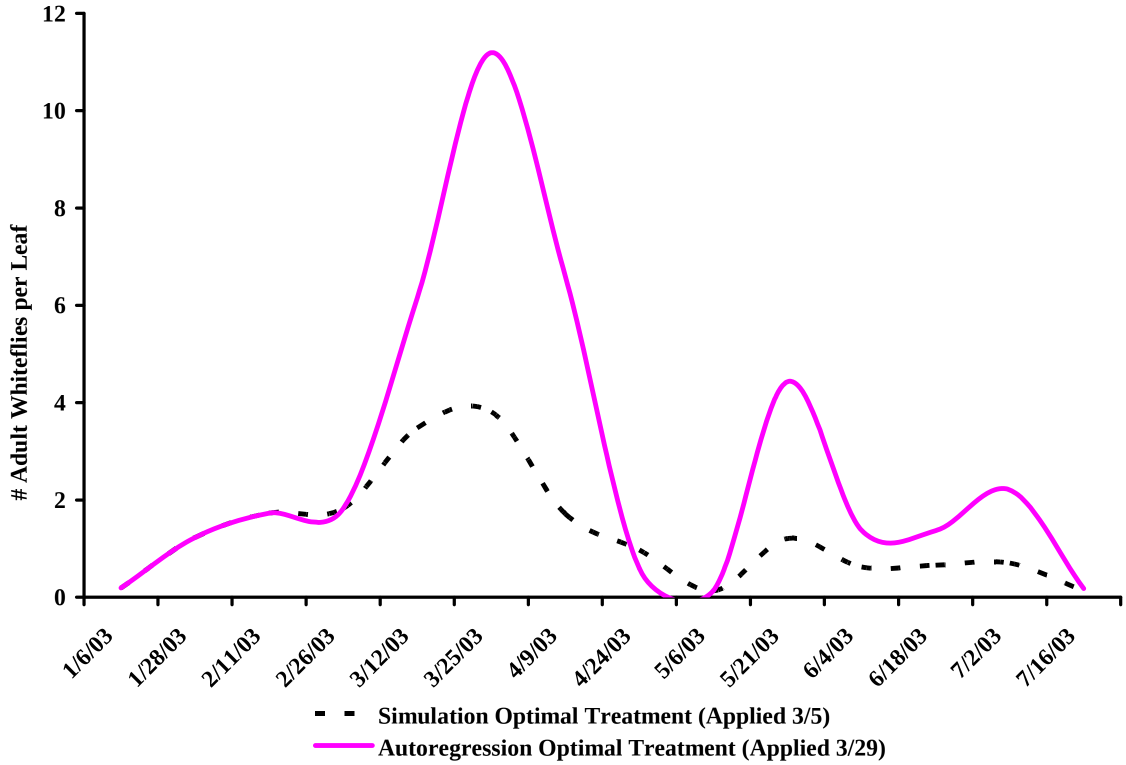
The solid line represents the estimated adult whitefly population series from the autoregressive model. The dotted line represents the simulated series, which replicates the observed sample, shown by the 13 large dots in the figure, very closely.[35] The actual observation was 505 cumulative whitefly-days. The simulation predicts 564 cumulative whitefly-days (10% error). The autoregressive model predicts 430 cumulative whitefly-

35 The observed sample ends in July.

days (15% error). The predicted series from the autoregressive model tends to predict the timing of the peaks and troughs in the population, but not their magnitude; the May and June peaks are too small and the troughs too high. The simulation does a better job of predicting the magnitude of population peaks and troughs. This excessive smoothing of the autoregressive model leads to overpredictions of the population during certain points in the season, such as in July and early August, and give the impression that the whitefly's population growth will always be relatively small after the growth observed in March and April. This result demonstrates that models, not just the quantity of data, matter in anticipating the effect of policies on invasive species population development.

An understanding of how the difference in the optimal treatment dates obtained from the two models affects development of the whitefly population is most easily obtained from examining the single treatment case. Figure 5.3 illustrates how the difference in the optimal treatment dates obtained from the two models affects the development of the whitefly population for the case of a single Esteem© treatment. When using the autoregressive model, the optimal date for a single Esteem© application is March 29, after the largest observed adult whitefly population peak. In contrast, the additional information used in the simulation model moves the optimal pesticide application date to March 5th, which is just before the adult whitefly population begins to build. Figure 5.3 shows simulated whitefly populations following single Esteem© applications on March 5 versus March 29. Prior to March 5, the populations are identical. The population generated by the March 5 application generates smaller population peaks than the March 29 application does, and higher profits. Profits from the March 5 application are about $1,000 more per acre than profits from the March 29 application, a difference of approximately 3% of net revenue per untreated acre.

Figure 5.3. Whitefly Population Development under Autoregressive and Simulation Models



To provide further perspective on the differences between the models and the implications for grower and policymakers' decisions, we compare the cost of the Esteem© regulations to growers estimated using the two approaches. While the single-application case was presented above in order to develop intuition regarding the two methods, estimating the cost of the Esteem© regulation to growers requires calculating optimal treatment programs for two and three applications. For each model, we calculate the profits, after spraying expenses, available from strawberry production when a grower behaves optimally in choosing application dates, but is bound by the use restriction to no more than two Esteem© applications per year (the "restricted" case), and when these are relaxed, allowing the grower to make a third application, if it would increase profits (the "relaxed" case). When the simulation model is used, the profits from the restricted case are about $7,800 per acre, and about $9,500 per acre for the relaxed case, a difference of about $1,700 per acre. In contrast, when the autoregressive model is used the profits from the restricted case are about $4,700 per acre, compared to about $7,000 per acre for the relaxed case, which is a difference of about $2,300 per acre. The simulation model's estimate of the cost of the regulation is smaller in magnitude ($1,700 versus $2,300), and as a percentage of profits from the associated relaxed case (18% versus 33%).

The autoregressive model's more pronounced smoothing of the population's peaks and troughs suggests that the whitefly's population growth will always be relatively small after the growth observed early in the season when, in fact, population peaks will occur late in the spring and again in the summer, which alters expected returns from application timing decisions. For example, it reduces the benefit of preemptively treating immediately before a population peak. Hence, although both models indicate that the combined effect of the regulations is to impose a cost on growers, the cost estimated using the autoregressive model is probably less accurate. This occurs because the effect of omitting available information from the analysis is magnified with every Esteem© treatment, and results in lower realized profits from a grower's optimal choices.

There are at least two weaknesses associated with the autoregressive model. First, the autoregressive model does not incorporate the biological relationship that the number of eggs in period t is a function of the number of adults in period t. Since the model does not include the feedback effect of reducing the number of adults in the future by reducing the number of adults, and hence eggs, today, this omission, as shown, miscalculates the optimal whitefly management choice relative to a model that uses additional available information. In this case, the autoregressive model undervalues the benefit of control.

Of course, if unlimited data were available, the performance of the autoregressive model would be vastly improved, as its structure could be expanded to include other relevant variables. However, our model comparison was motivated by the often limited data available for policymakers examining invasive species policy options. Keeping data limitations in mind, our options for addressing the limitation of the model regarding the adult-egg population feedback effect are limited, and costly in other ways. For example, an autoregressive model that estimated the current adult population as a function of the adult population in previous periods, rather than the egg population, would lose a different effect: the relationship between the number of adults and the number of eggs in a given period is dependent on temperature and other factors. On the other hand, because temperature and the adult population largely determine the egg population in a given period, using both lagged egg populations and lagged temperatures is problematic, because the egg population already reflects the influence of temperature—the rate of egg development is primarily a function of temperature. To the extent that any independent effects of those two factors can be disentangled, the resulting model would still be subject to a second criticism of the autoregressive approach.

The second, and more crucial defect is that the autoregressive model fails to accurately predict the population cycle observed in the sample. The estimated result smoothes away the peaks and troughs in the whitefly population. This is important because a grower responds to the actual, not the incorrectly forecasted, field conditions;

the cumulative effect of daily changes in the whitefly population plays a primary role in determining the optimal application timing.

5.8.2 The Effect of Regulation on Grower Decisions

The results of the analysis in this chapter show that grower decisions are affected by laws designed to prevent the development of pesticide resistance. For example, in section 5.4 we found that the restriction on the timing of the first Esteem© application causes growers in the Watsonville to lose an estimated $1200 in profits. Strawberry growers across the state are similarly constrained by this or one of the other Esteem© use restrictions in making production decisions. To accurately determine the costs and benefits of policies that regulate invasive species management, these effects on grower behavior must be identified. As shown, accurately modeling the interaction between production decisions and the biological changes associated with invasive species can identify the source of these effects.

5.8.3 Regional Differences in Effects from Invasive Species

The Esteem© use restrictions do not distinguish between conditions growers face in the Oxnard and Watsonville areas.[36] This analysis of optimal decisions for strawberry production in the Watsonville and Oxnard areas shows that growers in these two regions are constrained differently by the Esteem© use restrictions. Growers in Watsonville are constrained by the timing and maximum number of treatments. Oxnard growers, on the other hand, are constrained only by the restriction to two applications and are not bound by the timing requirement when two or three applications are used. As stated, these

[36] The 2005 version of the Section 18 label for Esteem differentiates the application frequency and timing requirements between Ventura County and the rest of California by adding the phrase “for strawberries planted before January 1, 2005”, which has no meaningful effect for this analysis.

differences occur primarily because of the difference in climate between the two regions, which allows the whitefly population to grow at different rates.

To properly assess the costs and benefits of the Esteem© use restrictions, analysis must be done in such a way that physical and economics differences between production regions are considered, even when the same crop is produced. By comparing the effects of the Esteem© use restrictions on grower behavior in the Watsonville and Oxnard areas, we show that growers in the Oxnard area may be less constrained by the Esteem© use restrictions than Watsonville growers are.

Attention to the potential effect of differences in regional production conditions will allow policy makers to make pesticide use restrictions, or other policies, that efficiently manage invasive species in agriculture. Including such differences is necessary when attempting to accurately anticipate a grower's difficulties associated with adjusting to the presence of a new organism, since the new organism may respond differently to the same management technique in different areas.

5.8.4 Importance of the Time Horizon in Invasive Species Management Analysis

Biological invasions, and hence the effects of regulation, can persist for more than one growing season. The analysis in section 5.7 studied the multi-season effect of the Esteem© use restrictions by simulating their effect on the size of migrating adult whitefly populations. In Chapter Six, we study the importance of time in greater detail as we account for how the use restrictions affect pesticide susceptibility over several seasons. In both cases, we demonstrate that decisions in one season affect those in the next. Hence, the relevant time horizon must be considered when assessing the impact of policies designed to regulate invasive species management.

6. An Analysis of Preventing Resistance Development through Pesticide Use Restrictions

The Esteem© emergency use restrictions are designed to slow development of resistance in the whitefly population, prolonging Esteem©'s effectiveness as a chemical control. As mentioned in section 3.4, the California Department of Pesticide Regulation (DPR) indicated that the use restrictions were based on two rationales—encouraging development and use of alternatives to Esteem© and preventing growers from depleting the susceptibility of the greenhouse whitefly to Esteem© before alternatives can be registered (Inouye, 2004). DPR was motivated by the perception that growers tend to use a relatively effective chemical without regard to the impact of its repeated use on the development of resistance.[37]

In this chapter, we compare the long-term benefits and costs of two Esteem© use restrictions designed to slow resistance development. The bioeconomic models for the Watsonville and Oxnard areas that were developed in Chapter Four are each combined with a deterministic model of pesticide resistance development. These new models are used to analyze two of the three use restrictions discussed previously—the two-application limit for Esteem©, and the requirement to combine Admire© with no more than two Esteem© applications. The restriction on the timing of the first application of Esteem© is not considered in this chapter because, given the assumptions used in this chapter, it does not influence resistance development. In addition, the optimal treatment date is not analyzed in this model. We assume that the optimal treatment dates in Chapter Five apply in the long-term, hence the use restriction requiring the application of

[37] Evidence exists of rapid development of resistance to pyriproxyfen, the active ingredient in Esteem, by other whitefly species in outdoor conditions (Li et al., 2000).

Esteem© when adult whiteflies first appear is ignored.[38] The goal of this comparison is to define sets of conditions for which the Esteem© use restrictions are or are not efficient in preventing resistance development.

In order to complete this analysis, we utilize our earlier assumption that the activities of one grower in no way influence the activities of another. This indicates that the size and share of the resistant whitefly population in the regional population can be taken as given. A result of this assumption is that, as the season-ending field population increases, so does the share of resistance in the field population in the following season. For example, if the number of adult whiteflies in other fields is fixed at 10 with no resistance and the number of adult whiteflies at the end of the season in the field in question is fixed at 10 with 50% resistance, then, when these whiteflies mix with the regional population between seasons, the new population has 25% (5 of 20) resistance. In contrast, if there are 100 adult whiteflies, 50% resistant, in the field in question (due to a poorly timed application, for example), then, when they mix with the same regional population between seasons, a new population forms that has about 45% resistance (50 of 110).

The analysis proceeds as follows. In section 6.1, we present the resistance development model. In section 6.2, we discuss the long-term economic impact of the two-application restriction for Esteem© on resistance development in both the Watsonville and Oxnard areas. In section 6.3, we discuss the combined

[38] This assumption is valid since the analysis in section 5.6 showed that applications made at times other than the optimal application timings resulted in larger inter-seasonal whitefly population, which, as discussed below, tend to increase the size of the resistant Esteem©-resistant whitefly population. Since we abstract from population size features in order to focus on the cross-season effects of management choices, it is not necessary to consider its effect on optimizing. For analytical convenience, growers maximize profits by choosing a single application program, used every season.

Admire©/Esteem© application restriction for both locations. Finally, in section 6.4, we discuss the policy implications of the analysis presented in this chapter.

6.1 Pesticide Resistance Development Model

No data exist that quantify the rate at which the greenhouse whitefly population develops resistance to Esteem© on strawberries. Consequently, we followed the approach of Regev, Shalit, and Gutierrez (1983), and created a simple deterministic model of how the Esteem©-resistant share of the greenhouse whitefly egg, nymph, and adult populations grows over time. The model is based on three factors identified in the entomology literature as affecting resistance development: (1) the effect of interseasonal migration on the proportion of resistant whiteflies in a field population (Dennehy et al., 2002; Denholm and Horowitz, 2000; Li et al., 2000), (2) the share of susceptible individuals killed by an Esteem© treatment (Denholm and Horowitz, 2000; Li et al., 2000; Horowitz and Ishaaya, 1994), and (3) the percentage of the pretreatment population that is naturally resistant before the first application of Esteem© (Tabashnik and McGaughey, 1994; Curtis and Otoo, 1986; Regev, Shalit, and Gutierrez, 1983).

In order to implement the model of Esteem© resistance, we use the fact that greenhouse whiteflies tend to remain on or near the host plant on which they were born until the plant is removed or its level of leaf nutrients declines (Benchwick and Ishida, 2005; Byrne, Bellows, and Parella, 1990). This means that the population in each whitefly-infested field remains relatively isolated during the season. This condition allows us to take advantage of the Hardy-Weinberg principle of genetic equilibrium, which states that the distribution of genetic material (such as genes for pesticide resistance) remains constant within the population when the following conditions hold (Wallace, 1981):

1. mating occurs at random between individuals of various genetic genotypes (homozygous susceptible, heterozygous susceptible / resistant, homozygous resistant); [39]

2. migration of individuals into or out of a geographic population does not occur;

3. selection in the form of differential survival or fertility of the different genotypes does not occur;

4. mutation of one allele into another does not take place; and

5. sampling errors resulting from the finite size of the population do not exist.

We make several assumptions to be sure that these conditions hold. For simplicity, we assume that resistance development can be modeled as the transfer of a single gene (Wallace, 1981), which supports condition one. To support condition two, we take advantage of the fact that greenhouse whiteflies tend to remain on or near the host plant on which they were born and assume that migration of susceptible individuals occurs only between planting seasons. To support condition three, we assume that the resistant and susceptible whitefly populations reproduce at the same rate. To support condition four, we assume that Esteem© resistance originated through random mutation and that no further mutations occur that affect the generation of resistance. To support condition five, we assume that all infested plants have the same greenhouse whitefly

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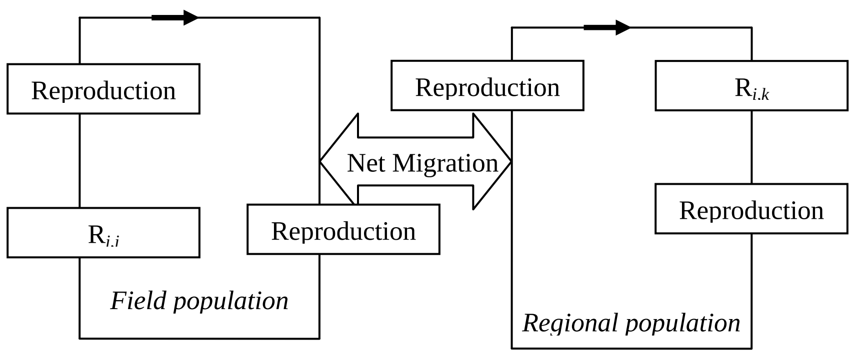
[39] We assume that each gene is made up of two alleles. Alleles can be thought of as the parts of a gene that express genetic characteristics. A heterozygous gene is one in which each of the two alleles expresses a different genetic characteristic; in this case one allele is considered “Esteem©-resistant” and the other “Esteem©-susceptible”. In contrast a homozygous gene refers to a gene in which both of the alleles express the same genetic characteristic – either both “Esteem-resistant” or both “Esteem©-susceptible”.

population per plant and that the Esteem© treatment is equally effective on all plants. No set of scientific data exists to support these assumptions for the strawberry/whitefly case; however, no set of scientific data exists that contradicts them, either. We have assumed the simplest possible specification for the relationship among these three factors in the absence of data.

A schematic of how the three primary factors affect resistance development is shown in Figure 6.1.

Figure 6.1. Factors affecting Whitefly Resistance to Esteem©



Source: Adapted from Comins (1977)

The boxes represent two populations of greenhouse whiteflies, each of which has some share of whiteflies that are naturally resistant to Esteem©. The box on the left represents the population in the field under analysis, and the box on the right represents whitefly populations in surrounding fields that are close enough for the various populations to mix between seasons. The thin arrows outlining each box represent the exchange of susceptible or resistant genetic material within each field population over time. The boxes labeled “reproduction” represents the process by which genetic material is transferred over time such that the distribution between resistant and susceptible whiteflies is held constant, all else being equal. Since the effect of migration on pesticide resistance development depends only on the relative shares of resistant whiteflies in the field and regional populations, the large double-pointed arrow represents the flow of genetic material between the observed and nearby fields between seasons (factor one). The *i*th application of Esteem© increases the number of resistant whiteflies in the field *j* population, represented by $R_{i,j}$; changing the distribution of susceptible and resistant whiteflies as described in factor two. (This does not violate the Hardy-Weinberg principle because the pesticide applications are an exogenous factor that changes the equilibrium in the field.) The source of the genetic material, factor three, is assumed to be from random mutation. The cycle in each side of the figure affects resistance development beginning with the migration of adult whiteflies into the field, which have a given distribution of resistance within the group. Next, reproduction increases the field and regional whitefly populations, while maintaining a constant distribution of resistance, given the Hardy-Weinberg assumptions. A series of one or more pesticide applications alters the distribution of resistance by eliminating a number of susceptible individuals from the population after each treatment. Reproduction continues during and after treatments, which preserves the post-application distribution of resistance within the application. Finally, the cycle repeats as the field is removed and migration between occurs and start of the next season.

We now discuss the initial values of the three factors, and how those values influence pesticide resistance development in the model. The particular values are not important themselves, but serve as a point to begin a discussion of the sensitivity of our results to these factors. Migration of susceptible whiteflies into a field population (factor one) can be a very important element in diluting the amount of Esteem© resistance in the field's population. Whenever the regional population has a smaller share of resistance than the field population and mixing occurs between the populations between seasons, there will be a reduction in the share of resistant individuals in the new field population. Several authors have studied the importance of immigration to the development of resistance in whiteflies and in general (Dennehy et al., 2002; Denholm and Horowitz, 2000; Li et al., 2000; Horowitz and Ishaaya, 1994; Taylor and Georghiou, 1979).

We analyze the influence of migration on resistance development by conducting a sensitivity analysis. We assume the effect of migration on the share of resistance in the population is not affected by the grower's treatment decision; in other words, we assume that no one grower can alter the distribution of resistance in the entire regional whitefly population by making treatments within his field. Making this assumption assures that susceptible whiteflies are preserved within the population. Note, however, that this assumption cannot be used if we wish to compute an example of coordinated regional management activities.

We examine the effect of changes in the initial share of resistance in the field population, caused by immigration, on the grower's optimal behavior across seasons. The sensitivity analysis ranges from zero change in resistance to a one hundred percent decrease in the share of resistant whiteflies between seasons. The zero change is the case in which no susceptible adult whiteflies enter the field after immigration. A hundred percent change refers to complete elimination of resistant whiteflies as a share of the field population. No scientific data are available regarding the share of resistance in the migrating whitefly population between seasons, but such data could be obtained through repeated observation.

We analyze the influence of the second factor, the kill rate of the application, on the development of pesticide resistance (Comins, 1977) by conducting a second sensitivity analysis. Very low kill rates tend not to increase resistance very much because many susceptible whiteflies survive, while high kill rates can increase it very quickly since only a few susceptible whiteflies are left in the population.

We consider kill rates between 10% and 90%.[40] A zero kill rate was not considered, since it is equivalent to not making any application at all. At the other extreme, the field data in Figures 4.5 and 4.6 shows Esteem© is not 100% effective against susceptible whitefly eggs, nymphs, and adults. This is simply because of the practical difficulty associated with using a sprayer to completely cover the undersides of affected leaves (Zalom, 2005). Bi, Toscano, and Ballmer (2002b) observed the kill rate of pyriproxyfen (in the Knack© formulation) against the greenhouse whitefly on outdoor strawberries at between 40% and 73% for adult whiteflies and 51% to 100% for nymphs, but did not observe whitefly egg kill rates in outdoor conditions.

As a benchmark for factor three, the resistance endowment, denoted R_0, we assume 0.01% of the initial field population is resistant as a result of random mutation. We also consider a second case, with an initial resistance endowment of 1%, to evaluate the effect of the size of the endowment on optimal grower behavior.

These three factors are combined into a mathematical model to measure changes in the resistant share of the population. Let $R_{i,j}$ represent the percent of the population that

[40] Comins (1977) found that the relationship between increased kill rates and resistance development is affected by the degree of density dependence (the degree to which the tendency of a pest population to return to its original size after a pesticide application is affected by the number of survivors). We assume undercompensating density dependence in the model (monotonic return of a population to its equilibrium level) since the whitefly population simulator assumes a carrying capacity.

is resistant after application *i* in field *j*, let 1- $R_{i-1,j}$ represent the percent of the population that is susceptible after application *i* in field *j*, and let 1- λ represent the deterministic Esteem© kill rate of the *i*th application. To calculate the portion of the resistant population after the first application of the first season, evaluate

$$R_{i,j} = \frac{R_{i-1,j}}{R_{i-1,j} + (1-\lambda)(1-R_{i-1,j})},\ j>0,\ \lambda \in [0.10, 0.90] \tag{6.1}$$

The numerator of Equation (6.1) is the share of the whitefly population that is resistant after the previous Esteem© application. The denominator represents the entire population after the previous Esteem© application, composed of the resistant and susceptible population. These determine $R_{i,j}$ through the kill rate, 1- λ . For instance, if 1- λ =0, meaning no whiteflies are killed by Esteem©, then the resistant population share after application *i* will be the same as after application *i*–1.

Calculating the resistant share of the population prior to the first treatment of the season, *i*=1, requires accounting for the influence of migration. Let *M* represent the percent net reduction in resistance due to migration, which occurs after the mixing of the field and regional population of adult whiteflies with different shares of Esteem© resistance. Evaluate

$$R_{i,j} = \left(\frac{R_{i-1,j}}{R_{i-1,j} + (1-\lambda)(1-R_{i-1,j})}\right)(1-M),\ j>0,\ M \in [0,1]\ \ \lambda \in [0.10, 0.90] \tag{6.2}$$

with R_0 at 1% by assumption. The only difference between Equations (6.1) and (6.2) is that the resistant share of the population is adjusted by the dilution in resistant genes as a share of the population through migration. Note that we can omit time subscripts since the only cross-field effect considered is immigration, which is not time-dependent.

Since no data exist on the rate at which Esteem© resistance develops as a result of the three factors, we conduct a sensitivity analysis for a six-season horizon by evaluating the profits for a range of migration and kill rates for each of the following treatment scenarios: one, two, or three Esteem© applications, with or without Admire©, for both the Oxnard and Watsonville growing regions. We then report the total discounted six-season increase in profits relative to an untreated acre. We selected six seasons as a conservative estimate of the typical period in which only one new chemical is permitted for control of an invasive pest. For example, DPR indicates that it is difficult to maintain an emergency registration for more than three years (DPR, 2001). In addition, alternative chemical treatments may be developed during this period, as has been the case for the greenhouse whitefly. Field trials for Oberon©[41] (spiromesifen), a potential alternative treatment to Esteem©, have occurred since 2003, the same year Esteem© use was started in strawberry fields. Oberon© has a different mode of action from that of Esteem©. Results so far show that Oberon© can control the greenhouse whitefly on strawberries in the Watsonville area with efficacy levels that are similar to those of Esteem© (Zalom, unpublished data).

We make two assumptions to simplify the temporal nature of this analysis. First, since no data exist on the relationship between the size of whitefly field populations in one area and the subsequent size of the whitefly field population in future plantings in adjacent fields, we assume that each season begins with the same size of whitefly

[41] Oberon is a registered trademark of Bayer Crop Protection.

population. Therefore, the cross-season effects are limited only to resistance development and migration; confounding population size effects are eliminated. Second, to estimate the profits obtained from whitefly management, we assume that the annual cycle of strawberry prices remains the same across years.

As a demonstration of the results for Equations (6.1) and (6.2) over time, the resistant share of the whitefly population is shown in Figures 6.2 and 6.3 when one, two, and three Esteem© applications are made every season. Although three factors are included in the equations, we show only level sets of the four-dimensional surface they create, holding time and resistance endowment constant; this is sufficient to demonstrate their operation.

Each graph shows the development of resistance as a share of the total population plotted over time for a single level of factor one (migration effects), set at 50%; factor two, the Esteem© kill rate, is set at 70%; and factor three, the resistance endowment, is set at 0.01% of the pretreatment population. Figure 6.2 shows how these values affect resistance development as the number of seasons increases, whereas Figure 6.3 shows how resistance develops as the number of treatments increases.

Figure 6.2. Resistant Population at End of Each Season as a Percentage of Total Population

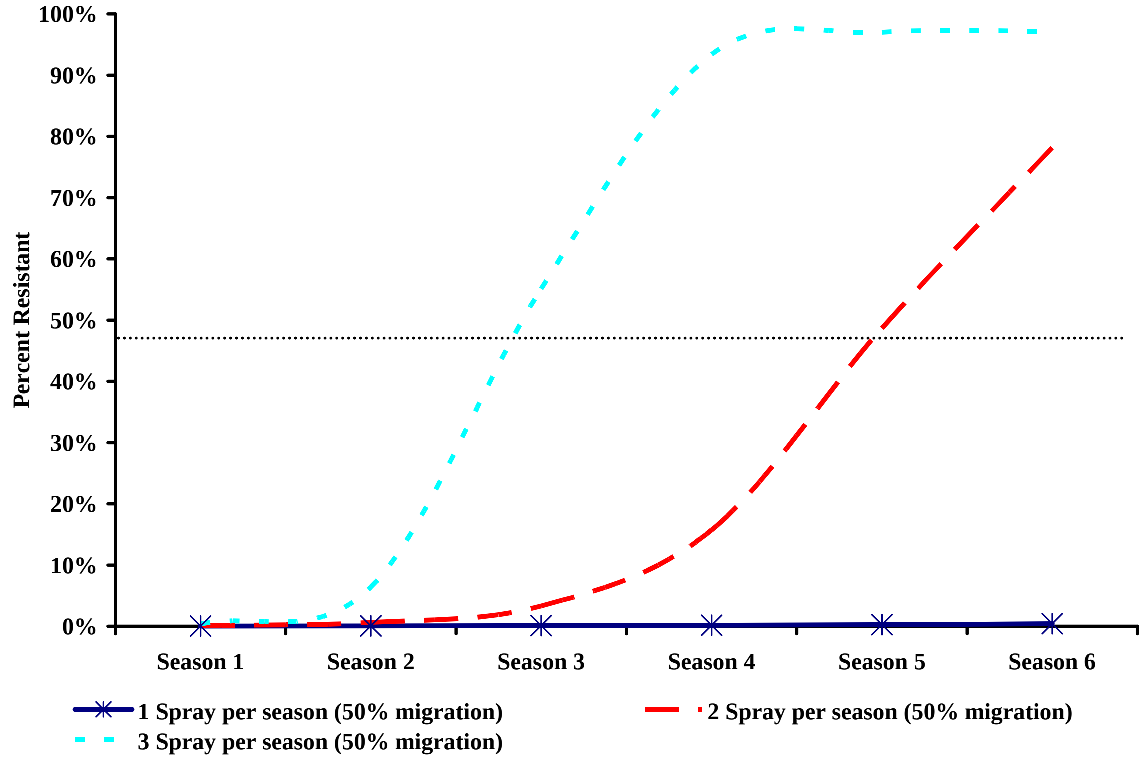


Figure 6.2 demonstrates that the speed with which resistance develops rises with the number of applications made per season. Given the values of factors one through three, when three Esteem© applications are made each season, 50% of the population becomes resistant after the third season. In the two-treatment program, a majority of the whitefly population becomes resistant during the fifth season while in a one-treatment program the resistant share of the population never becomes a majority during six seasons. The figure also shows that the resistant share of the population increases rapidly after about 20% percent of the population becomes resistant.[42]

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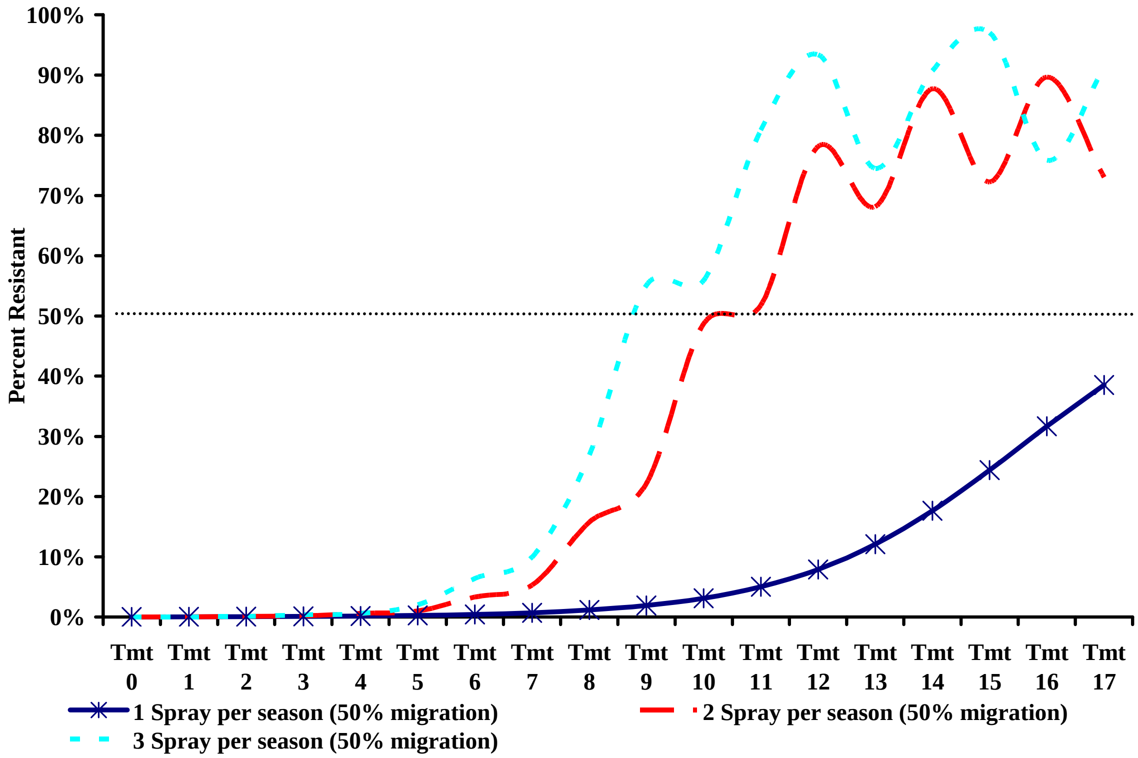
[42] To see whether rapid increases in resistance actually occur in natural whitefly populations, we compared this rate of resistance development with data available in the literature about pyriproxyfen resistance in other whitefly species. Horowitz and Ishaaya (1994) compared the LC_{50} (amount of active ingredient needed to kill 50% of the sample) of a laboratory reference strain of whitefly with a normalized level of pyriproxyfen resistance before and after three successive treatments of pyriproxyfen and found it increased

Figure 6.3 plots the size of the resistant share of the population based on the cumulative number of treatments. This figure illustrates the interplay between the number of treatments and migration effects that determines the development of resistance by treatment shown in Figure 6.2. The results are shown for a single level of migration effects, 50%; the Esteem© kill rate is set at 70%; and the resistance endowment is set at 0.01%, as in Figure 6.2.

Figure 6.3. Resistant Population after Each Treatment as a Percentage of Total Population



When three Esteem© applications are made each season, the simulation shows 50% of the population becomes resistant after the eighth treatment (Figure 6.3). In the two-treatment program, a majority of the whitefly population in the strawberry field

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554 times. Dennehy (2003) observed a 6,500-fold increase in pyriproxyfen resistance under laboratory conditions, as well as a 450-fold increase in resistance in a sunflower field in Israel. Horowitz and Ishaaya (1984) observed a 0.4-fold increase in resistance relative to the reference sample after a single field application in cotton.

becomes resistant after nine treatments while for a one-treatment program the resistant share of the population never exceeds 50% after 17 treatments. The development of resistance is offset each year by migration. When more applications are made per season, migration dilutes resistance in the population less often. This is represented by the “dips” in the two- and three-treatment programs shown in Figure 6.3. If three applications are made per year, the resistant share of the population increases more rapidly since resistance is not diluted from the population as often. Migration also affects the single-treatment case, but only by flattening the curve.

6.2 The Long-Term Benefits of the Restriction to Two Esteem© Applications

The increase in pesticide resistance over time reduces the benefit of each successive application. Use restrictions can prevent resistance development. In the following two sections, we discuss our comparison of the long-term benefits and costs of the Esteem© use restrictions designed to prevent resistance development. For editorial reasons, all of the tables discussed in these sections are provided at the end of the chapter on pages 164-171. These tables report the dollar effects of the treatment cases, such as those illustrated in Figures 6.2 and 6.3. Only the results for two applications per season are displayed. Ordinal comparisons to treatment programs of one or three applications per season are made in each table by shading the combination of kill rates and migration effects for which it is a profit maximizing program. The unshaded region indicates combination of kill rates and migration effects for which it is optimal to make three applications per season over the six year analysis period; the lightly shaded region indicates combinations for which it is optimal to make two applications per season over the six year analysis period; and the darkly shaded region indicates combinations for which it is optimal to make only one application per season over the six year analysis period. All profits discussed are increases relative to an untreated acre for two treatments of Esteem© each season, for six seasons. They are discounted at 3% per year, which was selected for convenience. The column labeled “natural decline in resistance” refers to the migration effect, and the “kill rate” measures the share of the susceptible whitefly population that is eliminated by each Esteem© application. Conclusions in our discussion are based on trends observed in the sensitivity analyses, and information summarized in the tables.

The results in Table 6.1 show that combinations of biological and management conditions exist for which three seasonal applications of Esteem© are optimal in the Oxnard area, while other combinations of factors make only one or two applications optimal. The unshaded values in Table 6.1 represent combinations of kill rate and migration effects for which a program of three Esteem© applications per season produces larger profits than one or two applications per season. As the kill rate increases, or if the resistant whitefly population is not regularly diluted through migration, then fewer applications each season are profit-maximizing because resistance increases more rapidly as the number of Esteem© applications per season increases. The light gray region shows the range of kill rates and migration effects for which two Esteem© applications each season are optimal. In this region, the Esteem© use restrictions are efficient at preventing resistance development. The darkest region represents combinations of values for which one application per season produces the largest increase in profit. Since we have shown in Chapter Five that a grower who does not internalize his or her impact on the development of pesticide resistance will have an incentive to make two Esteem© applications per year, this region indicates that conditions exist for which the use restrictions are too permissive.

The results in Table 6.1 also show that the importance of the migration effect on resistance development depends on the kill rate. The influence of the migration effect can be seen by holding the kill rate constant and comparing the change in results within the column. Migration has little effect on increased profits from whitefly management at low kill rates. This is because the low kill rates do little to alter the share of susceptible whiteflies in the population, so the dilution due to migration is correspondingly smaller. As the kill rate increases, however, the importance of the dilution of resistance through migration increases dramatically. This is shown by the wide variation in profits at high kill rates versus the near uniformity of profits across rates of resistance dilution at low kill rates. Holding the migration effect constant within each row of the table, we see that profits tend to increase with the kill rate until values around 60% or 70%, after which they decline.

The same analysis was conducted for the Watsonville area. That model had the same qualitative results, shown in Table 6.2, as the Oxnard model in Table 6.1.

Disaggregating the six-season totals by season reveals interesting patterns in the increased profits available from multiple Esteem© applications. In Table 6.3, which disaggregates the six-season increase in profits for the Oxnard area, migration is assumed to dilute 50% of the resistance from the population each season and the kill rate is set at 50%. In this case, two applications are optimal over the six-year period. A grower can initially obtain the most profit by making three applications per season, but by the third season the grower will receive smaller increased profits relative to a two-treatment program. This suggests that there are incentives for a grower not to internalize his effect on the development of pesticide resistance during the first few seasons in which a new pesticide is used.

The size of the population naturally endowed with Esteem© resistance prior to the first treatment, factor three, also affects the ranges of kill rates and declines in resistance for which the Esteem© use restrictions are optimal in the long-term. Tables 6.1 and 6.2 are based on the assumption that 0.01% of the population is resistant to Esteem© before the first treatment. As the share of the population that is initially resistant increases, restricting the number of applications to reduce the rate of resistance development provides larger economic benefits over time. Table 6.4 shows the increased profits relative to an untreated acre for the Oxnard model when the resistance endowment is 1.0%. The darkest shaded area shows the combinations of kill rates and migration effects where one treatment per season is optimal. The lighter gray area shows combinations where two treatments per season are optimal. Finally, the unshaded area shows where three treatments per season generate more profits than one or two do.

Three key results emerge from comparing Tables 6.2 and 6.4, which describe the

Watsonville model. First, the total profits available from strawberry production decline as the initially resistant share of the population increases, because the initial population has a larger resistant component that is not affected by Esteem© application and the resistant share of the population grows more rapidly. Hence, the grower has less control over loss of yields due to whitefly damage and profits are lower.

The second result is that the set of kill rates and migration effects for which it is optimal to make only one or two seasonal Esteem© applications expands when the resistance endowment increases. This implies that pesticide use restrictions may need to be stricter when the resistance endowment increases. At a methodological level, these results show the benefit of performing a sensitivity analysis using a model containing key biological parameters and grower behavior to inform policymakers about the long-term effects of regulations and prioritize biological data collection efforts according to their potential importance for policy choice.

The same method of analysis was conducted to see the impact of changes in the resistance endowment for the Oxnard-area model. The same qualitative results were observed as in the Watsonville model, as shown in Table 6.5.

6.3 The Long-Term Benefits of the Requirement to Use Esteem© with Admire©

In this section, we discuss the long-term benefits of the requirement to use Esteem© only if Admire© has been applied within ten days of planting. Although using Admire© will allow the whitefly population to develop resistance to it, in order to focus on the development of resistance to Esteem© we assume that no resistance to Admire©

exists in the population, or develops over time. We assume that Esteem©-resistant and Esteem©-susceptible whiteflies are equally susceptible to Admire©. This assumption simplifies the analysis considerably, because an application of Admire© kills the same proportion of Esteem©-susceptible and Esteem©-resistant whiteflies, leaving the rate at which resistance to Esteem© develops in the population unchanged.

Table 6.6 shows the results of the analysis under the combined requirement for the Watsonville bioeconomic model; Table 6.7 shows the same results for the Oxnard bioeconomic model. When compared with Tables 6.1 and 6.2, these tables show that the requirement to use Admire© with Esteem© always results in greater profits over the longer term than using Esteem© alone does. This provides long-term economic justification for the requirement to use Admire© in addition to Esteem©. The results also show that the requirement to use Admire© does not eliminate the cost of the restrictions to two or fewer treatments. The unshaded regions (optimal to make three Esteem© applications each season) of Tables 6.6 and 6.7 contain approximately the same number of kill rates/migration effect combinations as in the Esteem©-alone case.

In contrast with the results from the analysis when Esteem© is used alone, we find no range of kill rates and migration effects for which only one application is ever optimal for either Watsonville or Oxnard. This occurs because the losses associated with whiteflies are related to both the share of resistance in the population and its size. These results indicate that if the whitefly population can be kept small enough, more applications can be made without increased yield losses due to increased resistance over time. This also suggests that, when a second pesticide with a different mode of action such as Admire© can be used, use regulations on a pesticide can be relatively less restrictive because of the ability of the other chemical to kill invaders developing resistance to the first. The shaded areas in Table 6.6 and 6.7 show the combination of biological factors for which two applications are optimal in the Watsonville and Oxnard regions respectively, and the unshaded region shows the combination of factors for which three applications are more profitable than two.

As in the analysis for Esteem© alone, these results show that migration by Esteem©-susceptible whiteflies increases profits by diluting resistance in the whitefly population. As explained previously, at low kill rates migration has little effect on the size of the resistant share of the population, since few susceptible whiteflies are killed by each treatment. On the other hand, when kill rates are relatively high, the only way to reintroduce susceptible whiteflies into subsequent field populations is through migration. Hence, migration is important at higher kill rates. This effect of kill rates and migration on profits can be seen by observing the change in discounted profit within any column high kill rates in Tables 6.6 and 6.7. At low kill rates, there is little or no variation in discounted profits. At high kill rates, however, profits vary about 20%.

In order to have a sense of which of these scenarios are the most relevant to actual field conditions, we compare them with the observations made by Bi, Toscano, and Ballmer (2002). Observed kill rates were between 40% to 73% for adult whiteflies, and 51% to 100% for nymph whiteflies. Actual field conditions over the six-year horizon may, therefore, fall along the middle columns of these tables. In this analysis the initial values of the factors establish the policy choice. Nevertheless, as time passes, the optimal treatment program may actually move across the boundary between the three- toward the two-application program as resistance increases, if it does so faster than anticipated in this model. Hence it is important to know about Esteem© resistance in the regional population before deciding whether three applications are sustainable or whether the limit of two applications per season should remain as a use restriction.

We also analyze the effect of a change in the resistance endowment, R_0, from 0.01% to 1.0% of the population before the first application under the two use restrictions combined—the two-application limit and the requirement to use Admire©. As in the previous section, we change the resistance endowment. Although we only show the results for the Oxnard case (Table 6.8), results are similar for the Watsonville area: as the size of the initially resistant share of the population increases, the benefit from stricter use restrictions also increases. As in the Esteem©-only case, the set of combinations of values for kill rates and migration effects for which three applications are optimal shrinks when the resistance endowment grows. In addition, the region of values where only one application is optimal appears at high kill rates.

6.4 Summary of Results

This chapter combines the bioeconomic model described in Chapter Four with a deterministic model of pesticide resistance development to estimate the long-term costs and benefits associated with policy restrictions that affect management of the greenhouse whitefly in strawberries. We find that the combination of biological conditions and number of Esteem© applications, whether it is applied alone or in combination with Admire© at planting, affects the optimal profits available from strawberry production over time. We also find that there are conditions for which the Esteem© use restrictions maximize long-term profits. In the case of the Watsonville and Oxnard areas, there is a set of biological conditions for which the combined Esteem© use restrictions are optimal. The range of conditions for which more applications are optimal shrinks as migration is less effective at diluting resistance in the field population, as kill rates increase, and as the amount of resistance in the pretreatment population increases.

These results suggest that regional management of pesticide resistance may be more efficient than private management for two reasons. First, the optimal number of applications changes as biological conditions change, and no single grower can control the share of resistance in the regional population. Since susceptible whiteflies in nearby fields are needed to dilute the amount of resistance in any individual field, it may be useful to construct policies that create untreated buffer zones in which insects that are susceptible to the pesticide in question are allowed to reproduce.

Second, incentives exist for growers to abuse the public-good nature of the pool of susceptible whiteflies. The analysis in Table 6.3 shows that profits in the early years of a three-treatment/season program could be larger than those from a two-treatment/season program, even when a two-treatment program is optimal. In this case, growers have incentives to inefficiently reduce the susceptible population of whiteflies by making too many Esteem© applications. A regional management program could include measuring the share of resistance in the regional population. It could also include education programs to instruct growers about the economic consequences of depleting the pool of susceptible whiteflies too rapidly.

The approach used in this chapter also identifies priorities for further data collection. As discussed in section 6.3, the optimal long-term resistance management policy in the strawberry/whitefly case will depend on the values of various biological and management factors affecting the rate of resistance development. Knowing that the optimal management policy is sensitive to the values of certain factors encourages their careful measurement. In contrast, if the optimal solution is not sensitive to certain variables, such as dispersion rates, the value of additional data collection is relatively low.

Table 6.1. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season, Oxnard Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$6,334	$16,512	$20,971	$26,534	$39,517	$42,252	$37,959	$36,324	$34,566
10%	$6,334	$16,515	$20,986	$26,617	$40,253	$44,289	$40,097	$38,386	$36,530
20%	$6,334	$16,518	$20,995	$26,674	$40,816	$46,376	$42,496	$40,708	$38,761
30%	$6,334	$16,519	$21,002	$26,711	$41,213	$48,399	$45,216	$43,363	$41,310
40%	$6,334	$16,520	$21,006	$26,735	$41,468	$50,179	$48,327	$46,458	$44,279
50%	$6,335	$16,521	$21,009	$26,748	$41,615	$51,523	$51,875	$50,161	$47,831
60%	$6,335	$16,521	$21,010	$26,755	$41,692	$52,345	$55,744	$54,746	$52,237
70%	$6,335	$16,521	$21,011	$26,759	$41,727	$52,732	$59,271	$60,713	$58,013
80%	$6,335	$16,522	$21,011	$26,761	$41,740	$52,868	$61,265	$68,976	$66,327
90%	$6,335	$16,522	$21,012	$26,762	$41,745	$52,901	$61,755	$78,611	$80,927
100%	$6,335	$16,522	$21,012	$26,762	$41,746	$52,907	$61,797	$80,401	$112,900

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 0.01% of the initial population.

*Key:**
= 1 optimal
= 2 optimal
= 3 optimal

*The label "1 optimal" refers to the case when one Esteem© application per season produces the most profits, relative to the case when two or three applications are made, over the six-season analysis period. Similarly, "2 optimal" or "3 optimal" refers to the cases when two or three Esteem© applications per season produces the most profits over the six-season period, respectively.

Table 6.2. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season, Watsonville Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$2,105	$6,738	$8,787	$11,340	$17,649	$19,001	$16,961	$16,710	$16,064
10%	$2,105	$6,739	$8,794	$11,380	$17,985	$19,876	$17,852	$17,592	$16,936
20%	$2,106	$6,740	$8,799	$11,408	$18,245	$20,779	$18,849	$18,579	$17,910
30%	$2,106	$6,741	$8,802	$11,426	$18,430	$21,667	$19,976	$19,698	$19,012
40%	$2,106	$6,742	$8,804	$11,437	$18,549	$22,462	$21,261	$20,994	$20,282
50%	$2,106	$6,742	$8,805	$11,444	$18,618	$23,074	$22,727	$22,533	$21,782
60%	$2,106	$6,742	$8,805	$11,447	$18,654	$23,452	$24,333	$24,432	$23,618
70%	$2,106	$6,742	$8,806	$11,449	$18,670	$23,631	$25,811	$26,899	$25,990
80%	$2,106	$6,742	$8,806	$11,450	$18,676	$23,694	$26,653	$30,324	$29,345
90%	$2,106	$6,742	$8,806	$11,450	$18,678	$23,709	$26,859	$34,372	$35,104
100%	$2,106	$6,742	$8,806	$11,450	$18,679	$23,712	$26,877	$35,126	$47,131

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 0.01% of the initial population.
Increased profit represents the additional profit earned in a treated field, relative to an untreated acre.

Key:*
= 1 optimal
= 2 optimal
= 3 optimal

Table 6.3. Increased Profit per Season, by Number of Treatments, Under Increasing Resistance, Oxnard Model

Two Treatments	Season 1	2	3	4	5	6	Discounted Total
Increased Profit	$7,465	$7,250	$6,880	$6,317	$5,586	$4,815	$34,841

Three Treatments	Season 1	2	3	4	5	6	Discounted Total
Increased Profit	$10,251	$9,082	$6,701	$4,262	$3,021	$2,617	$33,230

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 1.0% of the initial population.

Table 6.4. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season, Under Increased Initial Resistance, Watsonville Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$2,047	$6,325	$7,439	$7,787	$9,561	$9,212	$8,135	$7,951	$7,735
10%	$2,063	$6,446	$7,810	$8,471	$10,520	$10,150	$9,000	$8,806	$8,605
20%	$2,074	$6,535	$8,115	$9,160	$11,591	$11,210	$9,969	$9,762	$9,575
30%	$2,082	$6,599	$8,350	$9,816	$12,787	$12,424	$11,071	$10,846	$10,673
40%	$2,088	$6,644	$8,517	$10,386	$14,110	$13,843	$12,350	$12,099	$11,939
50%	$2,092	$6,673	$8,626	$10,822	$15,507	$15,532	$13,873	$13,585	$13,433
60%	$2,095	$6,692	$8,694	$11,108	$16,822	$17,572	$15,751	$15,413	$15,260
70%	$2,097	$6,705	$8,733	$11,268	$17,798	$19,961	$18,185	$17,791	$17,615
80%	$2,098	$6,713	$8,755	$11,347	$18,308	$22,195	$21,517	$21,192	$20,938
90%	$2,099	$6,718	$8,767	$11,383	$18,502	$23,279	$25,409	$27,071	$26,657
100%	$2,100	$6,722	$8,775	$11,401	$18,570	$23,529	$26,621	$34,576	$45,797

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 1.00% of the initial population.

Key:
= 1 optimal
= 2 optimal
= 3 optimal

Table 6.5. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season, Under Increased Initial Resistance, Oxnard Model

	Kill Rate								
Natural Decline in Resistance	**10%**	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**
0%	$6,197	$15,600	$18,044	$18,800	$21,081	$19,566	$16,731	$15,357	$13,735
10%	$6,232	$15,868	$18,861	$20,350	$23,341	$21,790	$18,782	$17,333	$15,624
20%	$6,259	$16,066	$19,529	$21,885	$25,853	$24,304	$21,095	$19,559	$17,782
30%	$6,278	$16,207	$20,036	$23,319	$28,639	$27,186	$23,743	$22,105	$20,249
40%	$6,292	$16,305	$20,393	$24,540	$31,682	$30,543	$26,833	$25,074	$23,123
50%	$6,301	$16,370	$20,628	$25,459	$34,841	$34,517	$30,529	$28,627	$26,562
60%	$6,308	$16,412	$20,771	$26,054	$37,748	$39,259	$35,100	$33,036	$30,828
70%	$6,313	$16,439	$20,855	$26,385	$39,860	$44,690	$41,020	$38,812	$36,424
80%	$6,316	$16,457	$20,902	$26,547	$40,955	$49,620	$49,060	$47,102	$44,492
90%	$6,319	$16,468	$20,929	$26,623	$41,368	$51,971	$58,318	$61,302	$58,731
100%	$6,321	$16,476	$20,945	$26,660	$41,514	$52,511	$61,189	$79,099	$109,212

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 1.00% of the initial population.

Key:
= 1 optimal
= 2 optimal
= 3 optimal

Table 6.6. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season in Combination with Admire©, Watsonville Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$16,615	$23,576	$27,109	$31,902	$39,061	$40,471	$36,356	$36,166	$32,300
10%	$16,615	$23,579	$27,121	$31,986	$39,665	$41,744	$37,504	$37,239	$33,235
20%	$16,615	$23,580	$27,130	$32,044	$40,161	$43,112	$38,808	$38,455	$34,280
30%	$16,615	$23,581	$27,135	$32,082	$40,533	$44,535	$40,310	$39,857	$35,463
40%	$16,616	$23,582	$27,139	$32,106	$40,782	$45,925	$42,066	$41,505	$36,829
50%	$16,616	$23,583	$27,141	$32,120	$40,932	$47,126	$44,141	$43,502	$38,448
60%	$16,616	$23,583	$27,142	$32,128	$41,010	$47,965	$46,557	$46,027	$40,438
70%	$16,616	$23,583	$27,143	$32,132	$41,046	$48,399	$49,058	$49,441	$43,035
80%	$16,616	$23,583	$27,144	$32,133	$41,060	$48,557	$50,767	$54,556	$46,792
90%	$16,616	$23,583	$27,144	$32,134	$41,065	$48,596	$51,246	$62,153	$53,608
100%	$16,616	$23,583	$27,144	$32,135	$41,066	$48,603	$51,288	$64,309	$71,723

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 0.01% of the initial population.

Key:
= 1 optimal
= 2 optimal
= 3 optimal

Table 6.7. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season in Combination with Admire©, Oxnard Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$36,610	$53,280	$61,596	$73,087	$92,942	$109,819	$116,197	$143,095	$140,353
10%	$36,610	$53,281	$61,597	$73,091	$92,953	$109,852	$116,275	$143,555	$142,294
20%	$36,610	$53,281	$61,599	$73,094	$92,964	$109,884	$116,353	$144,022	$144,372
30%	$36,610	$53,282	$61,600	$73,098	$92,975	$109,917	$116,431	$144,498	$146,608
40%	$36,610	$53,283	$61,602	$73,101	$92,986	$109,949	$116,509	$144,982	$149,030
50%	$36,611	$53,284	$61,603	$73,105	$92,997	$109,982	$116,588	$145,475	$151,669
60%	$36,611	$53,284	$61,604	$73,108	$93,008	$110,014	$116,667	$145,978	$154,569
70%	$36,611	$53,285	$61,606	$73,112	$93,019	$110,047	$116,747	$146,490	$157,787
80%	$36,611	$53,286	$61,607	$73,116	$93,030	$110,080	$116,826	$147,012	$161,402
90%	$36,611	$53,286	$61,609	$73,119	$93,040	$110,112	$116,906	$147,545	$165,527
100%	$36,611	$53,287	$61,610	$73,123	$93,051	$110,145	$116,986	$148,088	$170,326

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 0.01% of the initial population.

Key:
= 1 optimal
= 2 optimal
= 3 optimal

Table 6.8. Six-Season Increased Profit (Discounted), Two Esteem© Applications per Season, Under Increased Initial Resistance, Oxnard Model

Natural Decline in Resistance	Kill Rate 10%	20%	30%	40%	50%	60%	70%	80%	90%
0%	$36,468	$52,613	$60,203	$69,867	$84,040	$89,293	$81,277	$67,983	$43,577
10%	$36,482	$52,679	$60,340	$70,175	$84,819	$90,809	$83,382	$70,769	$46,181
20%	$36,496	$52,746	$60,478	$70,487	$85,621	$92,409	$85,656	$73,877	$49,111
30%	$36,511	$52,813	$60,617	$70,802	$86,447	$94,103	$88,127	$77,389	$52,457
40%	$36,525	$52,880	$60,757	$71,121	$87,299	$95,904	$90,834	$81,415	$56,350
50%	$36,539	$52,948	$60,897	$71,444	$88,177	$97,827	$93,826	$86,120	$60,996
60%	$36,554	$53,015	$61,038	$71,771	$89,085	$99,890	$97,169	$91,764	$66,739
70%	$36,568	$53,083	$61,180	$72,103	$90,024	$102,117	$100,960	$98,789	$74,222
80%	$36,583	$53,151	$61,323	$72,438	$90,996	$104,539	$105,342	$108,052	$84,868
90%	$36,597	$53,219	$61,466	$72,778	$92,004	$107,197	$110,546	$121,630	$103,007
100%	$36,611	$53,287	$61,610	$73,122	$93,050	$110,142	$116,978	$148,044	$170,067

An interest rate of 3% is used for discounting.
All profits assumed to be earned in a lump sum at the end of the year.
Initial resistance was assumed to be 1.00% of the initial population.

Key:
= 1 optimal
= 2 optimal
= 3 optimal

7. Managing the Effect of Spatial Pest Management Externalities through Grower Coordination

7.1 Introduction

Changes in production conditions associated with biological invasions can be complex. As a result, modeling invasive species management decisions can be difficult. Externalities associated with spatial relationships among growers compound this difficulty. In order to create the optimal policy for invasive species management, one must consider the effects of management decisions made by a grower in one field on the decisions of growers managing adjacent fields. In this chapter, we use the bioeconomic model developed in Chapter Four to analyze explicitly how externalities caused by whitefly movement among adjacent host crop fields affect optimal invasive species management decisions, and to suggest the potential design of optimal management policies for a region.

The lack of information about the response of growers to the movement of invasive pests across multiple fields makes creating a regional management policy more difficult for a recently established invasive pest than for a long-established pest, whose range of economic and biological impacts on multiple producers is already understood. Bioeconomic models can suggest the types of policies that should be developed by projecting their impacts through generating growers' responses to regulatory alternatives and the resulting biological and economic outcomes, such as pest populations and profits.

To that end, we examine how pest management decisions in one whitefly host crop field affect the profits from producing fall-planted strawberries, another host crop, in an adjacent field and whether a given set of regulations will result in responses that favor the regional management of an invasive species, rather than management at the individual field level. The planting and harvesting decisions of a grower of another host crop affect the grower of the adjacent strawberry field by influencing the time adult greenhouse whiteflies migrate into it. This externality suggests that managing the whitefly on a regional basis will increase strawberry producer welfare relative to the outcome that would result from growers making these decisions independently. The analysis conducted in this chapter confirms this intuition: profits from regional greenhouse whitefly population management can exceed those from private, single-field level management. In such cases, obtaining these higher profits will require growers to coordinate their efforts. However, in this case we find that the amount of coordination required is limited and unlikely to be very costly; the only requirement is that information regarding field management be shared among growers of whitefly host crops, as detailed below.

This chapter proceeds as follows. First, we describe features of the strawberry/whitefly interaction that made coordinated whitefly management beneficial for fall-planted strawberry growers in the Oxnard area, and the methods growers of many host crops adopted to reduce the size of the regional whitefly population between 2002 and 2003.[43] Second, we use the bioeconomic model developed in Chapter Four to calculate whether management decisions of a grower in one field affect the optimal management decisions of a host crop grower in an adjacent fall-planted strawberry field. Finally, we use these results to determine what type of coordination policies could be used by fall-planted strawberry growers and their neighbors to increase the welfare of the strawberry growers.

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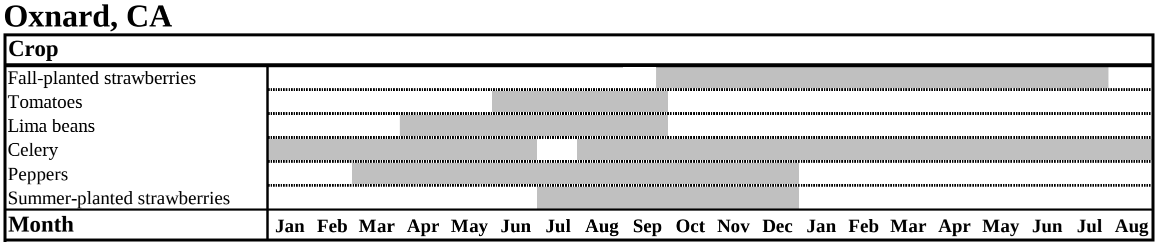
[43] Although we focus on the Oxnard area, qualitatively similar results occur between growers in the Watsonville area when a fall-planted field is located adjacent to a field that has been in place for more than one season.

7.2 The Effect of Spatial Relationships among Oxnard Area Growers on Regional Greenhouse Whitefly Population Development

The coordinated greenhouse whitefly management done in the Oxnard growing region during 2002-3 provides an interesting context for studying regional invasive species management policy. As discussed in Chapter Three, the greenhouse whitefly population in the Oxnard area moves through an annual cycle of host crops. Many crops grown in the area are viable greenhouse whitefly hosts, including tomatoes, lima beans, bell peppers, celery, and summer and winter strawberry plantings. Host crops are often in adjacent fields, well within the flight range of an adult whitefly. The duration and timing of planting, harvest, and removal of these crops are displayed in Figure 7.1.

Figure 7.1. Commercially Viable Lifespan of Greenhouse Whitefly Host Crops, Oxnard, CA



As Figure 7.1 shows, many greenhouse whitefly host crops are in the ground simultaneously. Fall-planted strawberries are planted between mid-September and early October and removed in July; tomatoes are planted in June and removed in September; lima beans are planted between April and June and removed between July and September; celery can be grown and harvested year-round, except for July–all plants are removed in order to prevent the development of a plant disease called mosaic; peppers are planted between March and June and removed between August and December; finally, summer-planted strawberries are planted in July and removed in December.[44]

Although adult greenhouse whiteflies tend to remain on or near the host plant on which they were born (Benchwick, 2005; Ishida, 2005; Byrne, Bellows, and Parella, 1990), the entomological literature mentions two factors that encourage them to migrate to other host crops. First, the adult whitefly population will move when the plant is removed (Byrne, Bellows, and Parella, 1990). Second, the adult whitefly population will move when the level of available nutrients in the current host crop is low relative to surrounding crops (Bi, Toscano, and Ballmer, 2002a).[45] These two factors are significant for the Oxnard area since many viable host crops are in the ground simultaneously, but are planted and removed at different times.

When any set of viable host crops are in the ground simultaneously, each will be growing with different amounts of vigor, based on their planting dates, psychology, and life cycle. The observations of Bi, Toscano and Ballmer (2002a) and Zalom (2004) indicate that differences in plant condition across host crops in an area determines a sequence of preferred hosts. Since newer plantings are growing the most vigorously and have relatively high leaf nutrient levels available for the whitefly to feed upon, these plants always become the most attractive food source for adult whiteflies. This means that if the plant nutrient level declines in the crops in one field, the adult whitefly will tend to migrate

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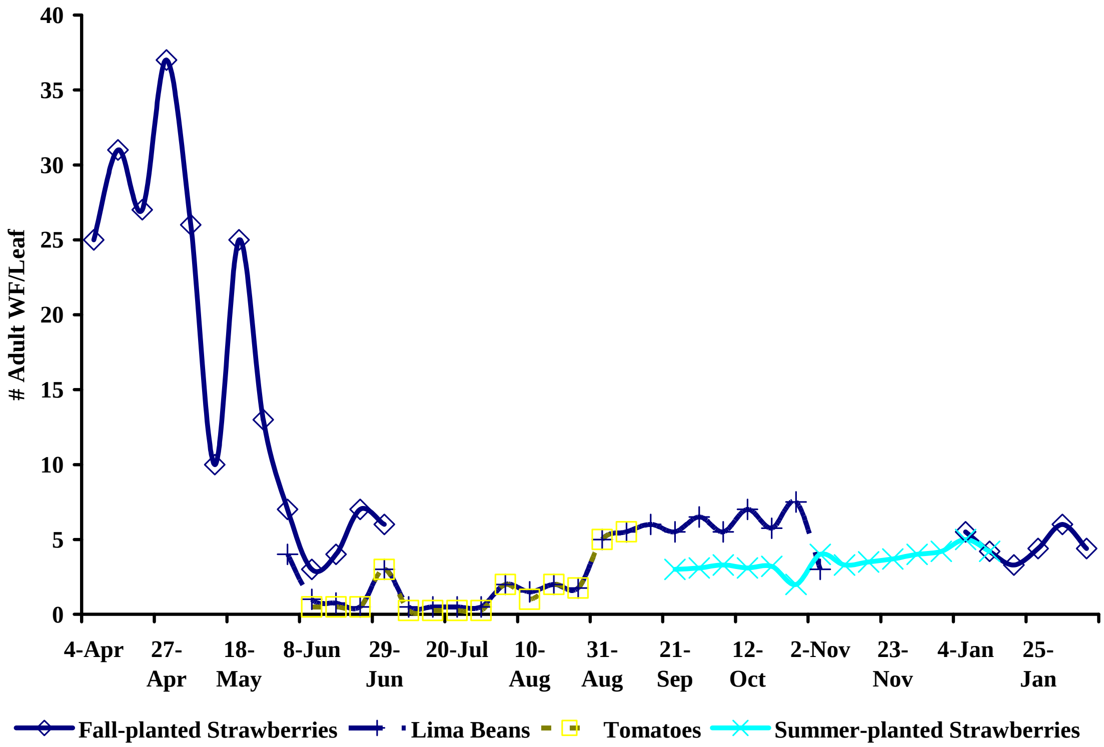
[44] Although celery is available almost year-round, scientists, growers, and pest control advisors uniformly report that the greenhouse whitefly tends to only be found in celery during the winter, and reproduces very little while it is there. The reason is that the whitefly tends to prefer other hosts relative to celery, and these are available during the other seasons of the year in the Oxnard area.

[45] Bi, Toscano, and Ballmer (2002a) observed that when the growth rate of fall-planted strawberry declined in late May and early June, the whiteflies started to settle on adjacent lima bean and tomato plantings. The decline in strawberry plant growth rate corresponds to a relative decrease in the level of nutrients available.

to the most desirable host plant in the area.[46] Similarly, if the plants in a field are removed, the adult whiteflies will migrate to a favorable host nearby, including commercially grown host crops; weeds, especially Malva; or even a bare field.

Figure 7.2. Average Number of Adult Whitefly per Leaf, by Host Crop, Oxnard, CA, 2000-1



Source: Bi, Toscano, and Ballmer, 2002a

Figure 7.2 displays an observed sampling of adult whiteflies populations per leaf on a sequence of four host crops in the Oxnard area, during a ten month period between 2000 and 2001. These data, reported by Bi, Toscano and Ballmer (2002a), show that since lima beans and tomatoes are growing vigorously at the time fall-planted strawberries decline in growth rate or are removed (in July), they become the preferred greenhouse whitefly hosts after fall-planted strawberries. Between July and September, summer strawberry plantings

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[46] The whitefly population will always move somewhere in these circumstances, even to a field with no vegetation at all. The point is that when a suitable host crop is nearby at these times, a decision maker can assume that will be where the population will go.

are in the ground simultaneously with lima beans and tomatoes, but are growing more vigorously than they are. Summer-planted strawberries, therefore, become the preferred greenhouse whitefly host plant after lima beans and tomatoes. Finally, fall-planted strawberries again become the preferred host by January, when summer plantings are removed.

The increase in the acreage of summer-planted strawberries in the Oxnard area, discussed in Chapter Three, has directly contributed to the development of the regional whitefly population. Prior to the increase in summer-planted acreage, a time gap existed when no relatively favorable whitefly host crops were present in the region. Originally, a whitefly population would move from fall-planted strawberries to lima beans and tomatoes during the middle of the summer, and then to again to other favorable hosts in the fall, such as fall-planted strawberries, while only celery or weeds were available to the greenhouse whitefly during the time between these hosts. These are relatively poor food sources compared to other hosts. As a result, only limited population growth occurs on these crops. The increased summer-planted strawberry acreage, however, provides a relatively better host crop, which now promotes the development of a relatively larger adult whitefly population that can migrate into fall-planted strawberries, causing more intensive yield loss over a longer period to the fall plants.

Because of the economic loss suffered due to the greenhouse whitefly, growers in the Oxnard area adopted the objective of controlling the development of the whitefly population through coordinated regional management. Many stakeholders participated in voluntary efforts to promote the regional management of the whitefly population in the Oxnard area, including growers of viable host crops such as strawberries and lima beans;

the Ventura County Agricultural Commissioner; pest control advisors; UC scientists; and owners of businesses adjacent to the affected agricultural areas. Representatives from these groups formed a team called the Whitefly Action Committee. The Committee's goals were to document the timing and size of whitefly migrations within the area, promote research on effective whitefly control, and develop a regional whitefly reduction strategy that all growers could follow.

In order to assess the progress of its whitefly reduction strategy, and to coordinate the grower's management efforts, the Whitefly Action Committee collected and distributed data about the size and timing of adult greenhouse whitefly population migrations between alternative host crop fields. To do this, the Committee took advantage of the observation that greenhouse whiteflies tend to remain on or near the host plant on which they were born until the plant is removed or its level of leaf nutrients declines (Benchwick and Ishida, 2005; Byrne, Bellows, and Parella, 1990). This means that the population in each whitefly-infested field remains relatively isolated during the season.

Members divided the whitefly-affected area between Oxnard and Ventura into 46 square-mile blocks. The movement of the whitefly population was observed by setting 32 cm^2 yellow sticky traps[47] at the outside edges of fields on the northwest, northeast, southwest and southeast corners of each of these blocks. After a twenty-four hour period, these traps were collected, and the number of adult whiteflies recorded. This sampling method generated observations of the quantity of adult greenhouse whiteflies passing by the 32 cm^2 area during a 24 hour period. In other words, the sample is a measure of the flow of adult whiteflies within that area at that time, and is not a direct measure of the size

[47] A yellow sticky trap is a rectangular card that has an area coated with adhesive. Any adult whitefly that lands on the area covered by the adhesive will remain attached to the card.

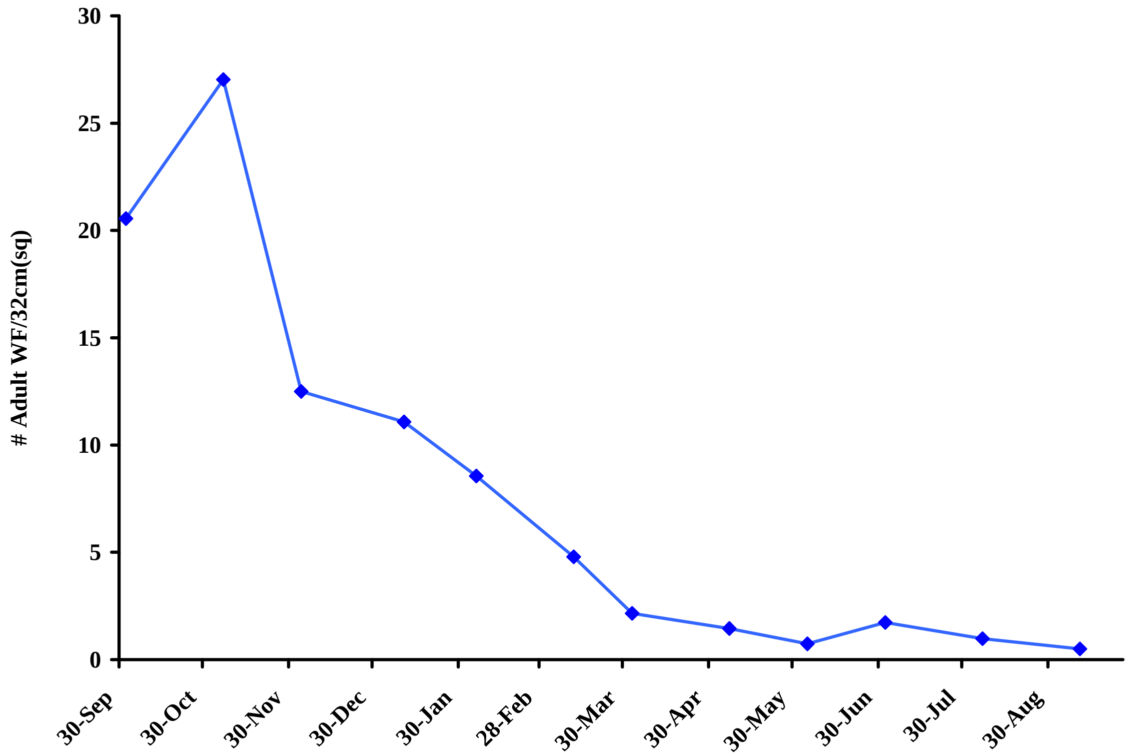
of the adult whitefly population moving into the field, which would have been prohibitively expensive to obtain. These observations were repeated on a monthly basis, between October 2002 and September 2003. After the monthly observation, the number of adults captured on the traps in each corner within each block was averaged into a single number. This number was used to represent the level of adult whitefly migration between alternative host crop fields within the entire block.

The monthly observations of adult whiteflies per $32cm^2$ per 24-hour period are the only data available to measure these migrations. Two features of the data collection procedure cause these data to provide only limited information about the movement of adult whiteflies in the area. First, the monthly interval between observations allows more than one whitefly generation to develop and move between plants. Hence, the sampling of the adult whitefly migration made in month t can only be suggestive of the size of the migrating population in month t+1. Second, the traps were placed at the outside corners of each square mile, providing only limited information about the movement of the adult whiteflies among crops at these corners, and no information about migrations within the 640 acres within each block. An average of the observations at the four corners of any given square mile is at best, therefore, a rough indicator of adult whitefly movement within that square mile.

Recognizing that these data are less than ideal, we used them to calculate a single monthly average adult whitefly migration rate so that any general trend in the size of the whitefly population could be observed during the period the Committee was active. This was done by averaging the 46 block-averages into a single number. This creates a monthly average adult whitefly migration rate per $32cm^2$ per 24 hours over the entire observed area.

As indicated, this number can be used as a very rough indicator of whether the overall amount of adult whitefly migration changed over time in the region. These averages are shown in Figure 7.3. These data show that an overall decline in the rate of adult whitefly migration was observed between September 2002 and August 2003. It is reasonable to assume that the decline in adult whitefly migration rates is related to declining field populations of greenhouse whiteflies, especially since it is supported by anecdotal reports. Migrations similar to the one in 2002-3 occurred between 1999 and 2002. In contrast, no migrations as large as those observed during the 2002-3 growing season have occurred since the formation of the Whitefly Action Committee in 2002. Smaller migrations result in larger profits for strawberry growers. Given the regression analysis performed in Chapter Four, declines in whitefly populations correspond to greater strawberry yields, which, all other things equal, lead to increased profits for strawberry growers.

Figure 7.3. Average Adult Greenhouse Whitefly per $32cm^2$/24 hour period, Oxnard, CA October 2002 - September 2003



During the data gathering process, the Whitefly Action Committee communicated its observations to stakeholders on a monthly basis. Actions made by growers in response to this information may have contributed to the decline in the size of adult whitefly migrations over time, as observed in these data. We interviewed each member of the Whitefly Action Committee, and asked what conditions they hypothesized led to the decline in the size of adult whitefly migrations, and thus the regional whitefly population, during the 2002-2003 season. The consensus of these seven interviewees was that a combination of factors was at work.

Members of the committee hypothesized that one factor contributing to the decline in adult whitefly migration was the use of Admire© at planting, followed by foliar applications of other pesticides, such as Esteem©. The combination of Admire© followed by Esteem© was more effective than any other possible combination of pesticides registered for use on strawberries prior to 2003. In fact, the California Department of Pesticide Regulation required that, if Esteem© was used in the selected field, Admire© must also be applied at the time of planting. The Committee and stakeholders supported this regulation in an effort to promote the use of relatively effective pesticides among growers in managing the whitefly.

A second factor that committee members hypothesized to have contributed to the decline in adult whitefly migration was changes in field management practices, especially the timely removal of old or abandoned host plants. These changes in field management practices were specifically suggested by the Committee, and were intended to limit the amount of host plant material available to the whitefly after the agricultural crop was no longer commercially viable. The interviewees indicated this recommendation led to earlier host plant removal than would otherwise have been done by growers in the area.

A third reason suggested by some Committee members was the perception that a cooler winter in 2002-3, relative to the previous two or three years, slowed the rate of whitefly population development.

The final factor the interviewees cited was coordinated whitefly population management among growers. Data provided by the Committee were the only data available to growers and PCAs regarding the regional nature of adult whitefly movement, the volume of whitefly migration, and the relationship between whitefly movement timing and host crops in the area. All of them thought that the Whitefly Action Committee's two-pronged approach, communicating specific whitefly management strategies and publicizing reports about the monthly aggregated whitefly population data, led to a more rapid decline in the whitefly population than would have occurred without the Committee's communication network. This was based on two perceptions. First, as a result of collecting and distributing the information provided by the Committee about, Committee members believed that individual growers used the information regarding the size and timing of whitefly population movements collected and distributed by the Committee to make different whitefly management decisions then they would have made without it.[48] Second, Committee members believed that the changes in management practices growers made as a result of being provided with this information led to a greater decrease in whitefly migration than would have occurred under the management practices growers would have used if the Committee had not distributed the information.[49] Both of these perceptions suggest that the most effective way to manage a pest, whose population builds as it moves through a continuous cycle of host crops, may be through regional coordination. Biology also suggests that regional coordination may be useful, because it can reduce the size and number of migrations into a strawberry field. The bioeconomic model will be used in the next section to assess the benefits of coordination to strawberry growers.

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[48] This perception could be tested using survey techniques; however, doing so was beyond the scope of this study. The interviews of fall-planted strawberry growers for this study indicated that the information provided by the Committee was essential for their decisions about whether or not to treat their field with Admire and Esteem. In fact, one grower indicated that without that information, he would "still be guessing" about how to make whitefly management decisions.

[49] There is no rigorous way to test the second hypothesis–the control cannot be constructed without undue risk of whitefly infestation to growers in the area. It appears that stakeholders used the strategy and data provided by the Committee to observe whether or not coordinated management decisions had any effect on the regional whitefly population. The subsequent whitefly population movement data suggest that the decline in the size of the whitefly population was related to these decisions.

7.3 *Economic Analysis of the Externalities of Pest Management*

In this section, the bioeconomic model developed in Chapter Four will be used to determine whether coordination increases profits when the externalities of field management practices affect invasive species management decisions. For this analysis, we assume that an adjacent host crop field is infested with whiteflies and that the timing of whitefly migrations is driven by the removal of a host crop in an adjacent field; if the adjacent field has no whiteflies, no migration is assumed to occur. For example, if a fall planting of strawberries has recently been made, and then the plants in an adjacent, infested, field are removed, then the adult whiteflies in that adjacent field will be displaced and will migrate to the strawberry field. For purposes of this analysis, immigration is defined as an increase in the number of adult whiteflies per leaf on all plants in the field as a result of their arrival from a source other than the observed field, and not the natural increase in the adult whitefly population associated with the reproduction of the whiteflies which entered the field at planting.

To determine the effect of these spatial relationships among producers on optimal greenhouse whitefly management in fall-planted strawberry fields, we will compare the optimal timing for Esteem© applications for a strawberry grower who only considers the effect of whitefly infestation at planting (reported in Chapter Five) with the optimal timing for a grower who also considers a second infestation later in the season associated with an immigrating adult whitefly population from another host crop. If the optimal timing of the Esteem© applications does not change as a result of considering the second infestation, then the strawberry grower's private whitefly control decision is unaffected by spatial relationships among growers. Alternatively, if the optimal timing of the Esteem© applications does change as a result of the second infestation, then coordination among growers may be needed in order to maximize returns from whitefly management.

We will also assess whether the Esteem© use restrictions themselves affect the need for the coordination of whitefly control activities among growers. It could be, for example, that a third Esteem© application could substitute for coordination. This would be the case if making a third Esteem© application would eliminate the need for growers to adjust the timing of Esteem© applications based on the timing of migrations in order to increase profits.

Finally, in this analysis, we do not explicitly consider the effect of strawberry grower decisions on neighboring growers, because data do not exist about the relationship between greenhouse whitefly population dynamics and yield losses for alternative host crops.

7.3.1 Two Esteem© Applications

In this subsection, we assess the effect of a second adult whitefly immigration on the optimal timing of two Esteem© applications on fall-planted strawberries in the Oxnard area. In each of these cases, we calculate the optimal timing of two applications of Esteem©, (after an Admire© treatment) given an infestation of adult whiteflies at planting, followed by a second immigration of adult whiteflies at various points in the strawberry growing season, which represents the effect of decisions made by growers of other host crops. To ascertain the effect of a second immigration on optimal Esteem© application timing at any point in the season after the Admire© application loses its efficacy, we consider twelve different possible weeks for a second infestation. We then compare the optimal Esteem© treatment dates with the privately optimal application timings calculated in Chapter Five.

The results of this analysis show that multiple whitefly immigrations may make it optimal to change the timing of an Esteem© application. The level of coordination required in order for growers of fall-planted strawberries to realize this, changes over the course of the season. First, there are points during the strawberry growing season when the only way for a strawberry grower to optimally time his Esteem© applications is for him to receive information from adjacent growers about intended host plant removal times. In these cases, the grower would find it optimal to change at least one Esteem© application date, and would need to make this decision before he could observe the host plant removed; in other words, for this analysis, coordination is required when a grower would find it optimal to adjust an application time to a week prior to the host crop removal, before a second migration occurs. Second, there are other points in the season when the grower may find it optimal to change at least one Esteem© application date, but would observe the second immigration before the newly optimal application timing. In this situation, coordination has no value to the grower.

Second, whitefly immigrations due to host plant removal on March 1 or February 1 in an adjacent field require coordination for a fall-planted strawberry grower to maximize profits. Profits from strawberry production can be increased by coordinating management activities due to a March 1 adult whitefly immigration, which corresponds to a celery harvest. If two Esteem© treatments are made during the season, and the effects of the March 1 immigration are considered, the optimal timing of the first application changes from November 1 to November 8, and the optimal timing of the second application changes from the week of January 13 to the week of January 6. Even though neither of the application dates changes much, profits increase by changing the timing of the applications. However, the growers need to coordinate in order for the strawberry grower to identify the optimal application dates, because both Esteem© applications occur before the celery harvest. An information exchange between growers is the only means for a strawberry grower to know how migrations of adult whiteflies from the celery field will affect optimal Esteem© application dates for his strawberry field.

In the case of a February 1 whitefly immigration, the optimal timings for the Esteem© applications are the weeks of November 1 and February 3. No communication between adjacent growers would be required prior to making the first Esteem© application, since it remains unchanged from the privately optimal time. In contrast, the grower must obtain information prior to the second application in order to adjust the application date, which will no longer be January 13 as before. Since this will affect the timing of an application that would have been made before the migration, this information is assumed to come only from notification, and coordination is required. The second application is later in order to control the population from the first and second immigrations. The second application maintains a lower adult whitefly population for a longer period, relative to when a second migration is not considered in the application timing decision. The case of a second immigration on May 1 also fits this category.

We found two cases when a grower would find it optimal to change one or more application dates, but would not have to coordinate with adjacent growers because he would observe immigration prior to adjusting management decisions: a second migration on December 1, or on November 1. The first case that we examine for which communication may not be necessary is a December 1 immigration. Now the optimally timed Esteem© applications are done the weeks of November 1 and February 3, instead of November 1 and January 13. Growers will not be required to exchange information before the first Esteem© application in order for the optimal treatments to be made. Grower observation of the December 1 migration should be sufficient to adjust the timing of the second application. In this case, the population under the optimal control program is slightly between January 13 and early March, relative to the applications that does not account for the second migration. This occurs because the migrating population increases the number of eggs recently oviposited in the field. The number of eggs left by the January 13 application creates a relatively large spike in the adult population, by early April, of about five adults per leaf. In contrast, the second optimally timed application on February 3 allows these eggs to mature into nymphs, takes advantage of Esteem©'s efficacy against nymphs to decrease that population, and results in a subsequent adult population spike of about 2.5 adult whiteflies per leaf. Also, since Esteem© has been modeled as less effective against adult whiteflies as eggs or nymphs, a December 1 application only will only reduce the combined adult population, whereas a later application would eliminate a larger percentage of the total population by eliminating eggs and nymphs.

The second case in which coordination was unnecessary involves a November 1 migration, again in connection with a celery harvest. If two Esteem© treatments are made, the weeks of November 1 and December 30 are optimal. Again, absent the grower accounting for the second immigration of adult whiteflies into his field, these applications would occur on November 1 and January 13. The grower can observe the development of the combined whitefly application before making a decision about when to make a second application. In this case, the grower does not need to exchange information with the celery grower since the November 1 celery harvest and ensuing greenhouse whitefly migration are observed prior to the optimal second application. The optimal timing of the application changes because the December 30 application reduces the combined nymph populations from the eggs laid by the first and second immigrations by more than the January 13 application.

The remaining ten cases we examined are weeks in the fall-planted strawberry growing season when a second immigration of adult whiteflies would not induce a grower to change the timing of his Esteem© applications. As a representative example, we discuss a second adult whitefly immigration into a fall-planted field after removal of a summer-planted strawberry field around January 1. We chose this one because it is an actual case observed in the adult whitefly movement data collected by the Whitefly Action Committee.

We find that if a second adult whitefly infestation occurs around January 1, the optimal weeks for two Esteem© applications remained November 1 and January 13, as calculated in section 5.6. Applications at these times resulted in the highest profits for the fall-planted field. In this case, this program reduces the February, early-March adult whitefly population by more than waiting to make the second application. This occurs because the Esteem© application kills enough of the eggs from both the original and secondary immigration of adult whiteflies to make it preferable to any other time. In addition, the cooler temperatures at this time slow egg production, making the combined effect of the January 13 application on the adult and egg population more important than the more powerful effect of a later application on the nymph population. Members of the

Whitefly Action Committee confirmed this interpretation of the data (Benchwick, 2005; Ishida, 2005; Malone, 2005).

Other dates in the season when growers would not find it optimal to change any application timings, in addition to January 1, include February 15, March 15, April 1 and 15, and May 15. Each of these cases follow the same logic as the January 1 case: the highest profits were obtained by not changing the optimal Esteem© application timing relative to the dates reported in Chapter Five.

The analysis in this section shows that pest management decisions in one field affect the profits from producing fall-planted strawberries in an adjacent field. We have shown that strawberry growers would either make no changes to his Esteem© application timing due to a secondary adult whitefly immigration; will find it optimal to change the timing, but would not need to coordinate with adjacent growers to do so; or will find it optimal to change the timing and will need to coordinate with adjacent growers. When a grower finds it optimal to make these changes, the amount of coordination required is limited– the only requirement is that information related to field management be shared among growers of whitefly host crops.

7.3.2 Three Esteem© Applications

In this subsection, we assess the effect of second whitefly infestations on the optimal timing of three Esteem© applications (after an Admire© application) on fall-planted strawberries in the Oxnard area. The purpose of this analysis is to assess whether or not allowing three Esteem© applications would substitute for coordinated pest management by eliminating an increase in profit through sharing information. As in the previous subsection, the results of this analysis show multiple whitefly immigrations may make it optimal to change the timing of an Esteem© application. As in the two-application case, the level of coordination required in order for growers of fall-planted strawberries to realize this changes with the timing of the second infestation. The ability to recognize any divergence between the optimal private and optimal multi-producer management responses to an invasive species informs the policymaker about the benefits of coordination. This, in turn, allows the policymaker to evaluate the benefits of instituting mandatory coordination and compare them to its costs, if voluntary coordination does not occur.

We analyze one second infestation date in detail for each of three categories. The first category contains a second infestation date for which a grower will find it optimal to change one or more application dates, but coordination is required in order for him to maximize profits from strawberry production. As in the two-application case, March 1 and February 1 fit into this category, and February 15 has moved into it. The second category includes a second infestation date for which a grower will find it optimal to change the timing of his Esteem© applications, but no coordination is required in order for him to maximize profits. As in the two-application case, December 1 and 15 fit this category, but November 1 drops out of this class, and May 15 is now included. The third category contains a second infestation date for which a grower will not find it optimal to change application dates and coordination will not be necessary to increase the profit from strawberry production. As in the two-application case, this includes March 15, April 1 and 15. November 1 and May 1 are also now included in this group.

To illustrate the first category, we examine the effects of a second immigration on March 1, due to a celery harvest, on optimal Esteem© application timing. This resulted in optimal applications during the weeks of November 1, January 6, and March 5. Although the immigration will not have occurred yet, it is optimal to make the second application later by a week (January 6 instead of December 30) and the third made later by over a month (March 5 instead of January 29), relative to the single-field model. No coordination between adjacent growers would be required prior to making the first Esteem© application. However, since the grower may not be able to observe the migration before having to change the timing of the second application, coordination must occur, through information exchange, prior to the second and third applications in order for the strawberry grower to maximize profits.[50] The reason for the change in application timing is that making the second application later kills nymphs that will mature later, preserving yields when plants produce berries the most rapidly (during March through May in the Oxnard area) by reducing the adult population at that time. It is optimal to make the third application later because it slightly reduces the recently-arrived adult whitefly population, and kills the eggs they would already have oviposited. Since the fresh season ends soon after this application (most plants are producing for the processed berry market by May), this result indicates that the optimal timings emphasize protecting the fresh, rather than processed, harvest.

To illustrate the second category, we examine the case of a celery harvest occurring around November 1, coordination was unnecessary, as in the two-application case. An immigration at this date resulted in the optimal timing of the third application being one week later, around February 5 instead of January 29, when the effects of a second immigration are included in a grower's decision. The change in optimal timing can be explained by a larger, but delayed population peak caused by the second immigration of

[50] A second migration on February 1 had the same qualitative result, just as in the two-application case.

adult whiteflies, which is managed by the later application date. Although the grower would find it optimal to change the timing of the second application because of the second immigration, the grower can rely on his own observation make this change, and no coordination is needed.

For second infestation dates in the third category, optimal application dates do not change as a result of the second infestation. Consider the removal of a summer-planted strawberry field around January 1 in an adjacent field. It does not change the optimal timing for Esteem© applications in a fall-planted field, as was true in the two-application case in section 7.3.1. Hence, the optimal timing for making the three treatments remains the same as in Chapter Five, with applications done the weeks of November 1, January 6, and February 5. In this case, the timings of the second and third Esteem© applications remain profit-maximizing, despite the second immigration, and the timing of the first remains unchanged from November 1. In contrast with the results of the two application case in section 7.3.1, these simulations indicate that when three applications are available it can occasionally be optimal to make the second application soon after the second immigration, rather than waiting for the population to grow and making the application right before a projected population peak.

We now examine whether the availability of a third application changed whether or not fall-planted strawberry growers would voluntarily coordinate their whitefly management decisions. There are two ways of assessing its effect: for the season as a whole, and for individual weeks. First, for the season as a whole, a third application does not eliminate the benefit of coordination because there are still second migration weeks for which coordination increases the strawberry grower's profits. Second, the benefits of coordination changed for some second migration weeks. Four dates changed category for the required amount of coordination necessary to maximize profits. First, a second migration on November 1 changed from it being optimal to change application dates, but not necessarily exchange information, to no difference in the optimal dates between the privately optimal solution in Chapter Five. In this case, making any applications earlier, as when only two applications are permitted, is not necessary since the third application is able to optimally reduce the population. The application on May 1 changed in the same manner.

Second, a second migration on February 15 changed from it being optimal to not change any application dates and to not coordinate, to it being optimal to change an application date and needed to coordinate in order to maximize profits. The second and third applications must now be done on December 1 and January 6, which are both prior to the second migration. This series of applications reduces the adult whitefly population slightly, compared to the series of applications calculated without including the effect of a second migration, which will preserve more fruit during this period of increased production.

Third, a second migration on May 15 changed from it being optimal to not change any application dates and to not coordinate, to it being optimal to change an application date but not necessary to coordinate in order to maximize profits. In this case, allowing a third application makes it valuable to rearrange the application timing so that the adult whitefly population is, again, reduced during April. This change, however, allows the adult whitefly population to be higher in January than in the privately optimal case.

These cases demonstrate that even when a third Esteem© application is allowed, occasionally the optimal timing of one Esteem© application must be adjusted, relative to the single-field model, when a second immigration occurs, and that coordination may or may not be needed in these cases. Other cases exist when a grower would not find it optimal to adjust his Esteem© application timing, relative to the single-field model. Because cases exist when a fall-planted strawberry grower would find it optimal to change the timing of his Esteem© applications and coordination will be needed, relaxing the Esteem© use restrictions to allow three Esteem© applications, as opposed to two, does not remove the possibility for increased profits by coordinating; communication may still be required. On the other hand, as these results show, allowing more applications changes the times of the growing season when coordination is required to maximize profits.

7.4 Cooperative Invasive Pest Management

The analysis in section 7.3 demonstrates that a relationship exists between the expected value of learning about whitefly immigration dates and the incentive to coordinate management decisions. To maximize profits, the grower must form an expectation about the timing of future whitefly infestations and calculate any changes these will make on the optimal timing of Esteem© applications. When a grower expects that a future infestation will change the optimal timing of his Esteem© application, it is possible that the only way for him to verify this is to communicate with neighboring growers. Alternatively, if the grower expects that these infestations will occur at other times of the growing season, communicating with neighboring growers is irrelevant because the optimal treatment dates either do not change, or the grower will calculate the changes to the optimal Esteem© application times on his own. In the absence of any information, there is a positive expected benefit of communicating for the strawberry grower, because in some cases knowing the likely date of a future infestation and adjusting application dates accordingly will increase profits.

Based on the analysis in this chapter, it is apparent that when coordination is required among growers to increase profits, it can come in the form of an exchange of information. If a strawberry grower is about to plant, he needs to know the date whiteflies may move from adjacent fields into his as a result of the management choices of its grower. The plant removal date, for example, can be communicated to the strawberry grower based on the neighboring grower's experience with these crops.

The exchange of information regarding the presence of whiteflies in adjacent fields, and the likely time of their migration, can be done via informal communication among pest control advisors or growers. When the grower finds it optimal to change Esteem© application dates, and cannot make this calculation based on his own observation, this communication must take place at or before the first application date. The incremental costs associated with the transfer of this information could be covered by a surcharge to strawberry growers for asking pest control advisors (PCAs) to observe the edges of adjacent fields, in addition to their usual services of observing the pest conditions in the grower's fields (Benchwick 2005; Ishida 2005). This method assumes that PCAs will know the planting and removal dates of specific fields, which is common practice. Alternatively, policy makers may desire to enact a formal coordination requirement, administered by some type of government entity, if informal methods of data gathering and communication do not emerge due to transactions costs or other coordination problems.

In either the formal or informal case, an information exchange program can only be economically justified if the benefit from the exchange is at least as great as its cost. The benefit from such a program comes from avoiding increased control costs, and reducing foregone yields. These could be accrued over one or several years.

To estimate the costs of such a program, one could use the notification requirements associated with methyl bromide application in California as an example. The direct costs of the methyl bromide notification program are negligible. In this program, growers are required to formally notify the occupants of property within a specified range of the application area of the timing of the methyl bromide application. Carter et al. (2005) estimated that the cost of a typical methyl bromide notification ranged between $2 and $10. The amount of time required for assembling and distributing information to notify adjacent growers about anticipated crop planting and removal dates would be comparable to assembling and distributing methyl bromide application notices. These notification costs represent between 0.01% and 0.03% of the value of the yield from an untreated acre of strawberries, given the average weekly price per pound of strawberries in the Oxnard area between 1999 and 2003. These costs are negligible to strawberry growers.

There are two reasons why information exchange may emerge voluntarily. First, coordination can be beneficial to strawberry growers producing in fields adjacent to ones with alternative host crops which generate populations of migrating adult whiteflies at certain times of the year. As shown, because adult whiteflies migrate across field, the management decisions of one grower affect other growers in the area. The analysis shown in section 7.3 demonstrates that if strawberry growers use information whitefly immigration dates to adjust Esteem© application timing, profits may increase relative to the case when information is not shared. This suggests that if growers of adjacent fields did not provide information for free, strawberry growers may be willing to pay for information in order to make optimally timed pesticide applications.

A second condition favoring voluntary coordination is that the net benefits from free-riding on the coordination efforts of others are small to growers of whitefly host crops, and may even be negative. Free-riding consists of benefiting from reduced whitefly populations as other grower share and utilize information about the timing of adult whitefly population migrations, while not sharing similar information with adjacent growers of host crops themselves. The benefits to free-riding include the alternative use of resources used for the cost of sharing information among growers. The result of this, however, is that the neighbor will not make optimally timed Esteem© applications, leading to a larger-than-optimal whitefly population at the end of the season. Other things equal, this results in a larger adult population migrating back into the free-riding grower's field at a future date, leading to foregone yields and increased control costs. When these costs exceed that of coordination, the net benefits to free-riding are negative.

7.5 Chapter Summary

In this chapter, we have used the bioeconomic model developed in this study to determine whether profits could be increased through coordinated whitefly management decisions when externalities occur as a result of spatial relationships among growers. We found that two sets of conditions exist, regardless of the current Esteem© use restrictions, under which coordination could increase profits. In some cases the results showed growers need to coordinate, via sharing information about the timing of the field management decisions in order to maximize profits in their own fields. In other cases, the results indicate that growers could observe the decisions of adjacent growers prior to making changes to his subsequent management decisions, making coordination unnecessary; however, if these observations could not be made, coordination would again be required. On the other hand, a third set of conditions would not increase profits: there are times of the growing season when a fall-planted strawberry grower would never find it optimal to change the timing of his Esteem© applications, relative to the results obtained from the single-field model. In these cases, coordination has no value to the grower.

The analytical results of this chapter have three important policy implications. First, permitting more applications of pesticides per year will not necessarily substitute for coordination among growers when seeking to control invasive species, such as the greenhouse whitefly. The analysis comparing optimal grower decisions when the two-application limit for Esteem© is imposed and when it is relaxed to allow three applications demonstrated that greater profits can be obtained through coordination in either case. The use of the methodology was essential, therefore, in identifying the incremental effects on producer behavior of changes in environmental regulations designed to manage an invasive species.

The second policy implication is that it is not always necessary to create a central agency for controlling the economic effects of invasive species. For the case of fall-planted strawberry growers in the Oxnard area, we used the bioeconomic model of whitefly management to determine when they would be willing to voluntarily coordinate their whitefly management efforts with growers of adjacent host crops. These results help explain the development of the Whitefly Action Committee, and the willingness of fall-planted strawberry growers to participate in it. Our analysis shows that in the cases where coordination is beneficial, fall-planted strawberry growers need to obtain information from growers of adjacent fields prior to the first application date, whether or not an infestation ultimately occurs. Furthermore, there were virtually no benefits to free-riding for fall-planted strawberry growers. In fact, they would find it profitable to provide such information to their neighbors themselves, in order to reduce the expected future whitefly population. When these conditions exist and adjacent growers find it profitable to provide the necessary information, voluntary coordination may be possible.

On the other hand, if growers of alternative host crops, whose profits are very small relative to those of fall-planted strawberry growers, do not find it profit-maximizing to exchange information when the cost of coordination exceeds its benefits, then two situations could occur. First, the growers could agree on a price the strawberry grower could pay to the grower of the adjacent field to compensate them for any effort to gather the required information. Second, if transactions costs are too great for voluntary coordination to arise, policy makers may be able to increase social welfare by mandating grower participation in an information systems managed by university cooperative extension, a regulatory agency, such as the California Department of Agriculture, or another government entity. The optimal design of such a program is outside the scope of this analysis. The results in this chapter simply suggest that there is a possibility that a mandatory program may increase social welfare under certain conditions. Again, however, the methodology presented in this paper was essential to identifying elements of such a program.

The analysis in this chapter demonstrates a method that policymakers can use to obtain information about the likelihood of growers successfully developing voluntary coordination measures. This chapter showed that a bioeconomic model can enable an analyst to evaluate a series of explanations for how a set of agricultural producers behave, and then provide a reasonable case for inferring that others in the same situation may act similarly. For example, this chapter explained why Oxnard area strawberry growers may or may not voluntarily coordinate their whitefly management strategies using the bioeconomic model developed in this study. All the available biological and economic information related to the greenhouse whitefly/strawberry interaction was incorporated into the model, but its value is not limited to these variables. An analyst can incorporate other factors identified by growers or policymakers as essential determinants of the emergence of voluntary coordination into the model and evaluate their contributions through sensitivity analysis, in order to see whether or not these are likely to affect the model's conclusions, much as the model was used in Chapter Six to evaluate the benefits of reduced resistance in the whitefly population,. In this way, the model both predicts behavior and provides a means of identifying future data collection priorities.

8. Conclusions

Developing a method for analyzing the effect of invasive species policy on grower behavior deserves particular attention from economists because regulations must often be chosen when only limited information is available about the damage the invader may cause, the response of growers to it, and the effect of regulation on that response. The overall goal of this study, therefore, has been to develop a theoretical and empirical approach for measuring the costs and benefits of invasive species management policy.

Our findings make specific contributions and, more broadly, demonstrate that it is essential to consider both economic and biological factors when creating policies that affect invasive species management. The key biological components of the model used in our study were the population dynamics of the greenhouse whitefly and the population strawberry-yields relationship. Similarly, the key economic component was the grower's profit-maximizing behavior in response to regulations. Modeling the two jointly permits the analyst to ascertain the determinants of changes in profits available to growers. The failure to include either of these components leads to an incorrect conclusion about how a grower's management choices will change when controlling a biological invader. These errors would occur as a result of miscalculating the optimal timing of management decisions, failing to anticipate what additional information would improve the analysis, and mischaracterizing the externalities from management decisions. In addition, the magnitude of these errors would change depending on the time horizon considered—the optimal long-term policy is very different from the optimal short-term policy, as shown by comparing Chapter Five and Six—or the number of growers—the management externalities of adjacent growers cause the value of the coordination policies to change throughout the season, as shown by comparing Chapters Seven and Five. The failure to model grower incentives with both economic and biological information obscures the nature of these differences.

8.1 Findings

In the course of our analysis, we have addressed the question of how the biological, economic, and regulatory features of an invasive species management decision affect the optimal management response. This was done by completing three research objectives, which were outlined in Chapter One. The first objective was to assess how the optimal timing of a grower's pest control applications is affected by pest biology, market prices, and government regulations. The second objective was to analyze how efficiently government regulations, such as pesticide use restrictions, preserve the ability to use pesticides by delaying the development of resistance. The final objective was to analyze the factors that affect successful management of an invasive pest when control is more effective on a regional level than on a farm-by-farm basis.

In Chapter Two, we discussed our research objectives in the context of the existing economic literature, and identified the contributions our research will make. One contribution is an empirical demonstration of how a model that uses incomplete information about the new biological and behavioral feedbacks in the ecosystem can be used to conduct policy impact assessment, calculate the optimal producer response to externalities, and identify data collection priorities, as discussed in chapters Five, Six and Seven. A second contribution is our demonstration of the effects on the grower's optimal response of information lost when statistical techniques are used. Finally, our study contributes to the entomology literature by modeling a specific instance of invasion: the recent establishment of greenhouse whitefly populations in strawberries.

In Chapter Three, we provided the factual background for the interaction between the greenhouse whitefly and strawberries. This includes features of the California strawberry industry which influence whitefly management decisions, a description of greenhouse whitefly biology and the economic loss it causes, methods used to manage the whitefly, and a specific set of regulations that affect whitefly management decisions. A number of characteristics of this system enhance its effectiveness as an illustration, including the complexity of the pest management decision, the need for only a relatively short series of data to model key biological features, and region-specific optimal pest management decisions. Furthermore, the spatial and temporal features of these characteristics require a rich decision making model. We considered several temporal features of this system, including the regular market price cycle for strawberries, the population dynamics of the whitefly, and the rate at which the whitefly develops resistance to pesticides. We also considered an important spatial feature of this system, the effect of whitefly movement across adjacent host crop fields on the whitefly control decisions of strawberry growers.

In Chapter Four, we developed the bioeconomic model used in this study for assessing the costs and benefits of invasive pest management policies. We used this model in Chapters Five through Seven to complete our research objectives.

8.1.1 Results for the First Research Objective

To complete the first objective, in Chapter Five, we analyzed the effects of use restrictions for a pesticide, Esteem©, on the optimal timing of a grower's pest control decision. In sections 5.2 and 5.3, we find that the limit on the number of Esteem© applications permitted by the use restrictions imposes a cost on a strawberry grower; he would prefer to make more applications. We also show, in section 5.3, that in the case of using Admire© with Esteem©, requiring the use of multiple pesticides may not necessarily reduce the costs of pesticide use regulations, and may increase them. The analysis in section 5.4 shows that imposing a restriction on the pesticide application timing can also be costly to the grower. In section 5.5, we compare the costs and benefits of these use restrictions in two geographically separate growing regions. Differences in climate and planting date, but not differences in market price, across the two regions make the optimal grower response to policy unique for each region, and change the costliness of the restrictions across regions. The results in section 5.6 show that the output price cycle for strawberries does not directly affect the optimal Esteem© application decision. Instead, the grower's choice of pesticide application timing is affected by the planting date, whether or not Admire© is used, the population dynamics of the whitefly, and the timing and application limits imposed by the use restrictions. Also, in section 5.7, we show that tradeoffs exist between current production and future economic loss from whitefly population growth.

Finally, in section 5.8, we demonstrated the importance of using available biological information about the new system formed by the interaction of the newly established invader and the incumbent species. The simulation model uses readily available data and physiological models to estimate the economic harm the greenhouse whitefly causes through decreased profits from strawberry production. The added information makes its whitefly population predictions more accurate than the autoregressive model, which only uses data on whitefly population levels. Though the simulation model is still constrained by data availability, it is better able to describe the feedback between grower management decisions and the biological interaction between the invader and host plants than the autoregressive model. This improvement is important for two reasons. First, it allows policy makers to better anticipate the effect of proposed regulations on grower behavior. Second, more accurate statements about the magnitude of the costs and benefits of various policies are possible, which may lead to different conclusions about policy impacts.

The cumulative findings from the first research objective are that government regulations do affect the optimal management response; that pest biology cannot be ignored when calculating it; and that economic variables may be less influential than expected, in some cases, in determining the optimal management response. These findings imply that policy makers must include all available information about both the biology and economic factors in a model of the new system created between the incumbent species and recently established invasive species, and then examine the sensitivity of the proposed solution to these factors, else inaccurate policies will result.

8.1.2 Results for the Second Research Objective

To complete the second objective, we assess the long-run effects of pesticide use policies on grower behavior and returns in Chapter Six. In order to do so, we modified the bioeconomic model developed in Chapter Four to include a pesticide resistance component. The results of this analysis contrast with those from the short-term analysis in Chapter Five: conditions exist for which the Esteem© use regulations are profit-maximizing, and others for which they are not. This suggests that government regulations can be used, under certain conditions, to delay the development of pesticide resistance–a particular concern for managing invasive species since few pesticides may be available or registered for use. These results also demonstrate how the use of available data to conduct a sensitivity analysis can establish priorities for future data gathering. These priorities may include more precise measurement of biological or economic factors which are likely to affect the optimal management decision, or determine how long data should be gathered before the optimal response can be accurately calculated.

8.1.3 Results for the Third Research Objective

To complete the final objective, we use a modified version of the bioeconomic model to determine how privately optimal management decisions are affected when pests move across fields, and when this justifies the use of public policy to improve producer welfare. The results in sections 7.3 and 7.4 show that at some points in the growing season, producers will not maximize profits from strawberry production unless they are provided a mechanism through which they can coordinate their whitefly control decisions with other growers. Information about the optimal response of growers to the biological, economic, and regulatory constraints of the invasive species management problem informs policy makers about incentives for voluntary coordination among growers. The issue for a grower is to determine, ex ante, whether or not coordination is beneficial. Thus, by completing the third research objective we have demonstrated a method for determining how growers might optimally manage an invader that moves across fields, calculated the conditions for which various institutions may be needed to improve producer welfare given their optimal response, and explained why growers of greenhouse whitefly host crops in the Oxnard area may have coordinated as they did during the greenhouse whitefly infestations during and before 2002-3.

8.2 Contributions

Our study contributes to the existing literatures in economics and entomology. Our primary contribution to both fields is methodological: we have developed a conceptual approach for evaluating how policies affect the management of recently established invasive species, even when limited information is available, and implemented it for a specific invasive species problem. The results of this study imply that any such approach requires accurately modeling the feedback among relevant biological, economic, and regulatory factors. The results can be used to calculate the costs and benefits of management alternatives, and identify which parameters and relationship most affect the results, which, in turn, aids in prioritizing data collection efforts to inform future policy decisions.

Our analysis in Chapter Four of a specific invader, the greenhouse whitefly, and host, field-grown California strawberries, contributes to the entomology literature by describing the economic significance of a new host-pest interaction, and by quantifying the rate of the invader's population development in under various treatment conditions.

Chapter Five demonstrates a method for analyzing which various economic, biological, and regulatory factors are determinants of the optimal management response, and how they affect the outcome. Upon knowing the effect of a given factor on the optimal response, the decision maker is then in a position to know whether that factor should be more measured more precisely. The benefit the decision maker would expect from the improved precision is to reduce any reduction in profits available from the misleading response calculated by the incomplete information model, and the “truly optimal” response from a complete information model.

Chapter Six demonstrates a similar method, except it was used to evaluate how the long-term policy conclusion may change depending on the precision with which biological factors determining the benefit of reducing the development of pesticide resistance are measured. Additionally, Chapter Six illustrated the value of using sensitivity analysis to assess which factors are most likely to alter policy conclusions. This assessment can in turn be used to prioritize data collection efforts.

The analysis in Chapter Seven demonstrates that a bioeconomic model can be used to evaluate whether or not voluntary coordination might be expected to emerge among producers who must each manage the same invasive species, but at different times of the year. All available information was incorporated into the model, giving policy makers a means to anticipate likely reaction to regional management policies.

In the end, these contributions suggest a method for efficient policymaking in connection with a newly arrived invader. We have demonstrated how changes associated with that invasion, and their associated externalities, affect production. In particular, we have shown that available information about these changes can be used to assess the likely response of a grower to an invasive species in agriculture. The method used in this study shows the importance of bioeconomic models for making an empirical assessment of the effects of regulations on the welfare of affected economic agents, on the efficacy of control of the pest, and for suggesting the types of information that would be most valuable for improving the economic efficiency of regulations as the invasion persists. When properly applied, this method considers both the economic and biological features of invasive species management in order to develop efficient environmental policy, even when limited data are available.

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