OPTIMAL PREVENTION AND CONTROL OF INVASIVE SPECIES:

THE CASE OF THE BROWN TREESNAKE

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ABSTRACT

This dissertation examines the optimal management of a nuisance species that threatens but is not thought to be prevalent in an ecosystem. The three central chapters focus on integrated prevention and control of the Brown Treesnake (*Boiga irregularis*) in Hawaii.

The first essay (Chapter 2) develops a general model of prevention and control of an invasive species, where new arrivals into the system are determined by prevention expenditures which decrease the rate of arrival. While most of the previous work considers these policy instruments separately, this essay shows how prevention and control may be optimally executed simultaneously over time. The loss-minimizing management program is identified, and compared to status quo management in Hawaii. An additional contribution of this essay is an explicit consideration of how minimum viable population and initial population considerations influence the balance and magnitude between these two policy instruments.

In the second essay (Chapter 3), we introduce uncertainty to the problem by allowing the time of invasion to be unknown. Invasion is modeled as catastrophe, defined as an irreversible event of uncertain time. Realization of the catastrophe, which bears the minimized penalty analyzed in Chapter 2, is dependent on a hazard function of pre-invasion investment in prevention. After invasion, the model returns to one of full certainty, where arrivals are determined by post-invasion prevention expenditures as in

the first essay. We find that treating invasion as catastrophe results in higher levels of prevention expenditures before the invasion.

The third essay (Chapter 4) allows for uncertainty throughout the model by replacing deterministic arrivals with a probabilistic arrival function. This degree of generality requires the introduction of a strict assumption. The model requires that after some population level, the prevention instrument becomes negligibly effective with respect to control. This essay shows that unless this threshold population and the size of the invading population are unreasonably large, optimal policy requires maintenance of exactly the population at which prevention is no longer necessary. The essay also shows that considering optimal management of an invasion without accounting for the chance of reinvasion will suggest a policy of eradication, regardless of the size of the invasion.

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CHAPTER 1

INTRODUCTION

1.1 Description of Problem

An emerging problem in natural resource policy is how to design efficient strategies for managing invasive species. Invasive species, those plants, animals, and microbes that are nonnative to an area and have caused or have the potential to cause economic and or ecological damage, threaten natural resources, biodiversity, and human health worldwide. [1] It is the aggressive nature of invasive species that leads to their success at inflicting damage. High fecundity, rapid growth, the ability to spread quickly, strong resilience, and omnivorous appetites often characterizes the nature of successful invaders. In addition to their aggressive traits, favorable environmental conditions and/or release from natural predators often assist in their success. Optimal management of these species is the focus of this dissertation.

Damages from invasive species are ecological as well as economic. These include lost biodiversity and reduced ecosystem services, as well as direct and indirect economic damages such as health damages or lost productivity. Caterpillars from the Asian gypsy moth (*Lymantria dispar*) cause extensive defoliation, reduced growth and mortality of host trees throughout the northern hemisphere, while hairs on larvae and egg masses lead to allergies in some people (Gansner et al. 1987). The Nile perch *(Lates niloticus)* was introduced to Africa's Lake Victoria in 1954 and has since contributed to the extinction of more than 200 endemic fish species through predation and competition for food

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[1] This definition of invasive species is from President Clinton's Executive Order 13112, signed on February 3, 1999.

(Mooney and Hobbs 2000). *Caulerpa taxifolia* is a marine alga widely used as a decorative aquarium plant. The alga was accidentally introduced into the Mediterranean Sea in wastewater, where it has now spread over more than 13,000 hectares of seabed. This invader forms dense monocultures that prevent the establishment of native seaweeds and exclude almost all marine life (Jousson et al. 2000). Tamarisk (*Tamarix ramosissima*) is a shrubby tree that can be found where its roots reach the water table, such as floodplains, along irrigation ditches and on lake shores. Tamarisk can tolerate a wide range of saline or alkaline soils and is able to dominate floodplain communities in the deserts of the Southwest United States due to its ability to tolerate water stress for extended periods of time. Tamarisk supports few native insects and thus is poor habitat for birds (Everitt 1980).

There is particular concern about protecting the state of Hawaii from invaders. Hawaii has the most endangered bird species in the nation (32), as well as important assemblages of rare native invertebrates. Invasive species are an important source cause of the decline of biodiversity around the world, second only to habitat destruction (Wilcove et al. 1998). Hawaii has much at stake.

Despite growing recognition of the issue, Hawaii and the rest of the United States lag far behind other regions with regard to biosecurity. Often touted as the biosecurity leader, New Zealand provides a good example of what a successful biosecurity program looks like. It is said that while Hawaii prevents approximately 1 percent of what they are attempting to keep out, New Zealand's success rate is closer to 90 percent (Honolulu Weekly August 2006). This apparent divergence can largely be attributed to the differences in the two region's biosecurity institutions.

New Zealand uses a combination of command and control based regulations, disincentives, and an advanced screening and inspection system to manage what enters the country. They begin with a long list of what is not permitted to enter the country. They use straight forward rules to guard against invasion of unwanted pests and diseases. For example, because New Zealand wants to keep out malaria, which is carried by mosquitoes; visitors and residents are not permitted to bring any material that may contain standing water, such as tires, into the country.

Not only is the list of prohibited items longer in New Zealand than Hawaii, but the rules are credible and well-enforced. Stiff fines and penalties are levied for disregarding regulations. Filing a false declaration with agricultural authorities can result in an instant fine of 200 New Zealand dollars. Deliberate attempts to bring in illegal foodstuffs can result in prison time and fines up to 100,000 New Zealand dollars. While fines and penalties do exist on the books in Hawaii for the illegal importation of certain plants, animals, and other potential risks, the enforcement of such penalties is questionable. Furthermore, most agricultural agencies responsible for inspection and control of these goods have no enforcement authority. The Hawaii Department of Agriculture cannot directly enforce regulations. Rather, they have to file complaints with the police. In contrast, managers in New Zealand can confiscate goods, force citizens to assist in their biosecurity efforts, prevent vehicle movement, and enter private land to control potential threats. The complementarity between regulation, management and enforcement is largely absent in Hawaii, as well as the rest of the United States.

Another major difference is New Zealand's advanced system of screening and inspection. Like Hawaii, New Zealand is host to a steady influx of visitors from all around the world, especially Asia. Every piece of arriving cargo and luggage from outside the country is x-rayed for the presence of fruit and meat products from abroad. The technology is augmented by specially trained dogs who can detect a wide variety of contraband agricultural products. Aside from luggage and cargo, each of the 50 million pieces of mail reaching the country each year from abroad is x-rayed and also inspected by the dogs. The Ministry of Agriculture and Forestry estimates that 90 percent of "risky" plants, seeds, pests, and food items are intercepted before they enter the country (MAF 2007).

Finally, the coalition of groups interested in New Zealand's biosecurity is strong, well-coordinated and well-supported to carry out and enforce the necessary biosecurity policy. Driving the coalition are largely economic interests, such as business and tourism, who recognize the potential harm invasive species may inflict on their own sectors. In contrast, biosecurity policy in Hawaii is largely separate from these types of economic interests. Instead, governmental and non-governmental agencies often find themselves at odds with the larger economic and business interests, and struggle to push biosecurity legislation through the state and local governments. Well-intentioned agencies do not have the same level of support or funding to carry out prevention and control of potential and existing threats. Efforts are disparate and uncoordinated, with jurisdictional constraints often limiting the ability of agencies to even attempt management of a particular problem.

A recent study of sustainable tourism in Hawaii, funded by the tourism authority focused primarily on the infrastructure needed for increasing the number of tourists, not on conservation, preservation, or restoration of natural resources on which the demand for tourism and the welfare of Hawaii's residents depend (DBEDT 2006).

The absence of support for biosecurity in Hawaii has resulted in a long list of potential and existing invaders. An existing invader, *Miconia calvescens*, is a South American tree intentionally introduced to Hawaii for its showy purple and green leaves. Its aggressive growth, shallow root system, tendency towards monotypic stands, and ability to crowd out native species threatens habitat for biodiversity and water quantity and quality. Unintentional arrivals of hitchhiking species have also plagued the state's natural systems. The noisy coqui frog (*Eleutherodactylus coqui*) arrived as a stowaway in plant media from the Caribbean or Florida in the early 1980's. The piercing mating call of the male frog, coupled with extraordinarily high densities on the island of Hawaii have led to falling properties values for homes within earshot of the invasions (Kaiser and Burnett 2006). The well-known invasion of the brown treesnake (*Boiga irregularis*) on the island of Guam poses a real and immediate threat to the state of Hawaii, due to the large and increasing volume of military transport between to the locales, as well as commercial air and sea traffic. The snake has extirpated 11 native bird species on Guam (Vice 2006, personal communication), causes hundreds of hours of power outages a year, and sends a stream of citizens to the hospitals each year to treat venomous snakebites. Eight individual brown treesnakes (hereafter, BTS) have been intercepted at the ports in Hawaii, accompanied by hundreds of credible snake sightings resulting in zero captures.

Typically, invasive species management occurs in response to an invasion that has already become a costly event with respect to both damage and control costs. While managers are pouring limited resources into these existing invasions, other species are silently entering the scene, some of whom may prove even more costly in the future. Furthermore, the amount of control devoted to the invasion is often less than adequate to even keep up with the growth of the species, leading to control expenditures that are essentially wasted and higher total future costs associated with the invasion. A more prudent approach would allow the management regime to be endogenous, by investigating how the management instruments should be implemented to minimize total expected losses associated with the invasion.

Complete treatment of the problem of invasive species in Hawaii would entail consideration of the biosecurity institution as well as each and every potential and existing threat to the state. This task is well beyond the scope of this dissertation. Instead, we follow the tradition of using resource economics to investigate the optimal policy regarding a single species that is recognized as threat by experts within and outside of Hawaii. Specifically, we consider the Brown treesnake. Cross-species issues, such as economics of scope in inspection activities are left to further research.

1.2 Management Taxonomy

We begin by reviewing the nature of policy instruments used in invasive species management. These include prevention, eradication, suppression, containment, and adaptation. In the global warming literature, it is common to make a distinction between mitigation (the reduction in greenhouse gases) and adaptation. In the case of invasive species, two mitigation functions are distinguished – that of prevention and control (Eiswerth and Johnson 2002, Perrings 2002).[2] The central question is how to execute these strategies optimally. Resource managers use a combination of these tools to ward off economically detrimental species. While we cannot feasibly address all of these instruments in this work, we will begin by looking at the ones most commonly employed in management, prevention and control.

1.2.1 Prevention

Prevention includes activities that reduce the likelihood of a pest's entry or establishment to the area of interest. Instruments commonly used for prevention include inspection, searches, quarantine, public education, risk assessments, import and exportation protocols, red (prohibited) listing, and green (allowed) listing. Port of entry inspection may be the most common instrument intended to catch invasive species before they enter a region. Agency personnel and dogs are trained to inspect cargo for the presence of potentially harmful species. Because there are economies of scope in many prevention activities, e.g., finding one species in an inspection while looking for another, additional and often excluded benefits may be attributed to this policy instrument.

Import permits, letters of authorization, quarantine and health certificates are other instruments used to prevent unwanted organisms from entering a region. Permit requirements, length of quarantine, and ease of obtaining all of the above will determine the success of these types of tools.

[2] Analogously, one could distinguish between two mitigation functions for global warming. Abatement is analogous to prevention, and sequestration is analogous to control.

An instrument that is formally and practically distinct from prevention and control is a mechanism widely known as early detection and rapid response (EDRR). The objective of this instrument is to catch the invader after it enters the region but before it becomes established. An example of EDRR is the BTS rapid response teams in the Pacific. Specially trained personnel have been organized specifically to respond to credible BTS sightings in Hawaii or on other Pacific islands at risk. If the teams catch the refugee snake, an invasion may have been prevented. In this work, EDRR is subsumed as part of the control category. We discuss the need to consider this instrument independently in later sections.

1.2.2 Control

Control entails reducing the impact a species has on the environment and economy. This strategy decreases or eliminates the population of an invader. Under the general control strategy there are three instruments that are commonly used. These are suppression (reduction of population, also referred to as removal or harvest), eradication (complete elimination of population), or containment (spatial restriction of the species). Manual, chemical, and biological control are the most common mechanisms to control invasive species.

Suppression seeks to draw the population down, without eliminating it entirely, and without concern for location. The suppression strategy removes a proportion of the population in each time period. Often annual or biannual reconnaissance will be conducted, and removal will occur based on ease of access, proximity to valuable "at-risk" resources, or number of individuals.

Eradication and containment are special cases of the suppression strategy.

While eradication is often the desired management outcome, it is often the least realistic. Complete removal of a species is complicated by strong species resiliency, refugia resulting from anthropogenic activities, high search costs, high probability of reinvasion, and incomplete information regarding the total population. Most successful eradication projects occur when the population is very small, easy to detect, or in the very early stages of establishment.

Finally, the objective of containment is to keep the species within some specified area. Containment of an animal species requires fencing or some type of natural barrier (e.g., high mountains or water) to keep the population contained. For a plant species, containment can make use of natural boundaries, such as rainfall or elevation limits, as well as harvesting around the perimeter of the invasion.

1.2.3 Adaptation

Adaptation requires changes in behavior, be it publicly or privately, in order to lessen the impact of an invasive species. This objective of this strategy is to reduce the adverse consequences caused by the species. We further consider adaptation as separable into actions that are passive, where the success of the new species is accommodated, and actions that are active, i.e. intervention that invests directly in reducing the damages of the new species or in the creation of substitutes. Active adaptation includes planting native trees, water catchments, flood control, and others, while passive adaptation involves avoidance activities, such as creating incentives for individuals to seek substitutes for the lost benefits. Passive adaptation also includes the choice of inaction.

The proposed taxonomy is illustrated in Figure 1.

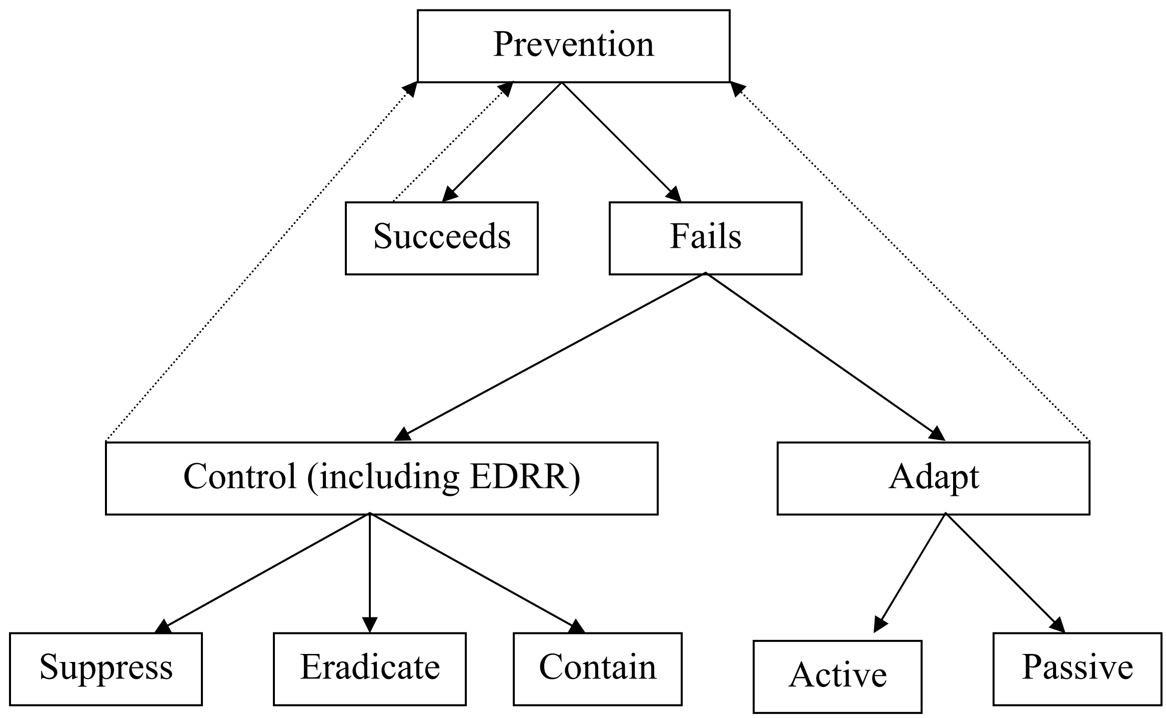

Figure 1.1. Invasive Species Management Taxonomy

1.3. Frontier of Knowledge

Economists have been studying the management of renewable resources since the beginning of the 20th century.[3] These pieces explore optimal intertemporal depletion of renewable resource stocks by choice of a single management instrument, harvest. These works share the feature that the resource stocks under consideration have both in situ and market values. Recently, an interest has emerged in those stocks with negative in situ value and potentially zero or insignificant market value. Conrad and Clark (1987) and Clark (1990) provide an appealing framework in which to solve for optimal steady state harvest levels and approach paths for renewable resources. What has not been fully developed in the literature to date is how to optimally manage a resource that is not yet present in the system of interest.

A useful body of literature has emerged in response to questions of invasive species management. A subset of work has focused on the management instruments themselves (Shogren 2000, Perrings 2005), while other studies have focused on both theoretical underpinnings of general invasions (Olson and Roy 2005, Finnoff and Tschirhart 2005, Leung et al. 2005) as well as more specific empirical case studies of current invasions and their economic impact (Heikkila and Peltola 2004, Pimental et al. 2005). Others have taken the theory they develop and have used it to address actual management questions empirically (Buhle et al. 2005, Knowler and Barbier 2005, Horan and Lupi 2005, Finnoff et al. 2005).

[3] See for example, Gordon (1954), Plourde (1970), Clark and Munro (1975), Krautkramer (1985, 1998).

Buhle et al. (2005) combine population elasticity analysis (how improvements in life cycle – survival, growth, reproduction – improve population growth) with data on control costs to determine cost-minimizing management strategy. The major limitation is that their analysis does not include damages from the invader itself. Their model assumes it is optimal to remove the species of interest, and the only question is how to do it at least cost.

To emphasize the interlinkage between human behavior and ecosystem response, Finnoff et al. (2005) extend the usual "damage function approach," by making the biological response to economic policy subject to two types of feedbacks – one linking the individual or firm responsible for the species introduction and the biological system, and another linking the policymaker, the individual, and the biological system. They show that the first linkage is less important ecologically, but has substantial implications economically. Ignoring the second type of feedback has less detrimental effects both ecologically and economically.

Leung et al. (2005) choose simple functional forms to describe damages, control, and prevention of invasive species. They derive necessary conditions describing optimal prevention and control, and perform comparative static analysis of these conditions. From these, intuitive rules of thumb relating optimal expenditure to parameter values are offered. For example, optimal control expenditures increase with the value of the system and decrease with uncontrollable damages. Optimal prevention expenditures are strongly dependent upon the degree of preventability of invasions and decrease as invasions become more unpreventable.

The limitation of this paper is that it does not allow for simultaneous prevention and control, only prevention in the “uninvaded” state of the world, and control in the “invaded” state.

Other works of interest include Horan and Lupi (2005), who examine the design and efficiency of a tradable permit system for invasive species. They show that the permit system cannot be first-best efficient since an excessive number of different permit types would have to be traded at vessel-specific rates, and information would be required of all potential invaders, including potential expected damages. They illustrate the features of a second-best market, which involves a single type of permit and focuses on a few potential invaders as target species.

Finnoff and Tschirhart (2005) characterize *redundant* versus *invasive* species. Redundant species are those less successful species in an ecosystem that provide “biodiversity insurance” for when something in the system changes replacing the previously successful species. If a species is redundant in a system it cannot be invasive, and a successful invader cannot be redundant. They develop a management theory for identifying redundant and invasive species based on four physiological parameters – two respiration parameters, one solar energy intake parameter, and one environmental preference parameter.

Olson and Roy (2005) is the work that comes closest to our ideal model of integrated management instruments under uncertainty. In this paper they examine optimal prevention and control strategies for a randomly introduced biological invasion. Our models extend this work by introducing a minimum viable population to the system of interest, and by considering implications of an uncertain initial population.

Olson and Roy assume that growth will begin following the first arrival, and that the planner knows the size of the initial invasion population.

Furthermore, their work is a purely theoretical piece, without application to an actual invasive species management question facing managers.

The literature reviewed above has taken a single species approach to solving for efficient invasive species management. Obviously, interactions with native species and other invasive species are important, but as a start we continue in a similar vein and consider optimal management of a single species at a time.

The frontier of knowledge seems to have reached but not surpassed the two important issues in optimal invasive species management of simultaneous management instruments and uncertainty. This dissertation advances the frontier by addressing both of these considerations explicitly, first in a general theoretical framework, followed by an illuminating case study from the invasive species capital of the nation, Hawaii.

1.4. Brown Treesnake as a Case Study

It is believed that the BTS arrived to Guam as a stowaway from the Australia/New Guinea region in military transport following the Second World War (Savidge 1987). The snake's presence was not seen as a major threat to the island until the early 1980's when densities of 100 snakes per hectare were recorded on certain parts of the island. Control efforts began soon after. That these density levels were attained before the problem was officially recognized gives some indication of the cryptic and secretive nature of this animal.

Although densities have declined dramatically since then to an average of 10-20 snakes per hectare, damages persist in the form of power outages (due to snakes on power lines), lost biodiversity (the snake extirpated 11 of 18 native forest birds on Guam), and medical visits (from snakebites, mostly to young children).

Because of the high and increasing volume of transport between Guam and Hawaii, especially between military units, the snake poses a direct and immediate threat to Hawaii. There have been eight verified interceptions of the snake on the island of Oahu, all at ports of entry (Rodda et al. 1999, personal communication 2007).[4] Aside from these interceptions, there have been several credible sightings after which rapid response teams were deployed but no snake was captured, and several hundred snake sightings that were not confirmed as being a BTS.

BTS is an ideal candidate for studying the implications of uncertainty in invasive species management because of the plethora of uncertainties associated with its seemingly imminent arrival to Hawaii. There are at least three distinct uncertainties associated with the snake's invasion of Hawaii. Because of the number of uncertainties involved in the optimization problem, there is currently no methodology for a single tractable model. Instead, a set of models is used to help inform optimal management decisions regarding the timing, magnitude, and balance between prevention and control instruments.

The first major uncertainty with respect to the snakes is the probability of its arrival to Hawaii. The probability that a single snake will make it to one of the islands and escape unseen from the port of entry is a function of many variables. These include

[4] Barbers Point Naval Air Station, Schofield Barracks, Honolulu International Airport, and Hickam Air Force Base

but are not limited to the effectiveness of the prevention program in place in Hawaii, the rigor of the control technology on Guam, the frequency of transport between the two places, and the habitat surrounding the snake's entry vector. This probability has obvious implications for optimal management of the species, as it influences the expected losses from invasion.

The second uncertainty involves how many snakes are actually present on the main island of concern, Oahu. Home to most of Hawaii's major air and seaports, Oahu is the most populated island and the major tourism destination in the state. While the official count is zero, conversations with scientists, the interception of eight snakes over the last twenty years and a number of credible snake sightings leading to zero captures suggest the possibility of a small population. The number of snakes currently in Hawaii may have important implications for the ideal mix of prevention and control policies. If a reproducing population has already been formed, returns to control may be significant in that catching a few snakes early may have high benefits.

The final type of uncertainty involves how many snakes are required for an incipient population in a given area. In other words, will the arrival of one snake be enough to begin a self-sufficient population (without depending on more arrivals), or is there some threshold number of snakes that is necessary to "spark" a population?[5] Given the latter, what exactly is this "spark population?" This uncertainty may have profound implications for determining the steady state population at low numbers of snakes.

While less of a concern, an additional source of uncertainty surrounds the number of snakes that will invade at one time.

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[5] Mitochondrial DNA evidence suggests that the entire population of snakes on Guam may have originated from a very few individuals (Rawlings et al. 1998 as cited in Engeman and Vice 2001).

Obviously the probability of a multiple snake invasion is significantly less than that of a single snake invasion.

1.5. Research Strategy and Overview of Principal Chapters

In this dissertation, we employ a set of models to address these uncertainties. We begin with the simplest case, a fully deterministic model where arrivals are determined by prevention expenditures, to illuminate tradeoffs between the two policy instruments in question. We then use the shortcomings of this model to motivate the remainder of the dissertation.

Chapter 2 develops a general model of prevention and control of an invasive species, where new arrivals into the system are determined by prevention expenditures which decrease the rate of arrival. While most of the previous work in this area considers these policy instruments separately, this essay shows how prevention and control should be optimally executed simultaneously over time. The loss-minimizing management program is identified, and compared to status quo management in Hawaii. An additional contribution of this essay is an explicit consideration of how both minimum viable population and initial population considerations influence the balance and magnitude between these two policy instruments.

In Chapter 3, we introduce uncertainty to the problem by allowing the time of invasion to be unknown. Invasion is modeled as catastrophe, defined as an irreversible event of uncertain time. The timing of catastrophe, which bears a penalty, is dictated by a hazard function which depends on pre-invasion investment in prevention. After invasion, the model returns to one of full certainty, where arrivals are determined by post-invasion prevention expenditures as in Chapter 2. We find that the explicit consideration of uncertainty regarding the time of invasion results in higher levels of prevention expenditures before the invasion than in the fully deterministic model.

Chapter 4 allows for uncertainty throughout the model by replacing deterministic arrivals with a probabilistic arrival function. This degree of generality requires the introduction of a strict assumption, however. The model requires that after some population level, the prevention instrument becomes negligibly effective with respect to control. The essay shows that unless this threshold population and the size of the invading population are unreasonably large, optimal policy requires maintenance of exactly the population at which prevention is no longer necessary. The chapter also shows that considering optimal management of an invasion without accounting for the chance of reinvasion will suggest the need for a policy of eradication, regardless of the size of the invasion.

In addition to advancing the theory of optimal invasive species management, a secondary purpose of this work is to close the gap between the economic models and the reality of issues faced by decision makers. To the extent possible, it is the author's hope to shed light on how to improve invasive species policy in the Pacific and beyond.

CHAPTER 2

A DETERMINISTIC MODEL OF PREVENTION AND CONTROL[6]

2.1 Introduction

Resource economics provides a useful framework for investigating optimal management strategies for dealing with invasive species. Instead of maximizing gains from a species with positive economic harvest value, and potentially positive *in situ* value, the problem of invasive species involves removing a species with negative *in situ* value and potentially zero harvest value. In general, policy makers must determine the proper balance between prevention expenditures that lower the probability of new introductions and control expenditures that limit the growth rate and/or invasive population. Optimal policy regarding invasive species will minimize the expected damages and costs of control within an ecosystem and will include full consideration of the cycle of prevention and control needed over time.

We can use the tools developed by renewable resource economics to minimize harvest and damage costs from the invader, so long as the species in question is present in the system of interest. Much of the work in the invasive species literature to date mirrors the renewable resource literature in that it solves the optimal harvest of a species over time. Shogren (2000) began the discussion with a static model resulting in a condition dictating optimal harvest of the generic invader. Dynamics were introduced by Eiswerth and Johnson (2002) and Perrings (2002), providing time trajectories for optimal harvest.

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[6] This chapter draws heavily on Burnett, K., S. D'Evelyn, B. Kaiser, P. Nantamanasikarn, and J. Roumasset (2007). Beyond the Lamppost: Optimal Prevention and Control of the Brown Treesnake in Hawaii, manuscript.

Rarely, however, have policy makers or economists integrated prevention and control for optimal intertemporal allocation of resources.

With few exceptions, the empirical literature has handled prevention and control separately. Either prevention or control policies are investigated, holding the other constant, or there is not a complete characterization of the threat. This separation presents particular challenges in translating theory to action because the net benefits of prevention and control are endogenous (dependent) on policy interventions undertaken in each stage. In response, an economics of integrated prevention and control (e.g. Pitafi and Roumasset 2005, Olson and Roy 2005, Burnett et al. 2006) is slowly evolving. Optimal control theory is combined with biological and economic parameters to solve for the optimal expenditures on prevention and control over time. Applications, when attempted, have been mainly illustrative to date. In this paper we aim to improve both theory and application. We illuminate theoretically how expenditure paths for prevention and control change simultaneously in response to various biological and economic parameters, and in particular, the challenging problem of how to differentiate between the benefits of prevention and control when an initial arrival does not immediately translate into an established population. We solve for expenditures for every population level and each time period for the real-world case of the BTS. We find that the conventional wisdom that "an ounce of prevention is worth a pound of cure" does not reveal the whole story. Depending on the interaction of biology and economics, the message may be much richer than this.

2.2 Model

We employ optimal control theory to determine the paths of expenditures that minimize the present value of prevention expenses, removal costs, and damages over time. For the sake of computational simplicity and clarity of exposition, we begin with a deterministic model. Each period, the snake population is known and new entrants arrive on a continuous basis. The solution involves a steady state population of snakes and corresponding time paths of expenditures on prevention and removals.

$$\underset{x_t, y_t}{Max}\ \varphi \text{ where } \varphi = \int_o^{\infty} -e^{-rt}\left(\int_0^{x} c(n_t)d\gamma + D(n_t) + y_t\right)dt \tag{2.1}$$

Subject to

$$\dot{n} = g(n) - x + f(p) \tag{2.2}$$

$$n_0 = n(0) \tag{2.3}$$

$$x \geq 0 \tag{2.4}$$

$$y \geq 0 \tag{2.5}$$

where *n* is the population, *c* is the unit cost of removal, *D(n)* is the damage function, *y* is prevention expenditures, $g(n)$ is the growth function, *x* is the harvest level and *f(y)* describes how many new individuals are added to the current population as a function of investment in prevention.

The current value Hamiltonian for this problem is:

$$H = -\int_0^x c(n)d\gamma - D(n) - p + \lambda[g(n) - x + f(y)] \qquad (2.6)$$

Application of the Maximum Principle leads to the following conditions:

$$\frac{\partial H}{\partial x} = -c(n) - \lambda \leq 0 \qquad (2.7)$$

$$\frac{\partial H}{\partial p} = -1 + \lambda f'(p) \leq 0 \qquad (2.8)$$

$$\frac{\partial H}{\partial n} = -c'(n)x - D'(n) + \lambda g'(n) = r\lambda - \dot{\lambda} \qquad (2.9)$$

$$\frac{\partial H}{\partial \lambda} = g(n) - x + f(p) = \dot{n} \qquad (2.10)$$

For all internal solutions, we get the following

$$\lambda = -c(n) = \frac{1}{f'(p)} \qquad (2.11)$$

Equation (2.11) states that at every period where there is positive spending on prevention and control, the marginal costs of each will be equal to the shadow price of snakes. Funds should be spent until the dollars are equally effective at preventing and removing snakes.

Since removal costs are linear with respect to *x*, a "bang-bang" solution is obtained, such that removal only occurs at the optimum steady state.[7]

Thus, if the initial population is smaller than the steady state, the optimal program involves spending on prevention alone until equation (2.8) holds with equality.

This general model is a useful starting point to begin thinking about the tradeoffs faced between prevention and control activities. However, this model neglects two significant realities concerning the growth and the initial population of the species.

A natural dilemma that enters the problem when the species in question is not actually present in the system is the wide range of uncertainties surrounding the hypothetical invasion. For example, when will the invasion occur? And will the arrival of a single individual necessarily result in an established population of the species in question, or is there some minimum number of individuals that must arrive for a population to take hold? In the general model above, the main uncertainties are related to Equations (2.2) and (2.3).

In Equation (2.2), the question is at what population will growth actually begin? Is the arrival of one individual sufficient to begin a self-sustaining population, or does establishment require the arrival of many more individuals? Another ambiguity that arises in Equation (2.2) is how individuals are added to the population. In the general model, additional arrivals are determined by how much is spent on prevention. Realistically, there is some probability distribution governing arrival of the new entrants. Equation (2.3) assumes that we know with certainty the current population of the species of interest, while in reality this number is typically unknown.

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[7]A bang bang solution is obtained when the control variable "bangs" against one boundary in the control set (including corner solutions) and then against another, in succession. (Chiang 1992, p. 164).

These shortcomings motivate much of this dissertation.

2.3 Parameterization

The immediate obstacle to estimating economic impacts to Oahu, as with any potential invasive species in a new habitat, is that there is no direct evidence on which to base cost, damage, and growth function parameters. Instead, we obtain rough estimates based on indirect evidence from Guam and the subjective assessments of invasive-species research scientists and managers.

The resulting parameters are discussed below, followed by results.

2.3.1 Growth

We utilize the logistic function,

$$g(n) = bn\left(1 - \frac{n}{N_{MAX}}\right), \tag{2.12}$$

to represent the potential growth of the snakes. In this case, the intrinsic growth rate, *b*, is 0.6, based on based on estimated population densities at different time periods on Guam (Rodda et al. 1992 and personal communication 2005). The maximum elevation range of the snake may be as high as 1,400 m (Kraus and Cravalho 2001), which includes the entire island of Oahu. There are approximately 150,000 hectares of potential snake habitat on Oahu. Assuming an average maximum population density of 50 snakes/hectare, carrying capacity (N_{MAX}) for the island of Oahu is 7,500,000 snakes.

2.3.2 Damages

Major damages from BTS on Guam include lost productivity and repair costs due to power outages, medical costs from snakebites, and lost biodiversity from the extirpation of native bird species.

Guam has a land area of approximately 53,900 hectares, with a maximum elevation of about 400 meters. With a population density of 50 snakes per hectare, the carrying capacity for Guam is 2,695,000 snakes. With approximately 272 hours of power outages per year attributable to snakes (Shwiff et al. 2006), we estimate that there are $1.01*10^{-4}$ power outages per snake per year. Fritts estimates that an hour-long power outage on Oahu causes $1.2 million in lost productivity and damages (Fritts 1998, personal communication through Brooks Kaiser). Positing a linear relationship between snake population and power outages, the expected damage per snake on Oahu, in terms of power outage costs, is $121.11.

Guam has experienced a snake-bite frequency average of 170 bites per year, at an average cost of $264.35 per hospital visit (Shwiff et al. 2006). Thus the expected number of bites per snake per year is at least $6.31*10^{-5}$, implying an expected cost of $0.02 per snake. Oahu's population density below 1,400 m is approximately three times that of Guam's, so we adjust the expected costs for Hawaii to $0.07 per snake.

The BTS has extirpated 61% (11 of 18) of Guam's native bird population since its arrival (Vice 2006, personal communication). Contingent valuation studies have estimated the average value of the continued existence of an endangered bird species at $31 per household per year for Hawaii (Loomis and White 1996).

There are eight endangered bird species on Oahu whose main habitat is below 1,400 meters and are at considerable risk of extirpation.

To obtain a conservative estimate, we assume that the birds are valuable to households on Oahu alone. We assume that at carrying capacity, there is roughly a 98% chance of losing a single species and another 3% chance of losing a second bird species. Using an expected value to 280,000 Oahu households of losing one species of $8.68 million, the expected per snake damage level is $1.13 per year, assuming that each snake is equally likely to contribute to the extirpation.[8]

Thus, expected damages from human health factors, power outages, and expected endangered species losses can be expressed as:

$$D = 122.31 \cdot n_t \,. \qquad (2.13)$$

To the extent that nonresident values, including existence values from preservation, are not reflected in this equation, this damage function represents a lower bound estimate of true damages from the BTS.

2.3.3 Removal Cost

To date there has not been a successful capture of BTS based on a credible sighting report or other search activities in Hawaii. However, recent closed population studies on Guam have examined how hard it is to catch snakes, in terms of "trap nights," which can be converted to dollars.

[8] To calculate expected per snake damage level, $\frac{(\$8.68\text{m} * .95) + (\$8.68\text{m} * .03)}{7{,}500{,}000}$

Parameterization of the cost function was based upon information provided by Gordon Rodda (2006, personal communication). Rodda studied an enclosed area of five hectares containing roughly average levels of both snakes and prey for over a year. During that time, he observed the life cycle patterns, relative sizes, and the success rates of two capture techniques. The first removal method, setting traps, had a relatively high success rate with larger snakes but was completely ineffective at capturing the smaller ones. Visual searches, on the other hand, had much lower success rates than trapping, but were able to remove all sizes of snakes. In Rodda's enclosure study, all capture data was collected and the individual was recorded and then released back into the enclosure.

Rodda estimated that were these methods put into practice on Hawaii, each night of trapping would cost roughly $150 per 5-hectare area, whereas visual searches would cost closer to $300 per area per night. The expected number of nights to catch a single snake if somewhere on the island by each of the two methods was estimated. We also calculated the fraction of a night (or fraction of the island searched) before the first of 100 snakes were found by each of the two methods. Thus the final cost function is based upon spending 1/6 of the time in visual searches and the other 5/6 removing the population through trapping. Under this marginal cost function, removing a snake from a population of 1 will cost $92.5 million, removing a snake from a population of 100 costs $335,356, and removing a snake, should the population reach carrying capacity, will cost approximately $29.

The resulting marginal cost function is:

$$c(n) = \frac{1.547 * 10^7}{n^{0.8329}} \quad (2.14)$$

2.3.4 Deterministic Arrival

We assume that prevention expenditures buy a reduction in the number of snakes that arrive and become established. From conversations with BTS managers and scientists, under current prevention expenditures of $2.6 million, Hawaii faces an approximate 90% probability that at least one snake will arrive over a ten-year time horizon. Assuming that each snake arrives independently, this produces a 20.6% probability of at least one snake arriving in any given year.

If expenditures increased to $4.7 million, the probability of at least one arrival would decrease two-fold, to about 45% over the ten-year horizon. Finally, if preventative spending is increased to $9 million per year, the probability of an arrival decreases another two-fold, to about 20%. These percentages correspond to a yearly probability of arrival of 5.8% and 2.2% respectively. We convert these probabilities to expected values using the Poisson distribution.

The Poisson distribution enables us to predict the expected number of snake arrivals over any given period of time so long as the following conditions are met:

a) At least one probability of arrival for some number of snakes over a given amount of time is known

b) Snake arrivals can take place on a continuous time basis with no one time more probable than any others

c) Each arrival is independent of any others (note: this does rule out a group of snakes arriving together)

Once we know that the probability of *x* snakes arriving over the course of *t* periods, then we can use this simple formula to determine the Poisson distribution's primary parameter, λ, by means of the following formula:

$P(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}$ over the given period of time.

From conversations with snake managers and scientists, the probability that there are no snake arrivals over the course of 10 years is roughly 0.1. From the formula above, for any given 10 year period $P(0) = e^{-\lambda}$, because x=0. Thus, λ would equal-ln (.1)= 2.30259. Thus we would expect to have 2.3 snakes arrive over a 10 year period.

Table 2.1. Calculating Snake Arrivals using the Poisson Distribution

Prevention expenditures (y)	Probability that at least 1 snake will arrive in 10 years	Probability that no snake will arrive in 10 years	Probability that no snake will arrive in a given year ($f(0)$)	Implied Poisson λ ($\lambda = -\ln[f(0)]$)
2.6 million	0.9	0.1	$0.1^{1/10} = 0.794328$	0.230259
4.7 million	0.45	0.55	$0.55^{1/10} = 0.941968$	0.059784
9 million	0.2	0.8	$0.8^{1/10} = 0.977933$	0.022314

The Weibull distribution is used to fit the arrival function because of its flexible shape and ability to model a wide range of failure rates (e.g., in engineering, such as capacitor, ball bearing, relay and material strength failures). Here, the Weibull describes failure of the prevention barrier.

The resulting function is

$$\lambda(y) = \exp(2.3 - 0.00224 y^{0.5}) \tag{2.15}$$

2.3.5 Spark Population

One of the major uncertainties surrounding the establishment of the BTS on Oahu is the number of snakes at which the population becomes self-sufficient. While this number could theoretically be one (if a female snake arrives impregnated or gravid, potential parthenogenesis, etc.), it is also possible that this number may be much higher. To the extent that snakes may arrive in different areas and must then find each other before the population begins growing independent of arrivals, this critical number which we refer to as the "spark population" may be a couple or a few snakes, or as high as one hundred or more. While the probability that a population becomes established is clearly a function of many complications, we employ the spark population parameter as a modeling device to represent these difficulties.

We begin with the assumption that it takes two snakes to form a self-sustaining population. Once this minimum or "spark" population is reached the population grows along a logistic growth path. We follow this specification with the usual assumption made in resource economics that the population begins with the first arrival, to see how this assumption changes policy implications regarding the two management instruments.

2.4 Results

2.4.1 Spark Population of Two

As mentioned previously, there is great uncertainty surrounding the present population of snakes in Hawaii, although the number is estimated to be between zero and 100. For this reason, we investigate two cases. First, we determine optimal policy if there are no snakes in Hawaii, and second, we determine optimal policy given an initial population of 50 snakes.

Our analysis finds that the optimal strategy is to keep the local population to just under the minimum reproducible population (a steady state of 2 snakes). This is done through significant spending on prevention, followed by additional smaller expenditures on removals once arrivals reach the minimum reproducible population. Given our functional forms, if the current population is zero, then today it is optimal to spend $2.94 million on prevention only, an amount very close to what authorities are currently spending. With this level of spending, it takes about 10 years to reach n=2, at which point removal expenditures should begin to keep the population in a steady state. In the steady state, $3.2 million is spent to keep all but 0.84 snakes from entering the island and $1.6 million to remove 0.84 snakes every year.

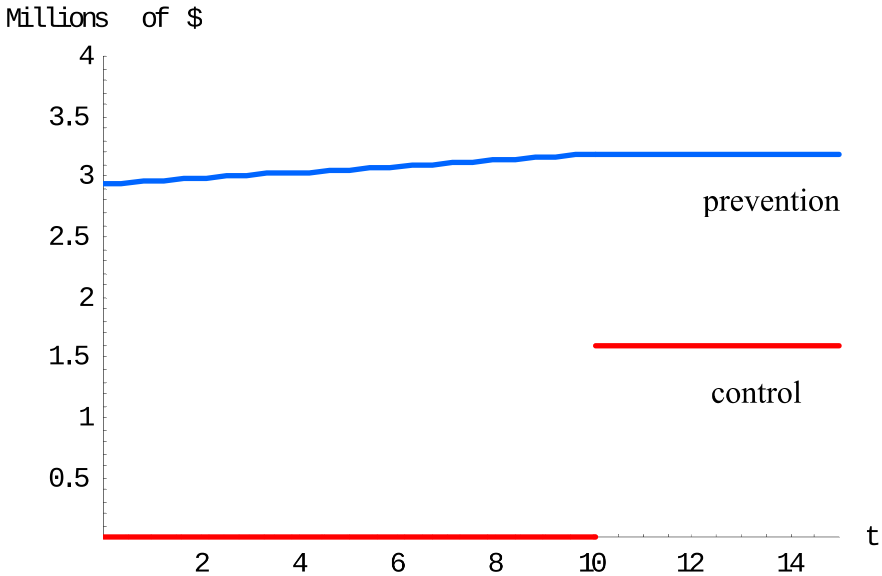

Figure 2.1. Optimal Prevention and Control Expenditure Paths: Case 1 (n0=0)

Figure 2.1 above illustrates the optimal expenditure paths for removing and avoiding snakes on Oahu. The optimal paths require prevention and removal expenditures that increase with time and snake population. The steady state level of snakes is 2.[9] Figure 2.2, below, illustrates the optimal policy starting with 50 snakes on Oahu. After removing 48 snakes immediately at a cost of nearly $75 million, $1.6 million should be spent per year removing snakes and $3.2 million preventing more from entering.

[9] The optimal population is actually 1.99999 (*ad infinitum*), since the optimal population requires maintenance right below the spark population of two. Therefore, there is no formal steady state.

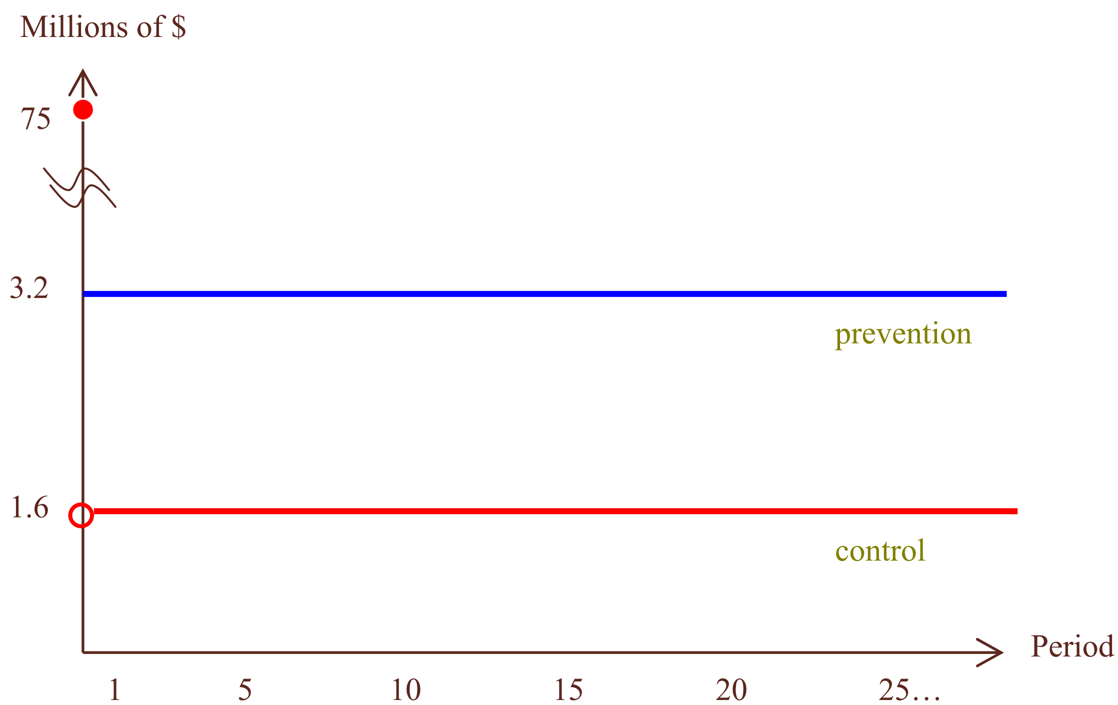

Figure 2.2. Optimal Prevention and Control Paths: Case 2 (n0=50)

Table 2.2. Summary of the Optimal Policy

	1st period		Steady state	Present value	
	n_0 =0	n_0 =50	n=2	n_0 =0	n_0 =50
Removal, x	0	48	0.184	-	-
Cost of x	0	75.6 million	1.60 million	65 million	154 million
y	2.94 million	3.19 million	3.19 million	158 million	195 million
Arrivals	0.216	0.184	0.184	-	-
Damage	$0	$243	$243	$11,000	$12,100
Total	2.94 million	78.8 million	4.79 million	223 million	349 million

Whether or not we are currently spending “enough” on prevention or control depends on the actual number of snakes currently present in Hawaii. If indeed there are no snakes in the state, current prevention expenditures are remarkably close to optimal. However, if there is a small population of close to 50 snakes, optimal policy calls for significantly increased removal expenditures (from $76,000 to $75 million) and approximately $340,000 more in prevention measures. This result emphasizes the need for better information regarding the current population of snakes in Hawaii.

2.4.2 Status Quo vs. Optimal Policy

It is difficult to compare the optimal program to Hawaii’s actual strategy, as we cannot be sure of the manager’s response in combating BTS at different population levels. We thus derive several alternative scenarios that a manager might choose.

Table 2.3. Losses from Following Alternative Status Quo Policies

Alternative status quo steady states	Loss vs. Optimal
1	$53.3 m
2	$973,000
10	$479.2 m
100	$614.9 m
10,000	$1.27 b
100,000	$2.09 b
1,000,000	$5.46 b
Business as usual	$24.2 b

Note: m: million, b: billion

In all the scenarios listed in Table 2.3, the manager continues to spend what is currently being spent each year until they abruptly decide to keep the snake population constant. In the first scenario, the invasive is discovered early (when the population is only 1 snake), and population is maintained at that level. In each succeeding scenario the manager switches policy later and allows for a higher number of snakes to remain on the island. Improper management of BTS can easily cost Oahu millions of dollars. Even if the problem is ignored only until the optimal population of 2 snakes is reached, almost a million dollars in value is still lost. The situation is much worse if ignored even longer. If the status quo is maintained until the snake population reaches 10,000 snakes, over $1 billion is forgone. If the snakes multiply until they reach a population of 1 million, over $5 billion is lost. In the business-as-usual scenario, managers continue to spend exactly $76,000 on control and $2.6 million on prevention, regardless of the actual population. This policy will result in a population right below the carrying capacity of 7.5 million and results in losses exceeding $20 billion.

2.4.3. Sensitivity to Spark Population

A common tradition in modeling fisheries or other biological populations involves approximating growth with a logistic growth function without assuming any minimum viable or "spark" population size. We follow this tradition and solve the model without the spark population in this section as an exercise in sensitivity analysis.

Table 2.4. Optimal Policy without Spark Population

	1st period		Steady state	Present value	
	n_0=0	n_0=50	n=1.73	n_0=0	n_0=50
Removal, x	0	49.48	1.21	-	-
Cost	0	87.7 million	11.8 million	515 million	667 million
y	11.1 million	3.34 million	3.34 million	190 million	167 million
Arrivals	0.00574	0.167	0.167	-	-
Damage	$0	$210	$210	$9,410	$10,500
Total	11.1 million	91.0 million	15.1 million	705 million	833 million

While the steady state population of 1.73 is not very different from the previous case, total expenditures are significantly higher, since there is more growth to prevent and control. Expenditure on prevention is also higher than in the previous case because reproducing snakes are more costly to the island and thus need to be controlled more intensively.

To explore the symmetry of sensitivity to spark population, we also check to see if instead of two snakes it takes four snakes to establish a population. We find that erring on the high side results in larger losses than erring on the low side. Efficient spending decreases for prevention and control; there is now less growth to prevent and control in the optimal solution. The values of the optimal programs are also lower. For example, if there are currently zero snakes in Hawaii, steady state prevention and control levels are $2.5 and $1.4 million a year, respectively. The total value of this program is $179 million, about $50 million less than when the spark population is assumed to be two. These results suggest that being conservative when setting the spark population may be lead to lower losses than being too optimistic with the assumption of the spark population (e.g., 4 snakes); larger spark population assumptions may lead to drastic underspending on both policies. The loss function of spark population error size is nonsymmetrical; underestimating the spark population will cause higher spending, thus avoiding higher losses, while overestimating the spark population will result in much lower spending, leading to more significant future losses due to unanticipated growth that is not being controlled.

2.5. Conclusion

In this chapter, we developed an integrated model for the prevention and control of an invasive species. The generality of the model allows it to be used for both existing and potential threats to the system of interest. The deterministic nature of arrivals in the model allows for a clear examination of the tradeoffs inherent when choosing between prevention and control strategies. This work contributes to the economics of invasive species literature by explicitly considering the implications of minimum viable population levels. While our assumption of the spark population does not change the result that a low steady state population of snakes is preferred, the value of this program is much lower, due to the absence of expensive growth at very low populations. Another contribution of this work is the consideration of uncertainty regarding initial population levels. Higher initial populations will call for significantly larger investments in removal to accommodate a rapid reduction to the low steady state.

Application of this theory to the threat of the BTS to Hawaii provides useful insights and policy prescriptions. If the official count is correct and there are really no snakes in Hawaii, and the minimum viable population requires two snakes, current prevention expenditures of $2.6 million a year are close to the optimal first period level of $2.94 million. These expenditures should be gradually increased over the next ten years and maintained indefinitely at $3.2 million. In contrast, if there are already fifty snakes in Hawaii, current expenditures on prevention are insufficient and should be increased and maintained at this same level.

As for removal expenditures, if there are currently zero snakes in Hawaii, the optimal policy requires zero expenditure. However, if there is a small population of 50 snakes already on Oahu, the status quo policy falls glaringly short by over $75 million. The immense difference in recommended control policies is a result of high marginal costs of removal at low populations. Even a limited amount of additional information regarding the initial population may increase efficiency of policy recommendations. For example, if managers believe there is a 1/3 probability that there are currently 50 snakes and a 2/3 probability of zero snakes, then a naïve policy prescription might be to spend the weighted average of $25 million on removals. Balancing prevention and control as if there are zero snakes when there is actually a substantial probability that some snakes are already present is clearly erring in the direction of too little control.

Furthermore, additional data collected after this analysis was complete (see Appendix following this chapter) suggests that there is more than a 2/3 probability than there are two or more snakes already in Hawaii.

When the population has not been identified but there exists a substantial probability that there is one, early detection is the appropriate strategy. While the foregoing analysis subsumes early detection and rapid response (ED/RR) into the control instrument, additional insight may be gained by modeling ED/RR as an independent strategy. Our result that optimal management entails control at very low populations suggests that explicit modelling of ED/RR is warranted. Control at low populations will also help to focus attention on the technology of search; as the main objective is keeping the population below that which is required for establishment. Undoubtedly, the vast difference in recommended control policies implies a need for better information regarding current populations of snakes; a greater level of diversification between strategies is warranted. Status quo removal expenditures hardly take into account the possibility that snakes may be present in any number, and support giving priority to prevention when establishment by snakes already present may be more likely that establishment by new entrants.

In computing the optimal outcome, we encountered quantitative challenges regarding the specification of functional forms for all four essential components: growth, damages, costs of removal, and arrivals. In particular, choosing functional forms that both accurately reflected our understanding of the biological and economic processes and resulted in computationally feasible equations required several simplifications upon which further research might improve.

The deterministic arrival of a fraction of snakes per year was used as an approximation for the probabilistic event of a snake's arrival. Ideally, the model would replace this arrival function with an explicit function describing the probability that a snake arrives in any given period. This simplification was made for two reasons. First, because of the uncertainty surrounding the initial population, building a straightforward probability distribution is highly complex. Furthermore, there is imperfect scientific information concerning the probability distribution of a snake's arrival to Hawaii.

However, additional scientific information might improve the ability to estimate the probabilities associated with successful establishment. In particular, a better understanding of the probability of a snake mating and reproducing would enhance our ability to accurately assess the probability of establishment separate from the probability of arrival. The scientific evidence from Guam does suggest that male-female ratios are not one-to-one, with perhaps many fewer females than males moving into transport zones (Rodda 2005, personal communication). An extended model would also consider the extent to which future introductions matter, which should be rapidly decreasing with population size.

The main limitation of the model in this chapter is the deterministic nature of arrivals. The next two chapters address this shortcoming by relaxing the assumption that arrivals are determined by prevention expenditures. We begin by allowing for uncertainty regarding the time of invasion (Chapter 3, "Invasion as Catastrophe"). The following chapter allows for uncertainty throughout the invasion process, although what is gained in the generality of uncertain arrivals is lost by other restrictive assumptions.

For example, the probabilistic nature of arrivals in Chapter 4 requires the assumption of a population after which prevention is not necessary, and it also requires us to limit the initial population to zero.

APPENDIX TO CHAPTER 2

Data on expert opinions regarding the number of snakes currently in Hawaii was gathered following the analysis conducted in Chapter 2. Discussions with expert scientists and resource managers who have worked with the Brown treesnake issue for many years. Because most agree that there is now a small incipient population of BTS on Saipan, the issue was discussed in terms of both Saipan and Oahu to facilitate comparison between the two locations.

Many scientists assigned a high probability to an existing population in Hawaii between 2 and 99, and most assigned a zero probability to the chance of a large (n >10,000) population, although one expert assigned a small (5%) probability of this.

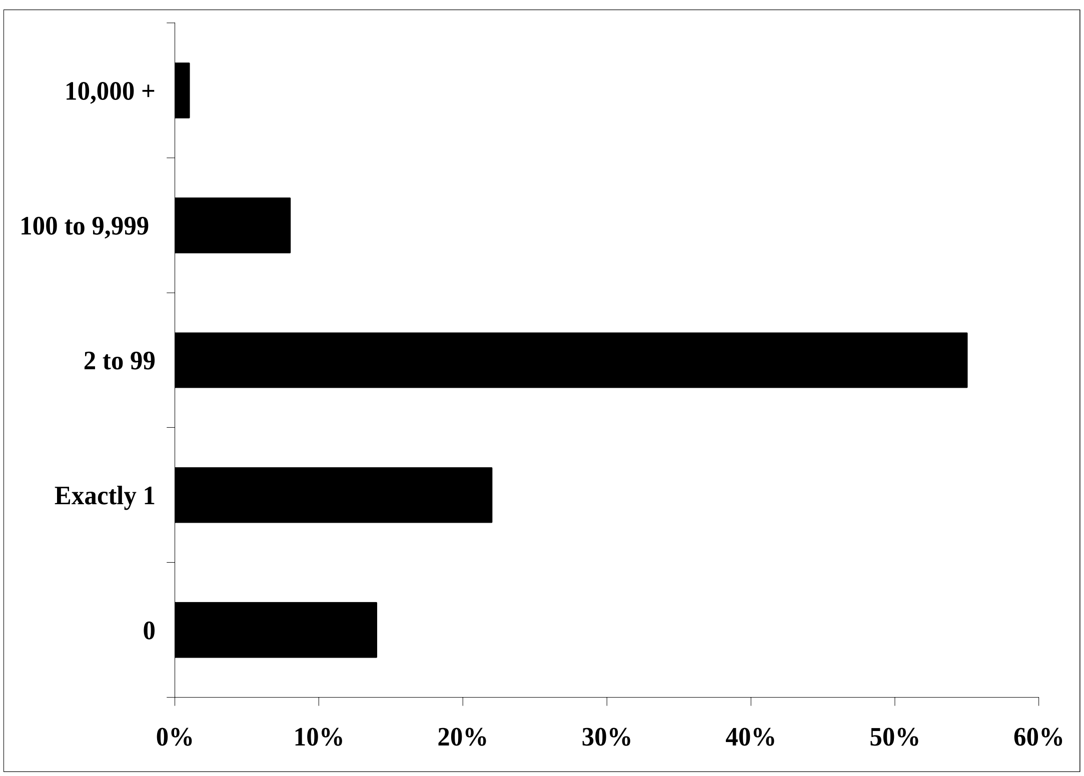

Figure A2. Average Expert Opinion Regarding Current BTS Presence on Oahu

CHAPTER 3
UNCERTAIN TIME OF ARRIVAL: INVASION AS CATASTROPHE[10]

3.1. Introduction

As described in Chapter 2, it is widely believed that it is not a question of if, but when, the snake will arrive and establish in Hawaii. Furthermore, it is feared that once the snake is here it will be difficult to completely eradicate, due to the snake's cryptic nature and the associated high search cost. These characteristics motivate the model of invasion as an irreversible event of uncertain time, or catastrophe.

In the model, we assume that invasion happens only once. We define invasion as the arrival of enough snakes to form an incipient or self-sufficient population (the "spark population" from Chapter 2). For establishment to occur, these would likely need to arrive in the same location and at the same time. While it is possible that dispersed snakes which arrived in an independent time and location could eventually lead to establishment, the issues of age and spatial differentiation make this possibility highly unlikely.[11] Relatedly, while it is possible that more than the spark population of snakes could arrive at any one time, this probability is low enough such that we do not consider it here. We do investigate the issue of higher invasion levels in the following chapter.

Because we assume an infinite time horizon, the invasion will happen, the uncertainty involves when it will occur. The objective is to optimally postpone the

[10] This chapter draws from collaborative work with Yacov Tsur and James Roumasset.
[11] Sexual maturation for BTS is thought to be reached at age 2-3, therefore the dispersed snakes would need to be at least this old to start reproducing (Rodda et al. 1999). Spatial differentiation is likely a more important concern, since the snakes may have arrived at different locations, and therefore must locate the other to begin populating.

invasion, given a predetermined penalty (the minimized present value from the general model in Chapter 2) associated with the arrival of the invasion.

As invasion in this case is characterized by the arrival of enough snakes to be considered established, we assume away the possibility of a secular increase in snakes before establishment occurs.

3.2. Model

We follow Tsur and Zemel (1998, 2004) and model invasion as an irreversible event with an uncertain arrival time. The invasion brings with it a penalty, and is governed by a hazard function, which is the probability that the invasion will occur given that it has not yet occurred. Knowler and Barbier (2005) follow a similar tack in their model of a private commercial plant breeding industry that imports an exotic plant species into a region. The risk associated with invasion is modeled using a probabilistic hazard function, the key determinants of which are the characteristics of the exotic plant and the number of commercial nurseries contributing to its dispersal. Their results suggest that the presence of a risk of invasion does not imply that it is socially optimal to prevent commercial sales of an exotic. They also derive assumptions under which no sales of the exotic are socially optimal.

The uncertain invasion time is denoted *T*. After *T* the model assumes perfect certainty, where the planner has perfect information regarding the snake population and the number of arrivals per period (i.e., management according to the paths in Chapter 2 resumes).

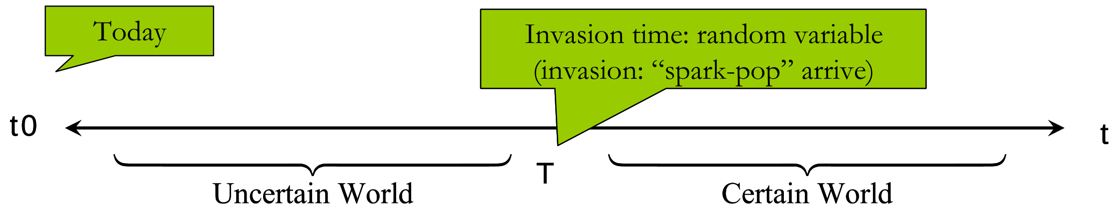

Figure 3.1. Timeline of Events

The model is solved in two stages: pre and post invasion. We begin with the post-invasion problem and solve for the optimal trajectories of prevention expenditures and removal to the steady state after invasion. The minimized total cost and damages φ (or penalty) from the invasion are realized at (uncertain) time *T*.

The post invasion model was detailed in Chapter 2. In this chapter we focus on the solution to the pre-invasion portion of the model.

Beginning at time t_0, we spend y_t on prevention activities each period to postpone the invasion time *T*. We assume invasion happens only once, and has not yet occurred today at time t_0.

Random variable *T* has a continuous probability density function *f(t)*, where t is a realization of T.[12]

[12] The following probability discussion and associated transformations are standard in the literature (see e.g., Kiefer 1988 and Greene 2000).

The cumulative probability is

$$F(t) = \int_0^t f(s)ds = \text{Prob}(T \le t) \tag{3.1}$$

F(t) specifies the probability that the invasion has occurred by time t. The upper tail area of the distribution is given by the survival function

$$S(t) = 1 - F(t) = \text{Prob}(T \ge t) \tag{3.2}$$

S(t) specifies the probability that the invasion has not occurred by time t. Given that the invasion has not occurred at time t, the probability that it will occur in the next short interval of time, say δ, is

$$\lambda(t,\delta) = \text{Prob}(t \le T \le t + \delta \mid T \ge t) \tag{3.3}$$

A useful function for characterizing this aspect of the distribution is the hazard rate,

$$h(t) = \lim_{\delta \to 0} \frac{\text{Prob}(t \le T \le t + \delta \mid T \ge t)}{\delta} \tag{3.4}$$

$$= \lim_{\delta \to 0} \frac{F(t+\delta) - F(t)}{\delta S(t)} \tag{3.5}$$

$$= \frac{f(t)}{S(t)} \tag{3.6}$$

Roughly, *h(t)* is the rate at which invasion will be completed at time t, given that it has not occurred before t. Because we assume the invasion happens only once and has not happened yet, the hazard rate will be useful in modeling the uncertain arrival of the BTS to Hawaii.

In our model we assume that invasion is not only a function of time, but also of how much managers invest in prevention activities. Therefore, our hazard rate will be a function of prevention expenditures y_t, and will be denoted $h(y_t)$.

We can use the integrated hazard function to write the expected value of losses given invasion at time *T*. First, note that

$$h(y_t) = \frac{-d\ln S(t)}{dt}, \qquad (\text{since} \frac{-d\ln S(t)}{dt} = \frac{-d\ln(1-F(t))}{dt} = \frac{f(t)}{1-F(t)} = h(y_t)) \tag{3.7}$$

Define the integrated hazard function as

$$\Lambda(t) = \int_0^t h(y_\tau)d\tau \tag{3.8}$$

Using (7) above,

$$\Lambda(t) = \int_0^t \frac{-d\ln S(\tau)}{d\tau} \tag{3.9}$$

$$\Lambda(t) = -\ln S(t) - \ln S(0) \tag{3.10}$$

Because invasion has not yet occurred, survivorship at time 0 (today) is 1,

$$\Lambda(t) = -\ln S(t) - \ln 1 \tag{3.11}$$

Therefore,

$$\Lambda(t) = -\ln S(t) \tag{3.12}$$

$$e^{-\Lambda(t)} = S(t) \tag{3.13}$$

Thus

$$h(y_t) = \frac{f(t)}{S(t)} = \frac{f(t)}{e^{-\Lambda}} = \frac{f(t)}{e^{-\int_0^t h(y(\tau))d\tau}}, \tag{3.14}$$

and

$$f(t) = h(y_t)e^{-\int_0^t h(y(\tau))d\tau} \tag{3.15}$$

The pre-invasion problem is to:

$$\underset{y_t}{Max}\ V \text{ where } V = \int_0^\infty h(y_t)S(u_t)\{\int_0^T -y_t e^{-rt}dt - \varphi e^{-rT}\}dT \tag{3.16}$$

Subject to

$y_t \geq 0$

Where y_t represents prevention investment at time *t*, $h(y_t)$ is the investment dependent hazard rate, $S(u_t)$ is the survival function, where $u_t = \int_0^T h(y_t)dt$, and φ is the minimized penalty to be realized upon invasion at time *T*. The stream of prevention expenditures are summed from time zero to the time of invasion, and the penalty φ is discounted to time of realization *T*. The rate of discount is *r*.

Taking the derivative with respect to y_t and setting it equal to zero,

$$\frac{\partial V}{\partial y_t} = -\int_{t=T}^{\infty} h(y_t)S(y_T)e^{-rt}dT - \int_{t=T}^{\infty} \frac{\partial[h(y_t)S(y_T)]}{\partial y_t}[\int_{t=0}^{T} y_t e^{-rt}dt + \varphi e^{-rT}]dT = 0 \qquad (3.17)$$

From (3.17), the first order condition is then

$$\underbrace{-\int_{t=T}^{\infty} h(y_T)S(T)e^{-rt}dT}_{\text{Expected cost of spending \$1 at time t}} \underbrace{-\int_{t=T}^{\infty} h(y_T)S_{y_t}(T)[\int_{t=0}^{T} y_t e^{-rt}dt + \varphi e^{-rT}]dT}_{\text{Cost of future losses (change in survival function)}} =$$

$$\underbrace{h'(y_T)S(T)[\int_{t=0}^{T} y_t e^{-rt}dt + \varphi e^{-rT}]}_{\text{Benefit of spending today (change in hazard from spending now)}}$$

(3.18)

The two terms on the left hand side are the marginal costs of pre-invasion investment. The first term describes the expected cost of spending in time period t. The second component is the cost of future losses resulting from a change in the survival function, due to the fact that the invasion has not yet occurred. Although spending a dollar today decreases the likelihood of invasion today, the inevitability of invasion implies these avoided losses will be borne in the future. This term describes this increase in cost due to the change in the survival function (S_{y_t}).

Finally, the right hand side of equation (3.18) is the expression for the marginal benefit of pre-invasion spending. The change in the hazard rate as a result of spending today provides a benefit in future losses foregone.

3.3 Results: Pre-commitment of Prevention Funds

Parameterization of the above problem, using even the simplest of distributions, proved to be unwieldy and produced little insight into the question of optimal prevention investment over time. Therefore, we move to discrete time for the analysis of pre-invasion spending levels.

From Chapter 2 (section 2.3.4), under current annual prevention investments ($2.6 million) the probability that one snake arrives in any given year is 20.6%. This chapter requires not one but two snakes to arrive together, and furthermore be in similar age cohorts, over 2-3 years old. These restrictive assumptions lead us to reduce the probability of this type of invasion to approximately 8%, given status quo levels of expenditures. Using this data, we estimate a hazard rate of

$$e^{-y_t/1.05} \tag{3.19}$$

where prevention investments y_t is in millions of dollars.

The problem is then to:

$$\underset{y_i}{Max}\ \ W \text{ where } W = \sum_{T=0}^{\infty} e^{-y_T} e^{-\sum_{t=0}^{T-1} e^{-y_t}} [\sum_{t=0}^{T} y_i (1+r)^{-t} + \varphi(1+r)^{-T}] \tag{3.20}$$

The first order condition to this optimization problem is:

$$\begin{aligned}\frac{\partial V}{\partial y_i} = [\sum_{i=1}^{n} e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}} (1+r)^{-i}] + e^{-y_i} \sum [\{\sum_{i=i+1}^{n} y_i (1+r)^{-i} + \varphi(1+r)^{-i}\} * e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}}] \\ -[\{\sum_{i=1}^{i} y_i (1+r)^{-i} + \varphi(1+r)^{-i}\} * e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}}] = 0\end{aligned} \tag{3.21}$$

Rearranging (3.21), we find that

$$\underbrace{[\sum_{i=1}^{n} e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}} (1+r)^{-i}]}_{\text{Marginal cost of spending}} + \underbrace{e^{-y_i} \sum [\{\sum_{i=i+1}^{n} y_i (1+r)^{-i} + \varphi(1+r)^{-i}\} * e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}}]}_{\text{Marginal cost of spending now (increased probaility of invasion later)}} =$$

$$\underbrace{[\{\sum_{i=1}^{i} y_i (1+r)^{-i} + \varphi(1+r)^{-i}\} * e^{-y_i - \sum_{j=0}^{i-1} e^{y_j}}]}_{\text{Marginal benefit of spending now (reduced probaility of invasion now)}}$$

(3.22)

Using this hazard rate and the penalty of $239 million from Chapter 2, we find that optimal pre-invasion prevention should be approximately $3.2 million today, a level higher than status quo expenditures, and only slightly larger than the level of prevention recommended by Chapter 2. These expenditures should decrease over time, since the inevitability of the invasion draws closer, represented formally by the survival function (that is, the "survival of the no invasion spell") getting closer and closer to zero. Optimal prevention is illustrated for a 30 year time horizon in Figure 3.2 below.

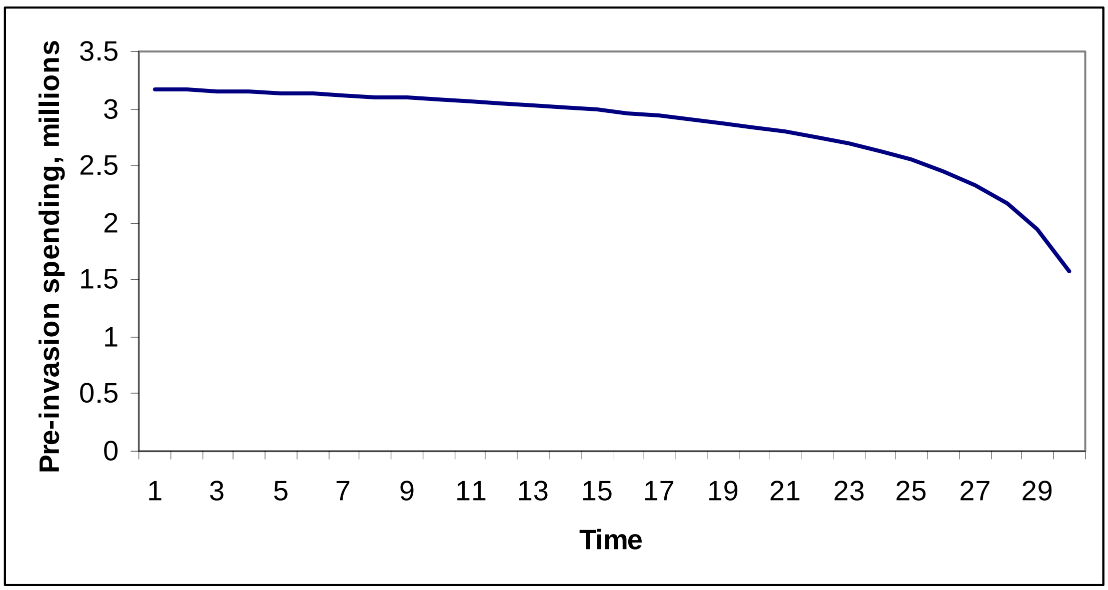

Figure 3.2. Optimal Pre-invasion Spending, 30-year Time Horizon

3.4 Results: Re-Evaluation of Prevention Funds

In any given period, if the invasion occurs, the manager or planner resorts to the paths of prevention and control as dictated by the deterministic model of Chapter 2. The above analysis assumes that the planner has to make an *a priori* commitment of prevention funds over a specified time horizon. However, if the invasion does not occur in the current period, it is unlikely a planner would follow a schedule of decreasing prevention investments over time. Rather, the manager would reevaluate the problem and determine a new level of prevention, based on the absence of arrival. The problem the manager faces is exactly the same as before, that is, as long as the invasion did not occur, the past expenditures on prevention do not influence the new optimal level of investment. Therefore, the solution to the problem will be exactly the same as in the previous period. Prevention expenditures are therefore constant in every period prior to invasion.

The problem will then be:

$$\underset{y}{Max}\ Z \text{ where } Z = \int_0^\infty h(y)e^{-h(y)T}\{\frac{y}{r}(e^{-rT}-1)-\varphi e^{-rT}\}dT \qquad (3.23)$$

The first order condition for this optimization problem is:

$$-\underbrace{\int_0^\infty h(y)*-h'(y)Te^{-h(y)T}\{\frac{y}{r}(e^{-rT}-1)-\varphi e^{-rT}\}dT}_{\text{Marginal cost (when increase y 1 unit, probability happens later increases)}} - \underbrace{\int_0^\infty h(y)e^{-h(y)T}\{\frac{1}{r}(e^{-rT}-1)\}dT}_{\text{Marginal cost of spending}} =$$

$$\underbrace{\int_0^\infty h'(y)e^{-h(y)T}\{\frac{y}{r}(e^{-rT}-1)-\varphi e^{-rT}\}dT}_{\text{Marginal benefit (when increase y 1 unit, probability decreases)}} \qquad (24)$$

Using the parameterization described above, we find that the optimal level of pre-invasion spending is \$2.96 million a year, for every year until invasion. Figure 3.3 below illustrates.

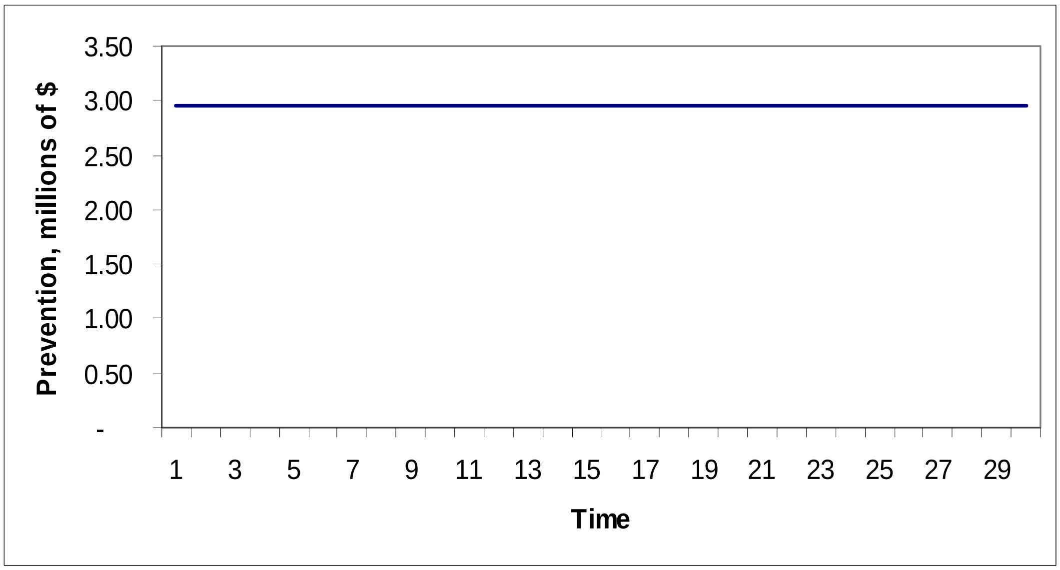

Figure 3.3. Constant Optimal Pre-invasion Spending, 30-year Time Horizon

An interesting result is that optimal prevention is higher under the explicit assumption of uncertainty regarding the time of invasion. This result has been shown many times in the area of environmental irreversibility (Arrow and Fisher 1974, Henry 1974, Kolstad 1996), in literature concerning the precautionary principle (Gollier et al. 2000, Gollier and Treich 2003) and in papers examining optimal capital stock levels under uncertainty (de la Croix and Licandro 1995, Abel and Eberly 1999, Mash 1999). The concept of "irreversibility effect" was originally proposed by Arrow and Fisher (1974) and Henry (1974).

They demonstrated that, for a binary-choice or linear utility model, if there is uncertainty about the costs and benefits of a choice if one of the binary choices is irreversible, a decision maker would find it beneficial to err their decision away from the irreversible choice when there is a possibility of learning about the uncertainty in the future compared to the case when there is no future learning.

The precautionary principle has been analyzed in terms of the effect on rational decision-making of the interaction of irreversibility and uncertainty. Authors such as Epstein (1980) and Arrow and Fischer (1974) show that irreversibility of possible future consequences creates a "quasi-option" effect which should induce a risk neutral society to favor current decisions that allow for more flexibility in the future (see also Fisher and Hanneman 1987). Gollier et al. (2000 p. 245) conclude that "more scientific uncertainty as to the distribution of a future risk — that is, a larger variability of beliefs — should induce society to take stronger prevention measures today."

3.4.1. Comparative Static Results

We also analyze the behavior of optimal prevention with respect to the hazard rate, discount rate, and size of the penalty.

3.4.1.1. Discount Rate

Optimal prevention is found to be decreasing in the rate of discount. We find that under lower hazard rates, prevention will be lower than in the baseline case. However, for higher hazard rates, prevention can be above or below the baseline case. This is because for high enough hazard rates, prevention becomes ineffective, as the invasion becomes more likely to occur. Figure 3.4 below illustrates the relationship between prevention and discount rate for a range of hazard rates.

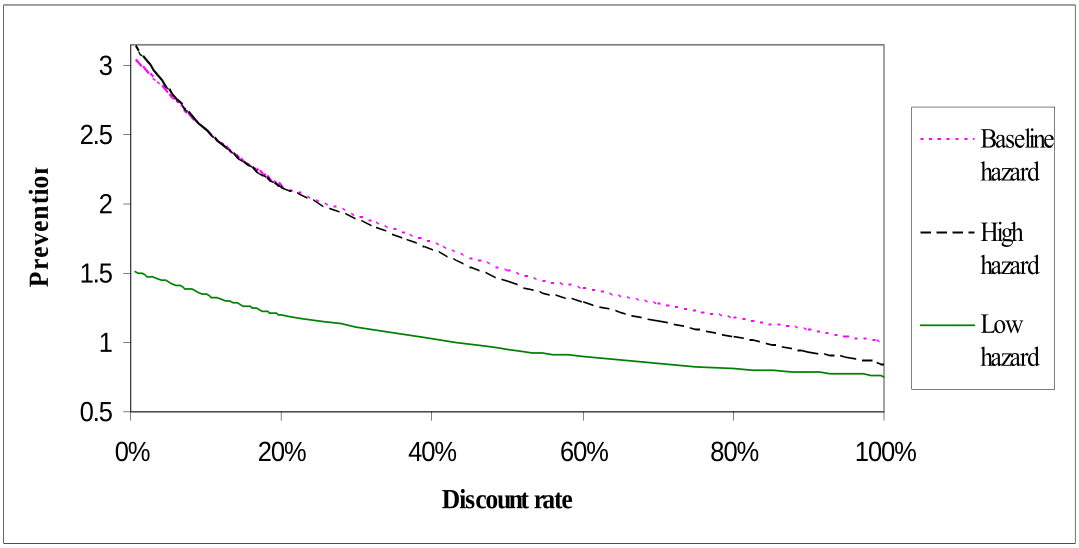

Figure 3.4. Relationship between Prevention and Discount Rate for Different Hazard Functions

3.4.1.2. Hazard Rates and the *Prevention Kuznets Curve*

We find the relationship between optimal prevention and the hazard rate to be approximately inverse-U shaped. This is because initially as the hazard rate increases, prevention becomes more worthwhile, but at high hazard magnitudes, prevention does less good than at lower hazard rates. This *Prevention Kuznets Curve* holds at all three penalty levels, with higher penalties requiring higher prevention and lower penalties requiring lower levels prevention in the optimal solution. Also note that the maximum prevention levels are increasing with level of penalty. Figure 3.5 illustrates the relationship between prevention and hazard rate for a range of penalties.

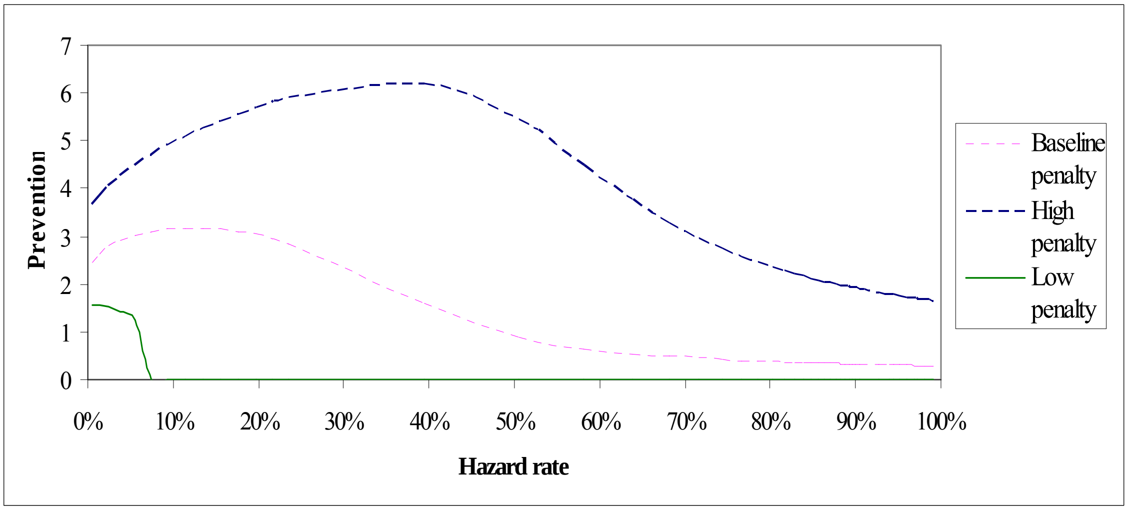

Figure 3.5. *Prevention Kuznets Curves* for Different Penalty Levels (2% discount rate)

3.4.1.3. Penalty

Finally, optimal prevention is found to be increasing in the size of the post-invasion penalty. The higher the cost of the invasion is, the higher the prevention in the optimal program. Figure 3.6 illustrates for a range of hazard rates below.

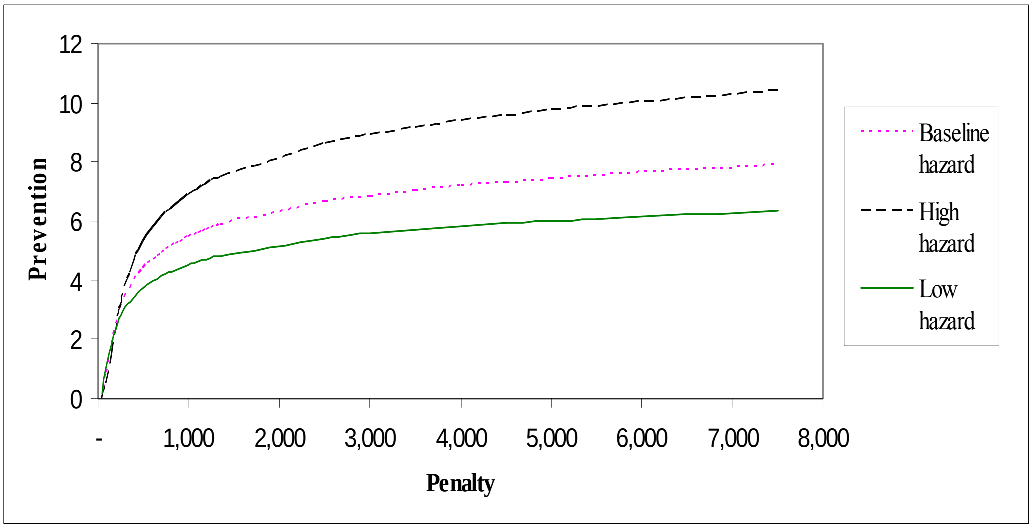

Figure 3.6. Relationship between Prevention and the Penalty for Different Hazard Levels (2% discount rate)

3.5 Conclusion

This paper develops a two-stage model for the optimal management of a potential invasive species. The arrival of the BTS is modeled as an irreversible event with an uncertain arrival time, or catastrophe. The model is solved in two stages, beginning with the second stage, or post-invasion, identifying optimal management after the snake has invaded. In this stage of the model we assume perfect certainty regarding population size and arrivals. The loss-minimizing paths of prevention and control are identified, resulting in a minimized present value penalty associated with the invasion.

After calculating this penalty, we return to the first stage of the model, pre-invasion, and solve for the level of prevention expenditures that will minimize the total value of the invasion, pre and post-invasion. Here we assume that the time of invasion is unknown. Spending on prevention will delay but not avoid the arrival of the snake to Hawaii.

Using discrete time to characterize the invasion horizon, we find that if prevention investments are required to be pre-determined, expenditures made before the invasion should be decreasing over time. However, if the planner is allowed to re-evaluate the problem following a non-event, optimal prevention investments will be constant. Regardless of whether or not the resource manager must pre-commit to a time path of prevention expenditures, prevention is increasing in the size of the post-invasion penalty and decreasing in the rate of discount. The relationship between efficient prevention and the hazard rate is found to be inverse U-shaped. Initially, it becomes more efficient to spend more on prevention as the hazard rate increases, but after some level, optimal prevention will be falling with the hazard rate. That is, if the hazard rate is extremely high, prevention is not as useful as control. As the hazard rate increases from zero, optimal prevention must then increase. However, if the hazard rate is very low, high levels of prevention are not warranted. Therefore, before the extreme case of a 100% hazard rate, optimal prevention must again be falling. This logic supports the empirical finding of the inverse U-shaped relationship.

For the case of the BTS potentially invading Hawaii, we find that under a regime of pre-commitment, pre-invasion expenditures on prevention should be approximately $3.2 million today and decreasing every year until invasion. However, if the planner is permitted to re-evaluate the threat following a non-event, prevention will be lower ($2.96 million a year) and constant until invasion. An interesting implication of both results is that the explicit consideration of uncertainty with respect to arrival time increases the efficient level of prevention expenditures in the current period.

This result is in accordance with literature on optimal capital stock under uncertainty and the precautionary principle.

Once invasion occurs, optimal management requires lower annual expenditures on prevention ($3.1 million) but requires $1.6 million to be spent on control annually to keep the population at its steady state level of two snakes. Prevention expenditures are found to be higher than those of control in this case since by assumption there is no growth before the spark population of snakes, which in this case turned out to be the same as the steady state. Thus control expenditures are dedicated solely to removing the additional growth produced by the small population of snakes every year. Since growth is expensive to remove at low populations, the benefits of prevention are significant. This result is sensitive to several parameters, including the cost of removal. If marginal control costs were higher at the steady state level, it is easy to imagine that control expenditures may then overtake prevention in the optimal program.

The major limitation of this model is that uncertainty is only assumed prior to invasion. After establishment has occurred, we assume that the planner learns about the invasion immediately and that there are no further sources of uncertainty, as in Chapter 2.

Another limitation of this work is the requirement that establishment begins after the arrival of two snakes. The model does not allow for existing snakes to find each other and begin populating. Future work should be able to address the considerations of age cohorts and spatial relationships of the individuals. The model also abstracts from the issue of discovery, which may also be important.

CHAPTER 4

PREVENTION AND PROBABILITIES: INVASION UNDER UNCERTAINTY[13]

4.1. Introduction

This chapter explores three additional models for finding the optimal prevention and control of the Brown treesnake in Hawaii. First, we operationalize the theory developed in Pitafi and Roumasset (2005). To find an analytical solution to this particular model, it will be necessary to make a simplifying assumption about the population level where prevention becomes inefficient with respect to control (hereafter, n_c). Because for reasonable assumptions of n_c this simplification leads to exactly the optimal solution, this methodology is found unsuitable, at least for the specified parameters in our application. The second approach is similar to the approach in Chapter 3 in that arrivals are assumed to be deterministic following invasion albeit the model employs a decision tree instead of the catastrophe approach. Finally, a "strong arm" approach is offered, wherein various strategies are articulated and evaluated in order to find the lowest cost program.

The weakness of the model developed in Chapter 3 is that uncertainty only occurs before the invasion. Following the invasion, the manager is assumed to observe arrivals and the population perfectly as in Chapter 2. Pitafi and Roumasset (2005) developed a theory which allows for re-invasion of the system if the population drops below a threshold level, and allows for the implementation of cyclical prevention and control. If the population is sufficiently low, this model requires reconsideration of the prevention

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[13] This chapter draws from collaborative work with B. Pitafi and J. Roumasset. See also Pitafi and Roumasset (2005), "Some Resource Economics of Invasive Species," manuscript.

strategy, as invasion may again occur. This chapter clarifies this theory and uses it to solve for optimal integrated management of the BTS in Hawaii.

In the previous model, after the invasion time *T*, all future additions to the population are known with perfect certainty. That is, snakes arrive according to a function determined by investment in prevention. In this chapter, new snakes arrive according to a probabilistic arrival function, which is a function of how much is spent on prevention.

The benefits of prevention cannot be understood or estimated without knowing the costs of post-invasion control. We begin by solving for the population of snakes that minimizes total costs and damages associated with the invasion. We then solve for optimal prevention based upon the relationship of the optimal population to a threshold level of snakes n_c, after which prevention expenditures are negligibly effective, relative to removal of the snakes. If the optimal population is above this threshold, prevention is only efficient until invasion occurs, after which expenditures are dedicated to control activities. The alternative case is when the optimal population is at or below this threshold, and reinvasion is possible. Then, the model solves for the optimal cycle of prevention and control to minimize total losses over time.

An additional restriction of this model is that growth begins immediately, that is, there is no spark population.

4.2. Model

4.2.1. The Control Problem

The model of optimal integrated prevention and control begins with the control problem. The social planner starts with the following problem:

$$Max\ V \text{ where } V = \int_0^{\infty} -e^{-rt}\left(\int_0^{x} c(n_t)d\gamma + D(n_t)\right)dt \tag{4.1}$$

Subject to

$$\dot{n} = g(n) - x \tag{4.2}$$

$$n_0 = n(0) \tag{4.3}$$

$$x \geq 0 \tag{4.4}$$

Current value Hamiltonian:

$$H = -\int_0^{x} c(n)d\gamma - D(n) + \lambda[g(n) - x] \tag{4.5}$$

Invoking the Maximum Principle (assuming an interior solution for *x*) we arrive at the following first order conditions:

$$\frac{\partial H}{\partial x} = -c(n) - \lambda = 0 \tag{4.6}$$

$$\frac{\partial H}{\partial n} = -c'(n)x - D'(n) + \lambda g'(n) = r\lambda - \dot{\lambda} \tag{4.7}$$

$$\frac{\partial H}{\partial \lambda} = g(n) - x = \dot{n} \tag{4.8}$$

Taking time derivatives of (4.6) yields

$$\dot{\lambda} = -c'(n)\dot{n} \tag{4.9}$$

Substituting (4.6), (4.8), and (4.9) into (4.7) yields

$$-c'(n)x - D'(n) - c(n)g'(n) = -rc(n) + c'(n)\dot{n}\,. \tag{4.10}$$

Replacing *x* in (10) using the equation of motion,

$$-c'(n)[g(n) - \dot{n}] - D'(n) - c(n)g'(n) = -rc(n) + c'(n)\dot{n}\,, \tag{4.11}$$

or

$$D'(n) = rc(n) - c(n)g'(n) - c'(n)g(n) \tag{4.12}$$

Efficient control requires that the marginal benefits of removal (damages avoided) be equal to the marginal costs of removal along the optimal path. The above conditions give us the optimal time paths of *n* and *x* that maximize *V*.

In order to motivate the case for prevention, we assume that the maximized *V* is negative and denote its absolute value by V^*.

4.2.2. The Prevention Problem

We begin with the control problem above to determine an optimal population (n^*) of snakes after an invasion of n_0 snakes. If the control problem yields an optimal $n^* > n_c$, optimal prevention expenditures will be determined in the following manner. Prevention expenditure in every period is *y*, and the resulting probability of introduction is *p(y)*. If there is introduction in a period, control and damage costs amount to V*, determined by the control problem above. If the steady state population is above n_{crit}, we follow the optimal trajectory of control determined by the control problem (which minimizes V) and discontinue prevention efforts. If there is no introduction, we simply continue to spend on prevention. This is illustrated by the probability tree in Figure 4.1 below.

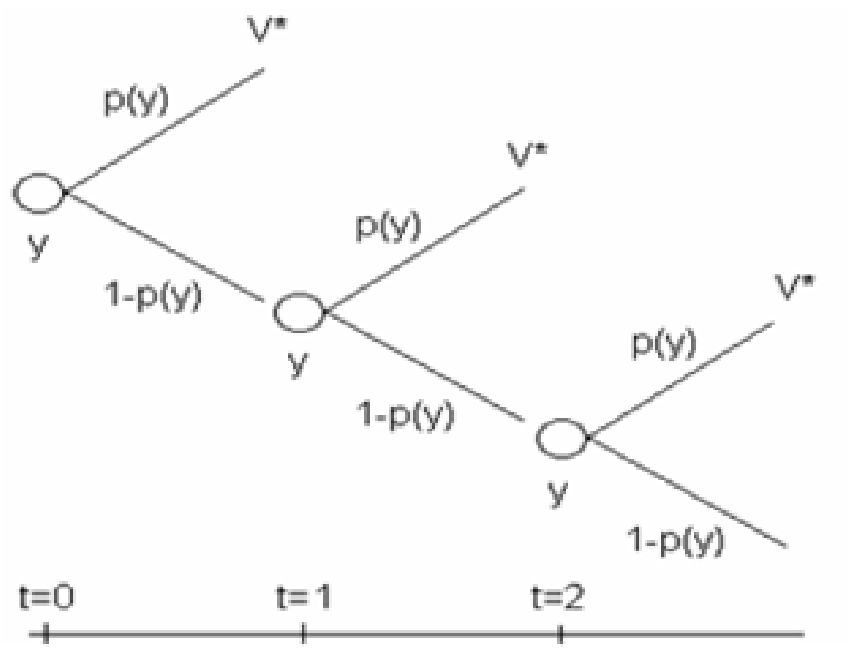

Figure 4.1. Optimal Prevention when n*> n_c (from Pitafi and Roumasset, 2005)

As shown in Pitafi and Roumasset (2005), the expected present value of prevention and control costs (including damage) in this first case is:

$$W = \left(\frac{p(y)\, V^* + [1+r]\, y}{r + p(y)} \right) \tag{4.13}$$

Prevention expenditures *y* should be chosen to minimize W. This produces the following condition for optimal y:

$$\frac{\partial W}{\partial y} = 0 \Rightarrow \frac{\partial}{\partial y}\left[\left(\frac{p(y)\, V^* + [1+r]\, y}{r + p(y)} \right) \right] = 0 \tag{4.14}$$

$$(1+r)\left[r+p(y)\right]+\left[r\ V^{*}-(1+r)y\right]\ p'(y)=0 \tag{4.15}$$

However, if we solve the control problem above and $n^* \leq n_c$, then it is optimal to keep the population below the critical level. In other words, it is now worth it to spend on prevention to keep the population below this level. We are now presented with the problem that after reaching the optimal steady state n^* the manager must again worry about future introductions. As before, as long as there is no introduction, the manager will spend *y* every period on prevention. The difference is that now if there is an introduction of size n_0, our control problem requires us to reduce the population back below n_c, and after the population is back to n^* the manager must reinvest optimally in prevention, as illustrated in Figure 4.2.

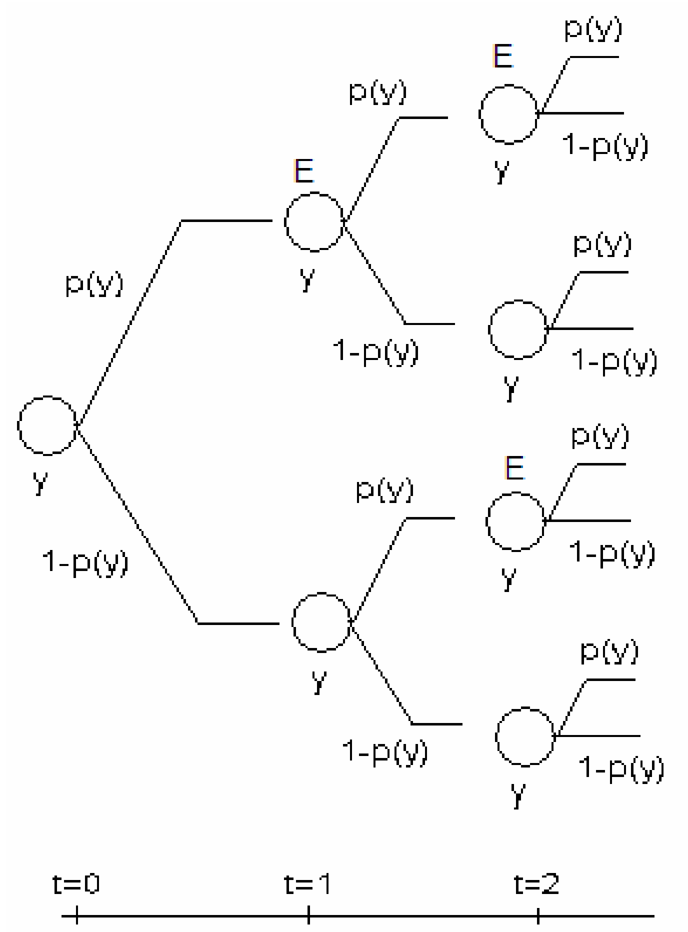

Figure 4.2. Optimal Prevention when $n^* \leq n_c$ ("eradication")

The expected present value of prevention and reduction back to n^* is:

$$Z = y + \frac{[y + p(y)\,E]}{(1+r)} + \frac{[y + p(y)\,E]}{(1+r)^2} + \frac{[y + p(y)\,E]}{(1+r)^3} + \dots$$
$$= \sum_{t=1}^{\infty} \frac{[y + p(y)\,E]}{(1+r)^t} = y + \frac{y + p(y)\,E}{r(1+r)} \qquad (4.16)$$

where E is the cost of going to n^* from n_0 plus the damages at n_0.

This gives us the following condition for optimal y:

$$-\frac{p'(y)E}{(1+r)}=1 \tag{4.17}$$

4.3. Probability of Arrival

The growth, damage and removal cost functions follow those described in Chapter 2. The difference now is in the way in which snakes arrive in the model. Before, snakes were added to the population according to a deterministic arrival function. Now, snakes arrive probabilistically depending on prevention expenditures.

Precisely how a self-sustaining population of BTS will begin is an issue of much debate within the community of experts. Opinions vary widely on how many snakes are currently in Hawaii, as well as the chance of these snakes starting a viable population. The author spoke with five scientists and/or natural resource managers closest to this issue. The discussions centered around three issues: presence of snakes (see the Appendix to Chapter 2), probability of these snakes forming an incipient population, and the number of arrivals. Because most agree that there is now a small incipient population of BTS on Saipan, each issue was discussed in terms of both Saipan and Oahu to facilitate comparison between the two locations.

Many scientists assigned a high probability to an existing population in Hawaii between 2 and 99, and most assigned a zero probability to the chance of a large (n >10,000) population, although one expert assigned a small (5%) probability of this.

Expert opinions regarding the probability that *n* number of snakes will arrive in Oahu under different funding levels allowed us to estimate two distinct distributions, first the probability that between one and five snakes will arrive, and second the probability that five or more snakes will arrive. The chance that five or more would arrive at any one time was lower under both funding scenarios than the chance that between one and five snakes would arrive.

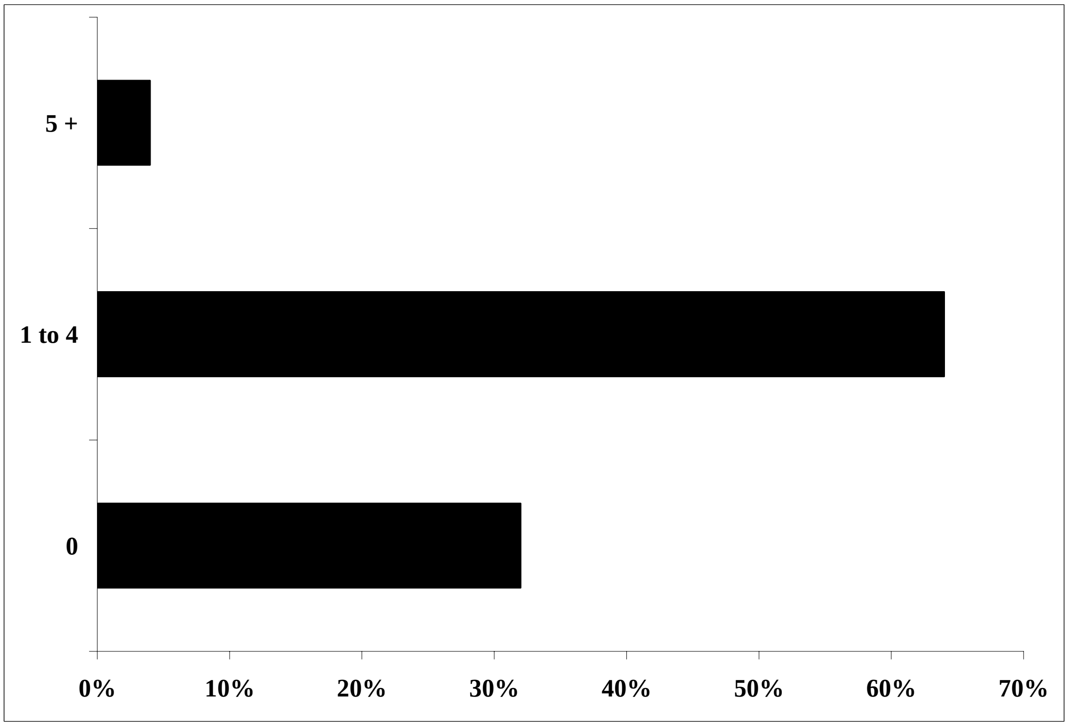

Figure 4.3. Average Expert Opinion Regarding Annual BTS Arrivals to Oahu, under Current Funding

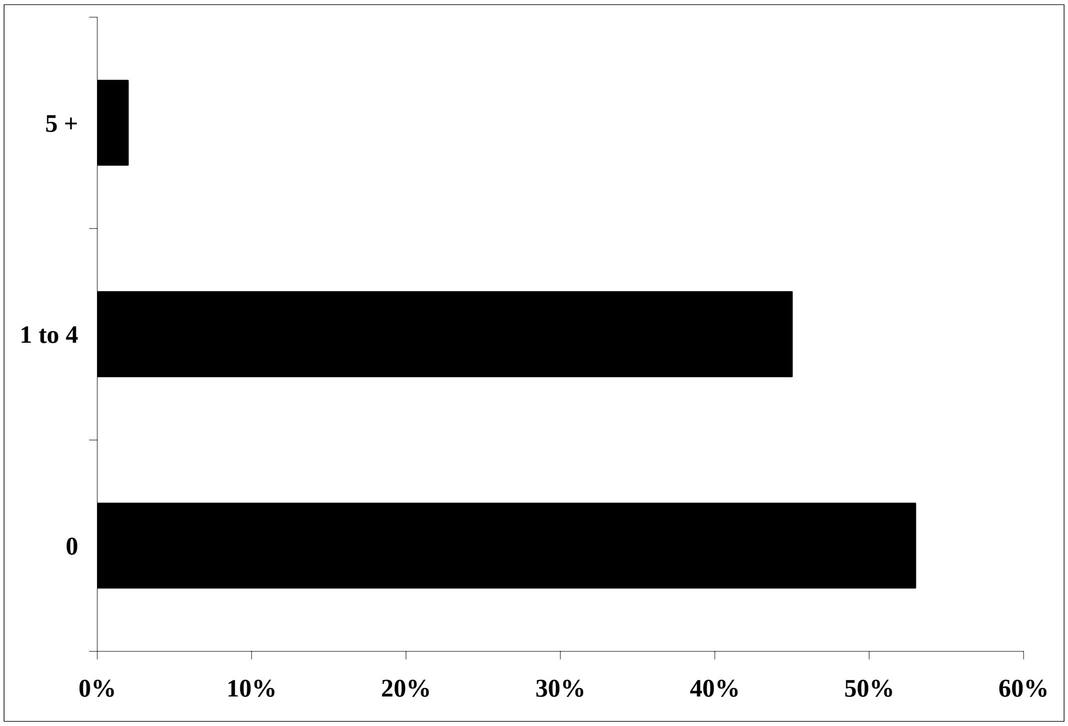

Figure 4.4. Average Expert Opinion Regarding Annual BTS Arrivals to Oahu, under Double Funding

Based on the above data, the we use the Weibull distribution to describe the probability that between one and five snakes arrive to Oahu in any given year, given annual prevention expenditures *y*,

$$p(y) = e^{-0.19y^{0.79}} \tag{4.18}$$

The distribution below describes the probability that five or more snakes will arrive to Oahu in any given year, given annual prevention expenditures *y*.

$$p(y) = e^{-0.99y^{0.99}} \tag{4.19}$$

Figure 4.6 and 4.7 illustrate these functions.

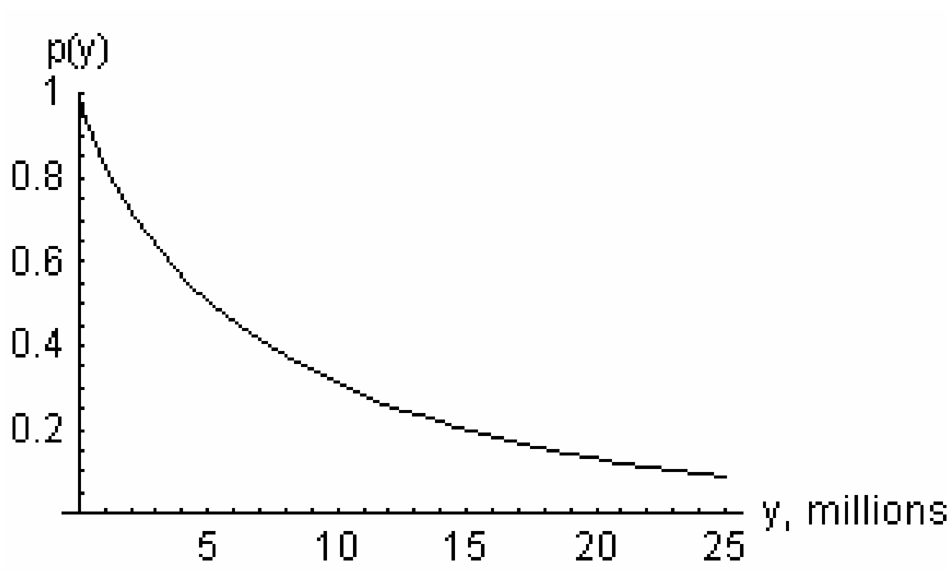

Figure 4.5. Probability that 1-5 Snakes Arrive in a Year, Contingent on y

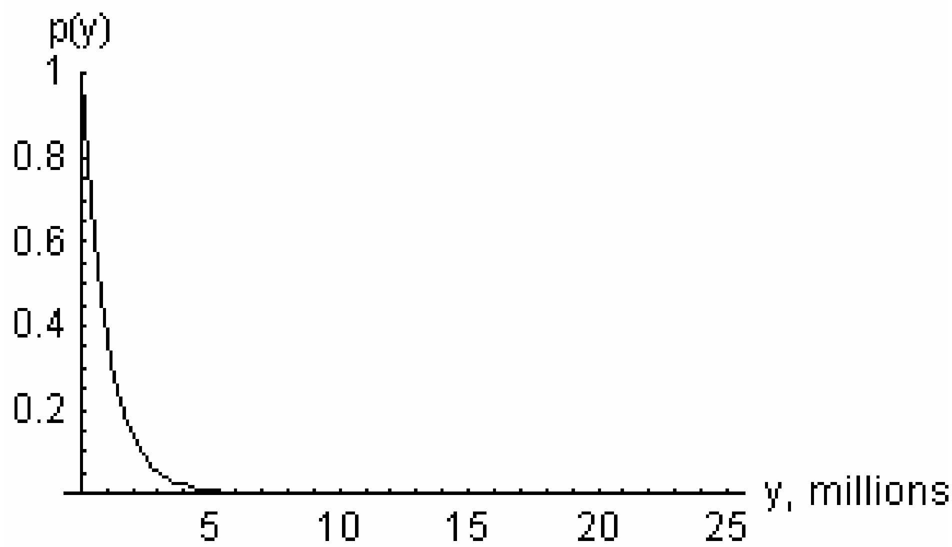

Figure 4.6. Probability that Five or More Snakes Arrive in a Year, Contingent on y

The shape of these functions indicates the dramatic difference in beliefs about the arrival of five or more snakes at a time for most spending levels. The inverse J-shaped curve describing the probability of five or more snakes arriving is much steeper and approaches zero far more rapidly than the curve describing between one and five snakes arriving.

4.4. Results

4.4.1. Optimal Population, Without Prevention

We find that without considering the need to spend on prevention, the optimal population of snakes on Oahu is zero. Regardless of our assumption about the number of snakes which invade Oahu, the corner solution of eradication is preferred to the maintenance of any interior solution as well as maintenance at the carrying capacity. This result is driven by the lack of the prevention requirement.

The problem begins by minimizing *V** given different assumptions about the number of snakes that invade Oahu. For example, if one snake arrives, the minimized management strategy (eradication and maintenance of zero snakes) is $92.6 million. It is important to note this value does not yet consider prevention expenditures as part of this program. Without prevention, minimized management programs are strictly increasing in population. Table 4.1 illustrates this for a sample of invasion levels (or initial populations, as we assume we start with zero snakes).

Table 4.1. Minimized *V** for varying Initial Populations

n_0	V* (where n*=0), in millions
1	$92.6
5	$121.1
10	$136.0
100	$199.87
1 million	$1,054

The next step in this analysis is to introduce prevention to the story. Because n*=0, it is necessarily less than n_c. Therefore, given the minimized value of the control program, *V**, Equation (4.17) is used to solve for the optimal level of prevention associated with each initial population. Once we have the optimal prevention level y*, we know both the probability of arrival associated with this expenditure level, as well as the minimized value Z*, which is the cost of the perpetual cycle of prevention and control. After an invasion of n_0 snakes, Z* includes the cost of returning to n*, which includes prevention and removal expenditures, as well as damages associated with the initial population and the steady state level of invasion (note if n*=0, damages will just borne at the initial population level since reduction is instantaneous). Table 4.2 summarizes these values for a range of invasion levels.

Table 4.2. Optimal Prevention, Probability of Arrival, and Value of the Prevention/Control Cycle, by Size of Invasion

n_0 (arrivals)	y*	p(y)	Z*
1	$19.5 m	0.14	$1.6 b
4	$22.5 m	0.107	$1.8 b
5	$4.8 m	0.008	$302.6 m
10	$4.9 m	0.007	$307.1 m
100	$5.4 m	0.0053	$327.6 m
1 million	$7.2 m	0.00101	$415.5 m

The magnitude of y* depends on the population's proximity to five. The probabilities of arrival for invasions below and above five snakes are significantly different (see figures 4.6 and 4.7 above). Because the probability that between one and five snakes will arrive is appreciably higher than the probability that five or more will arrive, optimal prevention is higher for the lower invasion levels. Within each range, optimal prevention is increasing in size of invasion. That is, the more snakes we expect to invade at one time, the more managers should be spending on prevention.

The probability of arrival is strictly decreasing in the level of invasion, and will decrease at a slower rate for invasion populations which are five or greater.

Z^* is increasing in the size of invasion within each range, with higher invasion sizes leading to lower final costs than smaller invasions, due to the smaller probability of arrival associated with larger invasions.

4.4.2. Optimal Population, With Prevention

After solving for the minimized Z^*'s associated with every population level, we look across all population levels and find the smallest expected present value.

4.4.2.1. Uncertainty Regarding n_c

The n_c threshold represents the population of snakes after which prevention becomes negligibly effective with respect to control. Practically, this threshold represents the point where growth becomes rapid enough such that additional arrivals are no longer considerable compared to how fast the snake population is growing naturally. Setting this threshold is difficult, as setting it too low seems implausible (if there is only a few snakes, arrivals would seem important) while higher thresholds may misrepresent the significance of the growth of existing snakes. Therefore, we present four cases to see how this number affects optimal management policy. In this section the invasion level is assumed to be one. We investigate how changing this assumption alters management recommendations in the next section.

In all four cases in which the initial population is one snake, we find that the optimal population of snakes is equal to our assumption of n_c. In other words, maintenance of a population at which prevention is unnecessary is always the optimal choice. Whether n_{crit} is assumed to be 2, 5, 10 or even 100, with a low initial population the loss minimizing program involves growth to and perpetual maintenance of this population level. Table 4.3 below summarizes these four cases.

Table 4.3. Results when One Snake Invades

Case	n_{crit}	n*	PV losses	Deviation from Status Quo
1	2	2	$509.2 million	$26.7 billion
2	5	5	$575.6 million	$26.6 billion
3	10	10	$631.6 million	$26.6 billion
4	100	100	$859.8 million	$26.3 billion

Consider for example Case 3, with n_c =10. Losses associated with populations before 5 snakes exceed $1 billion, as these entail high cyclical prevention expenditures over time. In Figure 4.8 below, these losses surpass what we are able to illustrate on the *y* axis. Because the probability of arrival is significantly lower for larger invasion sizes, losses associated with population maintenance of the 5th through 9th snakes are lower but increasing, until the population of 10 snakes is reached, where by assumption prevention is no longer effective (relative to control) and so the optimal program is dedicated to control efforts. The present value of the program consisting of growth from 1 to 10 snakes and perpetual maintenance of a 10 snake population is $631.6 million.

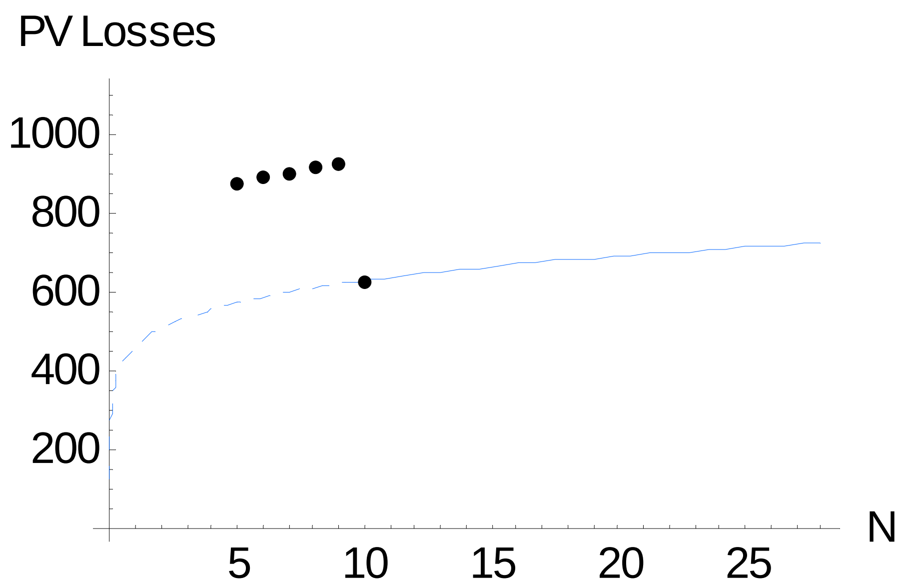

Figure 4.7. Present Value Losses (in millions), n_0=1, n_c =10

These results imply that with an initial population of one snake, it was always preferred to wait until the population at which prevention becomes negligibly effective to control efforts is reached. We tested how high n_c would have to be to make something besides $n^* = n_c$ hold. We find that n_c would have to be at least 118 snakes in order to justify population maintenance at a lower level.

If n_c =118, then maintaining a population of just over five snakes would be preferred to maintaining a population of 118.

4.4.2.2. Uncertainty Regarding Size of Invasion

Because the number of snakes that will arrive at any one time is uncertain, we ran the same cases above under the assumption that five snakes invade Oahu. The optimal population will again match the population level at which prevention is assumed to no longer be necessary. Present value losses will be higher due to the larger initial invasion.

Table 4.4. Results when Size of Invasion is Five

Case	n_{crit}	n*	PV losses	Deviation from Status Quo
5	2	2	$538.3 m	$28.2 b
6	5	5	$607.3 m	$28.1 b
7	10	10	$666.4 m	$28.0 b
8	100	100	$907.2 m	$27.8 b

For contrast, imagine a large invasion of 100 snakes. In three out of the four cases, we find results similar to those above, with maintenance of the minimum prevention-excluding population the loss-minimizing choice. Table 4.5 below summarizes these four cases.

Table 4.5. Results when Size of Invasion is One Hundred

Case	n_c	n*	PV losses	Deviation from Status Quo
9	2	2	$617.0 million	$31.1 billion
10	5	5	$686.1 million	$31.0 billion
11	10	10	$745.8 million	$30.9 billion
12	100	**5**	$988.7	$30.7 billion

However, in the final case, where both the initial population and the prevention-excluding population are high (100), we find that maintenance of a lower population (n*=5) is indicated. Figure 4.9 below illustrates the optimality of the five snake population. In this case, the probability of the 5th snake arriving is appreciably less than lower populations of snakes arriving, making the optimal cycle of prevention expenditures much lower than the previous population, and the minimum of populations following it. Given a high enough initial population, the cost savings from not having to spend on prevention do not outweigh the damage expenses and control cost to maintain this level of population. This differs from Case 4, which also assumes n_c =100. In Case 4, however, we begin with a population of 1 snake, therefore there are no control costs for many years, as well as lower damages while the population naturally grows to 100 snakes.

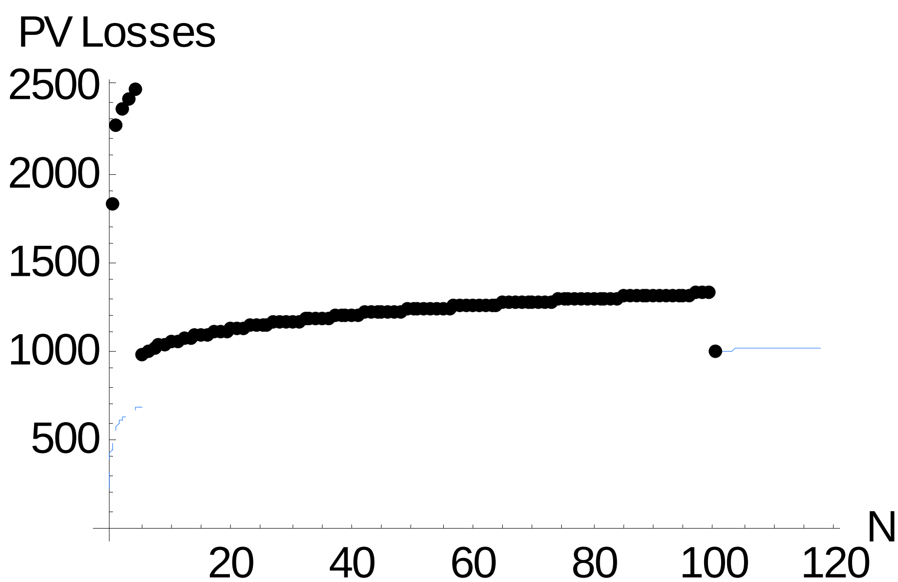

Figure 4.8. Present Value Losses (in millions), n_0=100, n_c =100

4.4.3. Status Quo vs. Optimal Program

If managers continue to spend what they are currently spending on prevention and control, the population will reach 7.5 million snakes, the natural carrying capacity for Oahu, in approximately 35 years. Not surprisingly, a population of 7.5 million snakes will result in extremely high losses. The magnitude of losses will depend on our assumption of invasion level. If one snake invades, present value losses are estimated at $27.2 billion. This value is increasing in the level of invasion. If five snakes invade, present value losses are $28.7 billion, and with a 100 snake invasion they reach $31.7

billion. The cost savings of the optimal programs compared to these status quo losses are summarized in the last columns of Tables 4.3-4.5

4.5. Deterministic Value Post Arrival

One problem with the first methodology used in this chapter is that the threshold population parameter "n_c" is actually endogenous. It will become efficient to stop spending on prevention when the expected marginal benefit of prevention is less than the expected marginal benefit of control. Because these benefit levels are uncertain, we make the model tractable by assuming this threshold and performing sensitivity analysis regarding this level.

An alternative methodology using the probability trees described in this chapter would be to evaluate the programs implied by the probability tree using the steady state of 2 snakes we found in the previous chapters. This requires a slightly different interpretation of each tree. Tree 1 (Figure 4.1) will be similar to the model developed in Chapter 3, where arrival of the invasion is uncertain, but once it happens we follow the deterministic paths as indicated by Chapter 2.

First, we solve for the minimized value of tree 1. The first step is solve for optimal prevention using Equation (4.17), where V* is the minimized present value penalty from Chapter 2, $239 million. Optimal y is given by:

$$y = \frac{[r + p(y)]}{p'(y)} + \frac{r\ V^*}{1+r}\ .$$

We find that optimal prevention is quite low at approximately $150,000 a year, which results in a high probability (96%) of two snakes arriving.

Equation (4.13), $W = \left(\frac{p(y)\, V^{*} + [1+r]\, y}{r + p(y)} \right)$, is then used to find the minimized total value of following tree 1's program. The minimized present value of this program is $234 million.

4.6. "Strong Arm" Methodology

Method two, described in section 4.5, provides a veracity check on method one, but has the disadvantage of assuming away uncertainty after the initial arrival. The third method provides the alternative of articulating specific strategies, e.g. as informed by methods one and two and evaluating those strategies, without assuming away ex post uncertainty.

We know that once snakes arrive to Hawaii it will be optimal to reduce the population to some number. The question is, what is that number? For example, if two snakes arrive, should the population be reduced to zero, one, two, or should we let it naturally grow to a higher steady state? This methodology offers a way to articulate various strategies and compare the present value of each program. Tree number 2 (Figure 4.2) can be used to articulate and examine other strategies of prevention and control. In this section we use the tree to represent the policy of eradication should the population ever exceed two snakes followed by prevention to reduce the probability of reinvasion. This program checks the desirability of eradication should the population ever exceed two snakes, after which prevention will be optimally chosen to decrease the probability of re-invasion of another two snakes. Every population level checked will require a new minimization equation and corresponding first order condition to obtain optimal prevention. Figure 4.9 illustrates the "eradication" tree for a target ceiling of two snakes.

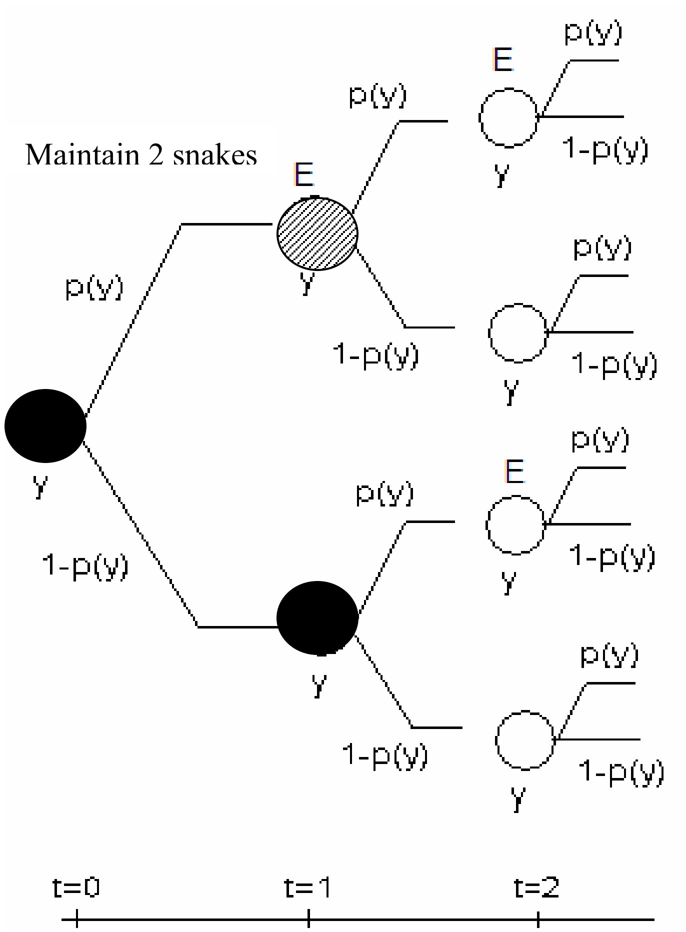

Figure 4.9. Optimal Prevention to Maintain the Two-Snake Population

Assuming an initial population of zero snakes, the manager will spend y on prevention, and with probability p(y) two snakes will arrive. If two snakes arrive, the problem is represented by the shaded node above. Now the question is how best to spend on prevention to maintain a two snake population. Prevention y will be chosen to minimize the total value of a program involving maintenance of a two-snake population and eradication of any arrivals above that level. This program is close to the one developed in section 4.2.2, but now the objective is to maintain two snakes rather than zero. Rewriting the minimized present value Z from Equation (4.16) to account for this change,

$$Z' = \frac{(1+r)y + \dfrac{p(y)^2 E + yp(y)(1+r)}{r}}{p(y)+r} \tag{4.20}$$

where E is the cost of eradicating from four to two snakes ($12.8 million in our case).

The new first order condition governing optimal prevention is then

$$\frac{\partial W}{\partial y} = \frac{-[(1+r)y + \dfrac{(1+r)yp(y) + E\,p(y)^2}{r}]p'(y)}{[r+p(y)]^2} + \frac{1+r+\dfrac{(1+r)p(y) + (1+r)yp'(y) + 2Ep(y)p'(y)}{r}]}{r+p(y)} \tag{4.21}$$

Using Equation (4.21), we find that optimal prevention in tree 2 (Figure 4.2) is $2.74 million, resulting in a probability of invasion of 66%. Plugging these into the Z' equation, the minimized present value of this program is then $266 million. This confirms that eradicating to two is preferred to eradicating to zero, the present value of which is $1.7 billion. The same methodology can be used to evaluate other specific target levels.

That is, choose a target ceiling level, e.g., four snakes, and otherwise follow the same procedure as in Figure 4.9.

4.7. Conclusion

This chapter explores three additional models for finding the optimal prevention and control of the Brown treesnake in Hawaii. First, we operationalize the theory developed in Pitafi and Roumasset (2005). To find an analytical solution to this particular model, it will be necessary to make a simplifying assumption about the population level where prevention becomes inefficient with respect to control (hereafter, n_c). Because for reasonable assumptions of n_c this simplification leads to exactly the optimal solution, this methodology is found unsuitable for this problem. The second approach is essentially the same as in Chapter 3's catastrophe model in that arrivals are assumed to be deterministic following invasion. Finally, a "strong arm" approach is offered, wherein various strategies are articulated and compared to find the lowest cost program.

The first method develops the Pitafi and Roumasset (2005) model of prevention and control of an invasive species and illustrates it with a case study of the threat of the BTS to Hawaii. While the model innovates on current literature by allowing for uncertainty with respect to arrivals, it requires two restrictive assumptions. The first requirement is that after a threshold population (n_c), prevention is no longer necessary and the program switches to one of control only. The second strict assumption is that the system starts as completely uninvaded. A range of assumptions regarding both n_{crit} and the number of snakes that will invade the uninvaded system are tested to see how these restrictions affect policy implications.

Because the benefits of prevention cannot be understood without knowing the costs of post-invasion control, the analysis begins by solving for the steady state level of snakes which minimizes the post-invasion control program. Theoretically, we know that it is possible that if the initial population is high enough or if the damages are low enough, the steady state population without prevention may involve corner solutions of accommodation without control, complete eradication, or removal to some interior steady state population. From our case study of the BTS in Hawaii, we find that for any level of initial invasion, and without yet including the cost of prevention, eradication is the preferred control strategy. Under the optimal policy of eradication, increasing the initial population will not affect the steady state, just the approach path to it.

However, when the cost of perpetual eradication, reinvasion, and prevention is included, the optimal population will depend on the population level at which prevention expenditures cease (n_c). We find that for most invasion sizes, the optimal population will be the same as the one at which prevention is assumed to be unnecessary. We do not explicitly include search in this model. To the extent that n_c may represent the population at which the invasion is discovered, this result suggests that adding the consideration of search may not change the optimal solution. However, if the critical threshold is large enough, e.g. 118 snakes in the one-snake invasion case, it may be worthwhile to spend perpetually on prevention and maintain a smaller population. This solution suggests that by the time this population is found, it may already be too large. This implies a need to keep the initial population from rising to that level before it is found.

The finding that without prevention eradication is the optimal strategy regardless of the size of the invasion explains the common belief in invasive species management that the ideal size of an invasive species population is zero. This essay reveals that disregard of the probability of reinvasion and the associated expense of keeping a zero population can result in costly management mistakes in the future.

A problem with the Pitafi and Roumasset (2005) method is that the result is likely to be sensitive to the assumption of n_c. One way to resolve this would be with an algorithm that has a way of checking whether the n_c assumption is verified; however, so far this algorithm does not exist.

An alternative methodology using the first probability tree (Figure 4.1) described in this chapter is offered. Here we evaluate the value of the programs implied by the probability tree using the steady state of two snakes we found in the previous chapters. This requires a slightly different interpretation of the probability tree. Tree 1 is similar to the model developed in Chapter 3, where arrival of the invasion is uncertain, but once it happens we follow the deterministic paths as indicated by Chapter 2. We find that optimal prevention is quite low at approximately $150,000 a year, which results in a high probability (96%) of two snakes arriving. The minimized present value of this program is $234 million.

Finally, we offer a "strong arm" method of calculating the optimal program of prevention and control of the Brown treesnake in Hawaii. We find that optimal prevention in tree 2 is $2.74 million, resulting in a probability of invasion of 66%. The minimized present value of this program is then $266 million. This confirms that eradicating to two is preferred to eradicating to zero, the present value of which is $1.7 billion.

This approach provides a basis for a numerical algorithm that searches over different possible strategies. This leaves a tractable but difficult programming problem, which leave for further research. Nevertheless, the applications in this chapter lend preliminary support to Chapter 2 and 3, although full examination would provide a program based on this procedure.

Happily, there is some concordance between approaches two and three, which yield optimal prevention expenditures in the range from two to three million dollars. This range is similar to that found in the previous two chapters, adding to the robustness of the prevention recommendation.

CHAPTER 5

CONCLUSIONS

5.1. Summary

The literature to date on invasive species management has largely taken a single instrument approach in a world of perfect certainty. Because resource managers employ several instruments across time in the face of many uncertainties, this dissertation takes a closer look at these two complications that have been disregarded to some degree in formal modeling thus far.

BTS is an ideal candidate for studying the implications of uncertainty in invasive species management because of the plethora of uncertainties associated with its seemingly imminent arrival to Hawaii. There are at least three distinct uncertainties associated with the snake's invasion of Hawaii, regarding current population, minimum viable population, and probability of arrival. Because of the number of uncertainties required for the complete optimization problem, there is currently no methodology for a single tractable model.

Even with simplifying assumptions, the problem becomes intractable very quickly. For example, assume that the following conditions hold. First, the initial population of snakes is zero. An invasion is defined by two snakes arriving every period, and the spark population is two. If the population is ever equal to one snake, it is assumed that that snake perishes of natural causes and no control is required to bring the population down to zero. We can then represent the first three periods in an infinite probability tree as Figure 1.

In the first period, the manager spends y on prevention and either two snakes arrive or not. If two snakes arrive, the manager has the choice of harvesting either zero or one snake. If no snakes arrive in the first period, the manager continues to spend y on prevention. The manager will then be faced with a variety of choices in the third period, depending on whether snakes arrived in the previous period, and on how many snakes the manager harvested that period. To the extent that the final branch of any one possibility can be written as an expected value, we can choose the paths of prevention and control to minimize this value (see Epstein and Zin (1991) for the related problem of recursive utility).

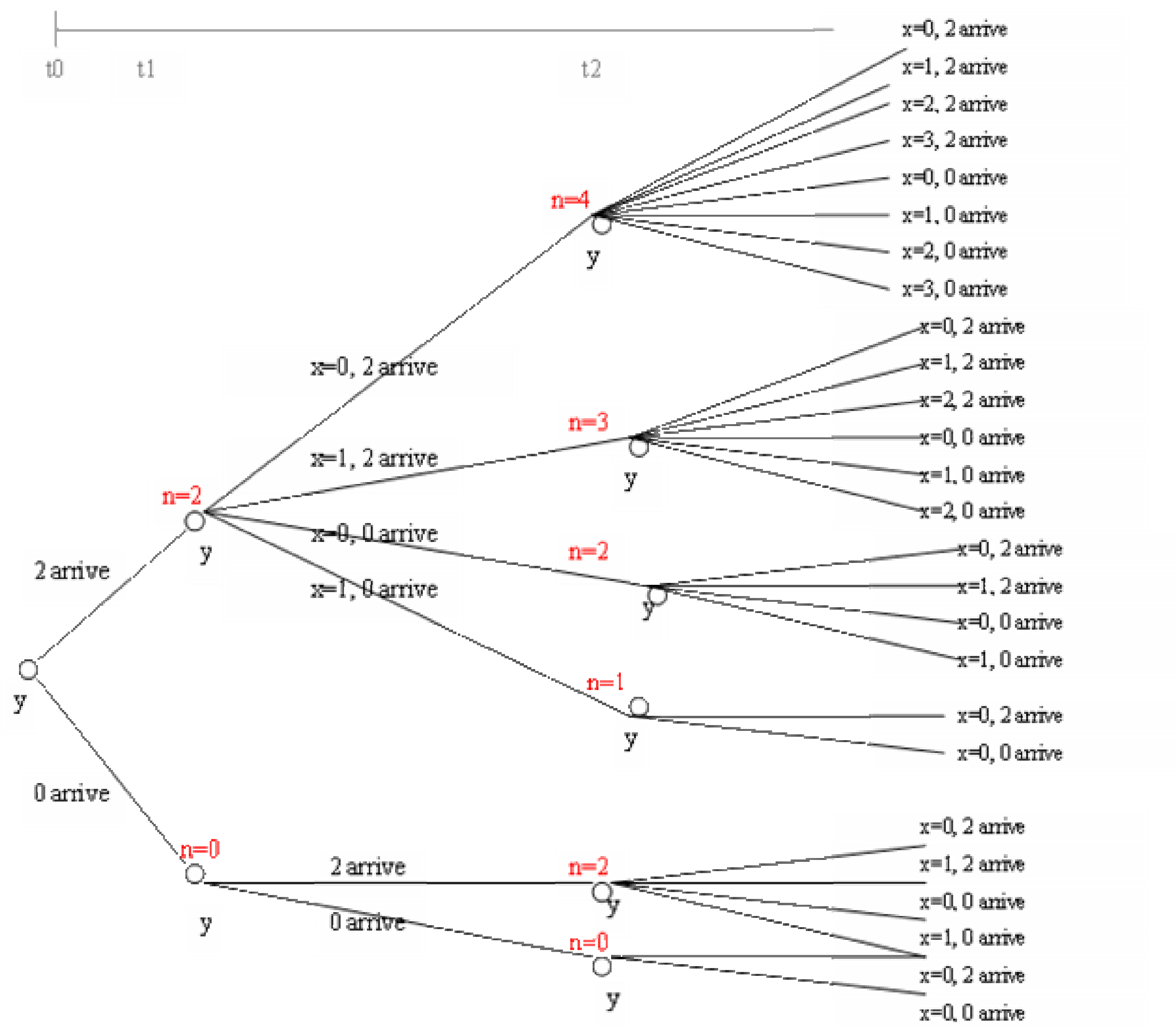

Figure 5.1. A Representation of the Simplified Problem of Simultaneous Prevention and Control

As depicted in Figure 5.1, a closed form solution for choosing prevention (y) and control (x) is not straightforward, even given the number of simplifications this conceptualization requires. Because the tree is infinite both horizontally (over time) as well as vertically (over states), it is not readily simplified into a tractable minimization problem.

Instead of pursuing what may be mission impossible, I set forth a set of models with different simplifying assumptions in order to illuminate optimal management decisions regarding the timing, magnitude, and balance between prevention and control instruments. We begin with the simplest case, a fully deterministic model where arrivals are determined by prevention expenditures, to illuminate tradeoffs between the two policy instruments in question. We then use the shortcomings of this model to motivate the remainder of the dissertation.

Chapter 2 develops an integrated model for the prevention and control of an invasive species. The generality of the model allows it to be used for both existing and potential threats to the system of interest. The deterministic nature of arrivals in the model allows for a clear examination of the tradeoffs inherent when choosing between prevention and control strategies. This work contributes to the economics of invasive species literature by explicitly considering the implications of minimum viable population levels. Whether or not we include the "spark population" does not change the result that a low steady state population of snakes is preferred, although the value of this program is much lower, due to the absence of expensive growth at very low populations. This work makes another contribution by examining the implications of uncertainty regarding initial population levels. Higher initial populations will call for significantly larger investments in removal to accommodate a rapid reduction to the low steady state.

Application of this theory to the threat of the BTS to Hawaii provided useful insights and policy prescriptions. If the official count is correct and there are really no snakes in Hawaii, and the minimum viable population requires two snakes, current prevention expenditures of $2.6 million a year are close to the optimal first period expenditures of $2.96 million. These expenditures should be gradually increased over the next ten years and maintained indefinitely at $3.2 million. In contrast, if there are already fifty snakes in Hawaii, current expenditures on prevention are insufficient and should be increased and maintained at this level.

As for removal expenditures, if there are currently zero snakes in Hawaii, the optimal policy requires zero expenditure. However, if there is a small population of 50 snakes already on Oahu, the status quo policy falls glaringly short by over $75 million. The immense difference in recommended control policies is a result of high marginal costs of removal at low populations, which are a consequence of the difficulty of finding these individuals. Even a limited amount of additional information regarding the initial population may increase efficiency of policy recommendations. For example, if managers believe there is a 1/3 probability that there are currently 50 snakes and a 2/3 probability of zero snakes, then a naïve policy prescription might be to spend the weighted average of $25 million on removals. Assuredly, the vast difference in recommended control policies implies a need for better information regarding the current populations of snakes, and that a greater level of diversification between strategies is warranted.

Status quo removal expenditures hardly take into account the possibility that snakes may be present in any number.

The main limitation of the model in the first essay is the deterministic nature of arrivals. The next two chapters address this shortcoming by relaxing the assumption that arrivals are determined by prevention expenditures.

Chapter 3 develops a two-stage model for the optimal management of a potential invasive species. This model explicitly considers one important source of uncertainty, the time of invasion. The arrival of the BTS is modeled as an irreversible event with an uncertain arrival time, or catastrophe. The model is solved in two stages, beginning with the second stage, or post-invasion, identifying optimal management after the snake has invaded. In this stage of the model we assume perfect certainty regarding population size and arrivals. The loss-minimizing paths of prevention and control are identified, resulting in a minimized present value penalty associated with the invasion.

After calculating this penalty, we return to the first stage of the model, pre-invasion, and solve for the level of prevention expenditures that will minimize the total value of the invasion, pre and post-invasion. Here we assume that the time of invasion is unknown. Spending on prevention will delay but not avoid the arrival of the snake to Hawaii.

Using discrete time to characterize the invasion horizon, we find that the optimal pre-determined expenditure path is decreasing over time (and truncates at the time of population establishment). However, if the planner is allowed to re-evaluate the problem at the beginning of each period, optimal prevention investments will be constant. Regardless of the planner's commitment to the investments, prevention is increasing in the size of the post-invasion penalty and decreasing in the rate of discount. The relationship between efficient prevention and the hazard rate is inverse U-shaped, revealing a *Prevention Kuznets Curve*. Initially, it becomes more efficient to spend more on prevention as the hazard rate increases, but after some level, optimal prevention will be falling with the hazard rate. This is intuitive. If the hazard rate is extremely high, prevention is not as useful as control. As the hazard rate increases from zero, optimal prevention increases. However, if the hazard rate is very low, high levels of prevention are not warranted. Therefore, before the extreme case of a 100% hazard rate, optimal prevention must again be falling. This supports the empirical finding of the inverse U-shaped relationship.

For the case of the BTS potentially invading Hawaii, we find that under a regime of pre-commitment, pre-invasion expenditures on prevention should be approximately \$3.2 million today and decreasing every year until invasion. However, if the planner is permitted to re-evaluate the threat following a non-event, prevention will be lower (\$2.96 million a year) and constant until invasion. An interesting implication of both results is that the explicit consideration of uncertainty with respect to arrival time increases the efficient level of prevention expenditures in the current period.

Once invasion occurs, optimal management requires lower annual expenditures on prevention (\$3.1 million) but requires \$1.6 million to be spent on control annually to keep the population at its steady state level of two snakes. Prevention expenditures are found to be higher than those of control in this case since by assumption there is no growth before the minimum viable population of snakes, which in this case turned out to be the same as the steady state. Thus control expenditures are dedicated solely to removing the additional growth produced by the small population of snakes every year. Since growth is expensive to remove at low populations, the benefits of prevention are significant. This result is sensitive to several parameters, including the cost of removal. If marginal control costs were higher at the steady state level, it is easy to imagine that control expenditures may then overtake prevention investments in the optimal program.

We should also emphasize the implications of the “bang bang” nature of the optimal removal solution. Because the marginal cost of control is linear in the rate of harvest, the current solution requires instantaneous removal of any snakes above the steady state level. Work in progress relaxes the assumption of linearity in rate of harvest, which will lead to smooth removal paths to the steady state. Although the current model recommends a large ($75 million) and immediate outlay on control followed by significantly smaller annual investments ($1.6 million) to maintain the two-snake population, the alternative marginal cost function will initiate control policies which essentially “spread out” this large initial investment. Removals under this program will occur at a slower rate, since the model will not permit an instantaneous arrival to the steady state. Because the removal process will take longer, total investments in control will be higher.

The major limitation of this model is that uncertainty is only assumed prior to invasion. After establishment has occurred, we assume that the planner learns about the invasion immediately and that there are no further sources of uncertainty, as in Chapter 2. Chapter 4 relaxes this assumption and allows for uncertainty throughout time.

Chapter 4 explores three additional models for finding the optimal prevention and control of the Brown treesnake in Hawaii. First, we operationalize the theory developed in Pitafi and Roumasset (2005). To find an analytical solution to this particular model, it will be necessary to make a simplifying assumption about the population level where prevention becomes inefficient with respect to control (hereafter, n_c). Because for reasonable assumptions of n_c this simplification leads to exactly the optimal solution, this methodology is found unsuitable for this problem. The second approach is essentially the same as in Chapter 3's catastrophe model in that arrivals are assumed to be deterministic following invasion. Finally, a "strong arm" approach is offered, wherein various strategies are articulated and evaluated and the dominant program distinguished from the programs that are dominated.

We begin by extending the theory of invasive species management under uncertainty (Pitafi and Roumasset 2005). Previously, these authors developed a model for integrated prevention and control, but did not show the applicability of their model using the threat of a specific invasive species. Chapter 4 illustrates the model numerically with a case study of the threat of the BTS to Hawaii. While the model extends previous modeling by allowing for uncertainty with respect to arrivals, it requires two restrictive assumptions. The first requirement is that after a threshold population (n_c), prevention is no longer necessary and the program switches to one of control only. The second strict assumption is that the system starts as completely uninvaded. A range of assumptions regarding both n_{crit} and the number of snakes that will invade the uninvaded system are tested to see how these restrictions affect policy implications.

Because the benefits of prevention cannot be understood without knowing the costs of post-invasion control, the analysis begins by solving for the steady state level of snakes which minimizes the post-invasion control program. Theoretically, we know that it is possible that if the initial population is high enough or if the damages are low enough, the steady state population without prevention may involve corner solutions (zero or carrying capacity) of accommodation without control, complete eradication, or removal to some interior steady state population. From our case study of the BTS in Hawaii, we find that for any level of initial invasion, without including the need for and cost of prevention, eradication is the preferred control strategy. Under the optimal policy of eradication, increasing the initial population will not affect the steady state, just the approach path to it. It is important to emphasize that this will only be true before including the need for prevention.

However, when you include the cost of perpetual eradication, reinvasion, and prevention, the optimal population will depend on the population level at which prevention expenditures cease (n_{crit}). We find that for most invasion sizes, the optimal population will be the same as the one at which prevention is assumed to be unnecessary. We do not explicitly include search in this model. To the extent that n_{crit} may represent the population at which the invasion is discovered, this result suggests that adding the consideration of search may not change the optimal solution. However, if the critical threshold is large enough, e.g. 118 snakes in the one-snake invasion case, it may be worthwhile to spend perpetually on prevention and maintain a smaller population. This solution also suggests that by the time this population is found, it may already be too large. This implies a need to keep the initial population from rising to that level before it is found.

The finding that without prevention, eradication is the optimal strategy regardless of the size of the invasion explains the common belief in invasive species management that the ideal size of an invasive species population is zero. This essay reveals that disregard for the probability of reinvasion and the associated expense of maintaining a zero population can result in costly management mistakes in the future. Not only may funds be needlessly and ineffectually spent on species that may prove to be impossible to eradicate, but these funds may be diverting attention from potentially more pressing invasions.

A problem with the Pitafi and Roumasset (2005) method is that the result is too dependent on the assumption of n_c. One way to resolve this would be with an algorithm that iterates on the choice of n_c until that choice can be verified as optimal, i.e. substantial prevention expenditures after n_c is reached would not increase the value of the program. This programming challenge remains.

First, an alternative methodology using the first probability tree (Figure 4.1) described in this chapter is offered. Here we evaluate the programs implied by the probability tree using the steady state of 2 snakes we found in the previous chapters. This requires a slight modification of the probability tree. Tree 1 is similar to the model developed in Chapter 3, where arrival of the invasion is uncertain; but once it happens we follow the deterministic paths as indicated by Chapter 2. We find that optimal prevention is quite low – approximately $150,000 a year – which results in a high probability (96%) of two snakes arriving. The minimized present value of this program is $234 million.

Finally, we offer a “strong arm” method of calculating the optimal program of prevention and control of the Brown treesnake in Hawaii. We find that optimal prevention in tree 2 is $2.74 million, resulting in a probability of invasion of 66%. The minimized present value of this program is then $266 million.

This confirms that eradicating to two is preferred to eradicating to zero, the present value of which is $1.7 billion.

This approach provides a basis for a numerical algorithm that search over different possible strategies. This leaves a tractable but difficult programming problem, which we put aside for further research.

Optimal prevention expenditures are found to be in the range of two to three million dollars annually in four out of the five models presented within this dissertation, with only one framework implying a lower prevention level. Nevertheless, the applications in this chapter lend preliminary support to Chapter 2 and 3, although full examination would provide a program based on this procedure.

5.2. Synthesis of Policy Implications and Directions for Further Research

In summary, this dissertation has been as much about what we are not able to say regarding efficient BTS policy as it has been about what we are able to say. In this spirit, we now synthesize what we believe to be justifiable policy recommendations, and conclude with recommendations regarding how future research should be designed to provide a more complete policy agenda.

As illustrated by the three chapters above, strategies for the efficient management of the BTS will depend on a number of uncertain parameters, including the current number of snakes in Hawaii, the minimum viable population size, the critical threshold after which prevention becomes negligibly effective compared to control, and the size of the actual invasion. However, we are able to make some cautious recommendations based on the results of these three analyses.

First, regardless of the magnitude of the parameters mentioned above, current expenditures on prevention are too low. Chapter 2 recommends a modest increase of just over $300,000. When the time of invasion is uncertain, as in the catastrophe model of Chapter 3, current prevention expenditures require a more dramatic increase of over $2 million. We make this recommendation with caution because Chapter 4 recommends maintenance of populations that will not require any level of prevention expenditure, unless the threshold after which prevention is not required or the size of the invasion is unreasonably large.

Our results concerning the control strategy lead us to two strong recommendations. First, a higher level of diversification between policy instruments than is currently being practiced today is indicated. While status quo prevention is nearly adequate undermost assumptions, resources dedicated to control are sorely lacking. The presence of uncertainty regarding the initial population and spark population requirement suggest more funds should be directed to searching for snakes that may already evaded detection in Hawaii.

Second, the dramatic difference in the recommended levels of control suggests a serious need for more information regarding current population levels. Expenditures on control recommended by Chapter 4 will depend on invasion size, but are also significantly higher than current removal outlays. An improved model should be able to show to what extent the naïve policy of taking a weighted average of control policies is a decent approximation.

If it is not possible to model this analytically, due to the complications regarding how to include the many different types of uncertainty, this model may involve Monte Carlo simulations, where arrivals are a random draw each period.

The noted importance of current population levels to the implementation of efficient policy has led to an increased interest in the value of information regarding population size. The only variables that a typical manager observes with certainty are the number of the invasive successfully harvested and the effort required to achieve that harvest. In future work, we will develop connections between observable data (removal effort and number of snakes removed) and the unobservable invasive stock. If the effort-harvest function is stochastic but known, we can develop a model which allows for beliefs about the invasive population to be updated each period, allowing the manager to tailor the control strategy appropriately. One interesting preliminary result of this work is that the optimal harvest is higher than in the deterministic framework since the additional population information that the harvest reveals is valuable in and of itself.

While the essays in this dissertation subsume early detection and rapid response into the control instrument, ED/RR is actually an independent strategy and should be modeled as such in future work. Our result that optimal management entails control at very low populations suggests that explicit consideration of ED/RR is necessary. Control at low populations requires attention to be focused on search, as the main objective is keeping the population below that which is required for establishment. Undoubtedly, the vast difference in recommended control policies implies a need for better information regarding current populations of snakes, and that a greater level of diversification between strategies is warranted.

Status quo removal expenditures hardly take into account the possibility that snakes may be present in any number, and support the belief of a very low probability of establishment, which may not be the case.

The models described in this dissertation abstract away from the important consideration of space. Damages from invasion and management costs may vary significantly across spatially differentiated landscapes. For example, losses due to BTS may be higher in more densely populated native bird communities and closer to major power lines. Additionally, the probabilities of arrival and subsequent growth should be higher with increasing proximity to the ports of entry and cargo handling areas. Consequently, returns to prevention and control are expected to be greater around these areas. Future work will address the effect of spatial variation in damages, costs, and biological growth on policy instrument choices over time using the case study of the BTS. Using Geographical Information Systems (GIS) software, it is possible to generate a spatially-explicit optimal early detection/rapid response and control policy, given the eventuality that prevention of the snake's entry has already failed or will eventually fail at either the airport or the shipping harbor, regardless of budget.

Currently, resource managers employ prevention and control instruments both independently and simultaneously towards a variety of threats. Often projects are funded based on ease of control and likelihood of successful management, rather than on potential losses from the invasion. Another important policy question is how to prioritize management when faced with multiple threats and limited funds. Future work should focus on prioritization of both existing and potential threats based on expected losses.

Other fruitful avenues for future research in this area remain. In this work we framed the problem as one of resource economics. Future work will integrate ecological modeling, including population dynamics and species interactions, directly into the economic model. A promising start would be modeling the dynamics of two state variables, where each could represent the population of a predator or prey-like species. While these interactions have been modeled in the ecological sciences, they have yet to be included in the economic models of invasive species management. Stochastic dynamic programming may provide another useful approach to the problem of uncertainty.

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