The bio-economics of managing invasive plant externalities in forests with heterogeneous landowner preferences

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Abstract. Forest invasive plants can cause market (MES) and non-market ecosystem service (NMES) losses to private forest landowners. Because bio-invasions create spatial-dynamic ecological-economic linkages among landowners, bio-invasion control is a weaker-link public good and is likely to be underprovided. We hypothesize that heterogeneity in forest landowner preferences is a major determinant of bio-invasion spatial externalities. To test this hypothesis, we develop a spatial-dynamic model of bio-invasion and control with two agents that value differently the MES and NMES produced by their forestlands. The bio-invasion spreads within and across lands according to short, and long-distance dispersal mechanisms and landowners make control decisions that ignore the impacts on their neighbors. In the absence of long-distance dispersal, they both control the bio-invasion regardless of their preferences. In the presence of long-distance dispersal and the case of heterogeneous preferences, a central planner controls the bio-invasion. In the case of decentralized management, however, the MES landowner implements bio-invasion control, but the NMES landowner does not, causing a reduction in the aggregate payoffs, compared to the centralized management case. We compare uniform and non-uniform payments for ecosystem services (PES) and find that a PES to the NMES landowner only is enough to mitigate the externality whereas a non-uniform PES is costlier and leads to a non-additional participation of the MES landowner.

Keywords: spatial-dynamic modeling; externalities; forest ecosystem services; invasive plants.
JEL D62, Q23, G57

I.   INTRODUCTION

Effective control of biological invasions is critical for both the health of forest ecosystems and the welfare of human communities that benefit from them. The U.S. is experiencing an extensive forest invasive plant problem. Most forest invasion studies have considered the case of a central planner, which is relevant for public lands in the western U.S (e.g., Horie et al., 2013). However, more than half of U.S. forests are owned or managed by private parties. Also, forest landownership is expected to become increasingly fragmented: 70% of private forest landowners in the U.S. are above 70 years old (USFS 2015). Family landowners report a diverse set of ownership motivations and management objectives driven by both nonmarket ecosystem services (NMES) and market ecosystem services (MES) (Butler 2008). Invasive species management on private forests differs from that on public forests because of the strategic nature of decentralized management and the potential for spatial-dynamic externalities in invasion management among multiple, heterogeneous landowners (Fenichel, Richards, and Shanfelt 2014; Atallah, Gómez, and Conrad 2017). Many forest invasive plants are dispersed through short-distance (SDD) and long-distance dispersal (LDD) mechanisms, as opposed to a dispersal to the nearest neighboring spatial unit only. This dispersal pattern creates spatial linkages among private land parcels that go beyond the contiguous land parcel, a departure from a major assumption made in bioeconomic models of invasive species spread and control (Aadland et al., 2015; Epanchin-Niell and Wilen 2012, 2015). This ecological feature is crucial in modeling how externalities are generated on private lands and how private actions affect and are affected by the invasion risk over the entire landscape (Atallah, Gómez, and Conrad 2017).

In this paper, we consider the case of glossy buckthorn in white pine forests. Glossy buckthorn (*Frangula alnus* P. Mill.) is a shrub that is non-native and invasive in North America.

Buckthorn is one of around 20 non-native woody plants that threaten eastern US forests (Webster et al., 2006). It aggressively colonizes forest edges and its moderate shade tolerance (Sanford et al., 2003; Cunard and Lee 2009) allows colonization of forest understories where it can form a dense, persistent layer affecting NMES such as preventing recreation and changing fauna and flora habitats (Frappier et al., 2003; Fagan and Peart 2004; Cunard and Lee 2009; Lee and Thompson 2012; Koning and Singleton 2013). Through competition, buckthorn affects MES provision by delaying the regeneration and growth of economically important forest trees such as the eastern white pine (Fagan and Peart 2004; Frappier et al., 2004; Koning and Singleton 2013). Buckthorn recruitment and spread occur entirely from seed (Godwin 1943; Lee and Thompson 2012), which are bird-dispersed (Godwin 1943; Catling and Porebski 1994). Its aggressive colonization of forest edges, moderate shade tolerance, and dispersal are traits shared with other forest invaders, such as Japanese barberry and Amur honeysuckle. It inhibits the growth and regeneration of native trees.

Spatially-explicit bioeconomic models of invasion spread and control can inform effective prevention and control of forest invasive plants, the sustainability and resiliency of forest ecosystems, and the sustained provision of forest MES and NMES. To do so, such models need to represent how preferences over forest MES and NMES drive landowner decisions and how divergence in such preferences and management objectives can, under certain conditions, contribute to the generation of bio-invasion risk from the parcel level to the landscape level through. They can then be useful for policymakers and stakeholders to compare the effectiveness of current uniform technical and financial assistance programs (e.g., USDA NRCS) to alternative, non-uniform incentives that build on the knowledge about the private incentives of

different ownership types (as driven by preference heterogeneity), their strategic behavior, and their contribution the landscape-level bio-invasion risk.

The hypothesis of this research is the following: fragmenting private forest landownerships such as in the Northern U.S. can act as drivers of bio-invasions at the landscape level. That is, heterogeneity among landowners managing ecologically-connected, transboundary resources can have a detrimental effect on the aggregate landowner welfare (Dayton-Johnson and Bardhan, 2002; Baland et al., 2007) and can increase the wedge between centralized and decentralized management (Oates 1972; Besley and Coate 2003). To test this hypothesis, we develop a spatial-dynamic model of bio-invasion and control with two agents that value differently the MES and NMES produced by the forest. We parameterize the model to represent two white pine forest stands invaded by the glossy buckthorn. One stand is managed for household recreation (i.e., NMES) and the other for timber (i.e., MES). We use non-cooperative and cooperative game theory to find conditions that lead to an underprovision of bio-invasion control and estimate the social cost of the externality. Finally, we compare the effectiveness of uniform and non-uniform payments for ecosystem services in achieving the socially efficient level of bio-invasion control.

There are three major differences between most existing related models and those we propose. *First*, in previous literature, eradication is assumed to be ecologically feasible, and focus is put on economic optimality (Epanchin-Niell and Wilen 2015). However, in the case of invasive plant management, eradication is not necessarily ecologically possible mostly because of temporal lags in symptom expression, imperfect control strategies, or spatial-temporal scale mismatch between spread and control (Homans and Horie 2011; Aadland, Sims, and Finnoff 2015). Incorrectly assuming ecological feasibility plausibly leads to an underestimation of

expected damages and overestimation of the effectiveness of private and public expenditures. *Second*, land manager preferences, management objectives, damages, costs, time preferences, and planning horizons have been assumed to be homogenous among landowners (e.g., Epanchin-Niell and Wilen 2015). Assuming away landowner heterogeneity precludes the analysis of tradeoffs between centralized and decentralized management when spillovers are present (Belsey and Coate 2003). Preference heterogeneity and the extent of spillovers can determine the magnitude of the gap between centralized and decentralized management payoffs, in the case of public good provision (Oates 1972; Besley and Coate 2003). However, society's preference over centralized versus decentralized management is theoretically ambiguous when both resource and preference heterogeneity are present and significant (Costello and Kaffine 2016). The models we propose here can help characterize how resource and preference heterogeneity parameters drive the divergence between centralized and decentralized solutions. *Third*, spillover effects have been studied in the context of local, deterministic dispersal (Epanchin-Niell and Wilen 2015) or among immediately adjacent neighbors who differ only by their location on the landscape (e.g., Rich et al., 2005a; 2005b). Little research has considered spillover effects that are generated by within-parcel decisions and that can affect both adjacent and distant parcels through SDD and LDD dispersal mechanisms (Atallah, Gómez, and Conrad 2017). Specifications of externalities that do not account for LDD might underestimate the role of private incentives and strategic decision making in decentralized management on the resultant landscape-level risk generation.

II. METHODS

We use classical non-cooperative (simultaneous and sequential moves) and cooperative (Nash bargaining) game theory with two neighboring forest landowners to estimate the social cost of

the externality under the different game settings. We model each forest stand as a cellular automaton that stochastically updates its invasion states (uninvaded, invaded at increasing levels) in discrete time steps based on the invasion state and distance to contiguous and noncontiguous cells to which it is ecologically connected through SDD (Atallah et al., 2015) and LDD mechanisms (Atallah, Gómez, and Conrad, 2017). The value of forestland located in a cell evolves over time and depends on the bio-invasion state of each cell. The model has two landowner types. Landowner *A* manages a forest stand for its NMES and perceives the negative impact of the invasive plant on the recreation value of the forest. Landowner *B* manages their private pine forest to produce timber and perceives the negative impact of the invasive plant on pine tree through a delayed regeneration and growth of young seedlings. Both managers choose a bio-invasion strategy to maximize the discounted expected utility from the MES and NMES provided by their trees, subject to the ecological invasion risk dynamics within and across their forestland (Kovacs et al., 2014). Landowners are heterogeneous in their preferences for MES vs. NMES, but they face the same costs of bio-invasion control. We use the Nash equilibrium solution concept to solve a *simultaneous-move, non-cooperative game* where the landowners do not cooperate and do not share any information about their strategies. We also use the subgame perfect Nash equilibrium concept to solve a *sequential, non-cooperative game*, where one player moves first (i.e., as determined by the bio-invasion path) and the other player observes the move and makes their choice accordingly (Tirole, 1988). In both simultaneous and sequential move cases, we consider situations where the bio-invasion starts in forestland *A* (i.e., *A* moves first) and forestland *B* (i.e., *B* moves first).

Data collected over simulation runs are the expected utility realizations under each strategy combination. Outcome realizations for a given run within an experiment differ due to

the randomness of the bio-invasion process and its initial conditions. The model is written in Java using AnyLogic software.

III.   A MODEL OF EXTERNALITY PRODUCTION AND CONTROL

Our model considers two agents whose utilities are spatially connected through a network, composed of the combination of two independently managed grids. The grids represent forestlands that are linked through the short- and long-distance dispersal of an invasive plant, glossy buckthorn. Landowner A's recreation value is the product of their consumer surplus (CS) per recreation day and their average user days (UD) (Rosenberger et al. 2013). Both CS and UD are nonlinear functions of the longest connected sub-network composed of uninvaded forest stands, representing a forest recreating trail. The bio-invasion affects utility through its effect on the Landowner B's net revenues which are impacted by a delayed growth of young trees in invaded stands (i.e., adult trees are not affected). Each landowner's action to control the invasive plant determines their utility and the utility of the other landowner because they are connected through a biophysical network of trees and invasive plants; the actions of each of them within their parcels have spatial and dynamic consequences for the neighboring land parcel.

Grid G_A represents forestland A and is the set of $I*J$ cells denoted by their row and column position (i, j). Each cell (i, j) represents a pine tree. Similarly, grid G_B represents forestland B and consists of $M*N$ cells denoted by their row and column position (m, n). Each pine tree is modeled as a cellular automaton that updates its diameter (i.e., timber yield) and infestation states in discrete time steps (t) based on its own current diameter and infestation state and the infestation state of its neighbors (i.e., SDD process) and non-neighboring pine trees (i.e., LDD process). Each tree's infestation state transitions are governed by a discrete-time Markov chain model (i.e.,

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the probability distribution of the next state depends only on the current state and not on the sequence of events that preceded it). A tree in cell (i,j) or (m,n) and state *Healthy (H)* transitions to state *Infested-undetectable* (I_u) once seeds are dispersed to it, and they successfully germinate. This transition probability depends in a distance and density-dependent way on the number of infested pine trees on the landscape. Subsequently, the invasive plant reaches a size that makes it visually identifiable or detectable, at which point the tree transitions to state *Infested-detectable* (E_d) and a landowner can make a bio-invasion control decision. The transition to state *Infested-moderate* (I_m) and later to state *Infested-high* (I_h) occurs as the invasive plant grows, forms a clump, and produces berries that can then be dispersed to the landscape via the SDD and LDD processes.

An externality emerges when the privately optimal management strategy in one forestland causes the bio-invasion to spread to the neighboring parcel (Figure 1) thus affecting the neighboring landowner's utility. We next describe the managers' private utility maximization problems.

[Figure 1]

Economic Model

Each landowner's objective is to maximize their utility by choosing an invasive plant control strategy, $\mathcal{W}$. The optimal shading strategy $\mathcal{W}^*$ translates into a set of cell-level control variables $\{z_{i,j,t}\}$ equal to 1 if control takes place and 0 otherwise. The objective of a landowner of type A is to choose the set of binary control variables $\mathcal{W}$ that maximize the following expected discounted net recreation value, where E is an expectation operator and ρ is a discount factor:

$$\max_{\mathcal{W}} \mathrm{E} \sum_{t \in T} \rho^t \left\{ CS\left(\sum_{(i,j)}^{G_A} x_{i,j,t} \right) * UD\left(\sum_{(i,j)}^{G_A} x_{i,j,t} \right) - c \sum_{(i,j)}^{G_A} z_{i,j,t} \right\} \qquad [1]$$

subject to

$$x_{i,j,t} - x_{i+1,j,t} = x_{i,j,t} - x_{i,j+1,t} = 0 \; \forall \; (i,j)|x_{i,j,t} = 1 \tag{2}$$

$$E(\boldsymbol{s}_{i,j,t+1}) = \mathbf{P}^{\mathrm{T}} \, \boldsymbol{s}_{i,j,t} \tag{3}$$

In Eq. (3), $CS\left(\sum_{(i,j)}^{GA} x_{i,j,t} \right) = a_0 + a_1 \sum_{(i,j)}^{GA} x_{i,j,t} + a_2 \left(\sum_{(i,j)}^{GA} x_{i,j,t} \right)^2, a_0 < 0, a_1 > 0, a_2 < 0$ is

the consumer surplus per recreation day, $UD\left(\sum_{(i,j)}^{GA} x_{i,j,t} \right) = b_0 + b_1 \sum_{(i,j)}^{GA} x_{i,j,t} +$

$b_2 \left(\sum_{(i,j)}^{GA} x_{i,j,t} \right)^2, b_0 < 0, b_1 > 0, b_2 < 0$, is the average user days, and $z_{i,j,t} = 1$ if control takes

place in cell (m,n) in period t with unit cost c and zero otherwise. Eq. (1) is a spatial

connectivity constraint that ensures that the argument of the CS and UD functions is a trail

uninterrupted by the bio-invasion. Equation (3) is the equation of motion, specified as a cell-level

infection state transition equation where $\mathbf{P}$ is the infestation state transition matrix.

Landowner B's utility is equal to the timber revenues, which are a linear function of the

number of pine trees, their diameter, and timber values. The objective of a landowner of type B is

as follows:

$$\max_{W} E \; \sum_t^T \rho^t \sum_{(m,n)}^{GB} (r_{d,m,n,t} - z_{m,n,t} \, c) \tag{4}$$

subject to $E(\boldsymbol{s}_{m,n,t+1}) = \mathbf{P}^{\mathrm{T}} \, \boldsymbol{s}_{m,n,t}.$ [5]

In Eq. (4), $r_{d,m,n,t}$ is the revenue in cell (m,n) at time t that depends on timber diameter $d_{m,n,t}$

and $r_{d,m,n,t} = p_0 \, d_{m,n,t}$ if $d_{m,n,t} \le \tau_0$ for seedlings, $r_{d,m,n,t} = p_1 \, d_{m,n,t}$ if $d_{m,n,t} \ge \tau_1$ (young

trees), and $r_{d,m,n,t} = p_2 \, d_{m,n,t}$ if $d_{m,n,t} \ge \tau_2$ (mature trees), where τ_0 , τ_1, τ_2 are timber

diameter thresholds that command net prices p_0, p_1, p_2 (i.e., prices net of production costs

excluding bio-invasion control costs), where $p_0 < p_1 < p_2$. The damage of the bio-invasion for

G_B occurs through a delay of the transition from diameter state τ_0 to diameter states τ_1 and τ_2. As

in Eq. (1), $z_{m,n,t} = 1$ if control takes place in cell (m,n) in period t with unit cost c and zero

otherwise.

More generally, a landowner's utility function can be generalized as $U_t = U(\lambda, U_t^A, U_t^B)$, where λ varies from 0 to 1 as a landowner's type corresponds to an exclusively timber-driven type ($\lambda = 0$) to exclusively NMES-driven type ($\lambda = 1$).

Model of Spatial-Dynamic Externality Dispersal

The invasive plant is primarily introduced to forestland through bird-dispersed seeds through a long-distance dispersal mechanism (LDD). All external grid boundaries are reflecting (i.e., when the bio-invasion reaches the boundary of a grid representing, say, a road, it might be bounced back inside it according to Eq. 3 and 5). In contrast, according to the LDD process, the bio-invasion can move off one grid along the inter-grid boundary in search of a new host. According to the SDD, in each time step, a *Healthy* pine tree can receive invasive plant seeds at time *t+1* from any of its eight neighboring trees if they are in state *Infested-moderate*. Seeds successfully germinate if $u_t < 1 - e^{-\alpha}$ and do not germinate if $u_t \geq 1 - e^{-\alpha}$, where u_t is a random draw from $U \sim (0, 1)$. The LDD mechanism, in contrast, causes trees in state *Healthy (H)* to transition to state *Infested-undetectable* (I_u) with a distance and density-dependent probability a_1 and then to state *Infested-detectable* (E_d) with probability α_2. The transition to state *Infested-moderate* (I_m) occurs with a probability α_3, and the transition to state *Infested-high* (I_h) with a probability α_4. We define these probabilities and their associated parameters in Table 1. First, we focus on probability α_1, which drives the distance and density-dependent specification of the externality. This probability depends on the number and location of trees in state I_m or I_h within the same forest land parcel and in the neighboring parcel. The distance and density-dependence of this probability captures the impact of a landowner's private bio-invasion control actions, within a grid, on the spatial damages borne by their neighbor at the border of and within the adjacent grid.

The transition matrix **P** in Eq. (8) governs the SDD and LDD mechanisms. It can be expressed as follows: [1]

$$\mathbf{P} = \begin{pmatrix} (1-\alpha_1) & \alpha_1 & 0 & 0 & 0 \\ 0 & 1-\alpha_2 & \alpha_2 & 0 & 0 \\ 0 & 0 & 1-\alpha_3 & \alpha_3 & 0 \\ 0 & 0 & 0 & 1-\alpha_4 & \alpha_4 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \qquad [6]$$

In Eq. (6), limiting the notation to G_A for brevity, α_1 can be expressed as:

$$\alpha_1 = \Pr\big(s_{i,j,t+1} = I_u \,\big|\, s_{i,j,t} = Healthy;\, s_{N_{i,j,t}}\big) = 1 - e^{-(N\alpha + \gamma_{A,B,t})} \qquad [7]$$

Probability α_1 depends on the state of the SDD neighborhood of cell (i,j) which is denoted by $N_{i,j,t}^{SDD}$ and describes the number of cells in the immediate neighborhood (eight neighbors) that can contribute to the bio-invasion (i.e., in state I_m or I_h). Accordingly, $N_{i,j,t}^{SDD} = \{0\,...\,8\}$ and the first term of the exponential rate will have $\{0, ...\, 8\alpha\}$, depending on the number of immediate neighbors that are in state I_m or I_h. Rate $\gamma_{A,B,t}$ is a power-law dispersal parameter specified by the spatial-dynamic, distance- and density-dependent dispersal function defined in Eq. (8a). In order to calculate the total number of infested pine trees in each period that constitute the LDD neighborhood $N_{i,j,t}^{LDD}$, we introduce indicator variables x and y equaling 1 if a pine tree in column n and row m is in state *Infested-moderate* (I_m) *or Infested-high* (I_h) and 0 otherwise. If $x = 1$, the corresponding forestland rows that have $y = 1$ contain pine trees in state I_m or I_h that contribute to the long-distance dispersal from G_A to G_B. If $x = 0$ for all columns n (i.e., there are no cells in G_A that have glossy buckthorn producing berries that can be dispersed), the denominator equals 0, $\gamma_{A,B,t}$ is not defined, and no dispersal occurs from these columns.

$$\gamma_{A,B,j,t} = j^{-\gamma} \frac{\sum_n^N x \sum_m^M y\big((x,y)|\, s_{m,n,t} = \{I_m, I_h\}\big) * x}{\sum_n^N x\, M(N-x+1)} \qquad [10a]$$

The transition rate $\gamma_{A,B,j,t}$ is inversely proportional to the distance from the shared boundary (i.e., distance from column j in G_B to column N in G_A, regardless of its row position in column j).[2] We choose a power-law specification because it allows the bio-invasion long-distance dispersal to have new foci emerging beyond the bio-invasion front, which is consistent with modeling bird flight and seed dispersal. Dynamic parameter $\gamma_{A,B,j,t}$ is also proportional to the total number of pine trees that are in state I_m or I_h in G_A, weighted by their column position n (the numerator in Eq. 8a). Weighting by column positions n allows infested cells closer to the bordering column to contribute more to the externality than cells situated farther from the boundary (i.e., cell-level distance dependence). The denominator in Eq. (8b) allows the multiplier of the power-law expression to vary between 0 and 1 as the number of cells in state I_m or I_h in G_A varies between 0 and $M*N$ (i.e., density dependence).

Similarly, dispersal within G_B and from G_B to G_A is given by:

$$\gamma_{B,A,n,t} = (N-n)^{-\gamma} \frac{\sum_i^I x \sum_j^J y((x,y)\,|\,s_{i,j,t}=\{I_m,I_h\})*y}{\sum_j^J y\,I(J-y+1)}, \gamma>0, \sum_j^J y\,I(J-y+1)>0 \qquad [10b]$$

This specification of dispersal is in contrast with fixed externality dispersal rates in the extant resource and environmental economics literature, and with assumptions that spatial considerations only matter in that they define the spatial limit to private actions, and that managers ignore how their management in one cell affects payoffs through multi-cell dispersal. Bio-invasion and economic parameters are presented in Table 1 and Figure 1.

[Insert Table 1 here]

IV. COMPUTATIONAL EXPERIMENTS AND SOLUTION FRAMEWORKS

Experiments, each consisting of a set of 100 simulations, differ based on the strategy pairs employed in both forestlands to control the invasive plant. Outcome realizations for a given run

within an experiment differ due to the random location of initial infestations on the grid where

the infestation is initialized and stochastic dispersal within and between forestlands. Data

collected over simulation runs are the discounted utility realizations under each strategy pair.

Model Initialization

Pine trees are initialized as *Healthy* and of similar age distribution in both parcels G_A and G_B,

50% seedlings and 50% young trees. At the first timestep, 2% of each parcel are infested with the

invasive plant's seeds. That is, certain cells in each grid are chosen at random to transition from

state *Healthy* to state *Infested-undetectable*. Subsequently, the invasive plant grows and

transitions to *Infested-detectable*. At this point, a landowner can visually detect the presence of

the invasive plant, and the plant produces seeds that can be spread to neighboring and non-

neighboring locations according to the Markov transition process given by Eq. (3) and Eq. (5).

The dispersal occurs both within and between forestland parcels. We consider initial conditions

where the bio-invasion starts in one forestland and moves to the other and a scenario where it

starts simultaneously in both forestlands.

Solution Frameworks and Game Theoretic Solution Concepts

We first solve the central planner problem and find the cooperative solution (*C*). Second, we

solve for the noncooperative solution (*NC*).

Central Planner (CP)

The social planner chooses the pair of bio-invasion management strategies $(\mathcal{W}_A, \mathcal{W}_B)$ that

maximizes the total expected payoff π_T, defined as the sum of the discounted expected payoffs

of G_A (π_A) and G_B (π_B). The following maximization problem is solved:

$$\max_{(\mathcal{W}_A, \mathcal{W}_B)} \pi_A + \pi_B, \qquad\qquad [11]$$

subject to Eq. (3) and Eq. (5).

Noncooperative Disease Control, or Decentralized Management (DM)

We use the Nash equilibrium solution concept to solve a simultaneous-move game where the landowners independently make decisions. We use the subgame perfect Nash equilibrium concept to solve a sequential game where one player moves first, and the other player makes their decision accordingly (Tirole, 1988).

The expected cooperative surplus is defined as the difference between the total expected central planner payoff and the total expected noncooperative payoff ($\pi_T^{NC} = \pi_A^{NC} + \pi_B^{NC}$). The expected cooperative surplus is also a measure of the Pareto-inefficiency caused by noncooperative bio-invasion control and an estimate of the social cost of the externality.

V.   RESULTS AND POLICY IMPLICATIONS

In the absence of LDD, the DM and CP solutions are identical: Both landowners control the bio-invasion, and the strategy pair solution is (*control*, *control*). This result is consistent with Oates' Decentralization Theorem which states that, without spillovers, the decentralized provision of a public good will produce a level of welfare that is at least as high as a centralized provision (Oates 1972, 1999).

[Table 2]

In the presence of LDD and preference heterogeneity, the DM solution consists of G_A not controlling and G_B controlling the bio-invasion, i.e. strategy pair (*no control*, *control*), which produces lower aggregate payoffs than strategy pair (*control*, *control*) (Table 3a). The magnitude and resolution of the social externality depend on (1) the extent of preference heterogeneity, (2) the degree of spillovers (i.e., the externality parameters), (3) the prospects for coordination, (4) the strength of the strategic complementary of bio-invasion control, and (5) cost of control.

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Below, we discuss how the social cost of the externality and the optimal strategy pair changes as we change these four factors.

First, in the absence of preference heterogeneity, the CP and DM solutions are identical, and there is no bio-invasion externality: if both landowners are of type G_A, the CP and DM solutions both consist of (*no control*, *no control*) (Table 3b). Similarly, if both landowners are of type G_B, the CP and DM solution both consist of (*control*, *control*) (Table 3c). Second, if externality parameter γ is larger so that the spillover decays faster over space, the same results as in Table 2 would be obtained, i.e., no externality. In the absence of LDD, G_A finds it optimal to control the bio-invasion. Third, if the potential gains to cooperation are large enough, the landowners might reach a Pareto-efficient transfer payment agreement. For instance, the solution to a Nash bargaining game leads to (*control*, *control*) with a transfer payment of $20/acre from G_A to G_B, which leads to a Pareto efficient outcome (Table 3a, cooperative game).

[Table 3]

Fourth, given that bio-invasion control on one parcel is a strategic complement to control on the adjacent land in the presence of spillovers (Fenichel, Richards, and Shanafelt 2014; Atallah, Gómez, and Conrad, 2017), a first move by G_B should increase the net value of control for G_A and replicate the CP solution without bargaining. We conduct additional simulations where the bio-invasion onset and bio-invasion control are sequential in a Stackelberg-type leader-follower game. We find that a first-move by G_B reduces the wedge between CP and DM payoffs (i.e., the difference between $19,325 and $18,929 in Table 4, or $396, compared to the difference between $12,864 and $12,402 in Table 3, or $462) but not enough to change the DM resulting strategy pairs: (*no control*, *control*) (Table 4). This result is in contrast with the strong complementarity is disease control in Atallah, Gómez, and Conrad, 2017), which causes a first

move by one of the players to reduce the cost of control to the other players enough to incentive them to control the disease, thus making the DM solution replicate the CP outcome.

[Table 4]

Fifth, an increase in the cost of control widens the wedge between CP and DM payoffs enough to make (*no control*, *control*) the optimal strategy pair (Table 5) and a decrease in the cost of control makes (*control*, *control*) the optimal strategy pair under both CP and DM settings, thus eliminating the externality (Table 6).

[Table 5]

[Table 6]

Policy implications

Both private bargaining and a uniform subsidy or payment for ecosystem services (PES) that reduce control cost by half lead to the optimal strategy pair (*control*, *control*) that mitigates the externality (Table 6). It is not immediately clear, however, which is more socially efficient and has higher prospects of implementation. Given the presence of conservation programs that provide PES for landowners to control invasive species (e.g., NRCS), among others, considering a reduction on the cost of control in our model is probably more relevant to the current policy context of controlling forest invasive species in the U.S. Since 2008, forest landowners in the U.S. have had access to technical and financial assistance to manage invasive species and pests through the Environmental Quality Incentives Program (EQIP), Wildlife Habitat Incentive Program (WHIP), Agricultural Management Assistance Program (AMA), and the Conservation Stewardship Program (CSP). Before then, landowners had access to the National Conservation Innovation Grants (CIG) (USDA NRCS 2017). A common feature among these programs is that

they provide uniform payments, regardless of landowner type, provided the landowner net revenues are below a million dollars a year.

We consider a non-uniform PES scheme where only G_A is eligible for the payment. We find that (*control*, *control*) is the optimal solution for both the CP and DM problems, suggesting that PES eligibility based on landowner preferences can lead to the CP solution under DM at lower public expenditures than a uniform PES. Despite their potential to promote the provision of ecosystem services, PES have a basic problem stemming from asymmetric information: landowners have private information about their costs and opportunity costs of controlling bio-invasions. Only the landowner knows whether they would have undertaken bio-invasion control in the absence of a PES, that is, whether bio-invasion control would have been truly additional. However, where land ownership types and corresponding preferences are observable, as in the case of private forest landownership, a government might design non-uniform PES schemes based on heterogeneous resource preferences to avoid paying for non-additional practices such as bio-invasion control for type G_B. We argue that the modeling framework provided here can produce results that reduce information asymmetry in the returns to bio-invasion control to ecologically connected landowners. Such results might then support designing PES eligibility to be based on landowner preferences with the objective of increasing the efficiency of public conservation expenditures.

[Table 7]

VI.   NEXT STEPS

The political economy literature on local public goods has theoretical results suggesting that without spillovers, CP solutions are superior and DM becomes preferred at a threshold level of

spillovers (Oates 1972; Besley and Coate 2003). This model can be used to identify threshold levels of the SDD and LDD parameters beyond which DM is welfare-improving. Spatial-dynamic externalities in natural resources are multi-dimensional and simultaneously determined by a multitude of static and dynamic parameters such as the SDD and LDD parameters, size and age structure of the tree population and initial infestation levels. Rather than a comparative statics exercise, a multi-variate spillover threshold would need to be determined through multi-way sensitivity analyses.

Second, in this model, except for the sequential games, landowners are assumed to interact in one-shot noncooperative and cooperative games. A more realistic depiction of managers' strategic interaction might involve reevaluating strategies and learning over time. Third, to expand the test of the hypothesis suggesting that heterogeneity among landowners has a detrimental effect on the aggregate landowner welfare (Dayton-Johnson and Bardhan, 2002; Baland et al. 2007), future steps would involve adding landowners with multiple ownership objectives and varying the relative weights landowners put on MES and NMES (parameter (λ, page 10). By doing so, the relationship between landowner preference heterogeneity and welfare can be characterized (a nonlinear relationship is proposed by the theoretical model of Dayton-Johnson and Bardhan, 2002).

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Table 1. Model parameters

Parameter	Description	Value	Unit
Objective function parameters			
a_1, b_1	Intercept of consumer surplus (CS) and user days (UD) functions	-2.97 [a] 9.32 [a]	$/UD days/year
a_2	Slope of CS and UD functions	0.24	unitless
a_3, b_3	Quadratic parameter of CS and UD functions.	-0.00017 [a]; - 0.0002 [a]	unitless
p_1, p_2	Timber prices for *Young* and *Mature* trees	0.11; 0.16	$/BF
$d_{m,n,t}$	Timber yields for *Young* and *Mature* trees	297; 594	BF/tree
c	Invasion treatment cost	2; 4; 6	$/tree
ρ	Discount factor	0.9959	year^{-1}
Spatial-dynamic externality parameters			
α	Short distance H to E_u transition rate	8	year^{-1}
γ	Long distance power-law parameter	3	unitless
L_1	Inverse of transition rate from Infested-undetectable to Infested-detectable	1	year
L_2	Inverse of transition rate from Infested-detectable to Infested-moderate	1	year
L_3	Inverse of transition rate from Infested-moderate to Infested-high	2	years
$\tau_{0, H}$	Waiting period between *Juvenile* and *Young* if *Healthy*.	15	years
$\tau_{1, Im}$	Waiting period between *Juvenile* and *Young* if *Infested-moderate*.	20	years
$\tau_{2, Ih}$	Waiting period between *Juvenile* and *Young* if *Infested-high*.	25	years
$I * J$	Grid G_A dimensions	49*16=784	rows x
$M * N$	Grid G_B dimensions	49*16=784	columns

[a] Values from Rosenberger et al. (2013)

Table 2. Payoffs ($) if G_A and G_B are not ecologically connected (optimal strategies and corresponding payoffs in bold; standard deviations in parentheses)

Strategies	*Payoffs ($)*		
	G_A	G_B	G_A+G_B
no control	2,217 (0)	- 4,755 (53)	-2,538 (53)
control	**3,323 (32)**	**12,007 (3,368)**	**15,330 (3,383)**

Table 3. Payoffs (\$) if G_A and G_B are ecologically connected, bio-invasion starts on both lands and control decisions are simultaneous.

Strategies		Payoffs		
(3a) Preference heterogeneity				
G_A	G_B	G_A	G_B	G_A+G_B
no invasion	no invasion	4,445	18,852	23,297
Noncooperative game				
no control	no control	1,571 (4)	-5,177 (43)	-3,606
no control	**control**	**1,694 (3)**	**10,708 (3,353)**	**12,402**
control	no control	-334 (18)	-4,977 (0)	-5,310
control	*control*	*1,542 (28)*	*11,322 (3,370)*	*12,864*
Cooperative game				
control	control	1,925	10,939	12,864
(3b) Both G_A (NMES) type				
no control	***no control***	1,571 (4)	1,571 (4)	***3,143***
no control	control	1,694 (3)	-334 (18)	1,361
control	no control	-334 (18)	1,694 (3)	1,361
control	control	1,542 (28)	1,542 (28)	3,085
(3c) Both G_B (MES) type				
no control	no control	-5,177 (43)	-5,177 (43)	(10,340)
no control	control	-4,977 (0)	10,708 (3,353)	5,758
control	no control	10,708 (3,353)	-4,977 (0)	5,758
control	***control***	11,322 (3,370)	11,322 (3,370)	22,643

Note: DM optimal strategies and corresponding payoffs in bold; CP optimal strategies and corresponding payoffs in italics.

Table 4. Sequential game results: Payoffs (\$) if G_A and G_B are ecologically connected, bio-invasion starts in either G_A or G_B and control is sequential.

| Strategies | | Payoffs (\$) | | |
G_A	G_B	G_A	G_B	G_A+G_B
no invasion	no invasion	4,445	18,852	23,297
G_A starts				
No control	No control	1,711	(5,063)	(3,352)
No control	**Control**	**1,888**	**16,895**	**18,783**
Control	No control	225	(1,723)	(1,498)
Control	*Control*	*1,280*	*17,838*	*19,118*
G_B starts				
No control	No control	2,135	(4,885)	(2,750)
No control	**Control**	**2,663**	**16,266**	**18,929**
Control	No control	807	(4,859)	(4,052)
Control	*Control*	*2,016*	*17,309*	*19,325*

Note: DM optimal strategies and corresponding payoffs in bold; CP optimal strategies and corresponding payoffs in italics.

Table 5. Payoffs (\$) if G_A and G_B are ecologically connected; case of higher control costs ($c_A = c_B = \$6/\text{shrub}$)

Strategies		Payoffs ($)		
G_A	G_B	G_A	G_B	G_A+G_B
no invasion	no invasion	4,445	18,852	23,297
No control	No control	1,566	-5,242	-3,676
No control	*Control*	*1,689*	*15,352*	*17,041*
Control	No control	-2,317	-4,987	-7,304
Control	Control	273	16,257	16,530

Note: DM optimal strategies and corresponding payoffs in bold; CP optimal strategies and corresponding payoffs in italics.

Table 6. Uniform PES ($c_A = c_B = \$2/$shrub); Payoffs (\$) if G_A and G_B are ecologically connected.

Strategies		Payoffs (\$)		
G_A	G_B	G_A	G_B	G_A+G_B
no invasion	no invasion	4,445	18,852	23,297
No control	No control	1,566	(5,242)	(3,676)
No control	Control	1,689	17,685	19,374
Control	No control	1,709	(4,987)	(3,278)
Control	*Control*	*2,906*	*17,987*	*20,893*

Note: decentralized optimal strategies and corresponding payoffs in bold; central planner optimal strategies and corresponding payoffs in italics.

Table 7. Non-uniform PES (c_A=\$2/ shrub; c_B=\$4/ shrub): Payoffs (\$) if G_A and G_B are ecologically connected.

Strategies		Payoffs (\$)		
G_A	G_B	G_A	G_B	G_A+G_B
no invasion	no invasion	4,445	18,852	23,297
No control	No control	1,566	(5,242)	(3,676)
No control	Control	1,689	16,518	18,207
Control	No control	1,709	(4,987)	(3,278)
Control	*Control*	*2,906*	*17,122*	*20,028*

Note: decentralized optimal strategies and corresponding payoffs in bold; central planner optimal strategies and corresponding payoffs in italics.
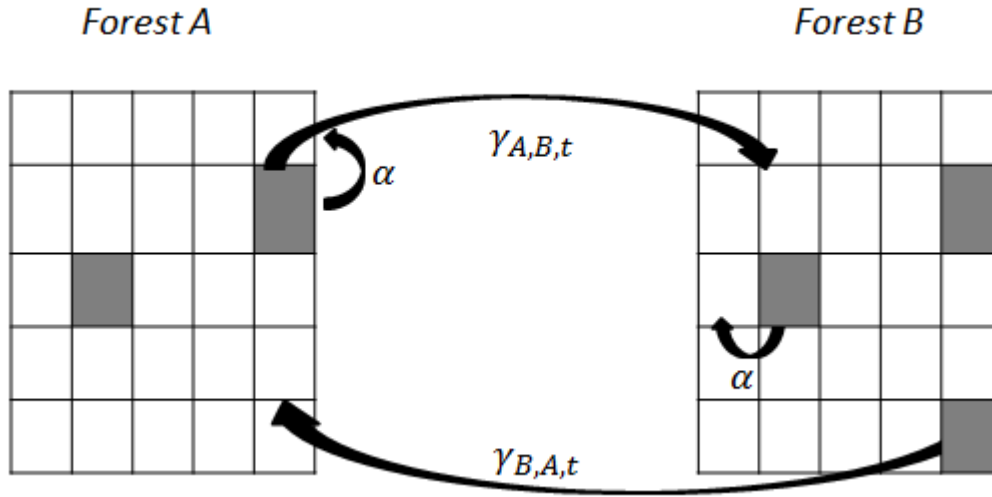
Fig. 1 Short-distance dispersal (α) and long-distance dispersal from A to B ($\gamma_{A,B,t}$) and from B to A ($\gamma_{B,A,t}$). Shaded cells represent infested cells on the grid.

FOOTNOTES

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[1] Each element in matrix P is a probability that a grid cell will be in one of the five states

$(Healthy, E_u, E_d, I_m, I_h)$ in period $t+1$, conditional on being in one of these states in period t

[2] This assumption implies that long-disease dispersal (LDD) does not capture whether *Infested*

cells in a bordering column n are clustered or uniformly distributed over the column. This

assumption might lead to an overestimation of LDD.