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The Economics of Forest Disturbances: Bookends of a Range of Economic Tools of Analysis

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The Economics of Forest Disturbances: Bookends of a Range of Economic Tools of Analysis

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Abstract

Forest insects play an essential role in forest ecosystems because they contribute to the regeneration of trees and provide new habitats for wildlife. However, forest insect infestations can become severe and cause economic problems due to the damage and destruction they cause in commercially valuable forest lands. The need for pest management arises when native forest insects expand their populations beyond an acceptable threshold and become "pests" or non-native species become invasive. Pest management problems can be solved using a range of economic tools; stochastic dynamic programming models and computable general equilibrium models can be considered "bookends" of tools as they focus on the microeconomic stand level and the overall macroeconomic level for government. Economists can help stand managers and policymakers make decisions on whether or not to take action to mitigate the disturbance by using these "bookend" tools to compare the potential costs and benefits of such action in the face of uncertainty and with respect to the direct and indirect consequences that may arise.

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1. Motivation

Forest insects play an essential role in forest ecosystems because they contribute to the regeneration of trees and provide new habitats for wildlife. However, forest insect infestations can become severe and cause economic problems due to the damage and destruction they cause in commercially valuable forest stands. The need for pest management arises when native forest insects expand their populations beyond an acceptable threshold and become "pests" or non-native species become invasive. Pest management is a component of forest management that requires attention and analysis. This essay aims to provide both policymakers and stand managers with methods of analyzing the potential costs of invasive pests (both native and non-native) in order to make informed mitigation decisions on investments to control the pest.

For countries that are reliant on agriculture, forestry and tourism/recreation, such as Canada, pest invasions can be extremely important (Moore, 2005). If the problem is severe enough, resources need to be allocated in order to suppress or eradicate the pest or to manage forests differently to account for the uncertainty of invasion. For forest managers, the invasion of pests introduces a level of uncertainty into their stand decisions on whether to harvest and how to replant as to maximize the harvest value of their stands. This problem can be analyzed using stochastic dynamic programming. Higher-level governments may be concerned with how a problem in one sector, such as forestry, can have reverberating impacts on other economic sectors, factors of production and output. This can be solved using a computable-general equilibrium, which can model an entire country's economy and evaluate feedback effects in all sectors and factors of production caused by shocks in one unique sector. The two unique perspectives require different inputs and produce unique results that can analyze and help solve the different problems that stand operators/managers, provinces or countries face when dealing with a potentially destructive pest disturbance.

2. Background Information

2.1 Invasive Species

The disturbance of ecosystems, particularly forests, by invasive species is a serious problem globally. Here, invasive species will be referred to as “insects and diseases that spread beyond their known usual range” (NRCAN, 2016). Native species such as the mountain pine beetle have become invasive in Canada. Non-native species are species that have been introduced into Canadian forests and invasive non-native species have become a major concern in Canada as of recent history (e.g., Emerald Ash Borer, brown spruce longhorn beetle).

The movement of non-native species from origin to new habitats is a not a new phenomenon. Even without the human factor, plants, insects and micro-organisms have migrated and established themselves in new locations through natural processes. However, the growth of international trade and travel and overall globalization increased the natural flow and movement of species across continents.

Invasive native and non-native pests can be incredibly harmful to their new habitats due to the damage and disturbance they cause in the ecosystems. The forest disturbance caused by these pests can cause damage through ecological means by impacting the productivity and quality of forestry products and through economic means by impacting trade, output levels, costs for government intervention, and job opportunities.

2.2 Establishment of Invasive Exotic Species

To understand the magnitude of the invasive pest problem facing the forest sector, it is important to understand the movement of these species and how they can establish themselves in new habitats. Management of invasive non-native species is typically sorted into three different processes: arrival, establishment, and spread (Liebhold et al., 1995). [1]

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[1] Material in sections 2 and 3 is largely based on Liebhold et al. (1995).

2.3 Arrival

There has been a natural ebb and flow of organisms across continents and water bodies for millions of years, which occurred independently of human activity. The geographical barriers faced in the past, such as oceans, mountains and vast land masses, prevented species from mixing and greatly influenced species divergence and speciation (Mayr, 1963). Basic weather can aid in the movement of non-native organisms. For example, adults or immature insects, plant seeds and fungus spores can be blown into new areas with the wind, storms or other major weather events (Krcmar-Nozic et al., 2000).

In the past century, growth in international trade and travel allowed humans and goods to overcome geographical barriers with increasing frequency, which unintentionally transported pests into new ecosystems around the world (Epanchin-Niell and Liebhold, 2015). Simberloff (1986) found that species introductions are correlated to shipping and trading routes as many North American pests have roots in Europe. Humans have altered the natural ebb and flow of organism movement through both purposeful and accidental introduction. Pests and animals have been found to "hitch-hike" to new areas by attaching onto transportation modes such as ship hulls, shipping containers, low quality wood packing material (or dunnage), passenger baggage, et cetera (Lovett et al., 2016). These pallets and other low quality wood packaging material pose a great risk to invasion as they can house immature life stages of phloem and wood boring insects and transport them to novel environments.

The growth of human activity has also, unintentionally, led to the disturbance of natural ecosystems for resources and relocation. The disturbance of ecozones makes the areas vulnerable to non-native pest establishment as competition is typically lower in such areas and leaves open "niches" that allow the organism to flourish.

The appropriate management strategy depends on the phase of invasion. One of the most efficient methods of preventing invasion at the arrival stage is to exclude the pest entirely. This can be accomplished by way of inspection of goods coming in from at-risk areas and quarantine of at-risk areas to prevent further spread.

2.4 Establishment

If non-native species are successfully introduced into new habitats, establishment is the next stage in the process of invasion in which the population persists for many generations. Another way to define establishment is "the point where the species reach population sizes at which extinction is no longer likely" (Lovett et al., 2016). Not all species that are introduced become established. Other factors also influence establishment such as number of natural enemies and level of competition, habitat suitability, size of original introduction, et cetera (Krcmar-Nozic et al., 2000). For example, in Canada, very few species succeed in establishment due to natural barriers such as variable climate and topography (NRCAN, 2016).

The process of establishment is full of uncertainty. First, it is uncertain if the species will successfully establish once it arrives in a new location as it is unable to adapt to its new environments (allee effect). These "founder populations" are typically small and are therefore at great risk of eradication; it is best to think of establishment in terms of the *probability* that the founder population will establish as a continuous function of its initial population size and other factors such as genetic diversity and intrinsic rate of reproduction. Other environmental factors can play into this probability function, such as climate and wind that can create favourable or unfavorable conditions for establishment. If the species does survive, there is a possibility of an "invasion lag." Invasion lags refer to the process by which species remain at relatively low densities until visible outbreak and therefore delay the onset of damage (Epanchin-Niell and Liebhold, 2015; Krcmar-Nozic et al., 2000).

Establishment is the point of invasion where it is most beneficial for managers to act and attempt eradication to reverse the process and eliminate possibilities of population bursts. It is likely that eradication will only be successful in circumstances where the invasive population is low in density and is restricted in its spatial distribution. During the establishment phase, population suppression tactics such as detection and destruction of infestations are required for eradication. For example, the use of *Bacillus thuringiensis kurstaki* (BTK) is used in aerial and ground sprays to suppress populations, pheromone treatments are used to disrupt mating, and general destruction of infested materials can also eliminate infestations and prevent further spread.

2.5 Spread

The final step of the invasion process is spread: the increase in size and scope of the established population. The spread of invasive species is in part driven by two separate processes: population growth and dispersal. Many previous papers have focused on spread models with respect to biological invasions, a generalized explanation of spread models can be found in Liebhold et al. (1995).

There are a variety of methods to halt spread and bring invasive populations back to manageable and eradicable levels. If the species can advance through the stages of invasion, the probability of eradication falls and costs increase due to eradication programming. Exclusion and quarantines can minimize invasive populations. For example, the Canadian Food Inspection Agency (CFIA) currently regulates the movement of logs, Christmas trees and other forest products to limit the movement of the pine shoot beetle. These methods are costly, as they require labour and time at border crossings to inspect all shipments and therefore impede trade. At this stage of invasion, it may not be possible to eradicate the species fully, but it is possible to slow down the spread. Lastly, the spread of invasives can be limited using biological and chemical controls such as aerial or ground spraying of BTK or other chemicals, importation of natural enemies to restore the population to a smaller size.

3. Impact of Pest Invasions

Pest invasions can be extremely costly and have lasting impacts ecologically, economically and recreationally. Pest invasions can cause major disruptions in forests and ecosystems. Economically, pest invasions and subsequent eradication programs can have major impacts on all players in the economy: producers, consumers, and the government.

3.1 Ecological Impacts of Pest Invasions

Exotic pests are similar to native forest pests as they both can cause damage to their ecosystems and both can have large effects on tree growth, reproduction and vitality (Liebhold et al., 1995). It is important to note that the impacts will depend on the type of damage caused by the insect and the traits of the pest; for example, the host specificity of the insect, its reproductive and dispersal capabilities, productivity, and nutrient cycling all play a role in the level of impact (Lovett et al., 2016).

Exotic pests pose a threat to forest species composition and productivity of their ecosystems because, once they spread, there are no natural enemies that can keep their populations in check and the trees do not have natural resistance to these pests. Exotic pests can transmit parasites or pathogens to trees or plants, which can lead to productivity and/or population declines or extinction (Moore, 2005). For example, the hemlock woolly adelgid killed the hemlock in eastern forests in North America upon introduction and the Chestnut blight killed the American chestnut (Lovett et al., 2016). As well, attacks from pests can lead to changes in forest structure or composition, interspecies dynamics and gains or losses to biological diversity (Allen and Humble, 2000). Generally, Lovett et al. (2016) found that the impact on trees happens in two phases. First, there is the initial physical disturbance to the tree (defoliation, nutrient blocking, root rot, etc.) and this phase may last for a few months or even years. However, the second phase occurs for decades to centuries afterwards. The insect can impact the competitiveness of the tree, impact its ability to grow and repair itself, and ultimately, these changes can "cascade through the ecosystem" (Lovett et al., 2016). These ecosystem and ecological impacts can later be fed into models to calculate the damage or predicted damage from exotic pests.

3.2 Economic Impact of Pest Invasions

The introduction of invasive exotic species into new cities and habitats, or the eruption of a native species outside of its usual range, can have profound economic implications. According to Allen and Humble (2000), the most common impacts from these disturbances are direct economic costs such as damage to timber resource value, tree mortality, growth reduction, reduction in wood quality, cost of control and implementation, and unrealized revenue from recreation and tourism. Exotic pests can cause substantial costs to the forestry sector in terms of lost revenues from dead or damaged wood caused by infestation or feeding. Invasives can damages trees in all stages of development and therefore can interfere with both natural and planted forest management objectives (Moore, 2005).

Overall, invasions of forests from disturbances such as pests are particularly challenging for policy makers as there is an "inherent interdependency of ecology and economics," the ecological invasions are often a result of economic processes such as trade and human movement (Holmes et al., 2010). It is difficult to quantify the economic losses resulting from establishment and spread rates as they can be unpredictable and highly variable (Holmes et al., 2010; Liebhold et al., 1995). As such, researchers have developed a variety of methods to quantify the wide array of impacts caused by invasive pests in our forests and regions.

4. Methods of Analyzing Pest Disturbances in Forests

4.1 Economic Background

There is a fundamental relationship between the economy and natural resources; economic activity uses natural resources to produce valuable goods and services; but, in doing so, economic processes also impact natural resources. In the context of forests, forest disturbances such as introduction of foreign pests, are an externality created by trade, an economic activity. These forest disturbances, whether it is a forest fire, invasion of native or non-native pest, are events that impede the flow of goods and services provided by forest ecosystems to those whom demand the goods and services (Holmes et al., 2008, as cited by Niquidet et al., 2015).

To place a value on this externality caused by pest disturbances, economists use non-market and market valuations. Non-market valuation refers to the valuation of goods that cannot be sold in a market (such as fresh air or wildlife) and is typically used as environmental valuation in welfare analysis. Market valuation refers to the use of market pricing. However, the calculation of non-market values is complex and time-consuming, and is often calculated incorrectly (Holmes et al., 2008, as referenced by Niquidet et al., 2015). Instead of placing a direct value on the externality itself, we can instead utilize various economic evaluation methods to calculate the overall impact of the externality. As per Niquidet et al. (2015), "impacts are based on flows, making it necessary to know the different dynamics of forest production, with and without the insect across time." Impact analysis requires the consideration of the time value of money, discounting future costs and benefits to a common present value, and requires the consideration of forest ecology, with respect to stands as a whole or trees individually (Niquidet et al., 2015).

Pest invasion and subsequent management and control strategies can be looked at from two different perspectives. Forest managers may also be interested in the impact of pest invasion due to the loss in value of their stands. Intensive forest management on productive forestland spurred by pest invasions will be costly. Policymakers may be interested in the economic impact of pests in their forests because the potential losses generated have direct effects on the forestry sector; however, there may be indirect effects that impact other sectors. Economic analysis is required to estimate the value of protecting against invasives.

There is a range of methods one may use to estimate the economic impact of forest pests. This essay will focus on two "bookends" of methods of economic analysis: on-site analysis and the macro-economic level. Economic analysis of the impacts is required to make informed decisions about management and mitigation efforts in forests. The on-site analysis will highlight how stand and operation managers can make management decisions that incorporate risk of pest invasion by using stochastic dynamic programming. On the other end of the spectrum, policymakers at the federal or provincial level need to have credible information to decide if management, suppression or eradication efforts should be implemented under threat of invasion. We can utilize a computable general equilibrium (CGE) to calculate a broad economic impact analysis of pest invasions in forests and compare it to mitigation costs to make informed mitigation decisions at a macro-economic level. The rest of the paper will be laid out as follows: description of the method, overview of the theory behind the method, and practical use of the method in the context of forestry management.

4.2 The Micro-Scale Bookend: Stochastic Dynamic Programming

Natural disturbance has implications at the stand level that economists can address using stochastic dynamic programming. In this section, I discuss stochastic processes, applications of forest management using stochastic dynamic programming and provide an example.

Description of Model

Forests are complex dynamic systems that are in a state of change at all times. Forest stands change with time in terms of quality, growth and mortality; these changes occur naturally or from human impact. Therefore, forest growth and yield are not deterministic: one cannot accurately predict the future state of the forest from the knowledge of its present state. When dealing with issues in forestry, it is important to recognize that there is uncertainty with respect to growth, quality and, especially, risk of natural disturbances. Growth and yield are stochastic processes, and managers must incorporate the uncertainty of disturbances or changes in growth (yield) into their management decisions. Stochastic processes allow for continuous (growth) and jump (disturbance) processes that must be accounted for when analyzing long-term horizons in the forestry industry.

Stochastic dynamic programming (SDP) is an optimization approach that can help forest managers address uncertainty. The stochastic aspect refers to the randomness of variables in the model and dynamic programming (DP) refers to the optimization technique whereby many sub-problems are recursively solved to provide solutions to the larger problems; it has been referred to as a "divide-and-conquer" approach or as a Markov decision process. In the case of optimal harvest, SDP will provide an optimal solution based on recursively solving the problem for each year of the management horizon. Specifically, SDP provides agents with a method to make optimal decisions on different management strategies by examining how the state variable evolves over time. A state variable is a measurable condition of the system and can be classified by various ecological characteristics such as age, height, volume, et cetera.

To determine optimal harvest policies, the agent must first identify the management objective. Typically in forestry, the objective is to optimize the net present value of the expected returns from the forest stand over an infinite horizon (Pukkala and Kellomäki, 2012). To develop the SDP model, the agent must also identify different management practices that can affect the stand's growth. Practices such as optimal rotation lengths, thinning years and/or intensities, spacing and, ultimately, harvesting can be examined within an SDP framework (Pukkala and Kellomäki, 2012). How the stand evolves over time is determined by its intrinsic growth and the decisions taken by the forest manager. These decisions could be to harvest the stand at some point in time, fertilize or thin the stand, take action against a pest, et cetera. Since the system evolves in a stochastic fashion, albeit influenced by the current state of the system and the management decision taken, a probability transition matrix is used to represent each decision or control variable (Buongiorno and Gilless, 2003). The impact of intrinsic growth and natural disturbances, such as wildfire and pest invasions, and the effect of a management or silivicultural decision are incorporated in the probability transition matrices. It is assumed that all past information about the forest system is embodied in the current state of the system, which is known as the Markov assumption. Then using the transition probabilities and the Markov assumption, SDP can solve the optimization problem and determine an optimal management strategy that takes into account uncertainty and the dynamics of the forest (Zhou and Buongiorno, 2011). SDP models can be utilized to estimate optimal strategies for a range of possible states of the world and therefore can test decisions when it is not feasible to test them in the real world (Bogich and Shea, 2008).

Economic Theory behind the Model

Central to SDP modeling is the structuring of the stochastic process, which is accomplished using Markov chains. (As a result of the Markov assumption, stochastic dynamic programming is sometimes referred to as Markov chain programming.) A Markov chain is the process in which the outcome of a given event can affect the outcome of the next event. In a Markov chain, there is a given set of states:

$$S = \{s_1, s_2, s_3 \dots s_n\} \tag{1}$$

The chain starts in any of these states and then moves successively to the next state. Each move is called a "step." The Markov chain recognizes that the process moves from state to state with some probability, which is described using transition probabilities (TPs). If the process is currently in state i, s_i, then the probability that it will move to state j, s_j , is denoted p_{ij}. It is important to note that p_{ij} depends on the current state, not the previous state (this is the Markov Assumption).

Following Buongiorno and Gilless (2003), we can set up an SDP model to depict a forestry management scenario. We can first construct a TP matrix for a given time horizon and states S={A, B, C, D, E}:

Table 1 Structure of a transition probability matrix

	A	B	C	D	E
A	p_{AA}	p_{AB}	p_{AC}	p_{AD}	p_{AE}
B	p_{BA}	p_{BB}	p_{BC}	p_{BD}	p_{BE}
C	p_{CA}	p_{CB}	p_{CC}	p_{CD}	p_{CE}
D	p_{DA}	p_{DB}	p_{DC}	p_{DD}	p_{DE}
E	p_{EA}	p_{EB}	p_{EC}	p_{ED}	p_{EE}

TP matrices are used to obtain the probability distribution of the next state depending on the initial state and can describe the distributions of the different states over time. An initial probability distribution provides the probabilities that a forest ecosystem (forest stand) is in various states at time = 0. Generally, the probability distribution of the stand's state in period t, p_t, is obtained by multiplying the probability distribution of the stand's state in the previous period, p_{t-1}, by the TP matrix, P.

$$p_t = p_{t-1} \times P \text{ , t=1,...T} \tag{2}$$

As T goes to infinity, the vector p_T converges to a vector of steady-state probabilities, p^*, which is independent of p_0 (the initial state probability vector).

Markov chains have been used in the context of forestry, in particular stand growth (Buongiorno and Gilless, 2003). Typically in stochastic forestry management problems, stand growth is described by a transition probability matrix that describes the probability that a stand would move from one state to another (Zhou and Buongiorno, 2011). States can be described in terms of stand volume, for example, Low, Medium and High volumes. However, states can also be in terms of other characteristics such as age, basal area, volume or diameter of trees (White, 1989).[2] Suppose we have the following TP:

Table 2 Transition probability matrix P

t	**t+1 (L)**	**t+1 (M)**	**t+1 (H)**
L	0.40	0.60	0
M	0	0.30	0.70
H	0.05	0.05	0.90

Given an initial state probability vector,

$$p_0 = [\,1 \quad 0 \quad 0\,]$$

[2] The volume of a forest stand, for example, is a continuous state variable. However, it is discretized into as fine or coarse a grid as the analyst desires.

We can follow the transition of the probabilities of the forest being in a particular state as:

After one step:

$$p_1 = p_0 \times P = [0.40 \quad 0.60 \quad 0]$$

After two steps:

$$p_2 = p_1 \times P = [0.16 \quad 0.42 \quad 0.42]$$

After t steps:

$$p_t = p_{t-1} \times P \text{ for t=1,\ldots T}$$

Steady-State Probability Vector, $\boldsymbol{p}^*$:

$$p^* = [0.07 \quad 0.12 \quad 0.82]$$

The vector of steady-state probabilities, p^*, will provide the probabilities of finding a given stand in state L, M or H in the long run. The steady state vector, p^*, depends on the process described by the TP matrix.

The steady state probabilities from the process above provide information on potential timber income from the stand. The expected long-run income can be determined by multiplying the steady state probability of the stands by their associated harvest amount and the dollar value of the stand as follows:

$$R = (\pi_L \times R_L) + (\pi_M \times R_M) + (\pi_H \times R_H) \qquad (3)$$

where R is the immediate return from the stand in state i under the stated policy.

A far more interesting calculation is the present value of the expected returns, taking into account the future value of money and discount rate, r. The discount factor in this case is described by the equation:

$$d = \frac{1}{(1+r)^n} \qquad (4)$$

where n is the step size between stages (usually ten years in forest models).

As per Buongiorno and Gilless (2003):

> *"We seek the present value of the expected return from a stand, over an infinite horizon, given its initial state, and management policy. The computations use backward recursion. We assume the present value of the expected return with t periods to go before the planning horizon, and then derive the present value of the expected return with t+1 periods to go."*

Letting V_{it} be the present value of the expected returns from an optimally managed stand in state i={L,M,H}, managed with a specific harvesting policy and with t periods to go before the end of the planning horizon. Then the present value of the expected return with t+1 periods to go is:

$$V_{i,t+1} = R_i + d(p_{iL}V_{Lt} + p_{iM}V_{Mt} + p_{iH}V_{Ht}) \qquad (5)$$

For a stand in state i, the expected present value return with t+1 periods to go is equal to the immediate return of the stand plus the present value of the expected returns with t periods to go (according to the chosen policy). Backward recursion is used in equation (5) above by setting the present value of the expected returns with t=0 periods to go at some arbitrary level (e.g., $V_{L0} = V_{M0} = V_{H0} = 0$). Then we can recursively calculate the present value of the expected returns with t=1,2,…T periods to go. Solving the SDP model by backward induction allows us to look back in time to determine the optimal strategy at each stage to get the desired point at the final stage (Bogich and Shea, 2008). Since the discounting factor is less than 1, there will be convergence as t increases: the present value of expected return V_{it} approaches a limit V_i^*, the present value of expected return for a stand that starts in state i and is managed according to the chosen policy for (infinite) time. The long-run expected return is found by multiplying the expected return for each potential starting state by the steady state probabilities found, p^*.

Thus far, no decision has been made in terms of choosing an optimal management practice for the stands. The Markov chain process simply allows us to predict the evolution of the forest stands under uncertainty and estimate the long-run returns to the stand. We can incorporate Markov chains into the Markov decision process to maximize the present value of the forest income over an infinite horizon.

In the initial example of Markov chains, the decision-maker considered stands under two management rules: no harvest or harvest when the volume of the stand is high (H). However, with SDP, the decision maker has the ability to decide what action to take at any state (e.g., cut or no cut). The ability to make a decision instead of abiding by a certain management rule changes the stand state, but also changes the TP matrix. Each unique decision will have its own TP matrix (as discussed above):

Table 3 Transition probability matrix with decision to cut

t	t+1 (L)	t+1 (M)	t+1 (H)
L	0.40	0.60	0
M	0.40	0.60	0
H	0.40	0.60	0

Table 4 Transition probability matrix with decision not to cut

t	t+1 (L)	t+1 (M)	t+1 (H)
L	0.40	0.60	0
M	0	0.30	0.70
H	0.05	0.05	0.90

This process is a Markov chain model and is known as a Markov decision process model: decisions at each state can lead to different outcomes. We can now incorporate our original objective, maximizing income from a stand over an infinite horizon, with the transition matrices from the Markov decision process.

Let V_{it} be the highest present value of expected return from a stand in state i={L,M,H}, within a specific policy rule, with t periods to go before the end of the planning horizon. Therefore, the highest present value with t+1 periods to go is related to the highest value with t periods to go by the equation:

$$\mathrm{V_{i,t+1}} = \max\left[\mathrm{R_{in}} + \mathrm{d}(\mathrm{p_{iLn}V_{Lt}} + \mathrm{p_{iMn}V_{Mt}} + \mathrm{p_{iHn}V_{Ht}}), R_{ic} + \mathrm{d}(\mathrm{p_{iLc}V_{Lt}} + \mathrm{p_{iMc}V_{Mt}} + \mathrm{p_{iHc}V_{Ht}})\right] \tag{7}$$

where p_{iLk} is the probability of a stand moving from state i to L by making the decision, k = {n,c} where n = do not cut and c = cut. Equation (7) is known as the Bellman equation (Bellman, 1957). From equation (7), we can see that the highest present value of income from the stands with t+1 periods to go is equal to the largest immediate return plus the discounted value of the highest expected future returns with t periods to go, where it is assumed that the decision in the next period is optimal.

We can compare the portfolio decisions by calculating the returns from each scenario. Therefore, we will choose option Y, as opposed to Z, if and only if:

$$\mathrm{R_{in}} + (\mathrm{p_{iLY}V_{Lt}} + \mathrm{p_{iMY}V_{Mt}} + \mathrm{p_{iHY}V_{Ht}}) > R_{ic} + \mathrm{d}(\mathrm{p_{iLZ}V_{Lt}} + \mathrm{p_{iMZ}V_{Mt}} + \mathrm{p_{iHZ}V_{Ht}}) \quad (8)$$

Similar to the expected returns from the Markov chains, equation (8) can be solved using backwards recursion and setting the highest net present value of expected return with t=0 periods to go at some level and then calculating highest present value of expected return for t=1,2…T and so on, and highlighting the optimal decision (whichever option had the highest present value). Since d<1, the solution will converge as time approaches infinity and in the limit will result in, V_i^*, the highest present value of the expected returns for the stand starting in state i and managed according to the best policy for the infinite time horizon.

We can also find the long-run probability vector and then calculate the expected returns by multiplying the highest present value of each state by the long run probability vector (van Kooten and Bulte, 2000). To calculate the long-run probability vector, we create a new transition matrix by taking the probability vector row for the optimal decision for each state i.

For example, if the optimal choice were to cut in the low and high volume state and not cut in medium volume state, the new transition matrix would be:

Table 5 Transition probability matrix with optimal decision rows (Matrix Φ)

t	t+1 (L)	t+1 (M)	t+1 (H)
L	p_{LL}^{c}	p_{LM}^{c}	p_{LH}^{c}
M	p_{ML}^{nc}	p_{MM}^{nc}	p_{MH}^{nc}
H	p_{HL}^{c}	p_{ML}^{c}	p_{HL}^{c}

If we assume that the transition matrices are reachable, then the matrix, Φ, can be rewritten as:

$\Phi = \begin{bmatrix} p^{c}[L] \\ p^{nc}[M] \\ p^{c}[H] \end{bmatrix}$, where $p^{i}[k]$ is the probability of taking optimal action i in given state k

In order to find the long run probabilities of being in state L, M, or H, we need to solve for

$\pi = \lim_{n\to\infty} \Phi^{n} = \begin{bmatrix} \pi_L \\ \pi_M \\ \pi_H \end{bmatrix}$.

Unfortunately, this result will collapse because the limit of Φ collapses to a null matrix as n →∞ (because $0 \le p \le 1$). Instead, we can calculate π as follows:

Let $I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

And $D = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$

Then, $\pi = D(I + D - \Phi)^{-1} = \begin{bmatrix} \pi_L \\ \pi_M \\ \pi_H \end{bmatrix}$

Now, we can simply calculate the expected returns:

$$ER = [\pi_L \quad \pi_M \quad \pi_H] \begin{bmatrix} R_L \\ R_M \\ R_H \end{bmatrix} = \pi_L R_L + \pi_M R_M + \pi_H R_H$$

where R_i is the returns from state i under the optimal decision.

Applications in Forestry: Stochastic Dynamic Programming

As stated previously, SDP provides agents with a method to make optimal decisions on different management strategies by examining how the state variable evolves over time. In the context of forestry management, different strategies such as thinning, reforestation, and fertilization can be examined with SDP.

Previous research has recognized the usefulness of SDP programing as a method of determining optimal economic strategies for timber management. The first North American application of dynamic programming to a forest production problem was conducted by Hool (1966). Hool (1966) recognized the probabilistic nature of forest growth under different management techniques and used dynamic programming to maximize harvest volume. Further research improved upon Hool's original study such as Lembersky and Johnson (1975), Lembersky (1976), Kao (1982), Routledge (1980), Martell (1980), and Reed and Errico (1984)(as cited by Dempster and Stevens, 1987). White (1989) advised that forestry management problems are suitable for stochastic dynamic programming based on the characteristics of problems faced by stand managers. For example, dynamic programming problems need to be broken down into smaller sub-problems to be solved. In forestry, stand optimization problems can be solved by breaking time into intervals (e.g. 1 year, 5 years) at which to take action (thin, fertilize, harvest). Additionally, forestry decisions can be described by using a limited number of state variables, such as basal area, age, and numbers of trees per hectare. This is useful in SDP because of the "curse of dimensionality" – when the number of states at each stage grows, the problem become harder and harder to solve. Thus, we can describe forest stands in a few simple states and avoid the curse of dimensionality, yet still providing enough detail to differentiate stands.

Lastly, White (1989) states that forest stands can adhere to the "principle of optimality" based on the time intervals set out at the start of the problem, but it is constrained by it as well. The principle states that the "optimal policy for all remaining stages is entirely independent of policies adopted in previous stage" (White, 1989). White utilizes an example of fertilization to explain the principle: if a stand in year

30 is fertilized, within ten years, it will be described as a stand with the same number of trees and basal area as a stand that was not fertilized in the previous stage. The previous actions and decisions made by the stand manager are now rendered irrelevant. The constraint placed on the problem is that the time interval between the stages must be sufficient enough to guarantee this condition, or else the internal time must be increased to ensure the principle of optimality holds. White notes that forest stand optimization problems fit the framework for stochastic dynamic programming and therefore dynamic programming can be useful for forest managers alike.

Teeter and Somers (1993) utilized a SDP program to determine density management for pine stands in southern US. It is not possible to maintain the stand at peak growth rate for the age of the timber; therefore, stand managers must enter into the stands and thin the trees at various points in the time horizon to help maximize growth (and thus value) of the stand. Teeter and Somers create a stochastic dynamic model to estimate the optimal number and timing of thinnings to meet their profit maximization objective. It was noted that it is wise to account for the dynamics of nature and fluctuations in pricing using stochastic methods instead of using deterministic or constant pricing, to help determine management decisions since timber prices vary over time and the per-tree value can change as well. The model assumed the stumpage prices to be stochastic and follow a Markov process. The results demonstrated that optimal net present value associated with the management strategies determined by SDP will be greater than those determined by deterministic models. Therefore, harvest decisions (to cut or not to cut) and decisions on how much to harvest should be made using stochastic models to account for the dynamics of nature and pricing.

Using SDP to make informed pest management decisions

In an extension from basic harvesting decisions based on dynamic growth, SDP models can be used to make informed decisions on mitigation and management programs for stand managers. The forest manager can estimate what his expected returns would be under optimal harvest management if he were to make a costly investment to eradicate or suppress the pest population (thus rendering his forest pest-free). He can also estimate what his expected returns would be under optimal harvest management if he were to let the pest invade his forest, and forgo the eradication/suppression costs. The manager should invest in the eradication program if the difference between the expected returns with or without the investment in suppression is greater than the cost of the investment in the program. If the program is more costly than the potential gain in returns, then it is not advisable to invest in the program.

We can model pest invasion by running two SDP scenarios: with a pest disturbance (forgoing the program) and without a pest disturbance (investing in the program). As an example of the foregoing model, we constructed transition matrices for natural disturbances (e.g., by mountain pine beetle or wildfire) and when action is taken to mitigate the disturbance. For each case, we have an associated transition matrix if the stand is harvested in any state. We then use the method described above to determine the optimal strategy (cut or leave stand uncut) and long-run expected return. We then compare the long-run solutions under the “do nothing” to mitigate disturbance and “mitigate” disturbance strategies. If the mitigate strategy leads to a higher expected return, it should be pursued as long as the difference in returns exceeds the cost of mitigation.

We created two scenarios and thus two sets of transition matrices: where there is a natural disturbance (pest or wildfire) that reduces the probability that a stand will mature fully, and where there is a natural disturbance, but mitigation action occurs that increases the probability that a stand will reach maturation. The transition matrices have 3 possible states (merchantable volume ranges), 2 scenarios (cut/no cut) and solve within 12 iterations.

First, we created a transition matrix where there is no natural disturbance (due to some mitigation action taken by the manager) and the manager has two actions to choose from: cut or no cut. If the manager decides to cut, they indirectly set the transition probabilities to the low state of volume (See Table 6). Each cell into the matrix represents the probability that a stand will be in that volume range in the next 10 years. From example, entry (1,1) states that the probability that a stand that has 0-400 m^3/ha of merchantable volume in period t will be in the same category in year t+1 is 0.30, and that it will be in the range of 400-700 m^3/ha with probability of 0.7 in year t+1.

Table 6 Transition probability matrix - no disturbance (mitigation action is taken) and planner harvests

t	t+1 (L)	t+1 (M)	t+1 (H)
L (<400m^3/ha)	0.3	0.7	0
M(400-700m^3/ha)	0.3	0.7	0
H(<700m^3/ha)	0.3	0.7	0

If the manager decides not to cut, then they allow their stands to grow and thereby lose any potential harvesting profits before the end of the time horizon (See Table 7). Thus, the transition probabilities do not change, as there is no harvest or disturbance to alter the probabilities.

Table 7 Transition probability matrix - no disturbance (mitigation action is taken) and planner does not harvest

t	t+1 (L)	t+1 (M)	t+1 (H)
L (<400m^3/ha)	0.3	0.7	0
M(400-700m^3/ha)	0	0.4	0.6
H(<700m^3/ha)	0	0	1

Next, we formulate a transition matrix where there exists a natural disturbance and the planner takes no action to mitigate the problem thus allowing the deteriorating effects of the pest to take over the stand. The natural disturbance interferes with stand growth (as mentioned in section one) and can damage or kill stands and thus reduce their merchantable volume levels. At this point, the manager has two possible actions to take: cut or no cut. If the manager decides to cut, they set all of the transition probabilities to the low state of volume (See Table 8).

Table 8 Transition probability matrix - disturbance (no mitigation action is taken) and planner harvests

t	t+1 (L)	t+1 (M)	t+1 (H)
L (<400m^3/ha)	0.4	0.6	0
M(400-700m^3/ha)	0.4	0.6	0
H(<700m^3/ha)	0.4	0.6	0

If the manager decides not to cut, then they allow their stands to grow and thereby lose any potential profits from harvesting before the end of the time horizon. Thus, the transition probabilities do not change due to the absence of a harvest policy ruling.

Table 9 Transition probability matrix - disturbance (no mitigation action is taken) and planner does not harvest

t	t+1 (L)	t+1 (M)	t+1 (H)
L (<400m^3/ha)	0.4	0.6	0
M(400-700m^3/ha)	0.1	0.4	0.5
H(<700m^3/ha)	0.05	0.1	0.85

We use Excel to run the stochastic dynamic program as outlined in the previous section. We use the program to run the transition matrices above and converge on a long-run equilibrium solution for the two scenarios (disturbance/no mitigation, no disturbance/mitigation). The program also allows us to find the long-run probability vector and the expected returns. It is important to note the parameters used to calculate the long-run vectors and expected returns. The discount rate utilized in this example is set to 5%. The returns are arbitrarily set. The return for a low state that is harvested is set to \$0/ha, medium state is set to \$4,472/ha, and high state is set to \$7,254/ha.

We run the SDP model for both scenarios: disturbance (no mitigation action has taken place) and no disturbance (mitigation action has taken place). The model converges after 12 iterations and solves for the long run expected return. Therefore, the example provides a solution that states that any spending on mitigation that is less than $270.47/ha is worth undertaking as the manager can make a profit off of the harvest as $270.47/ha is the threshold value of mitigation. If the cost of mitigation is greater than $270.47/ha, the manager is better off doing nothing and running at zero profit (See Table 10 below). Table 10 also outlines the optimal harvest decision for each possible state of the forest stand: low, medium, high (the optimal choice provides the manager with the highest possible pay off amongst the portfolio of options.) For either scenario (disturbance or no disturbance), the optimal choice for the stand manager is to not cut the stand if it is in a low volume state and to cut the stand if it is in a medium or high volume state.

Table 10 Calculating threshold cost of mitigation

Volume	**Disturbance (No Mitigation)**	**No Disturbance (Mitigation)**	**Threshold Cost of Mitigation**
Low	$1 622.84 *Optimal choice: No cut*	$1 893.32 *Optimal choice: No cut*	$270.47
Medium	$6 094.84 *Optimal choice: Cut*	$6 365.32 *Optimal choice: Cut*	$270.47
High	$8 876.84 *Optimal choice: Cut*	$9 147.32 *Optimal choice: Cut*	$270.47

The cost of mitigation at the stand level can include the cost of silvicultural practices such as thinning, cost of monitoring, or the cost of spraying the stands with substances such as BTK to prevent pest invasion. The threshold cost of mitigation is sensitive to the discount rate (See Table 11). As seen below, the higher the discount rate, the lower the threshold cost of mitigation. If we discount the future more, then we are not willing to pay as much to protect the forest stand against disturbances.

Table 11 Threshold costs of mitigation and discount rates

Discount Rate	Threshold Cost of Mitigation
1%	$1 753.37
2%	$902.73
3%	$553.26
4%	$375.30
5%	$270.47
6%	$202.61
7%	$155.84
8%	$122.15
9%	$97.12
10%	$78.08

Thus, it is concluded that a stand manager should take action to mitigate the disturbance if and only if the cost to mitigate is less than the threshold hold cost of mitigation as seen above in Table 11. If the cost to mitigate is greater than the threshold cost, then the cost of mitigating is greater than the benefit of mitigating and thus the manager should leave the stand alone and not take any further action.

Evaluation of SDP modelling as an analysis tool

SDP modelling is a powerful tool for analyzing forest management at the stand level as it can incorporate uncertainty and account for as many iterations of the problem as required. If there is uncertainty in the dynamics of the problem (in our case, the dynamics of the tree growth), then a Markov decision process can be adopted. Predictions of long-term effects of disturbances such has pests or fire can be difficult due to the immense amount of uncertainty that managers can face such as growth uncertainty, price uncertainty and uncertainty about what action to take optimally (Limaei, 2011). Therefore, using an SDP model that can represent the stochastic system of a forest stand setting with multiple states, can allow the manager to assess possible risks and make decisions on how to harvest their stand. However, the SDP model is highly sensitive to the price and stumpage parameters, discount rate, rewards of the various actions and of the transition matrices utilized. In addition, the SDP model is limited by the use of transition matrices. The transition matrices grow quickly as more states are included in the model, which reduces the accuracy in decision-making or makes the problem impossible to solve, which is referred to as the "curse of dimensionality" (White, 1989). Finally, the SDP model depicted here assumes that the manager does not take the actions of other managers and the growth or yield of other stands into account when making decisions. In reality, we know that the stand manager will not act independently of others in the sector as other players and factors will play into their stand management decisions.

4.3 The Macro-Level Bookend: Computable General Equilibrium

Description of Model

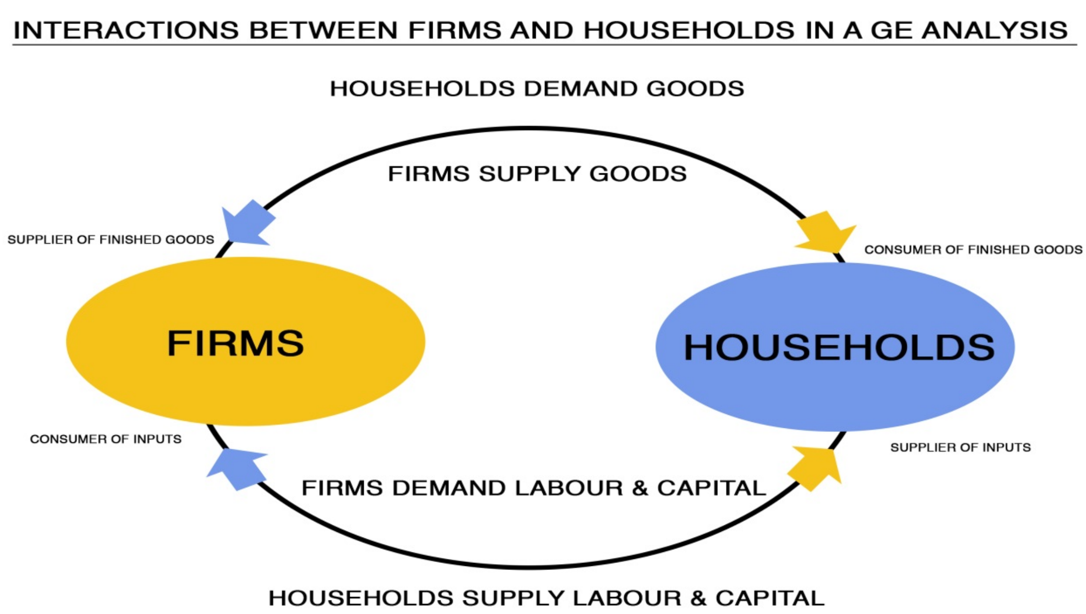
A computable general equilibrium (CGE) model can be used to assess economic impacts by combining microeconomic general equilibrium structure with real economic data. The model is a numerical representation of an economy and can be applied to global, multiple-region or single-region (country) economies. The CGE model is grounded in neoclassical microeconomic theory where prices are the main mechanism used to equate supply and demand across specified sectors of an economy (Ochuodho et al., 2012). The CGE model is calibrated using real economic data and can simulate how household-firm interactions and flows of capital and goods change in response to exogenous shocks to the model. The sectors are linked to each other so that a shock in one sector will have a ripple effect through other sectors and will affect factors of production such as labour, capital and land.

CGE models are "standard tools of empirical analysis, and are widely used to analyze the aggregate welfare and distributional impacts of policies whose effects may be transmitted through multiple markets" (Wing, 2004). CGE models have become an increasingly popular analysis tool in various areas of economics, such as international trade (e.g. Shields and Francois, 1994; Martin and Winters, 1996) and environmental regulation (e.g., Weyant, 1999; Boverberg and Goulder, 1996), due to their broad scope and flexibility in handling a broad range of policy issues. However, CGE models are becoming an increasingly popular method to examine forestry sector impacts due to their ability to accommodate different economic conditions and take into account that contraction (or expansion) in one-sector can leads to expansion (or contraction) in other sectors (Alavalapati et al., 1998). A number of studies have utilized a CGE model to examine the overall economic impacts of forestry supply shocks (e.g., Patriquin et al., 2007; Alavalapati et al., 1996, 1999; Ochuodho et al., 2012; Ochuodho and Lantz, 2014; Corbett et al., 2015)

Economic Theory behind the Model

Economic studies shifts in supply and demand of goods and services between households and firms. General equilibrium (GE) models study how prices and output are determined in more than one market simultaneously. GE focuses on the interactions and flow of capital, labour, goods and money between households and firms (as shown in Figure 1 below). Firms are assumed to be perfectly competitive, meaning they act as price-takers and are willing to supply any positive amount of output as long as price is equal to or greater than marginal cost (Besanko et al., 2011).

Figure 1 Interactions between firms and households in a general equilibrium analysis (Besanko et al., 2011)



Relating this to a simple economy, the GE can be best understood by the statement, “Everything depends on everything else” (Burfisher, 2011). Real prices are simultaneously determined in GE: price of goods, price of labour (wage), and price of capital (rent) – all prices are interdependent. In a GE model, prices will configure in such a way to equate supply with demand, therefore equating expenditures and incomes. Walras' Law states that, in a competitive equilibrium with a total of N markets, if supply equals demand in the first N-1 markets, then supply equals demand in the Nth market as well. On the condition that total expenditure must equal total income, if demand equals supply in the first N-1 markets, then supply will automatically equal demand, thus clear the market, in the Nth market as well.

In the 1980s, the economic literature aimed to apply Walrasian General Equilibrium to a realistic economy to evaluate policy options analytically by utilizing real economic data and specifying production and demand parameters (Shoven and Whalley, 1984). CGE models were created to mathematically represent an economy as a complete system of interdependent components, such as firms, households and government. CGE models bridge the gap between economic theory and policy change because CGE models can equilibrate economies for different regions and attach values to the projected impacts of policy changes (Mäler and Vincent, 2003). Economists use these models to examine various policy issues in an attempt to guide policy alternatives in areas such as environmental and resource management issues. The CGE model can be calibrated to represent the baseline scenario (no action taken) and then shocked to generate the policy scenario (action is taken). The post-policy scenario is created by exogenously shocking unique parameters in the model, such as supply or labour that would be impacted by the policy, causing the model to recalibrate it and converge to a new equilibrium (Wing, 2004). The pre- and post-policy equilibrium values can be compared to evaluate the overall impact of the policy.

Applications in Forestry: Computable General Equilibrium Model

CGE models have been used to examine how economies will respond to shocks in the forestry sector. A variety of topics have been explored, such as impacts of changes in stumpage pricing (Dee, 1991; Alavalapati et al., 1997) and interactions between land use and deforestation (Persson and Munasinghe, 1995; Cattaneo, 2001, 2002). In the past decade, regional CGE models have been increasingly used to examine the comprehensive impacts of foreign pest invasions in Canadian forests.

The invasion of foreign pests or outbreak of native pests can cause significant damage and hinder the productive capabilities of forestry sectors and regional economies. A pest invasion can substantially reduce the available supply of logs/timber, which can have reverberating impacts of other sectors such as agricultural sector due to the change in land use. A CGE model is a useful method to calculate how supply shocks caused by pests can be transmitted through the markets.

Studies such as Patriquin et al. (2007), Alavalapati et al. (1996, 1999), Ochuodho et al. (2012), Chang et al. (2012) and Corbett et al. (2015) have utilized CGE models to examine the overall economic impacts of forestry supply shocks.

Patriquin et al. (2007) looked at the regional economic impacts of mountain pine beetle (MPB) infestation in five areas of BC using a regional CGE model. The model tested the sensitivity of economic indicators in six economic sectors to changes in forestry exports due to MPB attack by assuming that the MPB infestation would directly impact timber supply. Results showed that there will be regional differences in the sensitivity of forestry export shocks and concluded that there exists a need for specific regional assistance to mitigate the future impacts of MPB. In the short term, local economies experienced boosts due to increased salvage harvests. However, in the long term, due to the shortage of timber supply, there would be negative impacts for the broad economy.

Ochuodho et al. (2012) examined the future impacts of climate change and forest adaptation in Canada from 2010 to 2080. The study examined 16 various adaptation, economic growth, climate change and timber supply scenarios. The model utilized six regions for the CGE model with 15 sectors defined to examine overall impacts. Findings suggest that the physical and economic impacts of climate change in Canadian forests will be substantial and unequally distributed across the regions.

Chang et al. (2012) utilized a CGE model to study the potential economic impact of the future SBW spread in New Brunswick. They relied on a SBW DSS (Decision Support System), created by Chang et al. (2007), to predict stand volume yield changes. Chang et al. integrated the pest population and stand dynamics into the CGE to examine how the harvest and associated industries will change over time.

The CGE model was a single-region recursive model, presented nine economic sectors with three primary production inputs (land, labour and stumpage), assumed steady growth rates and was calibrated to New Brunswick regional economy 2006 levels. The stumpage value was shocked in the model for sixteen different scenarios with varying outbreak severities, control levels and management techniques. The results demonstrate that a future SBW outbreak, either moderate or severe, will result in a $3.3-$4.7 billion decrease in present value output.

Most recently, Corbett et al. (2015) utilized a static, recursive CGE model to study the overall economic impact of the MPB epidemic in British Columbia. The MPB, a native forest pest to Canada, killed approximately 723 million cubic metres of forest from the early 1990s to mid-2000s, causing a massive supply shock in the BC forestry sector. The initial response to the epidemic by the BC government was to increase the annual allowable cut (AAC), the amount of wood harvested in a given year to ensure sustainability of the forest. The AAC uplift was imposed with the purpose of capturing the value of dead timber before it was rendered no longer merchantable by the MPB infestation (Patriquin et al., 2007). The AAC spiked in the initial years after the infestation; however, stands will take several decades to regrow in BC and thus the projected AAC will decline over the next several decades.

To model this, Corbett et al. (2015) used a static CGE model for the province of BC to simulate changes in provincial AAC as changes in stumpage. The model was calibrated to BC using 2009 symmetric IO models from Statistics Canada (Statistics Canada, 2011, 2012), and the economy was aggregated into 21 sectors. The three primary factors of production were specified as labour, capital and stumpage. In order to isolate stumpage as an input, Corbett et al. (2015) followed Ochuodho and Lantz (2014) and used total revenues from the sale of timber from provincial Crown stumpage data as the input value and subtracted it from capital in the forestry and logging sector. The CGE model was set up as a static model and solved recursively from 2009 to 2054. Similar to Ochuodho and Lantz (2014), in every period "the capital stock was updated based on a capital accumulation equation based on an endogenous growth rate as determined by endogenous return on capital rate and endogenous total savings. Total labour supply was assumed to grow exogenously at a constant rate over time… stumpage supply in all regional forestry and logging sectors was exogenously fixed over time under baseline conditions."

The CGE model and its equations were solved using General Algebraic Modeling System (GAMS) software, using a non-linear programming algorithm along with CONOPT3 solver (GAMS, 2012). The model was solved using two different scenarios: initial benchmark for 2009 and reduced timber supply caused by MPB. The initial benchmark replicated 2009 IO tables and the model solved for the dynamic base case growth path of the economy that allowed for capital and labour to grow. The reduced timber supply scenario captured the change in AAC by incorporating a constant reduction in AAC each year starting in 2010. The timber reduction was obtained by calculating the percentage decrease in estimated AAC from 2009 to 2054 from the provincial-level projections of the AAC (BC Ministry of Forest, Lands and Natural Resource Operations, 2012). The stumpage input was shocked each year the annual average change in timber to simulate the decline in AAC. Since stumpage is exogenous to the model, it is assumed that overall stumpage values fall with AAC. In order to calculate the overall impact of the MPB, the study compared the baseline scenario to the reduced-AAC scenario growth paths from 2009 to 2054. Using a 4% discount rate, the study suggests that the projected MPB epidemic will result in a $57.37 billion decline in BC's GDP in present value terms. The results also demonstrated a reduction in overall output and income when stumpage falls, which ultimately impacts consumption, investment, exports and imports. The study captured both the indirect and direct impacts of the MPB infestation on the provincial scale.

Evaluation of CGE as an analysis tool

CGE models provide useful insights into the effects of a policy change by comparing results of a baseline reference path of an economy to the results of a path where inputs have been exogenously shocked to simulate the potential policy change. CGE models were first created to overcome the limitations of Input Output (IO) models (Niquidet et al., 2015). IO models are used in economic impact analysis as they numerically represent inter-industry production and linkages between various sectors that result from increased demand and consumption in a unique sector (Wang and Charles, 2010). However, IO models do not provide a "theoretically-complete picture of either the supply or the demand size of the economy, in that it does not envision optimizing behavior on the part of economic organisms faced with alternative courses of action" (Christ, 1955). IO models are limited to their linear relationships, fixed prices, and do not take into account that agents in the economy can make optimal decisions based on options available to them and changes in relative prices (Christ, 1955; Alavalapati et al., 1998; Bandara, 1991).

CGE models can overcome these limitations as they incorporate "endogenous demand and price system, substitutability in production and demand, optimization of agent behavior, factor scarcity, and a more detailed treatment of institutions and the macroeconomic environment" (Alavapalati et al., 1997). CGEs are more effective in assessing the distributional impacts of macroeconomic policy changes in regional economies (Buetre et al., 2003).

Other benefits of using CGE models to analyze economic impact issues include the accounting and theoretical consistency of the modeling framework. Accounting consistency occurs because expenditures can never exceed incomes and the allocation is consistent because all factor markets must clear due to Walras' law. As well, CGE models can address a variety of policy issues due to its ability to model inter-industry linkages, which allows the user to uncover the ripple effects in the economy that may not be intuitive.

There are some drawbacks to using CGE models in analysis, however. For example, CGE models are thought of as "black-boxes" due to the complexity of the model's structure and inability of the public to analyze particular results (Wing, 2004). Further, CGE models do not account for the possibility of factor inputs being transferred to regions outside of the specified economy. For example, the model cannot predict the capability of labourers to move outside of the economy to search for jobs if there is a downturn in the economy and therefore results can be biased. Third, the results of the CGE model are extremely sensitive to parameter and specification settings. Therefore, lack of region-specific specifications or errors in the specifications can result in large biases and inaccuracies in the results.

Finally, the model cannot take into account how the policy change can impact economies outside the scope of the model, which can in fact indirectly impact sectors in the specified economy. These feedback effects are ignored and can impact the results of the analysis. To overcome this issue, a multi-region or global CGE model would be required.

5. Discussion and Conclusion

Forest insect infestations can grow to be severe and can cause economic problems due to the damage and destruction they can cause in commercially valuable forests. Therefore, there is a need for pest management as infestations increase and become more damaging to stands. The issue of forest management and dealing with pests or disturbances such as wildfires can be examined from two perspectives: the forest manager at a microeconomic level or the policymaker from a macroeconomic level. The forest manager needs to take into account growth uncertainty in order to make his decision on whether to harvest his stand or not. The policymaker needs to understand how a pest invasion in the forestry sector can have indirect and direct effects in the sector itself and other sectors as well such as agriculture in order to make a choice on optimal actions to take. Both perspectives have a need to compare the cost of doing nothing and the cost of taking action to mitigate the pest and this will play an important role in their decision-making. For the forest manager, they will take action against the pest if the impact on their future income streams is higher than the cost of taking action. Whereas for the policy maker, they will need to take action against the pest if the overall impact on the economy is high enough to warrant action.

Therefore, forest management decisions require a range of analysis tools in order to make optimal management choices. The forest manager does not take into account the impact that the pest has on other managers or other forest stands outside of his jurisdiction. Therefore, the forest manager would be best off using a stochastic dynamic programming model to account for uncertainty in growth, prices or stumpage rates, interest rates, and other factor that can impact his stand-alone and compare the cost of mitigation to the result. Whereas, the policymaker at a federal or provincial level needs to account for all stands and all transactions that will be impacted by a pest in their jurisdiction which can encompass the whole country or a few timber supply areas. Therefore, the policymaker is best off using a computable general equilibrium model that will allow him to account for all the indirect and direct effects that a loss in timber supply or revenue will have on the macro economy.

It is important that we develop a range of economic analysis tools, as each decision-maker is unique and require different inputs to solve for their optimal management strategies. Pest management is an example of a management practice that requires different analysis tools to create optimal strategies for the various players in the economy. Pest invasion, either native or non-native, poses a risk to the value of forest stands and the supply of timber in Canada. Examples of invasions such as the native mountain pine beetle in British Columbia and Alberta or the gypsy moth in eastern Canada can show that pest invasions can be extremely costly and require attention from policymakers and stand managers in the early stages to prevent significant losses.

Future research can focus on incorporating greater use of population dynamics of invasive pests. For SDP modelling, future research should focus on improving the transition matrices for the stand growth when faced with a pest invasion, wildfire, or combination of both. This can include speaking to specialist to understand how different stands will grow or decline as a result of specific pests or changes in the frequency of wild fires. Therefore, future research can focus on specific significant pests in Canada such as mountain pine beetle crossing into central and eastern Canada or the potential for gypsy moth to invade British Columbia. Another topic may focus on the links between fire suppression and pest outbreaks as fire suppression can increase the likelihood of pest outbreaks due to a greater supply of vulnerable trees. It is important to note that the transition matrices are sensitive to the age and species of the stand. For CGE modelling, future research should focus on improving the timber loss that will result each year as a result of pest invasion. This can improve the accuracy of the results and will better inform policymakers on the consequences of taking action or no action when faced with a pest management issue. Finally, climate change and carbon accounting will influence the results of these two analysis methods and can be accounted for as well with future research.

To close, pest management problems can be solved using a range of economic tools; however, SDP models and CGE models can be considered bookends of the tools as they focus on the microeconomic stand level and the overall macroeconomic level for governments. Economists can help stand managers and policymakers make decisions on whether to take action and what action to take by weighing the costs and benefits in the face of uncertainty and with respect to the direct and indirect consequences that may arise as result of the actions taken. To improve the accuracy of these tools, it is important that policymakers, economists and scientists/researchers work together to incorporate spatial processes; pest spread rates and pest damage in trees into the models to make them as realistic as possible.

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Appendix – TIPSY Example of SDP Model

We can use realistic data to create a transition probability matrix and construct an SDP model. To begin constructing the example model, we obtained stand yield data for the Quesnel timber supply area (TSA) using British Columbia Ministry of Forests, Lands and Natural Resource Operations' TIPSY model (2017). TIPSY is the ministry's growth and yield prediction model, it predicts the yield of both managed and unmanaged stands.[3] TIPSY is the primary source for yield tables for managed stands and for economic analyses for the forest industry in BC. The growth data are in ten-year increments, starting at 0 and followed by 20 decades (mature trees are 200+years old) and provides yield tables for single species even-aged stands. For each decade, the data provide merchantable volume per hectare, volume per tree, recovered lumber volume (measured in mbf), and sawmill and other residuals. We use TIPSY data to formulate transition matrices for the Quesnel TSA for two scenarios: where there is a natural disturbance (pest or wildfire) that reduces the probability that a stand will mature fully, and where there is a natural disturbance, but mitigation action occurs that increases the probability that a stand will reach maturation. The transition matrices have 18 possible states (merchantable volume ranges), 2 scenarios (cut/no cut) and solve within 12 iterations.

First, the TIPSY data provide a transition matrix where there is no natural disturbance (due to some mitigation action taken by the manager) and the manager has two actions to choose from: cut or no cut. If the manager decides to cut, they indirectly set the transition probabilities to the low state of volume (See Table 12). Each cell into the matrix represents the probability that a stand will be in that volume range in the next 10 years. From example, entry (1,1) states that the probability that a stand that has 0-20 m^3/ha of merchantable volume in period t will be in the same 0-20 m^3/ha category in year t+1, and that it will be in the range of 20-40 m^3/ha with probability of 24% in year t+1. %.

[3] TIPSY refers to the Table Interpolation Program for Stand Yields. Further information can be located at: https://www.for.gov.bc.ca/hts/growth/tipsy/tipsy_description.html

Table 12 Appendix - Transition probability matrix - no disturbance (mitigation action is taken) and planner harvests

Range of Volume (m^3/ha)	(0,20]	(20, 40]	(40, 60]	(60, 80]	(80, 100]	(100, 120]	(120, 140]	(140, 160]	(160, 180]	(180, 200]	(200, 220]	(220, 240]	(240, 260]	(260, 280]	(280, 300]	(300, 320]	(320, 340]	(340, 360]
(0,20]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(20, 40]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(40, 60]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(60, 80]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(80, 100]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(100, 120]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(120, 140]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(140, 160]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(160, 180]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(180, 200]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(200, 220]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(220, 240]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(240, 260]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(260, 280]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(280, 300]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(300, 320]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(320, 340]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(340, 360]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

If the manager decides not to cut, then they allow their stands to grow and thereby lose any potential harvesting profits before the end of the time horizon (See Table 13). Thus, the transition probabilities do not change, as there is no harvest or disturbance to alter the probabilities.

Table 13 Appendix - Transition probability matrix - no disturbance (mitigation action is taken) and planner does not harvest

Range of Volume (m^3/ha)	(0,20]	(20, 40]	(40, 60]	(60, 80]	(80, 100]	(100, 120]	(120, 140]	(140, 160]	(160, 180]	(180, 200]	(200, 220]	(220, 240]	(240, 260]	(260, 280]	(280, 300]	(300, 320]	(320, 340]	(340, 360]
(0,20]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(20, 40]	0.00	0.29	0.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(40, 60]	0.00	0.00	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(60, 80]	0.00	0.00	0.00	0.20	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(80, 100]	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(100, 120]	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(120, 140]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(140, 160]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(160, 180]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(180, 200]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.75	0.25	0.00	0.00	0.00	0.00	0.00	0.00
(200, 220]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.30	0.00	0.00	0.00	0.00	0.00
(220, 240]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00
(240, 260]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.57	0.00	0.00	0.00	0.00
(260, 280]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.71	0.00	0.00	0.00
(280, 300]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.43	0.00	0.00
(300, 320]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00
(320, 340]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50
(340, 360]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Next, we formulate a transition matrix where there exists a natural disturbance and the planner takes no action to mitigate the problem thus allowing the deteriorating effects of the pest to take over the stand. The natural disturbance interferes with stand growth (as mentioned in section one) and can severely damage or kill stands and thus reduce their merchantable volume levels. Thus, the transition probability matrix resembles a lower triangular matrix, as the stands do not reach high volumes. At this point, the manager has two possible actions to take: cut or no cut. If the manager decides to cut, they set all of the transition probabilities to the low state of volume (See Table 14).

Table 14 Appendix - Transition probability matrix - Disturbance (no mitigation action is taken) and planner harvests

Range of Volume (m^3/ha)	(0,20]	(20, 40]	(40, 60]	(60, 80]	(80, 100]	(100, 120]	(120, 140]	(140, 160]	(160, 180]	(180, 200]	(200, 220]	(220, 240]	(240, 260]	(260, 280]	(280, 300]	(300, 320]	(320, 340]	(340, 360]
(0,20]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(20, 40]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(40, 60]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(60, 80]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(80, 100]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(100, 120]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(120, 140]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(140, 160]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(160, 180]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(180, 200]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(200, 220]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(220, 240]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(240, 260]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(260, 280]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(280, 300]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(300, 320]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(320, 340]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(340, 360]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

If the manager decides not to cut, then they allow their stands to grow and thereby lose any potential profits from harvesting before the end of the time horizon. Thus, the transition probabilities do not change due to the absence of a harvest policy ruling.

Table 15: Appendix- Transition probability matrix - disturbance (no mitigation action is taken) and planner does not harvest

Range of Volume (m3/ha)	(0,20]	(20, 40]	(40, 60]	(60, 80]	(80, 100]	(100, 120]	(120, 140]	(140, 160]	(160, 180]	(180, 200]	(200, 220]	(220, 240]	(240, 260]	(260, 280]	(280, 300]	(300, 320]	(320, 340]	(340, 360]
(0,20]	0.76	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(20, 40]	0.75	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(40, 60]	0.00	0.74	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(60, 80]	0.00	0.71	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(80, 100]	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(100, 120]	0.00	0.00	0.81	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(120, 140]	0.00	0.00	0.00	0.82	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(140, 160]	0.00	0.00	0.00	0.85	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(160, 180]	0.00	0.00	0.00	0.84	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(180, 200]	0.00	0.00	0.00	0.00	0.85	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(200, 220]	0.00	0.00	0.00	0.00	0.86	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(220, 240]	0.00	0.00	0.00	0.00	0.75	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(240, 260]	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(260, 280]	0.00	0.00	0.00	0.00	0.00	0.85	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(280, 300]	0.00	0.00	0.00	0.00	0.00	0.86	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(300, 320]	0.00	0.00	0.00	0.00	0.00	0.00	0.86	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(320, 340]	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(340, 360]	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

We use the statistical computing program R to run the stochastic dynamic program as outlined in the previous section. We use the R program to run the transition matrices above and converge on a long-run equilibrium solution for the two scenarios (disturbance/no mitigation, no disturbance/mitigation). The program also allows us to find the long-run probability vector and the expected returns. It is important to note the parameters used to calculate the long-run vectors and expected returns. The discount rate utilized in this example is set to 5%. The action to "not cut" has no value – the forest is left to grow and to harvest at a later date. The action to "cut" has a value of:

$$Cut\ value = a \times v(t) - \ b \ (9)$$

where a is the price per m^3/ha of merchantable wood, where v(t) is the volume of the harvest of merchantable wood, and b is the price incurred to cut the wood at that point in time.

We run the SDP model for both scenarios: disturbance (no mitigation action has taken place) and no disturbance (mitigation action has taken place). The model converges after 12 iterations and solves for the long run expected return. The disturbance (no mitigation action has taken place) scenario converges and solves for an expected return of $0/ha. The no disturbance (mitigation action has taken place) scenario converges as well and solves for an expected return of $29.43/ha. Therefore, the example provides a solution that states that any spending on mitigation that is less than $29.43/ha is worth undertaking as the manager can make a profit off of the harvest. For any spending on mitigation that is greater than $29.43/ha, the manager is better off no taking the mitigation action and running at zero profit. The cost of mitigation at the stand level can include the cost of silvicultural practices such as thinning each cycle, cost of monitoring, or the cost of spraying the stands to prevent pest invasion.