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The Spatial-Dynamic Benefits from Cooperative Disease Control in a Perennial Crop

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We develop a novel spatial-dynamic model of landowners managing a disease in a perennial crop. We use the model to investigate the dynamic gains from cooperation to address the spatial externality resulting from disease vector dispersal. We find that solving for the complete time path of control decisions is important; cooperation leads to each landowner investing more in treatment in early years than in cases where one agent free rides on the other's control. Our model is based on Pierce's Disease of grapevines in California's Napa Valley but is applicable to a range of diseases in perennial crops.

Key words: bioeconomic model, closed-loop solution, collocation, optimal control, spatial disease modeling, vineyard management, wine economics

Introduction

Diseases that damage productive agricultural crops impose significant costs both through foregone revenue from losses in yield, quality, and production and through expenditures undertaken to mitigate those losses. In grapes, the loss of a vine can cause multiyear losses in production, resulting in significant foregone revenues and expenditure. For example, Alston et al. (2013) estimated that Pierce's Disease (PD) of grapevines—which clogs grapevine xylem and often results in vine death—imposes a total expected welfare loss of $92 million/year in California. Additionally, Fuller, Alston, and Sambucci (2014) estimated that powdery mildew can cost growers in California over $350/acre, and savings of up to $48 million/year could be realized if varieties resistant to powdery mildew were developed.

In many cases, disease pressure in a given location is dependent on decisions made by nearby property owners or managers because vectors and diseases can spread over space. The potential spatial externalities and resulting coordination issues across management units complicate the decisions of managers across the landscape. For perennial crops, particularly those that are slow to mature and potentially remain productive for many years, these issues are exacerbated because disease that takes a plant out of production effectively removes productive capital from the operation and can result in ripple effects across space and time. Here we develop a spatial-dynamic model of multiple landowners managing a vector-borne disease in a perennial crop context and use the model

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to investigate the gains from cooperation to address the spatial externality resulting from vector dispersal.

As our model system, we use PD in the Napa Valley of California, a well-known wine region with a history of chronic PD, vectored mainly by the native Blue-Green Sharpshooter (BGSS), which is native to the area. Grapes produced in the Napa Valley are strikingly valuable; although Napa County produced roughly 4% of the total volume of grapes crushed for wine in California in 2014, the winegrape crush in Napa County that year was valued at nearly $720 million, or approximately 24% of the total winegrape crush revenue in the state (U.S. Department of Agriculture, National Agricultural Statistics Service and California Department of Food and Agriculture, 2015).[1]

Since no effective pesticide or other control protocol currently exists for the BGSS and PD in the Napa Valley, growers and policymakers have been concerned about the current and potential economic losses caused by the BGSS, and they are keenly interested in developing effective control strategies. This concern has grown substantially, following a "huge" outbreak of PD in Napa and Sonoma Counties in late 2015, with some growers reporting vineyard blocks in which 50% of vines were infected (Alley, 2016; Franson, 2015). Furthermore, in a series of interviews we conducted with growers in the Napa Valley regarding management of PD, many individuals stated that in vineyards near riparian corridors (where the BGSS spends its winters), PD causes major economic losses. A recurring theme in the interviews was that vineyard managers worried if and how their neighbors were controlling for PD and how it might affect them.

Much of the literature on the economics of controlling agricultural pests in a spatial, dynamic, or spatial-dynamic context has focused on either annual crops (e.g., Marsh, Huffaker, and Long, 2000; Zacharias and Grube, 1986) or livestock (e.g., Bicknell, Wilen, and Howitt, 1999; Hennessy, 2007). For example, Brown, Lynch, and Zilberman (2002) considered the spatial spread of vectors of PD in a perennial crop (grapes) but effectively treated the crop as an annual, modeling damages as reducing revenues year by year rather than reducing the capital stock of vines. Livestock models often bear some similarities to perennial crop models, in that deaths from disease imply multiyear effects reflecting the gestation period until maturity and longevity of livestock, but the dynamics are typically much longer for tree crops and vines.

While many important examples of models of pests and diseases of perennial crops have been published (e.g., Regev, Gutierrez, and Feder, 1976; Alston et al., 2013; Fenichel, Richards, and Shanafelt, 2014; Fuller, Alston, and Sambucci, 2014; Atallah et al., 2015; Grogan and Mosquera, 2015), these have not addressed the potential benefits from cooperation between management units (e.g., vineyard operations, farms) in disease control. Jones, Vere, and Campbell (2000) and Grimsrud et al. (2008) examined spatial externalities from the spread of weeds across pasture; the latter introduced the possible role of government cost-sharing in weed control. The role of cooperation in optimal pest control using a spatial-dynamic model was addressed by Bhat and Huffaker (2007) in the context of a nuisance beaver population, using game theory to show that the potential economic gains from cooperation among land managers can be substantial. Benefits from cooperation in addressing a pest with spatial spread were more fully examined by Epanchin-Niell and Wilen (2015), who used a spatially explicit model of a newly introduced invasive species. They found that benefits from cooperation can be realized even with limitations on the geographic scope over which land managers coordinate in controlling the invasive species.

We contribute to the current literature by i) modeling a long-lived perennial crop that takes years after planting to mature and reach full productive potential, so lost production resulting from vine damage or death cannot be restored immediately; ii) incorporating the investment decision (vine replacement) in addition to the decision to treat the vector (and therefore, the disease) in each period; and iii) measuring the full dynamic (net present value) benefit of cooperation between growers for a range of cooperation (and non-cooperation) scenarios. The last contribution is important because

[1] The Napa Valley is a designated American Vineyard Area (AVA) that is a part of Napa County, which also contains the city of Napa. Data are available on the basis of counties and crush d istricts (District 4 coincides with Napa County).

Case 1: Social Planner (Both blocks treat)	Case 2A: Unilateral (Block 1 does not treat, Block 2 treats)
Case 2B: Unilateral (Block 1 treats, Block 2 does not treat)	Case 3: No control (Neither block treats)

Figure 1. Selected Cooperation and Non-Cooperation Strategies

decisions made in a given year regarding disease control and investment can have long-lasting effects on vineyard profitability in multiple vineyards.

We specifically address how the size of the initial infestation and the dispersal processes of the vector affect treatment and investment decisions of landowners, how these optimal decisions change when one landowner free rides on the treatment undertaken by the other landowner, and how they are affected by changes in the effectiveness of the treatment option. Additionally, we explore how the rate of capital turnover (life-expectancy of the vines) changes the benefits from cooperation and the balance between expenditure on preventive treatment versus replacement investment. Finally, we ask how heterogeneity across vineyards, here modeled by different prices of grapes, maps to the benefits from cooperation.

We find that whether the blocks cooperate in disease management results in subtle but meaningful effects on the vector population and the proportions (and numbers) of vines that become diseased and are replaced. An intuitive result is that when neighbors do not treat, growers are likely to invest more in treatment than they would under full cooperation. While this intuition holds over the majority of the time interval we examine for the optimal solution, it is not universally true. In the initial periods of the optimal solution, fully cooperating growers invest more in treatment because, with coordination, they can drive the vector population to low levels, an outcome that is not possible when they do not cooperate and some do not treat. We also show that the magnitude of the gains from cooperation depends heavily on the gestation period between planting and maturity of vines: gains are greater when the gestation period is longer. Finally, we show that the benefits from cooperation increase at a decreasing rate with increases in the efficacy of treatment. Besides providing insights into the spatial dynamics of addressing agricultural pests and diseases, our results generate a set of testable hypotheses that can be used to understand more generally cooperation across a landscape (e.g., conserving habitat for an endangered species, groundwater pumping).

Bioeconomic Model of Spatial Pest and Disease Externalities

We develop a spatial-dynamic bioeconomic model to examine growers' decisions about PD control and investment in vines. We acknowledge that vines that are just planted do not bear grapes immediately by accounting for both a stock of bearing vines and a stock of nonbearing vines (akin to including capital vintages in a model of capital accumulation or multiple age/size cohorts in fishery economics). Both bearing and nonbearing vines are affected by PD.

We use the model to investigate three specific scenarios in which growers cooperate in BGSS control to varying extents (figure 1): 1) Social Planner Scenario: Two growers on adjacent blocks cooperate in their control decisions (equivalent to two growers fully cooperating); 2A) and 2B) Unilateral Scenarios: One grower controls and the other does not; and 3) No Control Scenario: Neither grower controls the pest on their block. In scenarios 2 and 3, the grower or growers not controlling the pest respond to natural or pest-induced mortality by investing in new (nonbearing) plants to replace those that have died. While the model is motivated by PD in the Napa Valley, it also is applicable to other pests and diseases that affect grapevines or other perennials in other places.

Xyllella fastidiosa, the bacterium that causes PD, is spread by BGSSs when they feed on infected host plants and then move onto other uninfected plants. The main breeding habitat for BGSSs is the riparian zone, although irrigated landscaped areas can also host breeding populations (Pierce's Disease/Riparian Habitat Workgroup, 2000). While many BGSSs will remain in riparian areas throughout their lifecycle, some adult female BGSSs leave the area in the spring and lay their eggs on new growth in surrounding vineyards. A BGSS infected with *X. fastidiosa* can transmit PD with an efficiency of up to 90% at any given feeding (Purcell, 1979).

The flight range for the BGSS is not far; most insects do not travel more than 800 feet from where they hatch (Hill, 2010). Nevertheless, the damage they inflict in riparian-adjacent vineyards can be substantial. In interviews we conducted with growers, many individuals stated that in vineyards near riparian corridors, PD caused major economic losses; some vineyard managers stated that it was the main reason why they abandoned vineyard blocks in the most seriously affected locations.

Let N_i represent the insect population on land managed by grower i and N_j represent the insect population on neighboring properties. While the model can hold for any number of properties, we focus on the two-property example to generate insights into the spatial dynamics. The (instantaneous) population growth for the insect on Block i is

$$\begin{aligned} \dot{N}_1 &= F(N_1) + \delta_{1,1}N_1 + \delta_{1,2}N_2 - \beta_1 S_1 N_1 \\ \dot{N}_2 &= F(N_2) + \delta_{2,1}N_1 + \delta_{2,2}N_2 - \beta_2 S_2 N_2 \end{aligned} \qquad N_i(0) = N_i^0,\ i = 1,2, \tag{1}$$

where $F(N_i)$ is the growth function of the BGSS population in each block and $\delta_{i,j}$ is the element of the ith row and the jth column of the 2×2 dispersal matrix in which $\delta_{i,j}$ represents the rate at which BGSSs exit (δ is negative when $i = j$) and enter (δ is positive when $i \neq j$) a given block; N_i^0 represents the initial level of BGSS infestation in each block. S_i is the quantity of pest control used by grower i on Block i, and β_i measures the effectiveness of the control, so $\beta_i S_i N_i$ measures the effect of the quantity of pest control used on the pest population relative to pest carrying capacity. Note that we represent the control in this case as a pesticide, although a cost-effective option does not currently exist for the Napa Valley. However, the control could also be thought of as the removal of BGSS host plants or another method that reduces the number of BGSSs in the vineyard block.

Dynamic Model of Vineyards

Vineyards are modeled as capital stocks; disease causes a loss of capital, a departure from annual crop models in which the pest causes a loss of yield only in current production (Brown, 1997; Brown, Lynch, and Zilberman, 2002). Each stock has a separate equation; since grapevines take between three and five years to mature and produce adult yield, it is not plausible for growers to buy replacement vines that will bear immediately. Hence, planting new vines adds to current costs but does not affect current revenue.[2]

The state equations for the changes in the stock (measured in numbers) of nonbearing and bearing vines, A_i^{NB} and A_i^B, are

$$\dot{A}_i^{NB} = I_i - \mu A_i^{NB} - d^{NB} A_i^{NB} N_i \quad \text{for} \quad i = 1,\ 2 \tag{2}$$

$$\dot{A}_i^{B} = \mu A_i^{NB} - d^{B} A_i^{B} N_i - \eta A_i^{B} \quad \text{for} \quad i = 1,\ 2 \tag{3}$$

where I_i represents the number of nonbearing vines planted to replace the bearing and nonbearing vines killed by disease and natural death; d^j, $j = NB, B$, measures the damage to the nonbearing or bearing stock, respectively, that is caused by BGSSs; μ is the proportion of vines that mature from nonbearing to bearing each year; and η is the proportion of vines that die from natural causes each year.

Additionally, total production by grower i is constrained by the total amount of land in a given block, which can be greater than the sum of all planted acres if the grower chooses to leave some land idle. Equation (4) captures the land constraint:

$$\alpha_i \bar{A}_i \geq A_i^{NB} + A_i^B, \tag{4}$$

where α_i converts acres to vines (its units are vines/acre).

[2] PD kills the entire grapevine, including the root system. Therefore, grafting is not an option for vine replacement.

Table 1. System of Equations for Unilateral Scenario 2A

Block 1 (Treating Block)	Block 2 (Nontreating Block)
$\max_{I_1,S_1} \int_0^T e^{-\rho t}\pi(A_1^B(t), S_1(t), I_1(t))dt + e^{-\rho T}\frac{\pi(A_1^B(T), S_1(T), I_1(T))}{\rho}$	$\max_{I_2} \int_0^T e^{-\rho t}\pi(A_2^B(t), I_2(t))dt + e^{-\rho T}\frac{\pi(A_2^B(T), I_2(T))}{\rho}$
$\dot{N}_1 = F(N_1) + \delta_{1,1}N_1 + \delta_{1,2}N_2 - \beta_1 S_1 N_1$ $\dot{N}_2 = F(N_2) + \delta_{2,1}N_1 + \delta_{2,2}N_2$	$\dot{N}_1 = F(N_1) + \delta_{1,1}N_1 + \delta_{1,2}N_2 - \beta_1 S_1^* N_1$ $\dot{N}_2 = F(N_2) + \delta_{2,1}N_1 + \delta_{2,2}N_2$
Objective function and equation (1) for Block 1.	Objective function and equation (2) for Block 2.

Notes: S_1^* is the optimal solution from the program for Block 1 when Block 2 is not treating. We are solving for the closed-loop solution.

Cooperative and Non-Cooperative Models

Each of the proposed scenarios falls somewhere on the spectrum from cooperation to non-cooperation. In the Social Planner (cooperative) scenario, the two landowners simultaneously choose both expenditure on treatment to control the pest population ($S_i(t)$) and expenditure on investment in replacement of vines lost to PD ($I_i(t)$) to maximize the net present value (NPV) of grape production across the blocks of land from today (time 0) to an exogenous period T, at which point the blocks are sold (equation 5). Specifically, the (joint) objective function is

$$(5) \qquad \max_{I,S} \int_0^T \sum_{i=1}^{2} e^{-\rho t}\pi(A_i^B(t), S_i(t), I_i(t))dt + e^{-\rho T}\sum_{i=1}^{2}\frac{\pi(A_i^B(T), S_i(T), I_i(T))}{\rho},$$

where $\pi(\cdot) = pYA_i^B(t) - w^S(S_i(t)) - w^I(I_i(t))$, ρ is the discount rate, Y is the yield per vine on Block i that is healthy and has reached bearing age, p is the price per ton of the grapes crushed, and the cost functions for control and investment are $w^S(S_i)$ and $w^I(I_i)$, respectively. The optimization problem is subject to the BGSS dynamics (equation 1), grapevine dynamics (equations 2 and 3), and the land constraint (equation 4).

The objective function includes a salvage value or sale price of land in period T, which is a function of the terminal period profit from utilizing the land for winegrape production (and is discounted back to the present). It is assumed that the price of land in period T is the present discounted value of profits and that profits remain constant in the future. The inclusion of a salvage value captures the fact that the growers are not only interested in the stream of profits from production but also are considering the state of production when the land is sold.

In the No Control scenario, we assume that neither grower controls the pest (treatment $S_i(t) = 0$ for all t) but that the two landowners still maximize their respective profits by choosing investment in each period in nonbearing vines. Specifically, each grower solves

$$(6) \qquad \max_{i} \int_0^T e^{-\rho t}\pi(A_i^B(t), I_i(t))dt + e^{-\rho T}\frac{\pi(A_i^B(T), I_i(T))}{\rho}$$

subject to the BGSS dynamics in equation (1), with $S_i = 0$ and equations (2)–(4) for their respective block.

In both of the Unilateral Scenarios (2A and 2B in figure 1), we assume that one grower applies pesticide while the other grower does not treat at all. The models for this case are represented in table 1 for the example that Block 1 is treated and Block 2 is not. The corresponding system of equations exists in the converse case.

Optimization Conditions for Social Planner Scenario

In this section, we illustrate the optimization conditions for the Social Planner scenario, in which the two blocks are managed jointly to maximize their combined profits. Because the land constraint (equation 4) does not vary over time, we utilize a Lagrangian formulation for optimal control problems with state constraints rather than the canonical Hamiltonian set up (Chiang, 2000; Kamien and Schwartz, 1991). The Lagrangian is

$$\begin{aligned} L \quad = \quad & \sum_{i=1}^{2} \left[\pi(A_i^B(t), S_i(t), I_i(t)) + e^{-\rho t} \frac{\Pi(A_i^B(T), S_i(T), I_i(T))}{\rho} + \lambda_i^{NB}(t)\dot{A}_i^{NB} \right. \\ & \left. + \; \lambda_i^B(t)\dot{A}_i^B + \psi_i(t)\dot{N}_i + \overline{\lambda}_i(t)(A_i^B(t) + A_i^{NB}(t) - \alpha_i \overline{A}_i) \right], \end{aligned} \tag{7}$$

where the costate variables, λ_i^{NB} and λ_i^B, represent the shadow values of nonbearing and bearing vines, respectively; ψ_i is the shadow price of the insect on Block i, which is negative since the insects are a bad; and $\overline{\lambda}_i$ captures the shadow value of the land.

Assuming a full interior solution, the Pontryagin conditions on the control variables, S_i and I_i, are that the quantity of the control in each period is set such that marginal cost of treatment equals marginal benefit (equations 8 and 9).[3] Specifically, the marginal cost of an additional unit of treatment is equal to the value of the marginal damage avoided (which is positive $-\psi_i \beta_i N_i > 0$ since $\psi_i < 0$), and the marginal cost of vine replacement is equal to the shadow value (marginal benefit) of a nonbearing vine (λ_i^{NB}). Equations (8)–(13) represent the first-order necessary conditions for the Social Planner scenario.

$$\frac{\partial L}{\partial S_i} = -\frac{\partial w^S(S_i)}{\partial S_i} - \psi_i \beta_i N_i = 0 \qquad \text{Treatment in Block } i \text{ in } t \tag{8}$$

$$\frac{\partial L}{\partial I_i} = -\frac{\partial w^I(I_i)}{\partial I_i} + \lambda_i^{NB} = 0 \qquad \text{Investment in Block } i \text{ in } t \tag{9}$$

$$\begin{aligned} \dot{\psi}_i = \psi_i \left(\frac{\partial F}{\partial N_i} + \rho - \beta_i S_i \right) - \sum_{j=1}^{2} \delta_{i,j} \psi_j & \qquad \text{Shadow price of BGSS} \\ + \lambda_i^{NB} d^{NB} A_i^{NB} + \lambda_i^B d^B A_i^B & \qquad \text{in Block } i \text{ in } t \end{aligned} \tag{10}$$

$$\dot{\lambda}_i^{NB} = \mu(\lambda_i^{NB} - \lambda_i^B) + \lambda_i^{NB}(\rho + d^{NB} N_i) - \overline{\lambda}_i \qquad \text{Shadow price of nonbearing vines in Block } i \text{ in } t \tag{11}$$

$$\dot{\lambda}_i^B = -pY + \lambda_i^B(\rho + \eta + d^B N_i) - \overline{\lambda}_i \qquad \text{Shadow price of bearing vines in Block } i \text{ in } t \tag{12}$$

$$\overline{\lambda}_i(A_i^B(t) + A_i^{NB}(t) - \alpha_i \overline{A}_i) = 0 \qquad \text{Land constraint} \tag{13}$$

The necessary conditions given in equations (8)–(13) highlight the linkages between BGSS populations and vine loss and the corresponding stocks of bearing and nonbearing vines across space and time. For example, the spatial externality—the effect of one grower's pest control actions on another's pest population and corresponding profitability—is explicitly shown in equation (10); the rate of change of the shadow price of the BGSS in Block i (ψ_i) is a function of the shadow price of the BGSS in Block j owing to BGSS dispersal between blocks (represented by the elements of the dispersal matrix, δ_{ij}).

Equations (11) and (12) describe the determinants of the shadow values of nonbearing and bearing vines and their interdependence. The shadow value of the nonbearing vine accounts for the fact that the vine will mature and become profitable only in the future (equation 11), whereas the shadow price of the bearing vines is a function of the value of the grapes sold and the mortality attributable to natural causes and PD (equation 12). A similar result is found when habitat (e.g.,

[3] Chiang (2000) showed that additional state-space equations must be satisfied to check the robustness of the solution when there are constraints on the state variables that do not include the control variable.

coral reef or mangrove) contributes to the population of a commercial fish stock; the value of the habitat is determined by the value of the fish stock (e.g., Sanchirico and Springborn, 2011). Equation (11) also shows how the rate at which vines mature from nonbearing to bearing (μ) plays a role in determining the shadow price of nonbearing vines and bearing vines. (Note that all of these equations are solved simultaneously and therefore are integrated.) A larger difference between the shadow prices of nonbearing and bearing vines occurs when the vines mature more slowly (i.e., when the maturation rate, μ, is lower).

The trade-off between space used by nonbearing vines and that used by bearing vines is expressed in the land constraint. Growers maximize profit by having the largest proportion of bearing vines possible; however, they are constrained in this respect by vine death due to PD and other loss. If we assume that the land constraint is binding, then we can show that $\dot{A}_i^B = -\dot{A}_i^{NB}$ and, from equations (2) and (3), the optimal investment in each t is

$$I_i = \underbrace{d(A_i^{NB}N_i + (A_i^B N_i)}_{\text{Vines lost to PD}} + \underbrace{\eta(A_i^B),}_{\substack{\text{Vines lost to}\\ \text{natural causes}}} \tag{14}$$

where optimal investment in each time period replaces the vines lost to PD and natural mortality.[4]

Spatial-Dynamic Simulations

Functional Forms and Parameter Values

With respect to the specific functional forms, we balance parsimony and flexibility. We chose quadratic cost functions for investment and treatment and a quadratic growth curve for the BGSS population (logistic growth). To the extent possible, our parameter values were chosen by reviewing the relevant literature as well as consulting experts, but data are not available on some aspects, especially since we are examining a hypothetical scenario in which an effective BGSS treatment becomes available in the Napa Valley. Consequently, estimates for some parameters are just that—our best "educated guesses" that are unlikely to represent any one vineyard accurately but do provide useful insight into the benefits from cooperative disease control. Appendix A includes a table of parameter values along with additional information on functional forms, model calibration, and validation.

Numerical Methods

We use pseudospectral collocation to solve for the optimal dynamics of treatment and investment over time (Garg et al., 2010). Specifically, we approximate the optimal control model with a nonlinear programming (NLP) problem, in which we assume that our controls are approximated with an nth degree polynomial over a period from 0 to T. The algorithm ensures that the residual error of the constraints is minimized at the collocation points. The collocation points and degree of polynomial are chosen to balance speed of convergence to a solution and numerical error; we used sixty-five collocation points. One advantage of this approach over more typical two-point boundary value methods, such as shooting, is that we can directly incorporate the state and control constraints into the problem (Judd, 1998). This feature enables us to find optimal solutions that might reside on the boundary of the control set for a period of time. A second advantage is the ability to handle larger-scale dynamical systems, such as the one in this paper with two blocks, two controls for each block, and two state equations per block. The solution method was implemented using TOMLAB

[4] Equation (13) allows for the possibility of land abandonment. If $\overline{\lambda}_i = 0$, land may be abandoned. If $\overline{\lambda}_i > 0$, then all land must be planted in vines. In sensitivity analysis not included here, we find that land is abandoned when the cost to replace vines is very high. However, within the parameter space we examine here, all land remains in production because it is still relatively inexpensive to replace vines rather than forego production.

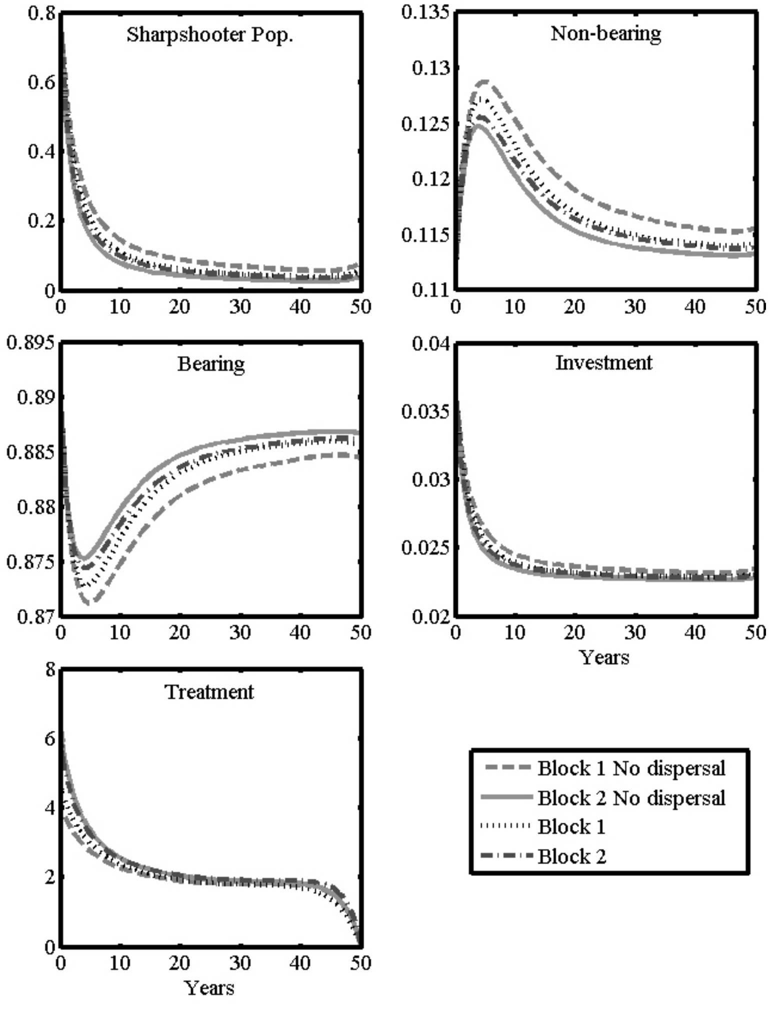

Figure 2. Social Planner Optimal Solution With and Without Dispersal

Notes: Sharpshooter Pop refers to the BGSS population. *Nonbearing* and *Bearing* refer to the proportions of bearing and nonbearing vines in the vineyard block, respectively; *Investment* refers to the proportion of vines in the block that are replanted in a given year; and *Treatment* represents generic treatment (more easily thought of as a pesticide) units.

(v. 7.8) (Holmström, 2001; Holmström, Göran, and Edvall, 2005) and the accompanying PROPT toolbox (Edvall and Rutquist, 2010). The approximate NLP is solved using the general-purpose nonlinear optimization package, SNOPT.

Results

In the sections that follow, we explore optimal management decisions in terms of treatment and replacement of diseased vines for the two blocks in our analysis—one with lower-priced grapes (Block 1) and one with higher-valued grapes (Block 2). Grapes grown on Block 2 are double the price of those on Block 1. Grape prices in Napa are highly heterogeneous, differentiated by variety, appellation, and growing conditions, among other things. For example, growers we interviewed estimated that their grapes were worth \$1,000–\$15,000/ton.

We first construct a "base case" scenario in which both blocks are managed cooperatively to examine the role of pest dispersal in determining optimal treatment and corresponding vector population, investment in replacement vines, and the quantity of bearing and nonbearing vines.

We then analyze alternative non-cooperative (Unilateral and No Control) scenarios to measure the benefits from cooperation for our base case. We build off the base case scenario by undertaking sensitivity analysis to explore the effects of changes in the parameters representing maturation rate, pesticide kill rate, and price of grapes. We find all three parameters to be important in determining the size of the benefit from cooperation. The maturation rate plays the largest role of the three and is one of the factors often omitted in models of pest control.

Role of Pest Dispersal on Optimal Solution

As noted, to develop intuition about the optimal dynamic investment and treatment decision, we first illustrate the Social Planner solution, in which the two blocks are managed to maximize the sum of their profits (figure 2). We also highlight the consequences of pest dispersal for the optimal solutions by comparing the Social Planner solution with and without dispersal. Initially, we assume that each block starts out with a stock (or portfolio) of nonbearing and bearing vines in which new plantings just offset deaths from PD and natural mortality, such that the entire block is planted and the balance is preserved (in a steady state). We also assume for the base case that the initial BGSS populations in both blocks is at 75% of their carrying capacity, representing a large initial infestation (we consider other initial conditions in sensitivity analysis).

Overall, we find that the solutions without dispersal envelope the solutions with dispersal, which highlights the "averaging" role of dispersal based on relative population sizes (e.g., Sanchirico and Wilen, 2005).[5] That is, under the current assumptions, the BGSS dispersal gradient acts to eliminate differences in the relative densities of BGSSs across the two blocks (figure 2). For example, on Block 2 without dispersal, the population density of BGSSs is lower, and the proportion of bearing vines to nonbearing vines is greater than with dispersal (figure 2). With dispersal Block 2 receives a higher return to control costs since the opportunity cost of having nonbearing vines is higher than for Block 1; however, with dispersal, the effect of the treatment spreads over the two blocks, resulting in the BGSS population and proportion of bearing vines being very similar across Blocks 1 and 2. The results for Block 1 mirror those for Block 2; on Block 1 without dispersal, the population of BGSSs is larger, and the proportion of bearing vines to nonbearing vines is smaller than with dispersal.

In general, the optimal solutions have the "catenary turnpike" property where the optimal solution is to spend as long as possible near the optimal steady-state and to deviate from that path only near the boundaries (near $t = 0$ and $t = T$) (Samuelson, 1965). For example, the BGSS population is swiftly reduced to under 20% of carrying capacity within ten years and investment quickly reaches an equilibrium where it is directly offsetting disease and natural mortality (equation 14), which is maintained until the terminal period is approached.

Because the sale price of land depends on the productive capacity of the land at time T, the optimal investment path is stable toward the end of the horizon to maintain a high stock of bearing vines. Optimal treatment, however, starts to rapidly decline toward the end of the horizon, as the costs of treatment begin to exceed the returns to be reaped over an ever-shorter future; changes in the BGSS population large enough to have a meaningful effect on the rate of vine disease take several years to be realized. Eventually, optimal treatment is zero in T. Intuitively, the landowner is not be able to reap the benefits from treatment in those later periods because it takes time for the nonbearing vines to mature.

Cooperative vs. Non-Cooperative Outcomes with Dispersal

In figure 3, the optimal cooperative (Social Planner) and non-cooperative (Unilateral and No Control) results are illustrated in the case of BGSS dispersal. The Social Planner solution is the

[5] We also explored a "source-sink" case in which the vector population in one block is high and BGSSs move from that block onto the other and not in both directions. However, our results did not change substantially.

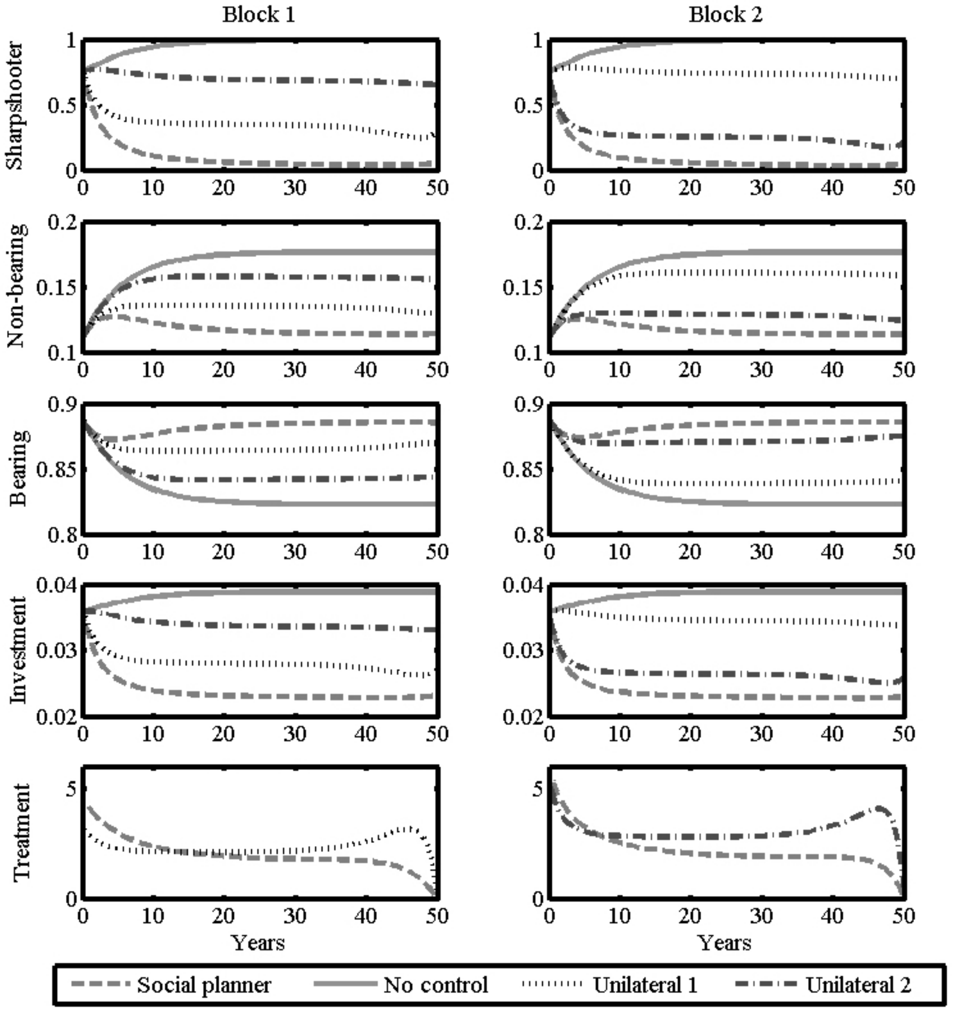

Figure 3. Optimal Solutions for Alternative Cooperation Scenarios

Notes: Sharpshooter Pop refers to the BGSS population. *Nonbearing* and *Bearing* refer to the proportions of bearing and nonbearing vines in the vineyard block, respectively; *Investment* refers to the proportion of vines in the block that are replanted in a given year; and *Treatment* represents generic treatment (more easily thought of as a pesticide) units.

same as that in figure 2. Not surprisingly, we find that the Social Planner solution results in the lowest BGSS population and the highest proportion of bearing vines in all time periods. In the No Control case, with no treatment by either grower (Case 3), the BGSS population in both blocks reaches 100% of carrying capacity within twenty years. Without treatment, the only mode of addressing diseased vines is investment (vine replacement); in order to keep up with disease loss, replacement takes place at a rate reflecting the sum of vines lost to disease and those that die off otherwise once the vector population reaches carrying capacity.

The other two scenarios, in which one block treats but the other does not, are reflected in the Unilateral scenarios (2A and 2B). For example, when Block 2 does not treat, the BGSS population there remains roughly at the initial conditions of 75% of carrying capacity, which results in higher rates of dispersal to Block 1, reducing control in Block 1 relative to what it would be without dispersal (figure 1). The fact that the BGSS population in Block 2 does not reach its carrying capacity highlights the free-riding benefits that dispersal generates. We also find that Block 1 treats, but not enough to match the Social Planner levels, and the result is a BGSS population slightly below 50%. The same pattern is evident when Block 2 treats but Block 1 does not.

Table 2. Gains from Cooperation (Percentage of NPV over Fifty Years)

		Block2	
		Treat	**No Treat**
Block 1	**Treat**	–	3.09%
	No Treat	1.86%	3.77%

A counterintuitive result, which is highlighted only because we are solving for the full spatial-dynamic solution, is that the ordering of treatment expenditure between the Social Planner and Unilateral solutions switches over time. That is, we find that treatment expenditure in a given block—say, Block 1—is initially higher in the Social Planner solution than when only Block 1 is being treated. Over time, however, the treatment expenditure in Block 1 when Block 2 is free riding exceeds the Social Planner amount. In fact, it exceeds it on the "turnpike" portion of the path, which is approximately equal to the steady-state values. Therefore, a steady-state analysis would reach a conclusion that seems intuitive: that is, if your neighbor does not treat, then you will need to exert more effort treating. This intuition is contradicted in early years, however, because under cooperation the landowners are able to drive the BGSS population low enough to reduce optimal treatment applied in the future.

The cases with free riding also exhibit interesting behavior near the terminal period. In these cases, the level of treatment increases for a short period, which drives down the damages from BGSSs on the nonbearing stocks. The result is a slight increase in the proportion of bearing stocks immediately before the landowner is going to sell, as a means of increasing the terminal value. After the increase in treatment and as the terminal period approaches, the returns to treatment are decreasing and treatment levels begin to approach zero.

Table 2 compares the difference in NPV between the Social Planner solution, the No Control solution, and the "in-between" (Unilateral) cases where only one block treats. The potential gains from cooperation are measured with reference to the Social Planner case; for example, if both blocks do not treat, then the cost from non-cooperation and not treating is 3.77% of the NPV of the variable profit (revenue minus control and vine replacement costs). The gains for Block 2 when introducing treatment on Block 1 are higher than the gains for Block 1 when introducing treatment on Block 2 because Block 2 produces higher priced grapes; the cost resulting from additional disease is higher on Block 2 than Block 1, *ceteris paribus*. We also find that overall gains are relatively modest in terms of percentages at the base case parameter levels.[6]

Sensitivity Analysis

In this section, we investigate the implications of the maturation rate, the efficiency of the treatment, and the relative output prices on the gains from cooperation.[7] The maturation rate provides insights into the importance of treating vines as capital stocks that take time to bear fruit, in contrast to annual crops. We vary the efficiency of treatment because we hypothesize that the gains from cooperation might be lower if efficiency is high enough (for instance, when each block has a very effective treatment option), *ceteris paribus*. Finally, since grape prices in the Napa Valley range substantially over many factors including variety, management, and location within the region, we vary the output price in Block 2 relative to Block 1 to better understand how economic heterogeneity in the presence of spatial externalities maps to the returns from cooperation.

[6] To put the percentage gains from cooperation in perspective, the NPV of fifty years of production without disease ranges from approximately $200,000/acre for the grower with the lower-priced grapes up to approximately $400,000/acre for the grower with the higher-priced grapes. These values fall within the range of published values of vineyard land in the Napa Valley (California Chapter of the American Society of Farm Managers and Rural Appraisers, 2015).

[7] Appendix figure B1 shows an additional sample sensitivity analysis of the pesticide kill rate on the optimal level of treatment over time for each grower in the Social Planner case.

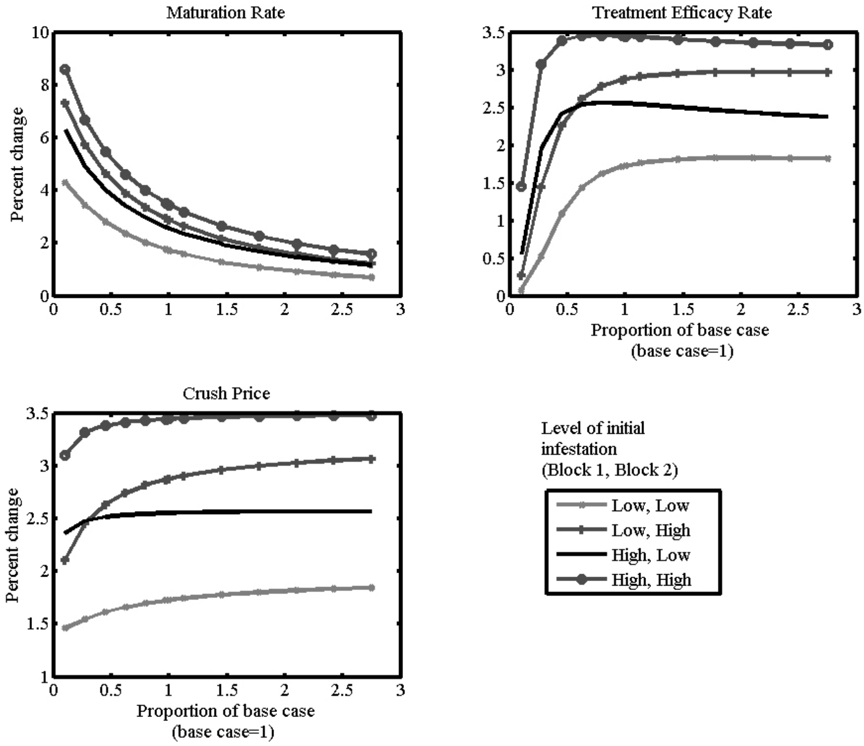

Figure 4. Sensitivity Analysis on the Gains from Cooperation

Similar to the calculations of the gains above, we examine the NPV of the vineyard profit streams over fifty years as a percentage of the NPV of the Social Planner solution. In this case, however, we compute the average proportional gain from cooperating (*AGC*) across the three versions of non-cooperation and compare that average across a range of scenarios in order to have one summary indicator of the gains. Explicitly, we calculate

$$AGC = \frac{1}{NPV_{T,T}} \left(NPV_{T,T} - \frac{1}{3} \left[NPV_{NT,T} + NPV_{T,NT} + NPV_{NT,NT} \right] \right), \tag{15}$$

where T = "treatment" and NT = "no treatment" and the subscript order corresponds to the block number.

In addition to considering the impacts of the different parameters, we also examine the *AGC* over a range of BGSS initial conditions in each block to understand when the gains might be greater, *ceteris paribus*. The sets of initial conditions are: Low, Low=(0.1, 0.1); Low, High = (0.1, 0.75); High, Low = (0.75, 0.1); and High, High = (0.75, 0.75), where 0.1, for example, reflects a case where the BGSS population is at 10% of carrying capacity. (Recall that the base case initial condition for the BGSS population is 75% of carrying capacity in both blocks; this is the High, High case.) Therefore, for each parameterization, we are solving the four scenarios starting from four initial conditions.

Case 1: Maturation Rate

Maturation is measured as the proportion of nonbearing vines that mature to bearing each year; in the base case it is 0.2. When we force the vines to mature faster (and thus, shorten or eliminate the period of time in which they are nonbearing), winegrapes become more like an annual crop in the model. We find that the gains from cooperation are reduced as maturation rate increases (figure 4).

Since the length of time for which vines are out of production is shorter, the opportunity cost of allowing vines to become diseased is reduced—so it matters less whether the blocks are treated and thus whether the blocks are managed cooperatively. We also find that the proportional gains from cooperation are greatest in a severe outbreak, with high rates of BGSS infestation in both blocks, and the relative gains show that, *ceteris paribus*, the economic damages are greater in the block that produces higher-valued grapes.

Case 2: Kill Rate

Starting at low efficacy of treatment (β), marginal increases in efficacy have large impacts on the gains from cooperation (figure 4). However, once the kill rate reaches approximately our base case, additional gains become minimal. Interestingly, at low efficacy, gains from cooperation are smaller when the block with lower-valued fruit begins with a low infestation and the block with high-priced fruit begins with a high infestation (L,H). However, at higher kill rates, the benefits from cooperation are larger in the L,H case, which is intuitive since a block producing high-priced fruit with a high infestation will benefit more from an effective pesticide compared to a block producing low-priced fruit. The reversal arises because—in a scenario in which treatment is not very efficient—the high-value grape grower can benefit from an increase in treatment on the neighbor's block.

Case 3: Output Price

In the Napa Valley, the crush price of winegrapes varies substantially, differentiated by variety, appellation, and growing conditions, among other things. The mean price of grapes sold for crush in Napa County is more than $4,000/ton for recent vintages.[8] We examine two blocks with grape prices that bracket this mean ($3,000 and $6,000 for Block 1 and Block 2, respectively) and vary the relationship between the prices of grapes from the two blocks. In general, as the crush price increases in the model, more control is utilized and a higher percentage of diseased vines are replaced; as a result, the number of BGSSs on the property falls.

Figure 4 shows the change in gains from cooperation as the crush price for grapes from Block 2 changes, holding constant the crush price for grapes from Block 1. The proportional gains from cooperation increase with the price received for grapes. Intuitively, gains are greatest when the initial infestation is highest in both blocks and smallest when the initial infestation is lowest. Since the price for grapes from Block 1 does not change, treatment on Block 1 does not change except in the Social Planner case.

The benefit from cooperation is smaller with lower crush prices and larger with higher crush prices; when crush prices are low, growers have less to lose and act more like No Control growers. However, the change in the benefit from cooperation resulting from an increase in crush prices begins to level off as crush prices get higher; past a certain price threshold, the additional returns to increases in investment and in treatment begin to diminish owing to the land constraint; the land can only hold a certain number of vines ($\alpha_i \overline{A}_i$), and investment in new vines past that number does not bring additional benefits.

Conclusion

Because pests do not respect property boundaries, land managers often have indirect, but powerful, effects on adjacent properties through their pest control decisions. Using a novel bioeconomic model of multiple capital stocks, we have explored these interactions across heterogeneous vineyard blocks,

[8] A mean price for Napa County grapes of $3,600/ton was calculated as a five-year average of crush prices per ton, weighted by total tons produced in each year, for years 2010–2014, and rounded to the nearest $50/ton. Prices have trended up in more recent vintages.

where growers choose how much to spend on pest control, which determines the corresponding BGSS populations and the resulting spread of PD. These results indicate that when vector control is coordinated across blocks, producers can be better off in terms of the profitability of their operations over time. We also find that understanding the spatial dynamics of these decisions is important, as cooperative outcomes can result in more investment in treatment in early years than in cases where one agent free rides on the other's control.

Our results further support work done by Regev, Gutierrez, and Feder (1976); Jones, Vere, and Campbell (2000); Bhat and Huffaker (2007); and Epanchin-Niell and Wilen (2015) in demonstrating the importance of considering effects on adjacent properties and benefits from cooperation across those properties. We calculate the benefit from cooperating in pest control as ranging from roughly 1% to 4% of the NPV of returns on the individual blocks, which—taking into account Napa Valley grape and vineyard prices—translates to a significant opportunity cost. These gains represent potential for improving both individual action as well as policy, especially in times of a PD outbreak. Growers of higher-valued grapes could negotiate side payments to their neighbors in exchange for additional control. Growers in the region can and do coordinate in riparian re-vegetation, and in the past grant funding has been offered to subsidize these efforts.[9] Neighborhood groups in the Napa Valley have also met regularly to coordinate disease control, notably in the case of grapevine leafroll, and a similar strategy could work well for PD control, especially when disease pressure is high.

We also find that the gains from cooperation and other outcomes are more sensitive to some parameters than others. The vine maturation rate, in particular, stands out as important in this respect, highlighting the necessity of modeling investments in vineyards and other long-lived perennials as capital stocks. Similar issues arise in understanding disease management in tree crops—such as almonds, oranges, rubber, or coffee—which have a significant lag between planting and production and a potential productive life of decades.

While we considered a generic treatment for the vector, future work could consider more specific controls, such as re-vegetation to remove the riparian plants that harbor breeding populations of the BGSS. One vineyard manager interviewed stated that the removal of host plants can reduce PD-related vine loss by up to 90%. Others did not estimate such high effectiveness, but most stated that riparian re-vegetation could yield substantial economic gains, provided that work in the riparian area was not too difficult because of rocky or steep conditions. However, the process of design, approval, and implementation of a riparian re-vegetation plan can take over a year to complete (Pierce's Disease/Riparian Habitat Workgroup, 2000). Comparing grower profitability with and without the ability to re-vegetate could be useful in determining the benefit from having two choices of control type, and whether and how much it could help growers to remove barriers to using this control, such as the extensive approval process.

Another interesting possibility would be to incorporate the configuration of the spatial landscape more directly into the analysis. In the base case, growers are assumed to farm square blocks of four acres in area. However, when the geometry of the block changes, PD pressure changes as well; growers with more river frontage are more likely to experience greater PD incidence, *ceteris paribus*. Therefore it is likely that the control strategy and profitability will also change, and this will map into the benefits and incentives to cooperate.

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[9] Using public funding to subsidize coordinated efforts is not a new idea and is discussed further in Grimsrud et al. (2008).

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Appendix A: Model Parameterization

Table A1. Base Level Parameter Values and Explanations

Parameter	Explanation	Value
w_1^S	Unit cost of control ($/unit/application)	10.50
w_2^S	Quadratic cost parameter	78.75
w_1^I	Unit cost of investment ($/vine)	13.50
w_2^I	Quadratic cost parameter	20.25
d^{NB}	Damage per insect per vine for nonbearing vines (nonbearing vines killed/insect/block)	0.020
d^B	Damage per insect per vine for bearing vines (bearing vines killed/insect/block)	0.018
K	BGSS carrying capacity	100
β	Proportion of insects killed per vinespace of treatment applied (BGSS/vinespace/acre of treatment application)	0.10
Y	Yield/vine (tons); calculated using 1,000 vines per acre and 3.82 tons per acre.	0.00382
$\overline{A}$	Scale unit at which the problem is solved (acres)	4.0
ρ	Annual discount rate	0.05
α	Annual rate of vine maturity from nonbearing to bearing (proportion of vines/year)	0.20
η	Annual non-PD death rate (proportion of vines/year)	0.025
p_1	Crush price for Block 1 in two-grower model ($/ton)	3,000
p_2	Crush price for Block 2 in two-grower model ($/ton)	6,000
δ_{ij}	Dispersal between properties; symmetric but negative when $i = j$ and positive otherwise	0.0875

Table A1 summarizes the parameters used in the model. In many cases, values were chosen by reviewing the relevant literature as well as consulting experts. In other cases, data were not available, especially since we are examining a hypothetical scenario in which an effective BGSS treatment becomes available in the Napa Valley; these estimates are our best "educated guesses."

We model profits per acre on each four-acre block using the following equation:

$$\text{(A1)} \qquad \pi\left(A_i^B(t), S_i(t), I_i(t)\right) = p_i Y A_i^B(t) - w_1^S S_i(t) - w_2^S S_i^2(t) - w_1^I I_i(t) - w_2^I I_i^2(t).$$

Costs of treatment and investment are quadratic to reflect adjustment costs to treatment and investment (marginal costs are increasing in the quantity of the control).

The revenue and cost parameters are based on information from interviews with growers and industry sources. For example, the information on investment costs is loosely based on the Cabernet Sauvignon Vine Loss Calculator for Napa (Klonsky and Livingston, 2009). Note that because so few Napa Valley growers used pesticide for PD prevention purposes, information from another set of interviews with growers in Temecula, California, was used as well. Information on quantity produced and acreage (used to calculate yields) as well as crush prices from (rounded) historical average prices of Napa Valley winegrapes is based on data from the Crush and Acreage Reports (U.S. Department of Agriculture, National Agricultural Statistics Service and California Department of Food and Agriculture, 2015), and the number of vines per acre was adapted from University of California Cooperative Extension Cost and Return Studies for Northern California (2000–2011). The block acreage ($\overline{A}$) was in the range of block sizes reported by growers interviewed in Napa County.

For several of the biological parameters, exact measures were not available. These parameters were discussed with Barry Hill, the (now retired) California Department of Food and Agriculture entomologist, and sensitivity analyses were conducted. These included the pesticide kill rate (β) and the damage parameters (d^{NB} and d^B), which can be interpreted as the probability that any one insect will infect a vine. (Note that currently available pesticides do not address PD effectively in the Napa Valley, so benefits are estimated using a range of βs, representing current and potential kill rates.) The natural growth rate of the BGSS population, R, and measure of BGSS carrying capacity,

K, were determined in the same fashion. The dispersal matrix is based on the same methods and was created under the assumption that the properties are fully integrated and insects migrate in both directions in our base case.

The rate of vine maturity, μ, is based on vines that reach maturity at five years of age, which was typical for growers interviewed. The model operates under the assumption that since vines can be replaced each year, a fraction (0.2) of all of these nonbearing (immature) vines become bearing (mature) each year. The non-PD death rate is based on interviews with growers.

The salvage value is a reflection of the expectation of future profits from the block. Without guidance on what the expectation might include, we used two formulations. We assumed that the expectation was based on future revenues given the number of bearing vines existing at the final period, T. We also investigated using net profits evaluated at T. We found that the qualitative results were similar but that the revenue formulation resulted in more stable numerical solutions, especially as the parameter space was stretched in the sensitivity analysis. Therefore, we report the results where the salvage value has the following formulation:

$$\text{(A2)} \qquad \Pi\left(A_i^B(T)\right) = \frac{p_i Y A_i^B(T)}{\rho}.$$

We validate our model by comparing our calculated NPV of the land (production over the fifty years, plus the salvage value) with published Napa County land prices (California Chapter of the American Society of Farm Managers and Rural Appraisers, 2015).

Appendix B: Sensitivity Analysis Example

We conducted a sensitivity analysis on the parameters in our model, but including that analysis for all parameters and scenarios is not possible due to space constraints. One particularly interesting example of our sensitivity analysis is that of the pesticide efficacy (i.e., the "kill rate") on optimal pesticide application. With a high initial pest infestation, regardless of the strength of the pesticide, it will initially be applied at relatively high rate to "knock down" the infestation and then will level off as t nears T. In all cases examined, a high-strength pesticide will be applied at a higher rate in early time periods than a lower-strength one—although in the case of a low initial pest infestation, this effect is marginal and its duration is short. In the low initial infestation cases, the less-effective pesticide is applied at a lower rate in early time periods and the application rate slowly increases over time as t nears T—although the application rate is still low compared with a high infestation case.

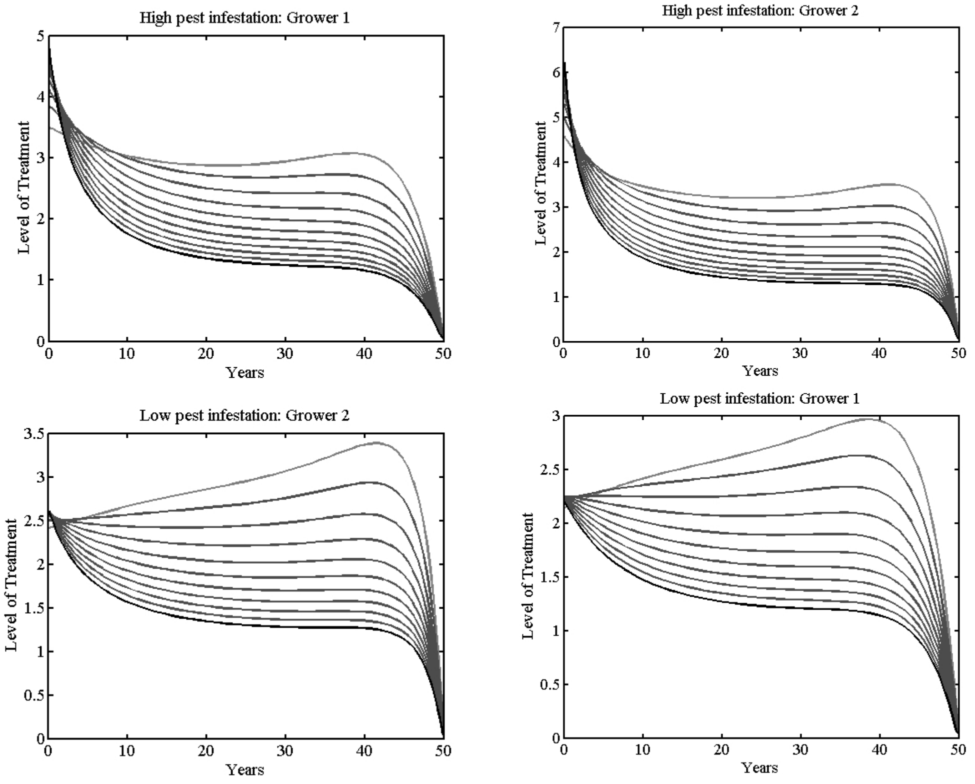

Figure B1. Sensitivity Analysis of Pesticide Efficiency on Application

Notes: Grey (topmost) line represents 50% of baseline efficiency; lowermost line represents 150% of baseline efficiency.