ABSTRACT

Title of Dissertation: THE ECONOMICS OF SPRUCE BUDWORM MONITORING AND MANAGEMENT IN EASTERN CANADA

Alexandre I.E. Holm Perrault
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Dissertation Directed by: Professor Lars J. Olson
Department of Agricultural and Resource Economics

This dissertation uses techniques that were developed for renewable natural resource and invasive pest management to describe the two principal challenges of eastern spruce budworm (SBW) monitoring and management in Eastern Canada, with a specific focus on the province of Quebec. The primary empirical components of this dissertation can be found in Chapters 2 and 3. Chapter 1 provides the necessary historic, entomological, ecological and policy context to understand Chapters 2 and 3. Chapter 4 provides a conclusion to this dissertation by proposing extensions that would make the models presented in Chapters 2 and 3 more readily applicable to real-world spruce budworm management. These extensions involve making the models spatially explicit, as the models presented in Chapters 2 and 3 are spatially crude for the sake of tractability.

Chapter 2 describes the management of an endemic irruptive forest pest and, using the spruce budworm-balsam fir forest interaction, proposes an optimization model that determines optimal pest treatment and forest harvest levels for a single, dimensionless forest stand that is

currently undergoing an active budworm outbreak. Budworms cause both growth reductions and mortality on the forest biomass stock, and increasing forest biomass will provide budworms with more prey, causing their growth rate to increase. Treatment decisions are limited to three discrete possibilities (0, 1 or 2 on the landscape) that impose mortality on budworms, while harvests remove a proportion of the forest biomass. Using a numerical solution algorithm, we find that the optimal policy is generally to apply treatments over budworms and to harvest the forest at a sustainable rate, which confirms that the current management programs used in Eastern Canada are welfare-improving relative to letting an outbreak run its course. The time path for our baseline scenario indicates that budworms can be treated down to endemic levels quickly. Sensitivity analysis describes scenarios where budworm levels will rebound every year as well as scenarios where the optimal policy is to clearcut the forest as quickly as possible.

Chapter 3 considers the pre-outbreak monitoring phase for spruce budworm management. This context is informed by the Early Intervention Strategy, a management practice that is currently being successfully employed in New Brunswick and other Maritime provinces. EIS requires extensive monitoring and proactive treatment. As such, we adapt a model known as CESAT to determine the locations for which EIS would yield positive net benefits in eastern Quebec. Under our baseline scenario, we find that EIS is optimal in some zones bordering New Brunswick, which indicates that EIS is unlikely to be welfare-improving over current management practices used in Quebec. Under different assumptions, however, we find that EIS is optimal across a much larger landscape, yielding millions of CAD net benefits over a thirty year horizon.

THE ECONOMICS OF SPRUCE BUDWORM MONITORING AND MANAGEMENT IN EASTERN CANADA

by

Alexandre Ismaël Eliot Holm Perrault

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Advisory Committee:
Professor Lars J. Olson, Chair/Advisor
Professor Rebecca Epanchin-Niell, Co-Advisor
Professor Maureen Cropper, Dean's Representative
Professor Erik Lichtenberg
Professor Jorge Holzer

Dedication

Dedicated to the memory of Pamela Holm.

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Après tout cela, il ne reste qu'une chose à dire : enfin, tabarnak!

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List of Abbreviations

EIS	Early Intervention Strategy
FP	Foliage Protection
CESAT	Cost-efficient Surveillance Allocation Tool
DSS	Decision Supporty System
Btk	*Bacillus thuringiensis* var. *Kurstaki*
DDT	Dichlorodiphenyltrichloroethane
DBH	Diameter at breast height
SBW	(Eastern) Spruce budworm
SM	Spongy moth (formerly Gypsy moth)
ALB	Asian longhorn beetle
EAB	Emerald ash borer
MBP	Mountain pine beetle
L2	Second larval instar
L4	Fourth larval instar
IEQM	Inventaire écoforestier du Québec méridional (Ecoforest Inventory of Southern Quebec)
BMMB	Bureau de mises en Marché des bois du Québec (Quebec Timber Marketing Board)
FPL	Forest Protection Limited (New Brunswick)
SOPFIM	Société de protection des forêts contre les insectes et maladies (Forest Insect and Disease Protection Corporation of Quebec)
NPV	Net present value
CGE	Computable general equilibrium

Chapter 1: Introduction: The Biology, Ecology and Economics of Eastern Spruce Budworms and their Forests

1.1 Introduction

The eastern spruce budworm (*Choristoneura fumiferana*) is an economically and ecologically significant pest in eastern Canada and New England[1]. Budworm caterpillars eat the nettles of coniferous trees; their preferred hosts are balsam fir, white spruce, and red spruce, and they can also be found in black spruce, tamarack, eastern hemlock, and white pine [Talerico, 1983]. The spruce budworm belongs to the genus *Choristoneura*, which consists of moths that feed on coniferous foliage.

At low population densities, budworm feeding does not cause significant harm to trees, and budworms form an integral part of the ecology of eastern forests. Periodically, however, budworm densities increase to the point where they completely defoliate trees. Several (3-5) consecutive years of severe defoliation will cause trees to die [Huff et al., 1984]. Even in the absence of tree mortality, pronounced defoliation will reduce growth rates and increase injury in trees. Three

[1]Throughout this dissertation, I use the terms "budworm" and "spruce budworm", as well as the abbreviation "SBW", interchangeably to refer to the eastern spruce budworm. This is common practice in the literature (see, for example, Talerico [1983]). All such references should thus be understood as shorthand for eastern spruce budworm. The western spruce budworm, mentioned briefly in this chapter, is a closely related species that does not form the basis of this study. Nonetheless, lessons from the study of eastern spruce budworm are applicable to the study of western spruce budworm.

years of defoliation are generally enough to kill a terminal leader [Huff et al., 1984]. Widespread tree deaths cause economic, social and ecological damage, especially as trees are left to rot and lose their value.

In this chapter, I present literature, models and empirical research on the biology, ecology and economics of spruce budworms and the forests they inhabit, and I complement these contributions with insights from invasive species and fragile ecosystems literature. This chapter will help guide research presented in subsequent chapters. However, these chapters will have novel models that were developed to each address one aspect of budworm management. This dissertation covers three aspects: the harvest-treatment aspect, the pre-outbreak surveillance aspect, and the multi-spatial interdependence aspect.

Chapter 2 presents a bioeconomic model for harvest and treatment decisions for an established outbreak. This chapter employs a novel modeling approach where biomass stocks of budworm pests and forest resources are modeled in discrete time (as opposed to continuous time approaches such as Ludwig et al. [1978] and Ludwig et al. [1979]), with each time step having before and after phases. The two choice variables are the proportional harvest of the forest biomass and the discrete application of treatments to suppress the budworm biomass. Chapter 2 was developed with the foliage protection strategy in mind, which is why the initial spruce budworm infestation level is assumed to be high.

Chapter 3 models surveillance decisions in a pre-outbreak context under an early intervention program, and thus assumes that the initial spruce budworm infestation level is very low. It adapts the CESAT model [Epanchin-Niell, 2020] to the spruce budworm management question and specifically to an examination of the early intervention strategy by employing a single detection method, a single treatment program, and a pest that can enter all parts of the landscape

rather than through a single point of entry. There is a single choice variable, which is the number of surveys sent into each part of the landscape. Treatment is a response to a survey outcome rather than a model choice. Chapter 3 analyzes choices with and without a limited budget and determines how survey resources might best be placed in Eastern Quebec to minimize the total expected damages from outbreaks and costs from a survey and treatment program.

Chapter 4 provides descriptions of how the Chapter 2 and Chapter 3 models should be adapted to a multi-spatial context. Chapters 2 and 3 were developed without considering spatial pathways. In Chapter 2, this meant restricting ourselves to a single, dimensionless landscape. In Chapter 3, this meant modeling budworm infestation events as an exogenous and continuous process. If early detection of developing outbreaks and active treatment of advanced outbreaks minimizes budworm spread across the landscape, this will capture additional benefits that were not considered in Chapters 2 and 3.

This chapter distinguishes between the ecology of spruce budworms and their biology. I use biology to refer to the behavior and life cycle of spruce budworms, and ecology to refer to their interactions with their forest habitat. A forestry planner hoping to design and implement a forest protection program must understand both.

From an economic modeling perspective, two aspects of budworm biology are relevant: the year-over-year reproduction rate within a tree stand and the dispersal rate across a forested area. Year-over-year reproduction is a simplification of the budworm life cycle. This life cycle is described in subsection 1.3.1.

In terms of budworm ecology, planners are principally interested in the rate at which budworm larvae consume foliage, the natural predation and stressors to which budworms are subject, and the effects of treatments on local budworm densities. Biology and ecology are linked: pre-

dation is a key component of year-over-year reproduction, since it determines the survival rate of larvae. Budworms suffer from high natural mortality: over 90% of early-instar larvae will die before they can become moths, due to starvation, parasitism, or predation. A forest manager seeking to minimize budworm damages must apply treatments that cause additional mortality to budworms; optimal timing and the importance of additionality are explored in section 1.4.

Despite recent and rapid advancements in knowledge, budworm dynamics are still not fully understood due to the fact that outbreaks have generally been observed only after the outbreak phase had begun. Entomologists have, therefore, been forced to work backwards from limited sample data to determine how endemic outbreaks become epidemics. Two competing hypotheses have emerged, based on the same set of data from a research project in Green River, New Brunswick that was carried out from 1945 to 1959. The earlier hypothesis, formulated by Morris [1963], holds that budworms are characterized by two equilibria, one with low density and one with high density. Disturbances can cause feedback loops which drive low-density populations to a high-density equilibrium. The second hypothesis, suggested by Royama [1984] after re-analysis of the Green River data, is that spruce budworm follows a regular oscillatory pattern. The implications of these two hypotheses are fully explored in section 1.3. Throughout all chapters of this dissertation, I assume that the double-equilibrium theory holds, as this is consistent with the most recent evidence.

Recent findings have suggested that the Morris hypothesis holds true, although this by no means represents a consensus [Sturtevant et al., 2015][2]. Under the assumption that the double-equilibrium hypothesis does hold, researchers in New Brunswick developed a new strategy,

[2]This was also reflected in my conversations with policy planners and entomologists in Canada. Notably, the former chief entomologist of Ontario shared his concerns about the recent re-appraisals with me.

known as the Early Intervention Strategy (EIS), to deal with spruce budworm outbreaks, which consists of monitoring the landscape, identifying increasing densities of budworms prior to the realization of full outbreaks and interrupting the feedback loop to prevent epidemics. This strategy has been implemented in other Maritime provinces, such as Newfoundland and Labrador and Nova Scotia, with varying degrees of success. By comparing treatment programs in different EIS provinces, we are able to determine the barriers to EIS success.

Two other strategies can be adopted when confronting a spruce budworm outbreak. The simpler of these strategies is to do nothing. Given the high cost of salvage harvesting and active budworm monitoring and the under-development of road infrastructure into northern and remote regions, doing nothing and accepting losses will often be the only available or reasonable option. The second strategy, which is widely used in Ontario, Quebec, Saskatchewan, Alberta and British Columbia and was traditionally used in Maritime provinces, is known as Foliage Protection (FP). This strategy consists of aerially spraying *Bacillus thuringiensis* var. *Kurstaki* (Btk) and tebufenozide in order to suppress defoliation just enough to delay or prevent the death of trees. Management is explored fully in section 1.5.

Planning for spruce budworm must be done on a long-term horizon, as action plans must be developed for 25 or 50 year horizons, and in conjunction with planning for other threats to the forest. While the present dissertation deals only with spruce budworm, certain strategies for budworm management will have co-benefits. For example, monitoring resources devoted to SBW may also have value for monitoring other pests, and efforts to diversify the forest inventory and increase its resilience to SBW will also help prevent against other pest epidemics. Maintenance of forest integrity can preserve habitat for vulnerable species such as caribou. Managers will consider these co-benefits when planning activities.

In this chapter, I present a comprehensive literature review on the biology, ecology and management of eastern spruce budworms. I build simplified, generalized models for each facet of management, and these models can serve as the priors for more focused research. Subsequent chapters contain their own literature reviews, but these are more specialized, as they present literature that pertains to the specific management problem at hand.

This chapter is organized as follows. Section 1.2 presents a generalized literature review with a discussion of other relevant invasive and irruptive endemic pests, highlighting the similarities and differences between the two. Section 1.3 focuses on the biology and life cycle of budworms. Section 1.4 focuses on the ecology of budworms, including their relationship to forests, their predators and parasites, and the chemical and organic agents that can be used to treat them. Section 1.5 discusses the economic impact of spruce budworms, the three available management strategies currently in use, and the history of budworm management. Section 1.6 discusses and concludes.

1.1.1 Motivation

Spruce budworm dynamics have not been extensively studied in economics literature. As such, most economists, even ones who have knowledge of natural resource and pest dynamics, are probably unaware of the particularities of spruce budworm management.

This chapter establishes the current state of affairs in spruce budworm literature, and explores the extant models of budworm and forest dynamics. These models will allow us to to develop our theories and empirical methods, which are, for the most part, novel. In contrast to the economics literature, the forestry, dendrochronology and entomology literature on spruce

budworm outbreaks is very well developed. This literature contains many parameters which we will use to calibrate models in subsequent chapters.

The purpose of this chapter is to provide an overview of spruce budworm management that will allow the uninitiated to quickly understand the context of budworm management and the state of literature on budworm management. Establishing this baseline will make the rest of this dissertation easier to understand.

1.2 Invasive and irruptive endemic insects

While the damages caused by invasive species have received extensive, and deserved, attention in natural resource economics literature, less attention has been paid to native species that display irruptive dynamics. Examples of such species include bark beetles, present in western North America, cone beetles, present in eastern North America, and the various budworms, present throughout the northern part of the continent. While many of the dynamics of irruptive species are similar to those of invasive species, the philosophy underlying their management is fundamentally different. For example, it is neither optimal nor feasible to eliminate an endemic irruptive species from its native region. Techniques developed to deal with invasive species can inform the response to endemic species, but the specifics of fighting any specific endemic species will be unique to that species. In the following subsections, I discuss relevant insights from other literature on endemic and invasive species, fast and slow processes, and the economics of tipping points in ecosystems.

1.2.1 The economics of invasive and irruptive species control

The spruce budworm has received significant attention in the ecological and forestry literature, as covered in sections 1.3 and 1.4. However, the economic literature on spruce budworms is sparse, especially when compared to other species such as spongy moth, emerald ash borer, jack pine budworm and mountain pine beetle. Studying the dynamics of other irruptive and invasive species provides insight as to how best to evaluate the damages caused by spruce budworm, and work on the mitigation of the economic consequences of other species can be used to design optimal management strategies for spruce budworm.

1.2.1.1 Invasive pests

Olson and Roy [2005] provide a generalized description of optimized prevention and control decisions for invasive species. Species are introduced at a rate ω, which can potentially be reduced through screening in some cases. Planners must minimize the sum of prevention costs, treatment costs and damages. In some cases, corner solutions are optimal, such that all resources should be spent on treatment, or on prevention. In other cases, there will be interior solutions for treatment and prevention, such that resources should be divided between each. The authors provide five propositions that describe how the initial invasion size, invasion growth rate, introduction rate and planner's risk attitude affect prevention and control decisions. Certain aspects of this framework are relevant to the other chapters in this dissertation. Others, such as reductions in the rate of introduction, are not. While the introduction rate can be observed for an endemic pest, pathways tend to be natural, and as such planners can only react. Prevention as defined by Olson and Roy is therefore not possible, and the planner's decision will be whether to control

early, to control later, or to adapt to changing realities.

In Chapter 3, we describe management for a variety of invasive species such as the spongy moth [Epanchin-Niell et al., 2012], emerald ash borer [Yemshanov et al., 2014] and Asian longhorn beetle [Yemshanov et al., 2017] that are relevant to the specific context of survey resource allocation. I do not repeat this discussion here, and will instead focus on one additional species that is not covered in Chapter 3: the invasive brown tree snake in Pacific Island ecosystems. This species is illustrative as it shows the consequences of improper management.

The damages from invasive pests are often severe, and thus planners must determine the best course of action prior to and after arrival and be ready to act decisively. Invasive brown tree snakes (*B. irregularis*), native to tropical Oceania, have caused extensive damage to wildlife on Pacific Islands. In Burnett et al. [2008], the authors model optimal search-and-eradication strategies on Oahu, Hawai‘i. Potential damages are inferred from Guam, where a population introduced in the 1950s has led to the local extinction of birds, power outages, and human injury. The authors determine the policies which minimize avoidance expenses, eradication costs and damages. Optimal policies change according to the status of the invasion. Removal only occurs at the optimum steady state. Below this steady state, only prevention should occur. Brown tree snakes are modeled with an Allee effect, whereby at least two snakes are required for population growth. Damages are linear in the number of snakes, whereas marginal removal cost is decreasing in the number of snakes. A Weibull function is used to model the introduction rate. If the initial snake population is above the optimal steady state, a majority of it should be removed as quickly as possible. This is true even for small snake populations ($n = 50$). Thus, in the case of invasive species, full eradication is often the optimal policy if feasible. This is not necessarily the case for endemic pests, which may play an important role in the ecosystem.

1.2.1.2 Endemic pests

Invasive and endemic irruptive species are distinct insofar as invasive species are exotic to the regions they infest, whereas endemic irruptive species are native to their ecosystems, and can often be keystone species whose removal would negatively impact their predators. Irruptive species can, however, become invasive once they reach ecosystems where they had not previously become established, and this is likely to increasingly occur across North America as climate change shifts the weather patterns of woodlands. This is the case for mountain pine beetles, which have drifted east on winds across the Rocky Mountains and now threaten the Boreal forest of the Prairies [Safranyik et al., 2010]. It is expected that, depending on habitat connectivity, MPB could spread to Ontario and Quebec by the end of the 21st century. In contrast, eastern and western spruce budworms are already present throughout North America, being found in all ten Canadian provinces as well as Yukon and the Northwest Territories. Nonetheless, changing climate conditions will increase the suitability of northern forests to budworm, and will thus increase the population density of larvae in these forests through reduced mortality.

The economics of mountain pine beetles have been studied in multiple ways. Corbett et al. [2016] use a CGE analysis to determine the effects of the MPB infestation on the economy of British Columbia. Timber contributes 7.8% to provincial GDP in BC, and directly contributes 0.8% to GDP. The authors find that, at a 4% discount rate, provincial GDP would decrease by 1.34%, or 57.4 billion CAD, in current (2009) terms over the period of 2009 to 2054. By calculating compensating variation, the authors predict that total welfare would decrease by $90 billion over this period. The authors note that carbon considerations are not included in these calculations. Peter and Bogdanski [2010] consider the economics of salvaging forests harmed by

mountain pine beetles, and establish the conditions under which salvage of a dead stand is profitable. Whether or not to harvest a stand will depend on the cost to harvest (which depends, for example, on road access) and on the ability of the stand to regenerate. While some stands will be profitable to salvage on their own, other motivations such as recreation and fire risk may justify the salvage of unprofitable stands. The authors emphasize that replanting salvaged areas with lodgepole pines could potentially set the stage for future MPB pandemics. Replanting decisions are a key part of any strategy to fight irruptive species, as they will allow forestry managers to mitigate the damage these species cause in the future. Sims et al. [2010] create a bioeconomic model to capture the dynamics of mountain pine beetles and the responses of a social planner to these infestations. This model is then used to compare the outcomes of different management scenarios. While this bioeconomic model inspires my approach here, one key difference between the Sims et al. model and the ones I will present is that there are very few effective and economical pesticide treatments that can combat mountain pine beetles, due to the speed with which they kill trees. As such, the only option available to many managers is to adapt to the new realities posed by MPB. In contrast, given that spruce budworm take multiple years to kill their hosts, the range of options available to managers is greater.

Cone beetles are insects that destroy the seeds of coniferous trees, preventing their reproduction. Up to 90% of a seedling crop can be destroyed by these beetles [Kegley, 2006]. Subspecies include the red pine cone beetle and the white pine cone beetle. While these beetles pose a threat to forest plantations, control efforts have received very little attention in the literature. This may be due to the fact that effective controls have been developed, suggested and implemented. Prescribed burns are a popular control method (see Miller [1978], McRae et al. [1994] and Natural Resources Canada [2013b]). Recently, pheromone traps have also shown promise as

a control method [Miller, 2007]. Cone beetles were a major problem in Canada in the 1970s and 1980s, but have since become less prevalent as a threat.

Not all endemic irruptive pests are equally destructive. The forest tent caterpillar is the most significant endemic pest affecting broadleaf forests in Canada [Cooke, 2022]. However, the forest tent caterpillar is better described as a nuisance than as a threat. Forest tent caterpillars defoliate trees, but do not cause these trees to die before they can be harvested [Chang et al., 2011]. The economic literature on forest tent caterpillar is limited, but this gap in the literature is probably justifiable, given the lower damages caused by forest tent caterpillar relative to invasive species such as emerald ash borer and Asian longhorn beetles. The entomological literature on forest tent caterpillars is well-developed, however. Forest tent caterpillars affect trembling aspen forests, and their cyclic outbreak-and-decline dynamic has a mean period of about ten years [Roland, 1993]. It is known that habitat fragmentation will increase the duration of forest tent caterpillar outbreaks [Roland, 1993, Roland and Taylor, 1997]. Habitat fragmentation allows forest tent caterpillars to "escape" from the threats of predators and parasites, since the forest tent caterpillar is able to disperse across a fragmented landscape more easily than its natural enemies [Cooke, 2022]. Forest fragmentation will disrupt the natural predator-prey relationship that governs the oscillation of the forest tent caterpillar population. When it comes to the human relationship with forest tent caterpillars, familiarity breeds contempt: Chang et al. [2011] found that households in Saskatchewan were willing to pay for forest tent caterpillar control. The nuisance of defoliation and habitat degradation is enough to make the public willing to treat forest tent caterpillars, even if there is no specific benefit to the timber industry.

Spruce budworms are, by far, the most economically significant endemic pest in Eastern Canada [MacLean et al., 2019]. Extensive literature exists on spruce budworm dynamics, impact

and management, and many such articles are cited in the sections below. Economic impact studies are much more limited, and what studies exist are primarily cost-benefit analyses (see Huff et al. [1984], Chang et al. [2012a], Chang et al. [2012b] and Liu et al. [2019]). As budworms are the focus of this dissertation, these studies are discussed further in subsection 1.5.5, with the exception of Chang et al. [2011], which was calibrated on both spruce budworms and forest tent caterpillars and which can be applied to other endemic pests.

Chang et al. [2011] presents a unique approach to estimating endemic pest damages. A contingent valuation approach is used to determine the willingness-to-pay for future budworm and forest tent caterpillar outbreak prevention of residents of New Brunswick and Saskatchewan. Generally speaking, respondents supported efforts to combat endemic forest pests (at a rate of about 80% in each province). Despite the fact that New Brunswick is more economically dependent on forestry than Saskatchewan, respondents in Saskatchewan had a higher willingness-to-pay for outbreak prevention ($71.44–$104.48) than in New Brunswick ($59.26–$86.19). This may be explained by the fact that Saskatchewan has a higher median income than New Brunswick. In New Brunswick, 23.1% of the value of the willingness-to-pay was for recreation and 39.4% was for ecological considerations, such that total non-market benefits are $53.87 per household for the households willing to pay $86.19.

The literature on endemic pests allows us to make a few preliminary determinations about the optimal policies that managers can employ. First, if pest control is prohibitively expensive or has a low probability of success, then the best managers can do is adapt harvest schedules to reduce losses and change stand mixes in restocking plantings to reduce susceptibility. Second, a pest that is easily countered will become part of normal operating costs rather than overwhelming management efforts. Third, there is high awareness of endemic pests in affected regions. The

general public tends to be familiar with these pests and with the effects that they have on the local economy. As such, active management of endemic pests is likely to have high social acceptability.

1.2.2 Fast and slow processes

Ludwig et al. [1978] developed a mathematical model for insect dynamics that posited the existence of fast and slow processes, and this analysis was specifically formulated for spruce budworms. This model is cited below, in subsection 1.4.4. Insects have a fast dynamic, while forests have a slow dynamic. The authors establish a stepwise process. Once fast and slow variables are established, slow variables are held fixed and the long-term behaviour of fast variables is analyzed. Equations are scaled to reduce parameters, and parameter values are used to establish the equilibria for fast variables. The authors describe two stable and one unstable equilibria. The third step is to hold fast variables fixed and determine the response of slow variables. The fourth step will be to analyze the long-term behaviour of fast variables given the response from slow variables. The fifth step is to combine the results and describe the behaviour of the complete system. The authors describe transition equations for forests and budworms, as well as the relevant quantities for these transition equations.

In Ludwig et al. [1979], the authors adapt the Ludwig et al. [1978] model to determine spatial diffusion. They establish the minimum width of a strip of forest needed to support an outbreak, as well as the necessary width that a barrier would need in order to prevent outbreaks from spreading from strip to strip. Unlike in Ludwig et al. [1978], however, the authors do not consider the dynamics of the slow system, instead holding them fixed.

Vardas and Xepapadeas [2015] consider the generalized problem of renewable resource

management when the resource regenerates so slowly that parameters such as carrying capacity are treated as fixed by agents. Time scale separation results in externalities, because management rules will be derived from a misspecified function. The authors model biomass as a fast process and carrying capacity as a slow process. Carrying capacity will slowly change due to processes such as climate change (exogenous forcing) or industrial pollution. Cooperative and non-cooperative solutions are explored. Optimal regulation in a non-cooperative context will maximize discounted aggregate benefits from harvesting activity net of environmental damages. This will therefore involve optimization with a damage function. Ignoring this damage function is likely to lead to overharvesting.

It is appropriate to treat budworms as a stock with fast dynamics and trees as a stock with slow dynamics. Budworm stocks are affected by rapid changes in external conditions, such as predation and weather. Trees, meanwhile, are affected over a longer horizon, reacting to climatic shifts and cumulative years of pest pressure. If a hands-off management framework is employed, budworms can also be considered as a form of exogenous forcing.

1.2.3 The economics of tipping points

A literature has emerged on the economics of fragile ecosystems whose ecological integrity can be compromised if they cross a threshold. Crépin [2007] discusses the economics of a fishery in a fragile coral reef, and develops a generalizable framework. The author's framework uses a fast and a slow vector, like Ludwig et al. [1978] and Ludwig et al. [1979], in addition to a perturbation parameter. There are two concave functions, one of which governs the fast vector and the other which affects the fast and slow vectors. There is additionally a non-concave function

that governs the effect of changes to the fast and slow vectors on the fast vector. The ecosystem provides ecosystem and harvest values, which are additively separable. The fast vector can be affected by the social planner. In Crépin's model, the fast vector is algae and the slow vector is coral. These compete for sunlight. Harvesting fish will allow algae to thrive, and harm coral. There are steady states, which are either equilibria or saddle points. Once a low equilibrium has been reached, it may take a long time to get back to the high equilibrium again, due to non-convexities. In some cases, a high equilibrium might not be attainable at all. Crépin finds that, if the fishery is "optimally" managed from the perspective of fish stocks, but without taking the coral ecosystem into account, this will make the ecosystem much more vulnerable to passing an irreversible threshold and ending up in a low equilibrium.

Within a single planning cycle, a vulnerable forest can be analogized to the coral reef. Tree death is irreversible and inevitable once a certain amount of defoliation has been reached. Outbreaks of spruce budworm, if not contained, will cause massive tree death across a landscape. In subsection 1.3.2, I discuss the two dominant theories of spruce budworm outbreaks, which are the oscillatory theory and the double-equilibrium theory. If the double-equilibrium theory holds, then a "high" equilibrium in terms of budworms will be the root cause of a "low" equilibrium in terms of healthy trees, and the analogy to Crépin's model is even more appropriate.

1.3 The biology of spruce budworms

A generation of spruce budworms lives for a year, from summer to summer, before reproducing itself. In this section, I discuss characteristics of spruce budworm larvae, dynamics within a year, dispersal, and dynamics over a medium to long-term outlook. Budworm larvae

pass through a half-dozen instars before they pupate. Following the pupal stage, they emerge as moths. Moths then mate and fly, potentially travelling up to 200 km depending on currents. There are two competing theories on budworm dynamics, and each of these theories has different implications for management.

1.3.1 The life cycle of spruce budworms

Spruce budworms thrive in the softwood forests of eastern Canada and northern New England, where they feed on the nettles of softwoods, preferring spruce and fir. Female and male moths breed and then fly to new trees to lay eggs on nettles during the summer. These eggs hatch into larvae in August, and they remain dormant in branches over winter. Caterpillars emerge in the spring and feed on needles, flowers and buds. Their eating patterns can destroy new shoots [Balch, 1958]. They pupate for ten to fourteen days in June and July, and emerge as moths [Talerico, 1983]. Unlike spongy moths, both male and female budworm moths fly, which makes the use of sex pheromones ineffective to control populations [Régnière et al., 2019].

A generation of spruce budworms lives its entire life from August until July of the following year, when moths take flight and land on trees, laying the next round of eggs [Talerico, 1983]. Budworms pass through six instars between being laid as eggs and pupation. Eggs, laid in July, hatch in August, feed, and then form hibernacula as they overwinter. They will emerge from these shelters as second-instar larvae in April or May. They then molt through four more instar until they reach their sixth instar, whereupon they consume the greatest percentage of foliage of any instar. The first five instars will generally eat the nettles and buds of one shoot, while the sixth instar will eat the foliage of two or more shoots. Finally, in late June or early July, the larvae will

pupate into moths over 8 to 12 days, emerging and dispersing to other trees [Talerico, 1983].

Due to predation, pests, weather, the natural defenses of trees and competition for resources, the mortality rate among budworms is high, generally being between 95% and 99%. When mortality is at the higher end of the spectrum, populations are stable and endemic. When mortality is low, however, populations can irrupt. This will lead to outbreaks which can quickly spread across the landscape. This is explored in the following subsection. For a treatment program to be effective, it must impose additional mortality, which is to say that the mortality it imposes must mostly kill budworms which would not otherwise have died.

If mortality from treatment is not additive, then the budworms killed by treatment would, generally, have been the weakest members of the population, who would otherwise have died of insufficient resources. This is problematic because it means that the remaining budworms face less competition for resources. The body weight of survivors would be larger, and females would be more fecund.

In section 1.5, I lay out the history of budworm treatments. Early budworm treatment programs involved DDT spraying. Besides the environmental issues involved with DDT's broad scope, mistimed application led to massive die-off of budworms, followed by a population bounce-back shortly after die-off.

1.3.2 Two theories of budworm dynamics

Knowledge about SBW dynamics is evolving, and there is uncertainty about how endemic populations irrupt into outbreaks [Régnière et al., 2019]. Currently, two theories predominate about how endemic populations become outbreaks. Both originate from the same observations,

taken in Green River, New Brunswick. The first, known as the double-equilibrium theory, holds that external shocks cause SBW population levels to irrupt above usual levels. The second, known as oscillatory theory, holds that a periodic predator-prey relationship governs SBW outbreaks. If the first theory holds, it is possible to reduce, delay or prevent outbreaks through management of either the underlying forest or spruce budworm populations. If the second theory holds, the best forestry managers can hope for is to reduce the scale of damages [Régnière et al., 2019].

The double-equilibrium theory was first developed by authors such as Balch [1958] and Morris [1963]. This occurred in a context where DDT treatments for budworms were first being developed, and thus where the results of early spray efforts could be observed. Morris produced life tables for spruce budworm. These life tables lent themselves to analyses such as Ludwig et al. [1978], as described in section 1.4. Balch determined that outbreaks occurred after several years of favorable conditions, could be seeded by moth flights, and were self-sustaining once they had developed. The Ludwig et al. [1978] model specifically identified the low and high equilibria in a double-equilibrium model.

The oscillatory theory was developed by Royama [1984] after re-examining Morris's data. Royama rejected the theory that egg-carrying moths significantly upset a theoretical endemic equilibrium. Under the oscillatory theory, budworm dynamics do not have equilibrium conditions. Instead, they feature peaks and troughs where the population process has two components: a primary oscillation around a main trend, and a secondary fluctuation around this primary oscillation. Outbreaks are seeded by the local survival of larvae. At most, a moth invasion will accelerate an outbreak towards a higher peak (Royama describes such invasions as "fertilizer"). The seeming synchrony of outbreaks across landscapes could then be explained by the fact that density-independent factors such as weather will be correlated across locations. Therefore, what

appears to be "spread" is, instead, the simultaneous increase of endemic populations across a landscape.

The most recent research supports the double-equilibrium theory. Régnière and Nealis [2019] examined fourteen data sets, including the one used by Royama, and concluded that high densities were associated with low fecundity and low densities with high fecundity. This implies that low density plots were migration sinks and high density plots were sources. Régnière and Nealis reject the Royama hypothesis that migration is a symptom rather than a cause of budworm outbreaks. They conclude that density-dependent dispersal will offset local population declines, which will overwhelm small-scale efforts to counter budworms with pesticides. The implication is that management must be targeted at a landscape scale if they are to be successful.

Despite these findings, there is still controversy concerning which theory is correct [Sturtevant et al., 2015]. If, in fact, oscillatory theory is correct, then current early intervention efforts in New Brunswick are merely correlated with a local trough in budworm populations. This would imply that future efforts will fail when the underlying outbreak oscillates back towards a peak.

1.3.3 Model: the budworm cycle

All notation in this section is specific to this section, and borrowed from literature sources.

While ecological models can focus on the multiple life stages of budworms in detail, economic and policy modeling is easier when the complexities of life stages are distilled down to single stages. Régnière et al. [2019] describe transitions between egg, larval and adult stages. In order to get a year-to-year model for larval transitions, I first transcribe the Régnière et al. transitions from one stage to the next, and then simplify these into a single transition equation. These

equations treat ecological conditions as exogenous, and therefore can provide a good description of how budworm populations are expected to evolve in the short-term.

Survival from early-instar larvae to emergent adults is given by the ratio $S = A/N$, which is the ratio of emerged adult density to larval density. Based on data derived from four datasets in Gaspésie, Régnière et al. calculate this ratio empirically, fitting it to a Weibull function. This is given by:

$$S = \frac{p_0 + p_{0,S}}{N}(1 - \exp\{[(p_1 + p_{1|2013} + p_{1|2014} + p_{1|S} + p_{2|2012} + p_{2|2013} + p_{2|2014})N]^{p_3}\}) \quad (1.1)$$

N is the density of early instar larvae from a collected sample, and A is the density of emerging adults from a pupal sample. The parameters p_0 and $p_{0,S}$ are, collectively, the carrying capacity, with p_0 being observed across all datasets and $p_{0,S}$ representing additional carrying capacity in a dataset that was collected by the SOPFIM and not by the authors. The parameters $p_1, p_{1|2013}, p_{1|2014}, p_{1|S}$ test for differences in slope between datasets, and the parameters $p_{2|2012}, p_{2|2013}, p_{2|2014}$ test for the effectiveness of insecticides. The parameter p_3 is a shape parameter.

This empirical formulation is useful when parameterizing a model; parameter values are, themselves, presented in Régnière et al. [2019]. In general terms, I rewrite equation (1.1) as:

$$S = \frac{A}{N} = \frac{\bar{A}}{N}(1 - \exp\{[(\alpha - \tau)N]^{\eta}\}) \quad (1.2)$$

This equation thus links larval density to adult density. The next step is to determine how

adults relate to eggs. Régnière et al. write this transition[3] as:

$$\log(E) = \log(F_I A_I + F_Y A) \tag{1.3}$$

The egg density is given by E, $F_I A_I$ is eggs per shoot from immigrated moths A_I due to fecundity F_I, F_Y is the fecundity of local adults and A is the density of local adults.

To complete the loop, we need the hatching rate of eggs, which will determine the population of larvae in the next period. Régnière et al. calculate this as a simple log-linear relationship[4], given by:

$$\log(N) = \beta_0 + \beta_1 \log(E) + \varepsilon \tag{1.4}$$

where ε is an error term, β_0 is the intercept and β_1 is a coefficient that represents successful hatch-and-survival.

I rewrite equation (1.2) as $A = SN$, and use this to rewrite equation (1.3) as $\log(E) = \log(F_I A_I + F_Y A) = \log(F_I A_I + F_Y SN)$. Finally, by adding time subscripts, I rewrite equation (1.4) as:

$$\log(N_{t+1}) = \beta_0 + \beta_1 \log(F_I A_{It} + F_Y S_t N_t) + \varepsilon_t \tag{1.5}$$

This gives us a simplified transition equation that can be both calculated empirically and used in a theoretical formulation.

The survival rate S_t depends on the carrying capacity of the forest, which is considered in

[3] This is equation (1) in Régnière et al. [2019].
[4] This is equation (5) in Régnière et al. [2019].

section 1.4. As competition for resources increases, the survival rate of larvae to the adult stage decreases. Insecticide treatment of forest stands will aim to reduce this survival rate.

1.3.4 Parameterization of the budworm cycle model

Parameterization of the budworm cycle is straightforward. Régnière et al. [2019] calculate values for the parameters in the above model. These parameter values can thus directly inform our model. Sensitivity analysis in a simulation can then be used to determine how modifications to the parameters would affect conclusions.

1.4 The ecology of spruce budworms

Spruce budworms are a key part of coniferous North American forests, as they are prey for birds and invertabrates. In this section, I describe the interactions between budworms, their forests, and their predators and trace the history of spruce budworm outbreaks across Canada in the 19th and 20th centuries. I present a basic slow-and-fast process ecological model, adapted from Ludwig et al. [1978] and Ludwig et al. [1979].

1.4.1 The hosts and predators of spruce budworms

Talerico [1983] provides a summary of spruce budworm predator-prey interactions. As mentioned in the introduction, eastern spruce budworms prefer balsam fir, white spruce, and red spruce, and they also eat the nettles of other species such as black spruce, tamarack, eastern hemlock, and white pine. Eggs tend to be found primarily in the outer perimeter of the tree crown, but can even be found as deep as the bark. Larvae preferentially feed on staminate flowers. They

stay in place until all food is consumed, and then move on. Balsam fir are the most vulnerable hosts, followed by white spruce, red spruce and black spruce. This preference can be explained by the timing of bud emergence [Greenbank, 1963]. Mature and overmature trees are the most susceptible to attack [Jennings and Crawford, 1985].

Trees can defend themselves against budworms. Talerico distinguishes between "qualitative" and "quantitative" defenses. Qualitative defenses include alkaloids, terpenes and cyanide, which is to say the toxins secreted by trees, and quantitative defenses include foliage toughness as well as tannins. Talerico acknowledges that the distinction is arbitrary (for example, terpenes may also be "quantitative"), but largely it comes down to between-species variation in the degree of defense (i.e. species with more qualitative defenses are more resistant than species with fewer qualitative defenses) versus within-species variation (i.e., for a given species, a tree with more quantitative defenses will be better protected than a tree with fewer quantitative defenses).

Food abundance is related to individual budworm size as well as to budworm density: as the food supply in a forest decreases over the course of an outbreak, larvae will be smaller, with reduced fecundity [Talerico, 1983].

An understanding of the predators of spruce budworms is critical to integrated pest management [Jennings and Crawford, 1985]. Different life stages face different predators. Eggs are eaten or are suspected to be eaten by phalangids, mites, spiders, plant bugs, lacewings, beetles, ants, and possibly birds such as warblers. Mites are particularly voracious, with each mite eating, on average, 0.68 budworm eggs a day. When budworms are on trees and in a larval stage, their predators include coccinellid beetles (i.e. ladybugs), squirrels, and birds such as chickadees, vireos, sparrows, warblers and nuthatches. Small larvae are not generally considered to be desirable food sources for birds. Some larger budworm larvae will drop to the forest floor to avoid

predators. This is an effective survival tactic, but it still leaves them exposed to ants, spiders, carabid beetles, and insectivorous mammals such as voles, mice and shrews. Pupae are immobile and thus susceptible to predation, especially by spruce coneworms, which pupate several days later than budworms, but also by the other arboreal predators of larvae. When moths take flight, dragonflies, robber flies, and birds such as kinglets, vireos, warblers and chickadees will prey on them if they can catch them. Female moths are more vulnerable than males due to their heavier bodies, egg burden, and less rapid flying. Ovipositing and coital moths are also vulnerable to predation by arboreal predators.

According to the oscillatory theory, described in subsection 1.3.2, predator success rates determine budworm outbreaks. The double-equilibrium theory focuses on the importance of local climatic and forest health conditions, and holds that predators are opportunistic and will seek other prey when budworm levels fall below outbreak levels. Under the double-equilibrium theory, which I assume holds throughout these essays, predation is one part of the ecosystem's response to fluctuating budworm levels, and a determinant of the within-stand larval survival rate and of the reproduction success rate for adults. It is not, however, the main driver of outbreaks.

1.4.2 Timeline of spruce budworm outbreaks

Spruce budworm outbreaks occur over several generations, and multiple years of sustained defoliation are required before trees die. Since budworm prefer to eat new foliage rather than old foliage, old foliage will be preserved in the early stages of an attack, which prevents tree asphyxiation. The amount of time required for a stand to experience massive death will depend on stand composition: balsam fir die after 4 to 7 years of defoliation, depending on local conditions,

while white and red spruce require one more year to die than balsam. Black spruce tend not to die until outbreaks are severe and sustained [Talerico, 1983]. Outbreaks tend to begin in stands where there is an abundant supply of food.

Over the course of the 20th century, the duration of outbreaks was inversely related to their severity [Navarro et al., 2018]. Once an outbreak is ubiquitous across a landscape and defoliation has become widespread, collapse will eventually occur due to disease, starvation and emigration [Régnière et al., 2019]. It stands to reason that an outbreak that exhausts its available resources faster will also collapse faster. As discussed in subsection 1.4.3, outbreaks have historically tended to last 30 to 40 years [Sturtevant et al., 2015]. The severe outbreak of 1968-1988 identified by Navarro et al. [2018] was therefore significantly shorter than a typical outbreak.

Because defoliation takes several years to become severe, because several years of cumulative defoliation are required before death occurs, and because standing dead trees can be harvested for timber [Liu et al., 2019], the effects of a spruce budworm outbreak on stand yield will be delayed. Chang et al. [2012b] described a theoretical moderate or severe outbreak in 2012 as having effects that begin to be felt in 2017, and have a maximum harvest impact from 2027 to 2031. This provides different options for SBW treatment: a forest stand can be saved by aerial spraying of Btk and tebufenozide after it experiences defoliation, but by this point the infestation will have spread to adjacent stands. For defoliation to be visible through aerial surveys, outbreaks will have reached sufficient density to spread to neighboring stands: once a defoliation threshold of 25% has been reached in trees, budworms tend to disperse due to competition for food [Régnière et al., 2019].

The least understood phase of budworm outbreaks is, paradoxically, the most interesting and important phase. There is very little knowledge about the early dynamics of budworms, and

comparatively more knowledge about late-stage dynamics [Régnière et al., 2019]. Modeling the early dynamics of spruce budworms has proven to be the most challenging part of this dissertation. Chapter 3 provides some attempts to model early dynamics. Sensitivity analysis will account for uncertainty.

Early detection requires intensive, on-the-ground monitoring. Whether it is even feasible will depend on the density of road networks and the availability of resources, and whether it is worth pursuing will further then depend on economic, social, political and ecological considerations pertaining to the stand. Early detection is a pre-requisite for any intervention strategy that could prevent large-scale outbreaks. The question of how to optimally manage outbreaks is explored in subsection 1.5.2.

1.4.3 A history of Canadian spruce budworm outbreaks

Knowledge of spruce budworm behavior in New Brunswick dates back to the 1770s [Morris, 1963], and the dendrochronology of budworm habitats in Quebec has been reconstructed to about 3000 BCE [Morin et al., 2007]. Fossilized droppings from spruce budworms allow a much longer timeline: fossils have been discovered in Saguenay bogs dating back to 6000 BCE. The habitats of spruce budworms are relatively young: the spruce-fir forests of Quebec date to about 11,000 years ago, when glaciers retreated at the end of the last great Ice Age.

The first European settlement of what is now Quebec dates to the early 17th century, and European migration became sustained by the middle of the 17th century[5]. The intensive, industrialized management and replanting of forests that has occurred since European settlement has

[5]While Morin et al. characterize the pre-settlement forest as "virgin" (see Fig. 1 in their paper), this could be seen as an ahistorical characterization [McCann, 1999].

led to larger and more intense outbreaks. Three large, well-documented outbreaks occurred over the course of the 20th century: from 1905 to 1930, from 1935 to 1964, and from 1968 to 1988 [Navarro et al., 2018]. The third of these outbreaks was the most severe. These periods cover the occurrence of outbreaks over the entire Canadian landscape, as reconstructed through dendrochronology: in New Brunswick, for example, the worst of the first two outbreaks occurred from 1912 to 1920 [Balch, 1958] and from 1947 to 1958 [Royama, 1984], while the worst years for defoliation in New Brunswick during the most recent outbreak were 1975 and 1983 [Chang et al., 2012a]. There is uncertainty about the effects of climate change will have on the length of time between future outbreaks, and it is thus possible that the interval between outbreaks will shorten.

At their maximum extents, the eastern spruce budworm outbreaks of the 20th century led to annual defoliation totalling 11, 25 and 58 million hectares, successively. During the 1970s-1980s outbreak, the government of New Brunswick spent $100 million on forest protection programs and established the most extensive aerial spraying program in the world [Chang et al., 2012a]. This same outbreak affected about 50% of the forested land of Quebec [Navarro et al., 2018]. The extent of budworms is limited by geography, both to the North and South, and the availability of food. It is expected that climate change will cause the range of budworms to shift north.

1.4.4 Model: interactions between budworms and forests

As with subsection 1.3.3, all notation is specific to this subsection.

A good model for the interaction between budworms and forests is described in the fast-and-slow model presented in Ludwig et al. [1978]. Spread dynamics are well described by Lud-

wig et al. [1979]. I therefore combine the two to present a model for budworm-forest interactions in continuous time.

Ludwig et al. [1978] captures budworm population density as a function of the forest's carrying capacity and predation. Larval density is given by B, which transitions in continuous time. Ludwig et al. present[6] this as:

$$\frac{dB}{dt} = r_B B(1 - \frac{B}{K_B}) - \beta \frac{B^2}{\alpha^2 + B^2} \tag{1.6}$$

such that r_B is a linear growth parameter representing the growth rate of budworms, K_B is the carrying capacity of the forest, and the term $\beta \frac{B^2}{\alpha^2+B^2}$ represents predation by vertebrates (i.e. birds), where β is a habitat factor and α is a scale factor that determines the saturation of SBW. This growth rate does not take treatment or diffusion into account. In a steady state, $\frac{dB}{dt} = 0$. Note that the term K_B is here held fixed, but will vary according to the slow dynamics of the forest.

The rate of change $\frac{dB}{dt}$ is a "fast" process. Predation by vertebrates can vary much more rapidly than foliage can replace itself, and as such disturbances to the predation parameter will cause rapid changes to the growth rate of budworms. It is worth noting that this notation implies a continuous process, such that it needs to be adapted for use in a discrete time context. This is straightforward and omitted here.

Equilibria will exist when equation (1.6) is equal to zero. This will occur when $r_B B(1 - \frac{B}{K_B}) = \beta \frac{B^2}{\alpha^2+B^2}$. As noted by Ludwig et al. [1978], one such value occurs for $B = 0$. Since $r_B B(1 - \frac{B}{K_B})$ is linear and $\beta \frac{B^2}{\alpha^2+B^2}$ is quadratic, there are up to three other potential roots, de-

[6] This is equation (3) in Ludwig et al. [1978].

pending on the values of the parameters. Ludwig et al. rewrite[7] equation (1.6) as:

$$R(1 - \frac{\mu}{Q}) = \frac{\mu}{1 + \mu^2} \tag{1.7}$$

when at equilibrium, where $R = \frac{\alpha r_B}{\beta}$, $Q = \frac{K_B}{\alpha}$ and $\mu = \frac{B}{\alpha}$. The left hand side is the growth rate of μ and the right hand side is the death rate of μ, where μ is the scaled density of budworms.

The slow state variable, S, is the total surface area of branches in a stand. It is bounded by upper limit K_S. The health of trees and foliage is summarized in variable E, bounded by upper limit K_E. The transition equation for S is given[8] by:

$$\frac{dS}{dt} = r_S S[1 - (\frac{S}{K_S} \times \frac{K_E}{E})] \tag{1.8}$$

where r_S is the intrinsic branch growth rate. Two equilibria exist: $S = 0$ and $S = \frac{K_S}{K_E}E$. Note that due to the sign on $\frac{S}{K_S}\frac{K_E}{E}$, increases in E and decreases in S will both lead to increases in $\frac{dS}{dt}$.

The transition equation for the health of forests[9] follows:

$$\frac{dE}{dt} = r_E E(1 - \frac{E}{K_E}) - P(\frac{B}{S}) \tag{1.9}$$

where P is the rate of energy consumption by budworms. Increases in the density of budworms will cause declines in E, and thus declines in $\frac{dS}{dt}$. Ludwig et al. demonstrate numerically that S is a slow process, approaching its maximum over a 30 year period, whereas B can grow rapidly from a low initial equilibrium. Once a critical threshold for budworm density is reached,

[7] This is equation (9) in Ludwig et al. [1978].
[8] This is equation (21) in Ludwig et al. [1978].
[9] This is equation (22) in Ludwig et al. [1978].

S collapses rapidly to near-zero levels.

The carrying capacity of budworms per acre, K_B, relates to the per-branch carrying capacity, K' (which is an estimated parameter), the available foliage, S, the health of forests E, and the threshold for health, T_E. Ludwig et al. write this relationship[10] as:

$$K_B = K'S\frac{E^2}{T_E^2 + E^2} \tag{1.10}$$

For large values of E relative to T_E, this is approximated by $K_B = K'S$.

Ludwig et al. [1979] consider a spatial application of the budworm model. They rewrite function (1.6) in one-dimensional space[11] as:

$$\frac{dB}{dt} = \frac{\sigma^2}{2}\frac{\partial^2 B}{\partial X^2} + r_B B(1 - \frac{B}{K_B}) - \beta\frac{B^2}{\alpha^2 + B^2} \tag{1.11}$$

Here, σ^2 is the variance of diffusion and X is a rectangular co-ordinate. With equation (1.11), the "fast" process in the Ludwig et al. [1978] model becomes diffusive, while the "slow" process remains spatially fixed, and affected by a diffusive stock. As the term $\frac{\sigma^2}{2}\frac{\partial^2 B}{\partial X^2}$ increases due to increasing spread of budworms from infested to uninfested forests, slow stocks will collapse across the landscape.

1.4.5 Parameterization of the interaction model

Ludwig et al. [1978] provide empirical parameter estimates for each value in their model. Additionally, growth functions for different species of trees, based on site indices, are calculated

[10] This is equation (20) in Ludwig et al. [1978].
[11] This is equation (6.1) in Ludwig et al. [1979].

in Carmean and Hahn [1981]. It is therefore possible to calculate the expected height and surface area of a tree depending on local conditions, in the absence of pests, and then to estimate how the above model would predict damages to these trees. We use a similar parameterization method in Chapter 2 when building our growth-impact model, with some changes based on the specific objectives of that chapter.

1.5 Managing budworm outbreaks

Budworm outbreaks can be managed through treatment, and different treatment options exist for managers. In this section, I discuss the economics of spruce budworm outbreaks and control, the history of budworm management, and the three available treatment strategies.

Careful budworm management can significantly reduce the costs associated with a budworm outbreak. The death of trees occurs after several years of cumulative defoliation. Depending on objectives, this gives managers time to act: even after defoliation occurs, trees can be saved or have their deaths delayed for several years. However, outbreak extents cannot be reduced once they have spread across the landscape.

1.5.1 A history of spruce budworm management in Canada

In the early 20th century, when forest resources in New Brunswick were more abundant and the pulp and paper industry was in its infancy, insect outbreaks were tolerable. By the 1940s, depleting forest resources meant that forest stocks had to be carefully managed in a sustainable way. Following the Second World War, decommissioned military bombers and commercially-available pesticides made insect population pulverization feasible [Kettela, 1975]. Ontario first

sprayed its forests in the 1940s, while New Brunswick launched its first widespread spray program in 1952. These programs used DDT. While they were successful in destroying budworm populations, compensation limited the ability of these spray programs to protect foliage. Furthermore, DDT is not a specific pesticide, and the ecological costs were thus not acceptable. The timing of treatments was fine-tuned from 1953 onward, and the nerve agent fenitrothion replaced DDT starting in 1968, as it showed similar effectiveness for budworms and less adverse effects on other fauna [Kettela, 1975].

Technology, techniques and chemical agents all improved through practice and research. The bacterial agent *Bacillus thuringiensis* var. *Kurstaki* (Btk) was first tested against SBW in 1960. By 1985, better varieties such as the isolate HD-1, better standardization of measurements and improved spray techniques meant that Btk had become widely used to kill spruce budworm larvae [von Frankenhuyzen, 1995]. Btk disrupts the feeding of SBW larvae, causing them to starve to death. Mortality is high but not total. Btk only affects lepidoptera, and therefore will not kill other forest insects. Thus, Btk has minimal ecological drawbacks. Tebufenozide (RH5992), which is similarly ecologically benign, began being used against spruce budworms in the late 1990s, after field trials in a balsam fir forest near Longlac, Ontario in 1993. It causes early moulting and thus interferes with budworm growth. It is harmless to Coleoptera, Orthoptera or Heteroptera but harmful to Lepidoptera [Cadogan et al., 1997]. In the Longlac study by Cadogan et al. [1997], mortality without treatment was about 67.5% on average with high variance. Depending on treatment, tebufenozide increased mortality to as high as 94%. Defoliation dropped from 61.6% to 6%. Surviving larvae had less body mass, such that the quality of moths would be lower. Further studies by Doucet et al. [2007] showed that early instar moulting could also be disrupted. Modern budworm spraying involves a mix of Btk and tebufenozide.

Moth spraying using phosphamidon was attempted in New Brunswick by Forest Protection Limited [Kettela, 1995]. This program was unsuccessful, since they did not limit egg deposition. Fortunately, these trials also yielded important insights into moth dispersal patterns. It is now understood that sea breezes concentrate moth flights, carrying them inland. Since these trials were unsuccessful, all budworm treatment programs currently in practice focus on larval budworms, not adults.

Budworm control has grown significantly more efficient and effective over the last few decades, due to focused research and technological innovation. Nonetheless, knowledge about how best to protect forests against spruce budworm defoliation is still evolving, and there is controversy about the degree to which forests can even be protected. This is discussed in the following subsection.

1.5.2 Early intervention or foliage protection?

If a forestry manager chooses to actively protect a forest from spruce budworm, two strategies can be employed. Traditional spruce budworm management involves foliage protection, whereas newer techniques have focused on early intervention.

Foliage Protection (FP) is a reactive strategy that involves spraying forests after defoliation occurs. Under FP, managers aerially spray affected blocks at regular intervals, based on available resources, in order to prevent tree death due to defoliation. Ideally, enough foliage should be preserved that trees will survive until shortly before their harvest, minimizing losses from rot. Some defoliation on treated trees is acceptable. For example, Chang et al. [2012a] describe a foliage protection program that reduces defoliation from 70% to less than 40%. This will reduce

the observed tree death across the landscape and thus limit damages.

A foliage protection strategy will not necessarily treat all defoliated populations. Rather, it will treat heavily impacted stands, based on prioritization criteria. Kettela [1975] describes these criteria. A map is made of the trees most likely to suffer tree mortality. Hazard factors include current defoliation, cumulative defoliation, tree vigor and expected budworm density, and areas with similar risk are delineated. This map is then used to plan spray operations. The economic value of stands is considered, since less accessible or less valuable trees might not be worth the expenditure of treatment efforts. Furthermore, linear spray tracts constrain the geometry of operations. Some tree death is thus accepted as part of foliage protection. For example, an FP program in New Brunswick might focus on protecting up to 50% of forested land from budworms [Chang et al., 2012a]. On-the-ground monitoring is used to complement protective efforts and guide decision-making, both in the current year and for the next. Foliage protection will slow the spread of infestations, since suppressed populations will be smaller and will feature physically weaker moths.

In contrast to FP, the Early Intervention Strategy (EIS) is a proactive strategy. EIS was developed for use in New Brunswick, and has been applied in other Maritime provinces. It involves proactive, on-the-ground monitoring of spruce budworm populations in order to detect increases in growth rates. Once budworm density (which can be defined per shoot or per branch) exceeds the irruption threshold, managers following an EIS strategy will spray the plot until populations fall back down below the threshold, preferably to a level where depensatory pressure will cause budworm density to fall back to endemic levels. While some defoliation can occur, it must be minimal enough that growth loss does not occur [Liu et al., 2019]. As examined in subsection 1.5.5, EIS has been shown to better protect the economic value of New Brunswick

forests than FP. A prescription of EIS to the entirety of Canada is not appropriate, however, and any endorsement of EIS due to theoretical optimization must therefore be qualified.

As mentioned in subsection 1.3.2, there are two competing theories for budworm dynamics: the double-equilibrium theory and the oscillatory theory. EIS assumes that the double-equilibrium theory is true [Johns et al., 2019]. If it is not true, then EIS efforts will ultimately fail, because suppression of the budworm population in an apparent "hot spot" will not affect the progression of the actual outbreak. FP, meanwhile, is agnostic as to the cause of outbreaks, and its success does not depend on the validity of either theory. While recent evidence has suggested that the double-equilibrium theory is in fact true [Régnière et al., 2019], this does not make EIS feasible in all contexts. Intensive on-the-ground monitoring (mainly through branch sampling, with potential contributions from sticky traps and citizen science) is required for EIS success. EIS must also be applied across a wide landscape, because hotspots would otherwise go undetected, leading to irruption of budworms and program failure. Efforts in New Brunswick are implemented at a provincial level, with buy-in from private landowners. New Brunswick is a relatively small province that is crisscrossed by roads, with population centres being located throughout the province. In contrast, Quebec is a large province whose population is heavily concentrated in the St. Lawrence Valley. While some forested regions of Quebec resemble New Brunswick in terms of demography, others are remote and have sparse road access. This will increase the cost of running an EIS program and reduce the benefits of such a program, since the cost of logging road construction must be incorporated into any calculation of economic benefits.

1.5.3 The importance of additionality in budworm treatments

Budworms suffer from high natural mortality, generally on the order of 90% for the larval stage [Carleton et al., 2019][12]. Part of this mortality consists of competition for resources. Effective treatment cause additional mortality to budworms: if mortality in the absence of treatment would be on the order of 95%, for example, and the necessary mortality to avoid damages is on the order of 99%, then treatments must cause that additional 4% of mortality. Timing is absolutely critical. If treatments are applied too early, they will kill the weakest budworms, reducing resource competition for survivors. The result will be that the surviving adults will be larger and more fecund. As is explored above in subsection 1.5.1, this was the precise problem which sank early management efforts in the 1950s.

In Quebec, the effectiveness of a spray program at imposing additional mortality is imputed [SOPFIM, 2022]. Samples of late-instar larvae are taken from scheduled treatment blocks prior to a treatment operations. Treated and untreated stands are sampled. Defoliation is then observed at the end of the treatment season. The reduction of defoliation relative to model predictions and relative to control plots can therefore be attributed to treatments. From this attributed reduction, one can then impute additional mortality. This is done in Chapter 2.

1.5.4 Sampling and monitoring spruce budworm populations

Whether an early intervention or foliage protection strategy is employed, the evolution of spruce budworm stocks are tracked through spruce budworm sampling [Johns et al., 2019]. Sampling programs are more intensive under EIS than FP, because the purpose of sampling is

[12]Much of the information in this subsection was shared with me through personal correspondence with a manager of New Brunswick's EIS program, Drew Carleton.

different. A foliage protection program will sample budworms to determine priority treatment blocks that would otherwise suffer heavy damages [SOPFIM, 2022], while an early intervention strategy will try and locate hotspots where budworm populations are rising [MacLean et al., 2019]. EIS sampling will usually occur in two waves. The first wave will seek out hotspots, while the second wave will delimit the shape of hotspots. There are several factors that explain why Quebec forestry planners have chosen to continue with FP instead of switching to EIS, but the logistics of sampling are one of the main reasons explaining this choice. Put simply, it is easier and cheaper to sample spruce budworm populations in New Brunswick or Nova Scotia than in Quebec[13]. The Maritime provinces have a high density of roads through forests. Crews can therefore reach sampling plots within a forest more easily. A high density of sample plots is required for EIS operational success [Carleton et al., 2019].

Sampling occurs during the fall and winter on the second instar of spruce budworm larvae (L2 in literature). The length of branch to be sampled has varied over time [Allen et al., 1984, Régnière and Sanders, 2022]. Current practice consists of taking one 75 cm branch sample from three different balsam fir or spruce trees [MacLean et al., 2019]. The average density among these three branches will determine the spruce budworm L2 population density at the sample point. Under EIS, a density of 7 L2/branch or higher will be enough to trigger control efforts [Johns et al., 2019].

L2 sampling should not be confused with the pre-spray sampling efforts deployed under foliage protection. These efforts are used to determine the efficacy rather than the location of treatments, and they involve taking a 45 cm branch tip sample to determine the density of feeding instars [SOPFIM, 2022].

[13]These observations were shared with me by forestry managers from both Quebec and Brunswick.

1.5.5 The economics of spruce budworm control

The economic consequences of spruce budworms manifest through timber losses, recreation losses and losses of ecological services. Outbreaks lead to reduced growth rates of trees and losses in the forest products sector. In regions where the forestry sector is an important employer, losses in the forestry sector can significantly impact other sectors due to multiplier effects [Chang et al., 2012b].

As mentioned earlier, the economic literature on spruce budworms is relatively sparse. Four relevant examples are Huff et al. [1984], Chang et al. [2012a], Chang et al. [2012b] and Liu et al. [2019]. These are reviewed in this subsection.

Huff et al. [1984] project the effects of spruce budworm outbreaks on the economy of Michigan, Minnesota and Wisconsin, where spruce-fir represented 6% of commercial forest land in the northern section of these states and where 75% of the growing stock was in mature or overmature stands. A static economic model was used to determine the market for spruce-fir resources from the Lake States prior to an outbreak, including responses to decreases in stumpage volume or increases in owner reservation prices. To determine short-run and long-run impacts and responses from an outbreak, the authors use a comparative static model. In the short-run, stumpage owners suffer revenue losses due to excess supply. Demand is not affected, although the quantity demanded will respond to the decrease in price. In the long-run, prices would increase due to shifts away from spruce-fir in favor of more resilient species. Active protection is not considered in the paper.

Chang et al. [2012a] consider both the market and non-market values of responding to future SBW outbreaks, although they only use foliage protection as the early intervention strategy

had not been fully developed at the time of their article's publication. Market values are calculated using a timber supply model to determine future timber supply under different scenarios, and non-market benefits are calculated using contingent valuation. Six scenarios are studied: budworm outbreaks can be moderate or severe, and the government chooses to protect 10%, 20% or 40% of the susceptible Crown forest. Two criteria were used: benefit-cost ratio and net present value. The findings were not identical: protecting 10% of the forest was judged to have the highest benefit-cost ratio under moderate and severe outbreaks, while protecting 20% of the forest yielded the highest net present value during a severe outbreak. The costs and benefits, at a provincial scale, are listed separately for 10%, 20% and 40% protection levels. The authors adapt the Canadian Forest Service's Decision Support System to re-optimize harvest schedules, account for salvage harvesting, and incorporate species-specific defoliation. Contingent valuation was derived from the 2007 mailed survey in New Brunswick, that was described in Chang et al. [2011] (reviewed in subsection 1.2.1.2). Notably, the authors find that maximal foliage protection, which has tended to be New Brunswick's strategy, is a sub-optimal policy. Foliage protection should therefore be more targeted.

Chang et al. [2012b] build on Chang et al. [2012a], but focus primarily on the effects of spruce budworm on the general New Brunswick economy, which they model as a small open economy, and on the sustainability of the New Brunswick forestry sector. Five-year annual averages for sawlog, pulpwood and combined stumpage are calculated for periods from 2012-16 to 2037-41, and dollar losses under 0%, 10%, 20% and 40% protection scenarios are determined for moderate and severe outbreaks. Using data from Statistics Canada surveys, impacts on the output, trade, returns on labor and returns on capital are calculated for forestry and logging, as well as for crop and animal production, fishing, hunting and trapping, support activities for forestry,

mining, oil and gas, utilities, manufacturing, transportation and warehousing, and for the remainder of the economy. The authors are therefore able to demonstrate that the effects of a downturn in forestry due to spruce budworm will have ripple effects on the New Brunswick economy, with the effects on mining, oil and gas and on manufacturing being greater than the effects on forestry. The rest of the economy, which consists of the sectors not explicitly named, will absorb some of the downturn from the forestry sector, but not to a sufficient degree to prevent the overall effects on the economy from being negative.

Liu et al. [2019] use a computable general equilibrium model, with producers, households and the government as economic agents, to compare the impacts of EIS, FP and do-nothing strategies in New Brunswick, under different assumptions of SBW intensity. This economic model focuses on the regional economic effects in New Brunswick, and the biological portion uses past budworm outbreaks and results from ongoing EIS trials, with sensitivity analysis. The study does not investigate the consequences of EIS in different institutional contexts. Similar to Chang et al. [2012a], the authors look at the effects of 5%, 10% and 20% foliage protection, which they contrast with a do-nothing approach and with EIS, under both moderate and severe outbreak scenarios. Dispersal is implicit, and not mentioned in the text. Costs and benefits of each strategy under moderate and severe scenarios are calculated at a province-wide level, and then simplified to a net benefit criterion. The cost of EIS, which does not vary based on scenario or success rate, is about equivalent to the cost of protecting 10% of the forest through FP under a moderate outbreak, and about half the cost of protecting 20% of the forest under a moderate outbreak. Sensitivity analysis was used to determine the impact of a partially-successful EIS strategy. The authors find that no protection would lead to timber losses worth between $178 and $273 million in NPV over 50 years, and that foliage protection would save between $124 and $188 million of timber value

in the forest over the same interval. EIS, if fully effective, would save the entire value at risk of the forest. The economy-wide implications of an uncontrolled outbreak were $24.6 to $35.3 billion over 50 years (NPV), and foliage protection would protect between $19.6 and $27.8 billion of this value at risk. Non-market values are calculated using household willingness-to-pay for a prevented outbreak. Ultimately, the authors find that, at 100%, 90% and 80% effectiveness, EIS has higher NPV under both moderate and severe scenarios than any intensity of FP, while having lower costs than 10% and 20% foliage protection. This represents a static evaluation, which is to say that the evaluation is done prior to the application of a program, with no possibility of updating strategies during the outbreak[14]. Furthermore, it assumes that EIS and FP strategies are at least partially successful.

Computable General Equilibrium (CGE) approaches are highly relevant for provinces such as New Brunswick where the economy is resource-dependent, with relatively fewer service sector or heavy manufacturing jobs than in Quebec or Ontario. These papers have convincingly argued for active management of spruce budworms, and Liu et al. in particular have provided a strong justification for New Brunswick's ongoing early intervention program. Our approaches differ in two ways. First, whereas the existing spruce budworm economic studies could be described as macroeconomic, ours are better described as microeconomic. To the best of our ability, we are modeling the individual decisions made by planners and determining optimal courses of action. Second, our theoretical approach allows for flexibility. While existing studies concentrate on the feasibility and benefits of certain regimes in given provinces, ours will allow for the description of the conditions that favor specific approaches. This tool could therefore be applied to regions

[14]It is worth noting that this represents an assumption, rather than an oversight, on the part of the authors. Earlier work considers the possibility of switching, but in this case the authors assume at least 80% success for EIS with no need to deviate, due to the success of early trials.

within provinces, where conditions may differ from those found elsewhere. Notably, I am interested in the possibility that the approaches used in New Brunswick may be more appropriate to the context of southeastern Quebec than the approaches used in north-central Quebec. While the question of optimal policy boundaries is complex and likely beyond the scope of this dissertation, my hope is that these chapters will provide an early foundation for such work.

1.5.6 Model: valuation of forests

In this subsection, I present a model for forest values. This model does not consider or propose management options. Rather, it is a tool which managers can use when planning surveillance and protection operations. It is the building block of a Decision Support System: stands can be prioritized based on their value. Stands are parts of forests. Forests belong to a region. Stands are indexed $j \in \{1, J_m\}$ in forest $m \in \{1, M\}$. As is the case with the other two models presented in this chapter, all notation is specific to this subsection.

A tree stand derives its harvest value from four factors: the market value of wood products p, the species mix of the trees in the stand s, the ease of access to the trees x, and the quality of the wood q. Forests are composed of stands, with each stand being defined as a grouping of geographically connected trees with a homogeneous mix of species. The first three factors are considered fixed in time, while the fourth, wood quality, depends on the status of an infestation.

Firms are price takers. The market value of wood products is exogenous to the harvest decisions of the firm. Firms will harvest trees if it is optimal for them to do so. They will realize losses in the present if this can prevent greater losses in the future. Firms also cannot influence an outbreak status. Wood quality depends on tree health, which depends on the degree of defoliation.

The harvest value of a stand is given by:

$$V_j^h = p \times f(x_m) \times g(s_j) \times q_j \tag{1.12}$$

This is to say that it is a linear product of functions of the four factors. Price, which does not vary based on stand, is constant and directly influences stand value. Quality is discrete, with at least two quality classes (high and low, plus potentially others based on degree of wood degradation), varies based on stand, and will be correlated across stands j within the same forest m. Species mix consists of a series of discrete classes, which will each have a different associated value of $g(s_j)$. As such, $g(s_j)$ is best understood as a piecewise function. The function $f(x_m)$ is continuous and will vary at the forest level. It is increasing at a decreasing rate as the ease of access x_m increases, such that $f'(x_m) > 0$ and $f''(x_m) < 0$.

The non-harvest value of a stand depends on aesthetic and climate value. It is, crudely, a function of forest health and ease of access, increasing in each, as well as of the discrete species classes. Non-harvest value is given by:

$$V_j^n = k(x_m, s_j, q_j) \tag{1.13}$$

The total value of a stand is the non-harvest value of the stand, until the time period in which it is harvested, plus the harvest value of a stand. With a discount factor δ and time of harvest t^h, the total value of the stand is given by:

$$V_j = \sum_{t=0}^{t^h-1} \delta^t V_j^n + \delta^{t^h} V_j^h \tag{1.14}$$

The value of a forest is then given by:

$$V_m = \sum_{j=1}^{J_m} V_j \tag{1.15}$$

1.5.7 Parameterization of the forest valuation model

How the forest value model is parameterized will be context-specific, based on the quality of forest inventories, whether land is primarily privately or publicly owned, and whether or not timber sales or auction results are regularly published by a governing body. In Quebec, the above model can be parameterized using data from public sources. Notably, the harvest value of trees, based on different species compositions and states of health, are available from provincial sources such as the Bureau de mises en Marché des bois du Québec [BMMB, 2013]. Road networks are available from Statistics Canada [2017]. Tree stand compositions are available from various tree inventories, such as the one published by the Ministère des Ressources naturelles et des Forêts (formerly the Ministère des Forêts, de la Faune et des Parcs du Québec or MFFP) [MRNF, 2017]. Tree health status is available from the MRNF's aerial surveys of tree disturbances [MRNF, 2013].

1.6 Discussion

Despite their widespread economic impact, spruce budworms have received comparatively little study in economics literature. Most academic literature on spruce budworms has focused on their biology or ecology. Economic studies of spruce budworms tend to focus on economic impact, using CGE models. My goal in this dissertation is to present a holistic economic con-

sideration of the spruce budworm management problem, and thus of endemic pest management problems more generally. In order to fill in the gaps caused by a lack of prior economic consideration, I draw on literature from the economics of invasive species management. Certain assumptions from this literature must be modified: for example, endemic forest pests do not have a single introduction event, such that pre-border control is impossible, and eradication of the endemic pest is not a desirable outcome.

The literature and models presented in this chapter will form the background elements of examinations of specific problems in spruce budworm management. In this dissertation, I present an intertemporal model for the management of forest stocks when faced with an endemic, irruptive pest in Chapter 2, and a model for optimal management of budworm populations through surveillance in Chapter 3.

Chapter 2: Optimal Management of an Endemic Irruptive Forest Pest (with. Prof. Lars J. Olson)

2.1 Introduction

Endemic irruptive forest pest management shares many similarities with the management of invasive forest pests, despite the fact that endemic species are, by definition, not introduced into ecosystems. One key difference is that, at low levels, endemic species cause minimal harms to the forest ecosystems they inhabit, such that eradication is not a desirable goal. Ecological and economic harms occur when endemic species irrupt across a landscape, with population densities rising to levels where they cause trees to die. At a sufficiently advanced stage of outbreak, this tree death will occur so quickly that salvage efforts will be unable to recover significant proportions of the value of dead forest stock. Thus, species density is critically important when managing endemic pest outbreaks.

In this chapter, we describe a model for an endemic forest pest that is experiencing an active outbreak. Control measures are applied to reduce growth and damages, while harvests reduce the forest biomass, reducing the available hosts for the pest. Our model is calibrated for and applied to spruce budworms, but can be extended to other forest pests. Preliminary parameters are set such that total eradication of the pest is not possible. This is done to reflect the fact that a

low budworm population will remain in the landscape even if control efforts fully suppress the outbreak. Control functions by imposing additional mortality, which will reduce feeding success, breeding success and thus intergenerational survival.

Our model makes a number of simplifying assumptions. First, dead trees are removed from the biomass stock instantly, rather than rotting at a set rate. Second, monitoring and measurement are not required in order to estimate the proportion of pests in the stand. Third, there is no uncertainty in the success of treatments in reducing the population density of pests. Fourth, we do not consider the case of mixed softwood and hardwood stands, which may lead to more sparse food and less reproductive success, resulting in a higher degree of protection for the softwood trees therein.

This chapter proceeds as follows. Section 2.2 provides a brief description of the current state of spruce budworm management practices in eastern Canada, section 2.3 outlines the general model, and section 2.4 discusses the empirical strategy and the available data. Section 2.5 presents the results of the baseline model and sensitivity analysis, which are discussed in section 2.6. The model draws upon priors established in Chapter 1, but is stylized to maintain tractability.

For the sake of consistency, all units used in this chapter must be converted to metric. Older literature uses imperial units, and we will note measurements in both imperial and their approximate metric conversions. For example, acres are converted to hectares by division by a factor of 2.471.

2.1.1 Motivation

When a forest is undergoing a spruce budworm infestation, forestry planners must make monitoring, treatment and harvest decisions. This chapter examines treatment and harvest. These two decisions are linked: if a forest is a commercial plantation rather than a park or ecological preserve, the wood in this forest will eventually be harvested when it meets economic and ecological criteria for harvest. If budworm treatment is reactive rather than proactive, its primary purpose will be to prevent or delay tree death until harvests can occur.

2.2 An overview of current management practices

As discussed in Chapter 1, budworm management can take a few different forms. Spray management involves either early intervention, where trees are sprayed before defoliation becomes ubiquitous, or foliage protection, where defoliated trees are treated to prevent further defoliation. Another option is to avoid spray treatments and to re-optimize harvest schedules given predicted defoliation and mortality. The final option is to do nothing, and treat budworm outbreaks as stochastic and exogenous.

Canada's Atlantic provinces employ early intervention strategies, with the notable exception of Gros Morne National Park in northwestern Newfoundland. This federally-administered park does not have harvested timber, and outbreaks are not sprayed within the park. As such, it essentially features a do-nothing strategy. In Quebec, most administrative regions are managed under a foliage protection strategy. One notable exception is in the Abitibi-Témiscamingue region of northwestern Quebec, where a lack of suitable aircraft, lower harvest values and low road density have led provincial managers to limit spray efforts and focus more on salvage harvest

incentives.

Conversations with forest managers in New Brunswick and Quebec[1] have allowed us to describe how budworm management occurs in different provincial contexts. Our challenge is to capture as much of the complexity of budworm management as possible while also presenting a generalizable, tractable and intuitive model. Certain aspects of our model reflect the actual constraints of budworm management. For example, in each period, sprays are administered once, twice, or not at all. Treatment is therefore a discrete decision which causes incomplete mortality in the pest. Other aspects of the complexity cannot be maintained. Our model presents the perspective of a stylized social planner who makes decisions on both treatment and harvest, with harvest being a continuous variable that reduces tree biomass.

This chapter mostly focuses on management in the context of Quebec, and is calibrated on Quebec data. Questions of early intervention are explored in Chapter 3 of this dissertation. There are some aspects of Quebec budworm management that are not reflected in this model. For example, Quebec produces a widespread sample of overwintering spruce budworm L2 populations when determining spray areas. We have assumed that sampling is implicit, and have not accounted for it[2]. Certain operational constraints are not considered, such as weather impacts and flight line restrictions for administering sprays. Labor is assumed available. Trees designated for cutting are cut. In reality, public bodies can incentivize a harvest, but harvest operations are carried out by private companies, whether they occur on public or private land.

[1]We would like to thank Drew Carleton, Alain Dupont, Taylor Scarr, Rob Johns, Luke Amos-Binks, Pierre Therrien, Frédérique Saucier, Lucie Bertrand, Stephen Yamasaki and François Villeneuve for their input.

[2]Quebec also collects L4 samples from branch tips immediately prior to spray operations. These have no impact on treatment decisions, and are instead used to assess the effectiveness of spray operations in reducing defoliation. These pre-spray activities do inform our model, because they allow us to calibrate defoliation based on population density.

2.3 Model

Our model describes budworm management over a homogeneous landscape that consists of a single, undifferentiated forest species. The budworm infestation has already progressed to an outbreak stage, and the only decisions available to the planner are harvest (which is proportional) and treatment (which a discrete decision to apply 0, 1 or 2 aerial sprays). We assume full information about both the forest and budworm stocks.

2.3.1 Summary of model parameters and primitives

The following tables summarize the model parameters that are used as model inputs and provide their location in the text.

Table 2.1: Model state variables

Symbol	Name	Description	Location in text	Value/units
s_t, x_t	Forest biomass	Stock of forest before and after harvests.	Established in subsection 2.3.2	Basal area per hectare
l_t, y_t	Budworm density	Per-branch early and late instar budworm density.	Established in subsection 2.3.2.	Measured in budworms per basal area biomass, based on branch conversion.
L_t, Y_t	Total budworm biomass	Per-hectare early and late instar budworm density.	Established in subsection 2.3.2 but described in subsection 2.3.5.1.	Measured in budworms per hectare.

Table 2.2: Model parameters: forests

Symbol	Name	Description	Location in text	Value/units
p	Timber price net of harvest costs.	We use BMMB stumpage rates as a proxy for timber value, with a baseline value of 20 CAD.	Established in subsection 2.3.3.	CAD per cubic meter.
δ	Discount factor.	Defined as $\frac{1}{1+\rho}$ where ρ is the discount rate.	Established in subsection 2.3.3.	Scalar.
r_F	Maximum growth rate of the forest.	Rate at which the forest biomass grows in the absence of budworms.	Described in subsection 2.3.4.3.	Scalar with a value $0 < r_F < 1$.
g_F	Growth reduction factor.	Links the late instar budworm density y_t to a percentage decrease in forest growth.	Described in subsection 2.3.4.3, with derivation in 2.3.6.1.	Positive scalar such that $-g_F$ is a negative scalar.
m_F	Forest mortality factor	Links the late instar budworm density y_t to a percentage increase in forest mortality.	Described in subsection 2.3.4.3, with derivation in 2.3.6.2.	Scalar with a value $0 < r_F < 1$.
K_F	Maximum forest capacity.	The theoretical limit on forest biomass in the absence of budworms.	Described in subsection 2.3.4.3.	Basal area per hectare.

Table 2.3: Model parameters: budworms

Symbol	Name	Description	Location in text	Value/units
$k(i)$	Treatment cost.	Cost per treatment, where i is $0, 1, 2$.	Described in subsection 2.3.3.	CAD, linear in treatments
β	Net larval production per adult.	This is the product of egg survival to the early larval stage and the fecundity of moths.	Described in subsection 2.3.4.1.	Scalar.
μ	Natural budworm mortality.	Can also be written as $\mu(0)$, which is to say mortality in the absence of treatments.	Described in subsection 2.3.4.1.	Ratio.
Y_{imm}	Contribution of immigration to adult moth population.	This parameter prevents total extinction and therefore captures endemic dynamics.	Described in subsection 2.3.4.1.	Measured in budworms per hectare.

Table 2.4: Variables

Symbol	Name	Description	Location in text	Value/units
h_t	Timber harvest.	This is a choice variable. $h_t = x_t - s_t$. The beginning of period stock s_t is harvested down to x_t and this transition value is sold at net price p.	Established in subsection 2.3.3.	Measured in basal area per hectare.
i_t	Treatment decision.	Can take the discrete values of $0, 1, 2$.	Described in subsection 2.3.4.1.	Indicator.
λ_t	Proportional budworm survival to the adult stage. Mortality is $m_t - \lambda_t$.	Depends on the treatment decision i.	Described in subsection 2.3.4.1.	$0 < \lambda_t < 1$.
$d(i_t)$	Additional Mortality due to treatments.	This is the additional mortality that affects budworms after natural mortality occurs.	Described in subsection 2.3.4.2.	Three discrete values. $d(0) = 0, d(1) = 0.5, d(2) = 0.75$

2.3.2 Generalized framework

The forest is a single dimensionless area. In each period $t \in \{1, T\}$, the forest contains a stock of trees and pests at the beginning and end of the period. These are as follows: the forest stocks at the beginning and end of period t are given by s_t and x_t, respectively, while the stock of pests at the beginning and end of period t are given by l_t and y_t[3]. x_t is the stock of trees after harvests and y_t is the stock of pests after treatments for population control and natural mortality.

[3]Lower-case variables represent scaled stocks of pests, dependent on the host. Upper case versions L_t and Y_t represent absolute stocks. See subsection 2.3.4.1

The timber growth function is given by $s_{t+1} = g(x_t, y_t)$, where g is increasing in x, decreasing in y, and strictly concave with $g(0; y) = 0$. We assume that $\lim_{y\to\infty} g(x, y) = 0$ such that there is complete mortality of the forest when all trees are infested. Harvest in period t is harvested from stock s down to stock x at cost $\int_x^s c(u)du$, and sold at price p.

The infestation evolves according to $l_{t+1} = b(x_t, y_t)$, where $b(x, 0) = 0$ and $b(x_t, y_t)$ is strictly concave, strictly increasing in x and strictly decreasing in y. The combination of natural mortality and mortality caused by control measures in period t will reduce l to y. l is an earlier instar than y, which is to say that y larvae are closer to becoming reproducing adults. In terms of larval instars, l_t can roughly be analogized to L4 budworms and y_t to L6 budworms.

2.3.3 Generalized economic model

There are two choice variables that can be manipulated by the social planner: the harvest (or proportional harvest) $h_t = s_t - x_t$ and the treatment decision function i, which will influence the transition of L_t to Y_t by imposing additional mortality.

Harvest is a continuous decision, but treatment has discrete cut-offs. A planner can choose zero, one, or two treatments. The cost structure will be linear with no fixed component. The cost structure for harvests is given by $\int_{x_t}^{s_t} c(u)du$, where $c(u)$ is the marginal harvest cost, while the cost structure for treatments is given by $k(i) = k^I * i^I + k^{II} * i^{II}$, where i^I and i^{II} represent treatment decisions and k^I and $k^I I$ are the costs of these treatment decisions. If one treatment occurs, $i^I = 1$ and $i^{II} = 0$, while two treatments implies $i^I = 1$ and $i^{II} = 1$. If no treatments occur, such that $i^I = 0$, then $i^{II} = 0$ necessarily. If no treatments are applied, then the costs of treatments will be zero.

The objective of the social planner is to maximize net social benefit. We assume that the discount rate ρ and the discount factor $\delta = \frac{1}{1+\rho}$ are invariant in time. In the most general terms, the social planner's objective can be stated as:

$$Б = \sum_{t=1}^{T} \delta_t [p \cdot (s_t - x_t) - \int_{x_t}^{s_t} c(u)du - k(i)] \tag{2.1}$$

where i is the treatment decision for the forest.

Prices are assumed invariant across time. This objective must be maximized subject to the two transition equations. This will yield a fundamental recursion relation of dynamic programming which can be written as:

$$V(s_t, L_t) = \max[p \cdot (s_t - x_t) - \int_{x_t}^{s_t} c(u)du - k(i)] + \delta V(g(x_t, Y_t), b(x_t, Y_t)) \tag{2.2}$$

2.3.4 Specific ecological models for budworms and tree stands

In this subsection, we describe specific transition equations for budworm and forests. All assumptions are as in subsection 2.3.2.

Budworms do not simply transition from late instar larval stage to late instar larval stage on a year-by-year basis; instead, they begin their lives in eggs, pass through several instars, pupate, become moths, disperse, and lay eggs. Our challenge is thus to relate this multi-stage model, which has been explored in entomological literature, to a model that only examines two stages of the life cycle, namely, the early and late instar larval phases. This is done because the early stage is the one for which larvae damage forests and are affected by sprays, while the late stage is the

one immediately before pupation and mating.

Similarly, forest biomass growth needs to be modeled using a single-stage process. We use the model proposed by Wilson and Ek [2019] to model whole-stand growth. Basal area per hectare is our biomass stock variable, because it gives us a consistent measure of the amount of land actually occupied by trees within a forested hectare. The other relevant measures of biomass are volume, diameter at breast height for an individual tree, and foliage. We present conversions for each.

2.3.4.1 A specific ecological model for budworms

One of the first attempts to model spruce budworms was put forward by Ludwig et al. [1978], who describe a series of transition equations for spruce budworm in continuous time. However, this model does not function in our context for two reasons. First, it describes "budworms" as an undifferentiated biomass, with no distinction made for different instars or breeding adults. Second, mortality only occurs due to natural predation or resource exhaustion. A more appropriate model for spruce budworms is one that will consider discrete time, have survival or mortality as a factor, and integrate resource exhaustion. The best such model will be a Beverton-Holt growth function

The Beverton-Holt growth function for spruce budworm can be motivated as follows. Spruce budworm exhibit a single generation life cycle. At the end of summer each adult produces b eggs. A proportion of these, α, survive to become larvae $L_{t,}$ at the beginning of period t. We assume α is constant. Thus, net larval production per adult is equal to $\beta = \alpha b$. A proportion, λ_t, of the larvae survive to become adults in the following period, $t + 1$. The adult survival rate

between periods is zero. Thus, the period-to-period transition equation for late-instar larvae can be written as:

$$L_{t+1} = \beta \lambda_t L_t$$

Larval survival depends on the biomass of larvae and foliage availability, which is a function of the basal area of trees, $F(s_t)$. Foliage provides cover from predators. In addition, when larvae are disturbed, they drop from their webbed shelters on silk threads. Those that land on host foliage continue feeding, and otherwise they usually do not survive. Thus, the per capita larval mortality rate within period t can be modeled as proportional to the instantaneous density of larvae per unit of foliage. This implies the instantaneous rate of change in larvae is:

$$\frac{dL}{d\tau}/L(\tau) = -\mu L(\tau)/F(s_t) \tag{2.3}$$

for $\tau \in [t, t + \Delta t]$, where μ is a survival/mortality scaling parameter. $F(s_t)$ is the surface area of foliage, which is given parameters in equation (2.18) and a generalized functional form in equation (2.19).

Below, we shall show that the right hand side of equation 2.3 is equivalent to the odds of mortality in period t. Rearranging gives the following differential equation:

$$\frac{dL}{L^2} = \frac{-\mu}{F(s_t)} d\tau$$

Integrating both sides yields:

$$\left[\frac{1}{L(t)} - \frac{1}{L(t+\Delta t)}\right] = \frac{-\mu}{F(s_t)}\Delta t$$

Solving for $L(t+\Delta t)$ gives:

$$L(t+\Delta t) = \frac{L(t)}{1 + \frac{\mu}{F(s_t)}L(t)\Delta t}$$

Thus, the proportion of larvae that survive to the end of the period is $\lambda_t = \frac{1}{1+\frac{\mu}{F(s_t)}L_t\Delta t}$. Letting $\Delta t = 1$ implies:

$$L_{t+1} = \frac{\beta L_t}{1 + \frac{\mu}{F(s_t)}L_t} = \frac{\beta F(s_t)L_t}{F(s_t) + \mu L_t} \tag{2.4}$$

which is a Beverton-Holt transition equation that includes foliage availability as a growth factor.

Spray treatments to control spruce budworm typically occur in spring and early summer, when budworms are feeding on foliage growth. The impact of treatment on larval growth is modeled as a change in the mortality parameter, μ, where $\mu(i_t)$ is defined to be the mortality parameter in period t under $i_t = 0, 1$ or 2 treatments. This leads to the following spruce budworm transition equation:

$$L_{t+1} = \frac{\beta L_t}{1 + \frac{\mu(i_t)}{F(s_t)}L_t} = \frac{\beta F(s_t)L_t}{F(s_t) + \mu(i_t)L_t} = b(s_t, L_t, i_t). \tag{2.5}$$

The timing of the model is as follows. Based on the larval biomass at the beginning of the spring, L_t, and the forest basal area, s_t, the planner chooses how many times to spray, $i_t = 0, 1,$ or 2. Larval mortality occurs, followed by pupation, moth emergence, mating, egg laying and

egg survival. This leads to a new larval biomass at the beginning of the next spring, L_{t+1}.

The period t larval survival rate can be expressed as:

$$\lambda_t = \frac{1}{1 + \frac{\mu}{F(s_t)} L_t} = \frac{1}{1 + \mu l_t},$$

where $l_t = \frac{L_t}{F(s_t)}$ is the density of larvae per unit of foliage. This is intuitively appealing as the survival rate depends on larval density and a survival/mortality scaling parameter, μ. The corresponding period t larval mortality rate is defined to be:

$$m_t = 1 - \lambda_t = \frac{\mu l_t}{1 + \mu l_t}$$

Rearranging yields $\mu = \frac{m_t}{1-m_t}/l_t$. From this it evident that μl_t is the period t mortality odds.

For fixed values of s and μ, L has two possible steady state values, $L = 0$ and $L = \frac{F(s)(\beta-1)}{\mu}$. Expressed in terms of larval density the steady state is $l = \frac{(\beta-1)}{\mu}$, or steady state mortality odds equal to $\beta - 1$.

Given different treatment mortalities, the relationship $\mu = \frac{m_t}{1-m_t}/l_t$ can be used to calibrate the parameter μ. If uncontrolled larval mortality at larval carrying capacity is 80% over period t, then $\mu(0) = \frac{4}{l}$. The carrying capacity emerges from the defoliation model. It is the asymptote at which defoliation nears 100%. This is established below, in subsection 2.4.2.1, but for now we note that it is 150 budworms per m^2 of branch surface area. This implies $\mu(0) = \frac{2}{75}$.

Given $\mu(0) = \frac{2}{75}$, if larval density is half carrying capacity then $\lambda = \frac{1}{1+\mu l_t} = \frac{1}{1+150/75} = 1/3$ (compared to $\lambda = 1/5$ at carrying capacity). This illustrates how larval survival is higher when larval densities are lower.

This calibration determines $\mu(i), i = 0, 1, 2$ from larval carrying capacity. A carrying

capacity of 120 budworms/m^2 of branch surface area implies $\mu(0) = 1/30, \mu(1) = 0.075$ and $\mu(2) = 0.15$.

Separating out the additional mortality from treatments, we can rewrite the transition equation as:

$$L_{t+1} = \frac{\beta F(s_t) L_t}{F(s_t) + \mu L_t} d(i_t) \tag{2.6}$$

In subsection 2.3.4.2 below, we establish the parameter values for this equation that pertain to spruce budworm. We will return to it later after establishing the transition equation for x_t, as this will allow us to establish the parameters pertaining to balsam fir.

Equation (2.6) can also be rewritten in terms of Y_t as:

$$L_{t+1} - Y_t = (\beta - 1) Y_t \tag{2.7}$$

A transition based on absolute populations of budworms per hectare will capture the fact that not all offspring will settle on the same hosts within the forested area. Thus, densities may fluctuate based on changes in available foliage. If the overall population remains constant, but the foliage decreases, the density of budworms will increase.

These equations provide us with the transition equations in the absence of positive or negative immigration. However, if moths from outside the landscape are migrating into the landscape, we would see a contribution of immigrant moths to the local egg stock[4]. We write this as Y_{imm}, and thus we can rewrite equation (2.7) as:

[4]These moths will not be subject to the in-stand late larval mortality μ and will be unaffected by spray treatments

$$L_{t+1} = \beta(Y_t + Y_{imm}) \tag{2.8}$$

The lack of a time subscript in Y_{imm} indicates that this is a constant immigration rate. This is a very strong assumption, but to modify it, we would need to adopt either a spatially-explicit formulation or assume some rate of change. The spatially-explicit formulation is explored in Chapter 4. Given that Y_{imm} is a constant, we exclude it from derivations based on equation (2.6).

2.3.4.2 Parameterizing the budworm transition equation

The model in equation (2.6) has three parameters: β, μ and $d(i_t)$. μ depends on λ. β represents the transition of adult budworms to next period's feeding budworm population, and μ is the natural mortality rate of feeding budworms.

Régnière et al. [2019] describes the short-run dynamics of spruce budworm outbreaks. This includes the realized fecundity of budworms and the survival rate of young larvae to the adult (moth) stage. Using parameters from Régnière et al. [2019] and from primary correspondence with the lead author, we modeled inter-generational reproduction using a code implemented in R. We describe L_{t+1} as a function of moths w_t and thus of pre-pupal larvae Y_t. Intermediate variables include the survival rate S which determines the rate at which larvae per shoot l'_t survive to moths per shoot a'_t, the defoliation rate Dr_t, cumulative defoliation D_t and the fecundity E_t. Larval growth is calculated based on 100 generated life cycles. Since we are interested in calculating β in the absence of confounding elements, we assume no eggs from immigrant moths and no treatments to protect foliage. Functional forms are established in Chapter 1, section 1.3.3.

Starting from the $L4$ per shoot density[5], which we write as l'_t, survival in each period to the adult stage is calculated with a Weibull function[6]:

$$S = \frac{0.11426}{l'_t}(1 - \exp\{[-4.69692 * l'_t]^{1.94932}\}) \tag{2.9}$$

The adult population is then the product of the larval population and the survival rate, such that emerging moths per shoot $a'_t = S * l'_t$. Defoliation is calculated from the larval population using a logit transformation[7]:

$$\log(Dr_t) = -2.504 + 12.23 * l'_t \tag{2.10}$$

Defoliation will determine the local fecundity of adults. Dr_t is the odds of defoliation in the present period. If D'_t represents new defoliation, then $Dr_t = \frac{D'_t}{1-D'_t}$, such that $D'_t = \frac{Dr_t}{1+Dr_t}$. Assuming 10% persistence in defoliation from the last period, cumulative defoliation is given by $D_t = D'_t + 0.1D_{t-1} = \frac{Dr_t}{1+Dr_t} + 0.1D_{t-1}$. The fecund adult population will consist of locally-pupated adults. Adults lay eggs according to their fecundity[8] at a rate:

$$E_t = 19.3568 * \frac{a'_t}{10^{D_t}} \tag{2.11}$$

A proportion of these eggs survive[9] to the $L4$ stage:

[5]We assume that there are 80 shoots per branch. Per-shoot density was used in Régnière et al. [2019], and parameters were calibrated based on this density. As such, our code to calculate β was based on this density.

[6]All scalars are established from table 1 of Régnière et al. [2019].

[7]This equation was calculated based on regressions shared in personal correspondence, and is the average defoliation rate in the absence of foliage protection efforts.

[8]This equation is taken from equation (5) and table 4 of Régnière et al. [2019], adjusted for no immigration.

[9]This equation is taken from equation (9) in Régnière et al. [2019].

$$\log_{10}(l'_{t+1}) = 0.598 \log_{10}(E_t) - 0.374 \tag{2.12}$$

The series of equations described above will define reproduction from the end of time step t to the beginning of time step $t+1$. We iterate over a 100 period horizon to calculate the long-term value of β using a starting point of $l_0 = 9$ budworms per branch, or $l'_0 = 0.1125$ budworms per shoot. These survive to the moth stage at the rate determined by equation (2.9) and cause defoliation as determined by equation (2.10). Surviving moths lay eggs at a rate determined by local defoliation, as per equation (2.11). Values of l'_t, Dr_t, D_t, a'_t and E_t were calculated for each $t \in \{0, 100\}$. These converge to steady states. To calculate β, we first divide the steady state value of l'_t, which is 0.2473491 by the steady state value of a'_t, which is 0.10499397. This yields $\beta^* = 2.36$. Since Y_t represents larvae just prior to pupation, we divide β^* by the hatch rate of pupae [Royama, 1984], which is 80%, to get a calibrated value of $\beta = 2.96$.

One source for μ is Royama [1984], who used data collected from 1947 to 1949 in New Brunswick, before the start of major spray operations, to determine the stage to stage survival rate of budworms. Royama's tables were created in a context of low and rising budworm populations. Royama determined that, without intervention, about $\lambda = 20\%$ of late-instar larvae survive to the pre-pupal stage. This will yield a mortality parameter of $\mu = \frac{4}{l_t}$, where l_t is the number of budworms per unit of foliage. A unit of foliage is defined as a branch tip 45 centimeters in length, since this is the sampling unit used to determine L4 densities prior to sprays. Thus, μ will change based on larval density as described above.

The treatment survival parameter $d(i_t)$ allows us to capture the additional mortality imposed by treatments without losing the non-linear aspects of μ. i_t can take the values of 0, 1 or 2.

By definition, $d(0) = 1$. $d(1)$ and $d(2)$ can be calculated empirically and subjected to sensitivity analysis. As a baseline, we use $d(1) = 0.5$ and $d(2) = 0.75$. This is based on the additional mortality imposed in an effective control period, as shown in Carleton et al. [2019], where one treatment is associated with 80-90% natural and additional mortality and two treatments are associated with 90-95% additional and natural mortality. Natural mortality μ therefore accounts for the majority (60-80%) of mortality.

The parameter Y_{imm} cannot easily be calibrated from literature, but it is used here for sensitivity analysis. This is described in subsection 2.5.1.

2.3.4.3 A specific ecological model for tree stands

The instar dynamics of spruce budworms mean that the evolution of larval stocks is best tracked in discrete time. The growth of trees is less sensitive to the choice of discrete versus continuous time. In this chapter, we use discrete time to describe forest stock evolution, as this maintains consistency with the budworm model.

The Beverton-Holt growth function is the discrete-time equivalent of logistic growth. In the absence of forest pest impacts, the Beverton-Holt transition equation can be expressed as $s_t = \frac{(1+r_F)s_t}{(1+r_F x_t/K_F))}$. This specification is convenient because $1 + r_F = F_x(0)$ and $F(K) = K$ so r_F and K_F denote intrinsic (net) growth and the maximum sustainable stock, respectively. We therefore use a modified Beverton-Holt model adjusted for host-pest interaction as the foundation for forest growth.

Spruce budworm affects both growth and mortality of the forest. We characterize these impacts through a growth reduction factor, $e^{-g_F y_t}$, and a mortality factor, $(1 - m_F y_t)$ that depend

on post-treatment larval density $y_t = Y_t/F(x_t)$. Beginning with s_t, there is harvest, then growth, and then mortality. This yields the following specification for the forest transition equation, where $x_t = s_t - h_t$:

$$x'_t = \frac{(1 + r_F e^{-g_F y_t})x_t}{\left(1 + \frac{r_F e_t^{-g_F y_t} x_t}{K_F}\right)} \tag{2.13}$$

and $s_{t+1} = (1 - m_F y_t)x'_t$.

The forest transition including mortality is given by:

$$s_t = (1 - m_F y_t)\frac{(1 + r_F e^{-g_F y_t})x_t}{\left(1 + \frac{r_F e^{-g_F y_t} x_t}{K_F}\right)} \tag{2.14}$$

Based on Erdle and MacLean [1999], we fix $x = 30$ m^2 as a starting point for the average forest basal area. From Wilson and Ek [2019], $K_F \approx 40$ and $r_F = 1.105$.

2.3.4.4 The relationships between basal area, volume and foliage weight for balsam fir

While basal area is a useful, and consistent, measure of biomass, budworm dynamics analysis requires an estimate of foliage, while economic analysis requires an estimate of volume, which can be approximated to merchantable timber volume. First, in order to determine the growth in volume, we need a conversion of basal area to volume. A useful simplification is to consider a balsam fir to be a cylinder with height H and area equal to a. If $a_t = \frac{x_t}{n}$, where n is the number of trees in the stand, the volume of timber in an entire stand can thus be approximated to:

$$vol = x \times H \tag{2.15}$$

which will hold for any tree species. Height is an inherent stand characteristic. It is related to the diameter at breast height of individual trees. Frank [1990] provides the relationship based on field observations of balsam fir, using diameter at breast height, or DBH. Across eastern North America, balsam fir were found to range from 12 to 18 meters in height, with a DBH range of 30 to 48 centimeters. Thus, the factor of height (in centimeters) to DBH is roughly 40 for balsam fir. However, without the number of stems n in a stand, converting basal area to mean DBH is tricky. For now, we parameterize $H = 15$ as a midpoint value, but allow volume to vary based on H, which we do observe in our data.

We can write balsam fir volume as:

$$vol_t = 15x_t \tag{2.16}$$

Thus, we have a direct conversion from basal area to volume for balsam fir[10].

Equation (2.6) contains the term $F(s_t)$, which represents the relevant unit of foliage. L4 larvae are typically sampled on 45 centimeter branch tips (see SOPFIM [2022], Régnière et al. [2019] and Régnière and Sanders [2022]). To determine a functional form, we adapt Lambert et al. [2005] and Régnière et al. [1989].

First, Lambert et al. describe the relationship between a tree's diameter at breast height (in cm) and foliage (in kg) as:

[10] A more precise conversion is given by Perron [2003], who gives volume for a single balsam fir as: $VMB = b_0 - b_1 D^2 - b_2 H + b_3 DH + b_4 D^2 H$ where VMB is merchantable volume, D is diameter at breast height, and H is the height of a tree.

$$fol_{kg} = \beta_1 D^{\beta_2} \tag{2.17}$$

where specific parameter values are $\beta_1 = 0.084$ and $\beta_2 = 1.6695$ (see Table 3 of Lambert et al. [2005]).

Régnière et al. measured the average branch surface area and foliage kilogram weight of a 45 cm branch tip. Balsam fir branch tips had a foliated surface area of $0.135m^2$ and featured 134 grams of foliage. White spruce branch tips had roughly the same foliated surface area ($0.134m^2$), but with 182 grams of foliage.

In balsam fir, one kilogram of foliage will be equivalent to $\frac{1000}{134} = 7.46$ branch tips.

In our model, s_t and x_t represent the basal area of a stand in m^2/ha. The basal area of a single tree in m^2 is given by $ba = \frac{s_t}{N}$ where N is the number of tree stems per hectare. The diameter at breast height of a single tree is given by $D = 2\sqrt{\frac{ba'}{\pi}}$ where D and ba' are measured in cm and cm^2. We would multiply s_t or x_t by 10^5 to convert m^2 to cm^2.

By bringing these various conversions together, the branch-tip equivalent foliage per tree for a balsam fir can be written as:

$$F(\frac{S}{N}) = 7.46 * 0.084(2\sqrt{\frac{10000s}{N\pi}})^{1.6695}$$

Multiplying the above by N yields the foliage units for a hectare of balsam fir as a function of basal area:

$$F(s_t) = 1673.37N^{0.16525}s_t^{0.83475} \tag{2.18}$$

A generalized form of equation (2.18) can therefore be given by:

$$F(s_t) = \theta s_t^{\gamma} \tag{2.19}$$

Where, for balsam fir, $\theta = 1646.45N^{0.16525}$, N is the number of trees per hectare (assumed roughly constant, which approximately holds due to the small magnitude of the exponent on N), and $\gamma = 0.83475$. We will use equation (2.19) for derivations.

2.3.5 Integrating the generalized framework with the specific ecological models

In this subsection, we integrate the models described in subsections 2.3.2, 2.3.3 and 2.3.4. This will form the basis of our empirical simulation, as described in section 2.4.

2.3.5.1 Spruce budworm growth and treatment

In the absence of any control, $L_{it} = \beta\lambda_t^0 L_{it}$ and therefore $b(x_{it}, Y_{it})$ would be a function of x_{it} and L_{it}. Holding biomass $x_{it} = s_{it}$ constant, a generalized growth function in the absence of dispersal can be given by:

$$L_{t+1} = \beta\lambda_t L_t \tag{2.20}$$

The term $\beta = \alpha b$ is the product of egg survival α and egg production b. It represents net L4 larval production per adult. λ_t is the proportion of larvae who survive to the adult stage Y_t. λ_t^0 represents natural mortality without treatment. If λ_t^I and λ_t^{II} are additional mortality from one

and two treatments, respectively, then

$$\lambda_t = \lambda_t^0 + \lambda_t^I(i_t^I) + \lambda_t^{II}(i_t^{II}) \tag{2.21}$$

where $i_t^I = 1$ for one or two treatments (zero otherwise) and $i_t^{II} = 1$ if two treatments occur (zero otherwise). Similarly, $\mu_t = \mu_t^0 + \mu_t^I(i_t^I) + \mu_t^{II}(i_t^{II})$.

In the absence of treatment, budworm growth converges asymptotically to the forest's carrying capacity for budworms, which will depend on biomass s_{it}. We restate equation (2.6) as:

$$L_{t+1} = \frac{\beta L_t}{1 + \frac{\mu^0}{F(s_t)} L_t} = \frac{\beta F(s_t) L_t}{F(s_t) + \mu^0 L_t} = \frac{\beta \theta s_t^\gamma L_t}{\theta s_t^\gamma + \mu^0 L_t} \tag{2.22}$$

Treatments will increase the natural mortality of budworms. Budworm treatment programs involve either one or two sprays. With treatment, we can modify equation (2.22) as:

$$L_{t+1} = \frac{\beta L_t}{1 + \frac{\mu(i_t)}{\theta s_t^\gamma} L_t} = \frac{\beta \theta s_t^\gamma L_t}{\theta s_t^\gamma + \mu(i_t) L_t} = b(s_t, L_t, i_t) \tag{2.23}$$

If $x_t = s_t$, then we have:

$$L_{t+1} = \frac{\beta L_t}{1 + \frac{\mu(i_t)}{\theta x_t^\gamma} L_t} = \frac{\beta \theta x_t^\gamma L_t}{\theta x_t^\gamma + \mu(i_t) L_t} = b(x_t, L_t, i_t) \tag{2.24}$$

These equations therefore provide the discrete-time transition equations for budworms. Equation (2.23) corresponds to the infestation transition equation from subsection 2.3.2.

Defoliation and harvest will reduce the total biomass of the forest, whereas natural regrowth will increase it, and thus the carrying capacity of the forest will be affected by the growth in the budworm population. In the next subsection, we discuss how the budworm population and harvest

decisions affect the biomass of the forest.

2.3.5.2 Growth and harvest of the forest

In the absence of harvest, $s_t = x_t$. The generalized transition equation is given by:

$$s_{t+1} = g(x_t, y_t) \tag{2.25}$$

Without harvest, the growth function given by equation (2.14) can be written as:

$$s_{t+1} = (1 - m_F y_t) \frac{(1 + r_F e^{-g_F y_t}) s_t}{\left(1 + \frac{r_F e_t^{-g_F y_t} s_t}{K_F}\right)} \tag{2.26}$$

This is the transition for s_t to s_{t+1} when no harvest occurs.

The next step is to incorporate harvest. Recommended harvests are either clearcuts or shelterwood cuts [Johnston, 1986]. Clearcuts of the forest stock s_t would reduce x_t to zero, so s_t is the constraint on harvest. Shelterwood cuts will lead to a portion of the forest being removed. Timing is critical, as our model considers two instances within each time step: the budworm treatment mating season, and the rest of the year. Harvests occur throughout the year, in winter as in summer [CSMOAF, 2010]. As a simplification, we will assume that harvests occur on the stock s_t, before sprays, defoliation or mortality can occur. This is a reasonable assumption given that sprays will not be conducted over an area that is being actively harvested. An area scheduled for a clearcut will not be treated at all. Any defoliation that occurs in such an area will be considered irrelevant. Thus, any portion of s_t that is removed will not be subject to defoliation or mortality. Mortality and defoliation will affect growth from x_t to s_{t+1}, and will be based on

the surviving pest stock Y_t (or y_t).

Harvest can be expressed in terms of volume or in terms of removed basal area. In our model, we will write it as the latter, such that $h_t = s_t - x_t$.

Thus, with tree harvest, the transition from x_t to x_{t+1} is given by:

$$x_{t+1} = (1 - m_F y_t) \frac{(1 + r_F e^{-g_F y_t}) x_t}{\left(1 + \frac{r_F e_t^{-g_F y_t} x_t}{K_F}\right)} - h_{t+1} \tag{2.27}$$

and we can write the transition equation for s_{t+1} in terms of s_t as:

$$s_{t+1} = (1 - m_F y_t) \frac{(1 + r_F e^{-g_F y_t})(s_t - h_t)}{\left(1 + \frac{r_F e_t^{-g_F y_t} (s_t - h_t)}{K_F}\right)} \tag{2.28}$$

Equation (2.26) corresponds to the timber growth function from subsection 2.3.2. Expression (2.27) can also be written as: $x_{t+1} = s_{t+1} - h_{t+1}$.

2.3.6 Simulating the marginal impacts of budworm density on defoliation, growth loss and mortality

As explained in subsection 2.4.2.1, we use the SOPFIM [2022] defoliation model to calculate the link between defoliation and budworm density. This requires us to calculate growth loss and mortality as a function of the incremental change in budworm density.

2.3.6.1 Impacts of budworm on forest growth

We calculate the impacts on growth and mortality in steps. The first step is to calculate the growth impact, which is non-linear. We restate equation (2.13):

$$x'_t = \frac{(1 + r_F e^{-g_F y_t}) x_t}{\left(1 + \frac{r_F e_t^{-g_F y_t} x_t}{K_F}\right)}$$

Using d to indicate the percentage change in y_t and x to represent a reference value of the basal area x_t, we write the percentage growth in basal area as $\xi(x, d)$, which equals growth minus x all divided by basal area, x, we have:

$$\xi(x,d) = \frac{1 + r_F \exp(-g_F d)}{\left(1 + \frac{r_F \exp(-g_F d) x}{K_F}\right)} - 1 = \frac{r_F \exp(-g_F d)(1 - \frac{x}{K_F})}{\left(1 + \frac{r_F \exp(-g_F d) x}{K_F}\right)}(1 + r_F \alpha) \tag{2.29}$$

where $\alpha = \frac{x}{K_F}$. The growth rate reduction is given by $1 - \frac{\xi(x,d)}{\xi(x,0)}$.

The denominator of the above equation is given by:

$$\lim_{x \to 0} \xi(x,d) = r_F \exp(-g_F d)$$

The theoretical upper limit of x is K_F/α. Thus, the numerator of the growth rate reduction function is given by:

$$\lim_{x \to K/\alpha} \xi(x,d) = \frac{r_F \exp(-g_F d)(1 - \alpha)}{1 + r_F \exp(-g_F d)\alpha}$$

The growth rate reduction can be written as:

$$1 - \frac{\xi(x,d)}{\xi(x,0)} = 1 - \left[\frac{r_F \exp(-g_F d)(1 - \alpha)}{1 + r_F \exp(-g_F d)\alpha}\right] / \left[\frac{r_F(1 - \alpha)}{1 + r_F \alpha}\right] \tag{2.30}$$

This can be written as $1 - \left[\frac{(1+r_F\alpha)\,(r_F\exp(-g_Fd)(1-\alpha))}{r_F(1-\alpha)\,(1+r_F\exp(-g_Fd)\alpha)}\right]$ and thus as:

$$\frac{r_F(1-\alpha)(1+r_F\exp(-g_Fd)\alpha)}{r_F(1-\alpha)(1+r_F\exp(-g_Fd)\alpha)} - \frac{(1+r_F\alpha)(r_F\exp(-g_Fd)(1-\alpha))}{r_F(1-\alpha)(1+r_F\exp(-g_Fd)\alpha)}$$

We can simplify the numerator as follows:

$$\begin{aligned} &r_F(1-\alpha)(1+r_F\exp(-g_Fd)\alpha) - (1+r_F\alpha)(r_F\exp(-g_Fd)(1-\alpha)) \\ &\quad = r_F - \alpha r_F + \alpha r_F^2\exp(-g_Fd) - \alpha^2 r_F^2\exp(-g_Fd) - r_F\exp(-g_Fd) + \\ &\quad\quad \alpha r_F\exp(-g_Fd) - \alpha r_F^2\exp(-g_Fd) + \alpha^2 r_F^2\exp(-g_Fd) \\ &\quad\quad\quad = r_F - \alpha r_F - r_F\exp(-g_Fd) + \alpha r_F\exp(-g_Fd) \end{aligned}$$

which can be finally simplified to:

$$r_F(1-\alpha)(1-\exp(-g_Fd)) \tag{2.31}$$

This allows us to write out a simplified equation for the marginal growth rate reduction due to budworm density:

$$\frac{(1-\exp(-g_Fd))}{(1+r_F\exp(-g_Fd)\alpha)}$$

Substituting $d = y_t$ and $\alpha = \frac{x_t}{K_F}$, the percentage growth reduction in x_t' as a function of x_t and y_t is:

$$\frac{(1-\exp(-g_F y_t))}{\left(1+r_F \exp(-g_F y_t)\frac{x_t}{K_F}\right)} \tag{2.32}$$

We use the values in table 2.7 to calculate g_F by running a non-linear regression defined by (2.32).

2.3.6.2 Impacts of budworm on forest mortality

The mortality impact is more straightforward. We have assumed that the mortality factor in equation (2.14) is:

$$1 - m_F y_t$$

If we assume that $y_t \in [0,1]$ with zero mortality when $y_t = 0$, then the marginal impact of an increase in budworm density on short-term mortality is given by the slope parameter m_F. The table 2.10 provides values of y_t and of one-year mortality percentages, which we use to calculate m_F.

2.4 Empirical strategy and available data

The model described in section 2.3 will be used to build a simulation model, described in this section. The data used to initialize this simulation are also described in this section. Spruce budworms are economically significant, impacting large chunks of the Canadian and Northern US forest, and they are well-documented. Thus, management issues surrounding spruce budworm are pertinent, and data on spruce budworms and their habitats are readily available. Data is

available from several jurisdictions, but we will focus on budworm in Quebec forests due to the level of detail in Quebec's forest inventories.

While budworms infest a wide variety of forest species, and take their name from spruce, balsam fir are the most logical choice of host to examine. The impacts of budworms on spruce are actually relatively mild, whereas budworms devastate balsam fir and pine stands. Balsam fir are economically significant, being widely harvested for softwood lumber or paper pulp. Most stands are mixed, so we will focus on balsam fir dominant stands while applying some assumptions as to their behavior.

2.4.1 Available data

The majority of our data is available from one of three sources, which are the Ministère des Ressources naturelles et des Forêts (MRNF) (formerly the Ministère des Forêts, de la Faune et des Parcs, or MFFP), the Bureau de mises en marché des bois (BMMB) and the Société de protection des forêts contre les insectes et maladies (SOPFIM). The first two sources are government sources, while the latter is a private nonprofit. The BMMB is subordinate to, but operationally separate from, the MRNF. The SOPFIM is mandated to carry out operations on public and private forest by the MRNF.

Forest inventory data is taken from the Inventaire écoforestier du Québec méridional (IEQM) [MFFP, 2017]. This data is a large, highly detailed set of polygons that includes tree mix, per-stem and per-hectare volume, per-hectare basal area, per-stem DBH, total stems per hectare and canopy information. The data is a snapshot, with compilation year being included in the metadata, and varying geographically.

Information on wood pricing is available from the BMMB [2022c]. Quebec has 191 tarification zones, each represented by a three digit code. Helpfully, number assignment is not random. All zones in the 150 range are located in the Bas-St.-Laurent region, while all zones in the 180 and 190 ranges are located in the Gaspésie region. Both of these regions are more similar to New Brunswick than they are to the remote, sparsely populated Côte-Nord, which represents all codes in the 900s except for 995 (Anticosti Island) and 998 (which includes Quebec's Far North and the Magdalen Islands, both of which have a negligible forest industry).

Each zone will have associated standing timber value as well as recuperation incentives for perturbations that include fire, windfall. Wood value and subsidies for affected stands for fir (sapin in French) and other species are available and adjusted on a quarterly basis, using a baseline that is established at the beginning of the BMMB's fiscal year, which runs from Q2 to Q1 of the next calendar year. Spruce budworm subsidies vary from $1.13 to $7.65 dollars per cubic meter in Quebec for the 2022-2023 fiscal year, with an average of $1.72. However, subsidies are highest in the Bas-St.-Laurent and Gaspésie, averaging $3.02 per m^3. The maximum subsidies are found in this region. Subsidies for spruce budworm are only available for fir and spruce, and do not vary according to wood quality or between fir and spruce.

The wood value system bears discussion. The BMMB is mandated to evaluate the merchantable per-volume value of standing timber (VMBSP) across the province [BMMB, 2022c]. This system is used both to calculate the annual royalty that long-term license-holders must pay to the government to maintain their rights, as well as the stumpage rate that must be paid out when harvesting standing timber. It is based on the principle of inter-regional equity. Wood will have a higher assessed value in regions where there is easy road and market access than in regions where wood is remote from labor and markets.

A supporting document is available here, in French, which explains the transposition of market data for fir, pine and spruce [BMMB, 2022a] onto value. The BMMB calculates the VMBSP based on the following formula:

$$VMBSP = \beta_0 + \beta_1(\frac{vol}{ha}) + \beta_2(CTMM) + \beta_3 Bids + \ldots + \beta_j x_j$$

The variable CTMM represents transport costs to mills and markets. The number of bids is then an instrumental variable with associated regression:

$$Bids = \delta_0 + \delta_1(\frac{vol}{ha}) + \ldots + \delta_j x_j$$

and explanatory variables include, among others, net mill revenue, price index, percentage of cavity in the wood, Herfindahl index, terrain difficulty, and number of times that the sector has been put on the market. The latter three variables are control variables. The price that results from these calculations is the minimum, not maximum, value. It is adjusted for planning and road construction costs for each region.

Value depends heavily on quality as well as location. A log that is at least 14 centimeters in diameter and 2.5 meters long is classified B, according to Quebec's scaling manual [BMMB, 2022b]. Excluding marginal regions, the value of B grade fir in Quebec averaged $14.50 CAD per m^3 in Q3-2023, with the highest value being $36.60 CAD.

All required data is thus publicly available, and has been used to build and calibrate the simulation model outlined below. Data is used to parameterize the model, but as our model simulates management on a theoretical landscape, the amount of data used in our model is less than the amount of data available to us. This suggests that many extensions on our model would

be possible.

Cost of treatment w_2 can be drawn either from literature or from field reports. Liu et al. [2019] use a value of $40 CAD per hectare for a single application of Btk or tebufenozide and $80 CAD per hectare for two treatments of Btk, while in personal correspondence with a New Brunswick forest health manager, we obtained an approximate average cost of $115 CAD per hectare for treatments when fixed costs were included. The SOPFIM, for its part, publishes tables of treatment operations and costs in Quebec. From these tables, we are able to calculate an average treatment value of $45 CAD per hectare. This is the value we will use when parameterizing our model.

2.4.2 Calculating parameter values for the model

The parameter values used in our simulation model combine values established in previous literature with values taken from the available data outlined in subsection 2.4.1.

2.4.2.1 Linking defoliation to budworm densities

The SOPFIM [2022] has created a model that predicts defoliation as a function of L4 budworm density per bud, which it uses to evaluate the success of its foliage protection programs[11]. For different larval densities, predicted defoliation in the absence of treatments is calibrated using control (untreated) plots and calculated as a counterfactual for plots that receive one or two treatments. The difference between observed defoliation and predicted untreated defoliation is the reduction in defoliation that can be attributed to the treatment activity.

The SOPFIM [2022] defoliation model uses a Logit regression to predict the percentage

[11] This model can be found in figure 15 and table 31 of the cited source.

of defoliation for different budworm densities per bud. Based on the associated budworms per branch values given in table 31 [SOPFIM, 2022], we calculate that there are approximately 105 buds per branch tip on average. With this ratio, we can calculate the buds per branch associated with different levels of defoliation. The table below lists defoliation for different L4 density levels, and the associated late instar larvae per branch under the assumption of 78% natural mortality.

Table 2.5: Defoliation midpoints

Defoliation (%)	$L4$/branch (l_t)	Late-instars/branch (y_t)
10%	2.2	0.5
30%	5.5	1.2
50%	9.6	2.1
70%	16.9	3.7
90%	41.5	9.1
99%	205.2	45.1

The last value is asymptotic. Budworm L4 densities of 200 larvae per branch tip are unlikely to be observed in nature.

2.4.2.2 Calculating budworm larval mortality with and without treatment

The budworm survival rate in the absence of treatment varies from instar to instar. The objective of an application of Btk or tebufenozide is to impose additional mortality between the second and sixth instars, which will reduce both the number of larvae feeding on trees in the current year and the number of moths that can reproduce. The SOPFIM [2022] model is once again helpful. For each observation of post-treatment defoliation, we are able to impute the number of early instar budworms that would have resulted in a similar level of defoliation in a hypothetical scenario without treatment. For example, in table 31 of their annual report [SOPFIM, 2022], plots that had 49.2 L4 larvae per branchtip and received two treatments had 92.4% predicted counter-

factual defoliation, but 47.8% realized defoliation. This would be equivalent to an untreated plot with an L4 density of 8.8 larvae per branch tip.

It would be incorrect, however, to say that the two applications of budworms caused 82% mortality (40.4 L4 budworms), because this would ignore the role of natural mortality. Natural mortality is very high in budworms. Using Royama's 78% natural mortality from late to pre-pupal instars, the 49.2 L4 larvae would result in 10.8 pre-pupal larvae, whereas the imputed 8.8 L4 larvae would result in 1.93 pre-pupal larvae. For 49.2 L4 larvae to yield 1.93 pre-pupal larvae, mortality is on the order of 96.1%. As such, 16.4% of mortality can be attributed to the two treatments.

By repeating the exercise for all of the values in table 31 [SOPFIM, 2022], we find that the impact of a second treatment is approximately half that of the impact of a first treatment. We separate additional mortality from natural mortality and obtain $d(1) = 50\%$ (one treatment) and $d(2) = 75\%$ (two treatments).

2.4.2.3 Tree growth and mortality impacts

The impacts of budworms on tree growth reduction and mortality are derived from Erdle and MacLean [1999]. They derived the pest-related impacts on one year diameter increment growth and five-year survival from different cumulative defoliation classes[12]. By using the SOPFIM model, we can use the Erdle and MacLean parameters to build a model that links budworm densities to basal area growth reduction and stem mortality. Erdle and MacLean's table is summarized below:

[12] See table 2 of the cited source.

Table 2.6: Growth loss (% of DBH increment) and five year mortality due to defoliation

Defoliation class (%)	Growth loss	Mortality (%)
$0-20\%$	0	5%
$21-40\%$	25%	5%
$41-60\%$	48%	15%
$61-80\%$	66%	40%
$81-100\%$	83%	80%

These values are calculated for a forest that has a mid-point basal area of 30 m^2/ha and 1492 $stems/ha$ on average [MFFP, 2017]. Diameter at breast height increments are calculated in terms of millimeters per stem. While diameter at breast height per hectare is similar in Quebec, the number of stems per hectare is much smaller, at about 1000 $stems/ha$ in the Saguenay-Lac-St-Jean region[13]. Using defoliation midpoints from the Erdle and MacLean table, we can establish the following per-hectare reductions in basal area growth for a basal area of 30 m^2/ha.

Table 2.7: One-year basal area growth increment to budworm density relationship

Defoliation (%)	Late-instars/branch (y_t)	Growth loss, %
0%	0	0%
30%	1.2	25%
50%	2.1	48%
70%	3.7	66%
90%	9.1	83%

The initial y_t value in table 2.7 is set to 0 to establish a starting point for the regression. There is no growth loss at this starting point.

By fitting a non-linear least squares regression to this data, we were able to calculate the parameter value of g_F from equation (2.32), restated here:

$$\frac{(1-\exp(-g_F y_t))}{\left(1+r_F \exp(-g_F y_t)\frac{x_t}{K_F}\right)}$$

From Wilson and Ek [2019] we have $K_F \approx 40$ and $r_F = 1.105$, and we fit g_F to the

[13]This is block 22D of the IEQM [MFFP, 2017].

following non-linear least squares regression where the independent variable is y_t and the baseline value of x_t is set to 30.

Using R [R Core Team, 2021], we run a non-linear regression of the data in table 2.10. We use an initial $-g_F$ value of -0.9, and achieve convergence after 9 iterations. The table below reports regression results with 4 degrees of freedom:

Table 2.8: Results of equation (2.32) regression

$-\hat{g}_F$	Std. Error	t-value	RSE
-0.4053	0.0437	-9.274	0.06866

The calculation of the mortality parameter m_F is more straightforward but requires additional assumptions. Again, using defoliation midpoints from the Erdle and MacLean table, we can establish the following 5-year mortality rates.

Table 2.9: Five year mortality to budworm density relationship

Defoliation (%)	Late-instars/branch (y_t)	Mortality (%)
10%	0.5	5%
30%	1.2	5%
50%	2.1	15%
70%	3.7	40%
90%	9.1	80%

Note that the mortality threshold is at approximately 35% defoliation, with 5% mortality representing normal mortality in an uninfested stand. In our stylized model, however, we linearize this relationship in order to calculate single-year mortality as a function of budworm density. For each five-year mortality rate m_5, we can calculate the one-year mortality rate m_1 as $m_1 = 1 - (1 - m_5)^{\frac{1}{5}}$. This yields the following estimates:

Table 2.10: One year mortality to budworm density relationship

Defoliation (%)	Late-instars/branch (y_t)	1-year mortality (%)
0%	0	0%
30%	1.2	1.0%
50%	2.1	3.2%
70%	3.7	9.7%
90%	9.1	27.5%

Once again, the initial y_t value in table 2.10 is set to 0 to establish a starting point in the regression, as is the initial mortality rate. We set the intercept to zero, and calculate regress the mortality percentage on y_t. Regression results for 4 degrees of freedom are below:

Table 2.11: Results of mortality regression

$\hat{m}_F$	Std. Error	t-value	RSE
0.0287	0.00201	14.26	0.0204

2.4.3 Empirical strategy

Our model is parameterized using the data described above, and these parameters are summarized in the table in subsection 2.3.1.

The parameterized dynamic optimization model is solved numerically to obtain optimal policy functions for spruce budworm treatment and timber harvest, along with the maximum value function that characterizes the discounted sum of benefits and costs under optimal management.

The problem is solved as a numerical dynamic programming problem using the value function iteration method. This algorithm implements Bellman's fundamental recursion relation using a set of nested loops. The outer loop iterates over periods-to-go, where the problem at each stage is solved, the maximum value function is updated, and then number of periods-to-go is incremented until the value function converges within a specified tolerance. Convergence of the value

function is ensured by the fact that the fundamental recursion relation is a contraction mapping from the space of value functions to itself. The intermediate loop nest iterates over a discrete approximation of the state space. In this case, the state space for forest basal area and budworm larval biomass is approximated by a discrete grid over $[0, s_{\max}] \times [0, L_{\max}]$ where $s_{\max}$ is the maximum sustainable forest biomass in the absence of spruce budworm and $L_{\max}$ is the maximum sustainable budworm biomass given a forest biomass of $s_{\max}$.

The baseline case is implemented over a 101×401 grid, yielding $40,501$ possible states. The inner-most loop nest iterates over the action space to perform an exhaustive grid search over the feasible set which finds the optimal policy and value from each state. The action space for harvest is approximated by a discrete grid with 401 points, and harvests are chosen subject to the feasibility constraint $0 \leq h_t \leq s_t$. Budworm treatment is defined on a grid of 3 points, that reflect the discrete choice of $0, 1,$ or 2 treatments. The criteria for value function convergence is:

$$\max_{s,L} \left| \frac{V_{N+1}(s, L) - V_N(s, L)}{V_N(s, L)} \right| \leq 0.0001 \tag{2.33}$$

where the maximum is over all $40,501$ states. Expressing the convergence criteria in terms of the absolute value of the percentage difference in value insures that convergence is not sensitive to units of measurement. Sensitivity analysis indicates that the optimal value and policy are robust to further refinements in the state space, action space and convergence criteria. The numerical solution algorithm is implemented using Intel Fortran [Intel Corporation, 2024] compiled on a 64 bit Windows operating system. Results are presented in the next section.

2.5 Results

In the results below, budworm biomass is calculated in terms of budworms per branch and forest biomass is calculated in terms of basal area per hectare. Policy results are plotted using the ggplot2 package in R [Wickham, 2016].

2.5.1 Simulation model results: baseline scenario

Our baseline scenario assumed the following parameters:

Table 2.12: Parameters of the baseline simulation

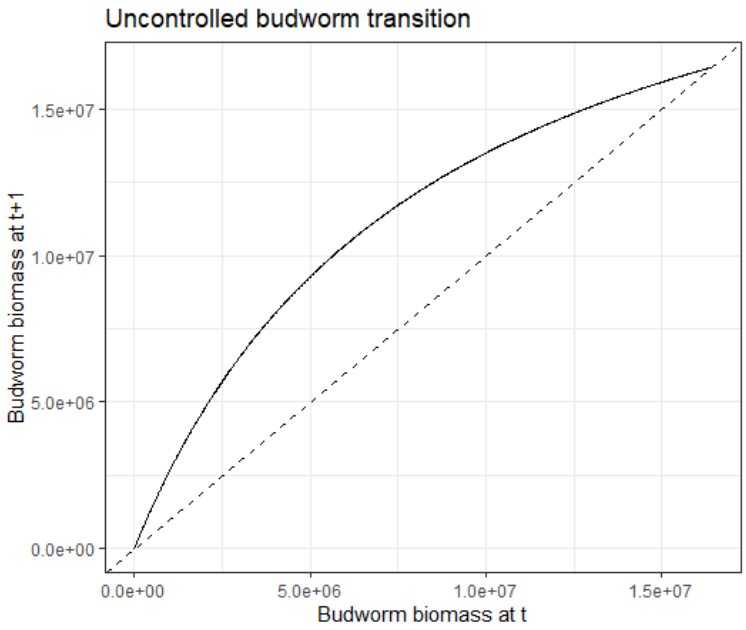
Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{1}{1.05}$

These values were, for the most part, established in the text of this chapter. One notable exception is Y_{imm}, which is the contribution of immigrant moths to the per-hectare budworm population. This value emerged from simulations: in early runs with zero immigration, treatment regimes started at roughly 20,000 budworms per hectare. We therefore set immigration at the midpoint between zero and the treatment threshold.

Without controls, the transition equation for budworms yields:

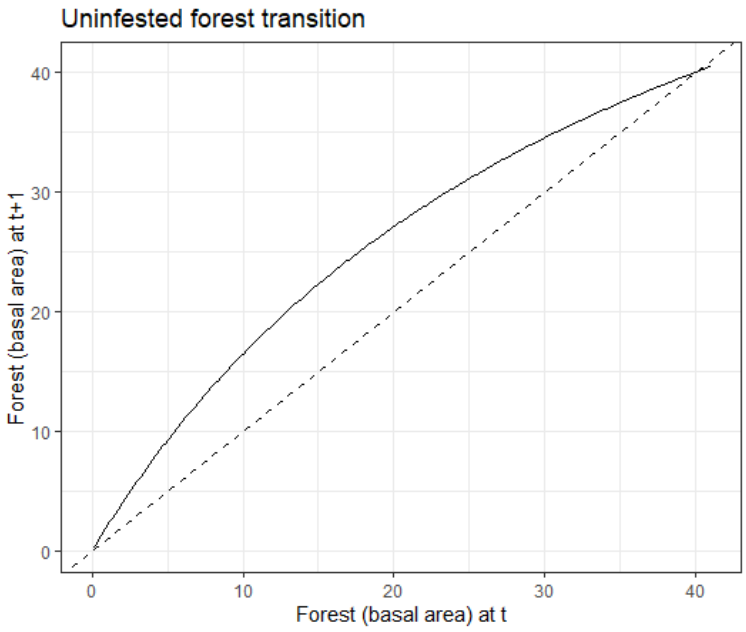
Figure 2.1: Uncontrolled Budworm Transition



Budworms will converge to a carrying capacity that is less than their theoretical limit due to the reduction in forest biomass at large budworm numbers. This will reduce available resources and therefore decrease the rate of survival.

In an uninfested forest, the transition equation for a stand is given by:

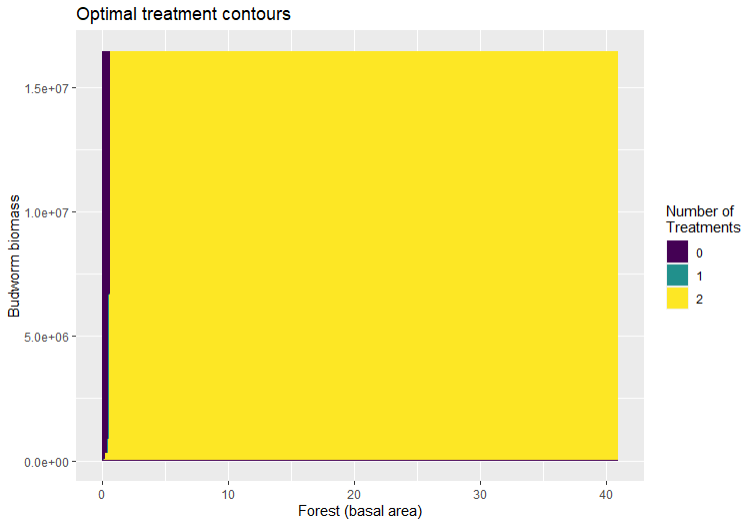
Figure 2.2: Uninfested Forest Transition



In such a forest, basal area will converge to its maximum value. A budworm infestation will reduce the maximum biomass that the forest can attain, because this land will be taken up by dead tree biomass, which is not counted as part of living biomass.

The planner has two policy choices: the treatment level and the harvest level. The contours for optimal policies are below:

Figure 2.3: Baseline optimal treatment contours

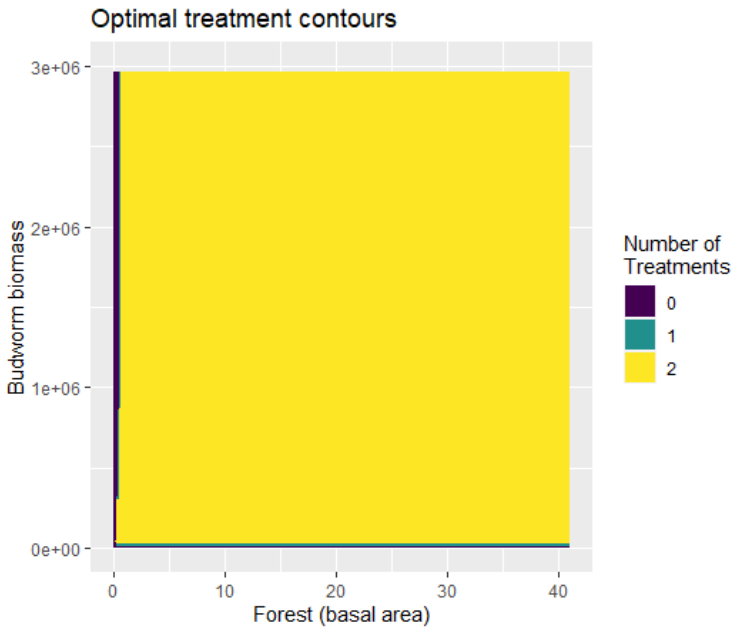


Zero, one or two treatments are possible. The optimal policy is generally to run two treatments, except at very low budworm levels or for low forest biomasses.

If we restrict the potential budworm population (i.e., the vertical axis), we note that the range of budworm biomasses for which a single treatment is optimal is thicker than the range for which no treatments are optimal. If there are between 1000 and 5000 budworms per hectare, a single treatment will be sufficient to control the budworm biomass, and this holds for any forest basal area that is sufficiently large to regenerate itself[14]. Above 5000 budworms per hectare, two treatments become necessary. Note that the treatment threshold is lower when immigration leads to budworm contributions than without it.

[14] A forest that is too small to regenerate itself will optimally be harvested to zero.

Figure 2.4: Baseline optimal treatment contours



The optimal budworm biomass as a function of the forest is below:

Figure 2.5: Baseline optimal budworm transition contours

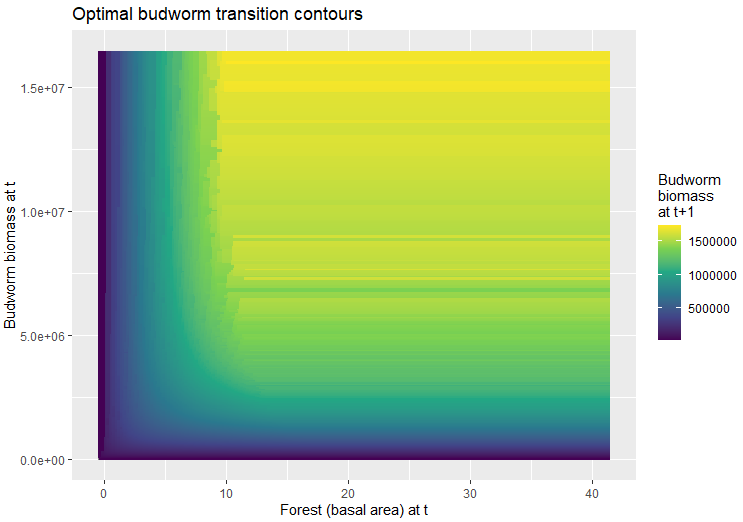
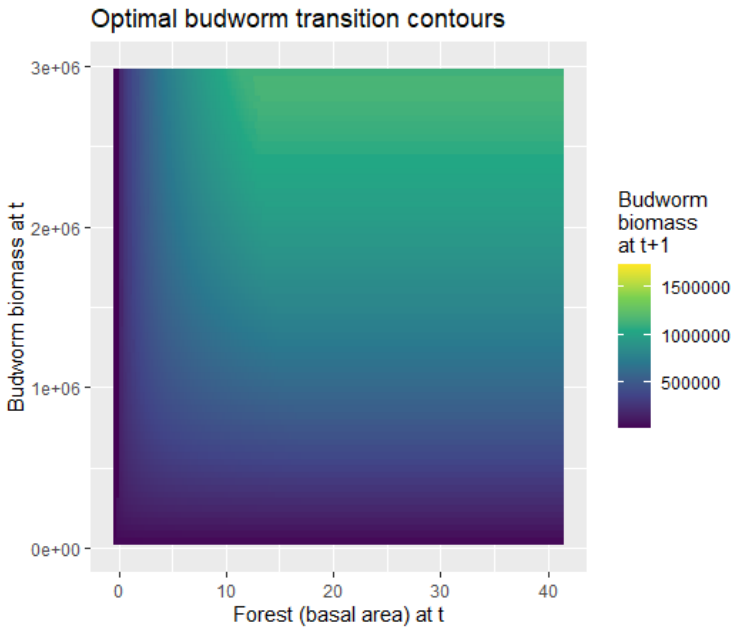


Figure 2.6: Baseline optimal budworm transition contours



Generally speaking, the optimal policy is to reduce the budworm biomass to a low level. This is accomplished using a mix of treatment and harvest. Two treatments are applied, and the forest is further harvested down to reduce the biomass available to budworms and thus the budworm population in the next period.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

Figure 2.7: Baseline optimal forest transition contours

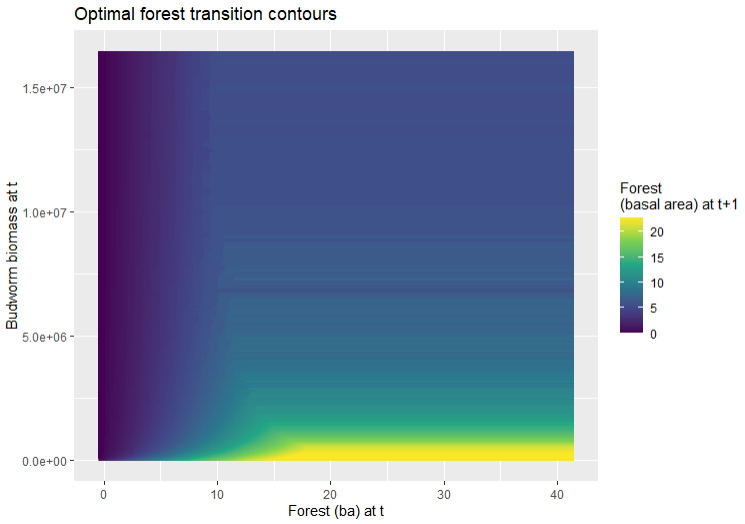
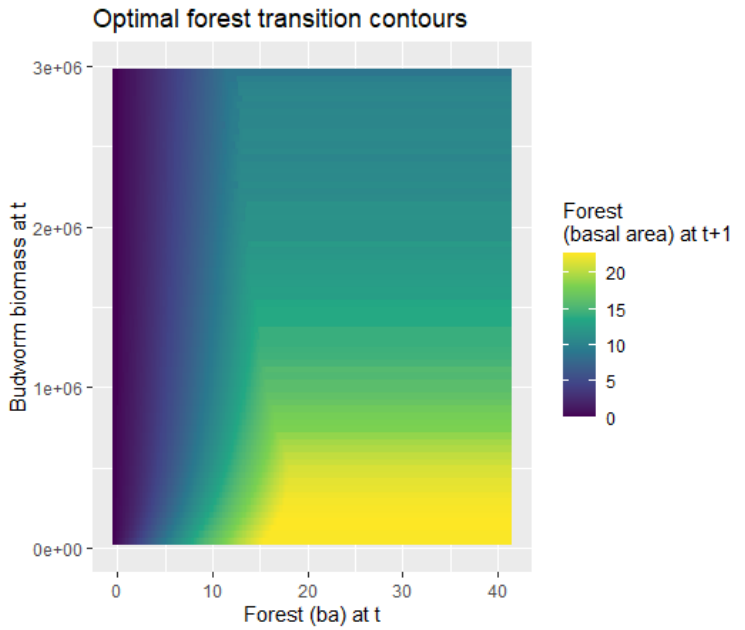


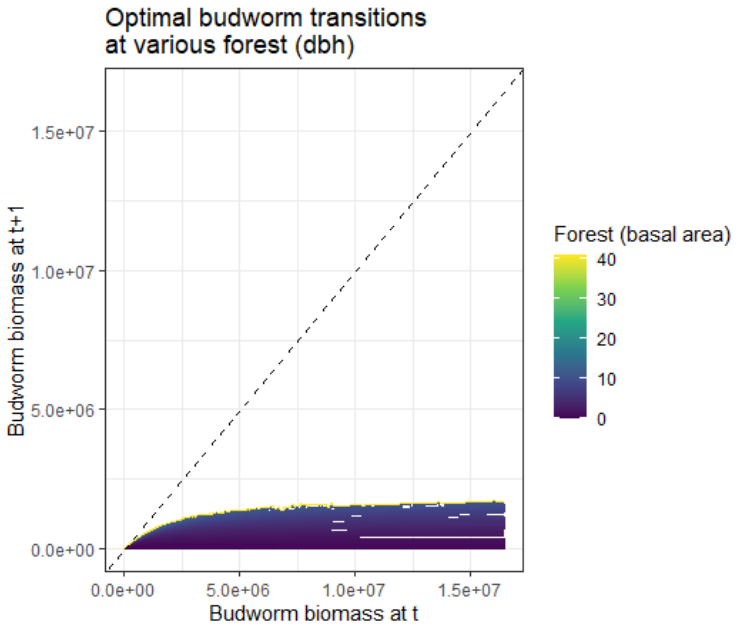
Figure 2.8: Baseline optimal forest transition contours



Next period's optimal forest biomass will determine the optimal harvest level. The forest will be harvested down to a level that will be expected to regrow to the optimal next-period biomass, given the budworm biomass. Harvest levels depend on both the economic value of harvest and on the benefits of budworm reductions given harvests.

The optimized transition equations for budworms and forests are given below:

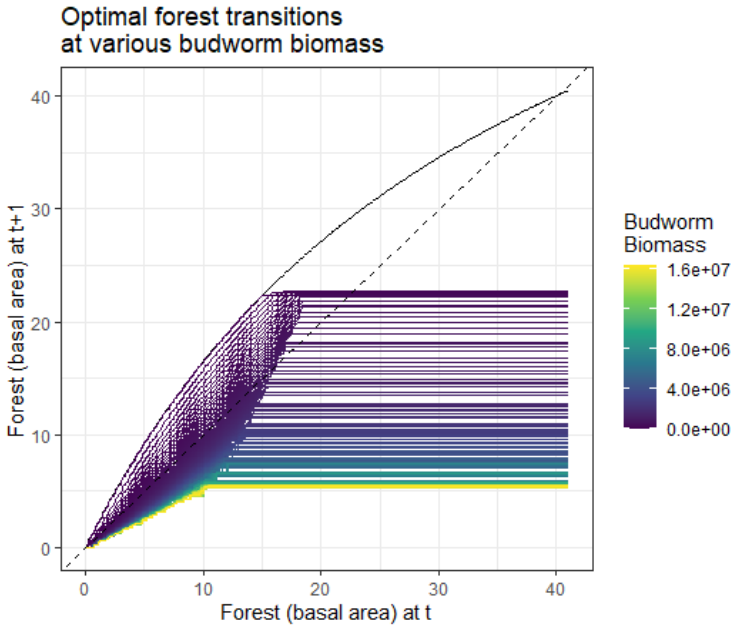
Figure 2.9: Baseline optimal budworm transition as a function of forest



The optimal budworm policy is always to reduce next period's number of budworms. The budworm level should eventually be driven below the Allee threshold[15]. These results suggest that an early intervention strategy, where feasible, should be employed. When EIS is not possible, an FP strategy should be employed. Note that this analysis cannot capture certain positive aspects from the presence of budworms, such as their role as a food source for birds. Elimination of budworms is not feasible nor advisable.

[15]Strictly speaking, the budworm growth model does not feature an Allee threshold, as the growth function is concave, and Allee thresholds imply a non-concave growth function. The interaction between the budworm growth and forest growth functions will instead lead to Allee-like behavior, as a small enough forest will make SBW growth rates fall below a sustainable level.

Figure 2.10: Baseline optimal forest transition as a function of budworms



The optimal harvest policy is to remove some of the forest, leaving enough biomass to regenerate and to be harvested in the next period. As the budworm biomass increases, so does the harvest level. This is done for two reasons. First, this will permit the planner to recuperate some of the harvest value in the present period that would otherwise be lost (i.e. due to dead wood rot). Second, it will reduce the biomass available to budworms in the next period, which will reduce budworm survival rates.

2.5.2 Time paths

The baseline parameters for our time path are set to $x_t = 10$ and $Y_t = \frac{K_B}{10} \approx 164,400$. These baseline parameters are used in both this analysis and in the sensitivity analysis.

With a 200 year horizon, the optimal policy will be to treat budworms down to a minimal level while initially harvesting the forest down to a low level. Subsequently, the optimal policy

will be to let the forest regrow to a high level and to harvest a steady amount every year. Budworm treatment will continue until budworms fall to an endemic level, where they will not exceed the Allee threshold.

Figure 2.11: Baseline forest time path

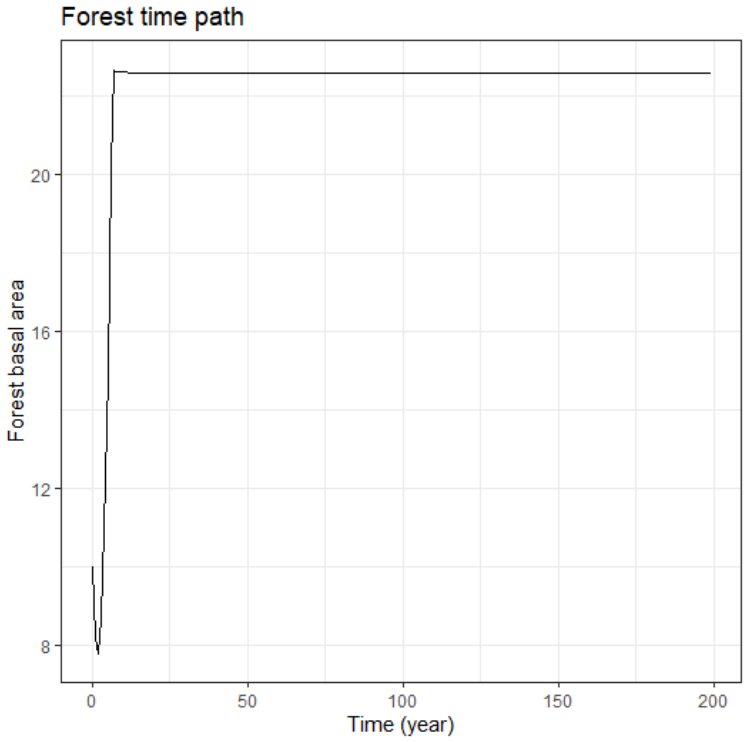
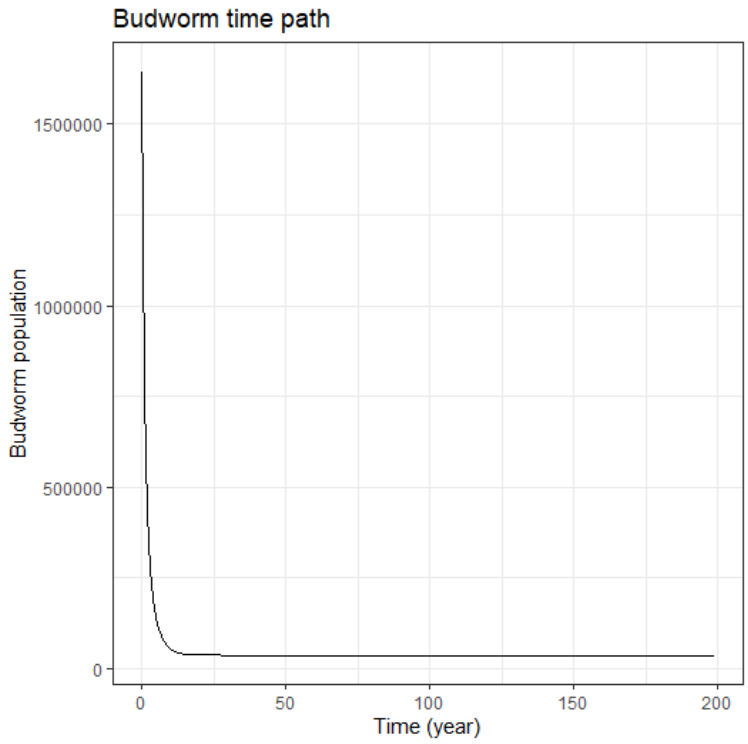


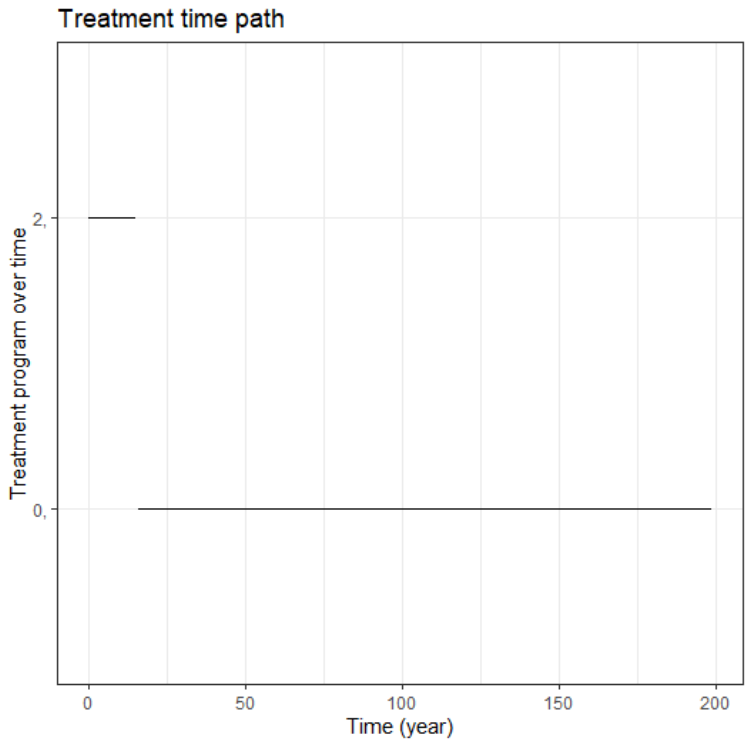
Figure 2.12: Baseline budworm time path



The long-term optimal budworm population will consist only of immigrated populations. This suggests that, in a realistic context, the optimal budworm population is an endemic level. This analysis does not capture spatial interdependence. Instead, the immigration rate is assumed constant. Spatial interdependence is left for future research. There are other limitations to interpretations of this time path, discussed in subsection 2.6.4.

The time paths for treatment, harvest and the pre-and-post harvest forest are below. The baseline is an initial basal area of 10 m^2 and an initial budworm biomass of approximately 1.6 million budworms per hectare.

Figure 2.13: Baseline treatment time path



The optimal policy will be to treat the initial population for a few years until levels drop to below the Allee threshold. Subsequently, treatments become unnecessary, and thus cease.

Figure 2.14: Baseline harvest time path

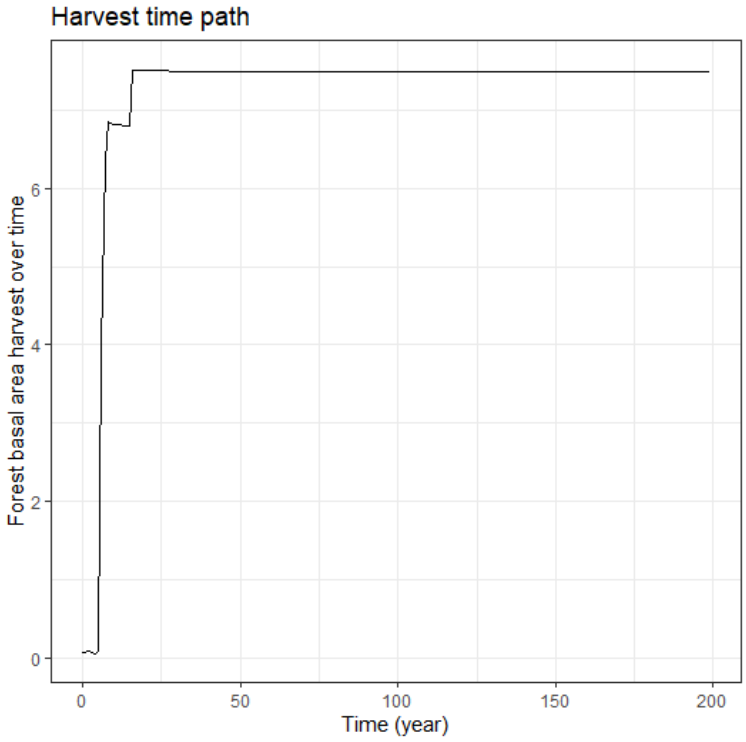
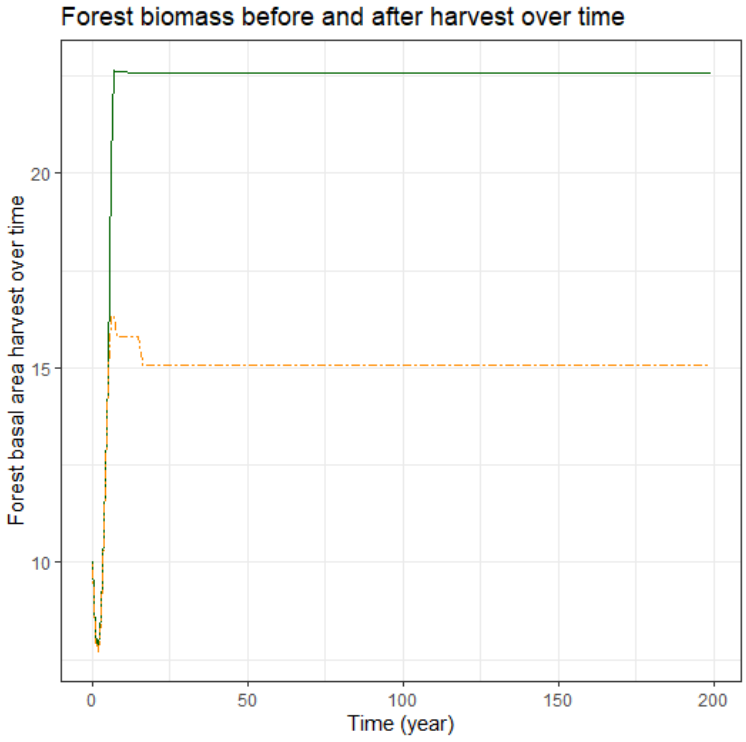


Figure 2.15: Time path of initial (s_t) and post-harvest (x_t) forest



2.5.3 Sensitivity analysis

For sensitivity analysis, we varied different parameters from table 2.12 and observed how model behavior changed as a result.

The following parameters were modified, one by one: p, β, $k(i)$, δ, g_F, m_F, r_F and Y_{imm}. All parameters other than δ, r_F and Y_{imm} were permuted twice: they were first doubled relative to the baseline, and then halved relative to the baseline. Results were then recorded. δ, r_F and Y_{imm} are special cases, as halving them was not logical.

In this subsection, graphs are provided for parameter changes that meaningfully changed the results of the model only.

2.5.3.1 Sensitivity to price changes

The price of timber was first doubled from 20 to 40, and then halved from 20 to 10. There were no changes to model behavior. The value function increased when prices doubled, and decreased when prices were halved.

2.5.3.2 Sensitivity to changes in larval production: doubled β

Egg production per adult β was doubled and halved.

First, we double β.

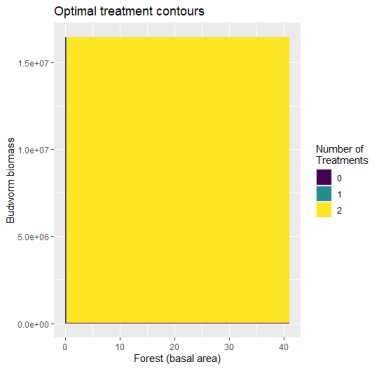
Table 2.13: Parameters: fourth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	**5.92**	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

Figure 2.16: Run 4 optimal treatment contours



Two treatments are almost always optimal. These results are therefore not much different from our baseline.

The optimal budworm biomass as a function of the forest is below:

Figure 2.17: Run 4 optimal budworm transition contours

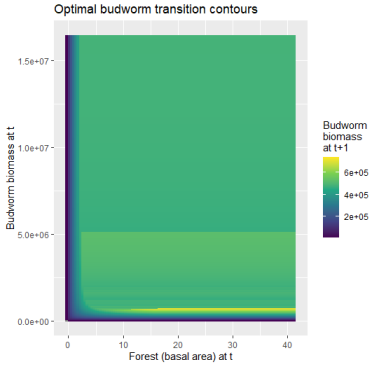
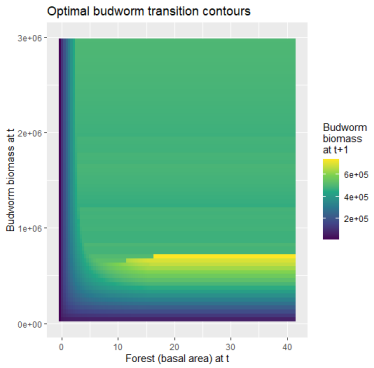


Figure 2.18: Run 4 optimal budworm transition contours



Budworms become harder to control through treatment alone due to their increased reproduction rate, although treatment should still be employed as the benefits outweigh the costs. There is a band at about 80,000 budworms per hectare where a high budworm biomass in the next period is tolerated. This band is the crossover between a harvest-led policy and a treatment-led policy.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

Figure 2.19: Run 4 optimal forest transition contours

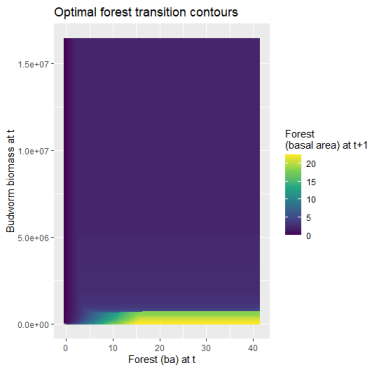
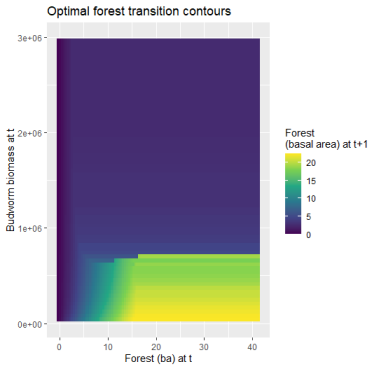


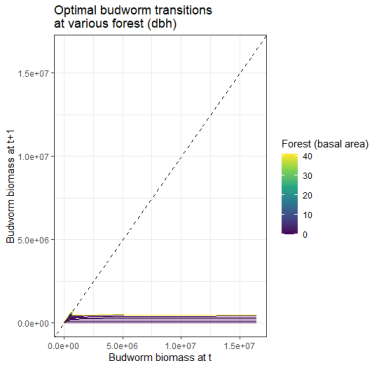
Figure 2.20: Run 4 optimal forest transition contours



Above 80,000 budworms per hectare, the forest should be harvested down to a low, but sustainable level. This will reduce the budworm population, which will lack resources, allowing treatment to push it down to a level that will not cause the forest to die out. The forest will replenish itself somewhat, and will then be harvested again. Below this level, treatment will be sufficient to reduce the budworm population to a manageable density. More forest can therefore be left to the next period.

For higher realized fecundity, the optimized transition equations for budworms and forests are given below:

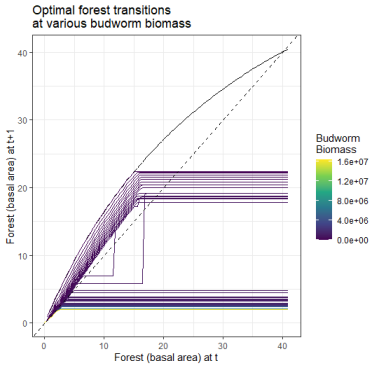
Figure 2.21: Run 4 optimal budworm transition as a function of forest



Budworm levels should generally be driven as low as possible, and this will be achieved thanks to a mix of treatment and harvest. At low budworm levels and high forest levels, some

slight budworm growth is acceptable.

Figure 2.22: Run 4 optimal forest transition as a function of budworms



The optimal forest transition is clear: for low relative budworm levels, the forest can be harvested at a low rate. As soon as levels rise, however, the optimal policy is to harvest the forest down to a low level so that budworms will run out of food. The L-shape in the forest transitions can be explained by the fact that relative budworm density is what matters rather than absolute density. A smaller forest will face pressure at a lower absolute budworm density than a larger forest.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. While treatments are maintained at a constant level throughout, budworm and forest levels will fluctuate around a steady state over time. In essence, human intervention will create an oscillating predator-prey cycle: the forest grows, the budworm population grows as a result, trees are harvested before they can die out, budworm levels fall to a level that can be suppressed through treatments, and the cycle repeats as the forest is now able to regrow.

Figure 2.23: Run 4 forest time path

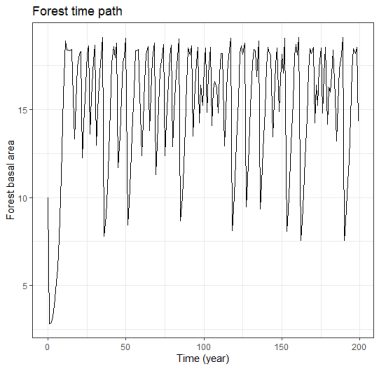


Figure 2.24: Run 4 budworm time path

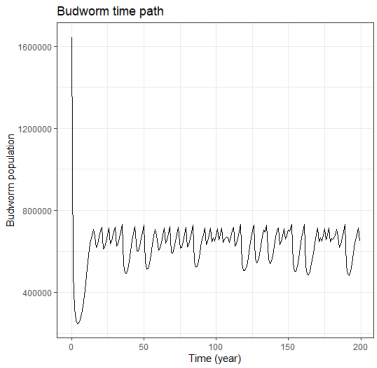


Figure 2.25: Run 4 treatment time path

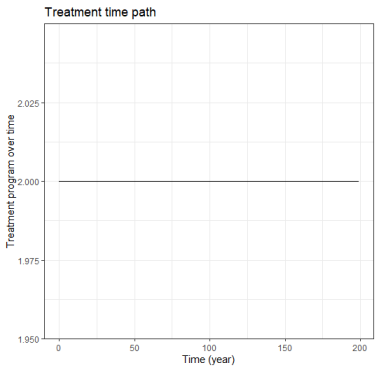


Figure 2.26: Run 4 harvest time path

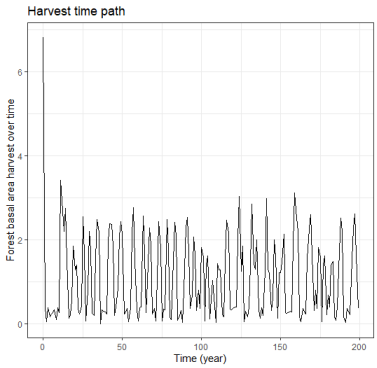
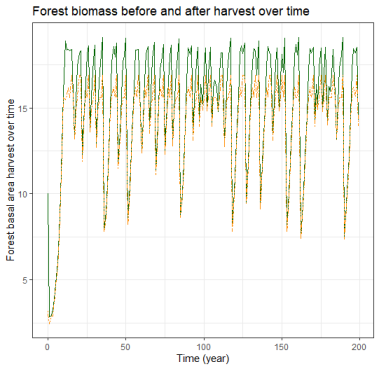


Figure 2.27: Time path of initial (s_t) and post-harvest (x_t) forest for Run 4



2.5.3.3 Sensitivity to changes in larval production: halved β

Secondly, we halve β.

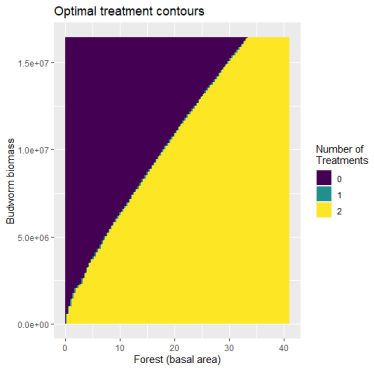
Table 2.14: Parameters: fifth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	**1.48**	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

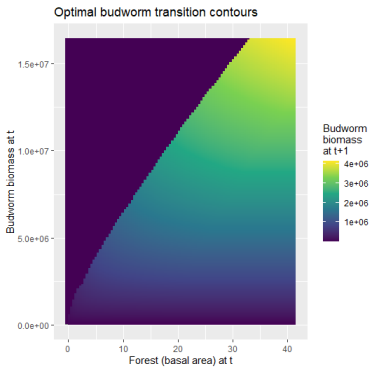
Figure 2.28: Run 5 optimal treatment contours



There is a very clear treatment boundary. The no-treatment and two-treatment zones are two separated contours, and there is a thin boundary between them where only one treatment is administered.

The optimal budworm biomass as a function of the forest is below:

Figure 2.29: Run 5 optimal budworm transition contours

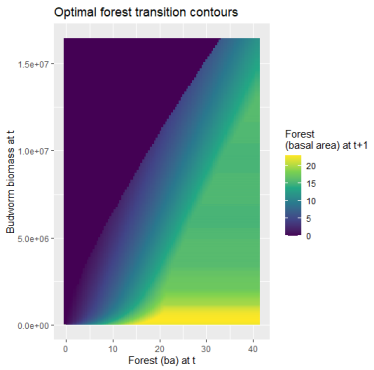


In the two-treatment zone, the best way to deal with budworms is with a treatment program. Above it, the best way to deal with them is to remove enough forest that their population drops. Removing as many budworms as possible is not the priority in the two treatment zone, however, and so there will be less need to increase harvest in addition to treatment. Treatment alone will be sufficient to reduce losses. These results may seem counterintuitive, but resource competition must be taken into account. If the realized fecundity is lower, then the remaining young larvae L_t

will have more feeding success as they will be more fit, and thus a large initial young budworm population (in a relative sense) will place tremendous pressure on the forest in the present period. On the other hand, predation and attrition would make it harder for a small population to reach these large levels. The optimal contours do not determine the feasibility of initial states, just optimal policy given initial states.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

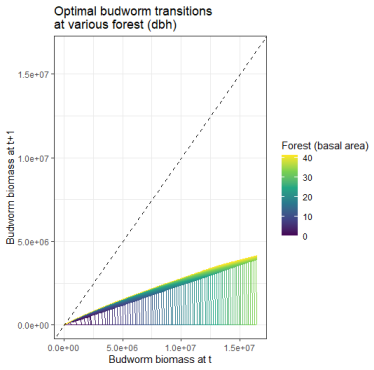
Figure 2.30: Run 5 optimal forest transition contours



Clearcuts happen in the no-treatment zone. Outside of this zone, harvest is increasing in budworm biomass, but the forest biomass in the next period remains high relative to the baseline scenario.

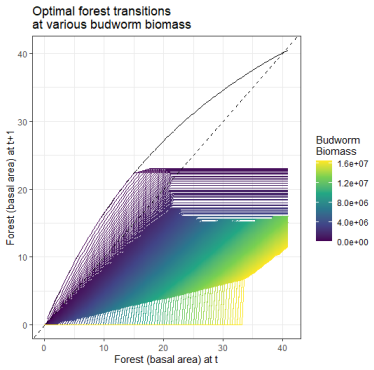
For lower realized fecundity, the optimized transition equations for budworms and forests are given below:

Figure 2.31: Run 5 optimal budworm transition as a function of forest



Instant eradication is possible, but would imply clearcuts. Otherwise, treatment will be effective at reducing the population in the next period. This will depend on the initial forest and budworm biomass.

Figure 2.32: Run 5 optimal forest transition as a function of budworms



The forest should be guided back to a path that will allow for a high and sustainable harvest, if possible. If this is not possible, then clearcutting is the only option.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. The forest is initially harvested to a low level, and then allowed to regrow to a high level. The budworm population is deprived of food and will fall to its long-term level, which is near zero. Two treatments are initially applied. Afterwards, treatments become unnecessary. The harvest level is constant once the forest biomass is sufficiently high.

Figure 2.33: Run 5 forest time path

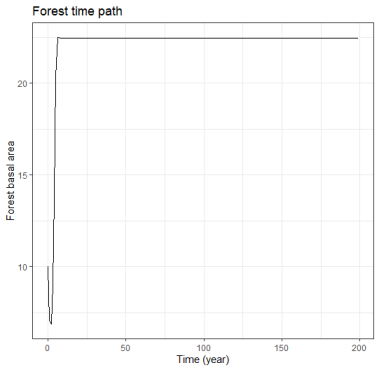


Figure 2.34: Run 5 budworm time path

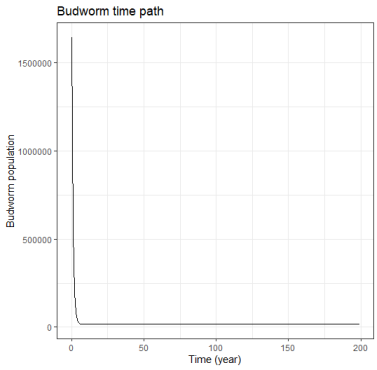


Figure 2.35: Run 5 treatment time path

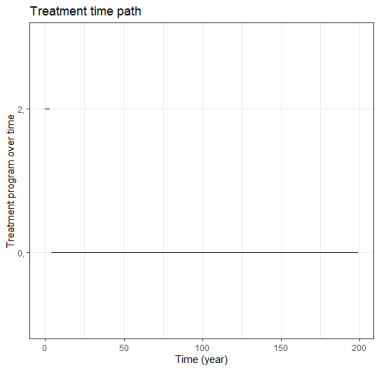


Figure 2.36: Run 5 harvest time path

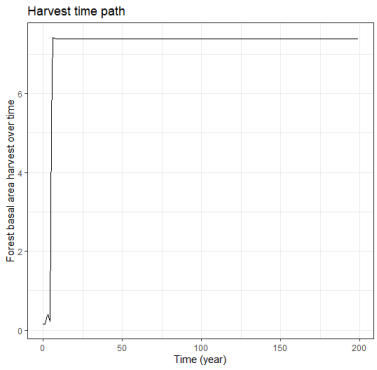
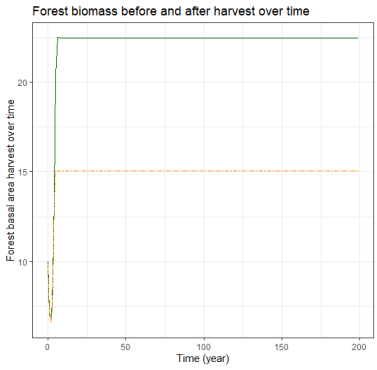


Figure 2.37: Time path of initial (s_t) and post-harvest (x_t) forest for Run 5



2.5.3.4 Sensitivity to treatment cost changes

The treatment cost $k(i)$ was first doubled to 90, and then halved to 22.5. Model behavior did not change relative to the baseline scenario. The value function increases when costs decrease and decrease when costs increase. The effect of a cost change is therefore similar to the effect of a price change.

2.5.3.5 Sensitivity to changes in the discount rate: quadrupled rates

The discount rate was first increased from 5% to 20%. Doubling the interest rate was not sufficient to change model behavior.

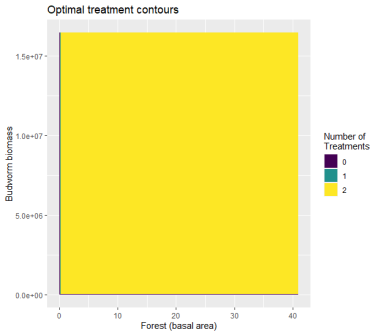
Table 2.15: Parameters: eighth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{\mathbf{1}}{\mathbf{1.20}}$

The contours for optimal policies are below:

Figure 2.38: Run 8 optimal treatment contours



Two treatments are generally optimal. However, the use of harvests to control the spread of budworms in addition to treatment depends on the initial budworm population, and this holds more or less flat for forests of any biomass over 0.5 m^2.

The optimal budworm biomass as a function of the forest is below:

Figure 2.39: Run 8 optimal budworm transition contours

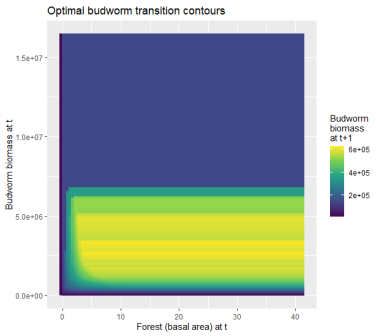
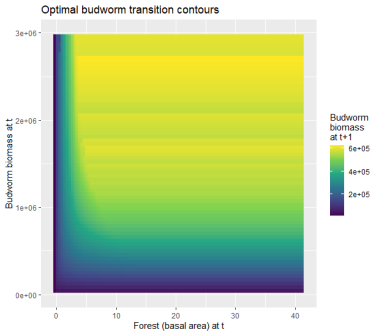


Figure 2.40: Run 8 optimal budworm transition contours



There is a policy cut-off around 60,000 budworms per hectare. Above this line, budworms should be suppressed as much as possible, which can be achieved by increasing harvests to near-clearcut levels. Below this cut-off, treatment is the primary way to control budworms. Harvests will be high but not near to clearcuts.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

Figure 2.41: Run 8 optimal forest transition contours

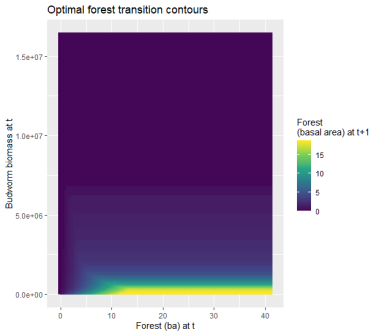
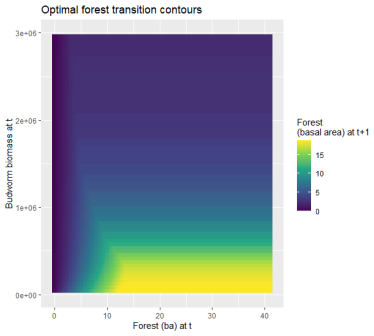


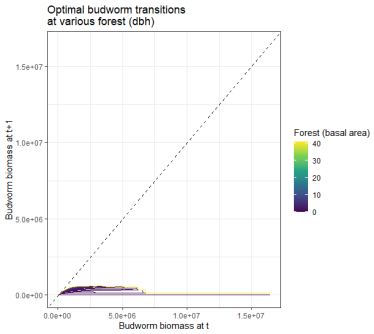
Figure 2.42: Run 8 optimal forest transition contours



The harvest is high and increasing in budworm biomass, but it is important to note that clearcuts are generally not optimal, unless the budworm biomass is uncontrollably large relative to the size of the forest. For budworm populations lower than about 40,000, a relatively high basal area will be left for the next period if the initial basal area is small.

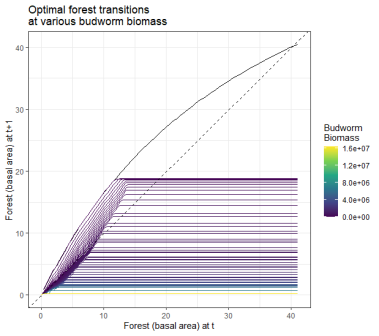
At higher interest rates, the optimized transition equations for budworms and forests are given below:

Figure 2.43: Run 8 optimal budworm transition as a function of forest



Budworm levels must be driven as low as possible as quickly as possible. Harvests will help to drive the population down.

Figure 2.44: Run 8 optimal forest transition as a function of budworms



The forest in the next period depends primarily on budworm biomass. For low budworm biomasses, the forest biomass in the next period can be relatively high, although not as high as in a lower interest rate setting. As budworm biomass increases, the distance between transition lines decreases. At the highest budworm biomasses, clearcuts occur.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. The forest is initially harvested to a low level, and then allowed to regrow to a high level. The budworm population is deprived of food and will fall to its long-term level, which is near zero. Two treatments are initially applied. Afterwards, treatments become unnecessary. The harvest level is constant once the forest biomass is sufficiently high.

Figure 2.45: Run 8 forest time path

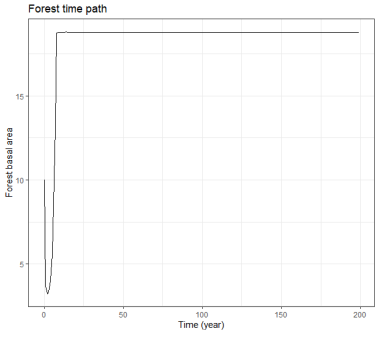


Figure 2.46: Run 8 budworm time path

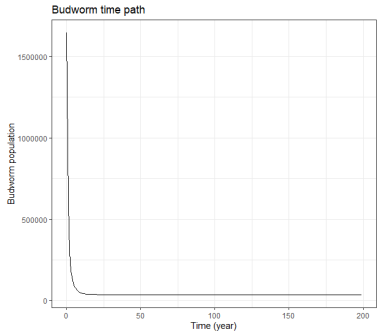


Figure 2.47: Run 8 treatment time path

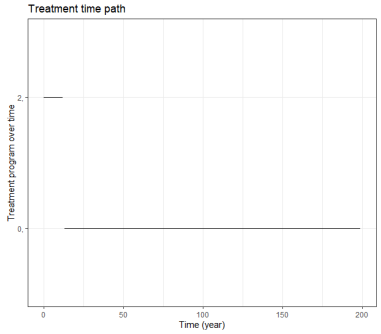


Figure 2.48: Run 8 harvest time path

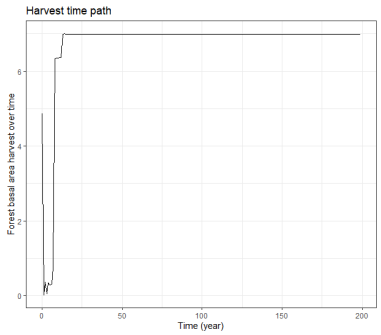
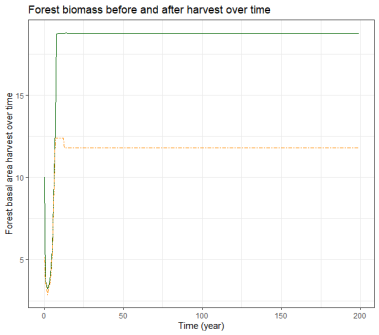


Figure 2.49: Time path of initial (s_t) and post-harvest (x_t) forest for Run 8



2.5.3.6 Sensitivity to changes in the discount rate: very low interest rates rates

The discount rate was then decreased from 5% to 1%. Halving the interest rate was not sufficient to change model behavior.

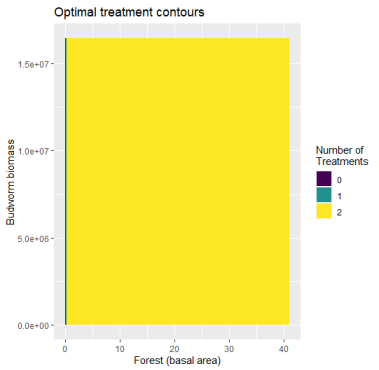
Table 2.16: Parameters: ninth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{\mathbf{1}}{\mathbf{1.01}}$

The contours for optimal policies are below:

Figure 2.50: Run 9 optimal treatment contours



Two treatments are optimal except for a small forest biomass. This holds true even for a small budworm biomass. There is a thin policy band where one treatment is optimal, and at near-zero biomasses, no treatments are optimal.

The optimal budworm biomass as a function of the forest is below:

Figure 2.51: Run 9 optimal budworm transition contours

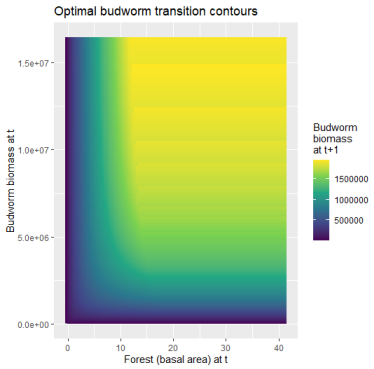
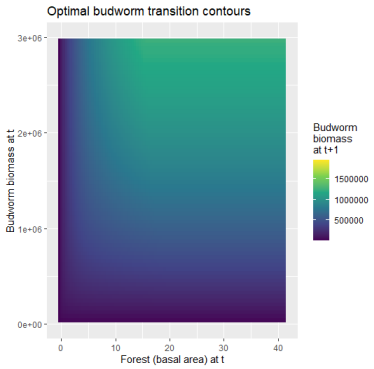


Figure 2.52: Run 9 optimal budworm transition contours



High budworm populations in the next period are acceptable if this period's budworms are high. This implies that there will not be a rush to chop down trees as quickly as possible if the outbreak is too big to be controlled by treatments.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

Figure 2.53: Run 9 optimal forest transition contours

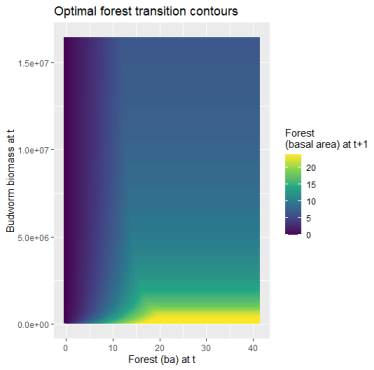
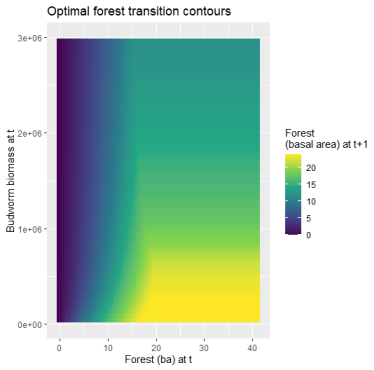


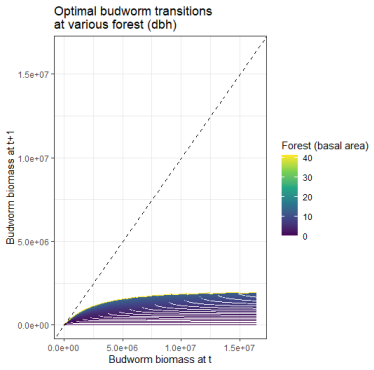
Figure 2.54: Run 9 optimal forest transition contours



As the discount rate is low, there is no need to cut down the forest as quickly as possible. Harvests occur at a sustainable rate, but do increase in budworm biomass.

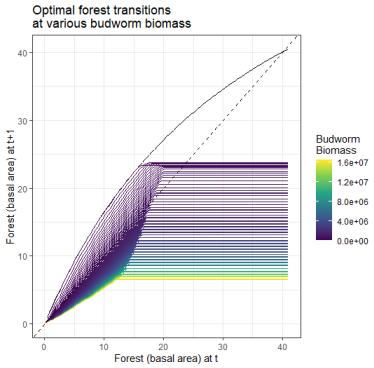
At lower interest rates, the optimized transition equations for budworms and forests are given below:

Figure 2.55: Run 9 optimal budworm transition as a function of forest



Budworm levels can be gradually driven to a manageable level. Treatment becomes a more important management method than clearcuts.

Figure 2.56: Run 9 optimal forest transition as a function of budworms



Harvest is increasing in budworm biomass but clearcuts are never optimal. Even for the highest budworm biomass, some forest will be left for the next period.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. The forest is initially harvested to a low level, and then allowed to regrow to a very high level. Treatments are applied for longer than in the baseline scenario. Harvest levels are steady in the long-term.

Figure 2.57: Run 9 forest time path

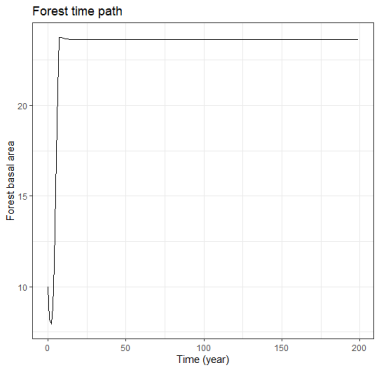


Figure 2.58: Run 9 budworm time path

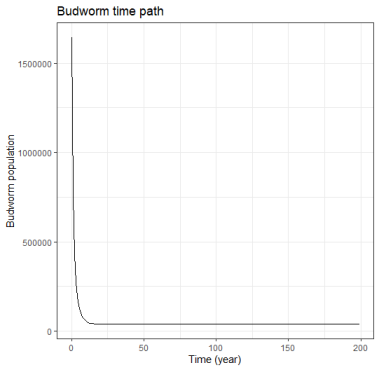


Figure 2.59: Run 9 treatment time path

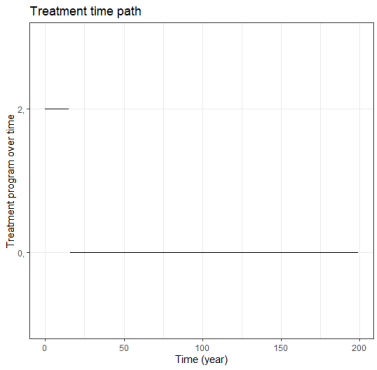


Figure 2.60: Run 9 harvest time path

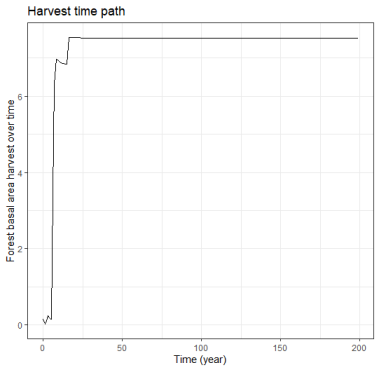
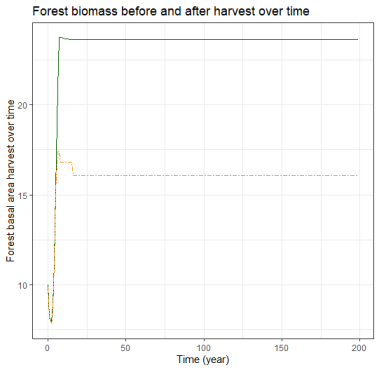


Figure 2.61: Time path of initial (s_t) and post-harvest (x_t) forest for Run 9



2.5.3.7 Sensitivity to changes in the growth budworm parameter

The budworm-growth interaction parameter g_F was first doubled to 0.8106 and then halved to 0.20265. Model behavior did not change. The forest biomass at the start of each period decreased when g_F increased and increased when g_F decreased, which is a straightforward and expected result given that g_F negatively affects the growth rate of timber.

2.5.3.8 Sensitivity to changes in the mortality budworm parameter: doubled m_F

We first increase the mortality factor m_F. This mortality factor relates relative budworm densities to the percentage death in the forest. If the budworm density increases, more trees will die (be removed from the biomass) in the next period.

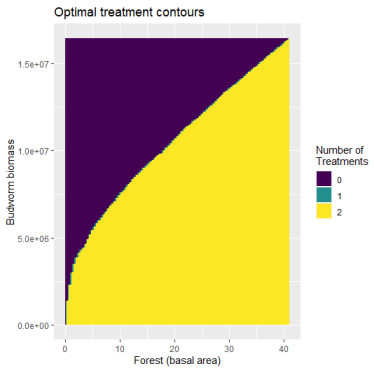
Table 2.17: Parameters: twelfth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	**0.0574**	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

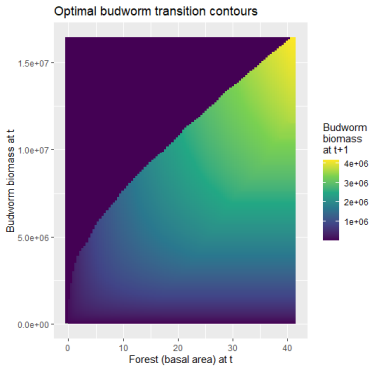
Figure 2.62: Run 12 optimal treatment contours



The treatment contours are similar to run 5 (where realized fecundity was decreased): there is a clear boundary between two treatments and non-treatment. There is a thin separation where one treatment is employed.

The optimal budworm biomass as a function of the forest is below:

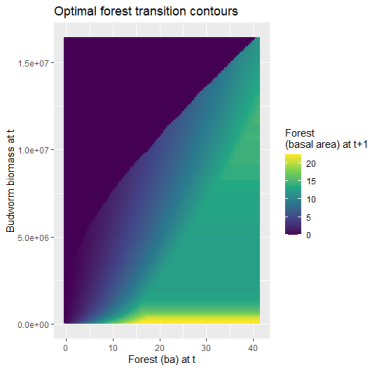
Figure 2.63: Run 12 optimal budworm transition contours



As is the case for run 5, we will treat the budworms below the treatment threshold and clearcut the forest above it.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

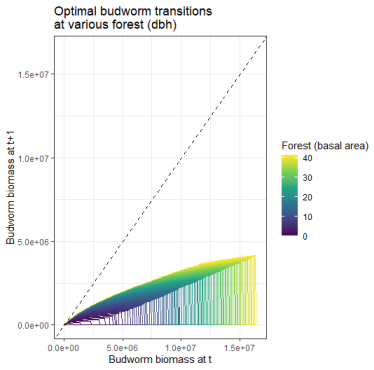
Figure 2.64: Run 12 optimal forest transition contours



Again, harvest is increasing in biomass, with clearcuts only occurring outside of the treatment boundary. Less forest is left over than in run 5. The next-period forest biomass will only be higher than 20 m^2/ha if the budworm biomass is very low.

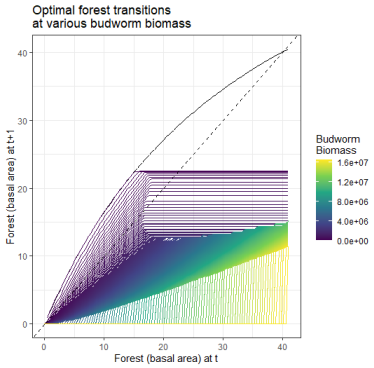
For a higher mortality interaction, the optimized transition equations for budworms and forests are given below:

Figure 2.65: Run 12 optimal budworm transition as a function of forest



Budworm levels should be driven as low as possible, and this will be achieved first by treatment, and if not, by increasing the harvest, possibly to clearcut levels.

Figure 2.66: Run 12 optimal forest transition as a function of budworms



As long as the budworm biomass is low, the forst biomass can be maintained at a high steady state. If the budworm biomass is high, however, harvests will increase. Very high budworm biomass will cause clearcuts (the flat line).

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. We run treatments initially for a few years, and then they become unnecessary as the budworm population is driven to a very low level. The forest and harvest are maintained at a high level over the time period.

Figure 2.67: Run 12 forest time path

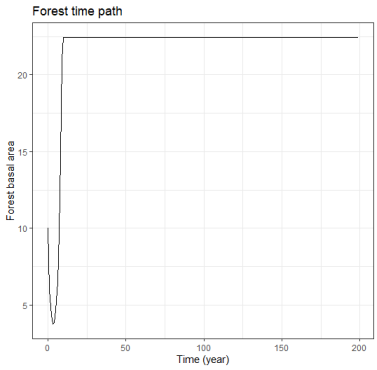


Figure 2.68: Run 12 budworm time path

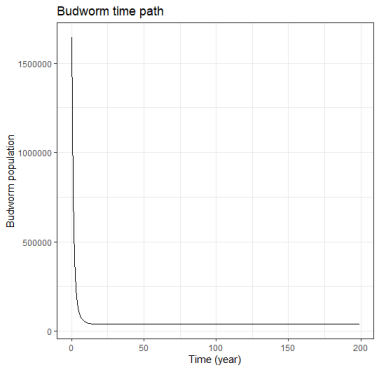


Figure 2.69: Run 12 treatment time path

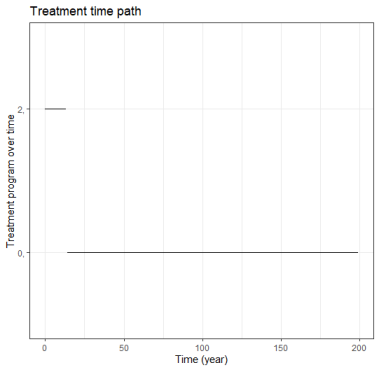


Figure 2.70: Run 12 harvest time path

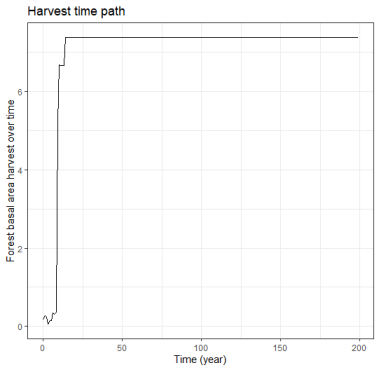
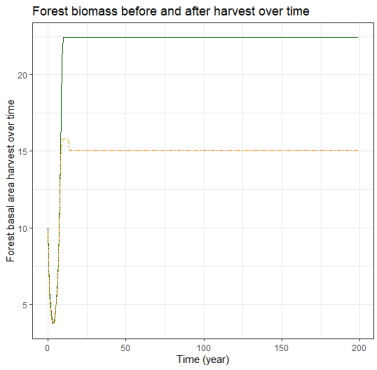


Figure 2.71: Time path of initial (s_t) and post-harvest (x_t) forest for Run 12



2.5.3.9 Sensitivity to changes in the mortality budworm parameter: halved m_F

The next step is to reduce the mortality-budworm factor by half.

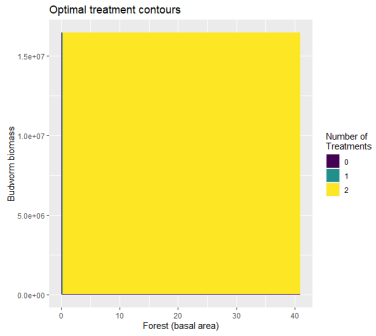
Table 2.18: Parameters: thirteenth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	**0.01435**	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	10000	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

Figure 2.72: Run 13 optimal treatment contours



Treatment contours are straightforward. Two treatments are used except if the budworm or forest biomass is very small. There is a sliver of small forest biomasses for which one treatment is used.

The optimal budworm biomass as a function of the forest is below:

Figure 2.73: Run 13 optimal budworm transition contours

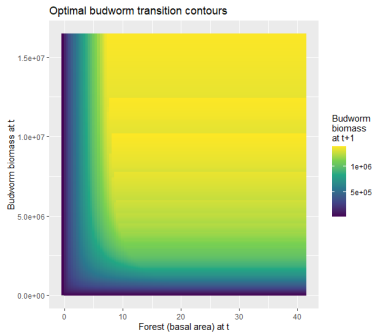
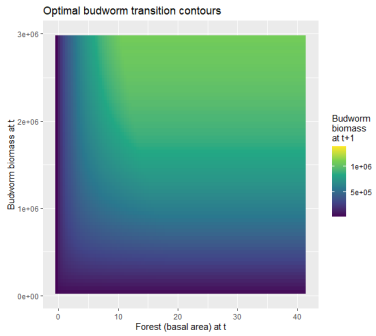


Figure 2.74: Run 13 optimal budworm transition contours



Higher budworm levels are acceptable if the forest and budworm biomass are high enough. This means that treatment will be the primary method used to control budworms.

The contours for optimal next-period forest biomasses given the budworm biomass are given below:

Figure 2.75: Run 13 optimal forest transition contours

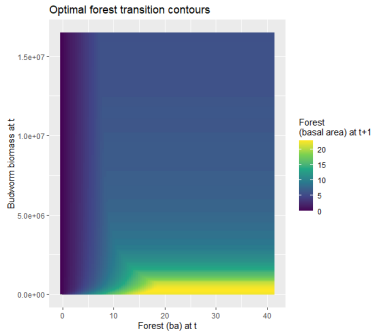
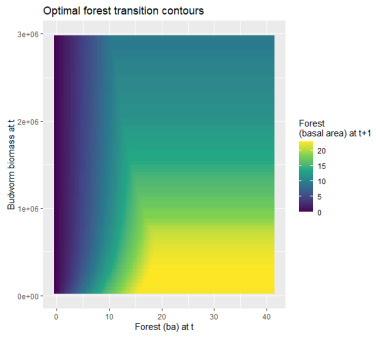


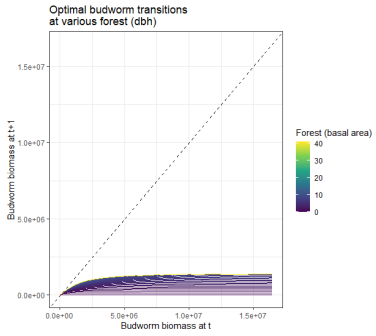
Figure 2.76: Run 13 optimal forest transition contours



Harvest increases in budworm biomass, but clearcuts will only occur when the forest biomass is already small.

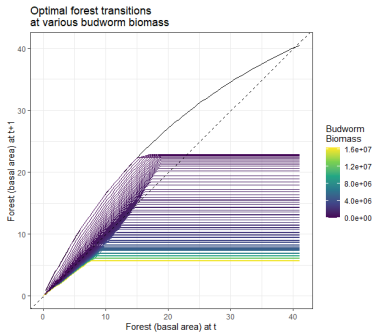
For a lower mortality interaction, the optimized transition equations for budworms and forests are given below:

Figure 2.77: Run 13 optimal budworm transition as a function of forest



Budworm levels can be maintained at a low, sustainable rate. Eradication is not a priority.

Figure 2.78: Run 13 optimal forest transition as a function of budworms



The forest biomass will be maintained at a steady rate as long as it is high enough. It is decreasing in budworms but at low budworm levels, the forest biomass will be high.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. Time paths are similar to run 12 despite the very different behavior of the transition equations. Budworms are driven to the low level a bit faster.

Figure 2.79: Run 13 forest time path

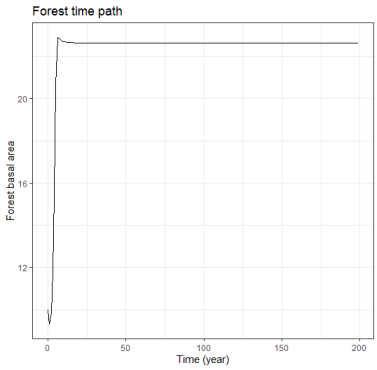


Figure 2.80: Run 13 budworm time path

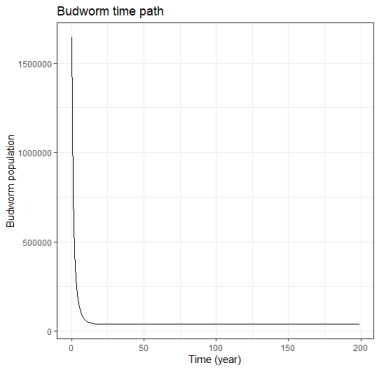


Figure 2.81: Run 13 treatment time path

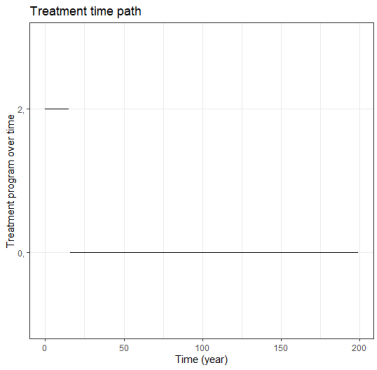


Figure 2.82: Run 13 harvest time path

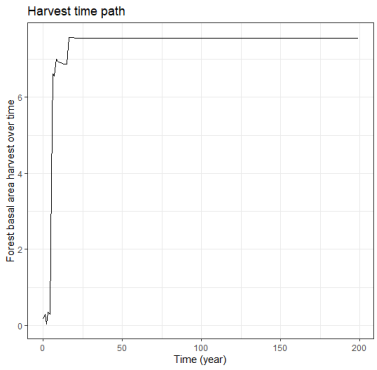
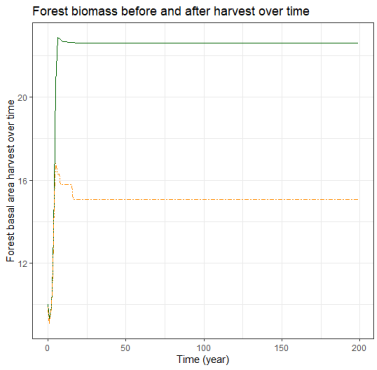


Figure 2.83: Time path of initial (s_t) and post-harvest (x_t) forest for Run 13



2.5.3.10 Changes to the growth rates of the forest

The forest growth rate r_F is first decreased to 1.0 and then increased to 2.0. Reducing the growth rate to 1 does not change model behavior. Increasing the growth rate will increase the sustainable harvest but otherwise leave model behavior unchanged.

2.5.3.11 Effects of a ten-fold increase in immigration

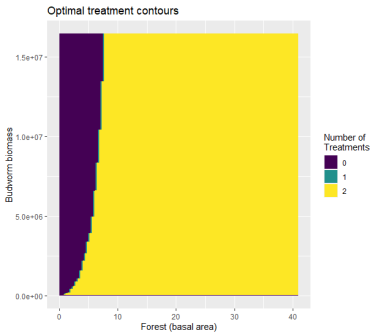
Table 2.19: Parameters: sixteenth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	**100000**	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

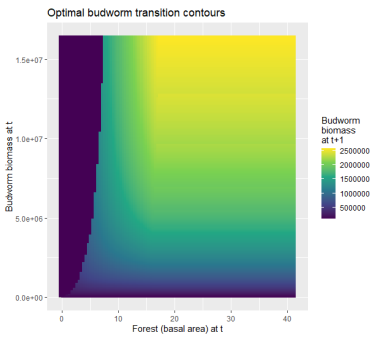
Figure 2.84: Run 16 optimal treatment contours



The no-treatment zone widens as the basal area widens, with a cut-off at about 7 m^2/ha.

The optimal budworm biomass as a function of the forest is below:

Figure 2.85: Run 16 optimal budworm transition contours



The no-budworm zone matches the no-treatment zone. The policy in this case is to clearcut the forest. This is shown from the contours for the optimal next-period forest biomasses given the budworm biomass:

Figure 2.86: Run 16 optimal forest transition contours

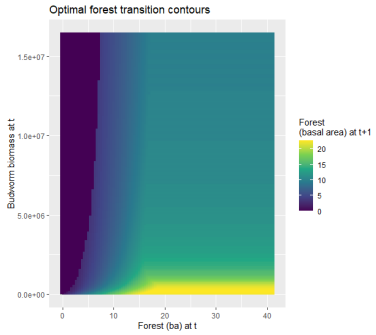
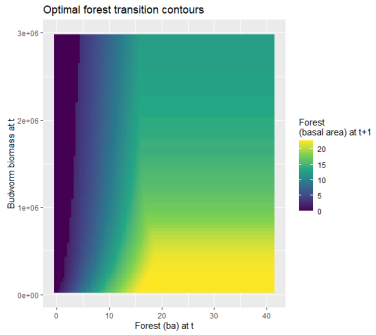


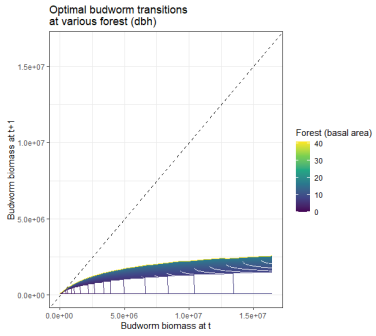
Figure 2.87: Run 16 optimal forest transition contours



Forest clearcuts only occur in the no-treatment zone. Otherwise, a relatively large forest biomass will be left to the next period.

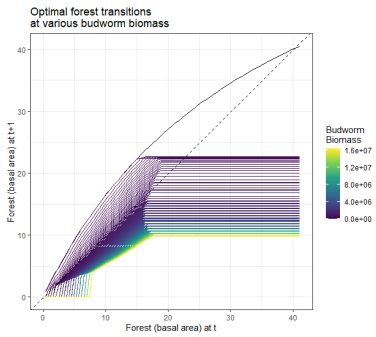
For high budworm immigration, the optimized transition equations for budworms and forests are given below:

Figure 2.88: Run 16 optimal budworm transition as a function of forest



Budworms cannot be eliminated unless a clearcut occurs. There will always be budworm immigration. As such, the transition should be pushed to its lowest level by using two treatments.

Figure 2.89: Run 16 optimal forest transition as a function of budworms



Even for a high budworm population, the forest in the next period will be harvested at a sustainable level. It will converge to a steady state.

The time paths for the forest, budworms, treatment, harvest and the pre- and post-harvest forest biomass are below. We will always apply treatments. Budworms are suppressed to the immigration level, and the forest is maintained at a high level, which allows for a steady harvest.

Figure 2.90: Run 16 forest time path

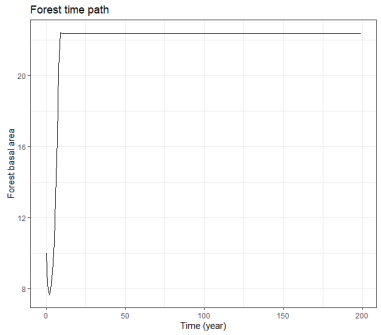


Figure 2.91: Run 16 budworm time path

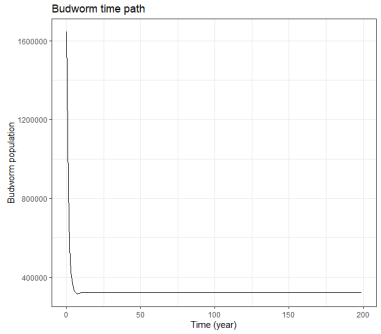


Figure 2.92: Run 16 treatment time path

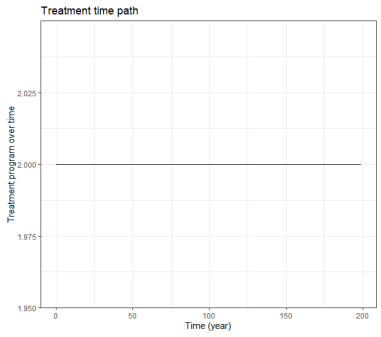


Figure 2.93: Run 16 harvest time path

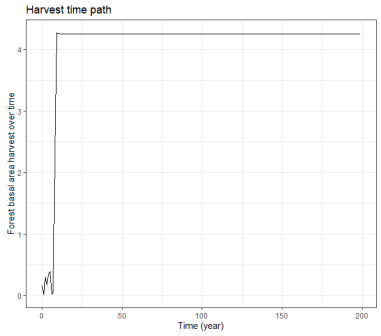
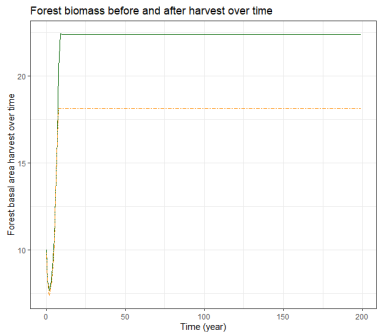


Figure 2.94: Time path of initial (s_t) and post-harvest (x_t) forest for Run 16



2.5.3.12 Effects of a hundred-fold increase in immigration

We increase immigration from 10,000 to 1,000,000.

Table 2.20: Parameters: seventeenth run

Parameter	r_F	K_F	g_F	m_F	β	θ	γ	B_{max}
Value	1.1	40.075	0.4053	0.0287	2.96	5035.71	0.83475	150

Parameter	d_o	d_1	d_2	Y_{imm}	p	$\frac{h}{dbh}$	$k(i)$	δ
Value	0	0.5	0.75	**1000000**	20	15	45	$\frac{1}{1.05}$

The contours for optimal policies are below:

Figure 2.95: Run 17 optimal treatment contours

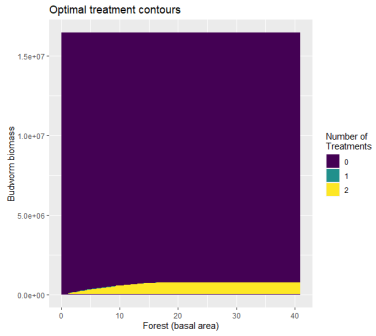
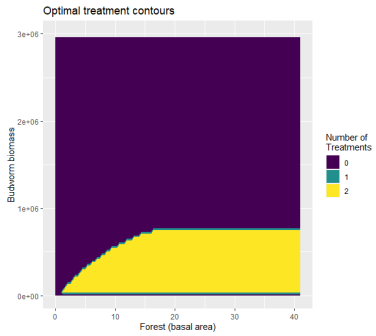


Figure 2.96: Run 17 optimal treatment contours



No treatment dominates, except at low inital budworm levels.

The optimal budworm biomass as a function of the forest is below:

Figure 2.97: Run 17 optimal budworm transition contours

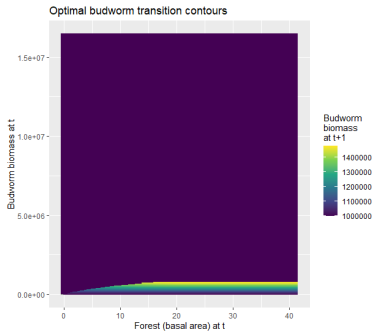
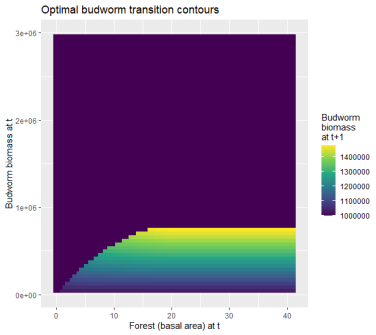


Figure 2.98: Run 17 optimal budworm transition contours



The no-budworm zone matches the no-treatment zone. The policy in this case is to clearcut the forest. Outside of this zone, high budworm levels must be tolerated. Treatment will reduce the budworm level but will not be sufficient to reach a low sustainable level.

The contours for the optimal next-period forest biomasses given the budworm biomass are as follows:

Figure 2.99: Run 17 optimal forest transition contours

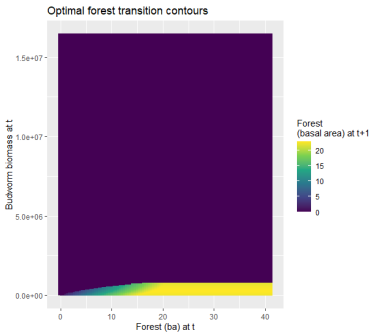
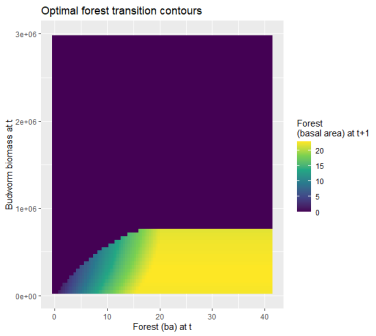


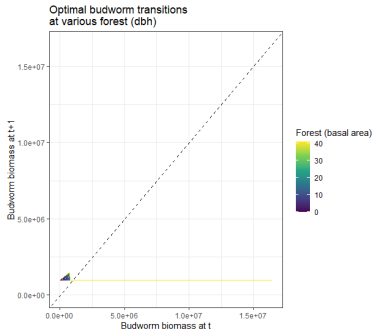
Figure 2.100: Run 17 optimal forest transition contours



Forest clearcuts only occur in the no-treatment zone. Otherwise, a relatively large forest biomass will be left to the next period. However, this will only last in the short-run. In the long-run, the budworm outbreak cannot be controlled, and clearcutting will be the only option. This will be shown in the time paths below.

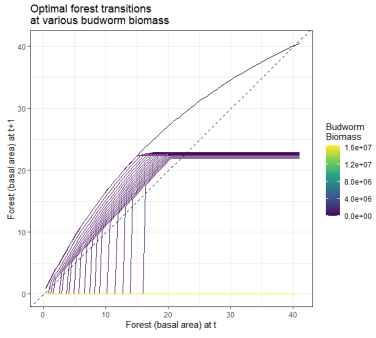
For high budworm immigration, the optimized transition equations for budworms and forests are given below:

Figure 2.101: Run 17 optimal budworm transition as a function of forest



The behavior of the budworm transition indicates that clearcutting will need to be used to remove budworms from the forest (or, more specifically, by removing the forest from the budworms).

Figure 2.102: Run 17 optimal forest transition as a function of budworms



Forest biomass will be left for the next period if the budworm population is very low. Otherwise, the forest will be clear-cut.

The time paths for the forest, budworms, treatment and harvest are below. The time path for the pre- and post-harvest forest biomass is excluded as results were flat lines at zero. We will clearcut the forest as quickly as possible. No treatments are applied.

Figure 2.103: Run 17 forest time path

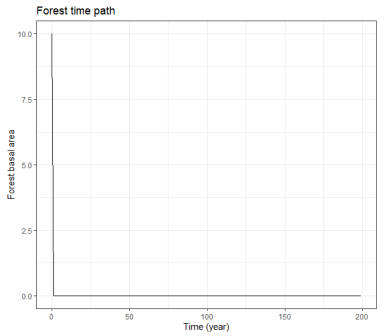


Figure 2.104: Run 17 budworm time path

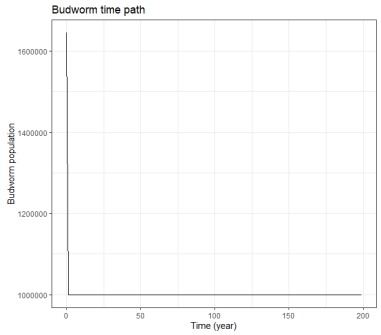


Figure 2.105: Run 17 treatment time path

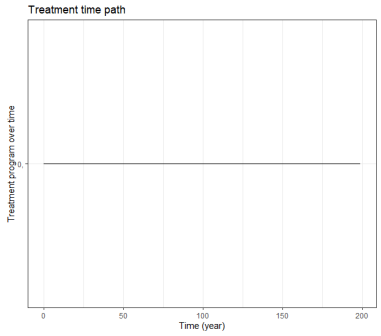
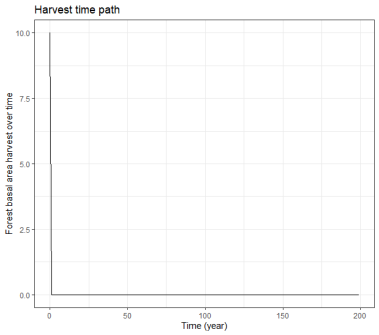


Figure 2.106: Run 17 harvest time path



2.6 Discussion

Our results indicate that budworms must generally be actively treated, except in specific circumstances when budworm densities are high and the forest biomass is low. Two treatments are generally optimal, except when the initial budworm biomass is low. This suggests that the management policies currently being employed in eastern Quebec and Canada's Maritimes are likely to be improvements over doing nothing. Conditions can change if the cost of treatment becomes prohibitively expensive or if trees have extremely low harvest value, as is the case in parts of western Quebec. Harvests will increase as the budworm density increases, which will help reduce the budworm population in addition to treatments.

Since budworms can be driven to endemic levels along our baseline time path, an early intervention strategy would potentially be welfare-improving over a foliage protection strategy in the Lac-Saint-Jean region of Quebec. However, this assertion comes with caveats, which are discussed in subsection 2.6.4.

2.6.1 Discussion of main results

Our primary results indicate that the optimal policy, according to our set-up, is to run an active treatment program for a few years while managing budworms down to a low level. The forest will grow slowly to its long-term steady state, and harvests will reach a long-term steady level.

The weakness of the main model is that it cannot account for variable rates of budworm survival success or immigration. Therefore, the model describes short-term behavior more accurately than long-term behavior. In the short-term, foliage protection will be optimal, or at least an improvement over a no-protection strategy. Some tree die-off is inevitable until budworms are controlled. Thus, Quebec's investment in its aerial spray program will improve social welfare relative to a do-nothing or immediate clearcut strategy.

2.6.2 Discussion of sensitivity analysis

Our model is sensitive to changes in realized fecundity (β), the discount factor (δ), the mortality-budworm parameter (m_F) and immigration (Y_{imm}).

Increasing the realized fecundity will make budworms more difficult to control through treatment alone. A mixture of harvest and treatment will need to be used. If the initial budworm population is very high, clearcuts may be optimal. Otherwise, there will be no long-term steady state for either budworms or forests. Instead, we will see an oscillation pattern around a long-term trend for each. Two treatments will always be applied each year in this scenario. Increasing realized fecundity will increase the reproduction of adult larvae (and moths) Y_t but will also increase competition among young larvae L_t. Pressure on trees will decrease.

Decreasing the realized fecundity makes budworms easier to control, but also has the odd effect of making clearcuts occasionally optimal. There is a treatment zone and a non-treatment zone. Treatments are used to reduce the budworm to near-zero levels. Initially, two treatments are applied for a short period of time. After this, no more treatments are required. Decreasing realized fecundity will decrease the reproduction of adult larvae (and moths) Y_t but will also decrease competition among young larvae L_t. Pressure on trees will increase, and as such a high initial L_t can potentially cause trees to die off, which will make clearcuts optimal.

Decreasing the discount factor by increasing the interest rate (δ) will change the model behavior significantly. The harvest will increase significantly above about 60,000 budworms per hectare, to near clearcut levels. Budworms should be suppressed as much as possible above this cut-off, and if the initial budworm population is below the cut-off, the long-term policy will still be to suppress budworms to their lowest level. Two treatments are used for a few years, and afterwards, they will not be necessary. The harvest level will be initially high, which will reduce the forest to a low biomass that will then regrow.

Increasing the discount factor by decreasing the interest rate (δ) reduces the urgency of eliminating budworms. The harvest level will be initially low, and as such the initial reduction of forest biomass will not be as severe as in a high discount rate setting.

When the mortality-budworm (m_F) is increased, there are distinct combinations of budworm and forest that will result in no treatments and clearcuts. Outside of these zones, budworms will be suppressed by a mixture of treatments and harvests. Individual budworms will place more pressure on trees.

When the mortality-budworm (m_F) is decreased, there is no clearcut zone. Budworms do not need to be suppressed as quickly as possible, and as such treatments are the best way

to manage outbreaks. Harvests are increasing in budworm biomass, but some forest biomass is always maintained if possible.

Increases in immigration will change the model behavior significantly. A tenfold increase in immigration will create a no-treatment zone for small to medium forest biomasses and moderate to large budworm biomasses. Inside the no-treatment zone, clearcuts are optimal. Outside of this zone, we will tolerate high budworm populations in the next period.

A hundredfold increase in budworm immigration will create a very large no-treatment zone, to the extent that treatment is only an option for large forests and small initial budworm biomasses. Clearcuts will be inevitable either in the short-term or long-term. At most, harvest can be delayed for one period. Afterwards, the optimal policy will be to cut the forest down completely.

The pattern that emerges from this sensitivity analysis is as follows: as budworms become harder to control, or their damages become more severe, the emphasis placed on treatment as the primary control method decreases. Harvests will increase as the planner seeks to minimize losses due to tree death and growth reduction, and in some cases, treatment will be abandoned in favor of clearcuts. Similar situations occur when the discount rate increases, as the reward from forest biomass and harvest in future periods will decrease.

When budworms become easier to control, budworms can be driven to a near-extinction level that will only be replenished by immigration. When their damages are low, there is no rush to control budworms as quickly as possible. As such, budworms can be slowly treated down to a low, sustainable level. The emphasis on harvests to control budworms decreases.

2.6.2.1 Sensitivity analysis and time paths

For the baseline parameters used in 2.5.2, the general rule of time paths is that they converge to a steady state. Planners will first harvest the forest down to a low level, and will then let it replenish to a high steady state. Subsequent harvests occur at a sustainable rate, corresponding to the replenishment rate of the forest. The budworm population can be driven to a low level, after which treatments will no longer be necessary.

There are two exceptions. First, doubling the fecundity of adults, as is the case with the parameters in table 2.13, leads to a situation in which the budworm population will always rebound from treatments. Two treatments are always applied. The budworm population will oscillate along a long-term mean, as will the forest and the harvest level. There is no constant steady state in such a situation. This scenario suggests that a mature outbreak that has exceeded the Allee threshold and cannot be removed from the forest must instead be managed on a rolling basis. Treatments will reduce the population, which will reduce the level of tree death. However, some tree death from budworms is inevitable in both the short term and long term. When the budworm biomass increases, so does the rate of harvest.

If there is a hundred-fold increase in the immigration parameter, as is the case for the parameters in table 2.20, then the optimal strategy will be to immediately cut down the forest, removing all available biomass for budworms. Treatments become irrelevant, and we immediately converge to a corner solution steady state. This suggests that an uncontrollable budworm infestation will lead to a total loss of the forest. The initial high level of immigration would not be likely to sustain itself at a high level, however, as local resource exhaustion would likely be accompanied by resource exhaustion across the entire landscape.

2.6.3 Implications of sensitivity analysis for management

Our baseline model implies that two treatments should always be applied, and that budworms can be driven to a low endemic level. Since initial conditions do not change, sensitivity analysis can help us to make more realistic policy assessments. Varying parameters will capture some, but not all, of the complexities of management.

The baseline model assumes a set rate of budworm reproductive and rearing success. Most entomological budworm models recognize that the survival and reproduction rates of budworms will vary from year to year. Therefore, variations in β help us to capture how policy prescriptions will change as budworm survival and reproduction rates change. The effect is complex: budworms will both compete with each other for food and decrease the predation rate of individual budworms. This leads to our observed Allee effect. High budworm populations coupled with low realized fecundity will lead to a steady state where budworms will overwhelm the forest before out-competing each other for resources. On the flipside, low realized fecundity and a low budworm population will lead to a manageable outbreak that should be treated slowly down to a reasonable level. High realized fecundity will generally lead to a forest that cannot be managed at a steady state. A sudden increase in β can cause a manager to switch from an early intervention strategy to a foliage protection strategy with no management steady state.

Changes in the discount factor will change treatment and harvest priorities. Long-term management becomes less important, and as such harvests are emphasized over treatments. Managers are more willing to cut the forest down to a level that will support much smaller budworm populations. The focus will shift away from foliage protection and towards harvest schedule optimization or even clearcutting. As the discount factor increases, forest stocks must be maintained

for longer, which will increase the importance of foliage protection or early intervention.

Changes to the mortality rate will change the treatment and harvest policy. Increases in mortality can make the forest unsalvageable. Therefore, a forest which can be considered weak to budworms in its initial conditions due to size or basal area will, under certain conditions, optimally be clearcut. Low-vulnerability forests will be preserved for longer, and will almost never be clearcut. The implication of this is that management that can reduce forest vulnerability will increase the pertinence of active pest management.

2.6.4 Limitations of the model

The biggest limitation of our model is the fact that initial conditions will not change. Sensitivity analysis helps to account for this. However, certain things cannot be captured by the sensitivity analysis.

First and foremost, this model does not capture the complexities of budworm population estimation in the landscape. We assume a known population. The result is that our model cannot directly determine the cut-offs between foliage protection and early intervention. At most, initial conditions could be variably described as favorable to foliage protection or early intervention based on the paths of forest and budworm stocks.

Tree mix is not incorporated into our model. Trees are undifferentiated biomass. As identified by Chang et al. [2012a], one management strategy for spruce budworms involves replanting forests will less vulnerable species. It is known that balsam fir are more vulnerable to spruce budworm outbreaks than pine or spruce [Greenbank, 1963, Jennings and Crawford, 1985, Talerico, 1983]. A long-term reduction in the vulnerability of the forest cannot be directly captured by

our model, although, as mentioned in the sensitivity analysis, changes to m_F will change model behavior.

The spatial aspect is discussed in Chapter 4. In short, omitting spatial inter-dependencies means that the immigration rate will not reflect the overall conditions of the forest. This cannot merely be captured by varying Y_{imm}. Rather, the spatially inter-dependent immigration response will be dynamic: treating or thinning the forest will have co-benefits that will reduce the intensity of the necessary response in downwind stands.

Chapter 3: Managing Spruce Budworm Outbreak Risks Through Optimized Surveillance Strategies (with. Prof. Rebecca Epanchin-Niell)

3.1 Introduction

While spruce budworms always exist at endemic levels in Northeastern North American forests and form part of their ecosystems, severe outbreaks occur at roughly 30 to 40 year intervals, depending on climatic conditions. These outbreaks kill vast swathes of forest, damaging the ecosystem and causing standing trees to lose their value steadily over time as they rot. Recently, techniques have been developed to actively manage spruce budworm populations before they reach outbreak levels [Régnière et al., 2019]. These techniques are known as the early intervention strategy (EIS), a program of surveillance and early control that seeks out hot spots with rising budworm populations and treats them down to endemic levels using biological control agents such as *Bacillus thuringiensis* var. *Kurstaki* (Btk) and tebufenozide. Active management under an EIS has the potential to significantly reduce timber losses [Liu et al., 2019]. In this chapter we examine the conditions under which a manager may choose to undertake surveillance for EIS as part of a spruce budworm mitigation program.

The purpose of this chapter is to extend proactive pest monitoring and treatment models to an endemic species. Proactive management tends to focus on exotic and invasive species. Spruce

budworms are uniquely suited to such a study, as they are present at low, endemic levels throughout the landscape at all times, and periodically rise to outbreak levels that cause widespread forest losses. The EIS program developed and implemented in New Brunswick relies on the detection of hot spots before outbreaks occur. Since proactive management is, theoretically, possible, we adapt a model designed for optimizating early detection and control of exotic pest outbreaks to endemic pest outbreaks. We implement this by adapting prior modeling approaches [e.g. Epanchin-Niell, 2020, Epanchin-Niell et al., 2014, 2012] to the spruce budworm EIS context. Our paper represents a novel contribution to the literature by showcasing how techniques and approaches used to survey invasive species can be applied to endemic irruptive species.

MacLean et al. [2019] have described the early intervention strategy as a "$300 million dollar solution to a $15 billion dollar problem" in Atlantic Canada, based on the present value of a 50-year outbreak horizon. The ratio of present value benefits to present value costs would therefore be 50 to 1. Despite the very high benefit to cost ratio, there are currently no plans to implement EIS in Quebec. This chapter explores the potential economic benefits of implementing an EIS program in Quebec, as well as where such a program would be economically warranted.

There are several ways to conceptualize the trade-offs involved in an EIS program. The framework we adopt here is the cost-benefit trade-off: we compare the costs of running a surveillance program for EIS in different parts of our landscape to the benefits, which are calculated based on avoided damages from an outbreak[1]. Any location with a benefit to cost ratio higher than one or positive net benefits would receive investments. This is the appropriate method to use when the available surveillance budget is significantly larger than the cost of running EIS at

[1]The alternative to EIS in our model is a foliage protection program (FP). Under an FP program, part of the damages from an untreated outbreak will be avoided, and part of the damages will be incurred. The benefits of EIS are therefore the portion of outbreak damages that are avoided by using EIS rather than FP, net of control costs.

cost-effective locations. Another method is to use a limited surveillance budget and unlimited treatment budget. The trade-offs would therefore be between the marginal benefits of running surveillance at different locations. This chapter uses both approaches.

Spruce budworm management involves two components: surveillance and control. In this chapter, we consider how a forestry manager deploys surveillance resources to avert the worst damages from spruce budworm outbreaks, and therefore focus on surveillance rather than control.

In Chapter 1, we discuss the controversy concerning the sources of budworm epidemics. Once again, we assume that the double equilibrium hypothesis holds and thus that early intervention can be effective. This is consistent with the current scientific majority opinion.

This chapter proceeds as follows. Section 3.2 reviews the management of invasive species that have similar characteristics to spruce budworms. Section 3.3 summarizes the implementation of the early intervention strategy for spruce budworm management in Eastern Canada, and describes the general parameters of our modeling approach. Section 3.4 describes the model's conceptual framework. Section 3.5 provides a mathematical specification of the model. Section 3.6 fits empirically-calculated values to the parameters from section 3.4, describes the landscape, and shows how predictions from this model will be tested empirically using a bioeconomic modeling approach. Section 3.7 provides the results from optimization of our model under baseline parameters and sensitivity analysis, and analyzes the implications of our results. Section 3.8 provides further discussion of these results and concludes the chapter.

3.2 Literature review: surveillance in invasive pest management

In this section, we review prior work on optimal surveillance and control of non-native invaders, and discuss how they relate to spruce budworm management.

A cursory survey of the literature did not uncover any economics or operations research articles that specifically deal with the problem of optimal sampling for spruce budworms. We therefore draw on extant economics and policy literature for invasive species management. Economic papers that discuss the general features of invasive species surveillance and control models are reviewed in Chapter 1. The literature review in this chapter therefore focuses on the various approaches used for specific invasive species. We cover three species and discuss the lessons that can be drawn from these for our analysis.

While the spruce budworm is an endemic species, surveillance and management approaches that have been developed for invasive insect species will inform our model. These include the emerald ash borer (EAB), the Asian longhorn beetle (ALB) and the spongy moth (SM, formerly known as Gypsy moth). The analyses developed for these pests can be compared to the one developed in this chapter.

3.2.1 Emerald ash borer management, the portfolio approach, and acceptance sampling

The emerald ash borer (*Agrilus planipennis* Fairmaire) is a beetle native to eastern Asia that has present throughout central and eastern Canada and the United States since at least 2002 [Natural Resources Canada, 2013a]. EAB affect both commercial and urban ash trees, and, if

untreated, they will kill 99% of ash trees in their vicinity within eight to ten years.

Survey-and-control models are used to guide EAB management. For example, Yemshanov et al. [2014] use a portfolio management approach and show that portfolio diversification can be used to achieve an optimal convex combination of portfolio variance and performance when surveying EAB in east-central Canada (Manitoba to Quebec). The main pathway of long-distance EAB movement is with firewood transported between campsites, so distribution of EAB on the landscape was estimated based on a simulated model of camper-based spread. Expected performance[2] varies across the landscape based on expectations of the likelihood of pest arrival, given the simulated spread model. In addition to covariance between locations, the authors consider the degree of similarity between locations d_{ij}. Given uncertainties about how ash borers spread, surveying dissimilar locations increases the likelihood of detection in uncertain locales. This approach is beneficial to risk-averse managers, since it can overcome bias caused by avoidance of high-error locations. The authors do not consider spatially-explicit factors such as proximity to amenities or transportation hubs, but identify these as a potential future area of research.

A portfolio approach becomes more relevant when the parameters of the pest's spread and survival are unknown. In this situation, it is beneficial to target a variety of different potential establishment points. As certainty increases, their results suggest that resources can be focused on the most likely infestation sites, but that less-likely infestation sites should still be surveyed, albeit at a lower intensity.

In Yemshanov et al. [2020], the authors consider acceptance sampling for EAB within the city of Winnipeg, where uncertain EAB spread is calibrated by using observed spread in the

[2]The authors analogize the performance measure I_{jk} to a financial asset, where expected return from a survey in region j is given by $\bar{I}_j$. I_{jk} represents the distribution of performance values $\mathbf{I}_j$ where $k = 1, \ldots, N$ and N is the number of elements in the set $\mathbf{I}_j$.

Minneapolis-St. Paul metropolitan area. Acceptance sampling defines an inspection method, an acceptance threshold for action, a decision rule and a sample size. Detection errors (which is to say false negatives) are inherent to EAB surveillance programs, and an acceptance sampling approach will keep the number of these detection errors below a defined acceptable error rate. The authors present an analogy of acceptance sampling as being akin to minimizing the damages caused by undetected defective items produced by an assembly line.

Yemshanov et al. [2020] apply this approach to Winnipeg's EAB detection and control program. The cost of the program varies based on the intensity of survey efforts, and different budget levels are considered. Two different objectives are considered: maximizing the expected area with detected infestations and minimizing the expected number of undetected infestations within all surveyed areas. The choice of objective influences the choice of strategy: the former involves selecting likely sites close to the initially infested area, while the second, which is an acceptance sampling approach, involves selecting areas with high host densities and high infestation rates. The first strategy resembles the strategy currently used in Winnipeg to control EAB. The authors find that if damages do vary by location, consideration of damages from undetected infestations will encourage policymakers to select sites at larger distances from the initial infestation site, since damages would be more severe at these locations due to the local value of the resources at risk. Costs are location-specific and method-specific, and depend on whether trees are streetside or on woodlots. The authors simulate constrained optimization for different budgets, with two sampling options (trapping and branch sampling) considered. Trapping is less expensive but has a lower detection rate than branch sampling. The manager's task is therefore to select a combination of branch and trap sampling that satisfies the chosen objective. For a small budget, branch sampling is preferred to trap sampling, and this is true for both objectives. There

is an optimality trade-off between the objectives chosen for the two sampling strategies, and the authors determine the frontiers of this trade-off, as well as the sensitivities of the objectives to parameters. The expected detection maximization approach was sensitive to survey costs, detection rates and infestation rates. The undetected infestation minimization approach was most sensitive to changes in host densities, and moderately sensitive to changes in infestation rates.

Yemshanov et al. [2020] illustrates the importance of choosing the right objective to optimize, since two similar approaches can have very different management implications. This article suggests to us that an early intervention program should focus on minimizing slippage, which will minimize the penalties from undetected infestations. Delimiting infestations should be a second-order priority, and can even be considered a part of post-detection management.

3.2.2 Asian longhorned beetle management and the CVaR approach

The Asian longhorned beetle (ALB) is a woodborer native to northeastern Asia that kill or degrade broadleaf trees. Their favorite host is maple, but they will also bore into other broadleaf trees such as willows, elms and poplars [Invasive Species Centre, 2024a]. Since they have no natural predators in North America, they have the potential to cause widespread economic and ecological damage should an initial invasion go unconfined. In an urban setting, ALB will decrease the quality of street trees, which will reduce the aesthetic, environmental and health benefits of trees.

Yemshanov et al. [2017] examine the ALB management program in the Greater Toronto Area (GTA) with a conditional value at risk (CVaR) minimization approach. This approach is useful because the spread of beetles is uncertain; historical data on ALB spread is used to

generate plausible invasion scenarios in the GTA. Furthermore, this approach is appropriate when managers are concerned about asymmetrical damage distributions, where the reduction in utility caused by right-tail scenarios is greater in absolute value than the increase in utility caused by left-tail scenarios [Yemshanov et al., 2017]. Under CVaR, the objective then becomes to minimize a weighted average of the expected damages and the conditional value at risk, with weights depending on the risk attitude of the manager.

The management model in Yemshanov et al. [2017] is a two-stage spatial optimization model. At the first stage, a quarantine zone is established around a known initial invasion. The quarantine zone has a certain number of ALB host trees, a subset of which are infested. Surveys are run that allow decisions about tree removal; the decision about where to deploy survey resources is the first-stage decision, and the removal decision is the second-stage decision. The manager must minimize the expected cost of surveys and tree removal across S different invasion scenarios, subject to a probabilistic constraint for successful pest eradication for all possible scenarios. Perfect certainty concerning eradication is not feasible, so the constraint is a margin of safety, similar to a confidence level in a hypothesis test.

It is possible for the planner not to run surveys. If an area is potentially infested and has not received survey resources, then it will be targeted for eradication. The costs of eradication in the absence of surveys are high, since all host trees within a potentially infested area must be removed. As such, the relative cost of a survey decreases if the severity of the infestation scenario increases. Costs are thus asymmetrical, with a long right tail. The CVaR represents the expected value in the right tail. The planner's problem is thus reformulated as a weighted minimization of expected program costs and the CVaR, with weights reflecting risk attitudes. Managers who are concerned about extreme damages will be more willing to increase spending on survey resources,

even if this leads to lower overall expected net benefits.

The management approach described in Yemshanov et al. [2017] was successful: as of 2020, the Asian longhorned beetle has been deemed eradicated in the Greater Toronto Area [Invasive Species Centre, 2024a].

3.2.3 Spongy moth, slowing the spread and the hot spot approach

From the perspective of a spruce budworm manager, the most informative invasive species is the spongy moth (SM). The spongy moth (previously Gypsy moth) causes defoliation of both broadleaf and coniferous trees, leading to death [Invasive Species Centre, 2024b].

Within their established range, spongy moth surveillance and management programs are similar to spruce budworm programs: traps and branch samples are used to assess local population densities, strategies can focus on either confinement or eradication, and aerial spraying is used to administer pesticides such as BtK that affect lepidopterae. Outside of their established range, traps are used to detect outlier SM populations that can then be eradicated. This can occur either far from the invasion front, or as part of a slow-the-spread program along the invasion front.

Spongy moth life cycles resemble those of budworms: larvae emerge in the spring, feed for 40 days, pupate, emerge as moths, mate and die. There are a few critical differences. For example, pheromone disruption is a more effective management method for SM than for SBW because female moths are flightless [Régnière et al., 2019], which is not the case for SBW. SM often spread long distances due to transported firewood, whereas SBW typically spreads through flight across continuous forest range.

SM is an invasive pest whose invasion frontier is expanding. Studying the management methods implemented along and beyond the frontier can inform spruce budworm management. In particular, new population clusters often first emerge from hot spots beyond the current infestation boundary. Tobin [2008] evaluates the US Slow-the-Spread program using a simulation model. Two management zones are defined: the evaluation zone and the action zone. The evaluation zone runs along the perimeter of the infested area while the action zone lies beyond the evaluation zone. Within the action zone, newly detected populations are eradicated, which implies high-intensity treatments and a high density of trap placements. In the evaluation zone, fewer traps are deployed and treatments are minimal, being primarily aimed at reducing damages. The total width of the evaluation and action zones is fixed at 170 km. The evaluation zone allows managers to estimate the rate of spread, and thus reducing it will make it harder for managers to evaluate the success of a slow-the-spread program. Reducing the width of the action zone will, for its part, increase the spread rate. Costs are increasing in action zone width. The authors simulate spread through the Midwest and Mid-Atlantic. As the budget increases, the spread rate across these region decreases, directly as a consequence of an increased action zone.

Epanchin-Niell et al. [2012] consider the trade-offs between eradication efforts and surveillance efforts with limited budgets. The authors develop a model and apply it to spongy moth management in California. The model optimizes surveillance efforts to minimize total costs and damages from SM incursions, including the costs of surveys. SM infestations are assumed to grow radially from hot spots, with actual arrivals occurring randomly but the region-wide rate being known. The model assumes that annual surveys are conducted, and that all detected populations are eradicated, with the eradication costs depending on the population's area when detected. Undetected populations continue to grow and damage trees. The choice variable in the model is

the sample density of surveys and the objective is to minimize the total long-term expected costs of surveillance, eradication and damages. Populations that are not detected before reaching a certain maximum size are assigned a penalty cost, reflecting eradication and damage costs from having reached that size undetected. There are therefore three cost components: penalty costs, sampling costs and eradication costs.

When applying their model to California, the authors consider optimal sampling strategies with and without a statewide sampling budget. The model is parameterized both for all of California and for each of California's 58 counties, which vary in their establishment rates and trapping costs. The statewide parameterization shows that existing management practices are close to optimal without incorporating heterogeneity. A county-by-county approach, however, dramatically reduces surveillance and eradication costs. Imposing restrictions on the sampling budget leads to increases in total management costs, as eradication and penalty costs increase. Current county-level trap densities are close to those in the optimized heterogeneous model, but management costs are significantly higher than under optimal heterogeneous management, driven by inefficient allocations within a few specific counties.

Sun et al. [2019] consider British Columbia's spongy moth eradication program, which is a collaborative effort between the federal and provincial governments. Part of the analysis involves the assumption that other jurisdictions will impose restrictions on BC timber products to prevent spongy moth importation. The authors focus on European spongy moth and ignore Asian spongy moth, which may imply underestimated co-benefits.

Starting in 1999, the Canadian Food Inspection Agency switched from an eradication approach to a slow-the-spread approach in Eastern Canada, with certain areas being designated as restricted. Cars and trucks from Eastern Canada frequently bring spongy moth into BC, ei-

ther through firewood transport or directly on vehicles. Border quarantine between Canadian provinces is impossible since there are no checkpoints.

BC's program involves monitoring, detection and eradication using Btk sprays. Total spray costs were CAD $5.3 million from 2000 to 2015, and monitoring and detection costs were CAD $8.6 million over the same period. Benefits consist of avoided future quarantine costs and tree and agricultural damage. This report therefore compares the costs and benefits of management, and the authors find a high benefit-cost ratio. SM affect both deciduous and coniferous trees, including fruit trees, which means that they impact orchards, forests and municipal trees. Monitoring occurs through pheromone traps. In southern Vancouver Island and the Lower Mainland, traps are laid in a 1.6 km grid. Outside of this area, they are placed along likely corridors. 6000 such traps are deployed across BC in high risk areas each year. If a low moth density population is detected, the next two years will usually feature a higher density delimitation grid. If the population increases or spreads in subsequent years, an eradication program is launched.

The program has been effective: as of 2019, the peak year for SM in BC was 1999, before the program was fully implemented. The authors compare the costs of the current management program to the expected net economic losses and increased quarantine burden if this program were to be abandoned. A 35 year horizon is used, by which time an infestation would have spread across the entire province. Yearly total program costs run from $500,473 to $2.13 million with a mean of $897,965 from 2000 to 2015. Damages are multifaceted, with quarantine costs, damaged commercial forests, damaged urban trees, agricultural costs and carbon emissions all being included. Different weights and assumptions are combined, resulting in four different scenarios. Three of the scenarios had benefit-cost ratios above one, ranging from 3.4 to 8.3. Only in the case where tree damage is low and no quarantines are required are benefit-cost ratios below

one, at 0.8. This is an unlikely scenario.

The approach used by Tobin [2008] differs from the approach used by Epanchin-Niell et al. [2012] and Sun et al. [2019] because it deals with the frontier of a mature, established SM infestation rather than long-distance spread far from the SM frontier. There is a geographic dimension to this difference; on the East Coast, SM populations are well established and thus can only be eradicated outside of their infested boundary. On the West Coast, eradication programs remain feasible. Eradication significantly reduces damages relative to a controlled and steady infestation, and thus early detection has significant positive benefits. Identifying the most at-risk hot spots allows managers to optimize the deployment of limited sampling resources.

The methods developed for spongy moth outbreak management in western North America can be readily adapted to the study of the spruce budworm early intervention strategy. Spread rates, establishment events, and the penalties of late treatment are all relevant features for a SBW decision support model, and are included in the present chapter's analysis. In particular, establishment rates in SM analysis correspond to the rate of hotspot establishment in SBW analysis, and the penalties of an SM infestation being allowed to mature are widespread, which resembles how missing a budworm hotspot will lead to an outbreak that affects timber values well outside of the initial hotspot.

3.3 Surveillance for a spruce budworm early intervention strategy

The model elaborated in our chapter is based on the early intervention strategy (EIS) used in New Brunswick, Nova Scotia and Newfoundland and Labrador. In this section, we review the sampling methodology used in these provinces for EIS programs, the factors that determine the

likely long-range and short-range spread of spruce budworms, and discuss how these relate to our modeling approach.

3.3.1 Background on current spruce budworm sampling

Spruce budworms go through several instars before they pupate and ultimately reproduce. While different provinces have different approaches to spruce budworm sampling, second instar (L2) sampling is used in Quebec and Canada's Atlantic provinces to determine population inventories for the upcoming year of operations. The second instar occurs in the winter and early spring [Talerico, 1983], so this is when forest managers in these provinces will collect budworm samples [Carleton et al., 2019, Johns et al., 2019].

MacLean et al. [2019] describe a sampling method that is typical of the one used in New Brunswick. The authors sampled one mid-crown branch from each of three balsam fir or spruce trees within a given location. Some samples were collected by partners in the forestry sector. Samples are sent to a lab, and the three-branch average is the amount of budworms for a given survey location.

It is expected that, for any given survey, some spruce budworm larvae will be found on the branches of sampled trees, since spruce budworms are an endemic species in Eastern Canada and thus always found at low levels in the landscape. MacLean et al. [2019] use a threshold of 7 second-instar larvae per branch in order to target treatments in an EIS program. This threshold was based on a survey in southern Quebec from 2012 to 2015, and represents an Allee threshold past which one would expect positive larval population growth rates and eventual outbreaks. This density of budworms is significantly lower than the density at which trees would begin to be

defoliated by budworm feeding.

The sampling procedure for EIS in New Brunswick is explained in Carleton et al. [2019]. Sampling has two phases. The primary sampling phase casts a wide net over the province, although samples are more concentrated in the North. Supplementary sampling will complement the primary phase, based on previous-year populations, observed defoliation, pheromone trap counts and the results of the primary phase. The aim of sampling is to have as complete a picture of the current extent of the spruce budworm population above the Allee threshold density in New Brunswick as possible, with the highest degree of precision in areas that have been identified for treatment.

The alternative active management strategy to EIS is foliage protection, or FP. While the objective of EIS is to find rising budworm population hotspots and treat them before they reach a stage where they damage forests, the objective of an FP program is to mitigate the defoliation damages from, and slow the spread rate of, an active budworm outbreak. EIS and FP cannot be implemented in the same stages of an outbreak. EIS must be implemented prior to the outbreak, while FP must be implemented after the outbreak begins.

While sampling occurs under both EIS and FP, the objective of sampling differs. The choice of EIS or FP is primarily motivated by geography, available resources and the stage of the budworm outbreak in the area under management. New Brunswick, which runs EIS, collects budworm samples over a much larger proportion of its forest than Quebec, which currently only uses an FP strategy in parts of the province under active management. There are a few reasons for this. New Brunswick is smaller than Quebec, has a forest that is more connected by road, has a forestry sector that is of higher relative economic importance, and has a higher percentage of privately-owned forest land. Spruce budworm sampling in Quebec is meant to support foliage

protection efforts, and foliage protection requires less extensive sampling than early intervention. In some regions of Quebec, such as Abitibi-Témiscaminque, very little active spruce budworm management occurs, and as such there are hardly any samples taken. FP programs are run on a very limited scale in these regions, with most outbreaks being allowed to naturally run their course. New Brunswick, on the other hand, samples forests in the north and south of the province, despite budworm only being present at large levels in the North. This is done because the south could still face pressure from northern budworm invasions.

3.3.2 Aerial and satellite surveys

In Canada, each province has a forestry ministry, and these ministries will fly aerial surveys to inventory their forests and assess their health. These flights are generally funded by a different budget than those used for forest protection programs, as they have multiple purposes outside of insect management. These flights have traditionally been used to detect defoliation from budworms, and they remain the primary method through which defoliation maps are produced [Rahimzadeh-Bajgiran et al., 2018]. In these defoliation maps, blocks of visible defoliation will be classified according to severity [MFFP, 2017]. For example, Quebec will classify defoliation into three categories: light (1%-35% defoliated), moderate (36%-70% defoliated) or severe (71%-100% defoliated) [SOPFIM, 2022].

Recent advances in satellite technology have meant that defoliation is now also continuously detected via satellite imaging[3] [Rahimzadeh-Bajgiran et al., 2018]. Defoliation only becomes visible from a satellite or plane once it has become ubiquitous on a tree and has reduced

[3]Different provinces use different satellites to assess defoliation. New Brunswick uses Sentinel-2 [Bhattarai et al., 2021] whereas Quebec uses Landsat [MRNF, 2023].

its photosynthetic capacity. While satellite detection used to use a binary defoliated/healthy classification, recent advances have made it possible to classify satellite imagery into the same defoliation classes that are used in aerial surveys [Donovan et al., 2021]. Regardless of the method used, a significant amount of foliage must be lost before aerial or satellite surveys can detect and classify defoliation. As such, it is reasonable to assume that by the time aerial detection occurs, an EIS program will no longer be feasible. The precise threshold of defoliation for which EIS cannot successfully reduce the budworm population to an endemic level is uncertain, but appears to be at around 28% defoliation [Johns et al., 2019]. This is considered a light level of defoliation by both Quebec and New Brunswick, and a foliage protection program would still be able to reduce the damages caused by budworms at such a level.

3.3.3 Hot spots, establishment and long-distance spruce budworm spread

While most of the models described in section 3.2 focused on detecting the introduction of a nonnative species to a location, spruce budworm management will aim to identify locations on the landscape where the endemic population is entering an outbreak condition. More specifically, with spruce budworms, under the double-equilibrium theory, the corollary to an establishment event is an in-migration of moths from other affected regions that cause local populations to increase in density and eventually result in expanding areas of defoliation. Based on prior work on invasive species surveillance, as described above, optimal targeting and investment levels for EIS surveys are expected to depend on both the frequency and location of potential new outbreaks, and on how such an outbreak (which is to say a high local population level) expands locally once it begins. To estimate where outbreaks might start, we must understand the factors

that attract moths to land and breed in a stand. When a given stand attracts a sufficient amount of moths, it will exceed the Allee threshold and become an outbreak hot spot.

The early dynamics of spruce budworms are not widely understood, and this is especially true for the origin points of spruce budworm outbreaks, which the term hot spot describes in our context. The apparent existence of hot spots was noted by Candau et al. [1998] and further explored in Candau and Fleming [2005]. These authors found that certain factors such as seasonal extremes and the abundance of susceptible foliage favor the establishment of a hot spot.

Bouchard and Auger [2014] explicitly seek to explain the occurrence of outbreaks, with a focus on finding hot spots. The authors study the early phase of an outbreak in Quebec (2002-2011). Nine epicenters are defined, each 75 km from one another. To predict the occurrence of an outbreak epicenter, the authors look at stand composition, age class and landscape features. The two most important predictors of a hot spot are elevation (negatively correlated with probability of defoliation) and balsam fir abundance (positively correlated with probability of defoliation). Spatial correlation can be observed up to 800 km, at a declining rate, after which spatial correlation is essentially null. Defoliation persists within cells, so modeling outbreaks as spreading from hot spots represents a reasonable assumption.

Chen et al. [2021] also simulate long-distance spread across a landscape. Using data collected from 1975 to 1985 over the totality of Maine, the authors develop a spatiotemporal continuous-time model that predicts defoliation across a landscape. Wind dispersal is what sustains outbreaks over time, and outbreaks become ubiquitous after three years. The authors find that July wind velocity and direction in the previous year provide a good predictor of spread from defoliated regions to new hosts, along with temperature, tree mix, and elevation. The model is more sensitive to changes in wind velocity than to changes in wind direction. The authors note

that an infestation in western Quebec that progressed against the direction of the prevailing wind occurred in a forest that was surrounded on its downwind side by hardwood trees, and that spread upwind was slower than in other similar outbreaks. The authors also argue that differences in elevation matter more than elevation itself. Moths taking off from lowlands are likely to be intercepted by higher ground, whereas moths taking off from high ground will fly higher from the onset. While the Chen et al. model is too complex for our purposes, its findings help guide our thinking when parameterizing the outbreak likelihood $e_j(t)$, described in equation (3.1).

In our model, we draw on the findings from Bouchard and Auger [2014] and Chen et al. [2021] to predict the locations of future hotspots by developing a model of relative risk based on elevation, where the risk of an outbreak is at its lowest in the most elevated part of the landscape and at its highest in the least elevated part of the landscape. Our model averages elevation across the individual zones of the landscape, and thus cannot capture local variations in elevation within a zone.

3.3.4 Short-distance spruce budworm spread

Candau et al. [1998] noted that the hot spots they observed were surrounded by radial gradients of decreasing defoliation frequencies, and this was equally noted in Bouchard and Auger [2014] and Chen et al. [2021]. Defoliation will drive budworms to seek new hosts in their immediate vicinity, and they will switch from balsam firs to white spruce as they exhaust local supplies of balsam fir [Greenbank, 1963].

Using the transition equations described in Ludwig et al. [1978][4], Kabir [2021] determined

[4]This paper, which is described in Chapters 1 and 2 of this dissertation, was the first to propose a mathematical model for budworms, tree energy reserves, and tree biomasses using continuous time transition equations.

that a travelling wave solution best models short-distance spruce budworm spread. On a uniform square landscape, this means that spread will be radial from the initial infestation point. The outbreak will quickly converge to a circular shape, even if the initial shape of the infested area is not circular, and this outbreak will eventually fill the entire landscape.

While the literature on hot spot establishment is sparse, the literature on short-distance spread patterns is practically non-existent, with Kabir being the only paper we found that focuses exclusively on short distance spread from an outbreak. Fortunately, defoliation data from the SOPFIM [2021], Quebec's insect management corporation, can be used to calibrate a spread model. This is described in sub-subsection 3.5.4.4.

3.3.5 Treatment under EIS

Treatment under an EIS program is conceptually simple. Liu et al. [2019] explain the rule that a treatment program will employ under an EIS program. Samples are collected as described above, and a positive detection will trigger a treatment block. If a density of less than 6 L2/branch is detected, no sprays occur. If density is between 7 and 20 L2/branch, a single spray is administered. If more than 20 L2/branch are detected, then two sprays are administered. Given that the treatment program for EIS depends on a simple decision rule, we assume that treatment under EIS is automatically triggered, rather than a choice variable.

Carleton et al. [2019] discuss post-sampling operations for EIS. These have three phases: risk assessment, treatment planning, and block planning. Risk assessment combines the results of the L2 survey with the New Brunswick forest inventory. Stand susceptibility is higher when the combined spruce and balsam fir percentage is higher. Susceptible stands in and around areas with

high or rising L2 levels are then prioritized for treatment. Using prioritized treatment areas as inputs, the treatment planning phase will use a model developed by FORUS Research to optimize treatment patterns[5].

Each detected hot spot results in a treatment block around the hot spot. We do not directly incorporate all of the complexities of EIS spray treatment into our model; the assumptions and simplifications we use are outlined in subsection 3.4.5.

3.4 Conceptual framework of the model

This section outlines the theory underlying our model. It proceeds as follows. First, we review the CESAT model developed by Epanchin-Niell [2020], which we adapt to a new model which represents the particularities of SBW management. We then describe the features of the new model, including the landscape, the spread of the budworm and the budget and decisions available to the planner. The mathematical formulation of our model is presented in section 3.5.

Our model focuses on optimal survey planning. We take as given that treatment blocks are optimized. This is appropriate given the nature of EIS operations, wherein all surveyed blocks that are flagged as being above acceptable threshold levels will be included in scheduled treatment blocks. The conceptual framework therefore assumes that treatment is a response rather than a choice variable.

Subsection 3.4.6 provides a simple graphical description of how the model works. It shows how propagules establish themselves in the landscape to become outbreaks and how surveys can

[5]In addition to prioritized blocks, parameters for treatment planning involve flight direction, turns, fuel burn, product deposition and treatment budget. Block planning is the last step before treatment flights. It determines whether Btk or tebufenozide should be used, as well as how setbacks such as opt-outs, settlements and waterways could impact optimal treatment blocks. These setbacks will be respected by the aircraft spray system.

then find these outbreaks.

3.4.1 Modeling approach: CESAT

The CESAT model outlined in Epanchin-Niell [2020] provides a good starting point for our work. The CESAT, or Cost-efficient Surveillance Allocation Tool, is a bioeconomic model that aims to optimize surveillance investments in order to minimize total surveillance, pest control and pest damage costs from potential introductions or outbreaks of pests across a landscape. The two questions to be answered when allocating resources are "where" and "how many" surveys or samples to deploy across the landscape in order to detect new outbreaks earlier. The value from earlier detection arises from being able to control the pest when it is less expensive, causes fewer damages, and can be more feasibly eradicated. We need to determine where survey resources should be deployed, and we need to determine how many surveys should be deployed to these locations to minimize long-term pest damage and management costs.

Under CESAT, and similar to Epanchin-Niell et al. [2014, 2012], pests are assumed to have an annual probability of establishment within a given location, and grow radially until detected and treated. Treatment and damage costs are increasing with time following establishment (i.e. increasing with the size of the incursion), as is detectability. Detection happens either through formal surveys or through background sources of detection such as citizen science. Establishment and detection are both treated as probabilistic processes, with the model keeping track of expected numbers of outbreaks on the landscape and detected outbreaks over time. An age class model is used to describe transitions in population ages or sizes and between undetected, detected but untreated, and quarantined populations. Quarantined populations are assumed to grow at a

slower rate than untreated populations due to treatment. Populations that are eradicated following detection are removed from the landscape.

In the baseline CESAT model, survey costs are assumed linear and increasing in sample density. Treatment, damage and eradication costs are assumed to depend on the pest outbreak size at detection. Detection probability depends on the density of surveys at a site, sensitivity of the sampling tool, and the size of an outbreak in each time period, such that detection depends on the both probability of a sample intersecting the outbreak and the sensitivity of the sampling method. Combining these features, total expected control and damage costs are convex and decreasing in trap density, because sampling increases the likelihood of detecting populations when they are less costly to manage.

Equating the marginal costs of surveys and the marginal benefits of surveys (i.e. marginal avoided control and damage costs) would yield an optimal investment solution in a simple case. In practice, due to the complexity of the model, CESAT identifies the optimal survey allocation using a "greedy" algorithm that allocates surveys iteratively across sites based on the additional net benefits of each survey in terms of reduced damage and management costs. The model can therefore identify optimal survey allocation with or without a constrained budget.

In the model, sites can vary in terms of damages, probability of passive detection, and pest introduction rate. Pests can vary in terms of survey sensitivity and cost, quarantine efficacy and cost, growth rate, and eradication cost. The model can therefore identify optimal survey allocation with or without a constrained budget. The model optimizes a fixed-time, spatially varying surveillance strategy that is deployed across a specified time horizon. Damages from non-detected or non-eradicated populations can persist beyond the survey time horizon. The CESAT model is implemented in R [R Core Team, 2021], as is our adapted version of the model.

3.4.2 Model application to EIS for SBW

We adapt the model from Epanchin-Niell [2020] to capture the biological and management context for potential EIS sampling for SBW in Quebec. As in prior work, we assume that the objective of the forestry manager is to deploy surveillance resources to jointly minimize management (survey and control) and damage costs from SBW outbreaks.

It is important to note that we use the word "outbreak" in the following section to describe an area where budworm population levels are rising above endemic levels. This should not be confused with the more commonly discussed notion of a spruce budworm outbreak, which will involve massive foliage consumption across a large landscape and which cannot be treated using EIS. We are essentially using the word outbreak to describe the conditions which, left untreated, would inevitably result in a large-scale outbreak across the landscape because the population has increased above the Allee threshold.

We assume that the manager's goal is to determine the locations where surveys should be deployed across the landscape as part of an EIS program to minimize total management (control and survey) costs and damages (to forest value) from SBW. This is accomplished by placing surveys where they will provide the greatest benefit, by enabling early detection and treatment of radially-growing SBW infestations before they reach levels that cause defoliation. If detected before reaching a stage that causes defoliation, we assume that treatments can reduce SBW populations back below the Allee threshold and avoid all defoliation and associated damages. However, once an outbreak exceeds a given size, generally the size when defoliation becomes detectable by ongoing aerial surveys, EIS control efforts are no longer effective, and foliage protection efforts will be implemented instead. Foliage protection reduces defoliation and tree mortality, thereby

limiting damages [Chang et al., 2012a], but does not prevent the spread of the outbreak. Because populations cannot be eliminated once they exceed a threshold size, surveys only provide benefits if detection occurs below that threshold. Thus, similar to Epanchin-Niell et al. [2012], we assume that if a population achieves a given size without detection, a penalty cost is incurred that represents the long-term costs and damages from the outbreak, as moderated by foliage protection efforts.

In our model of optimal surveillance and control, we assume that new outbreaks arise from long-range dispersal (similar to establishment events for nonnative species) that augments local populations to above the Allee threshold, as discussed in subsection 3.4.4. A new outbreak will be detected by EIS surveys if a survey happens to be implemented within the extent of the outbreak area.

3.4.3 Budworm arrival and establishment

Budworms are assumed to always be present at low levels throughout the landscape, forming an important part of the ecosystem. Outbreaks occur when their numbers exceed an Allee threshold [Johns et al., 2019]. Budworm spread occurs when local competition for resources creates pressure on the population, fuelling out-migration. Spread will occur in two ways: locally, over short distances, and in long-distance flights. When budworms migrate to new stands, they mingle with local populations. If the combined local population exceeds the Allee threshold, an outbreak will occur.

Our model considers the source of migration to be from outside the landscape. Propagule (i.e. migrant moth) pressure is thus an external parameter. We assume that invasion events happen

at a set rate, with the rate being allowed to vary in sensitivity analysis. Once propagules arrive into a zone, the likelihood of successful establishment will depend on the elevation of the zone. A moth migration that lands at a higher altitude will be less likely to succeed.

3.4.4 Budworm spread across the landscape

If a successful establishment event does occur in a zone, then an infestation of minimum size will be established and grow. Our model assumes that short-distance spread occurs radially. As the size of the infestation increases, surveys will be more likely to find it.

Once the outbreak reaches a certain size, it becomes visible through aerial detection. At this point, we consider it too large for EIS to be successful, and that it will be instantly detected. Crossing this threshold will force the manager to switch to a foliage protection program. These consequences are discussed below in subsection 3.4.5.

3.4.5 Surveillance, treatment and penalties

Our model defines surveys as detection surveys, and determines the annual deployment of these surveys on our landscape. While delimiting surveys are a feature of EIS [Johns et al., 2019], we consider this second wave of sampling to be included in post-detection management costs and thus do not model it. Our model functions with and without a budget. The budget, if used, applies solely to surveys. Treatment decisions are assumed to be unconstrained by cost. The cost of surveys is uniform for all sampling sites. Only one sampling method is used, and it is assumed to be equally effective across the landscape.

The planner selects how many sampling points to deply in each region of the landscape.

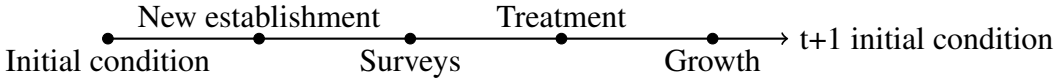
If at least one sample intersects with an infestation, then the EIS treatment program will be triggered.

Treatment is thus an automatic feature of the model rather than a choice variable. Each positively identified infestation that is below the visibility threshold will be treated in the same way, at the same cost and over the same area, whether the infestation is a year old or five years old. The effect will be the same: we assume that treatment is effective and will thus prevent all damages from an undetected outbreak as long as the infestation is found before it becomes visible through aerial detection. There is a penalty for not finding an outbreak before it crosses the aerial detection threshold. This penalty consists of the combined present value of the yearly costs of a foliage protection program and the damages to timber revenue that cannot be prevented through foliage protection. As discussed in subsection 3.5.4.6, we quantify these costs by adapting the method elaborated by Chang et al. [2012a].

3.4.6 A graphical description of the model

The figures in this subsection were created using the TikZ package for LaTeX [Tantau, 2013].

The timeline of events within a period t is shown below:

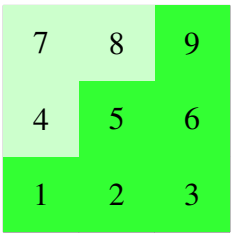


The initial condition represents the state of existing budworm outbreaks at the onset of time t. These are supplemented by additional establishments. Surveys will be deployed on the landscape, and treatments will then target identified outbreaks. Remaining undetected outbreaks will finally grow, which will result in the initial conditions in the next period.

The figures below are a representation of a potential realization of our model, rather than a

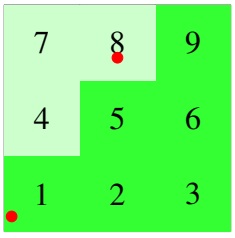
direct description of how our empirical model operates.

Let us consider a single landscape with $J = 9$ equally-sized zones. As a simplifying assumption, let us assume that these are distributed as a square.



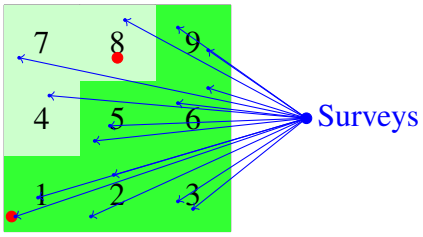
Dark green squares have a high outbreak likelihood. Light green squares are low value and at low outbreak likelihood. We expect that, on average every year, there will be propagule pressure resulting in three expected outbreaks on the landscape ($\sum_{j=1}^{9} e_j(t) = 3$). If we assume that stands with high likelihood are twice as likely to be affected by outbreaks as low likelihood stands, then this means that $e_j^H(t) = \frac{2}{5}$ and $e_j^L(t) = \frac{1}{5}$, although the precise locations where propagules land are unknown.

Suppose that, in period $t = 1$, the realization leads to two successful establishments on our landscape, in zones 1 and 8. On the diagram below, established infestations are shown as red dots.



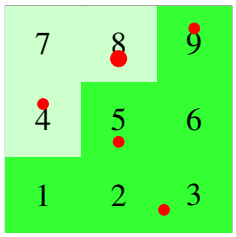
The budget allows for fifteen surveys a year within our landscape. Optimal survey deployment strategies will depend both on outbreak likelihood and on the timber value at risk from a successful outbreak establishment. For illustrative purposes, let us consider a scenario where

the identified optimal sampling strategy (i.e. the strategy that minimizes the expected costs and damages from SBW) deploys one survey to each low-risk zone and two surveys to each high-risk zone. This is illustrated by the blue arrows in the diagram below. If the survey (arrowhead) intersects an outbreak (red dot), the outbreak is detected and will be eradicated with probability 1.

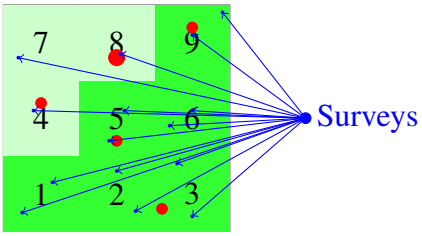


In this example realization, a survey intersects the infestation at j = 1, so that the outbreak is detected and eradicated, incurring that control cost. The infestation at 8 will continue to grow, as the survey sent into zone 8 does not find it.

In the next year ($t = 2$), there are four successful establishment events on the landscape, at $j = 3, 4, 5$ and 9. The outbreak in zone $j = 8$ will have grown from the last period, and is thus larger than the four new infestations.



The survey budget allows for fifteen surveys again. Again, two surveys are sent into each high-risk zone, and one survey is sent into each low-risk zone. The locations within zones to which surveys are sent will be different.



The existing outbreak at $j = 8$ is found and eradicated at the same cost as for the infestation at $j = 1$ last period. The new outbreaks at $j = 4$, $j = 5$ and $j = 9$ are found and eradicated. The outbreak at $j = 3$ will continue to grow until it is detected by a sample in a future period or until it reaches a threshold size where it is detected by aerial survey. If the outbreak at $j = 3$ reaches the size where it is detected by aerial survey, eradication will not be feasible, the manager will instead seek to minimize damages through foliage protection, and those associated costs and damages will be incurred.

3.5 Mathematical specification

In this section, we provide a mathematical specification for the conceptual model described above. Subsection 3.5.6 provides tables that summarize all variables and parameters described in this section.

We employ a fixed time horizon, T, which reflects the approach used in Chang et al. [2012a] and Liu et al. [2019]. The basis of our model is an age-class model, which we first describe for a single zone. We then show how it would be specified for multiple zones, which will correspond to the empirical implementation described in sections 3.6 and 3.7.

3.5.1 The age-class model

Initially, we specify the model formally for a single site of area M. Assume an annual likelihood of a new outbreak starting equal to probability $e(t)$. Following the start of an outbreak, the population grows and spreads across the landscape according to an underlying growth function, such that in the absence of control efforts the population occupies an area $A(a)$, dependent on its age a. In each time period, the population may be detected by survey efforts or not. If detected prior to reaching a threshold size[6] A_θ, the outbreak is suppressed back below outbreak levels and eliminated. However, if the outbreak reaches size A_θ without being detected, we assume that it is detected through aerial surveys and managed via foliage protection, incurring a net present value damage cost C_d.

We model population dynamics using an age-class model, in which we define a set of population age classes $a \in \{1, 2, \ldots, a_\theta\}$ and $x^a(t)$ is the expected probability of an undetected outbreak of age a being present at the focal site at time t. For a population of age $a = 1$, this equals the probability of a new outbreak introduction $e(t)$. Any existing outbreaks transition to age class $a+1$ in the following time period if undetected. Thus, an age class model for undetected populations can be specified as:

$$x^a(t+1) = \begin{cases} e(t) & \text{for } a = 1 \\ x^{a-1}(t)(1 - p_{det}(a-1, S)) & \text{for } a = 2, \ldots, a_\theta \end{cases} \tag{3.1}$$

where $p_{det}(a, S)$ is the probability of detecting an outbreak of age a given an investment S

[6] We use θ in this context as an abbreviation for the word "threshold".

in EIS detection surveys[7]. Following detection, a population of age $< a_\theta$ will be eliminated for a fixed treatment cost[8] C_τ. The expected number of detected outbreaks y_{det} in a given time period t is:

$$y_{det}(t) = \sum_{a=1}^{a_\theta - 1} x^a(t)(p_{det}(a-1, S)) \tag{3.2}$$

All populations that reach size A_θ undetected incur fixed cost C_d and are removed from the model.

3.5.2 Detection probability

The probability $p_{det}(a, S)$ that a population is detected in a given time period increases with survey investment S at the site, the size of the population $A(a)$ (measured as areal extent) and survey sensitivity y_s, which is defined as the likelihood that a survey will detect the outbreak if the survey is placed within the outbreak's areal extent. We also assume that survey placement is random with respect to the location of outbreaks, through one or both being random in space within the susceptible area of a site. The probability that a given population is detected by a survey (i.e., that at least one deployed survey successfully detects the outbreak) can therefore be estimated as a binomial distribution, where the number of trials equals the number of deployed surveys S, and the probability of success for each trial equals the survey sensitivity (y_s) times the probability of the survey intersecting the outbreak (the area of the population divided by the area of the focal site $\frac{A(a)}{M}$, or 1 if the outbreak is larger than the site). Therefore, the probability

[7] S is the number of surveys per year.

[8] Under EIS, the cost of control is fixed: if a population is detected before it exceeds the FP threshold, then it can be treated at a fixed cost. A radius of approximately one kilometer around the perceived epicenter is treated, consistent with literature on EIS implementation [Liu et al., 2019]. This will be large enough to reduce an early infestation to an endemic level.

$p_{det}(a, S)$ that an outbreak present at a site is detected by a survey in a single time period is given by:

$$p_{det}(a, S) = 1 - (1 - y_s \frac{A(a)}{M})^S \tag{3.3}$$

The model assumes that the total costs of surveillance at a site depend linearly on the number of surveys deployed at the site, with the cost per survey equalling C_s and total monetary annual survey investment at the site indicated by $C_s S$.

3.5.3 Net present value of expected costs and damages

The net present value (NPV) of expected costs and damages resulting from invasion establishment, detection, and management can be determined dependent on the level of investment in pest detection surveys. We consider application of a constant surveillance strategy (i.e., a constant investment level) over a fixed time horizon T and evaluate the total net present value of costs and damages associated with that strategy, including damages from all outbreaks that establish during the course of the surveillance program and those that were present on the landscape (but not yet detected) at the start of the program.

We assume that, prior to the start of the surveillance program, populations were arriving at a background rate $e(t)$ and probability of detection $p_{det}(a, 0)$. Thus, the expected number of undetected outbreaks present at the site at the start of the program ($t = 1$) can be calculated by recursively solving the following equations beginning at $t = -T_{past}$ (where T_{past} is the oldest population considered for detection at the start of the surveillance program) and iterating until reaching $t = 1$:

$$x^a(t+1) = \begin{cases} e(t) & \text{for } a = 1 \\ x^{a-1}(t)(1 - p_{det}(a-1, 0)) & \text{for } a = 2, \ldots, a_\theta \end{cases} \tag{3.4}$$

Recognizing that $x^{a(t)}$ is a function of S, we can rewrite it as $x^a(t, S)$. We can then calculate the net present value of total expected costs and damages with discount rate δ of investing S in pest detection surveys for T consecutive time periods (excluding surveillance costs) as:

$$TC^D(S) = \sum_{t=1}^{T} (y_{det}(t, S)C_\tau + x^{a_\theta}(t, S)C_d)(1+\delta)^{1-t} + \sum_{t=T+1}^{T+a_\theta} (x^{a_\theta}(t, 0)C_d)(1+\delta)^{1-t} \tag{3.5}$$

The first term represents the net present value of total control costs for outbreaks detected during the survey program, plus the total damage costs from populations that reached the threshold size without detection. The second term sums the damages from outbreaks that are not detected before the end of the survey program.

The total costs of surveys over this time horizon are calculated as:

$$TC^S(S) = \sum_{t=1}^{T} C_s S(1+\delta)^{1-t} \tag{3.6}$$

The objective for a single site is then to solve for the investment level S that minimizes the total expected costs of surveillance, treatment, and damages, which is to say equations (3.5) and (3.6). This optimization can then be applied across all sites.

One also can calculate the expected net benefits of any given investment level as the re-

duction in expected costs and damages with surveillance investment S relative to those without investment:

$$NB(S) = TC^D(S = 0) - TC^D(S) - TC^S(S) \tag{3.7}$$

3.5.4 Model with multiple zones

Having established the age-class model on a single zone landscape, we specify it across a landscape with multiple zones.

Our landscape is subdivided into zones of susceptible forested area[9] M_j where $j \in \{1, \ldots, J\}$ is a unique zone index for each zone. The parameterization of zones is discussed in subsection 3.6.3. Hectares are the unit for M_j. We use the zone index j to define all parameters and attributes unique to each individual zone M_j.

Thus, the variables and functions described in our age-class model can be given spatial subscripts j as appropriate. Certain parameters are spatially invariant. We start by describing these parameters.

3.5.4.1 Spatially invariant parameters

There are seven parameters that are spatially invariant and thus identical between the model described in subsection 3.5.1 and the model with multiple zones.

The threshold for aerial detection is assumed to be equal across the landscape. Thus, there are no spatial subscripts on A_θ or a_θ. The time to reach this threshold is identical across the

[9] Other features such as cities and bodies of water are excluded from the calculation of M_j. This becomes relevant during the calibration of M_j in subsection 3.6.3.

landscape.

The survey and treatment cost parameters C_s and C_τ are identical across the landscape. The survey sensitivity y_s is also uniform.

Finally, there is a single time horizon T and a single discount rate δ for the entire landscape.

3.5.4.2 The yearly budget

Our model features an optional[10] yearly surveillance budget B, which is allocated spatially across the landscape. If survey costs are identical across the landscape and given by C_s, then the yearly budget is:

$$B \geq \sum_{j=1}^{J} C_s S_j \tag{3.8}$$

If there is a survey budget, it will constrain yearly survey operations. Without a yearly survey budget, the number of surveys will be determined by net benefit maximization. The number of surveys per site per year is S_j. These are time invariant: if three surveys are placed in year $t = 1$, three surveys will be placed in year $t = 2$.

3.5.4.3 Outbreak risk

The background outbreak risk varies spatially, such that we can write it as $e_j(t)$. The components of this risk are the landscape-wide propagule pressure, the risk rating of zone j, and the size M_j of j.

[10]The simulation model can function without a surveillance budget, and is thus an option to be chosen when running the model.

3.5.4.4 Local spread and presence on a multi-zone landscape

The total area of infestations at j is given by $A(a_j)$, and the expected probability of an undetected infestation is given by $x_j^a(t)$. Areal spread is modeled using a quadratic equation. Writing the radius of $A(a_j)$ as $r(a_j)$, the growth rate of $A(a_j)$ is given by:

$$r(a_j + 1) - r(a_j) = \alpha_1 r(a_j) - \alpha_2 r(a_j)^2 \tag{3.9}$$

Equation (3.9) therefore describes the functional form of the age-class model for $A(a_j)$.

3.5.4.5 Finding outbreaks on a multi-zone landscape

The probability of detection in j is given by:

$$p_{det}(a_j, S_j) = 1 - (1 - y_s \frac{A(a_j)}{M_j})^{S_j} \tag{3.10}$$

The expected number of detected outbreaks is given by:

$$y_{j,det}(t) = \sum_{a=1}^{a_\theta - 1} x_j^a(t)(p_{det}(a_j - 1, S_j)) \tag{3.11}$$

3.5.4.6 Forest damages

Damages vary according to location, with C_{dj} being the net period t value of damages from an outbreak in zone j. This rating will be unique for each zone j, and it will be incurred at the time period t when the outbreak exceeds the threshold.

Damages occur over an outbreak horizon, and this horizon is the same regardless of how

far into the future C_{dj} is incurred. It will not be interrupted by reaching the end of the planning horizon T.

3.5.5 Objective function with and without a constraint

The net present value of treatment costs and damages in zone j are given below:

$$TC^D(S_j) = \sum_{t=1}^{T}(y_{j,det}(t,S_j)C_\tau + x_j^{a_\theta}(t,S_j)C_{dj})(1+\delta)^{1-t} + \sum_{t=T+1}^{T+a_\theta}(x_j^{a_\theta}(t,0)C_{dj})(1+\delta)^{1-t} \quad (3.12)$$

The net present value of survey costs is given by:

$$TC^S(S_j) = \sum_{t=1}^{T} C_s S_j (1+\delta)^{1-t} \quad (3.13)$$

The risk-neutral objective function is given by:

$$\min_{S_j} \sum_{j=1}^{J}[TC^D(S_j) + TC^S(S_j)] \quad (3.14)$$

subject to the constraint, restated from equation (3.8) as:

$$B \geq \sum_{j=1}^{J} C_s S_j$$

Thus, the manager minimizes program and damage costs by using survey resources, subject to the survey budget if applicable. If $B > \sum_{j=1}^{J} C_s S_j^*$ where $\sum_{j=1}^{J} S_j^*$ is the set of survey values

that minimizes equation (3.14), then the budget will not constrain survey allocation.

In each zone, the net benefit function is given by:

$$NB(S_j) = TC^D(S_j = 0) - TC^D(S_j) - TC^S(S_j)$$

The sum of net benefits is therefore given by

$$\sum_{j=1}^{J} NB(S_j) = \sum_{j=1}^{J} TC^D(S_j = 0) - TC^D(S_j) - TC^S(S_j) \tag{3.15}$$

Since $\sum_{j=1}^{J} TC^D(S_j = 0)$ will be constant for each j, minimizing equation (3.14) is the same as maximizing equation (3.15).

3.5.6 Summary of model parameters and primitives

The following tables summarize the model parameters that are used as model inputs and provide their location in the text.

Table 3.1: Model primitives

Symbol	Name	Description	Location in text	Value/units
T	Timeline.	Number of years over which our program is run.	Named in section 3.4 and established in subsection 3.5.4.6.	Set at thirty years, following Chang et al. [2012a].
δ	Discount rate.	Used to calculate the net present value of cost parameters	See subsection 3.6.6.	Baseline is 5%.
B	Survey program budget.	Surveys only, all other activities are excluded. The sum of C_{sj} cannot exceed B.	See equation (3.8)	$CAD total. Budget will vary as part of sensitivity analysis, and is optional.
J	Number of zones.	Each $j \in J$ is an indexed zone within our landscape.	Described in subsection 3.6.3. See Figure 3.2 for the map of zones in our landscape.	The index in our model is IEQM block index (e.g. 22A) combined with BMMB zone index (e.g. 187).
M_j	Size of j	Susceptible forest area within a zone j.	Established in section 3.5.4	Measured in hectares.
A_θ	Threshold area, at age class a_θ.	Area for which automatic aerial detection occurs and foliage protection is triggered.	Established in section 3.5.1	Measured in hectares.

Table 3.2: Cost and damage parameters

Symbol	Name	Description	Location in text	Value/units
C_s	Survey costs.	Constant across landscape.	See equation (3.8)	$\sim$ \$75 CAD per sampling location.
C_τ	Spray costs.	Cost of eliminating an outbreak if it is detected when small enough for EIS to be effective. We consider these costs exogenous and fixed in structure.	See equation (3.5)	Range of \$40-\$115 CAD per hectare, 320 hectares, total of \$12800-\$36800 CAD.
C_{dj}	Damages to forests due to an infestation.	Described in detail in subsection 3.5.4.6.	See subsection 3.5.4.6	Measured in present value CAD (30 year horizon). Can also be measured as CAD/ha.

Table 3.3: Spread variables and parameters

Symbol	Name	Description	Location in text	Value/units
a_j	Age class of infestations at j.	Measure of the maturity of an outbreak.	See subsection 3.5.1	Integer, $a = 1, \ldots a_\theta$.
$A(a_j)$	Areal extent of infestations at j.	Increasing in a_j, with spread patterns not depending on landscape features.	See subsection 3.5.1	Measured in hectares.
$e_j(t)$	Outbreak likelihood at j.	This is the likelihood of an outbreak occurring at j in each t.	See subsection 3.5.4.3.	Can be expressed as a scalar or as a relative rating between 0 and 1.
$x_j^a(t)$	Probability of an undetected outbreak at j at time t.	Like a_j, $x_j^a(t)$ is an age-class model.	See equation (3.4).	Equal to $e_j(t-1)$ if $a_j = 1$.

Table 3.4: Survey variables and parameters

Symbol	Name of variable	Description	Location in chapter	Value/units
S_j	Surveys sent to zones j.	If $s_j = 0$, no surveys are sent to j.	See subsection 3.5.4.2.	Integer (0,1,2,...), determines survey intensity.
y_s	Survey sensitivity.	Success rate of surveys. Constant across landscape.	See subsection 3.5.2.	Between 0 and 1.
$p_{det}(a_j, S_j)$	Probability of detection in j.	Increasing in S_j, decreasing in M_j.	See subsection 3.5.4.5.	Between 0 and 1.
$y_{j,det}(t)$	Expected number of detected outbreaks.	Increasing in $p_{det}(a_j, S_j)$ and in $x_j^a(t)$.	See subsection 3.5.4.5.	$y_{j,det}(t) \in \mathbb{R}_+$

3.6 Empirical strategy

We built an optimization model for spruce budworm management based on the model outlined in sections 3.4 and 3.5. The parameter values for this model were obtained from literature, empirical sources, and conversations with Canadian forest managers. In this section, we discuss how these parameters were sourced.

3.6.1 Sampling spruce budworms

Sampling costs vary based on location, population density, and accessibility, but can roughly be approximated at an average of $75 CAD per site[11]. We use this number as the baseline mean survey cost, and can vary it by a certain amount when doing multi-site analysis. Sensitivity anal-

[11]These numbers were shared with me by Drew Carleton, a program manager working in New Brunswick. Numbers in Quebec may differ but would likely be similar.

ysis on this parameter further allows us to show how monitoring decisions vary when sampling costs vary.

3.6.2 Calibrating treatment

The SOPFIM [2022] provides yearly activity reports that calculates total and average costs for spray blocks in Quebec. There are no fixed components to cost. Spray costs are about $40 CAD per hectare-application, such that a hectare that is sprayed twice will cost $80 CAD. In New Brunswick, the cost of treatment is about $115 CAD per hectare[12]. We start from the assumption that treatment costs do not vary based on location.

We assume that an eradication buffer of 320 hectares is necessary for each spot of treatment decisions, which corresponds roughly to a circle with a radius of 1 km[13]. The cost of an eradication program will thus be between $12,800 and $36,800 per identified treatment location during early intervention.

Our baseline assumption is that the eradication buffer is equal to the size at which automatic (i.e. satellite) detection occurs as well as the maximum size of an outbreak that can be treated using an early intervention strategy.

3.6.3 Defining the landscape

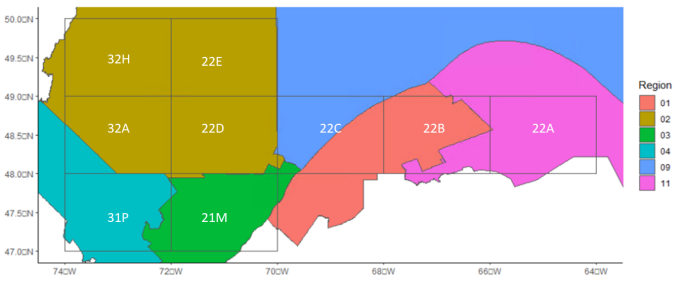
Our landscape combines two data sets: the Inventaire écoforestier du Québec méridional, or IEQM [MFFP, 2017], and the wood value zones of the Bureau de mise en Marché des bois [BMMB, 2022c]. The IEQM contains information on the biomass of forests[14], whereas the

[12] This value was provided by Drew Carleton.
[13] Again, this information was provided by Drew Carleton.
[14] We would like to thank Josée Martel and Ian Paiement for helping us to understand and utilize the IEQM.

BMMB zones will define the value of wood within that forest[15]. By combining the information from these two sources, we can define the average infestation risk for each zone and the value at risk in each zone for any possible infestation.

The IEQM blocks that we used are below:

Figure 3.1: Plot of IEQM blocks used in this chapter

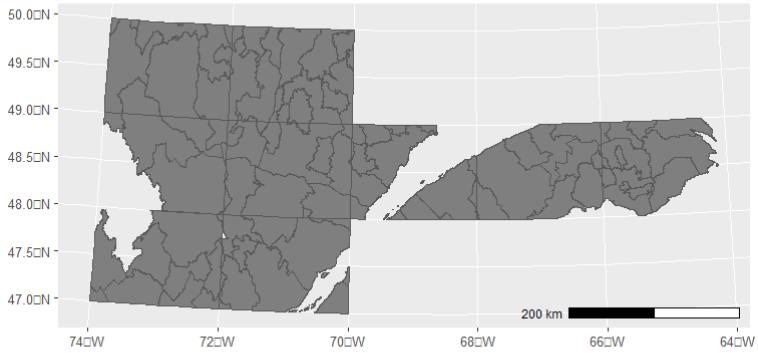


This map will allow us to situate references to blocks. The color-coded regions are Quebec's administrative regions. These regions do not have an impact on forest policy, but help situate the blocks. Block 22A is entirely within the Gaspésie–Îles-de-la-Madeleine region. Block 22B consists of parts of this region and the eastern portions of the Bas-Saint-Laurent. Block 22C is split between the Bas-Saint-Laurent and the Côte-Nord, with its southwestern corner being in the Capitale-Nationale region. Block 21M is nearly entirely within the Capitale-Nationale region. Despite the name, the city of Québec is located south of 21M, and as such 21M is primarily rural and forested. Block 31P contains portions of the Capitale-Nationale region, with the rest being part of the Mauricie region. Blocks 22D, 22E, 32H and 32A represent the Saguenay–Lac-Saint-Jean region, with the southwestern quarter of 32A being part of the Mauricie region.

[15] We would like to thank Hugo Therrien and Patrick Girard for their help in explaining how the BMMB establishes timber value.

The map of the zones in the area of study, generated using the ggplot2 package in R [Wickham, 2016], is below:

Figure 3.2: Plot of zones within blocks



The missing zones in the westernmost part of our area were not included in the IEQM's aerial surveys. There are no missing zones in the east: this gap consists of the St. Lawrence River and Gulf.

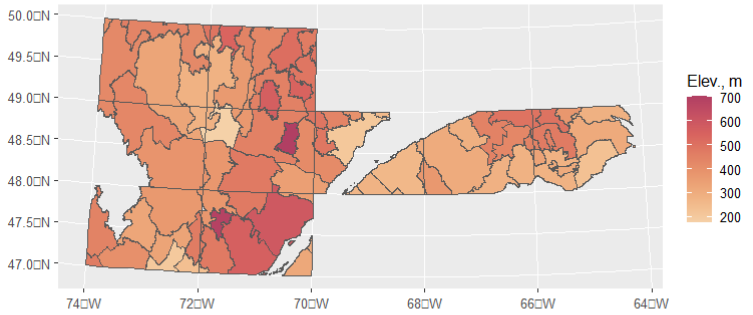
3.6.4 Calibrating infestation establishment and risk

The intrinsic outbreak likelihood depends on the characteristics of the forest. If a stand has a higher risk rating, it will be more likely to be the location of an outbreak epicenter, relative to other surrounding stands. For each of our defined forest areas (which is to say BMMB zones within IEQM blocks), we are able to assign absolute and relative risk ratings. The absolute risk rating is a scalar number, either positive or negative. The relative risk rating is the Z-normalized value of the absolute risk rating.

Bouchard and Auger [2014] note that elevation, fir percentage, hardwood percentage and mesic drainage are determinants of relative outbreak risk. Since we do not have access to mesic drainage and since the Bouchard and Auger model is not perfectly analogous to the one we use, we will use a simplified risk model where elevation is the sole determinant of risk. Risk is relative, and scaled so that all values are between 0 and 1. Elevation is calculated for each BMMB zone as the average of an elevation raster. The highest elevation zone was therefore the lowest risk zone, and the most low-lying zone had the highest risk.

The outbreak likelihood for a given zone is calculated as a linear function of elevation, where the coefficient on elevation is negative. Elevation across the landscape is below:

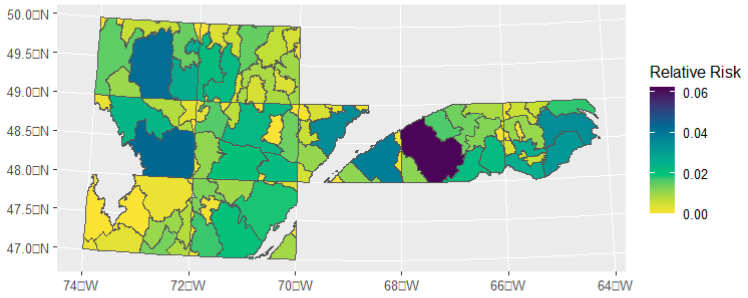
Figure 3.3: Elevation by zone



This elevation will give a likelihood score for each zone. This score can be multiplied by the forested area of each zone to obtain the total zonal outbreak risk factor. We normalize these outbreak risk factors by dividing them by the sum of factors, and this provides us with the likelihood that an outbreak will begin in a particular zone given that a single outbreak occurs

somewhere in the landscape. The outbreak likelihood across the landscape for a single outbreak is below:

Figure 3.4: Relative (normalized) outbreak likelihood by zone



This measure of likelihood will be higher in larger zones, all else equal, but it also corresponds to elevation: low-lying zones consistently have higher risk ratings than similar-sized zones at a higher altitude.

3.6.5 Calibrating local growth

To get parameter values for α_1 and α_2 in equation (3.9), we first observe defoliation data provided by the SOPFIM [2021]. Increasing areas of defoliation across different regions of Quebec are aggregated. This total area is then approximated to a circular shape, and the radius of the resulting circle is then calculated.

We identify five regional outbreaks across Quebec from 1992 to 2021. We calculate the radius of aggregate defoliation in each year as well as the change in radius from one year to the

next. We took care to exclude discontinuous years (for example, an observation in 1992 was dropped because the next year of defoliation was 1999), for a total of five deleted observations. Our sample had 73 degrees of freedom. The minimum radius was 0.48 km, the mean was 38.37 km, and the maximum radius was 158.99 km. We assume that the parameters of defoliation growth are equivalent to the parameters of outbreak growth.

A second-order polynomial regression is fit onto these observations. The range of empirical parameter values is presented in subsection 3.6.5. The linear component of the regression has a positive sign, and is greater in magnitude than the quadratic component. As such, the radius will increase until it reaches an asymptote. Using our parameter values, it takes approximately 7 years for a one-hectare initial infestation to reach an area of 1 square kilometer.

If radius and budworm population density are directly correlated, as is assumed in our model, then the outbreak will increase in intensity as it increases in radius. As such, a larger outbreak would, theoretically, cause more damages over its infested area. Our model uses strict cut-offs depending on whether a stand can be treated proactively or not. Subsection 3.5.4.6 discusses how value and damages are calculated.

Once an infestation successfully establishes itself, it will grow according to equation (3.9). The growth rate of an infestation can be calibrated from defoliation data, which is available in Quebec from the MRNF [2013] for 1992 until the present. Notable defoliation patterns were observed in seven different Quebec administrative regions. The infestation in Gaspésie region adjoins the one in the Bas-Saint-Laurent, and the one in the Saguenay-Lac-Saint-Jean region adjoins the one in the Côte-Nord. We therefore have five regional infestations, which are aggregated to circular areas. By regressing the growth rate on the lagged radius, the following parameter values are observed:

Table 3.5: Results of equation (3.9) regression

Estimator	Estimate	Std. Error	t-value
$\hat{\alpha}_1$	0.4796	0.0554	8.655
$\hat{\alpha}_2$	-3.69×10^{-3}	4.86×10^{-4}	-7.589

This regression has a residual standard error of 7.553 and an adjusted R^2 of 0.5265 on 73 degrees of freedom.

These values are calculated for kilometers of radius. If our minimum area $A_{min} = A(a_j) = 1\ ha = 0.01\ km^2$ for $a_j = 0$, then this implies that $r_{min} = r(a_j) = 0.0564\ km$. We would thus expect $r(a_j) = 0.0834\ km$ for $a_j = 1$ and thus that $A(a_j) = 0.0219\ km^2$, or 2.19 hectares, at $a_j = 1$.

3.6.6 Calibrating value and damages

Literature can provide a starting point for value at risk and damage calibration. Chang et al. [2012a] calculated the damages incurred under moderate and severe outbreaks across the forest of New Brunswick, and Liu et al. [2019] calculated avoided damages from running an early intervention program in New Brunswick. The authors use different time horizons, with Chang et al. using a 30 year horizon and Liu et al. using a 50 year horizon. The 30 year horizon is closer to the one we will consider. Chang et al. determine that an uncontrolled moderate outbreak will lead to a 17% reduction in cumulative harvest, while a severe outbreak will lead to a 24% reduction in cumulative harvest. Damages that occur on trees scheduled for imminent harvest will not lead to output losses, while damages that occur on trees whose harvest will occur in the medium or long term will lead to significant losses of output. An optimal foliage protection strategy will reduce damages to 10% under a moderate scenario and 12% under a severe scenario. In Liu et al. [2019], an early intervention strategy prevents all damages.

Translating these models to our forests will be trickier. Clearly, it is not appropriate to say that all infested areas are instantly lost forever. However, the 24% reduction in harvest value proposed by Chang et al. applies to entire forests. We must pose assumptions about how the value of the infested forest declines.

To calibrate damages, forest value must first be determined. Total forest value is the product of wood price[16], which depends on location and is provided by the BMMB [2022c], and forest inventory, which is provided by the IEQM, an open data product produced and distributed by the MFFP [2017]. The IEQM consists of blocks of forest data that cover the entirety of Quebec's forested land. Information includes stem density, merchantable volume density, stem composition and the like. Combining these data sets allows us to assign a total timber value to each zone in each block and to the block as a whole.

Our model assumes a 30 year outbreak horizon. As a baseline, we set the discount rate $\delta_t = 5\%$. This outbreak proceeds in two stages. For the first 10 years, the outbreak is local. It will grow from an area of 1 hectare to an area of 24.6 square kilometers, which is the area an infestation will occupy after 10 years according to the empirically-calculated parameters of equation (3.9). For these first 10 years, 50% of the lumber value of the infested area is lost[17]. We do not consider the possibility of spread to differently-priced zones. Any spread outside of the zone would have the same lumber price as spread within the zone. This is done for the sake of simplicity, and is reasonable given the difference in size between a zone and a full outbreak.

[16]The Bureau de mise en Marché des bois du Québec assigns forests in the province to a zone that determines the value of timber per cubic meter based on its quality and integrity. For balsam fir, there are three classes of wood. Living boughs and stems are considered lumber-quality and have values that are usually at least $20 CAD per cubic meter. Dead boughs and cuttings are in different classes, but have the same value, which is usually around 33 cents per cubic meter. Thus, losses from dead timber are over 98% for each affected tree.

[17]We assume that 50% of wood value over a 2460 hectare (24.6 km^2) will be lost over the 10 year period, regardless of the size of the zone within which the infestation is found. This allows us to avoid bias towards larger zones.

After 10 years, we assume that a 20 year outbreak occurs (years 11-30) across the entirety of the block within which the infested zone is found[18]. We assume that this outbreak will be managed through foliage protection, which is reasonable given that the area of study is a part of Quebec that already engages in widespread foliage protection programs.

3.6.7 Simulation of surveillance and management

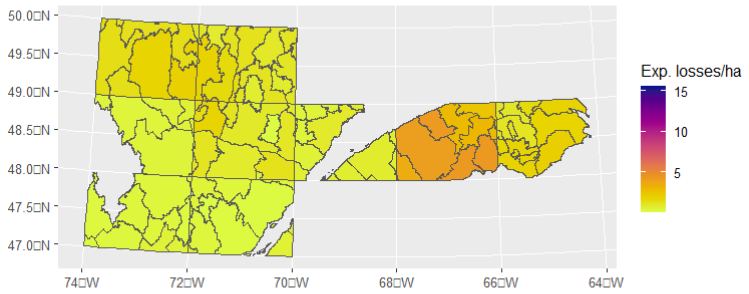
The parameter values derived in this section were used to build a surveillance model that applies the assumptions from section 3.4 and the mathematical specification from section 3.5. The initial landscape is a single forested area where propagule pressure is external and exogenous. Landscape locations are based on the BMMB zones whose parameters are shown in subsection 3.6.6. This model relates to a theoretical outbreak on an undisturbed Quebec landscape. Our aim is to show the cost-effectiveness and feasibility of an EIS program in different parts of Quebec, with necessary caveats based on the difference between management constraints in Quebec and New Brunswick (i.e. a lack of roads that would permit surveys in some forested regions). The surveillance model is implemented in R [R Core Team, 2021].

Maps in this subsection are generated using the ggplot2 package in R [Wickham, 2016].

Our baseline scenario is based on the parameter values presented in this section. Across the entirety of our landscape, the potential losses per hectare from a moderate infestation for each zone under our baseline scenario are mapped below:

[18]For example, let us assume that an outbreak occurs in zone 184 of 22A. Damages will occur within this zone for the first 10 years, and then across the entirety of block 22A for the remaining 20 years.

Figure 3.5: Losses per hectare by block-zone (baseline scenario)



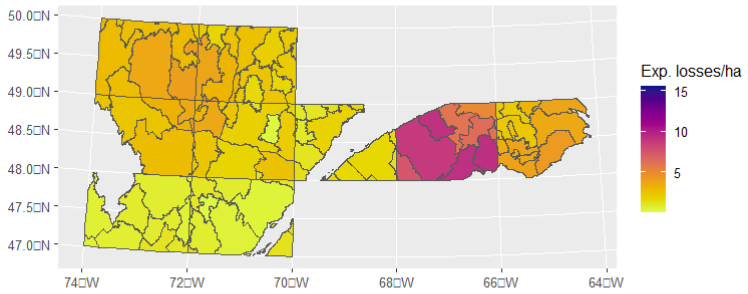
In section 3.7, we demonstrate baseline results with and without survey budgets, as well as sensitivity analysis based on variations of the discount rate and introduction rate. These scenarios are presented below.

Table 3.6: Table of baseline and sensitivity analysis scenarios

Scenario	C_{sj}	$C_{\tau j}$	e_t	δ_t	α_1	α_2
Standard	115	12800	0.1	5%	0.48	-3.69×10^{-3}
Low discount rate	115	12800	0.1	1%	0.48	-3.69×10^{-3}
High intro rate	115	12800	0.33	5%	0.48	-3.69×10^{-3}

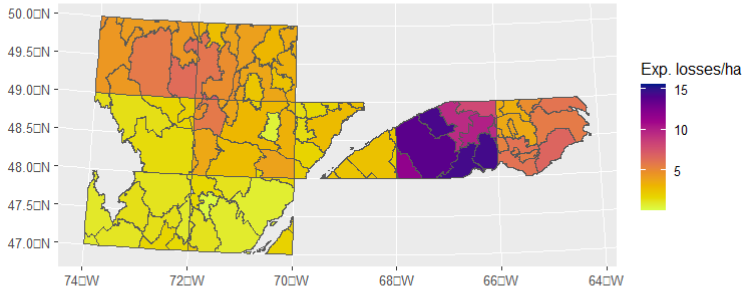
Across the entirety of our landscape, the potential losses per hectare from a moderate infestation for each zone under the low discount rate scenario are mapped below:

Figure 3.6: Losses per hectare by block-zone (1% discount rate)



Under a high introduction rate scenario, the losses per hectare are mapped below:

Figure 3.7: Losses per hectare by block-zone (3 year average introduction rate)



3.7 Results and analysis of results

In the results presented in this section, investments are plotted in terms of $ CAD per zone and surveys per zone. Yearly survey investments and the net present values of total investments, total expected net benefits and total expected remaining outbreak costs are stated on a landscape-wide basis in terms of $ CAD. Total yearly surveys are also stated on a landscape-wide basis, as an integer. The maps in this section are generated using the ggplot2 package in R [Wickham, 2016]. Landscape-wide statistics are summarized in the tables in subsection 3.7.5.

3.7.1 Model results: baseline scenario with an unconstrained budget

Under a baseline scenario with an unconstrained budget, a total of $101,430 is invested across the landscape per year, resulting in 882 total surveys per year on the landscape. The net present value of survey costs is $1,105,449. The remaining expected NPV of the outbreak cost is $4,503,888 across the landscape. If foliage protection were to be employed across the entire landscape instead of EIS, the total expected net present value of damages from an outbreak across our landscape would be $5,875,455. Expected net benefits are calculated according to equation (3.15). The difference between expected NPV damages without surveillance and the sum of NPV survey costs and remaining outbreak damages results in a net present value of total expected net benefits of $266,118.

Survey investments only occur in block 22B of the landscape under our baseline scenario, which explains the relatively low expected net benefits relative to total investments. In other words, foliage protection will be employed across most of the landscape, with the EIS program being limited to a small portion of the landscape adjacent to New Brunswick. Figure 3.8 shows

total investment across the landscape.

Figure 3.8: Total investment by block-zone (baseline scenario)

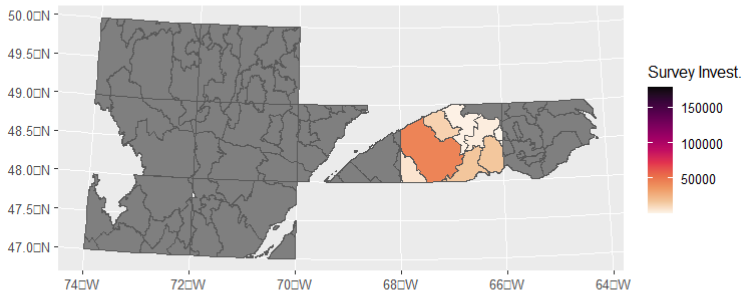
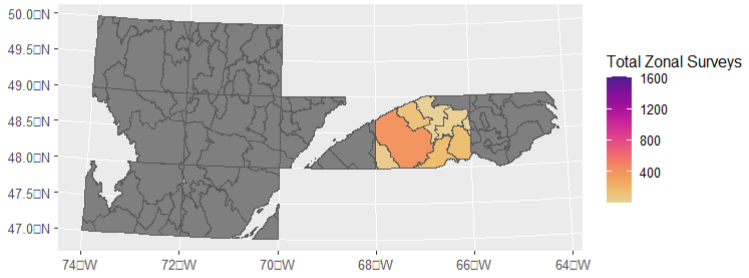


Figure 3.9 shows the number of surveys per block-zone across the landscape.

Figure 3.9: Total surveys by block-zone (baseline scenario)



As all investments are concentrated in block 22B, our next analysis focuses on results within this zone. Chart 3.10 shows the numbered BMMB zones within block 22B. This will help

situate summary statistics. Note that 000 is a code that indicates a body of water and is thus excluded from results.

Figure 3.10: Zones of block 22B

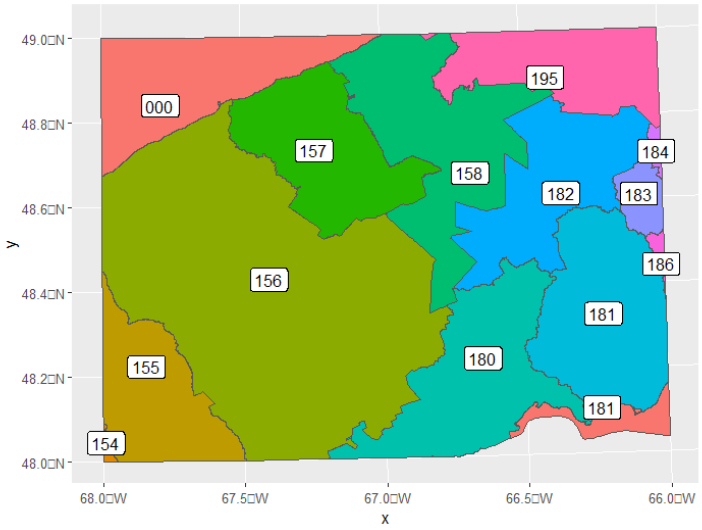
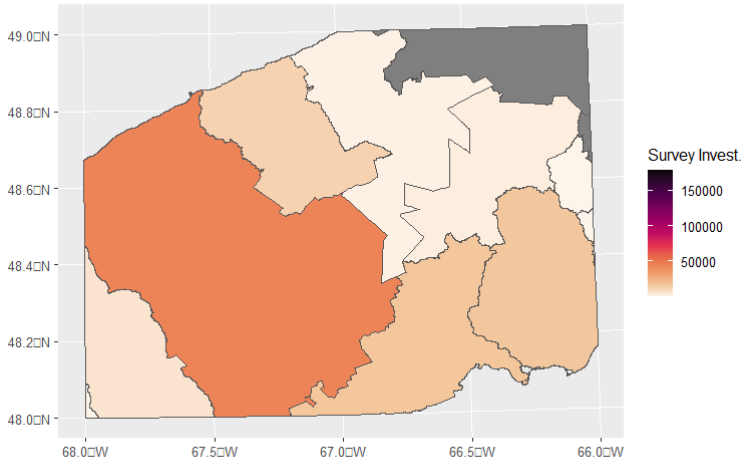


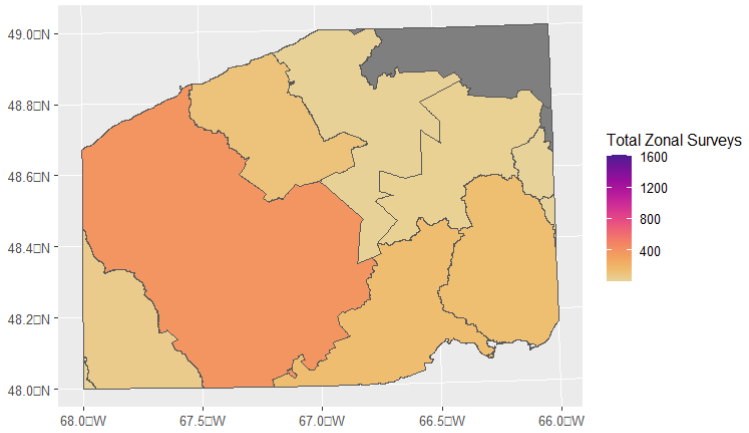
Chart 3.11 shows optimal total survey investment by zone. There are no survey investments in zones 184 or 195. Zones 154 and 183 have the lowest levels of investment, at $230 per year total, while zone 186 has a mere $460 in yearly investments. Zone 156 has the highest level of total investment, with $44,620 in yearly investments. This represents 44% of investments in block 22B and thus in our landscape.

Figure 3.11: Total investment by zone in block 22B (baseline scenario)



The map of total surveys in block 22B are below. A grand total of 882 surveys are deployed across block 22B. Zone 156 has the most surveys with 388, representing a density of 1.02×10^{-3} surveys per hectare. The investments in zones 154 and 183 correspond to 2 surveys per year. On an area-weighted basis, zone 155 has the highest survey density, with 1.14×10^{-3} surveys per hectare. Among zones with investments, zone 158 has the lowest survey density, with only 9.65×10^{-5} surveys per hectare.

Figure 3.12: Total surveys by zone in block 22B (baseline scenario)



Overall, our baseline results indicate that EIS is only beneficial in a small part of Quebec that neighbors New Brunswick. It has positive net benefits, but FP remains dominant outside of this block. These baseline results suggest that EIS should be explored in Quebec, but that running FP across Quebec instead of EIS may be optimal if limited EIS would result additional administrative or operational costs that are not captured by our model. This could be the case if, for example, separate administrative structures would be required for the FP and EIS programs.

3.7.2 Model results: baseline scenario with a constrained budget

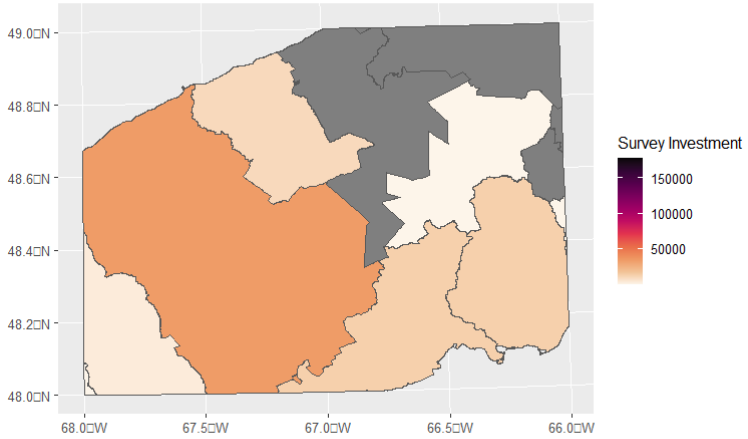
We consider three constrained budgets: a 25% reduction, a 50% reduction, and a 75% reduction. These reductions are relative to the total optimal expenditure, which is $101,430 under our baseline scenario, as described above. Since survey investments only occur in block 22B, we only present results for this block.

Restricting the budget by 25% results in $75,440 in annual investments in our block[19].

[19]Since our results are in bundles of investment, we round down from $0.75 \times 101,430$ to the nearest yearly budget

Figure 3.13 shows the distribution of investments per zone.

Figure 3.13: Survey investment by zone in block 22B, 25% budget reduction



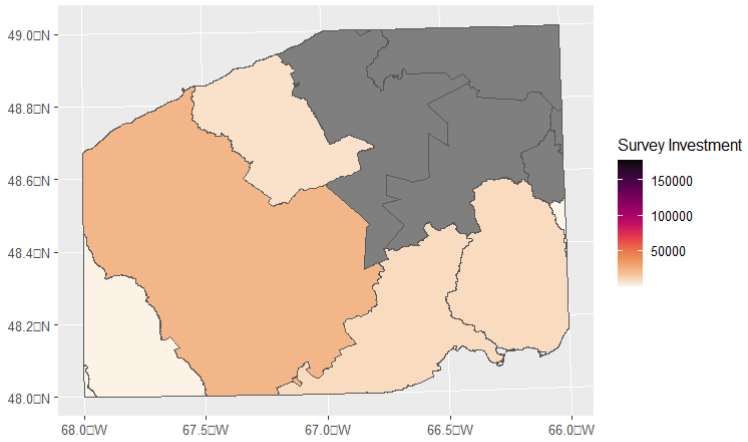
A total of 656 surveys are deployed across the block under this scenario. There are no surveys in zones 158, 183, 184 or 195. Zones 154, 182 and 186 have two surveys a year each. Zone 156 has the most surveys, with 300 per year.

The net present value of survey costs over our horizon is $822,193, while the NPV of expected net benefits is $253,001. Infestations across the total landscape (including blocks other than 22B) result in $4,800,261 in expected NPV damages.

Restricting the budget by 50% results in $50,600 in annual investments in our block. Figure 3.14 shows the distribution of investments per zone.

in our results. This is repeated for all budget-restricted analysis in this chapter.

Figure 3.14: Survey investment by zone in block 22B, 50% budget reduction

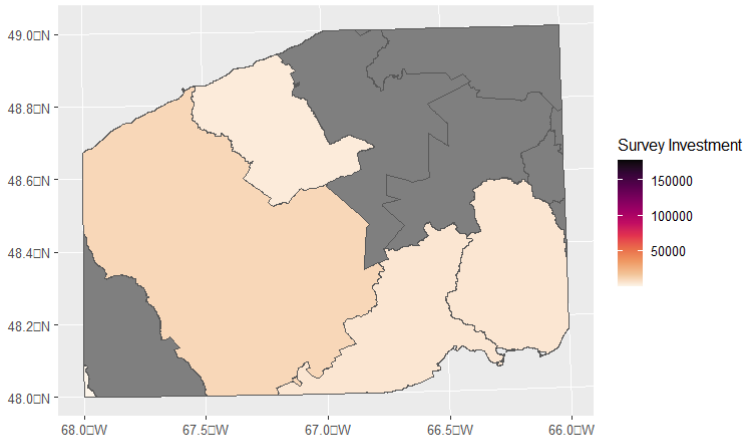


A total of 440 surveys are deployed across the block under this scenario. Zone 182 loses its two surveys. Zone 156 loses 98 surveys, representing the largest absolute survey reduction in a block. Besides zone 182, zone 155 sees the largest relative reduction in surveys, losing 69% of its surveys (22 out of 32).

The net present value of survey costs is $551,471, while the NPV of expected net benefits is $209,940. Infestations across the total landscape (including blocks other than 22B) result in $5,114,044 in expected NPV damages.

Finally, restricting the budget by 75% results in $25,300 in annual investments in our block. Figure 3.15 shows the distribution of investments per zone.

Figure 3.15: Survey investment by zone in block 22B, 75% budget reduction



A total of 220 surveys are deployed across the block under this scenario. Zone 155 loses its ten remaining surveys, while zone 186 loses its two surveys. Zone 156 loses 108 surveys, leaving it with a total of 94.

The net present value of survey costs is $275,736, while the NPV of expected net benefits is $128,429. Infestations across the total landscape (including blocks other than 22B) result in $5,471,290 in expected NPV damages.

3.7.3 Model results: net benefits and marginal net benefits as functions of investment

For each expenditure level, our model generated net benefit maximizing survey placement investments. Under our baseline scenario, we had 1049 possible yearly expenditure levels, ranging from a minimum of $230 to a maximum of $241,270.

Figure 3.16 plots the expected net benefits (which is to say the reduction in expected NPV

outbreak damages less the NPV of yearly survey investments) as a function of survey expenditure. The green vertical line represents our optimal budget, $101,430 per year. Expected net benefits peak at this expenditure level, and decline afterwards. At a budget of $233,680 or more, expected net benefits become negative.

Figure 3.16: Net benefit curve

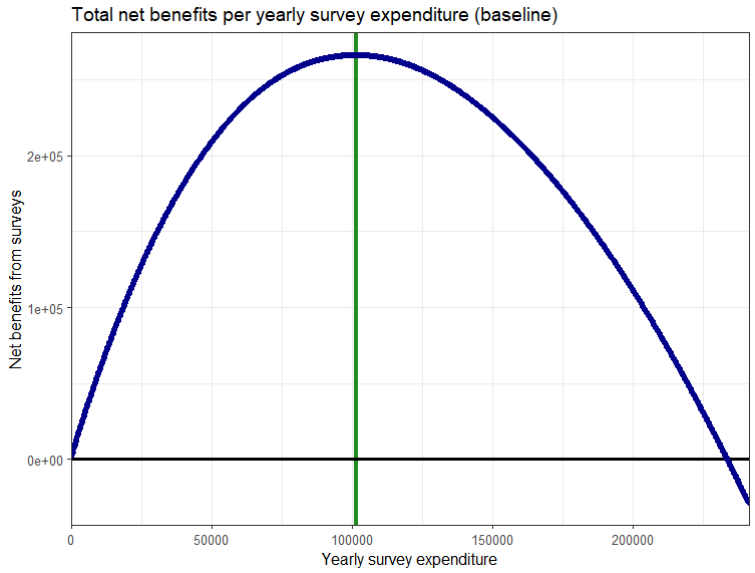


Figure 3.17 plots the marginal expected net benefits as a function of survey expenditure increments. Marginal net benefits are the difference in net benefits between an expenditure level and the preceding expenditure level. These become negative once the optimal allocation is passed, which is to say that each additional expenditure will reduce net benefits. Marginal net benefits are monotonically decreasing over the domain.

Figure 3.17: Marginal net benefit curve

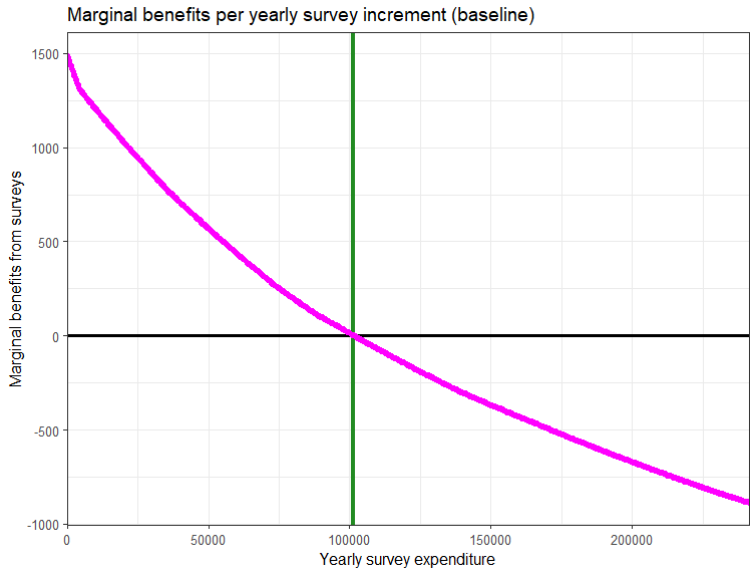
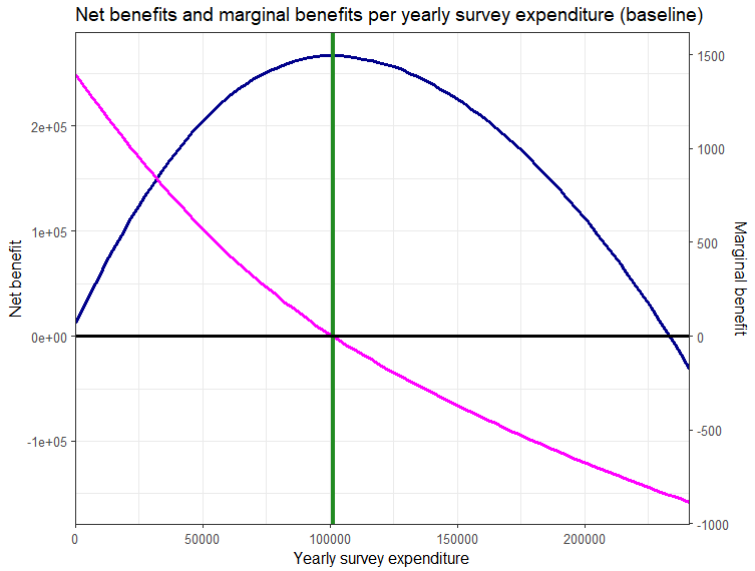


Figure 3.18 shows these curves side by side. Note that these curves have the same X axis, but different Y axes, as the variation in marginal net benefits is significantly less than the variation in net benefits.

Figure 3.18: Combined net benefit and marginal net benefit curves



3.7.4 Sensitivity analysis

Sensitivity analysis was performed with and without a budget constraint. Two parameters were found to impact treatment decisions: the discount rate δ_t and the introduction rate e_t. Our baseline discount rate is 5% and our baseline introduction rate is $\frac{1}{10}$. When we increased the discount rate to 10% or decreased the introduction rate to $\frac{1}{30}$, we found that surveillance no longer became optimal in any zone. Those results are thus omitted. Our sensitivity analysis therefore presents two scenarios: a 1% discount rate and a $\frac{1}{3}$ arrival rate. These results are in the subsections below.

3.7.4.1 Lowered discount rate, unconstrained budget

With a lowered discount rate, a total of $608,350 is invested across the landscape per year, resulting in 5290 total surveys per year on the landscape. The net present value of survey costs is $8,519,153. These result in a net present value of total expected net benefits of $5,759,608. The remaining expected NPV of the outbreak cost is $35,215,647 across the landscape. If foliage protection were to be employed across the entire landscape instead of EIS, the total expected net present value of damages from an outbreak across our landscape would be $49,494,408.

Figure 3.19 shows total investment across the landscape.

Figure 3.19: Total investment by block-zone (1% discount rate)

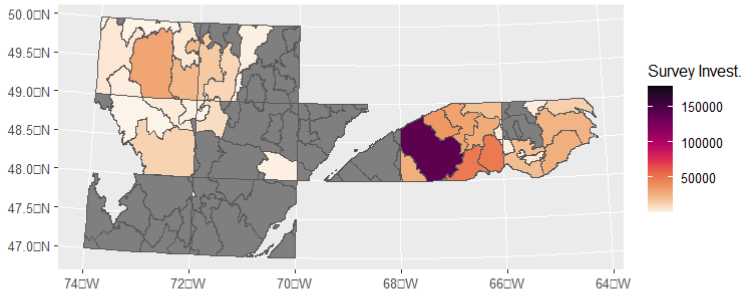
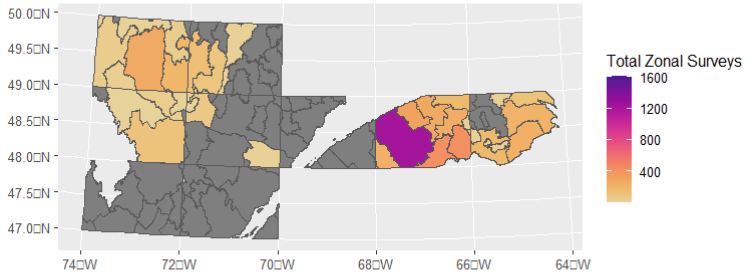


Figure 3.20 shows the number of surveys per block-zone across the landscape.

Figure 3.20: Total surveys by block-zone (1% discount rate)



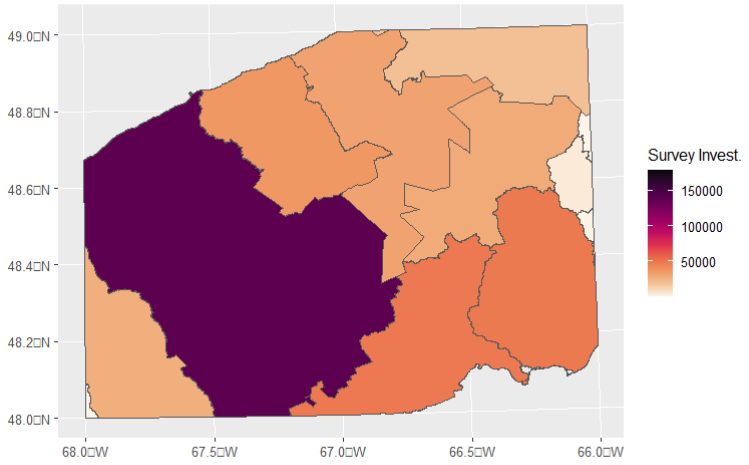
There are no investments made in blocks 21M, 22C and 31P (see Figure 3.1 for block references). Block 22B has the highest level of investment, with a total of 3345 yearly surveys at a cost of $384,675. This is followed by blocks 22A and 32H, which have 815 and 585 surveys.

Zone 180 of block 22B has the highest survey density in the landscape, with 3.31×10^{-3} surveys per hectare, while block 156 of this same block has the highest total number of surveys, with 1215. Block 22D has only 100 total surveys per year, with 75 of these being in zone 255, located in its northwestern corner.

In our model, damages depend on the value of the zone and of the block within which the zone is located. There are sharp cut-offs at the boundaries of blocks, which is why a zone that is split between two blocks might have a significant difference in survey investment and outbreak damages in each block. Nonetheless, we see two distinct geographic clusters emerge: there is a cluster of intensive investment in the Gaspésie peninsula, and another cluster around the Lac-Saint-Jean. We would expect the southern shore of block 22C to have investments, but it is likely penalized by the fact that the Gulf of St. Lawrence bisects it, significantly removing the total value of timber within the block and thus the total value at risk for this block. The lack of investments in the southern blocks of 21M and 22C are logical: these are blocks whose forests feature broadleaf trees and whose coniferous forests are located in mountainous areas.

The results below are for block 22B. The first plot, figure 3.21 is of zonal survey investment.

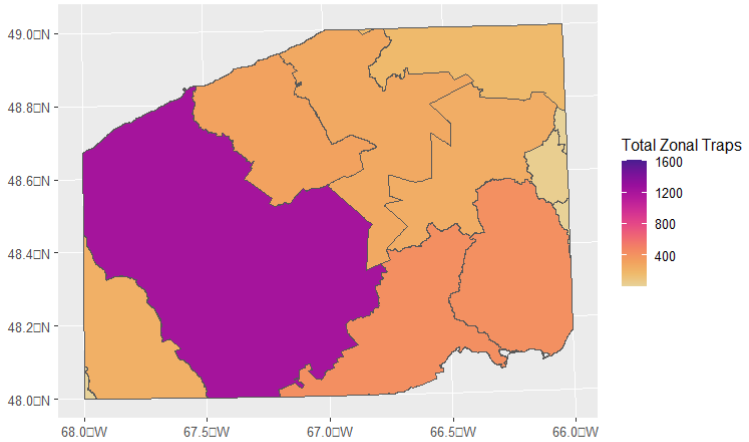
Figure 3.21: Total investment by zone in block 22B (1% discount rate)



Relative to the baseline scenario, presented in figure 3.11, investments are higher across the block. There are no zones without investment.

Figure 3.22 shows total investments in this block.

Figure 3.22: Total surveys by zone in block 22B (1% discount rate)

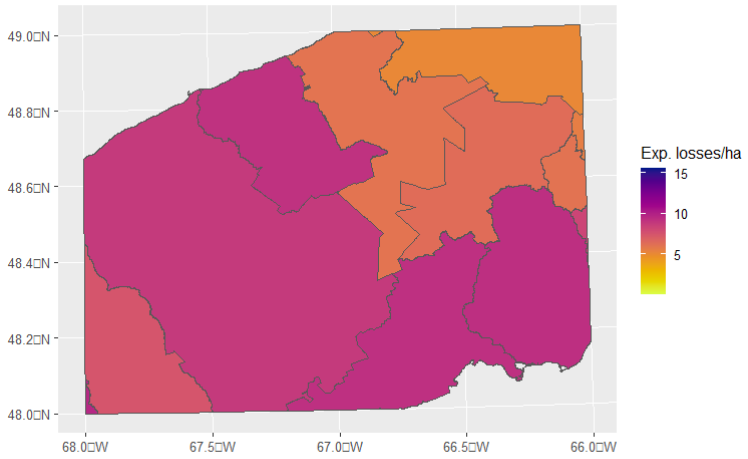


As usual, zone 156 has the highest total number of surveys, with 1215. A total of 3345

surveys will be deployed across block 22B. Block 22B therefore represents 63.4% of the surveys in the landscape.

The 30-year expected losses per hectare are plotted below in figure 3.23. These values are identical to those for block 22B in figure 3.6.

Figure 3.23: Losses under an outbreak scenario in block 22B (1% discount rate)

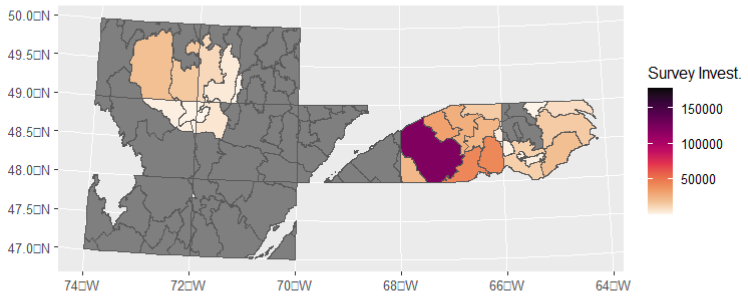


3.7.4.2 Lowered discount rate, with budget constraint

As in subsection 3.7.2, we consider three constrained budgets: a 25% reduction, a 50% reduction, and a 75% reduction. These reductions are relative to the total optimal expenditure, which is $608,350 under the 1% discount rate scenario. Results are presented for yearly investments per zone on a landscape-wide basis. These figures can be compared to figure 3.19.

Restricting the budget by 25% results in $456,320 in annual investments across the landscape. Figure 3.24 shows the distribution of investments per zone.

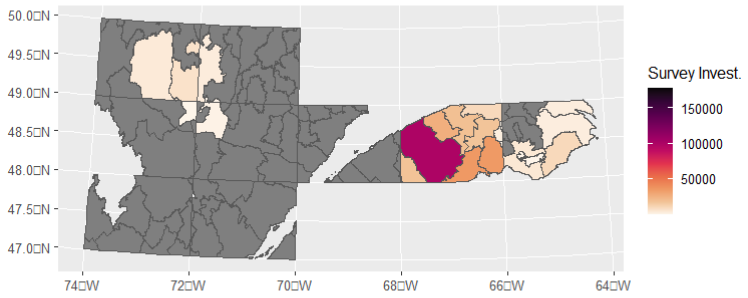
Figure 3.24: Survey investment by block-zone (1% discount rate), 25% budget reduction



A total of 3,968 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $6,390,170, while the NPV of expected net benefits is $5,599,357. The remaining infestations across the total landscape result in $37,504,881 in expected NPV damages.

Restricting the budget by 50% results in $304,060 in annual investments in our block. Figure 3.25 shows the distribution of investments per zone.

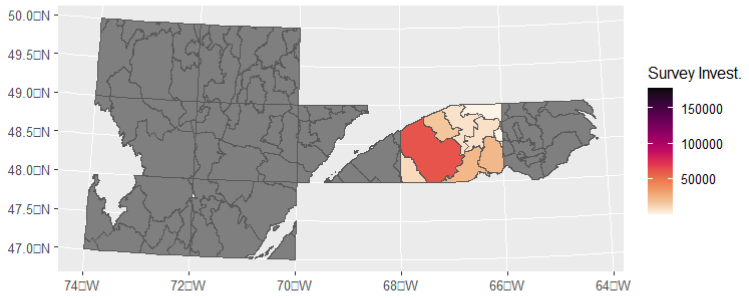
Figure 3.25: Survey investment by block-zone (1% discount rate), 50% budget reduction



A total of 2,644 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $4,257,966, while the NPV of expected net benefits is $4,994,662. The remaining infestations across the total landscape result in $40,241,780 in expected NPV damages.

Restricting the budget by 75% results in $152,030 in annual investments across the landscape. Figure 3.26 shows the distribution of investments per zone.

Figure 3.26: Survey investment by block-zone (1% discount rate), 75% budget reduction



A total of 1322 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $2,128,983, while the NPV of expected net benefits is $3,599,769. The remaining infestations across the total landscape result in $43,765,655 in expected NPV damages.

3.7.4.3 Net benefits and marginal net benefits as functions of investment for a lowered discount rate

For each expenditure level, our model generated net benefit maximizing survey placement investments. Under our baseline scenario, we had 4671 possible yearly expenditure levels, ranging from a minimum of $230 to a maximum of $1,074,330.

Figure 3.27 plots the net benefits as a function of survey expenditure. The green vertical line represents our optimal budget, $608,350 per year. Net benefits peak at this expenditure level, and decline afterwards. Net benefits do not become negative at any point in our domain.

Figure 3.27: Net benefit curve

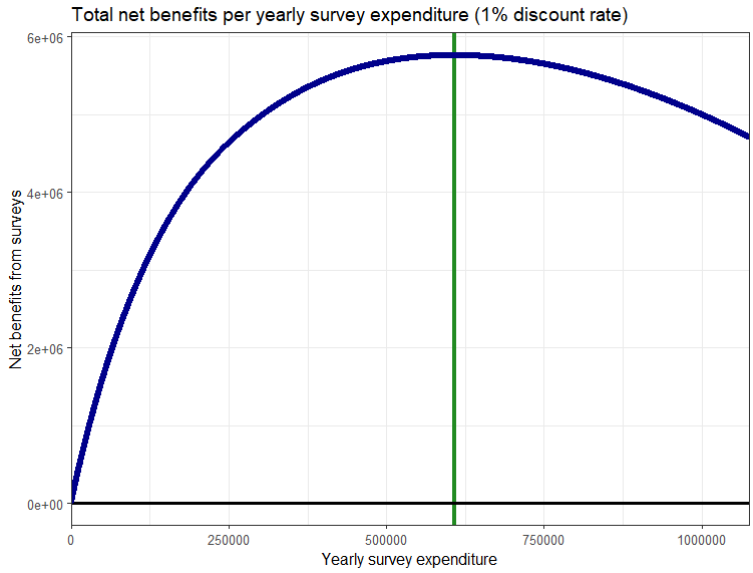
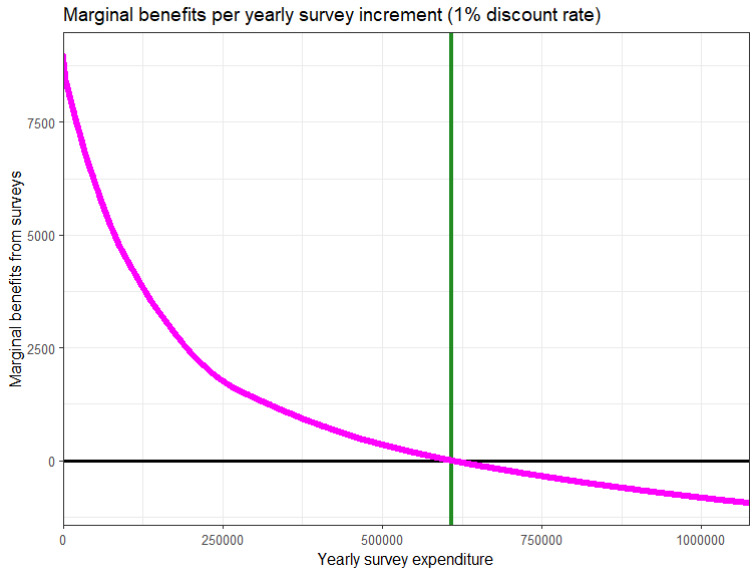


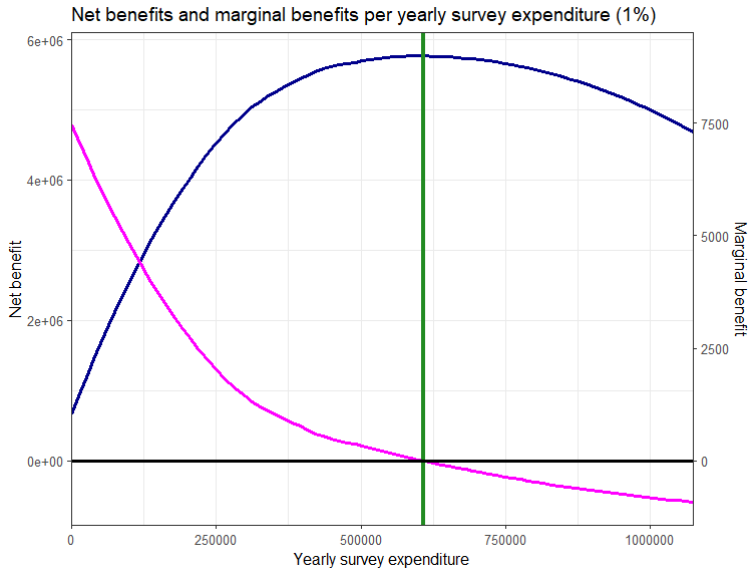
Figure 3.28 plots the marginal net benefits as a function of survey expenditure increments.

Figure 3.28: Marginal net benefit curve



As in subsection 3.7.3, figure 3.29 shows these curves side by side. Again we note that these curves have the same X axis, but different Y axes.

Figure 3.29: Combined net benefit and marginal net benefit curves



3.7.4.4 Heightened introduction rate, unconstrained budget

With a heightened introduction rate (and maintaining a 5% discount rate), a total of $983,710 is invested across the landscape per year, resulting in 8554 total surveys per year on the landscape. The net present value of survey costs is $10,721,102. These result in a net present value of total expected net benefits of $9,619,327. The remaining expected NPV of the outbreak cost is $27,181,579 across the landscape. If foliage protection were to be employed across the entire landscape instead of EIS, the total expected net present value of damages from an outbreak across our landscape would be $47,522,008.

Figure 3.30 shows total investment across the landscape.

Figure 3.30: Total investment by block-zone (3-year intro rate)

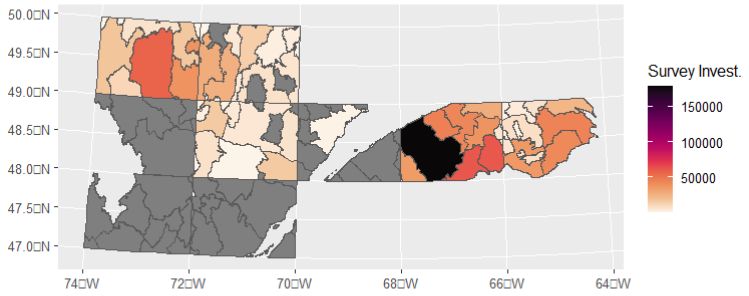
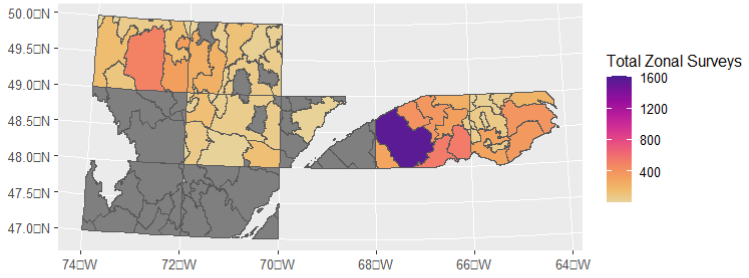


Figure 3.31 shows the number of surveys per block-zone across the landscape.

Figure 3.31: Total surveys by block-zone (3-year intro rate)



There are survey investments in each block except for 21M, 31P and 32A (see Figure 3.1 for block references). Block 22C has investment in a single zone (zone 934, with 10 surveys), unlike in the low discount rate case. As always, block 22B has the highest level of investment,

with a total of 3345 yearly surveys at a cost of $498,525 per year. Blocks 22A and 32H have 1565 and 1280 surveys per year, respectively.

The difference in survey investment patterns between the low discount rate and high introduction rate environments likely relates to how relative expected damages change as the introduction rate increases. The two plots below compare baseline risk (figure 3.33 to risk under a high introduction rate (figure 3.32).

Figure 3.32: Relative (normalized) outbreak likelihood by zone (3-year intro rate)

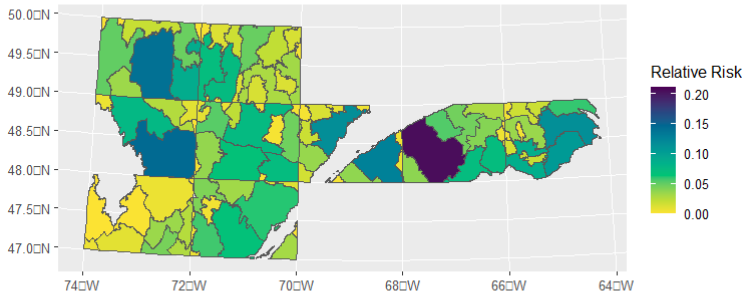
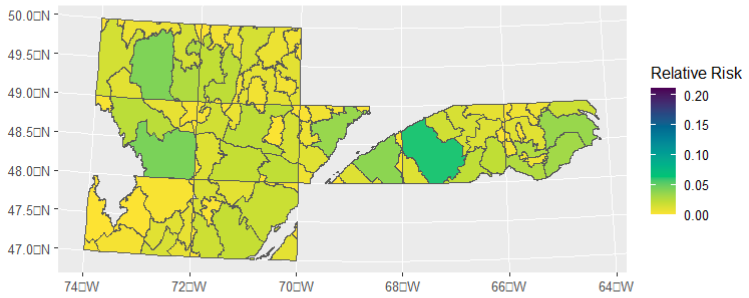


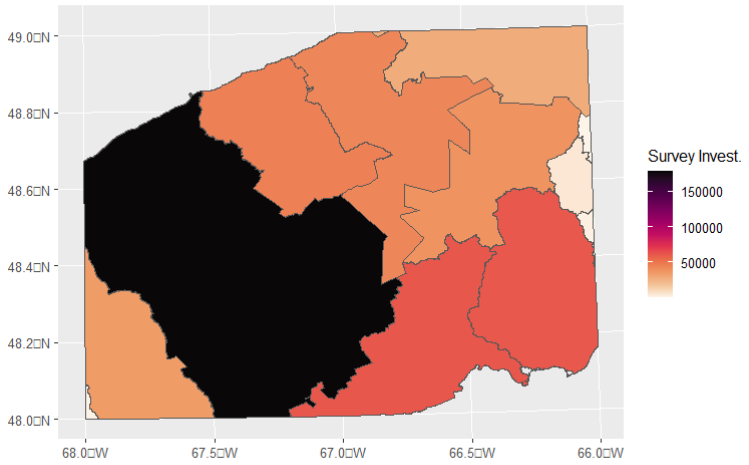
Figure 3.33: Relative (normalized) outbreak likelihood by zone (baseline)



In the high introduction rate environment, the high outbreak likelihood zone in block 32A does not receive investments because, as shown in figure 3.7, expected damages within this zone would be minimal.

The results below are for block 22B. The first plot, figure 3.34 is of zonal survey investment.

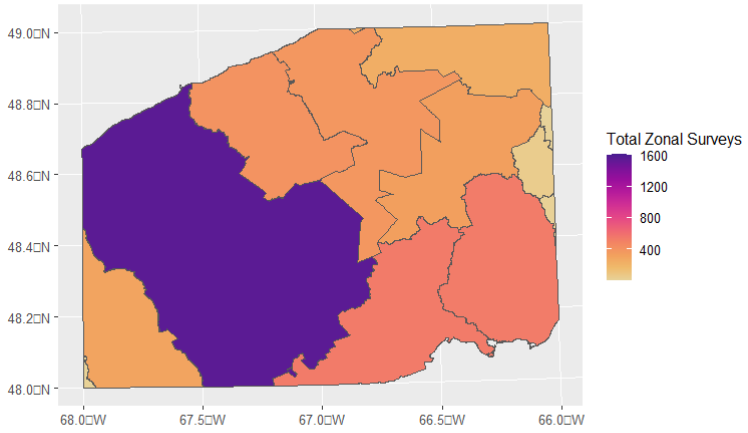
Figure 3.34: Total investment by zone in block 22B (3-year intro rate)



Relative to the baseline scenario, presented in figure 3.11, investments are higher across the block. There are no zones without investment.

Figure 3.22 shows total surveys in this block.

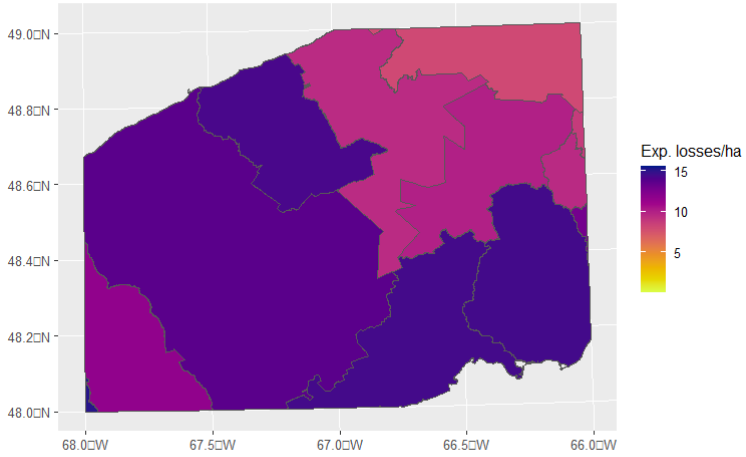
Figure 3.35: Total surveys by zone in block 22B (3-year intro rate)



As usual, zone 156 has the highest total number of surveys, with a total of 1545. A total of 4335 surveys will be deployed across block 22B. Block 22B therefore represents 50.7% of the surveys in the landscape.

The 30-year expected losses per hectare are plotted below in figure 3.36. These values are identical to those for block 22B in figure 3.7.

Figure 3.36: Losses under an outbreak scenario in block 22B (3-year intro rate)

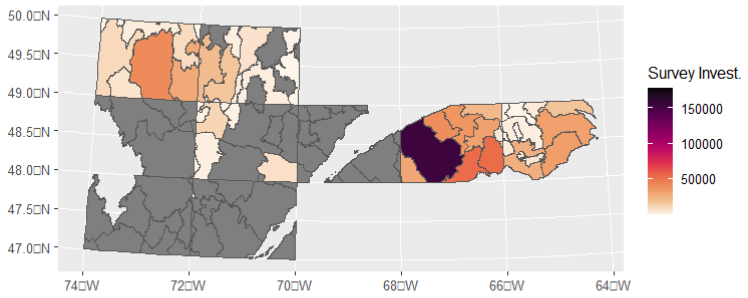


3.7.4.5 Heightened introduction rate, with budget constraint

Again, we consider a 25% reduction, 50% reduction, and 75% reduction in the budget. These reductions are relative to the total optimal expenditure, which is $983,710 under the 3-year introduction rate scenario. Results are presented for yearly investments per zone on a landscape-wide basis. These figures can be compared to figure 3.30.

Restricting the budget by 25% results in $737,610 in annual investments across the landscape. Figure 3.37 shows the distribution of investments per zone.

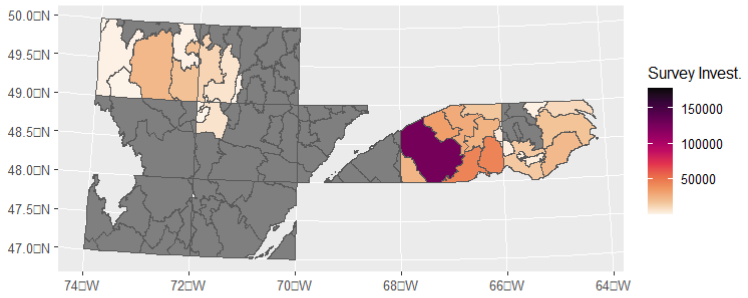
Figure 3.37: Survey investment by block-zone (3-year intro rate), 25% budget reduction



A total of 6414 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $8,038,947, while the NPV of expected net benefits is $9,342,702. The remaining infestations across the total landscape result in $30,140,360 in expected NPV damages.

Restricting the budget by 50% results in $491,740 in annual investments in our block. Figure 3.38 shows the distribution of investments per zone.

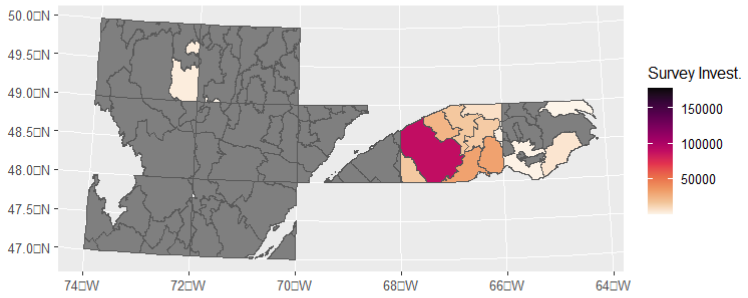
Figure 3.38: Survey investment by block-zone (3-year intro rate), 50% budget reduction



A total of 4276 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $5,359,298, while the NPV of expected net benefits is $8,342,098. The remaining infestations across the total landscape result in $33,820,612 in expected NPV damages.

Restricting the budget by 75% results in $245,870 in annual investments across the landscape. Figure 3.39 shows the distribution of investments per zone.

Figure 3.39: Survey investment by block-zone (3-year intro rate), 75% budget reduction



A total of 2138 surveys are deployed across the landscape under this scenario. The net present value of survey costs is $2,679,649, while the NPV of expected net benefits is $6,104,424. The remaining infestations across the total landscape result in $38,737,936 in expected NPV damages.

3.7.4.6 Net benefits and marginal net benefits as functions of investment for a heightened introduction rate

For each expenditure level, our model generated net benefit maximizing survey placement investments. Under our baseline scenario, we had 4371 possible yearly expenditure levels, ranging from a minimum of $230 to a maximum of $1,005,330.

Figure 3.27 plots the net benefits as a function of survey expenditure. The green vertical line represents our optimal budget, $983,710 per year. Net benefits peak at this expenditure level, and decline afterwards. This decline is not apparent over our domain, as the peak is near to the

maximum of our domain.

Figure 3.40: Net benefit curve

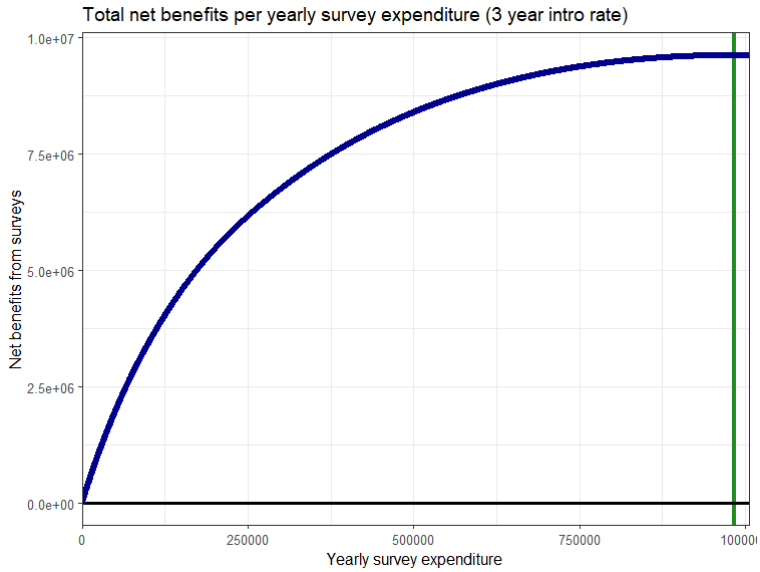
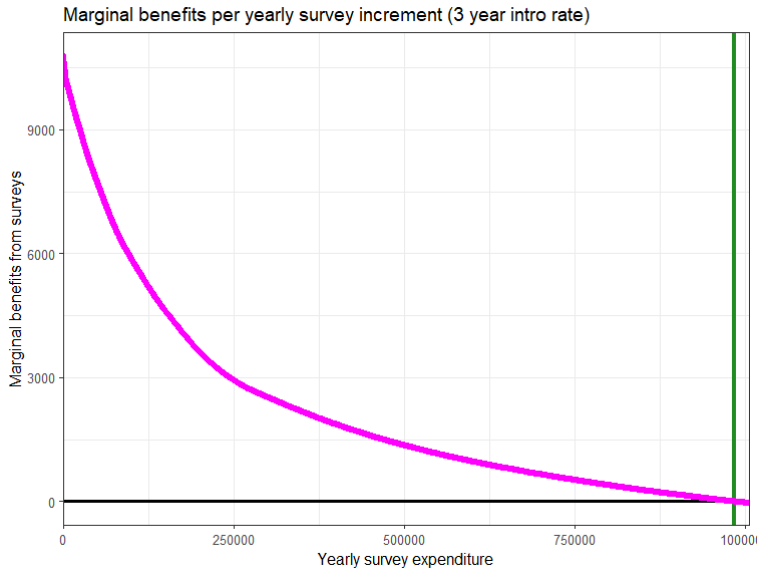


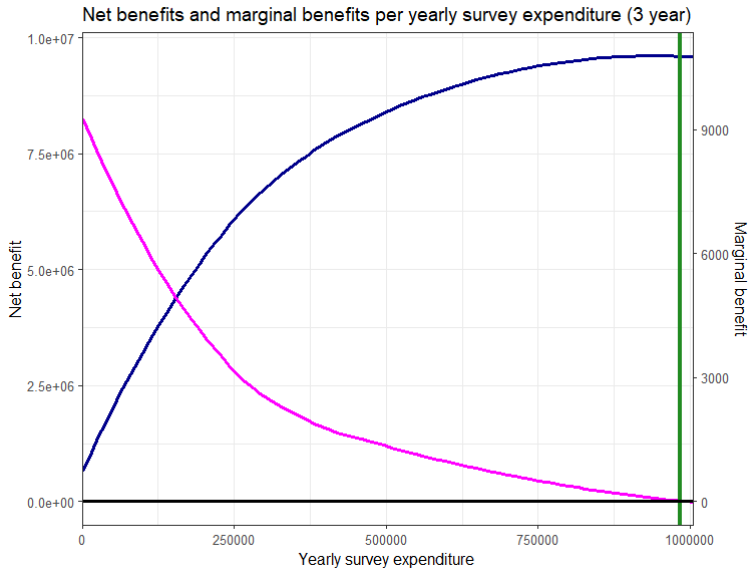
Figure 3.41 plots the marginal net benefits as a function of survey expenditure increments.

Figure 3.41: Marginal net benefit curve



Once again, figure 3.42 shows these curves side by side. Again we note that these curves have the same X axis, but different Y axes.

Figure 3.42: Combined net benefit and marginal net benefit curves



3.7.5 Summary of model results

The results from unconstrained analysis are below in table 3.7. These results represent subsections 3.7.1, 3.7.4.1 and 3.7.4.4.

The net present value of damages to the forest over a 30 year outbreak that is mitigated by foliage protection are higher by a factor of nearly 10 in our sensitivity analysis scenarios.

Table 3.7: Results: unconstrained analysis

Scenario	FP-managed NPV	Expenditure per year	Surveys per year	Survey exp. NPV	Remaining outbr. NPV	Net ben. NPV
Baseline	$5,875,455	$101,430	882	$1,105,449	$4,503,888	$266,117
1% discount rate	$49,494,408	$608,350	5290	$8,519,153	$35,215,647	$5,759,608
3-year intro rate	$47,522,008	$983,710	8554	$10,721,102	$27,181,579	$9,619,327

The results from budget-constrained analysis are below in table 3.8. These results represent subsections 3.7.2, 3.7.4.2 and 3.7.4.5.

Table 3.8: Results: constrained analysis

Baseline	FP-managed NPV	Expenditure per year	Surveys per year	Survey exp. NPV	Remaining outbr. NPV	Net ben. NPV
75%	$5,875,455	$75,440	656	$822,193	$4,800,261	$253,001
50%	$5,875,455	$50,600	440	$551,471	$5,114,044	$209,940
25%	$5,875,455	$25,300	220	$275,736	$5,471,290	$128,429

1% discount rate	FP-managed NPV	Expenditure per year	Surveys per year	Survey exp. NPV	Remaining outbr. NPV	Net ben. NPV
75%	$49,494,408	$456,320	3968	$6,390,170	$37,504,881	$5,599,357
50%	$49,494,408	$304,060	2644	$4,257,966	$40,241,780	$4,994,662
25%	$49,494,408	$152,030	1322	$2,128,983	$43,765,655	$3,599,769

3-year intro rate	FP-managed NPV	Expenditure per year	Surveys per year	Survey exp. NPV	Remaining outbr. NPV	Net ben. NPV
75%	$47,522,008	$737,610	6414	$8,038,947	$30,140,360	$9,342,702
50%	$47,522,008	$491,740	4276	$5,359,298	$33,820,613	$8,342,098
25%	$47,522,008	$245,870	2138	$2,679,649	$38,737,936	$6,104,424

3.8 Further discussion of results

In this chapter, we describe a theoretical model that captures the dynamics of single-shot spruce budworm survey planning for an early intervention scenario. We then implement a simulation model based on this theory, which we calibrate by using data from public sources. This simulation model allows us to determine the parts of Quebec for which an early intervention strategy could be successfully implemented. The two determinants of EIS optimality are infestation likelihood and timber value. EIS has already been shown to be successful in New Brunswick [MacLean et al., 2019]. Under our baseline scenario, the region of Quebec which is most similar to New Brunswick is the only one in which EIS should be conducted, and this region is the central part of the Gaspésie peninsula, between the St. Lawrence River and the Baie des Chaleurs. By relaxing the assumptions of our baseline scenario, EIS becomes beneficial across a much larger

landscape. Nonetheless, net benefits from running EIS are much lower than the expected damages from infestations that are not neutralized by EIS, which suggests that FP remains the optimal policy across most of our landscape.

Our model has limitations, and as such our results must be interpreted very carefully. Our model is in no way able to make solid policy prescriptions. It should be instead seen as an exploration of the concept of EIS in Quebec, and our results indicate that the possibility of EIS on a regional basis should, at the very least, be examined in more detail.

3.8.1 Discussion of main results

Given our baseline assumptions, our results indicate that EIS is geographically limited in terms of optimality. The regions of our landscape that are most likely to be optimal are those that border New Brunswick, where the program has already shown a high degree of success.

In our baseline scenario (a moderate outbreak with parameters established in sections 3.5 and 3.6 and summarized in table 3.6), block 22B was the only one for which survey investments were optimal. This makes intuitive sense and confirms baseline assumptions: block 22B borders New Brunswick along its southern edge and is therefore similar in geography, topology and human settlement patterns. Since EIS has seen success in New Brunswick, it is likely to see success in block 22B as well. Besides elevation, the complexities of geography cannot be directly captured by our model. Per-hectare losses will be the best proxy for these complexities: they depend on the timber stumpage rate and total biomass both across the block and within the zones of the block. The stumpage rate is influenced by factors such as proximity to mills, ease of road access, and terrain. Biomass reflects only the total softwood biomass. Block 22B has high

potential damages and high outbreak likelihood across its zones. These combine to create an area where EIS would be an optimal strategy, at least on a limited basis. EIS is not cost-effective in the rest of Quebec.

3.8.2 Discussion of sensitivity analysis

Our sensitivity analysis shows that our results are highly dependent on our assumptions. Lowering the discount rate or increasing the introduction rate will cause significant increases to expected damages across the landscape. As a result, EIS goes from being optimal in one block to being optimal in six blocks, with the pattern varying based on scenario. Under all scenarios, block 22B remains the most important block for EIS planning, but this intensive EIS program is twinned with a lower-intensity EIS across other parts of the landscape. Most notably, under each scenario, we see two distinct geographic clusters emerge for EIS, in the Gaspésie peninsula and in the Lac-Saint-Jean.

The introduction rate has a larger impact on expected damages, on investment, and on the benefits of surveys than the discount rate. It also leads to a different management prognosis. A single zone with a high outbreak likelihood is enough to trigger investments in a block that would otherwise not receive any investments. This is the case in block 22C in the high introduction rate scenario.

The implication of our sensitivity analysis for managers is that slight changes to our assumptions lead to large changes in optimal policies. Managers using a model such as ours to plan EIS activities must set assumptions carefully. In our baseline scenario, only a small portion of the Quebec landscape should be subjected to an EIS program. Modifying our assumptions re-

sults in EIS being optimal across much of Quebec's forested landscape. This would suggest that EIS should be at least investigated over Quebec's landscape, as it could potentially be welfare-improving over the current foliage protection strategy. On the other hand, if the most appropriate parameter assumptions are those of our baseline scenario, then EIS may not be worth pursuing in any part of Quebec, especially if parallel administrative structures for FP and EIS would result in costs that exceed potentially limited benefits.

3.8.3 Limitations of the model

As mentioned, the largest limitation of our model is the fact that each block is a distinct outbreak landscape. Outbreaks will not exceed the boundaries of the blocks where they were first established. This will cause distortions in prescribed surveys to border zones, and will prevent the model from properly capturing the interconnected nature of the landscape. Chapter 4 discusses how incorporating spatial dependencies into the model will increase its predictive power and policy relevance.

The second most important limitation of our model arises from how we model outbreak likelihood. We implicitly assume homogeneity within each of our zones, such that the average elevation is taken to be the elevation of the entire zone. We then assume that elevation is the primary determinant of introduction likelihood. This will make it difficult to realistically predict both spread pathways across the landscape and the specific locations where moth flights are most likely to land and create hot spots.

The third most important limitation of our model is the lack of spatial detail within zones for the operational phase of sampling. Survey costs are homogeneous across the entire landscape.

In reality, survey costs would vary significantly based on geography, and would almost certainly be the primary limiting factor preventing EIS activities in remote regions of Quebec. We have restricted ourselves to regions of Quebec where the forest is less remote, but we do not incorporate relevant details such as road networks leading to survey sites. Incorporating fine spatial detail such as road access and terrain slope would allow a planner to pinpoint not only the zones where a survey should be deployed, but the optimal locations of surveys within these zones.

The fourth most important limitation of our model is in how assumptions must be made about the evolution of damages over the course of a 30 year outbreak. While the data used to calibrate forest value is detailed and geographically-precise, spread modeling is not. We assume that all spread occurs within the zone of first infestation for 10 years and entirely within that zone's surrounding IEQM block from years 11 through 30. Edge cases clearly show how these assumptions limit our model: under our baseline parameters, it is optimal to invest in zone 155 of block 22B, but not in zone 155 in block 22C, which is adjacent. This is not realistic, and can only be explained by the lower value at risk of timber across the entirety of block 22C. As the plot of losses per hectare shows, there are some zones in 22C which actually have a higher value at risk than 22B, but these do not receive investment as they are surrounded by lower-value zones. Realistic spread modeling would allow our model to precisely determine the boundaries of geographic clusters where EIS would be optimal.

Chapter 4: Conclusion and Extensions

4.1 General conclusions

This dissertation was motivated by the gap between the economic importance and economic literature on eastern spruce budworms. As mentioned earlier in this dissertation, spruce budworms have been referred to as a "15 billion dollar" problem across Canada's Atlantic provinces [MacLean et al., 2019], a sum which is significant given Atlantic Canada's small population and dependence on forestry. However, as discussed throughout this dissertation, the economics literature on spruce budworms is sparse, and therefore this dissertation provides multiple novel contributions to this literature. In this chapter, I summarize the findings of the previous three chapters, and propose additional extensions that will make our models more realistic and therefore more relevant for policymakers.

This dissertation pursued three main goals. My first goal was to present the current state of affairs in a way that could be easily understood by the uninitiated. The second was to evaluate Quebec's control and harvest decisions by simulating management. The third was to model the early intervention strategy, currently employed in New Brunswick, in order to determine how it might be applied to Quebec. Other goals remain outside the scope of this dissertation, but could and should be explored with dedicated computational resources. The second part of the chapter discusses the implementation and advantages of these extensions.

4.1.1 Summary of main research results and contributions

This dissertation had two main empirical components. A novel simulation program was designed and implemented for each. Chapter 2 presented an optimization model that simulates the treatment and harvest decision for forests with an active spruce budworm outbreak. Chapter 3, for its part, focuses on pre-outbreak surveillance modeling.

In Chapter 2, we demonstrated that existing budworm treatment programs are efficient relative to a do-nothing baseline. Under our baseline conditions, budworms should be quickly reduced to a low level through a mixture of treatments and harvests. Harvests will remove the biomass available to budworms, and thus their survival rate. Clearcuts are rarely optimal, and harvests will reach a long-term steady rate that corresponds to the steady state of forests. At their steady state, budworms have a very small population. We varied eight parameters and examined how management choices and the value function changed. This allowed us to predict how changes to the circumstances of an outbreak would affect management decisions.

Chapter 2 presents the first ever discrete-time model for the spruce budworm treatment and forest harvest decisions. It is relevant to a real-world policy context for two reasons. First, it presents decisions on a year-by-year basis and therefore approximates the yearly planning cycle of forest resource managers. Second, it examines the costs and benefits of active management through aerial spraying and harvests, and thus represents the first theoretical evaluation of in-place management techniques.

In Chapter 3, we determined that, under our baseline scenario, the early intervention strategy used in Canada's Maritime provinces should be implemented in Quebec's maritime subregions, but not across the province. While these results are based on a fixed sampling cost, stands

with high stumpage rates are characterized by ease-of-access, which means that the results are likely to be strengthened rather than refuted when using a more realistic modeling process. Our sensitivity analysis found that the discount rate and the introduction rate had major effects on the optimal policies prescribed by the model. Increasing the discount rate or reducing the introduction rate will reduce or eliminate the optimality of EIS in Quebec. Decreasing the discount rate or increasing the introduction rate will make EIS a more attractive option, both within the region where the baseline scenario is optimal, and in regions in central Quebec where it was previously not recommended. Decreasing the discount rate will increase the present value of timber affected by an outbreak. Modifying the discount rate therefore has similar effects to modifying the degree of damage inflicted on the forest or modifying the underlying value of the forest.

Chapter 3 makes two main contributions to the literature. First, it builds on the CESAT model [Epanchin-Niell, 2020], adapting it to the spruce budworm management problem and, more generally, to endemic species management. Second, it directly compares the management practices used in New Brunswick to those used in Quebec. While initial evaluations of EIS compared its potential in New Brunswick to the counterfactual of foliage protection in New Brunswick [Liu et al., 2019], we instead evaluate the potential for EIS in Quebec to the existing practice, which is FP.

4.1.2 Management implications

The results of Chapters 2 and 3 suggest that current management practices are optimal relative to do-nothing approaches within the geographical areas of study. This corresponds to previous findings [Chang et al., 2012b, Liu et al., 2019].

Chapter 2 demonstrates that a foliage protection program should always be employed over an existing outbreak in our baseline scenario, which was calibrated on data from central Quebec. An early intervention strategy, if possible, will be optimal relative to foliage protection, as indicated by the fact that the model suggests reductions of the budworm population to the lowest feasible level. The baseline scenario can change, and our sensitivity analysis shows how changes would affect management decisions. For example, an increase in budworm fecundity could lead to a scenario where budworm populations cannot be easily controlled. The best strategy in this case would be a continuous treatment consisting of two sprays per period and oscillating harvests that increase as the budworm population increases. Decreases in the interest rate will lower the urgency of quick reductions in the budworm population, which suggests that the gap between the total social welfare of foliage protection and early intervention programs would narrow. Massive influxes of spruce budworms, for their part, may prompt managers to move away from foliage protection programs and towards immediate clearcuts of the forest, which would prevent losses from massive forest die-off.

Chapter 3 demonstrates that early intervention is not always optimal across Quebec, such that the currently-used foliage protection approach is the most optimal strategy. The early intervention strategy requires ease of access to forest stands. Using stumpage rates as a proxy for ease of access, the remoteness of most of Quebec's forest resources mean that foliage protection is the most optimal strategy under our baseline scenario. The Bas-Saint-Laurent region, which is geographically similar to New Brunswick, is the exception to this rule, and EIS can and should be applied to this region. The baseline scenario was calibrated to match assumptions used in New Brunswick (notably assumptions about the economic consequences of outbreaks as explained in Chang et al. [2012b] and Liu et al. [2019]). When we modify the baseline assumptions in our

sensitivity analysis, we find that a more frequent introduction rate or a higher present value of damages from successful outbreaks will result in EIS being optimal across a much larger portion of Quebec's landscape. The intensity of the program will never be as high as in the Bas-Saint-Laurent, however, and as such the approach suggested in other regions may be more akin to a hybrid program where EIS is used sparingly in anticipation of outbreaks, but with a higher possibility of failure than in the Bas-Saint-Laurent. Failure of the EIS program would then lead to a switch to foliage protection.

It is important not to confuse optimality with feasibility. While the sensitivity analysis in Chapter 3 indicates that EIS may well be optimal across large portions of Quebec, this does not necessarily mean that the current geography of Quebec would allow EIS to be implemented across Quebec. Ideally, a realistic model would map both optimality and feasibility, constraining assessments of optimality to areas where an EIS program could physically be implemented. This would allow a more realistic assessment of optimality, while taking into account the fact that EIS must be run across a wide area to be effective. Similarly, Chapter 2 suggests reducing the spruce budworm population as much as possible. While this is optimal, it may not be feasible, especially if survival and post-feeding reproduction rates are affected in dynamic or uncertain ways. As knowledge of budworm dynamics evolves, our simple bioeconomic model could be refined or replaced, resulting in more realistic and precise policy prescriptions.

4.2 Future perspectives

The empirical components of Chapters 2 and 3 use single-landscape models to model silvicultural management and preemptive surveillance decisions. However, real-world management

must take into account the reality of an interconnected forest landscape. Spruce budworm outbreaks in one forest stand will affect conditions in a stand hundreds or thousands of kilometers away. In this chapter, I discuss the importance and implications of multi-spatial management, the empirical strategies that would be employed to build such models, and the constraints that have prevented examination of multi-spatial problems in the preceding chapters.

4.2.1 Motivation

The motivation behind this chapter is to explore implications that had to be excluded from previous chapters of this dissertation for the purpose of empirical feasibility. Spatially-explicit simulations require detailed and computationally-intense models. Empirical simulation of spatially-explicit models would, nonetheless, be important when developing the sort of software that could be of use to forestry managers looking to implement early intervention and foliage protection strategies. The extensions proposed in this chapter would potentially allow the models of Chapters 2 and 3 to be integrated into forest management software.

4.3 Modeling endemic pests on complex landscapes

In this section, I describe the problem of endemic pest management and present a basic model that describes the economics of management decisions. I start with a generic, generalized model for endemic pests, and then discuss the special case of spruce budworms. The single landscape spruce budworm model is omitted, as it is covered in Chapter 2.

This section proceeds as follows. Subsection 4.3.1 reviews the tools and practices currently used in Canada for multi-spatial spruce budworm management. Subsection 4.3.2 describes our

generic multi-spatial endemic pest model. Subsection 4.3.3 models multi-spatial spruce budworm management based on the single landscape budworm model described in Section 3 of Chapter 2, including the implications of its objective function and transition equations.

4.3.1 Current spruce budworm multi-spatial management tools and practices

Spruce budworm management in Canada generally occurs at the provincial level, and decisions must therefore take province-wide consequences into account. With limited management resources, treatment and harvest efforts must account for spread rate impacts while prioritizing harvests in areas with relatively more valuable timber stocks.

MacLean et al. [2001] describe the spruce budworm decision support system (SBW DSS), which has been used to plan management in New Brunswick since the 1980s. The SBW DSS calculates three main components: defoliation impacts, protection priority, and protection strategy evaluation. These are then used to plan a five-year management planning cycle, which will include both the current harvest schedule and maps of priority spray blocks. The mean volume benefit for each spray block, measured in m^3/ha, can then be calculated. With limited treatment resources, such calculations are critical. Chang et al. [2012a] show that optimal management would protect about 10% of the New Brunswick forest[1]. This will not minimize timber losses, but will rather minimize the sum of timber losses and treatment costs. Targeting the optimal 10% of forest protection is therefore critical. Wasted resources will lead to higher-than-necessary damages in untreated high-value or high-vulnerability blocks and surplus protection in low-value or low-vulnerability blocks.

[1]EIS was still being developed when Chang et al. were publishing their model. As such, their article focuses on FP.

In areas where even foliage protection treatment is not a useful option, spatially explicit management will focus on optimizing harvest efforts across different landscape units given reductions in future yields due to spruce budworm outbreaks and given the price effects of accelerated harvests. One good example of this can be found in Huff et al. [1984], which measures the consequences of outbreaks across the US Forest Service's Resource Evaluation Survey Units in Minnesota, Wisconsin and Michigan. There are thirteen such units, and the forested land in these units consists of private woodlands, USFS (federal) lands, state lands and county lands. Private lot owners will have reservation prices, while public lands are governed by allowable cuts. Thus, total wood supply is produced on both price-inelastic public lands and price-elastic private lands. If there is a massive glut in timber on the market due to increased allowable cuts on public lands, private land owners will respond by reducing harvest efforts on their lands.

Harvest re-optimization in Canada can be constrained by the harvest schedule of crown lands. Hennigar et al. [2013] consider the possibility of a management strategy that both re-schedules harvests and plans harvests. Treatment can furthermore occur in three different ways: it can be applied in the first year of defoliation over 40% and all such years, one year after 40% defoliation, or at the peak of defoliation (>70%). Protection can be applied on 10%, 20%, 40% or 100% of the landscape. The authors constructed a stand impact matrix over all of New Brunswick, and projected growth and yield with and without defoliation. The effects of salvage and re-planning were primarily felt through the first 20 years of outbreaks, with up to 20% mitigation in harvest losses, but little benefits were observed in the long run. Treatment, for its part, had both short-run and long-run benefits that were higher than those that could be obtained from re-optimization alone.

4.3.2 Modeling a generic endemic pest on a complex landscape, with dispersal

The model described in this subsection assumes a landscape that is divided into J locations, indexed $j \in \{1, J\}$. In each period $t \in \{1, T\}$ and in each location $j \in \{1, J\}$, there is a stock of resources and pests at the beginning and end of the period. These are as follows: the resource stocks at location j at the beginning and end of period t are given by s_{jt} and x_{jt}, respectively, while the stock of pests at location j at the beginning and end of period t are given by l_{jt} and y_{jt}. x_{jt} is the stock of resources after harvests and y_{jt} is the stock of pests after treatments for population control.

If l_{t+1} represents the pest on the entire landscape, we have that $l_{t+1} = D \cdot b(l_t)$. Pests disperse across the landscape according to the dispersal matrix D, where:

$$\begin{bmatrix} l_{1t+1} \\ \vdots \\ l_{Jt+1} \end{bmatrix} = \begin{bmatrix} D_{11} & \dots & D_{1J} \\ \vdots & & \vdots \\ D_{J1} & \dots & D_{JJ} \end{bmatrix} \begin{bmatrix} b_1(x_{1t}, y_{1t}) \\ \vdots \\ b_J(x_{1t}, y_{1t}) \end{bmatrix} \tag{4.1}$$

Dispersal of the pest from location j to location i can thus be modeled as a function of the distance between the centroid of j and the centroid of i, dependent on directional vectors such as wind. For each element D_{ji} of the dispersal matrix given in equation (4.1), there will exist a corresponding two-dimensional vector $\vec{ji}$ which represents the distance and direction from stand j to stand i. We can thus describe D_{ji} as the product of the length of $\vec{ji}$ and of an orientation function, ω_{ji}. Thus, we have that:

$$D_{ji} = ||\vec{ji}||\omega_{ji} \tag{4.2}$$

While $||\vec{ij}|| = ||\vec{ji}||$, $\omega_{ij} \neq \omega_{ij}$. As such, $D_{ij} \neq D_{ji}$ and the matrix D is not symmetrical. The product of its elements will be 1, however, such that all pests disperse within the landscape, with none leaving the landscape, or being added from outside the landscape. While this is a simplified assumption relative to a realistic scenario, it captures the spatial correlation of spread, which is one of the essential features of endemic pest management.

For each location, the transition equation is given by:

$$l_{jt+1} = \sum_{k=1}^{J} D_{kj} b(x_{kt}, y_{kt}) \tag{4.3}$$

If $\sum_{k=1}^{J} D_{kj} > 1$, then the location j is a migration sink, while if $\sum_{k=1}^{J} D_{kj} < 1$, then the location j is a migration source.

The resource, x_{jt}, will not disperse across the landscape, and so the transition equations of x_{jt} for all $j \in \{, J\}$ are not correlated. The transition equation for x_{jt} is thus given by:

$$s_{jt+1} = g(x_{jt}, y_{jt}) \tag{4.4}$$

This implies that local growth of the resource depends only on local conditions at the end of period t.

4.3.2.1 Objective function of the multi-dimensional pest management problem

For each resource location or stand, there are two choice variables that can be manipulated by the social planner: the harvest (or proportional harvest) $h_{jt} = s_{jt} - x_{jt}$ and the treatment $\tau_{jt} = l_{jt} - y_{jt}$. In addition, the price of the resource is given by p, and the benefit from the resource is given by θ. As stated previously, these have cost structures $\int_{x_{jt}}^{s_{jt}} c_j(u)du$ and $\int_{y_{jt}}^{l_{jt}} k_j(v)dv$.

Once again, the objective of the social planner is to maximize net social benefit, which will occur across the landscape. In the most general terms, the social planner's objective can be stated as:

$$B = \sum_{t=1}^{T} \sum_{j=1}^{J} \delta_t [p \cdot (s_{jt} - x_{jt}) + \theta \cdot (l_{jt} - y_{jt}) - \int_{x_{jt}}^{s_{jt}} c_j(u)du - \int_{y_{jt}}^{l_{jt}} k_j(v)dv] \tag{4.5}$$

Prices and resource non-market benefits are assumed invariant in time and space. This objective must be maximized subject to the two transition equations. This will yield a fundamental recursion relation of dynamic programming which can be written as:

$$V(s_t, l_t) = \max \sum_{j}^{J} [p \cdot (s_{jt} - x_{jt}) + \theta \cdot (l_{jt} - y_{jt}) - \int_{x_{jt}}^{s_{jt}} c_j(u)du - \int_{y_{jt}}^{l_{jt}} k_j(v)dv] + \delta V(g(x_t, y_t), D \cdot b(x_t, y_t)) \tag{4.6}$$

Here, the notation $V(s_t, l_t)$ represents the fact that the value function is summed across all $j \in \{1, J\}$.

We have not assumed a budget for harvest and control efforts. Instead, we assume budget-unconstrained social benefit maximization. This is reasonable as harvest cost and pest control budgets are likely to be separate, if they exist. The next subsection will explicitly assume a treatment budget.

4.3.2.2 Multi-spatial management with a treatment budget

Incorporating a yearly treatment program budget will mean that the maximum number of treatments that can be applied, $\sum i$, will be limited according to $B_t = \sum_{j=1}^{J} \int_{y_{jt}}^{l_{jt}} k_j(v)dv$.

The objective function must therefore be maximized subject to this budget constraint and to the transition equation.

The problem then becomes:

$$\max Б = \max \sum_{j=1}^{J} \sum_{t=1}^{T} \delta_t [p \cdot (s_{jt} - x_{jt}) + \theta \cdot (l_{jt} - y_{jt}) - \int_{x_{jt}}^{s_{jt}} c(u)du - \int_{y_{jt}}^{l_{jt}} k_j(v)dv] \quad (4.7)$$

subject to equations (4.3), (4.4) and:

$$B_t \geq \sum_{j=1}^{J} \int_{y_{jt}}^{l_{jt}} k_j(v)dv \quad (4.8)$$

In each period, the Lagrangian can then be written as:

$$\begin{aligned} \mathcal{L}(x_{jt}, y_{jt}, \lambda, \gamma_j, \sigma_j) = [p \cdot (s_{jt} - x_{jt}) + \theta \cdot (l_{jt} - y_{jt}) - \int_{x_{jt}}^{s_{jt}} c(u)du - \int_{y_{jt}}^{l_{jt}} k_j(v)dv] \\ + \lambda(B_t - \sum_{j=1}^{J} \int_{y_{jt}}^{l_{jt}} k_j(v)dv) + \gamma_j(g(x_{jt}, y_{jt})) + \sigma_j(D \cdot b(x_{jt}, y_{jt})) \quad (4.9) \end{aligned}$$

The shadow price σ_j would then depend on D, which would capture complex spatial dynamics. Optimal interior solutions will describe a steady state in which welfare is maximized across the landscape in each period given the budget, growth rate of the resource, and spatially-

correlated growth rate of the pest infestation.

4.3.3 Modeling multi-spatial spruce budworm treatment and harvest

The model in subsection 4.3.2 describes multi-spatial natural resource management for an endemic pest that can spread across the landscape. This model cannot be directly applied to spruce budworms, however, as it assumes per-population treatment, whereas budworms are treated indirectly through the imposition of additional mortality during feeding stages.

Chapter 2 presents a version of an endemic pest optimization problem that is adapted to the realities of spruce budworm. However, empirical implementation of Chapter 2's model could only be developed for a single landscape, for two reasons. First, we were constrained by time and available computing resources. A multi-spatial model would be excessively complex and have a long development curve. Second, we chose to focus on the dynamics of single landscapes so that we can emphasize local harvest and treatment decisions. As such, local spruce budworm and forest management decisions are modeled, but invasions of spruce budworm are an exogenous and constant parameter.

Spruce budworm management decisions in Canada tend to happen at a province-wide level, which means that there will be criteria determining treatment priority for different wood stocks within the province. If a forested area has more value at risk than another area, for example, it will be prioritized over an area with less value at risk. This dimension is partially captured by the sensitivity analysis from Chapter 2. If an area is at higher risk because of its proximity to other outbreaks, or if it is seen as being a part of the landscape where an outbreak would damage surrounding forest, then it may have a lower or higher treatment priority. In this section, we

develop and present a spatially explicit version of the Chapter 2 model.

4.3.3.1 Model features and objective function

Each location must be categorized as an outbreak sink or source. If a forested area is a sink, then the contribution of dispersal to the outbreak will be positive, meaning that budworm population densities will be higher than expected. If a forested area is a source, dispersal will have a negative outbreak contribution, meaning that budworm population densities will be lower than expected. Treating budworms at the source will reduce the immigration pressure on sinks, while treating budworms at sinks will have no effect on budworms at the source.

The transition equations for budworms and forests are similar to those in Section 3 of Chapter 2. We modify the transition equation for budworms by adding a dispersal component, which we model as in subsection 4.3.2.

The generalized objective function is given by:

$$Б = \sum_{t=1}^{T} \sum_{j=1}^{J} \delta_t [p \cdot (s_{jt} - x_{jt}) - \int_{x_{jt}}^{s_{jt}} c(u)du - k(i_{jt})] \tag{4.10}$$

The treatment decision in each area j in period t is given by i_{jt}, and has the three possible values of 0, 1, and 2. $k(i_{jt})$ is the cost associated with this treatment decision. The objective function therefore does not depend on dispersal.

The fundamental recursion relation of dynamic programming is given by:

$$V(s_{jt}, l_{jt}, i_{jt}) = \max[p \cdot (s_{jt} - x_{jt}) - \int_{x_{jt}}^{s_{jt}} c(u)du - k(i_{jt})] + \delta V(g(x_{jt}, y_{jt}), D \cdot b(x_{jt}, y_{jt}, i_{jt})) \tag{4.11}$$

4.3.3.2 Transition equations

The transition equations for the multispatial spruce budworm model are as follows:

$$s_{jt+1} = g(x_{jt}, y_{jt}) = (1 - m_F y_{jt}) \frac{(1 + r_F e^{-g_F y_{jt}}) x_{jt}}{\left(1 + \frac{r_F e^{-g_F y_{jt}} x_{jt}}{K_F}\right)} \tag{4.12}$$

and

$$l_{jt+1} = b(x_{jt}, y_{jt}, i_{jt}) = \beta y_{jt} d(i_{jt}) D(x_{jt}) \tag{4.13}$$

Equation (4.12) is the same as the transition for s_{t+1} in Chapter 2. Equation (4.13) differs from its Chapter 2 equivalent in two respects. First, it is in terms of relative budworm density. Second, it has the dispersal factor $D(x_{jt})$ which will depend on the relative abundance of foliage. The term D in $D(x_{jt})$ is shorthand for $\sum_{k=1}^{J} D_{kj}$. If $D(x_{jt}) > 1$, then area j is a sink. If $D(x_{jt}) < 1$, then j is a source. For each $j \in J$, $\prod_{k=1}^{J} D_{kj} = 1$. Using relative budworm densities is appropriate due to the fact that local exhaustion of forest resources will lead to full out-migration to other stands.

4.4 Multi-spatial spread monitoring

Chapter 3 models spruce budworm monitoring and treatment across a landscape, since we are interested in the likelihood that stands become seeded by outbreaks. However, spruce budworm invasions to our landscape are treated as exogenous. This means that Chapter 3 can only provide a partial picture of optimal monitoring decisions. In this section, I discuss the importance of an interconnected landscape when determining the allocation of monitoring resources for the purpose of early intervention.

4.4.1 Multi-spatial spread monitoring in literature

As discussed in Chapter 1, there are two competing theories governing how spruce budworm outbreaks spread across the landscape: the double-equilibrium theory [Morris, 1963] and the oscillatory theory [Royama, 1984]. Spruce budworm monitoring for early intervention assumes that the double-equilibrium theory must hold.

According to double-equilibrium theory, budworms exist at endemic levels throughout the landscape when there is no outbreak. External and internal factors will combine to drive budworms above the Allee threshold. Specifically, moth invasions will increase the number of eggs laid within a stand, and favorable weather conditions in the spring and summer will increase the survival of larvae and the fecundity of local moths, respectively.

The early intervention strategy in New Brunswick makes use of a decision support system known as the SBW DSS [MacLean et al., 2001]. The SBW DSS involves a stand risk matrix that judges the invasion risk to each part of New Brunswick's landscape. The use of a DSS allows decision-makers to optimally direct monitoring efforts.

The literature on the spruce budworm early intervention strategy is fairly recent. The foundational literature appeared mostly in 2019 [MacLean, 2019]. Liu et al. [2019], who form part of this foundational literature, do not directly examine detection. Instead, it is assumed to be part of the operations costs of an EIS program, which is presumed to be successful.

Johns et al. [2019] provide the best description of how multi-spatial spread monitoring is used in EIS. Moth flights from hotspots will seed outbreaks throughout the rest of the landscape because they will emit moths in a density-dependent fashion. Without moth dispersal, outbreaks would be limited to smaller areas. Johns et al. note that multi-spatial spread implies that even if an outbreak has exceeded levels that can be controlled through EIS, the leading edge of the outbreak could still be treated using EIS. Conceptually, this is what is done in New Brunswick, where monitoring and treatment resources are concentrated in the North, along the border with Quebec.

Spatially-explicit modeling must take the effects of landscape and weather on budworm spread into account. It must also incorporate zone-to-zone spread and proximity to active outbreaks [Bouchard and Auger, 2014]. Inherent features such as elevation and balsam fir percentage will not be the only determinants of spread. Natural barriers such as mountains will also tend to limit spread.

Carleton et al. [2019] provide an overview of the operational requirements for successful early intervention. In addition to the factors mentioned above, both monitoring and treatment efforts must have social acceptability and there must be collaboration between industry and planners.

4.4.2 Modeling multi-spatial monitoring and early treatment

Chapter 3 has an exogenous rate of invasion. However, the pathways through which spruce budworms spread across a landscape are known, even if the specific spread pattern is not perfectly predictable [Greenbank et al., 1980]. Long-distance budworm flights will be carried by winds for distances up to 200 kilometers. They will intercept with landscape features such as hillsides [Chen et al., 2021], such that there are barriers to spread. The most accurate spatially-explicit model will be the one that uses spatial information to predict budworm spread pathways, and then predicts the likelihood that these spread pathways will result in successful outbreaks by using relative risk criteria such as those used in Bouchard and Auger [2014].

The most important information to incorporate into a spatial model will be prevailing winds. The Canadian Wind Atlas [Environment and Climate Change Canada, 2003] provides wind velocity and direction. Local weather conditions, for their part, are either incorporated directly into forest inventories [MFFP, 2017], or can be obtained from ECCC's gridded temperature and precipitation anomalies map (CANGRD) [Environment and Climate Change Canada, 2014].

We retain the general set-up from Chapter 3, and will not restate it here in its entirety. The most substantial change is in the realized and estimated outbreak risk, written as $\omega_j = \omega(e_j, \rho_j)$ and $\omega(\hat{e}_j, \rho_j)$ in Chapter 3, respectively. Once again, we will use D to indicate directional spread vectors. Let j be the area of interest and i be another location within the landscape m. The vector D_{ij}, if positive, is the pressure that moths from vector i impose on the forest in vector j. $D_{ij} = D_{ji}$, so if D_{ij} is negative, moths from j exert pressure on i. Relationships are assumed to be unidirectional, with each plot being either a sink, a source, or having no relationship with the rest of the landscape.

Outbreak risk is given by:

$$\omega(e_{jt}, \rho(D_{ij})) \tag{4.14}$$

with $\rho'(D_{ij}) > 0$, such that outbreak risk increases as dispersal from i to j increases. ω_j is similarly increasing in D_{ij}.

The risk-neutral objective function is given by:

$$\min \sum_{j=1}^{J} E[C_{dj} + C_{\tau j}] \tag{4.15}$$

This is minimized subject to the budget constraint:

$$B \geq \sum_{j=1}^{J} C_{sj} \tag{4.16}$$

and to transmission pathways:

$$corr(\omega_i, \omega_j) \neq 0 \quad if \quad D_{ij} \neq 0 \tag{4.17}$$

The evolution of the outbreak will determine how monitoring and treatment resources are allocated. In the early stages of an outbreak, monitoring and treatment resources will be directed towards source hotspots, since reducing infestations in these zones will reduce pressure throughout the landscape. If an outbreak at a source progresses to a point where only foliage protection can treat it, monitoring and treatment resources for an EIS program should shift to sinks.

As is the case in Chapter 3, equation (4.15) can be solved numerically through a simulation model. The CESAT-based model presented in Chapter 3 would need to be subdivided into distinct

landscapes which are linked through pre-determined migration pathways, based on the Canadian Wind Atlas.

4.4.3 Ease of access and the monitoring budget

The most important consideration when allocating treatment resources, especially with a limited treatment budget, is ease of access to the sampling site. One of the main reasons behind the success of EIS in New Brunswick is the dense network of roads that crisscross the forest[2]. Primary and secondary highways traverse forests to link cities and towns. New Brunswick's coastline is long relative to the size of the province, and much of the population lives along this coastline (with the exception of the capital, Fredericton, which is the third-largest city). The most direct route to link these settlements is frequently through the forest. Local rural roads jut off from these primary and secondary highways, and roads built by forestry companies further branch off from these. Therefore, it is easy to come very close to an optimal survey location in New Brunswick. Similar conditions exist in Nova Scotia, which has implemented EIS with some success.

Quebec, for its part, has a geography that makes EIS implementation more difficult[3]. The vast majority of Quebec's population lives in the St. Lawrence Valley, which has been mostly deforested for centuries. Most of Quebec's forest is remote from population centers, and there is generally only a single highway through heavily forested regions. Road access in Quebec is therefore much more limited.

The further survey crews can travel on highways and roads, the lower the sampling costs.

[2]This information was shared with me by New Brunswick forestry planners.

[3]In conversations with Quebec forestry planners, this geography was cited as the main reason why EIS has not been implemented across the province.

In most cases, the specific sampling location will be accessed on foot or by ATV, but minimizing the distance traversed by these means will reduce costs.

Slope and other barriers will also affect sampling costs. If the topography is less flat, sampling costs will increase. These variables are likely to have a smaller impact on cost than remoteness from a road, however, although they are still likely to be significant.

In the Chapter 3 model, I assumed that the cost to survey any specific location is fixed. This would be reasonable in New Brunswick, but this assumption would necessarily need to be dropped if the Chapter 3 model were to be developed into a decision support system for Quebec or Ontario.

The values of C_{sj} from equation (4.16) must necessarily be heterogenous across the landscape. They will directly depend on ease of site access, which will depend on the road network and other variables.

The best way to estimate costs as a function of distance will be OLS. The equation is below:

$$C_{sj} = \beta_0 + \beta_1 RoadDist_j + \beta_2 Slope_j + \varepsilon_j \tag{4.18}$$

$RoadDist_j$ will be the straight-line distance of the survey point from the nearest road, defined as any thoroughfare that is at least as big as a forest road. Road network data is available from a number of sources, including Canada's national road network [Statistics Canada, 2017]. $Slope_j$ is the slope, in degrees, of the survey point. Slope information is generally included as part the information included with stand statistics in forest inventories such as the IEQM [MFFP, 2017].

The effect of slope on survey costs is likely smaller than the effect of road distance. Eleva-

tion, for its part, should have no effect on survey costs, given that the bulk of travel occurs along highways and thus changes in elevation will be felt only gradually by survey crews.

4.5 Concluding remarks

Chapters 2 and 3 establish the fundamental components of a broader decision support system. In this chapter, I have described the additional work that would be necessary to fully implement these models in a decision support system, and I explore theoretical models that are outside of the scope of Chapters 2 and 3 of this dissertation. These theoretical models would represent significant improvements on the single landscape models from Chapters 2 and 3, as they would allow us to create models that can provide policy recommendations rather than being limited to policy evaluations.

4.5.1 The benefits of multi-spatial modeling

While the models presented in Chapters 2 and 3 of this dissertation allow for a generalized evaluation of existing management programs, multi-spatial modeling will be necessary to fully develop these models into decision support systems. When designing a decision support system, one of the most important decisions to be guided is the spatial allocation of resources. Without a spatially explicit model, the decision support system will not successfully provide guidance for the locations of survey, treatment and harvest activities.

The model in Chapter 2 determines the treatment and harvest decision in a unispatial context. Within each individual forest stand, the unispatial model will reasonably approximate decisions. However, each forest stand must be placed in relation to others, as outlined in section 4.3.3.

Otherwise, the recommendations for treatment and harvest will be sub-optimal. Each decision would be discrete, and thus some stands will feature excessive harvest or treatment while others will have insufficient harvest or treatment. Pathways will not be actively controlled, which will mean that treatment will not adequately slow the spread and will not have co-benefits outside of the stand in question.

The model in Chapter 3 is more spatially explicit than the one presented in Chapter 2 by design, as it allocates monitoring resources across a landscape based on landscape characteristics. Nonetheless, it still lacks sufficient spatial detail to be implemented as a decision support system. As outlined in section 4.4, it is necessary to determine both active spread pathways (which will allow a focus on sources and sinks, and thus make hot spot identification easier) and the costs of surveys to different locations (which will allow us to determine both the cost-benefit trade-offs of different survey locations and a more realistic number of surveys given the budget).

The most obvious and significant benefit of multi-spatial modeling is that it will allow planners to exercise greater control over the evolution of spruce budworm outbreaks. The development of EIS can, in some sense, be considered a decision to increase the operational intensity of budworm sampling surveys and thus the spatial precision of budworm population levels.

4.5.2 Limitations to multi-spatial modeling

The extensions enumerated above will make the models presented in this dissertation more realistic. However, they still will not capture all of the complexities of budworm management. Some of these could potentially be integrated, such as soil quality, climate variables, and labor market information. Others will necessarily be excluded until knowledge evolves, such as realis-

tic early dynamics and the effects of climate variables on growth and survival. Nonetheless, the addition of spatial detail to the models presented in Chapters 2 and 3 will be sufficient to develop them into useful decision support systems that can guide the management of early and mature spruce budworm outbreaks.

Beyond knowledge gaps, dimensionality is a major restriction on multi-spatial modeling. This problem can be illustrated by a simple example. The models presented in subsections 4.3.2 and 4.3.3 involve a dispersal matrix (see equation (4.1)) that relates budworm conditions across all parts of the landscape. On a single landscape, we have one dimension, and a $J = 2$ landscape will have two dimensions representing the directional relationship of $j = 1$ on $j = 2$ and of $j = 2$ on $j = 1$. Moving to a two-by-two grid landscape means that we have three relationships for each cell, resulting in twelve pathways. The number of dimensions to the dispersal matrix is given by J^{J-1} if there are no constraints on pathways. One way to get around this would be to restrict pathways to nearest-neighbors, but this would require additional assumptions about the limits of budworm spread, which we do not capture in section 4.3.

4.5.3 Future perspectives for spruce budworm control in Eastern Canada

The latest operational reports for spruce budworm control in Eastern Canada cover the 2023 year. Quebec and New Brunswick are the two provinces that were contrasted in this dissertation, and the perspectives for spruce budworm infestations in these provinces are very different. In Quebec, the area infested by spruce budworm has sharply increased in recent years [MRNF, 2023], as has the intensity of infestations. Declines in defoliation intensity eastern Quebec are offset by massive increases of visible defoliation in western Quebec. Collectively,

the Outaouais and Abitibi-Témiscamingue administrative regions saw an increase in defoliation of 887,568 hectares. 80% of the outbreak in the Outaouais is either moderate or intense. The Abitibi-Témiscamingue is spreading east and therefore threatens the north-central parts of Quebec's forests. While the area treated for spruce budworm in Quebec was less in 2023 than in 2022 [SOPFIM, 2022, 2023], this is entirely due to the devastating forest fires which hit Quebec in the summer of 2023, which prevented treatments on nearly 30% of scheduled zones. The perspective in New Brunswick is entirely different: spruce budworm has essentially stopped having a negative impact on New Brunswick forests. A mere 100 hectares of moderate new defoliation were identified in New Brunswick through satellite imagery in 2023 [NB-DNRED, 2024]. L2 surveys in 2022 showed the lowest populations since the start of the EIS program, and there was only a moderate bounce-back in 2023. Treatment programs in New Brunswick are minimal: as of March 2024, no large spray blocks are expected to be recommended for the 2024 season.

The EIS program has demonstrated short-term success in New Brunswick. The limitations to implementing EIS in Quebec have been discussed multiple times through this dissertation. Nonetheless, as climate change continues to push the range of spruce budworms north, more intensive control will likely become necessary in Quebec, and spatially-precise decision systems could allow Quebec's public servants to target intensive surveillance and treatment policies in a way that would massively reduce treatment costs and increase the health of the forestry sector.

Bibliography

Allen, D. C., Louis Dorais, and Edward G. Kettela (1984, October). Ch. 3: Survey and Detection. In D. M. Schmitt, David G. Grimble, and Janet L. Searcy (Eds.), *Managing the spruce budworm in eastern North America*, Number 620 in Agriculture Handbook, pp. 21–36. Washington, D.C.: USDA Forest Service.

Balch, R. E. (1958, April). *The spruce budworm in New Brunswick*. Ottawa, ON: Canada Department of Agriculture, Science Service, Forest Biology Division. Pages: 1-8.

Bhattarai, R., P. Rahimzadeh-Bajgiran, A. Weiskittel, A. Meneghini, and D. A. MacLean (2021, February). Spruce budworm tree host species distribution and abundance mapping using multi-temporal Sentinel-1 and Sentinel-2 satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing 172*, 28–40.

BMMB (2013). Ventes archivées et résultats.

BMMB (2022a, June). Guide explicatif du modèle de transposition des prix de marché - Modèle SEP 2022-2023. Guide, Bureau de mise en marché des bois.

BMMB (2022b). Manuel de mesurage des bois récoltés sur les terres du domaine de l'État - Exercice 2022-2023. Manual, Bureau de mise en marché des bois, Québec, QC.

BMMB (2022c). Tarification forestière.

Bouchard, M. and I. Auger (2014, January). Influence of environmental factors and spatio-temporal covariates during the initial development of a spruce budworm outbreak. *Landscape Ecology 29*(1), 111–126.

Burnett, K. M., S. D'Evelyn, B. A. Kaiser, P. Nantamanasikarn, and J. A. Roumasset (2008, August). Beyond the lamppost: Optimal prevention and control of the Brown Tree Snake in Hawaii. *Ecological Economics 67*(1), 66–74.

Cadogan, B. L., A. Retnakaran, and J. H. Meating (1997, April). Efficacy of RH5992, a New Insect Growth Regulator Against Spruce Budworm (Lepidoptera: Tortricidae) in a Boreal Forest. *Journal of Economic Entomology 90*(2), 551–559.

Candau, J.-N. and R. A. Fleming (2005, September). Landscape-scale spatial distribution of spruce budworm defoliation in relation to bioclimatic conditions. *Canadian Journal of Forest Research 35*(9), 2218–2232. Publisher: NRC Research Press.

Candau, J.-N., R. A. Fleming, and A. Hopkin (1998, November). Spatiotemporal patterns of large-scale defoliation caused by the spruce budworm in Ontario since 1941. *Canadian Journal of Forest Research 28*(11), 1733–1741. Publisher: NRC Research Press.

Carleton, D., Luke Amos-Binks, and Andrew Morrison (2019, March). Operational Requirements for a Successful Early Intervention Strategy.

Carmean, W. H. and J. T. Hahn (1981). Revised Site Index Curves for Balsam Fir and White Spruce in the Lake States. Research Note NC-269, USDA Forest Service, St. Paul, MN.

Chang, W.-Y., V. A. Lantz, C. R. Hennigar, and D. A. MacLean (2012a, January). Benefit-cost analysis of spruce budworm (*Choristoneura fumiferana* Clem.) control: Incorporating market and non-market values. *Journal of Environmental Management 93*(1), 104–112.

Chang, W.-Y., V. A. Lantz, C. R. Hennigar, and D. A. MacLean (2012b, March). Economic impacts of forest pests: a case study of spruce budworm outbreaks and control in New Brunswick, Canada. *Canadian Journal of Forest Research 42*(3), 490–505. Publisher: Canadian Science Publishing.

Chang, W.-Y., V. A. Lantz, and D. A. MacLean (2011, September). Social Benefits of Controlling Forest Insect Outbreaks: A Contingent Valuation Analysis in Two Canadian Provinces. *Canadian Journal of Agricultural Economics 59*(3), 383–404. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1744-7976.2010.01208.x.

Chen, C., P. Rahimzadeh-Bajgiran, and A. Weiskittel (2021, April). Assessing spatial and temporal dynamics of a spruce budworm outbreak across the complex forested landscape of Maine, USA. *Annals of Forest Science 78*(33), 1–14. Number: 2 Publisher: BioMed Central.

Cooke, B. J. (2022, November). Forest Landscape Effects on Dispersal of Spruce Budworm *Choristoneura fumiferana* (Clemens, 1865) (Lepidoptera, Tortricidae) and Forest Tent Caterpillar *Malacosoma disstria* Hübner, 1820 (Lepidoptera, Lasiocampidae) Female Moths in Alberta, Canada. *Insects 13*(11), 1013. Number: 11 Publisher: Multidisciplinary Digital Publishing Institute.

Corbett, L. J., P. Withey, V. A. Lantz, and T. O. Ochuodho (2016, January). The economic impact of the mountain pine beetle infestation in British Columbia: provincial estimates from a CGE analysis. *Forestry: An International Journal of Forest Research 89*(1), 100–105. Publisher: Oxford Academic.

Crépin, A.-S. (2007, February). Using Fast and Slow Processes to Manage Resources with Thresholds. *Environmental and Resource Economics 36*(2), 191–213.

CSMOAF (2010, October). Guide d'acquisition des connaissances de base pour l'apprentissage du métier d'opératrice ou d'opérateur de machines utilisées en récolte du bois. Guide, Comité sectoriel de main-d'œuvre en aménagement forestier, Québec, QC.

Donovan, S. D., D. A. MacLean, Y. Zhang, M. B. Lavigne, and J. A. Kershaw (2021, February). Evaluating annual spruce budworm defoliation using change detection of vegetation indices calculated from satellite hyperspectral imagery. *Remote Sensing of Environment 253*, 112204.

Doucet, D., C. Frisco, M. Cusson, E. Bauce, S. R. Palli, B. Tomkins, B. Arif, and A. Retnakaran (2007, August). Diapause disruption with tebufenozide for early-instar control of the spruce budworm, Choristoneura fumiferana. *Pest Management Science 63*(8), 730–736.

Environment and Climate Change Canada (2003, July). Global Map - Wind Atlas. Last Modified: 2016-04-21.

Environment and Climate Change Canada (2014, January). Canadian Gridded Temperature and Precipitation Anomalies (CANGRD).

Epanchin-Niell, R. S. (2020, January). Bioeconomic modeling for decision-support: optimizing early detection and control of invasive pests. Technical Report 6/19, USDA Animal and Plant Health Inspection Service, Washington, D.C.

Epanchin-Niell, R. S., E. G. Brockerhoff, J. M. Kean, and J. A. Turner (2014, September). Designing cost-efficient surveillance for early detection and control of multiple biological invaders. *Ecological Applications: A Publication of the Ecological Society of America 24*(6), 1258–1274.

Epanchin-Niell, R. S., R. G. Haight, L. Berec, J. M. Kean, and A. M. Liebhold (2012, May). Optimal surveillance and eradication of invasive species in heterogeneous landscapes. *Ecology Letters 15*(8), 803–812.

Erdle, T. A. and D. A. MacLean (1999, February). Stand growth model calibration for use in forest pest impact assessment. *Forestry Chronicle 75*(1), 141–152. Publisher: Canadian Institute of Forestry.

Frank, R. M. (1990). *Abies balsamea* (L.) Mill. Balsam Fir. In R. M. Burns and B. H. Honlaka (Eds.), *Silvics of North America (Conifers)*, Number 654 in Agriculture Handbook, pp. 26–35. Washington, D.C.: USDA Forest Service.

Greenbank, D. O. (1963). Host Species And The Spruce Budworm. *Memoirs of the Entomological Society of Canada 95*(S31), 219–223. Publisher: Cambridge University Press.

Greenbank, D. O., G. W. Schaefer, and R. C. Rainey (1980). Spruce budworm (Lepidoptera: tortricidae) moth flight and dispersal: new understanding from canopy observations, radar, and aircraft. *Memoirs of the Entomological Society of Canada 112*(S110), 1–49.

Hennigar, C., T. Erdle, J. Gullison, and D. MacLean (2013, February). Re-examining wood supply in light of future spruce budworm outbreaks: A case study in New Brunswick. *Forestry Chronicle 89*(01), 42–53. Publisher: Canadian Institute of Forestry.

Huff, D. J., B. A. Montgomery, J. A. Witter, and G. R. Gregory (1984, December). The Economics of Spruce Budworm Outbreaks in the Lake States: An Overview. *Great Lakes Entomologist 17*(4), 239–253.

Intel Corporation (2024). Intel® Fortran Compiler.

Invasive Species Centre (2024a). Asian Longhorned Beetle.

Invasive Species Centre (2024b). Spongy Moth.

Jennings, D. T. and H. S. Crawford, Jr. (1985, November). *Spruce budworms handbook : predators of the spruce budworm.* Number 644 in Agriculture Handbook. Washington, D.C.: USDA Forest Service.

Johns, R. C., J. J. Bowden, D. R. Carleton, B. J. Cooke, S. Edwards, E. J. S. Emilson, P. M. A. James, D. Kneeshaw, D. A. MacLean, V. Martel, E. R. D. Moise, G. D. Mott, C. J. Norfolk, E. Owens, D. S. Pureswaran, D. T. Quiring, J. Régnière, B. Richard, and M. Stastny (2019, October). A Conceptual Framework for the Spruce Budworm Early Intervention Strategy: Can Outbreaks be Stopped? *Forests 10*(10), 910. Number: 10 Publisher: Multidisciplinary Digital Publishing Institute.

Johnston, W. F. (1986, August). *Manager's handbook for balsam fir in the North Central States*. Number NC-111 in Manager's Handbooks. St. Paul, MN: USDA Forest Service.

Kabir, M. H. (2021, June). Reaction-diffusion modeling of the spread of spruce budworm in boreal ecosystem. *Journal of Applied Mathematics and Computing 66*(1), 203–219.

Kegley, S. (2006, February). Management Guide for Mountain Pine Cone Beetle. Guide 10.6, USDA Forest Service, Coeur d'Alene, ID.

Kettela, E. (1995). Ch. 10: Attempts to Develop Strategies to Control Spruce Budworm, Choristoneura fumiferana, Populations by Spraying Moths. In W.G.H. Ives and J.A. Armstrong (Eds.), *Forest insect pests in Canada*, pp. 113–118. Ottawa, ON: NRCAN Canadian Forest Service. Last Modified: 2013-04-03.

Kettela, E. G. (1975, August). Aerial Spraying for Protection of Forests Infested by Spruce Budworm. *Forestry Chronicle 51*(4), 141–142. Publisher: Canadian Institute of Forestry.

Lambert, M.-C., C.-H. Ung, and F. Raulier (2005, August). Canadian national tree aboveground biomass equations. *Canadian Journal of Forest Research 35*(8), 1996–2018. Publisher: NRC Research Press.

Liu, E. Y., V. A. Lantz, D. A. MacLean, and C. Hennigar (2019, June). Economics of Early Intervention to Suppress a Potential Spruce Budworm Outbreak on Crown Land in New Brunswick, Canada. *Forests 10*(6), 481. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.

Ludwig, D., D. G. Aronson, and H. F. Weinberger (1979, October). Spatial patterning of the spruce budworm. *Journal of Mathematical Biology 8*(3), 217–258.

Ludwig, D., D. D. Jones, and C. S. Holling (1978, February). Qualitative Analysis of Insect Outbreak Systems: The Spruce Budworm and Forest. *Journal of Animal Ecology 47*(1), 315–332. Publisher: [Wiley, British Ecological Society].

MacLean, D. A. (2019, December). Protection Strategy against Spruce Budworm. *Forests 10 (12)*(12), 1137. Number: 12 Publisher: Multidisciplinary Digital Publishing Institute.

MacLean, D. A., P. Amirault, L. Amos-Binks, D. Carleton, C. Hennigar, R. Johns, and J. Régnière (2019, May). Positive Results of an Early Intervention Strategy to Suppress a Spruce Budworm Outbreak after Five Years of Trials. *Forests 10 (5)*(5), 448. Number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

MacLean, D. A., T. A. Erdle, W. E. MacKinnon, K. B. Porter, K. P. Beaton, G. Cormier, S. Morehouse, and M. Budd (2001, October). The Spruce Budworm Decision Support System: forest protection planning to sustain long-term wood supply. *Canadian Journal of Forest Research 31*(10), 1742–1757. Publisher: NRC Research Press.

McCann, J. M. (1999, September). Before 1492: The Making of the Pre-Columbian Landscape. Part II: The Vegetation, and Implications for Restoration for 2000 and beyond. *Ecological Restoration, North America 17*(3), 107–119. Publisher: Temporary Publisher.

McRae, D. J., T. J. Lynham, and R. J. Frech (1994, July). Understory prescribed burning in red pine and white pine. *Forestry Chronicle 70*(4), 395–401.

MFFP (2017, October). Inventaire écoforestier du Québec méridional.

Miller, D. R. (2007, June). Limonene: Attractant Kairomone for White Pine Cone Beetles (Coleoptera: Scolytidae) in an Eastern White Pine Seed Orchard in Western North Carolina. *Journal of Economic Entomology 100*(3), 815–822.

Miller, W. E. (1978, October). Use of Prescribed Burning in Seed Production Areas to Control Red Pine Cone Beetle 13. *Environmental Entomology 7*(5), 698–702.

Morin, H., Y. Jardon, and R. Gagnon (2007, January). 17 - Relationship Between Spruce Budworm Outbreaks and Forest Dynamics in Eastern North America. In E. A. Johnson and K. Miyanishi (Eds.), *Plant Disturbance Ecology*, pp. 555–577. Burlington: Academic Press.

Morris, R. F. (1963). The Dynamics of Epidemic Spruce Budworm Populations. *The Memoirs of the Entomological Society of Canada 95*(S31), 1–12. Publisher: Cambridge University Press.

MRNF (2013, March). Données sur les perturbations naturelles - Insecte : Tordeuse des bourgeons de l'épinette.

MRNF (2017, October). Carte écoforestière originale et résultats d'inventaire.

MRNF (2023, October). Aires infestées par la tordeuse des bourgeons de l'épinette au Québec en 2023. Technical report, Ministère des Ressources naturelles et des Forêts, Québec, QC.

Natural Resources Canada (2013a, December). Emerald ash borer. Last Modified: 2015-08-04.

Natural Resources Canada (2013b, December). Red pine cone beetle. Last Modified: 2015-07-24.

Navarro, L., H. Morin, Y. Bergeron, and M. Montoro Girona (2018, December). Changes in Spatiotemporal Patterns of 20th Century Spruce Budworm Outbreaks in Eastern Canadian Boreal Forests. *Frontiers in Plant Science 9*(1905), 1–15. Publisher: Frontiers.

NB-DNRED (2024, March). Summary of Forest Pest Conditions 2023. Annual Report, New Brunswick Department of Natural Resources and Energy Development, Fredericton, NB.

Olson, L. J. and S. Roy (2005, October). On Prevention and Control of an Uncertain Biological Invasion. *Applied Economic Perspectives and Policy 27*(3), 491–497. Publisher: Oxford Academic.

Perron, J.-Y. (2003, June). Tarif de cubage général - Volume marchand brut. Technical report, Ministère des Forêts, de la Faune et des Parcs (now the Ministère des Ressources naturelles et des Forêts), Québec, QC.

Peter, B. and B. E. C. Bogdanski (2010). The economics of salvage harvesting and reforestation in British Columbia's mountain pine beetle-affected forests. Technical Report BC-X-425, NRCAN Canadian Forest Service, Victoria, BC. ISSN: 0830-045.

R Core Team (2021). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Rahimzadeh-Bajgiran, P., A. R. Weiskittel, D. Kneeshaw, and D. A. MacLean (2018, June). Detection of Annual Spruce Budworm Defoliation and Severity Classification Using Landsat Imagery. *Forests 9*(6), 357. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.

Roland, J. (1993, February). Large-scale forest fragmentation increases the duration of tent caterpillar outbreak. *Oecologia 93*(1), 25–30.

Roland, J. and P. D. Taylor (1997, April). Insect parasitoid species respond to forest structure at different spatial scales. *Nature 386*(6626), 710–713. Number: 6626 Publisher: Nature Publishing Group.

Royama, T. (1984, December). Population Dynamics of the Spruce Budworm Choristoneura Fumiferana. *Ecological Monographs 54*(4), 429–462. Publisher: Ecological Society of America.

Régnière, J., B. J. Cooke, A. Béchard, A. Dupont, and P. Therrien (2019, September). Dynamics and Management of Rising Outbreak Spruce Budworm Populations. *Forests 10*(9), 748. Number: 9 Publisher: Multidisciplinary Digital Publishing Institute.

Régnière, J., J. Delisle, A. Dupont, and R. Trudel (2019, September). The Impact of Moth Migration on Apparent Fecundity Overwhelms Mating Disruption as a Method to Manage Spruce Budworm Populations. *Forests 10*(9), 775. Number: 9 Publisher: Multidisciplinary Digital Publishing Institute.

Régnière, J., T. J. Lysyk, and M. Auger (1989, March). Population density estimation of spruce budworm, *Choristoneura fumiferana* (Clem.) (Lepidoptera : Tortricidae) on balsam fir and white spruce from 45 cm mid-crown branch tips. *Canadian Entomologist 121*(3), 267–281. Publisher: Cambridge University Press.

Régnière, J. and V. G. Nealis (2019, August). Density Dependence of Egg Recruitment and Moth Dispersal in Spruce Budworms. *Forests 10*(8), 706. Number: 8 Publisher: Multidisciplinary Digital Publishing Institute.

Régnière, J. and C. J. Sanders (2022, March). Abundance and distribution of foliage on balsam fir and white spruce in reference to spruce budworm ecology and absolute population density estimation. *Forests 13*(4), 534.

Safranyik, L., A. L. Carroll, J. Régnière, D. W. Langor, W. G. Riel, T. L. Shore, B. Peter, B. J. Cooke, V. G. Nealis, and S. W. Taylor (2010, October). Potential for range expansion of mountain pine beetle into the boreal forest of North America. *Canadian Entomologist 142*(5), 415–442.

Sims, C., D. Aadland, and D. Finnoff (2010, December). A dynamic bioeconomic analysis of mountain pine beetle epidemics. *Journal of Economic Dynamics and Control 34*(12), 2407–2419.

SOPFIM (2021). Documentation.

SOPFIM (2022, November). Rapport de réalisation des travaux 2022. Annual Report, Société de protection des forêts contre les insectes et maladie, Québec, QC.

SOPFIM (2023, November). Rapport de réalisation des travaux 2023. Annual Report, Société de protection des forêts contre les insectes et maladie, Québec, QC.

Statistics Canada (2017, March). National Road Network - NRN - GeoBase Series - Open Government Portal.

Sturtevant, B. R., B. J. Cooke, D. D. Kneeshaw, and D. A. MacLean (2015). Ch. 5: Modeling insect disturbance across forested landscapes: Insights from the spruce budworm. In A. H. Perera, L. J. Buse, and B. R. Sturtevant (Eds.), *Simulation Modeling of Forest Landscape Disturbances*, pp. 93–134. Geneva, Switzerland: Springer International Publishing Switzerland.

Sun, B., B. E. C. Bogdanski, and B. H. Van Hezewijk (2019). The Economic Feasibility of the Gypsy Moth Eradication Program in British Columbia. Technical Report BC-X-450, NRCAN Canadian Forest Service, Victoria, BC.

Talerico, R. L. (1983). Summary of life history and hosts of the spruce budworm. General Technical Report, USDA Forest Service, Broomall, PA.

Tantau, T. (2013). Graph drawing in TikZ. In *Proceedings of the 20th International Conference on Graph Drawing*, GD'12, Berlin, Heidelberg, pp. 517–528. Springer-Verlag.

Tobin, P. C. (2008, December). Cost Analysis and Biological Ramifications for Implementing the Gypsy Moth Slow the Spread Program. General Technical Report NRS-37, USDA Forest Service, Newtown Square, PA.

Vardas, G. and A. Xepapadeas (2015, April). Time Scale Externalities and the Management of Renewable Resources.

von Frankenhuyzen, K. (1995). Ch. 34: Development and Current Status of *Bacillus thuringiensis* for Control of Defoliating Forest Insects. In W.G.H. Ives and J.A. Armstrong (Eds.), *Forest insect pests in Canada*, pp. 315–326. Ottawa, ON: NRCAN Canadian Forest Service. Last Modified: 2013-04-03.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.

Wilson, D. C. and A. R. Ek (2019, October). Whole stand growth and yield models for major forest types in the Upper Great Lakes Region. Report, University of Minnesota, Minneapolis, MN. Accepted: 2020-09-22.

Yemshanov, D., R. G. Haight, F. H. Koch, R. Venette, K. Studens, R. E. Fournier, T. Swystun, and J. J. Turgeon (2017, July). A safety rule approach to surveillance and eradication of biological invasions. *PLoS ONE 12*(7), e0181482. Publisher: Public Library of Science.

Yemshanov, D., R. G. Haight, N. Liu, C. Chen, C. J. K. MacQuarrie, K. Ryall, R. Venette, and F. H. Koch (2020, March). Acceptance sampling for cost-effective surveillance of emerald ash borer in urban environments. *Forestry: An International Journal of Forest Research 93*(2), 280–296.

Yemshanov, D., F. H. Koch, B. Lu, D. B. Lyons, J. P. Prestemon, T. Scarr, and K. Koehler (2014, August). There is no silver bullet: The value of diversification in planning invasive species surveillance. *Ecological Economics 104*, 61–72.