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Making Decision Adaptive to Price Uncertainty and Risk Preference: A New Decision-Making Model for Forest Management

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MAKING DECISION ADAPTIVE TO PRICE UNCERTAINTY AND RISK PREFERENCE: A DECISION-MAKING MODEL FOR FOREST MANAGEMENT

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Abstract

While the forest grows, the price of timber fluctuates. Price uncertainty plays a key role in forestry due to the extended rotation length of growing trees. Like double sides of the same coin, risk preference and uncertainties should be considered together. This is because risk preference represents people's attitude toward that uncertainty when making management decisions. Risk preference is especially an important issue for forest management because forests are exposed to substantial uncertainties during their long growing period. However, most existing relevant studies either simply overlook the risk preference issue or fail to consider it together with a practical forest management decision-making approach. In this dissertation study, a behavior-based forest management model was developed to measure forest managers' risk preferences directly through their potential behaviors toward price changes. Besides, an adaptive harvest decision-making approach that incorporates varying levels of risk preference was established. Based on the models developed in this dissertation, numerical simulations were carried out to evaluate the impact of risk preferences in forest management outcomes. Results of simulations show that risk preference could indeed affect the performance of forest management. Besides, a properly selected risk preference level may bring extra risk premiums to forestry investment. In addition, sensitivity analyses found that there always exists a certain level of risk preference that will lead to the highest average return across different scenarios. Furthermore, a case study using the LSU Lee Memorial Forest as the sample site was carried out to demonstrate the adaptive harvest decision-making process using the method developed in prior chapters. The results of this case study not only confirmed the conclusions reached by numerical simulations, but also reiterated the importance of risk management strategy in forest management under uncertainties.

Chapter 1. Introduction

As a general rule of asset pricing, price equals expected discounted payoff (Cochrane 2005). Following this logic, the value of a piece of forestland dedicated to timber production is defined as expected discounted payoff that can be generated from it, i.e. the total expected profits by producing timber from this piece of forestland over infinite rotations. Since people started managing forests as a business, the objective of forest management has always been to get the highest profit from their investment. Commercial forestland owners, thereby, attempt to maximize the value of forestland primarily through optimal harvest scheduling, i.e. harvest and sell the trees at the right time to obtain the highest possible return.

Traditionally, forestland valuation and stand-level harvest decision-making approaches are based on discounted cash flow (DCF) approach and assume constant stumpage price and discount rate. With such assumptions, timber production is perfectly repeatable, i.e. every rotation will experience the same tree growth pattern, stumpage price, and interest rate, etc. In other words, timber production is assumed to be deterministic and not incorporating any types of uncertainties. A classic example of this type of approach is the Faustmann model (Faustmann 1849), which defines the value of a piece of forestland as the present value of all future harvest profits over infinite rotations and refers it as the Land Expectation Value (LEV). This model has been considered as a fundamental building block of forest management theories because it had answered a simple but basic question: how much is a piece of land worth if it is devoted to the growing of trees (Newman 2002). Following this model, forestland owners are supposed to determine the rotation length of a forest plantation at the initial stage of investment, and not to make any change in the middle of rotations. Many further efforts have been spent on this field following the framework of the Faustmann model, where the uncertainties are simply ignored.

In fact, uncertainties play key roles in forest management because of the extended investment cycle of forestry compared to other industries. Specifically, the common rotation length for a commercial forest plantation can often be more than 25 years or even longer in North America. Obviously, various forms of uncertainties are embedded in this long time horizon as the market and environmental conditions are always changing. Uncertainties, especially the price uncertainty, will greatly affect the forest management behavior and the value of forestland (Amacher, Ollikainen, and Koskela 2009). On the other hand, risk preference represents the attitude of a forestland owner in facing uncertainties. Risk preference can profoundly affect landowners' behavior in dealing with price uncertainty and make forest management decisions. In fact, risk preference and price uncertainty are like the two sides of the same coin, and thusly should be studied together. Among existing literature, several studies have discussed the issue of forest management under price uncertainty and other forms of uncertainties, but most of them just leave risk preference unaddressed. For a small portion of studies that tried to incorporate forestland owner's risk preferences into the decision-making process, their methods were either inexplicit or measuring landowners' risk preferences in indirect ways. In addition, these existing efforts in addressing this issue usually involved very complicated algorithms, which restrict them from being used for actual forest management decision-making. The specific pros and cons of existing efforts in this field are detailed in the following literature review chapter.

Considering the drawbacks of existing methods, ideally, we need a forest management model that is (a) able to address price uncertainty; (b) able to incorporate risk preference into the decision-making process in a direct and simple fashion; (c) capable of making forest management decision heuristically without requiring intensive computation, which enable it to be used in practice.

Therefore, this dissertation intends to establish the theoretical framework of a behavior-based forest management model that can address price uncertainty and risk preference at the same time. By using this model, this dissertation will also demonstrate how to explicitly measure forestland owner's risk preferences based on their behaviors, and how the varying risk preference among forestland owners will affect their decisions when dealing with price uncertainty, along with how those decisions result in differentiated returns of their investments in forestry. The results may contain implications for developing risk management strategies to deal with price uncertainty in forest management.

Specifically, the structure of this dissertation is organized as follows: After this introduction as chapter 1, chapter 2 is a literature review on the existing articles on forest management under price uncertainty and previous efforts to incorporate risk preference into forest management decision-making. Following that, chapter 3 illustrates the theoretical framework of a behavior-based model to conduct adaptive forest management considering both price uncertainty and risk preferences. Chapter 4 presents numerical simulations that show how varying risk preferences will affect forest management outcomes under different scenarios. Chapter 5 is a case study demonstrating empirical applications of this model to the management of LSU's Dean Lee Research Forest, which showcase how one can use this model to make harvest decisions adaptive to enhance forest management outcomes. Chapter 6 concludes the entire research and provides some further implications.

Chapter 2. A Review of Literature on Forest Management Consider Uncertainty and Risk Preferences

As mentioned in last section, the most essential forest management problem is to determine the optimal harvest age to maximize the value of a piece of forestland. The studies on such topic have been the frontier of forest management for decades (Amacher, Ollikainen, and Koskela 2009). Over the years, substantial portion of relevant literature are based on the framework that are originated from the seminal paper by Faustmann (1849), known as the Faustmann model. Essentially, as a deterministic discounted cash flow (DCF) type model, the Faustmann model assumes that the value of a piece of forestland, i.e. the land expectation value (LEV), is the summation of a series of harvesting incomes over infinite rotations. Based on this model, by choosing the optimal rotation length t , the landowner can maximize the land expectation value as

$$LEV = \frac{P(t)Q(t) - Ce^{rt}}{e^{rt} - 1} \tag{1}$$

where $P(t)$ is the stumpage price of trees at age t, $Q(t)$ is the stand volume at age t, C is the regeneration cost, and r is the interest rate. In classical Faustmann model, parameters like C and r are assumed constant over time, which is why such type of model is regarded as static model in forest management terminology.

Since Gaffney (1957) proved the superiority of Faustmann model over other static methods in the determination of optimal rotation length, many studies have been conducted to solve for optimal thinning age and rotation length, e.g. Bentley and Teeguarden (1965), Bentley and Fight (1966), and Heaps (1981). However, following the original Faustmann model, most of those studies assumed the same rotation will be perfectly repeating forever, i.e. every rotation will incur the same stumpage price, stand volume, and regeneration cost, etc. Apparently, these assumptions are too ideal to be true.

The effort to overcome such unrealistic assumptions started from several studies that incorporated unfixed rotation length by assuming a continuously increasing stumpage price trend (McConnell, Daberkow, and Hardie 1983, Hardie, Daberkow, and McConnell 1984, Yin and Newman 1995). In those studies, stumpage price uncertainty was addressed in a way that real stumpage price rises at a constant pace. Although being regarded as an initial exploration of forest management under price uncertainty, this constant-rising price assumption is not consistent with the true price behavior in stumpage market around the world. Rather than specifically setting a price behavior, a real breakthrough to relax the stringent assumptions of perfectly repeating rotation is the work by Chang (1998). In this paper, a generalized Faustmann model was presented, as:

$$LEV_1 = [P_1(t_1)Q_1(t_1) - C_1 e^{r_1 t_1}]e^{-r_1 t_1} + e^{-r_1 t_1} LEV_2 \quad (2)$$

where the LEV_1 is the current land expectation value for certain forestland, the LEV_2 refers to the new land expectation value after the first rotation. The difference between LEV_1 and LEV_2 is a generalization of the difference between current and future rotations, i.e. the difference in stumpage price, stand volume, and other variables. Within this framework, if the stumpage price, stand volume, and regeneration cost, etc. are given for all the future crops, the optimal rotation length for each crop can be solved explicitly. However, since the future land expectation value (LEV_2) is hard to predict, solving the optimal rotation age by using generalized Faustmann model still relies on examining the problem analytically. Thus, although generalized Faustmann relaxed the constraint of prefect repeating rotation theoretically, it is still difficult for landowners to address price uncertainty ex ante by solely using generalized Faustmann model. The randomness of stumpage price series is needed to be quantified in more explicit means.

One method to incorporate price uncertainty into forest management is the reservation price approach (Brazee and Mendelsohn 1988b, Lohmander 1987). By assuming an existing long-term mean stumpage price, a landowner decides whether to harvest a forest stand or not by comparing the observed market stumpage price and an age-dependent reservation price. Specifically, if the stumpage price observed at the time point of decision is above the reservation price, this landowner is directed to cut the trees at that age; otherwise one should wait another period of time for further decision. Obviously, compared to those methods that make harvest decision once at a time at the beginning of rotations, reservation price approach is an adaptive decision-making approach, i.e. harvest decisions are made heuristically at the end of each time period (usually a year) rather than only once at the very beginning. Thus, the landowner can make the optimal harvest decision adaptive to the changing stumpage price over time.

Previous study suggests that managing forestland adaptively using reservation price method will significantly boost the expected net present value (NPV) of a forestland compared to making harvest decision solely relying on Faustmann model (Brazee and Mendelsohn 1988a). Since its debut, reservation price has gone through extensive developments and modification to incorporate various types of incomes and uncertainties. For example, Brazee and Bulte (2000) present a modified reservation price model that include thinning incomes. Gong, Boman, and Mattsson (2005) integrate non-timber benefits into a reservation price model to make optimal timber harvest strategy. Susaeta and Gong (2019b) propose a reservation price-based framework to include both price uncertainty and the risk of natural disturbances. Other than theoretical analysis, there are also some applications of reservation price in empirical forest management cases (Susaeta and Gong 2019a).

While it is most common to solve optimal rotation age problem by directly maximizing the expected total cash value, one may also solve it from a marginal perspective. Specifically, solving the optimal timber harvest strategy problem from a marginal perspective means that one should consider from a perspective of incremental rate rather than the total cash value. Pressler (1860) developed the indicator rate formula to explicitly separates the incremental rate of a forestland value into three parts, i.e. the incremental rates of quantity, quality, and price. It represents the same solution to maximizing the classic Faustmann LEV (Johansson and Löfgren 1985). Furthermore, as pointed out by Chang and Deegen (2011), the Pressler's indicator rate formula is also compatible with the generalized Faustmann model and all corresponding analytical results and applications. With Pressler's indicator rate formula, different types of uncertainties could be separated out and dealt with individually. At each time point, the optimal harvesting strategy, i.e. harvest now or not, for a forest stand can be determined adaptively by following a marginal principle with respect to time.

However, for both reservation price approach and the Pressler's indicator rate method, making adaptive harvesting decision relies on one essential assumption: stumpage price follows a certain distribution with finite mean and variance. This assumption is not always true. Previous findings suggest that stumpage price can be purely stochastic, i.e. following a diffusion process (Hultkrantz, Andersson, and Mantalos 2014). As stated by Haight and Holmes (1991), the optimal harvest decision largely depends on the behavior of price series. Amid the coexistence of various price behaviors, more adaptive forest management methods were development. Among them, articles utilizing the Real Option Analysis (ROA) approach and Markov Decision Process (MDP) method stand for a substantial group of the existing literature.

Given the nature of an adaptive decision-making process, making optimal management decision largely relies on arrival of new information about the ongoing investment. As new information come in, the market condition and future cash flow may be uncovered gradually, which enables management to alter its initial operating strategy in response to unexpected opportunities or operating losses (Trigeorgis 1996). This issue can be addressed by real option analysis (ROA) approach. Real options refer to the right, without obligation, to undertake certain management actions, such as deferring, abandoning, expanding, staging, or contracting a capital investment project (Trigeorgis 1996). The real option analysis approach is the general application of real option valuation techniques to make capital budgeting decisions, especially for optimal stopping problem. In forestry, the optimal stopping problem refers to the landowner's decision in each period whether to harvest trees, wait for one more period, or salvage harvest in case of natural catastrophes. Conceptually, if treating these forest management actions as real options, one may solve for the optimal forest management strategy via solving and comparing these actions' implied real option values.

Depending on the types of option and time framework, various methods have been applied to solve real option value problems in forestry. One of the most common is the Black-Scholes model. For studies utilizing this method, forest investment opportunities are treated as European call options and their values can be explicitly solved by the Black-Scholes model. Since mid-1980s, a number of studies apply Black-Scholes model to solve forest management problems as real option problems such as timber harvesting contract (Shaffer 1984), alternative management options (Zinkhan 1991), and tree harvesting strategy (Gjolberg and Guttormsen

2002). However, although being regarded as valuable initial explorations of using ROA on forest management, many of those studies were not using Black-Scholes model in a correct fashion as they failed to fulfill the assumptions of Black-Scholes Model on price process. As Thomson (1991) pointed out, the optimal rotation cannot be determined by using Black-Scholes model unless the stumpage price follows a lognormal diffusion process. In addition, treating management actions as European style options imply that one can only take managerial actions at certain fixed exercise time points, which restrict it from been used in those cases where flexible timing is needed. For those cases, optimal stopping problem is often modeled as an American option because it implies the right to buy or sell the underlying asset during the time before or at the expiry date. In practice, timber harvest contract is often regarded as an American call option (Yin and Newman 1997).

As Hull (2000) indicated, the value of an American call option can only be solved numerically. For the discrete time framework, the dominant method to solve for the value of an American option is the binomial tree approach by Cox, Ross, and Rubinstein (1979). The binomial tree approach assumes that the price of underlying asset will either increase or decrease during a certain timespan. Each price node will be followed by another split to two other nodes with high and low prices until the expiry of option. Thomson (1992) employs the binomial tree method to determine the optimal forest rotation when the price follows a diffusion process and found the superiority of binomial trees methods over the traditional net present value approach due to its ability to incorporate flexibility. Following this first attempt, more efforts have been added to literature such as alternative management options (Duku-Kaakyire and Nanang 2004) and carbon sequestration income (Tee et al. 2014).

Binomial tree approach is only valid for the real option problems in discrete time scheme. For those under continuous time framework, the stochastic dynamic programming (SDP) has been used as an alternative method to solve real option problems in forest management. One pioneer work utilizing SDP to determine optimal harvest decision is by Norstrøm (1975). After that, a number of authors have expanded this approach into many specific issues, such as harvest decisions under stochastic carbon price (Chladna 2007), optimal rotation determination for uneven aged forests (Clarke and Reed 1989), and timber harvest contract valuation (Burnes, Thomann, and Waymire 1999), among others. Most studies of such kind utilize the finite-difference techniques to obtain numerical solutions of option values, which generate a lot of computational complexity (Yin 2001, Yin and Newman 1997, Di Corato, Gazheli, and Lagerkvist 2013, Insley 2002, Insley and Rollins 2005).

Beyond those real option related approaches, articles taking advantage of the Markov decision process (MDP) also represents significant efforts to address the forest management problem under uncertainties. As an extension of Markov chains, MDP approach is a discrete time mathematical framework widely used to solve optimal decision-making problems in many disciplines. In an MDP, the one who manages the system is called an agent, the condition of such system in each step is described by state s, and the agent is facing a finite set of actions A. For each state and action, there is a transition model $\mathrm{P}(\mathrm{s}'|\mathrm{s}, \mathrm{a})$, which describes the probability of getting to a new state s' given the current state s and a specific action a within the set A. In addition, a reward function is specified to regulate the rewards, which can be positive or negative, granted to the decision maker upon the move to a new state. The state transition of an MDP satisfies the Markov property, i.e. the future states of the process depend only upon the present state, but not a sequence of states prior that preceded it. The function that regulates what action an agent should take at each state is called a policy, which is essentially a function of states. Specifically, the optimal policy under MDP framework is measured by maximizing the management objectives, e.g. net present cash value, expected utility, etc. In additional, a discount factor may also be introduced to MDP to reflect the time preference of a decision maker and the opportunity cost of investment alternatives, even though the discounting criteria sometimes may lead to non-convergence problem in optimizations.

MDP has been an effective way to model forest management subject to various types of uncertainties, e.g. stumpage price uncertainty, timber growth uncertainty, etc. The initial effort of using MDP for forest management problem is made by Lembersky and Johnson (1975), in which MDP method is used to optimize the management policy for even-aged forestland. After that, applications of MDP in forest management are extended to many different specific situations, e.g. managing uneven-aged forest stands (Kaya and Buongiorno 1987), combining financial objective and ecological diversity (Lin and Buongiorno 1998), and multiple ecological objectives (Zhou and Buongiorno 2006), among others.

For majority of relevant studies, linear programming or quadratic programming techniques were employed to solve for the optimal policy that can maximize the expected utility function. Rather than simply determining the optimal decision for the initial stand state, MDP method supplies a comprehensive optimal decision rules available for any possible future states of such forest. The optimal policy consists of all decisions that an agent should do at every single possible state. Frankly speaking, such comprehensiveness also has its drawback. One problem of utilizing MDP is that, though it considers uncertainties, the policy is determined ex ante given the initial states. Appearently, the states must be finite, so that the possible future states are described as categories rather than infinite numbers of explicit conditions. Furthermore, the MDP problems in practice usually do not have close-form solution but rely on numerical techniques to solve for an optimal solution. Not to mention that it is impossible to foresee all possible conditions, even finding solution for MDP problem with a reasonable scale may consume extensive computational power. For example, Couture, Cros, and Sabbadin (2016) reported that a very powerful server computer with high-end processors and memories is not capable of solving problems with more than five stands due to the massive size of generated transition table.

Though out all these efforts mentioned in previous paragraphs, forest management under uncertainties have been investigated based on various types of models and from several different perspectives, e.g. different sources of incomes, different stand age classes, etc. However, compared to the massive amount of efforts that have been spent on optimizing management strategy from a pure objective stance, fewer literature has been dedicated to subjective side of uncertainty, i.e. risk preference, which stands for human's subjective attitude toward risk and uncertainty. A number of survey studies have showed that forestland owners' preferences toward risk and uncertainty will affect their management decisions, and thereby affect the valuation of forestlands (Feliciano et al. 2017, Laakkonen et al. 2018, Lunnan, Nybakk, and Vennesland 2006, Andersson and Gong 2010). Therefore, this topic is worthy of more attention by researchers.

Risk preference has been taken into consideration with a numbers of different timber harvest decision making models. For example, Gong (1998) develops a modified reservation price model to make adaptive optimal harvest decisions while explicitly incorporate landowners' risk preference. Specifically, in this model, the reservation price is determined by maximizing the expected utility of landowners instead of expected net cash value. By integrating expected utility function into the reservation price model, relevant literature has been expanded over extensive topics, such as optimal harvest strategy considering price uncertainty, risk of natural disturbance, and financial risk aversion (Susaeta and Gong 2019b). As an adaptive decision-making approach, reservation price approach provides an excellent way to adaptively make optimal harvest decision considering the impact of risk preference, while its assumptions on price process narrow it down from being used for more pervasive cases.

Several studies have addressed the optimal harvest scheduling problem with risk preference based on the MDP approach, which has better tolerance in price behaviors. For example, Couture, Cros, and Sabbadin (2016) measures the effect of risk aversion on the management of an un uneven-aged forest, Buongiorno, Zhou, and Johnston (2017) compare how three general categories of risk preference. i.e. risk seeking, risk neutral, and risk aversion, will affect the forest management decisions, and Zhou and Buongiorno (2019) set up an MDP-based model explicitly to address the optimal harvest scheduling issue under the expected utility framework.

The nature of MDP enables it to provide solutions to all possible future states rather than only for the initial one. While the solution can be comprehensive for all future states, after all it is provided upfront at the beginning, i.e. the optimal solution is either being provided one at a time ex ante. Taking risk preference into consideration does not solve this problem and could sometimes make it worse. For using MDP to carry out an adaptive forest management, one needs to run the entire dynamic programming process over again at each new step to ensure the optimized solution can still hold up because more unexpected information may come into the system. Even without incorporating the financial risk aversion, such repeated computations may add burdens to the already very extensive computational process required by MDP approach. If risk preference is also taken into consideration, even for a forest stand with reasonable size and class formation, conducting adaptive forest management using MDP may become unparallelly complicated and will consume tremendous amount of computational power.

Other than the MDP and reservation price approach that are both based on discrete time framework, some scholars also use dynamic programming techniques to address the same issue from a perspective of operational research (Tahvonen and Kallio 2006, Pagnoncelli and Piazza 2017, Lien et al. 2007, Gong and Lofgren 2008). Like many of those taking advantages of MDP, these operational research-type studies also address the risk preference issue as financial risk aversion explicitly through expected utility function framework.

Existing studies have already addressed the impacts of risk preference on forest management via several different methods and from several different aspects. A number of models have been developed to integrate risk preference into the forest management decision-making under uncertainties, and many meaningful results are raised from these models. In general, the consensuses of most existing literature are: First, financial risk aversion leads to a cutting cycle (or rotation) shorter than the optimal one determined with the risk-neutral assumption. Second, financial return under certain range of risk preference level will lead to a risk premium. Relevant studies have proved these two conclusions via either theoretical or practical ways. However, existing methods still have many drawbacks.

First, while there are some exceptions, e.g. (Buongiorno, Zhou, and Johnston 2017) and (Gong and Lofgren 2008), the majority of relevant studies use expected utility function to measure risk preference of forest managers. Although expected utility function is widely regarded as a straightforward and explicit way for this purpose, utility is not something that one can directly observe in practice. Therefore, it is difficult to measure one's risk preference in a precise and convenient manner by using expected utility function framework.

Second, many decision-making methods, e.g. MDP, are still ex ante methods, i.e. those methods determine the optimal harvesting policy once at the beginning. Due to the fact that all decisions are made beforehand, these non-heuristic decision-making approaches will make forestland owners more difficult to adjust their decision adaptive to unexpected changes in the interim. In fact, it is more suitable to use those ex ante methods to make project evaluation rather than making harvest decisions in practice.

Last but not least, many current adaptive forest management methods are too complicated for practical use. The complex mechanism and hungry needs for computational power restrict them from being used by common forestland owners in daily forest management practice. This may even partially contribute to the unpopularity of adaptive forest management among real world forestland owners.

Chapter 3. A Behavior-based Forest Management Model for Making Timber Harvest Decisions Involving Manager's Risk Preference

Obviously, it will be desirable if a new adaptive forest management method can overcome the shortcomings of existing methods mentioned at the end of the last chapter. Specifically, this method should be able to (1) solve the optimization problem heuristically to enable adaptive management; (2) address risk and uncertainty issues, (3) incorporate the varying level of risk preference in an explicit manner, and (4) easy to calculate in practice. Amid these four key features, I establish a behavior-based adaptive forest management approach in this dissertation. Built upon the Pressler's indicator rate formula, this method explicitly measures forestland owners' risk preferences through their potential behaviors toward different timber price situations.

3.1. Separation of the Annual Value-Added of a Forest

Before proceeding further, I want to reiterate that the phrase forest management in this dissertation refers to the management of a forest that is dedicated only to timber production. Therefore, the primary forest management decision to make by the landowner involves harvest timing, i.e. whether to harvest the trees in current year, or delay it to let trees grow for one extra year. One way to solve this problem marginally is to separate the annual increment, or value-added, of a forest into multiple parts, which can be either deterministic or random.

Conceptually, the annual value-added of a forest come from three sources: the quantity increment, quality increment, and price increment. The quantity and quality increments stand for the increased timber volume and improved timber quality as trees grow larger, and the price

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increment represents the possible extra value-added contributed by stumpage price change in such year. Clearly, the quantity and quality increments will be positive values for most years as biological volume of trees keep growing almost all the time. However, the price increments can either be positive or negative due to price uncertainty.

Pressler (1860) published his famous paper about the indicator rate formula, in which the annual value increment of a forest is separated through an elegant mathematical form as

$$(a + b + c)\frac{k}{k+1}; with\ k = \frac{h}{g} \tag{1}$$

where a is the rate of quantity increment, b is the rate of quality increment, c is the rate of price increment, h is the variable timber capital, and g is the fixed land capital. Note that the variable timber capital at the age t is the value of the existing forest at this age, i.e. $V(t)$, and the fixed land capital is the value of such forestland, i.e. the LEV. Obviously, a rational forestland owner should make the rate of total annual increment to be greater than the interest rate r.

According to Chang and Deegen (2011), the stumpage value of a forestland at age t can be expressed as

$$V(t) = \sum_{j=1}^{n} P_j(t)\, W_j(t) Q(t) \tag{2}$$

where $P_j(t)$ is the stumpage price of product class j in age t, $W_j(t)$ is the percentage of the product class j in the stand volume, and $Q(t)$ is the total stand volume at age t. Note that the yield of a timber stand usually consists of several products classes. For example, in the U.S. South, southern pine timber stands typically consists of pulpwood, chip-and-saw (CNS) logs and saw logs, sorted by unit value ascendingly. Therefore, as trees grow to larger size, the proportion of high value product class will also be increased. In fact, the quality increment stands for the value-added due to increased proportion of high-quality product class.

Mathematically, differentiating the equation (2) with respect to t, we get:

$$V'(t) = \sum_{j=1}^{n} P_j'(t)W_j(t)Q(t) + \sum_{j=1}^{n} P_j(t)W_j'(t)Q(t) + \sum_{j=1}^{n} P_j(t)W_j(t)Q'(t) \qquad (3)$$

However, in cases where product classes are not differentiated, a general stumpage price for all product class is used so that the quality increment is not considered. Accordingly, the parameters for quality increment and product class are removed from the equation, shown the following equation:

$$V(t) = P(t)Q(t) \qquad (4)$$

where the notations are the same as in equation (2).

Taking derivatives with respect to t on both side of equation (4), one gets

$$V'(t) = P'(t)Q(t) + P(t)Q'(t) \qquad (5)$$

Then, by dividing $V(t)$ into both sides, we get

$$\frac{V'(t)}{V(t)} = \frac{P'(t)Q(t)}{V(t)} + \frac{P(t)Q'(t)}{V(t)} = \frac{P'(t)}{P(t)} + \frac{Q'(t)}{Q(t)} \qquad (6)$$

With the two terms on the far right part of equation (6), the first one stands for the rate of price increment, i.e. the c in the Pressler's indicator rate formula; the second one stands for the rate of quantity increment, i.e. the a in the Pressler's indicator rate formula. Recall that the annual stumpage increment rate should be greater than the interest rate r, namely

$$(a + c)\frac{k}{k+1} > r, \qquad k = \frac{h}{g} = \frac{V(t)}{LEV}, \qquad a = \frac{Q'(t)}{Q(t)} \qquad (7)$$

With growth and yield models, the values of $Q(t)$ and $Q'(t)$ are assumed to be known at any age t. $V(t)$ can also be calculated as $P(t)*Q(t)$ as the current year stumpage price is known. In addition, the LEV, which stands for the value of land, is a constant. Therefore, the values of a and k are deterministic at any age t. However, the price increment rate, c, remains a random term. In fact, the value of c needs to be greater than a minimum value to maintain profitability if one decides to delay harvesting from age t to $t+1$. This relationship is shown as follow:

$$c \geq r\left(1+\frac{1}{k}\right)-a, \qquad k=\frac{h}{g}=\frac{V(t)}{LEV}, \qquad a=\frac{Q'(t)}{Q(t)} \tag{8}$$

Following equation (8), we can define a minimum required price increment rate x between age t and $t+1$, where

$$x=\min(c)=r\left(1+\frac{1}{k}\right)-a \tag{9}$$

With equation (9), the value of x can be calculated each year. This necessary price increment rate, namely x, serves as an important reference for forestland owners to make harvest decision under price uncertainty. A heuristic harvest decision-making approach incorporating both price uncertainty and risk preference can also be constructed based on it.

3.2. Level of Risk Tolerance – A Quantitative Measure of Risk Preference

Following the definition of the minimum required price increment rate x, a target price at age $t+1$ can be derived as

$$P^*(t+1)=(1+x)P(t) \tag{10}$$

where $P(t)$ is the current stumpage price when the landowner makes harvest decision, and $P^*(t+1)$ stands for a target price that the landowner needs to maintain profitability if harvest is delayed to the next year. Specifically, if the stumpage price in year $t+1$ is higher than the target price, the value of forest will increase and the decision to delay harvest is correct. Otherwise, the forest owner incurs a loss in value of forestland and the decision to delay harvest is in fact incorrect. Due to the price uncertainty, it is impossible to know whether the stumpage price will be higher than the target price or not. However, knowing the probability of such an event is possible. Conceptually, if this probability of incurring a loss when delaying harvest is lower than some level, a rational forestland owner may think that the probability of getting extra profit by waiting one extra year is minimal, so that it is not worth the waiting and the timber should be harvested right away.

Mathematically, the probability that the forestland owner will get extra profit by delaying timber harvest and wait for one extra year can be defined as follow:

$$\mathrm{Pr(Getting\ extra\ profit)} = \mathrm{Pr}\ [P(t+1) > P^{*}(t+1)] \tag{11}$$

Likewise, define the probability that a forestland owner will incur a loss if delay the timber harvest as:

$$\mathrm{Pr\ (Incurring\ a\ loss)} = \ \mathrm{Pr}\ [P(t+1) < P^{*}(t+1)] = \ 1 - \ \mathrm{Pr\ (Getting\ Extra\ Profit)} \tag{12}$$

Obviously, the probability of incurring a loss is a measure of the downside risk in the decision-making process. Such a probability serves as an important benchmark when measuring people's risk preference. In fact, the tolerances to the down-side risk are different among people. Risk-seeking persons are generally more tolerant of such a risk than risk-averse persons. Thus, based on (12), a decision rule can be established with a threshold probability level τ, which is the maximum level of probability of incurring a loss that can be tolerated by a forestland owner. If $\mathrm{Pr(Incrruing\ a\ loss)} > \tau$, meaning the chance that one can get extra profit by delaying harvest is too small to afford. Thus, the decision is then probably to harvest timber now. Otherwise, one should keep the trees and delay the decision to the next year.

In this study, this threshold probability level τ is named as the level of risk tolerance, which is a quantitative measure of the general risk preference of a forestland owner. The value of τ varies across different landowners and reflects their general risk preference. For example, a forestland owner with τ = 0.90 means one can tolerate the probability of incurring a loss as much as 90% for any single year. In another word, timber harvest should only be conducted when the probability of incurring a loss by delaying the harvest is greater than 0.90, i.e. the chance of getting extra profit by delaying harvest is less than 10%. Likewise, another more risk-seeking forestland owner may have a higher value of τ, e.g. 0.95, which means a higher tolerance on downside risks. In another word, this forestland owner is more risk seeking than the prior one with $\tau = 0.90$. Therefore, under this decision rule, a higher level of risk tolerance indicates a more risk-seeking preference in terms of management behavior, while a lower level of risk tolerance indicates a more risk-averse preference. Note that the value of τ is the level of risk tolerance for any single year over the rotation period. Due to the extended length of forestry investment, a landowner will potentially have many chances to harvest and sell the trees. In the meantime, trees keep growing over the rotation, which keeps the cost of carrying the timber asset at a low level. Therefore, at any single year, delaying the harvest and bet on the good price will appear in the future is an easy choice, unless the timber price is already extremely high and one will be very likely to incur a loss if delaying the harvest to the next year. As a result, the value of τ will be a large number in forestry (e.g. 0.90), which reflects the fact that forestland owners will only harvest the timber when the possibility of incurring a loss by waiting is extremely large.

Chapter 4. Numerical Studies Regarding the Impact of Risk Preference on Forest Management Outcomes

4.1. A Numerical Analysis Under Fixed Market Conditions

This chapter presents several numerical simulation studies to demonstrate how varying risk preferences will affect forest management decisions and valuation of forestland with price uncertainty. Specifically, the stumpage price series is randomly generated following a log-normal distribution to reflect the fact that price is changing on a percentage scale. The parameters of such distribution are calibrated pursuant to the Louisiana southern pine real stumpage price series from 1956 to 2015 (Louisiana Department of Agriculture and Forestry 2019). Specifically, the mean and variance for the original price series are $\$169.19/\mathrm{Mbf}$ and $\$65.73/\mathrm{Mbf}$, respectively. The growth-yield model employed is the same as the model used in Brazee and Mendelsohn (1988c) to enable direct comparison. Moreover, the minimum harvest age is set to be 12 years is set because the trees won't be large enough to be merchantable prior to this age by that age. Likewise, there is a maximum harvest age of 80 years, which implied the fact that a reasonable landowner will not wait for the harvesting opportunity forever but will have to cut the trees for some reason. Some other settings used include the interest rate r is set to be 0.04 and the regeneration cost C is assumed to be \$60 per acre.

Other than this behavior-based adaptive harvesting decision-making approach proposed in this dissertation, the classical Faustmann approach and the reservation price strategy are also included in this numerical study for comparison purpose. The forest management outcomes (i.e. mean LEV and mean rotation length) of these three models are compared. Specifically, the net present values of profits from the first 10 rotations are added up to approximate the true LEV, i.e. the value of such a piece of forestland. A total of 30 different scenarios with the level of risk tolerance varies from 0.5 to 0.99 have been analyzed. For each scenario, the numerical simulation has been running for 5000 times. The mean LEV and rotation length are extracted for comparison with other approaches. The mean LEV stands for the value of this piece of forestland under such level of risk tolerance, and the mean rotation length serves as a benchmark for the performance of forest management.

Shown in Table 1 is a summary of the mean LEV and rotation length for different levels of risk tolerance. In detail, the mean rotation length keeps increasing as the level of risk tolerance increases, while the mean LEV increases for the initial stage to a peak then suddenly decreases as the level of risk tolerance continues to increase. Essentially, the finding in rotation length fits the theories that risk-averse behaviors lead to shorter rotation length and earlier harvest age. However, the finding on the mean LEV is not consistent with the intuition that taking higher risk will always lead to a higher return, as is implied by many classical asset pricing model, e.g. the capital asset pricing model (CAPM) (Sharpe 1964). In fact, the realization of the full value for a piece of forestland relies heavily on the risk preference of its owner/manager, and there exists a certain level of risk tolerance that will bring on average the highest return to landowners. Whether individual landowners could tolerate such a level of risk is a separate matter. Namely, in this dissertation, I refer this level of risk tolerance that could bring the highest average LEV to forestland owners as the optimal level of risk tolerance.

The comparison of forest management outcomes among selected management approaches are shown in Figure 1 and Figure 2. As we can see from these two figures, under the changing price scheme, those two approaches considering price uncertainty show significant advantages over the classical Faustmann model, which overlooks the price uncertainty. Specifically, by applying the reservation price approach, we get a mean LEV of $4725 per acre and a mean rotation length of 26.3 years. Compared with the mean LEV of $2202 per acre and a

Table 1. Summary of Rotation Length and Mean LEV with different Risk Tolerance Level

The risk tolerance level	Mean Rotation Length (Year)	S.D. of Rotation length	Mean LEV (USD)	S.D. of LEV
0.50	14.30	2.64	2008.00	483.82
0.55	14.84	2.97	2200.91	536.31
0.60	15.43	3.33	2480.73	613.84
0.65	16.17	3.75	2774.14	624.54
0.70	17.07	4.29	3108.31	610.21
0.75	18.15	4.89	3391.05	725.46
0.76	18.34	4.90	3429.40	654.13
0.77	18.85	5.28	3609.48	718.12
0.78	19.05	5.34	3619.32	735.94
0.79	19.37	5.55	3750.66	728.76
0.80	19.65	5.84	3846.53	723.78
0.81	20.15	6.07	3942.33	674.14
0.82	20.56	6.29	4012.12	755.72
0.83	20.98	6.51	4118.49	735.64
0.84	21.53	6.90	4161.61	685.97
0.85	22.09	7.33	4265.06	705.68
0.86	22.81	7.81	4391.60	729.28
0.87	23.33	8.12	4506.81	740.42
0.88	24.31	8.64	4587.49	736.73
0.89	24.91	9.14	4657.39	694.90
0.90	25.92	9.71	4774.44	727.45
0.91	27.44	11.01	4784.20	796.96
0.92	28.78	11.81	4848.88	832.35
0.93	30.79	13.33	4850.85	954.48
0.94	32.68	14.31	5012.98	934.59
0.95	35.43	15.98	4815.15	1159.40
0.96	39.40	18.13	4695.00	1335.37
0.97	44.89	19.83	4453.26	1553.61
0.98	52.40	21.31	3946.02	1881.95
0.99	63.20	20.34	2904.47	2037.85

mean rotation length of 31 years under the classical Faustmann model, this is a huge improvement. The more impressive finding is on the performance of the behavior-based adaptive forest management model. Essentially, there is a non-linear relationship between the mean LEV and chosen level of risk tolerance. For a certain range of risk tolerance levels, the mean LEV by applying my behavior-based management approach could out-perform that of the reservation price approach, though the mean rotation lengths of the latter are slightly longer than that of the former for this range. As mentioned before, the reservation price approach assumes risk neutrality. Thus, the finding here implies that a certain degree of risk-seeking preference may lead to a better realization of the value of a forest, but at the expense of some degree of management flexibility due to the extended rotation length when compared to the risk-neutral approach, i.e. the reservation price approach.

4.2. Sensitivity Analyses of Market Conditions

In the above section, by establishing the level of risk tolerance (i.e. τ) as a measure of risk preference for an individual forestland owner, I demonstrate the impacts that varying risk preferences could bring for forest management outcomes under fixed market conditions (i.e. interest rate and market volatility). However, if those market conditions are changing, the pattern of such impacts brought about by the risk could also be changed. To figure out this interaction, multiple numerical sensitivity analyses are conducted to determine how the mean LEV and mean rotation length are impacted by varying levels of risk tolerance of forest owners as the market condition changes, i.e. various levels of interest rate or market price volatility. Specifically, the sensitivity analyses on interest rate and stumpage price volatility are carried out independently. Other than the default setting that $r = 0.04$ and $\sigma = 0.28225$, I have presented the cases for ten different levels of interest rate and price volatilities (Variances of price distribution). Therefore, for either the interest rate or stumpage price volatility, a total of 11 cases have been simulated following the same way described in the last section.

The full scenario of the relationship between mean LEV and the level of risk tolerance for selected levels of interest rate is presented in Figure 3. Essentially, for every level of interest

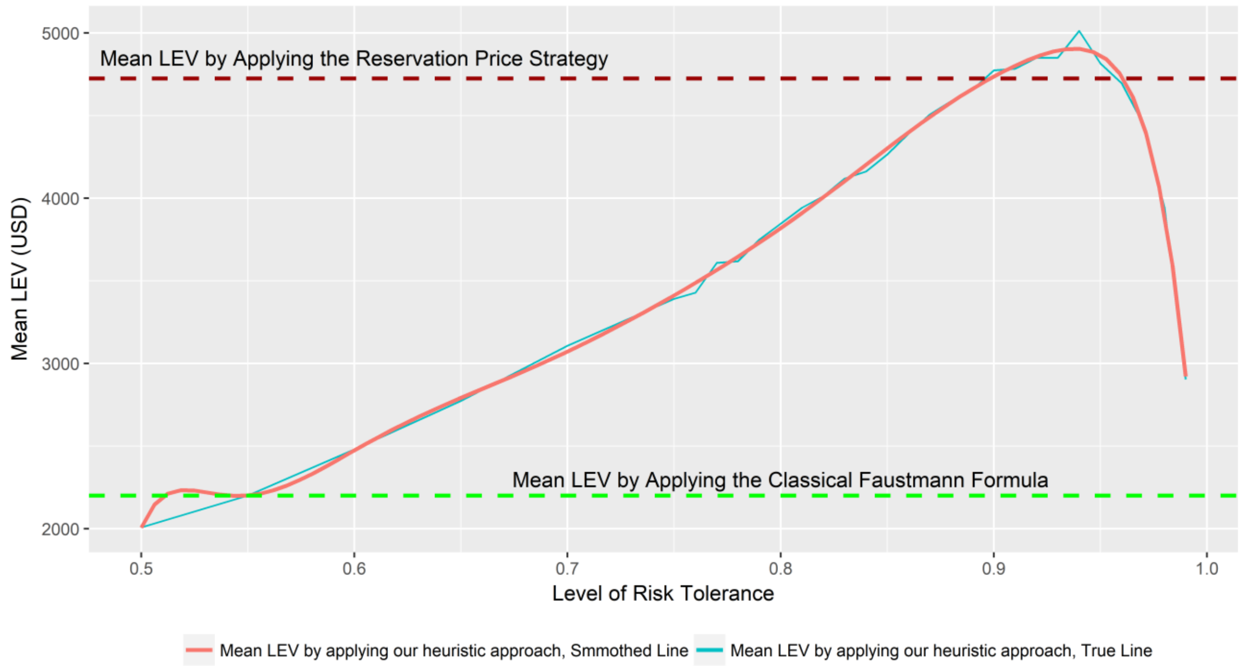

Figure 1. The Comparison on Mean LEV between the Reservation Price Approach, the Classical Faustmann Model, and our Heuristic Decision-Making Approach

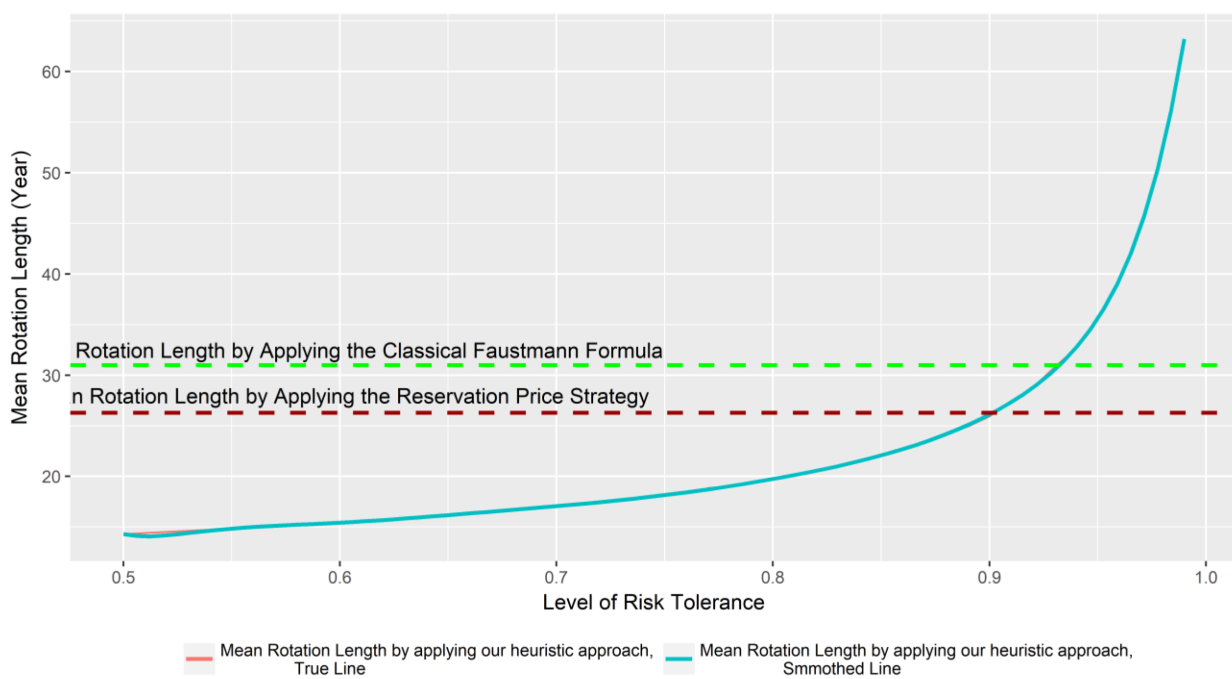

Figure 2. The Comparison of mean Rotation Length between the Reservation Price Approach, the Classical Faustmann Model, and our Behavior-based Heuristic Decision-Making Approach

rate, there exists a specific level of risk tolerance that will lead to the highest mean LEV, i.e. the optimal level of risk tolerance remains existing even if the interest rate changes. Moreover, as the interest rate increases, the curvature near the maxima of the mean LEV curve becomes flatter. This implies that the realization of forestland value relies less on risk preference when the interest rate increases. In other words, the valuation of forestland is more sensitive to its manager's risk preference under the low-interest scenario than under the high-interest scenario.

Specifically, how the optimal level of risk tolerance changes with respect to the interest rate is summarized in Table 2. In general, as the interest rate increases, the optimal level of risk tolerance is declining, while the mean rotation length is also decreasing. This finding indicates that a landowner should be more risk-seeking under the low-interest rate case because of the very low cost of carrying the timber asset. However, if the interest rate climbs to a higher level, the cost of carrying such a timber asset would rise to a level that is higher than the growth rate of trees. This would reduce the advantage of the forest as a self-appreciating asset, and force landowners to be more risk-averse to avoid incurring a further loss while waiting. The same facts are also presented graphically in Figures 4 and 5.

The relationship between mean LEV and levels of risk tolerance for selected stumpage price volatilities are presented in Figure 6. As shown in the graph, except for the case when $\sigma = 0.02$, all other cases appear to have one obvious single peak on the curve. However, the mean LEV curve displays an almost flat line for quite a range of risk tolerance levels when the stumpage price volatility is very small, i.e. $\sigma = 0.02$. In this case, since the stumpage price is very stable, it is very close to a constant pattern and the price uncertainty is nil. Thus, the impact of risk tolerance on the valuation of forestland becomes very small, i.e. the valuation of forestland is not sensitive to the risk preference of individual landowners. However, since the

Table 2. Summary of Sensitivity Analysis on Interest Rate

Interest Rate	Optimal Level of Risk Tolerance	Mean Rotation Length (Year)	S.D. of Rotation Length	Mean LEV (USD)	S.D. of LEV
0.005	0.97	47.24	20.61	78674.41	9710.99
0.010	0.95	37.94	17.38	37914.15	3962.97
0.020	0.95	37.08	17.40	15239.97	2334.84
0.030	0.95	36.24	16.62	8188.65	1625.27
0.040	0.92	28.67	11.70	4982.66	841.47
0.050	0.91	26.68	10.14	3221.13	530.05
0.060	0.91	25.87	9.53	2229.01	439.88
0.070	0.91	25.70	9.45	1608.32	336.21
0.090	0.89	22.82	7.67	866.09	175.09
0.110	0.87	20.90	6.49	502.41	128.38
0.130	0.84	18.58	5.15	302.12	70.70

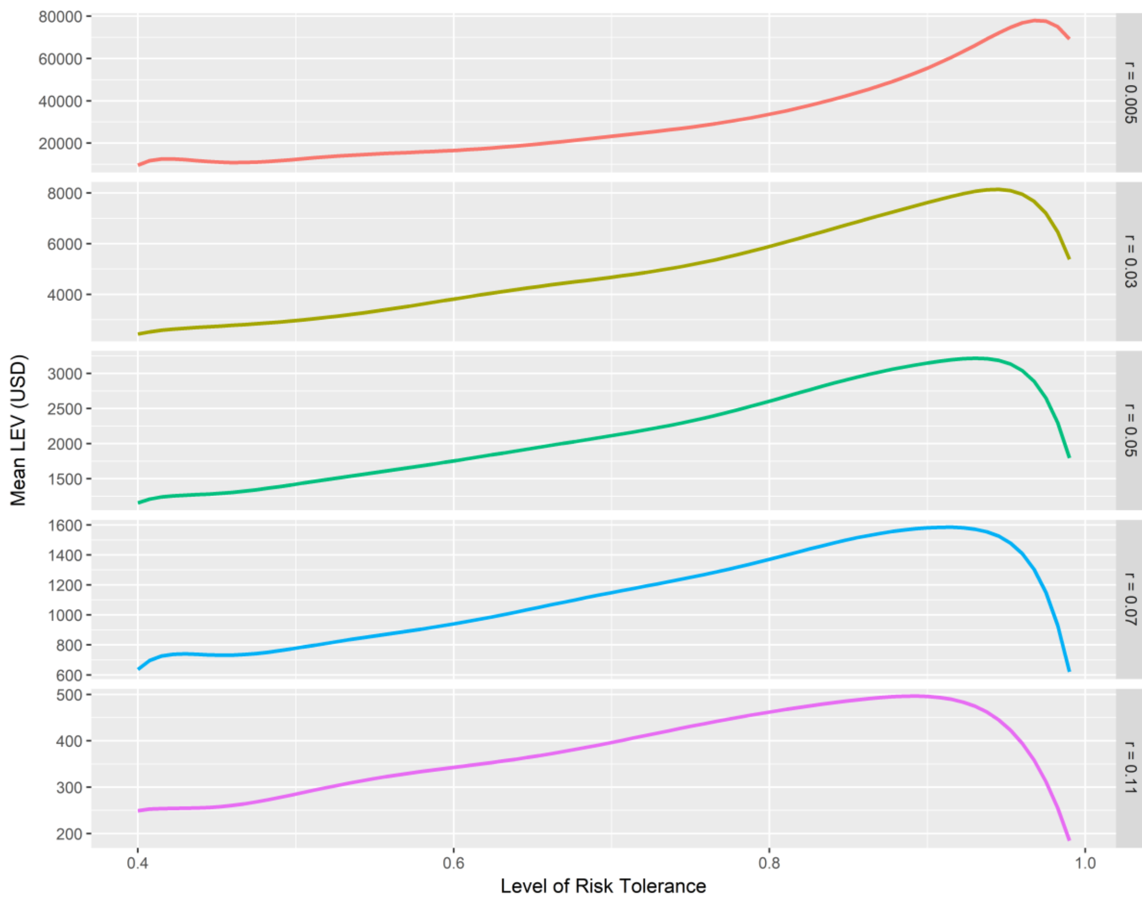

Figure 3. A Full Scenario of Mean LEV with Different Level of Risk Tolerance under Selected Level of Interest Rates.

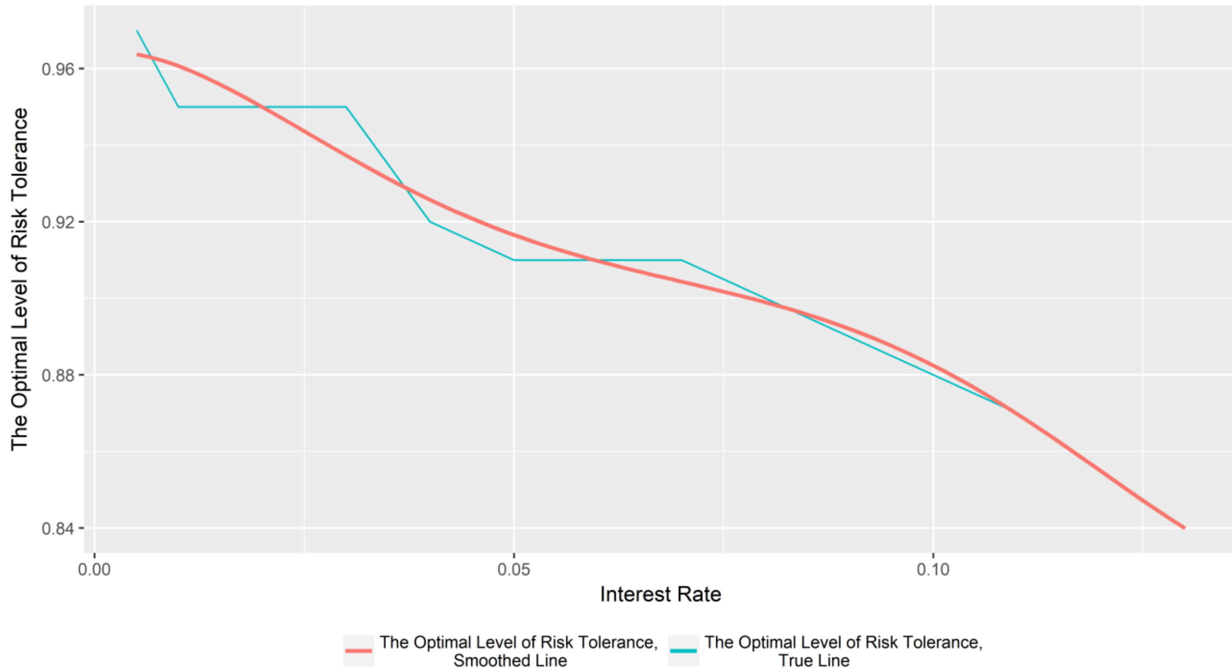

Figure 4. The relationship between the interest rate and the optimal level of risk tolerance

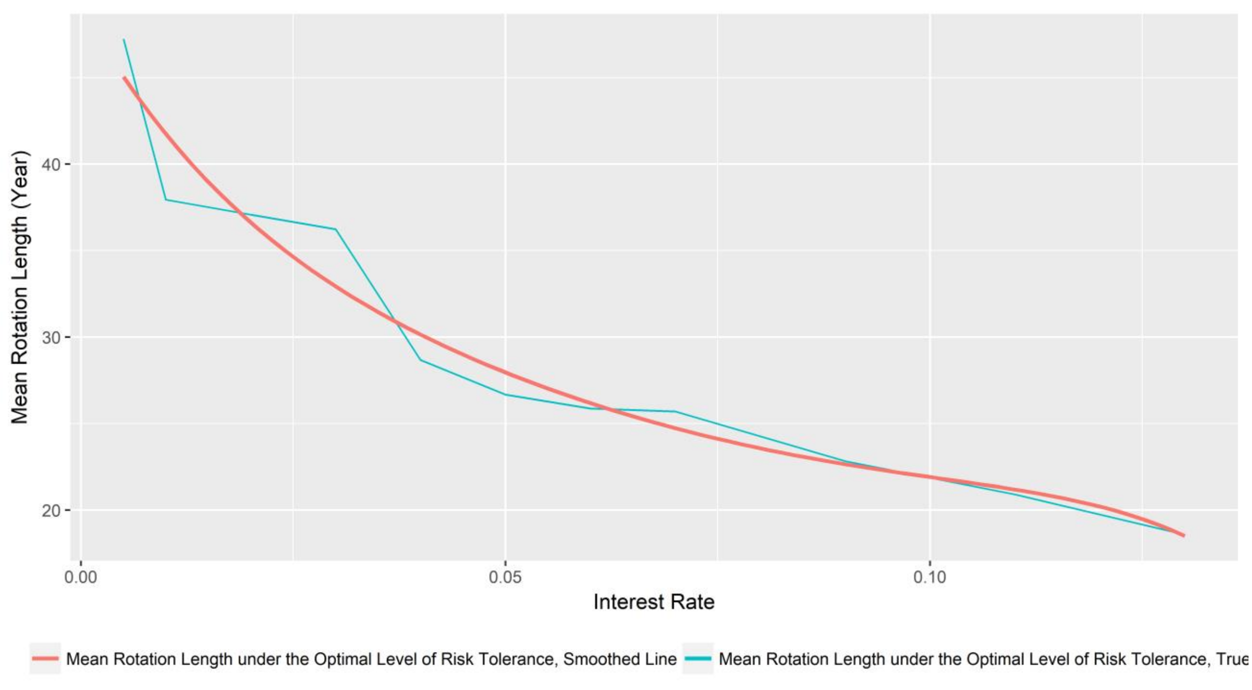

Figure 5. The relationship between the interest rate and the mean rotational length associated with the optimal level of risk tolerance.

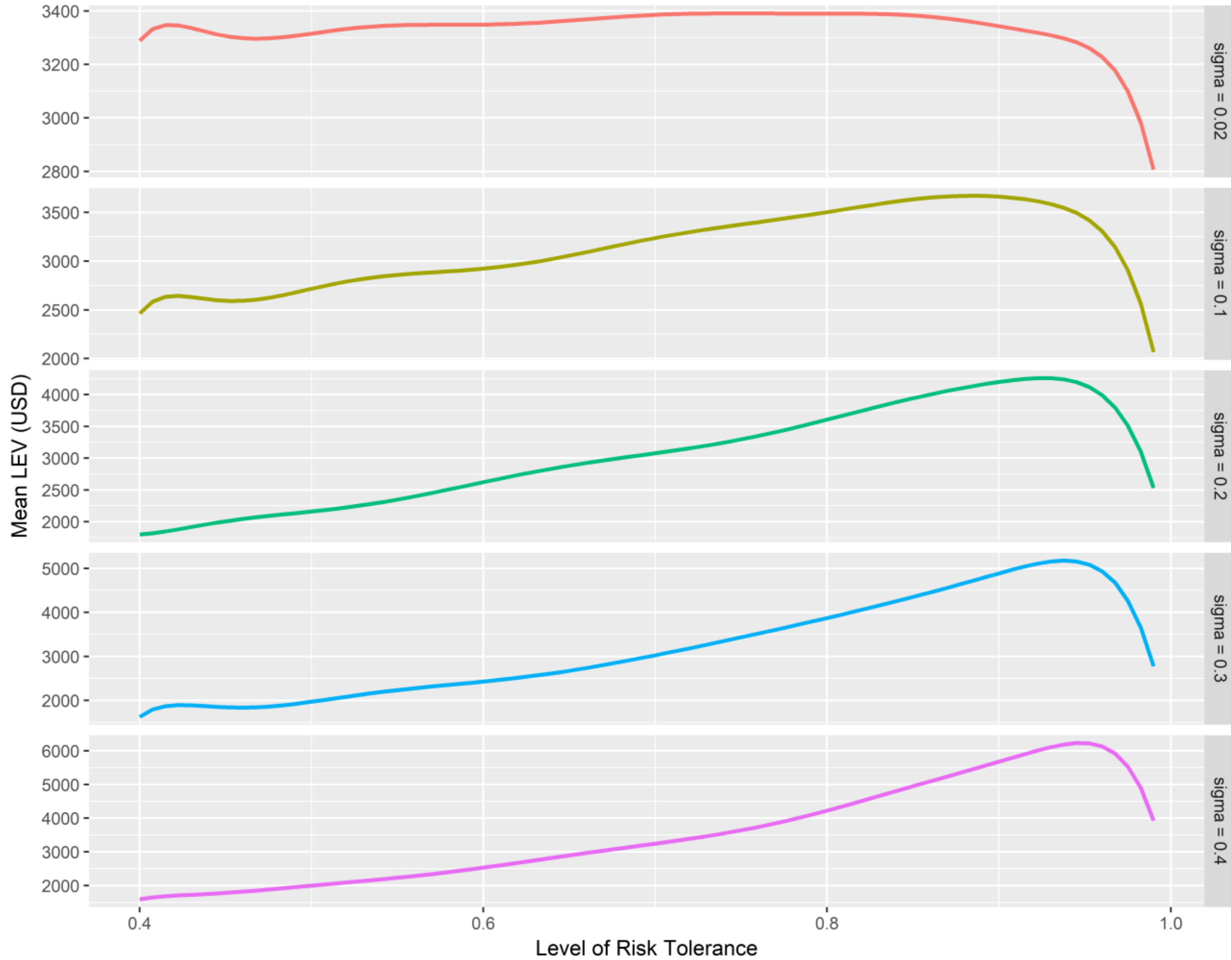

Figure 6. A full scenario of mean LEV with different levels of risk tolerance under selected levels of stumpage price volatility

price volatility still exists, there remains a level of risk tolerance that leads to the highest mean LEV. In other words, the optimal level of risk tolerance remains existing as the stumpage price fluctuates.

Shown in Table 3 is the summary of sensitivity analyses on stumpage price volatility. In essence, as the stumpage price volatility increases, the optimal level of risk tolerance would also increase, and the mean LEV associated with the optimal risk tolerance is also increasing. This finding implies that a risk-seeking strategy is preferred when price volatility is high. In this case, even if the landowner decides to postpone harvest because of a very low level of risk tolerance and missed an opportunity to sell the trees at a good price, the chance that another good price will be appearing is relatively high. However, if the price volatility is small, the risk preference of forestland manager plays a weaker role in management because the frequency and magnitude of a “good price” are both lower compared to the case with high-price volatility. In general, I found that the choice of risk preference is more important when the stumpage price volatility is high. A relatively large risk premium can be obtained by properly choosing the level of risk tolerance if the price volatility is high, but the mean LEV is not greatly affected by risk preference if the magnitude of price fluctuation is very small. The same fact is shown in Figure 7 as well.

Table 3. Summary of Sensitivity Analysis on Price Volatility

Price Volatility (σ)	**Optimal Level of Risk Tolerance**	**Mean Rotation Length (Year)**	**S.D. of Rotation Length**	**Mean LEV (USD)**	**S.D. of LEV**
0.02	0.77	30.48	3.22	3398.70	54.17
0.05	0.85	29.72	5.45	3487.50	148.57
0.1	0.88	29.18	7.69	3717.03	292.66
0.15	0.91	29.87	9.72	3984.35	486.09
0.2	0.92	29.95	11.31	4270.85	585.18
0.25	0.92	28.92	11.17	4618.54	713.59
0.28	0.93	28.67	11.70	4982.66	841.47
0.3	0.95	35.17	16.03	5294.01	1076.76
0.35	0.96	35.61	16.80	5653.76	1345.81
0.4	0.95	34.48	16.79	6268.31	1614.72
0.45	0.94	31.07	15.02	6805.42	1627.23

On the other hand, the trend on the mean rotation length with respect to the price volatility shows no clear pattern, as shown in Figure 8. Specifically, the mean rotation length associated with the optimal level of risk tolerance is fluctuating at a low level when $\sigma < 0.3$, but it jumps to a higher stage when the volatility σ reaches the level of 0.3. However, the mean rotation length then decreases to a lower value as the price volatility continues to rise. In fact, this chaotic pattern may imply that a highly fluctuating market will make such a harvest decision-making process unstable.

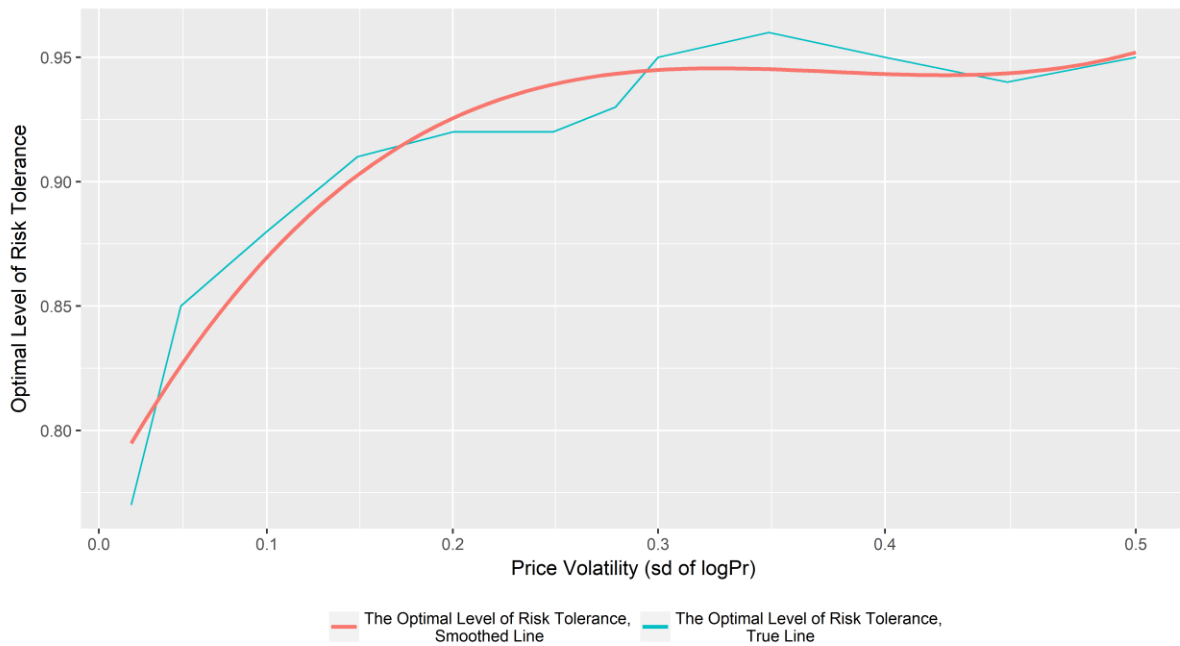

Figure 7. The relationship between the stumpage price volatility and the optimal level of risk tolerance.

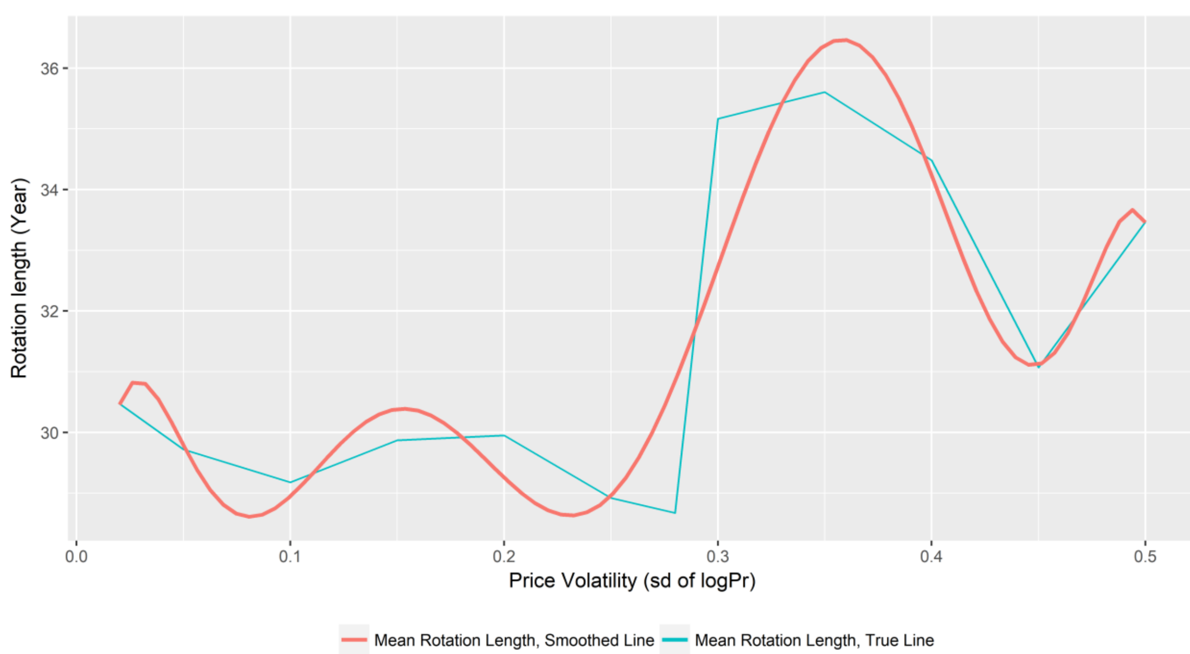

Figure 8. The relationship between the stumpage price volatility and the mean rotation length associated with the optimal level of risk tolerance.

Chapter 5. A Case Study of Adaptive Forest Management by Using the Behavior-based Forest Management Model

Based on the behavior-based decision model that I developed in this dissertation, in the last chapter the impact of risk preferences on forest management outcomes is presented. Clearly, by taking advantage of this model, forestland owners' management potential behavior toward price situations, i.e. tolerance on downside price risk, could be directly used as a benchmark to measure their risk preferences in a simple but explicit fashion. Furthermore, as an adaptive forest management approach that considers both price uncertainty and risk preference together, this model could have practical applications in real-world forest management. In this chapter, by using LSU Lee Memorial Forest as a sample site, I will demonstrate how to use this behavior-based model to conduct adaptive forest management to improve financial returns. In addition, this case study will also show that a proper risk management strategy can play a key role in forest management under the changing-price scheme.

5.1. A Summary of the LSU Lee Memorial Forest

Located between Franklinton and Bogalusa in the Washington Parish of Louisiana, Lee Memorial Forest is a 1210-acre research forest affiliated with the LSU School of Renewable Natural Resources. It was named after Professor J.G. Lee, Sr., who taught the first forestry courses offered at LSU and became the first head of the Department of Forestry in 1924. The LSU Lee forest originally began with a 1000-acre donation from the Great Southern Lumber Company in 1926. In 1991, it was augmented by another 210-acre gift from William A. Knight estate.

Although it is primarily managed for research, teaching, and demonstration purposes, the Lee Forest provides its own operating budget with the timber sales revenue. Thus, except for the land areas that are devoted to research and teaching, much of the remaining area in this forest is

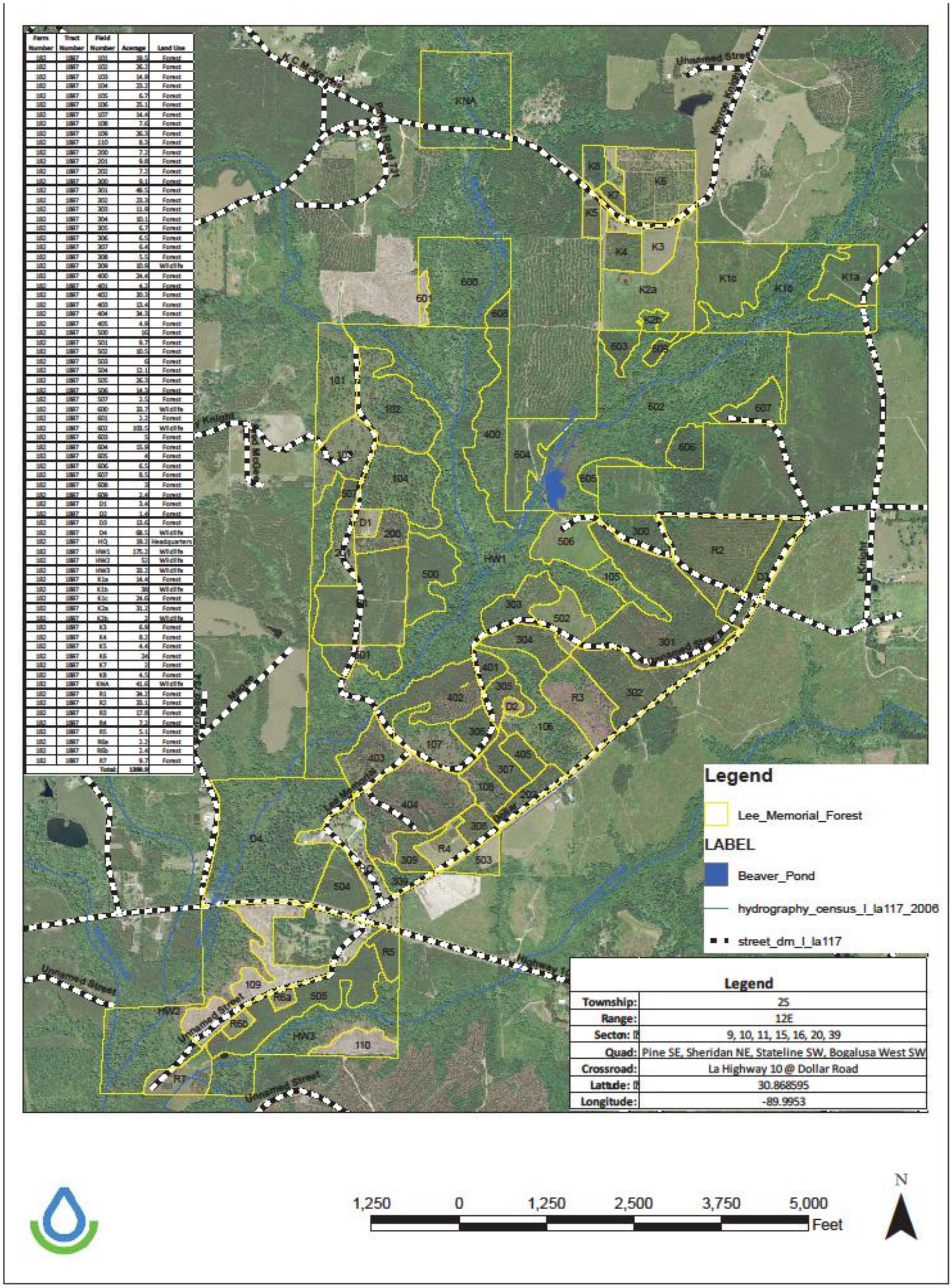

Figure 9. Planning Map of the LSU Lee Memorial Forest

still managed for harvesting incomes. Approximately, there are around 580 acres of even-aged southern pine forest, 70 acres of uneven-aged southern pine forest and 130 acres of managed hardwood bottomlands that are devoted to timber production. The planning diagram map of LSU Lee Memorial Forest is displayed in Figure 9.

5.2. Case Study Design

The primary objective of this case study is to test the behavior-based adaptive forest management method by using the real historical data of LSU Lee Memorial Forest over a 30-year period (i.e. 1988 to 2017). Specifically, I assume that a hypothetical forest manager took over the management of a part of the LSU Lee Memorial Forest in 1988 and started managing this forest by using the behavior-based model for 30 years until 2017. Given the same scenario data (i.e. stumpage price, catastrophic events, etc.), I will demonstrate how risk preferences will affect the harvest decisions made by the hypothetical manager, which eventually leads to different management outcomes. Moreover, other than demonstrating the impact of risk preferences on forest management outcomes, this case study will serve as a practical guide of how to use the behavior-based forest management model developed in this dissertation to make harvest decisions adaptively in real forest management practice.

The sample site involved in this case study is the 584-acre even-aged southern pine plantations, which are the primary source of harvestable timber in the Lee Forest. Based on the timber cruise data, I separate the sample site into five different blocks according to the age classes of trees grow on them. Specifically, the plant dates for the block one to five are 1949, 1979, 1940, 1969, and 1959, respectively. The sizes of them are, from block one to block five, 142 acres, 125 acres, 104 acres, 75 acres, and 136 acres, respectively. The information about age class, size, and site index of these five blocks are detailed in Table 4.

Table 4. Summary of the Case Study Site in LSU Lee Memorial Forest

Block	Year Planted	Initial Stand Age	Size (Acre)	Site Index	Bug Timber Harvest
1	1949	39	142	90	
2	1979	9	125	91	
3	1940	48	104	90	1989
4	1969	19	75	82	
5	1959	29	136	87	

The stumpage price and regeneration data used for this study are presented in Table 5. In detail, the real Louisiana annual average timber products stumpage price and the regeneration cost data recorded by the Lee Forest Office are used for this case study. In each year the hypothetical forest manager will make the harvest decision based on the real stumpage prices observed in Louisiana. In order to make this case study more realistic, the catastrophic events happened during the study period were also included in this case study. Specifically, Hurricane Katrina tore through Washington Parish on August 29, 2005, and the Lee Forest took a direct hit. Almost all the merchantable pine plantations were destroyed by this devastating hurricane. Thus, in this case study, if the timber stand age is greater than or equal to 10 in 2005, I assume the timber will be destroyed by hurricane Katrina and the stand will be replanted in 2006. In addition, the timbers in block 3 were clear cut in 1989 due to insect infection. Therefore, in this case study, I apply the rule that all timber stands in block 3 will be harvested in 1989 due to insect infections. Furthermore, I assume the plantation contains only one tree species, i.e. loblolly pine (*Pinus taeda*). As a practical case study, three major classes of timber products are considered in this study, i.e. sawtimber, Chip N' Saw (CNS), and pulpwood. The growth of trees and the proportion of timber product classes are projected by the Merchlobx software developed by the LSU School of Renewable Natural Resources (Chang et al. 2005).

Table 5. The Real Softwood Stumpage Prices and Southern Pine Regeneration Cost in Louisiana from 1988 to 2017

Year	Real Sawtimber Stumpage Price	Real CNS Stumpage price	Real Pulpwood Stumpage Price	Regeneration Cost
1988	18.82	6.59	5.53	149
1989	18.84	9.14	6.05	152
1990	19.83	9.85	5.70	155
1991	20.84	10.57	6.61	158
1992	23.73	14.41	7.42	162
1993	28.73	19.29	7.81	165
1994	34.53	22.57	7.23	168
1995	38.36	26.92	7.15	175
1996	33.74	25.00	6.85	181
1997	40.40	29.48	7.72	188
1998	40.85	27.56	8.70	195
1999	36.73	28.93	7.76	210
2000	33.87	28.63	6.52	225
2001	31.50	25.97	5.90	240
2002	32.11	28.19	5.52	255
2003	28.76	20.30	5.12	217
2004	29.34	20.65	4.77	179
2005	27.95	22.63	5.35	196
2006	25.72	20.72	4.16	212
2007	22.66	13.56	5.99	239
2008	19.11	13.93	5.33	265
2009	17.64	15.99	5.04	263
2010	16.49	12.04	5.15	261
2011	14.87	10.68	4.09	274
2012	14.73	10.11	4.10	287
2013	15.12	8.24	4.11	250
2014	15.32	8.36	4.51	213
2015	16.70	8.51	5.09	229
2016	17.53	8.86	5.50	244
2017	15.91	8.54	4.90	260

Conceptually, each year based on the projected tree growth and current timber price, the forest manager can calculate the target price for the next year using equation 9 in the Chapter 3. By looking at the percentile of this target price in the presumed price distribution, the probability that the price in next year will be lower than the target price can be derived. This probability is the de facto downside price risk in equation 12 of the Chapter 3. Therefore, the decision-mechanism here is to compare this downside price risk with the risk tolerance level. If the downside risk is higher than what can be tolerated, then the manager will harvest the timbers. Otherwise, the trees will be kept until the next round of decision-making a year later. Furthermore, since there are three product classes with different prices in this case study, each class will have its own target price. To handle this situation, I also calculate the value share of the three product classes each year and assume the harvest decision will be made only based on the product class with the largest value share among the three. For example, in a year when sawtimber, CNS, and pulpwood account for 10%, 20%, and 70% of the total stumpage value, respectively, the forest manager will make the harvest decision by comparing only the downside risk of the pulpwood price with the risk tolerance level because pulpwood stands for a majority part of merchantable timber value at that time.

To demonstrate the impact of risk preference on forest management outcomes, I set up three hypothetical managers who have different risk tolerance levels (i.e. 0.5, 0.7, and 0.9) in this case study. In each year, managers face exactly the same scenarios in terms of stumpage price, timber growth, and catastrophic events. The only difference between them is the risk tolerance level, which serves as the decision criterion to be compared with the calculated downside price risk. Obviously, due to differences in their risk tolerance levels, any of them could make unique harvest decisions individually in the interim, and eventually result in different management outcomes.

5.3. Empirical Results

In this case study, the three hypothetical forest managers have their risk tolerance level defined as 0.5, 0.7, and 0.9, respectively. For each of them, individual harvest decisions are needed to be made for each of the five blocks every year. Thus, there are 3 x 5 = 15 harvest decision tables that contain all management track records covering all five blocks managed under three risk tolerance levels. All decisions are made on an acre basis, and detailed decision track records are presented in Table 6 through Table 20.

As shown in Table 6, the manager took over the block one in 1988, when the stand age is 39. At that time, the majority product class was CNS with a 45.4% timber value share and the CNS price down-side risk was 0.09. Obviously, the downside risk was much smaller than the risk tolerance level, which is 0.5 for this hypothetical manager, so that the decision was keeping the trees for another year. Afterward, CNS remains its majority position until 1991 when Sawtimber took the majority with a value share of 42.9%. However, since the sawtimber downside price risk remains lower than 0.5, the stand was not harvested until 1993 when the sawtimber price downside risk jumped to 0.704, which is greater than what can be tolerated by this hypothetical forest manager. As a result, the timbers on this site were harvested in 1993 and generated an income of $6344.73 per acre. Then, the trees were regenerated in 1994 but all trees were wiped out by Hurricane Katrina in 2005 so that this manager had to plant the trees again in 2006. This new batch of trees had no commercial value until 2016 when the minimum amount of pulpwood became available. In 2016 and 2017, the downside price risk of the dominate product class, i.e. the pulpwood was much smaller than 0.5. Therefore, the trees were kept there for further growth.

For block two, the manager took over the site when the dominant product class is pulpwood in 1988. As shown in Table 7, the pulpwood downside price risk climbed to 0.5 in the year 1990, which triggered a harvest in 1990 and generated an income of $272.78 per acre. Thereafter, the trees were replanted in 1990 and became merchantable from 2001 to 2004. During this period, the dominant product class remains as pulpwood, but the downside price risk

Table 6. Harvest Decision Table for Block 1 If Risk Tolerance Level is 0.5

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	39	223.58	0.64	0.27	0.09					
1989	40	227.67	0.59	0.33	0.08	0.256	0.16	0.62		
1990	41	232.77	0.61	0.32	0.07	0.303	0.19	0.52		
1991	42	236.14	0.62	0.31	0.07	0.349	0.21	0.79		
1992	43	239.74	0.60	0.33	0.06	0.495	0.40	0.94		
1993	44	242.36	0.60	0.35	0.05	**0.704**	0.63	0.95	Harvest	6344.73
1994 to 2003	0 to 9	No Commercial Value								
2004	10	27.54								
2005	11	Katrina								
2006 to 2015	0 to 9	No Commercial Value								
2016	10	27.54	0.000	0.077	0.923	0.173	0.14	0.34		
2017	11	36.69	0.000	0.106	0.894	0.167	0.15	0.30		

Table 7. Harvest Decision Table for Block 2 If Risk Tolerance Level is 0.5

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	9	No Commercial Value								
1989	10	28.73	0.00	0.12	0.88	0.20	0.14	0.46		
1990	11	38.04	0.00	0.18	0.82	0.29	0.18	**0.50**	Harvest	272.78
1991 to 2000	0 to 9	No Commercial Value								
2001	10	28.73	0.00	0.29	0.71	0.56	0.71	0.23		
2002	11	38.04	0.00	0.39	0.61	0.60	0.80	0.18		
2003	12	44.36	0.00	0.45	0.55	0.56	0.57	0.18		
2004	13	51.98	0.00	0.53	0.47	0.59	0.59	0.12		
2005	14								Katrina	
2006 2007 2015	0 to 9	No Commercial Value								
2016	10	28.73	0.00	0.13	0.87	0.17	0.14	0.34		
2017	11	38.04	0.00	0.18	0.82	0.17	0.15	0.29		

had always been below 0.5, which lead to no harvest in the interim and all merchantable trees were wiped out in 2005 by Hurricane Katrina. For that reason, from 2006 to 2015, the tress on this site had no commercial value because of their young age. After that, in 2016 and 2017, the pulpwood downside price risk was less than 0.5 so that no harvest was carried out.

As shown in Table 8, the trees on block three were at the age of 48 when this manager took them over. In the first year, no decision was made due to the decision mechanism. However, as mentioned before, the trees on block three were infested by bugs thus they must be harvested right away to prevent further spread of bug infestation. Therefore, all trees on this site were harvested in 1989 regardless of the downside price risk of sawtimber, which was the dominant product class at the time. This bug harvest generated an income of $4081.94 per acre. After replanting in 1990, the tract had no commercial value until 2000, when a small amount of pulpwood became merchantable. In 2003, when the CNS product took a 50% share of the total value, the CNS downside price risk of 0.58 triggered a harvest. It is worth noting that the CNS downside price risk has been above 0.5 for several years before 2003, but at that time the pulpwood was still dominating the value proposition of the entire stand. Thus, no harvest decision was reached because of the relatively low pulpwood downside price risk. Furthermore, this early harvest also made the manager replant trees in 2004. When Hurricane Katrina hit the site in 2005, the stand age was only one so that trees are too young to be impacted. After that, new batch of merchantable timber became available in 2014 but no harvest was triggered until the end of the study period due to low downside price risks through those years.

Table 9 presents the harvest decision-making track record in block 4 for the manager with a risk tolerance of 0.5. In 1989, when the dominant product class is still pulpwood, the first harvest was carried out as the pulpwood downside price risk hiked above what can be tolerated

Table 8. Harvest Decision Table for Block 3 If Risk Tolerance Level is 0.5

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	48	259.20	0.77	0.18	0.05					
1989	49	259.44	0.73	0.22	0.05	0.28	0.10	0.51	Bug	4081.94
1990 to 1999	0 to 9	No Commercial Value								
2000	10	27.54	0.00	0.27	0.73	0.61	0.78	0.33		
2001	11	36.69	0.00	0.34	0.66	0.60	0.75	0.27		
2002	12	43.12	0.00	0.49	0.51	0.67	0.85	0.24		
2003	13	49.63	0.00	0.50	0.50	0.57	0.58	0.19	Harvest	561.91
2004 to 2013	0 to 9	No Commercial Value								
2014	10	27.54	0.00	0.13	0.87	0.13	0.13	0.16		
2015	11	36.69	0.00	0.17	0.83	0.19	0.15	0.35		
2016	10	43.12	0.00	0.24	0.76	0.21	0.16	0.46		
2017	11	49.63	0.00	0.31	0.69	0.16	0.14	0.27		

Table 9. Harvest Decision Table for Block 4 If Risk Tolerance Level is 0.5

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	19	73.52	0.01	0.39	0.60					
1989	20	79.94	0.01	0.48	0.51	0.27	0.16	0.65	Harvest	652.55
1990 to 1999	0 to 9	No Commercial Value								
2000	10	20.66	0.00	0.15	0.85	0.89	0.95	**0.79**	Harvest	201.43
2001 to 2010	0 To 9	No Commercial Value								
2011	10	20.66	0.00	0.09	0.91	0.24	0.33	0.32		
2012	11	24.73	0.00	0.14	0.86	0.20	0.26	0.23		
2013	12	29.30	0.00	0.17	0.83	0.15	0.14	0.13		
2014	13	37.42	0.00	0.19	0.81	0.17	0.15	0.24		
2015	14	42.63	0.00	0.25	0.75	0.20	0.15	0.38		
2016	15	48.25	0.00	0.30	0.70	0.22	0.16	0.48		
2017	16	54.27	0.00	0.36	0.64	0.16	0.15	0.29		

to 0.65. When trees became just merchantable in 2000, the price of pulpwood was at a high level again and a downside price risk of 0.79 was observed, which resulted in another harvest that year. During the time period between 2001 and 2010, the immature tress had no merchantable value but was small enough to survive Hurricane Katrina. Until the age 16 in 2017, the pulpwood downside price risk had been below 0.5 so that all trees were still there by the end of the study period.

For block five which was a 29-year old stand at the beginning of this case study, CNS product stood for more than half of the timber value in the first several years. The first harvest on this site was carried out in 1993 when the CNS downside price risk climbed above 0.5 to 0.62. After the first harvest until 2003, trees had no commercial value. However, the 11-year stand was wiped out in 2005 by Hurricane Katrina so that the planting cycle started all over again in 2006. In 2016, a pulpwood downside price risk of 0.62 was observed so that trees were harvested at such an early age for a harvest income of $261.91 per acre. As a result, the site was under regeneration by the end of the study period in 2017. The detailed management track record for this case are shown in Table 10.

In Tables 11 through 15, the harvest decisions and forest management track record by the manager who has a risk tolerance level is 0.7 are presented. As shown in Table 11, the downside price risk for the dominant product class in Block one (i.e. Sawtimber) jumped from 0.495 to 0.704 in 1993, which leads to the harvest decision. In fact, this is the same event that triggered harvest for the previous forest manager whose risk tolerance level is lower. Since there is no downside price risk ever became greater than 0.5 thereafter, the decisions made by this forest manager are exactly the same as those made by the previous manager.

Table 10. Harvest Decision Table for Block 5 If Risk Tolerance Level is 0.5

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	29	153.05	0.29	0.48	0.23					
1989	30	159.21	0.28	0.53	0.19	0.26	0.16	0.63		
1990	31	164.11	0.30	0.54	0.16	0.29	0.18	0.49		
1991	32	169.92	0.32	0.52	0.16	0.33	0.21	0.76		
1992	33	175.90	0.32	0.54	0.13	0.47	0.38	0.92		
1993	34	180.34	0.35	0.55	0.10	0.68	**0.62**	0.95	Harvest	3992.64
1994 to 2003	0 to 9	No Commercial Value								
2004	10	24.79	0.00	0.22	0.78	0.75	0.71	0.25		
2005	11	29.75	0.00	0.31	0.69	0.47	0.63	0.17	Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	24.79	0.00	0.10	0.90	0.27	0.18	**0.62**	Harvest	261.91
2017	0	No Commercial Value								

Table 11. Harvest Decision Table for Block 1 If Risk Tolerance Level is 0.7

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	39	223.58	0.64	0.27	0.09					
1989	40	227.67	0.59	0.33	0.08	0.256	0.16	0.62		
1990	41	232.77	0.61	0.32	0.07	0.303	0.19	0.52		
1991	42	236.14	0.62	0.31	0.07	0.349	0.21	0.79		
1992	43	239.74	0.60	0.33	0.06	0.495	0.40	0.94		
1993	44	242.36	0.60	0.35	0.05	**0.704**	0.63	0.96	Harvest	6344.73
1994 to 2003	0 to 9	No Commercial Value								
2004	10	27.54	0.000	0.077	0.923	0.539	0.55	0.10		
2005	11	36.69	0.000	0.106	0.894	0.487	0.64	0.19	Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	27.54	0.000	0.077	0.923	0.173	0.14	0.34		
2017	11	36.69	0.000	0.106	0.894	0.167	0.15	0.30		

As shown in Table 12, the initial conditions for the second hypothetical manager are identical to that faced by the first manager. However, unlike the previous case, the first harvest decision was made in 1991 by the second manager because the pulpwood downside price risk breached 0.7 that year. Note that the downside risk of pulpwood price was 0.502 in 1990, which triggers harvest if the tolerance level is 0.5. But in this case the risk tolerance level is 0.7, the same downside price risk will lead to a decision of keeping trees because it is 0.502 is still within the range that can be tolerated by this second forest manager. Due to this one-year postponement of timber harvest, trees became merchantable in 2002 but still wiped out by Hurricane Katrina in 2005. Because the downside price risk did not soar above 0.7 afterward, no timber harvest decision was made until the end of the study period in 2017.

As shown in Table 13, for block three, the decisions made by the second forest manager are identical to the first one because the bug infestation issue forces them to harvest the trees in 1989 and no downside price risk higher than 0.5 was observed for the product class with biggest value share (i.e. pulpwood) thereafter. For block 4, the first harvest happed in the year of 1994, when the timber value is dominated by CNS product and the downside risk of CNS price is 0.74. Afterward, in 2005, the timber stands again was wiped out by Hurricane Katrina when its age just reached 10. In 2016, then the stand age finally reached 10 again, the pulpwood downside price risk hit 0.73 so that harvest was triggered and an income of $215.15 per acre was generated. The detailed management track record of the second forest manager for block 4 was presented in Table 14.

For the management of block five, the only harvest decision made by the second forest manager is in 1994 as shown in Table 15. At this time, the CNS product took a 53% timber value share and the downside price risk for this product is 0.78, which is greater than the tolerance

Table 12. Harvest Decision Table for Block 2 If Risk Tolerance Level is 0.7

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	9	No Commercial Value								
1989	10	28.73	0.00	0.12	0.88	0.201	0.138	0.465		
1990	11	38.04	0.00	0.18	0.82	0.294	0.184	0.502		
1991	12	44.36	0.00	0.24	0.76	0.305	0.196	**0.712**	Harvest	376.20
1992 to 2001	0 To 9	No Commercial Value								
2002	10	28.73	0.00	0.32	0.68	0.564	0.776	0.148		
2003	11	38.04	0.00	0.34	0.66	0.555	0.565	0.174		
2004	12	44.36	0.00	0.47	0.53	0.583	0.584	0.118		
2005	13	51.98	0.00	0.53	0.47	0.178	0.337	0.021	Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	28.73	0.00	0.13	0.87	0.17	0.14	0.34		
2017	11	38.04	0.00	0.18	0.82	0.17	0.15	0.29		

Table 13. Harvest Decision Table for Block 3 If Risk Tolerance Level is 0.7

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	48	259.20	0.77	0.18	0.05					
1989	49	259.44	0.73	0.22	0.05	0.28	0.10	0.51	Bug	4081.94
1990 to 1999	0 to 9	No Commercial Value								
2000	10	27.54	0.00	0.27	0.73	0.61	0.78	0.33		
2001	11	36.69	0.00	0.34	0.66	0.60	0.75	0.27		
2002	12	43.12	0.00	0.49	0.51	0.67	0.85	0.24		
2003	13	49.63	0.00	0.50	0.50	0.57	0.58	0.19		
2004	14	56.67	0.00	0.59	0.41	0.54	0.55	0.10		
2005	15								Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	27.54	0.00	0.12	0.88	0.17	0.14	0.34		
2017	11	36.69	0.00	0.17	0.83	0.17	0.15	0.30		

Table 14. Harvest Decision Table for Block 4 If Risk Tolerance Level is 0.7

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	19	73.52	0.01	0.39	0.60					
1989	20	79.94	0.01	0.48	0.51	0.27	0.16	0.65		
1990	21	85.21	0.02	0.54	0.44	0.31	0.19	0.54		
1991	22	90.09	0.02	0.55	0.43	0.33	0.20	0.75		
1992	23	96.75	0.04	0.61	0.35	0.45	0.37	0.90		
1993	24	101.87	0.04	0.69	0.26	0.68	0.61	0.95		
1994	25	107.72	0.07	0.73	0.21	0.85	**0.74**	0.84	Harvest	2070.92
1995 to 2004	0 to 9	No Commercial Value								
2005	10								Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	20.66	0.00	0.06	0.94	0.32	0.20	0.73	Harvest	215.15
2017	0	No Commercial Value								

Table 15. Harvest Decision Table for Block 5 If Risk Tolerance Level is 0.7

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	29	153.05	0.29	0.48	0.23					
1989	30	159.21	0.28	0.53	0.19	0.26	0.16	0.63		
1990	31	164.11	0.30	0.54	0.16	0.29	0.18	0.49		
1991	32	169.92	0.32	0.52	0.16	0.33	0.21	0.76		
1992	33	175.90	0.32	0.54	0.13	0.47	0.38	0.92		
1993	34	180.34	0.35	0.55	0.10	0.68	0.62	0.95		
1994	35	187.00	0.40	0.53	0.08	0.89	**0.78**	0.89	Harvest	4970.57
1995 to 2004	0 to 9	No Commercial Value								
2005	10	24.79	0.000	0.062	0.938				Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	24.79	0.000	0.062	0.938	0.27	0.18	0.62		
2017	11	29.75	0.000	0.094	0.906	0.27	0.19	0.59		

level of 0.7. It is worth noting that the CNS downside price risk is 0.62 in 1993, which is enough to trigger harvest for the first hypothetical manager whose risk tolerance level is 0.5. But for the second manager who risks more to wait for one more year, a higher harvest income was generated at $4970.57 per acre.

The third forest manager has a risk tolerance level of 0.9, which means that this manager is more risk-seeking than the previous two. Table 16 detailed the third manager's decision track record for block one. Since the age of trees on this block was already 39 at the beginning of the case study, the product class with the largest value share has always been the sawtimber. However, different from the previous two managers who made a decision to harvest tree in 1993 when sawtimber downside price risk was 0.704, the third manager chose to wait in 1993 and actually decided to harvest tree in 1994 when the sawtimber downside price risk jumped over 0.9 to 0.904 this year. As a result, this delayed harvest generated an income of $7836.38 per acre, which is higher than in the previous cases. Similarly, Hurricane Katrina hit the site in 2005 and destroyed the 10-year old stand. After the first harvest, the downside price risk for the product with biggest value share had been in low levels that are not enough to trigger harvest, so that the trees were kept there until the end of study period in 2017.

Table 17 presents the track record of management decisions made by the third forest manager for block two. As one can see from this table, pulpwood had been the value-dominant product between 1989 and 1993 and CNS took larger value shares between 1994 and 1997. Due to the high tolerance level (i.e. 0.9), the relatively high pulpwood downside risks from 1991 to 1993 did not trigger harvest like the previous two cases, while this manager waited until the CNS downside price risk climbed above 0.9 in 1997 to conduct the harvest and got an income of $1948.39 per acre. Due to this delay in harvest, the regeneration took place in 1998 so that trees

Table 16. Harvest Decision Table for Block 1 If Risk Tolerance Level is 0.9

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	39	223.58	0.64	0.27	0.09					
1989	40	227.67	0.59	0.33	0.08	0.256	0.16	0.62		
1990	41	232.77	0.61	0.32	0.07	0.303	0.19	0.52		
1991	42	236.14	0.62	0.31	0.07	0.349	0.21	0.79		
1992	43	239.74	0.60	0.33	0.06	0.495	0.40	0.94		
1993	44	242.36	0.60	0.35	0.05	0.704	0.63	0.96		
1994	45	248.05	0.64	0.32	0.04	0.904	0.79	0.91	Harvest	7863.38
1995 to 2004	0 to 9	No Commercial Value								
2005	10	27.54	0.000	0.077	0.923				Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	27.54	0.000	0.077	0.923	0.173	0.14	0.34		
2017	11	36.69	0.000	0.106	0.894	0.167	0.15	0.30		

Table 17. Harvest Decision Table for Block 2 If Risk Tolerance Level is 0.9

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	9	No Commercial Value								
1989	10	28.73	0.00	0.12	0.88	0.201	0.138	0.465		
1990	11	38.04	0.00	0.18	0.82	0.294	0.184	0.502		
1991	12	44.36	0.00	0.24	0.76	0.305	0.196	0.712		
1992	13	51.98	0.00	0.34	0.66	0.416	0.346	0.868		
1993	14	58.62	0.00	0.46	0.54	0.559	0.523	0.846		
1994	15	68.23	0.00	0.57	0.43	0.807	0.694	0.768		
1995	16	75.60	0.01	0.65	0.34	0.895	0.841	0.733		
1996	17	83.89	0.01	0.68	0.31	0.808	0.808	0.719		
1997	5	91.09	0.01	0.71	0.27	0.941	0.915	0.877	Harvest	1948.39
1998 to 2007	0 to 9	No Commercial Value								
2008	10	28.73	0.00	0.20	0.80	0.194	0.291	0.233		
2009	11	38.04	0.00	0.29	0.71	0.169	0.404	0.206		
2010	12	44.36	0.00	0.32	0.68	0.151	0.248	0.269		
2011	13	51.98	0.00	0.41	0.59	0.120	0.207	0.087		
2012	14	58.62	0.00	0.46	0.54	0.105	0.174	0.071		
2013	15	68.23	0.00	0.46	0.54	0.131	0.132	0.097		
2014	16	75.60	0.01	0.48	0.51	0.134	0.134	0.158		
2015	17	83.89	0.01	0.50	0.49	0.178	0.140	0.312		
2016	18	91.09	0.02	0.52	0.47	0.195	0.146	0.406		
2017	19	99.26	0.03	0.56	0.41	0.148	0.138	0.243		

were not impacted by Hurricane Katrina in 2005. Since there was no downside price risk above 0.9 were observed between 1998 and 2017, the trees were kept there till the end of the study period.

For block three, the decisions made by the third manager were also identical to the previous two as shown in Table 18. This is because of the inevitable bug harvest in 1989, and relatively low downside price risks that were not large enough to trigger a harvest. Table 19 is the harvest decision table for block four if the risk tolerance level is 0.9. From this table one can see that the only harvest happened in 1997 when the value-dominant product class was CNS and the downside price risk for this product is 0.94. Apparently, like the case of block two, this risk-seeking manager again obtained a high harvest income by delaying harvest for a better price. In addition, due to this late harvest, another side-benefit is that this site was lucky enough to avoid being damaged by Hurricane Katrina in 2005. Similarly, as shown in Table 20, high tolerance for downside risk also resulted in a late harvest in block five in 1995. Like what happened to block four, the harvest in 1995 brings a higher income than harvest earlier and make the newly planted young trees going through Hurricane Katrina safely in 2005. However, due to the high tolerance in risk, no harvest was conducted after 1995 because the relatively low stumpage price was not able to push the downside price risk high enough to trigger a harvest.

Tables 21, 22, and 23 summarize the forest management outcomes across all the five blocks by these three hypothetical managers with different risk preference levels equal to 0.5, 0.7, and 0.9, respectively. All numbers shown in this table are values compounded to the end of this case study (i.e. 2017) with an interest rate of 0.06. Specifically, the cash position is the value of the accumulated harvest incomes minus the regeneration costs from any specific site. Timber value is the net value of the standing timber remaining at the site in 2017. In detail,

Table 18. Harvest Decision Table for Block 3 If Risk Tolerance Level is 0.9

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	48	259.20	0.77	0.18	0.05					
1989	49	259.44	0.73	0.22	0.05	0.28	0.10	0.51	Bug	4081.94
1990 to 1999	0 to 9	No Commercial Value								
2000	10	27.54	0.00	0.27	0.73	0.61	0.78	0.33		
2001	11	36.69	0.00	0.34	0.66	0.60	0.75	0.27		
2002	12	43.12	0.00	0.49	0.51	0.67	0.85	0.24		
2003	13	49.63	0.00	0.50	0.50	0.57	0.58	0.19		
2004	14	56.67	0.00	0.59	0.41	0.54	0.55	0.10		
2005	15	0.00	0.00	0.63	0.37				Katrina	
2006 to 2015	0 to 9	No Commercial Value								
2016	10	27.54	0.000	0.077	0.923	0.17	0.14	0.34		
2017	11	36.69	0.000	0.106	0.894	0.17	0.15	0.30		

Table 19. Harvest Decision Table for Block 4 If Risk Tolerance Level is 0.9

Year	Age	Total Volume (ton)	Sawtimber Value Share	CNS Value Share	Pulpwood Value Share	Sawtimber Downside Price risk	CNS Downside Price risk	Pulpwood Downside Price risk	Event	Income
1988	19	73.52	0.003	0.350	0.647					
1989	20	79.94	0.003	0.385	0.612	0.27	0.16	0.65		
1990	21	85.21	0.007	0.413	0.580	0.31	0.19	0.54		
1991	22	90.09	0.009	0.440	0.551	0.33	0.20	0.75		
1992	23	96.75	0.017	0.462	0.522	0.45	0.37	0.90		
1993	24	101.87	0.022	0.505	0.473	0.68	0.61	0.95		
1994	25	107.72	0.030	0.515	0.455	0.85	0.74	0.84		
1995	26	114.77	0.045	0.525	0.430	0.94	0.89	0.85		
1996	27	120.39	0.056	0.534	0.411	0.86	0.85	0.81		
1997	28	124.58	0.066	0.548	0.386	0.97	0.94	0.93	Harvest	3465.71
1998 to 2007	0 to 9	No Commercial Value								
2008	10	20.66	0.038	0.962	-0.030	0.38	0.46	0.63		
2009	11	24.73	0.062	0.938	-0.056	0.25	0.52	0.40		
2010	12	29.30	0.094	0.906	-0.241	0.16	0.25	0.29		
2011	13	37.42	0.115	0.885	-0.020	0.14	0.23	0.12		
2012	14	42.63	0.167	0.833	-0.084	0.14	0.21	0.12		
2013	15	48.25	0.206	0.794	0.075	0.15	0.14	0.13		
2014	16	54.27	0.246	0.754	0.094	0.15	0.14	0.19		
2015	17	60.75	0.281	0.719	0.072	0.18	0.14	0.31		
2016	18	68.23	0.320	0.680	-0.082	0.22	0.16	0.48		
2017	19	73.52	0.350	0.647	-1.109	0.16	0.14	0.28		

Table 20. Harvest Decision Table for Block 5 If Risk Tolerance Level is 0.9

Year	**Age**	**Total Volume (ton)**	**Sawtimber Value Share**	**CNS Value Share**	**Pulpwood Value Share**	**Sawtimber Downside Price risk**	**CNS Downside Price risk**	**Pulpwood Downside Price risk**	**Event**	**Income**
1988	29	153.05	0.121	0.562	0.317	0.24	0.09	0.43		
1989	30	159.21	0.143	0.558	0.299	0.26	0.16	0.63		
1990	31	164.11	0.156	0.558	0.286	0.29	0.18	0.49		
1991	32	169.92	0.174	0.553	0.273	0.33	0.21	0.76		
1992	33	175.90	0.197	0.546	0.256	0.47	0.38	0.92		
1993	34	180.34	0.224	0.534	0.243	0.68	0.62	0.95		
1994	35	187.00	0.253	0.516	0.231	0.89	0.78	0.89		
1995	36	190.77	0.278	0.505	0.217	0.95	**0.91**	0.87	Harvest	6140.37
1996 to 2005	0 to 9	No Commercial Value								
2006	10	24.79	0.000	0.062	0.938	0.61	0.73	0.13		
2007	11	29.75	0.000	0.094	0.906	0.32	0.28	0.41		
2008	12	38.58	0.000	0.123	0.877	0.24	0.33	0.33		
2009	13	44.85	0.000	0.172	0.828	0.18	0.42	0.22		
2010	14	51.54	0.000	0.213	0.787	0.16	0.26	0.30		
2011	15	57.73	0.000	0.259	0.741	0.11	0.19	0.07		
2012	16	66.99	0.000	0.301	0.699	0.12	0.19	0.09		
2013	17	73.63	0.003	0.338	0.659	0.13	0.13	0.10		
2014	18	81.05	0.003	0.373	0.624	0.14	0.14	0.18		
2015	19	87.50	0.006	0.404	0.590	0.19	0.14	0.34		
2016	20	93.33	0.009	0.433	0.558	0.20	0.15	0.41		
2017	21	100.69	0.016	0.464	0.520	0.16	0.14	0.27		

the value of standing timber here refers to the value of live trees growing on this site, which can be calculated as the Faustmann Forest value minus the classical Faustmann land expectation value based on the stumpage price and regeneration cost in 2017.

As one can easily observe from these three summary tables, the cash position stands for a vast majority of the total final value position realized through forest management. In detail, compounding the harvest income over time easily expands their magnitude, while the standing timber values at the end of the study are not high due to the low stumpage price. Apparently, as shown for evidences from the last 30 years in Louisiana, harvesting and selling trees at the right time to take advantage of a good stumpage price is by far the most effective forest management strategy. A similar conclusion was also reached by Gould (1960) based on the experience of managing Harvard Forest. In addition, as one can also observe, a moderately higher risk tolerance in general delayed harvest but lead to better management outcomes. For example, for the block 5, the third forest manager who waited longer for a good price eventually obtained a significantly higher total cash position than the previous two managers. Theoretically, if the timber harvest is delayed, the cash position and the standing timber value are supposed to trade-off. This is because a delay in timber harvest will result in a delay in regeneration. Thus, the timber stand should be younger and has less volume than those stands have been harvested earlier. However, in the case study, Hurricane Katrina exerted a great impact on the management as an unexpected catastrophic disaster. Given the fact that Katrina wiped out all merchantable forests, some sites with young-age trees in 2005 were fortunate enough to be spared. On the other hand, for most sites that harvest are conducted earlier, managers lost those merchantable trees and even needed to pay for the regeneration cost again in 2006. A typical example is the Block five, for which the three managers harvested trees in 1993, 1994, and 1995, respectively.

The third manager, who is most risk-seeking among these three, took the highest harvest income and, fortunately, avoided the impact of Katrina on this block. However, taking risk does not always bring benefit. Taking the management of block three as an example, the first manager harvested the trees in 2003 when the CNS downside risk reached 0.57, which is not high enough to trigger harvest for the manager two whose risk tolerance level is 0.7. As a result, the second manager missed the chance to harvest tress earlier but lost all merchantable stands during the hurricane season of 2005.

From the results presented in Table 21 through Table 23, the impact of risk preference on forest management outcomes are clearly presented. Compared to the first forest manager whose risk tolerance level is 0.5, the one with risk tolerance of 0.9 eventually gains an over $2 million additional income for the study site, which is truly modest in size. The total value realized by the manager two was also slightly higher than the first manager. Given the large differences among management outcomes, it is obvious that a proper risk management strategy is the key to the success of forest management under uncertainties.

Table 21. Summary of Forest Management Outcomes by the Hypothetical Forest Manager Whose Risk Tolerance Level $\tau = 0.5$

	Size	**Initial Stand Age**	**Total Cash Position**	**Standing Timber Value**	**Total**
Block 1	142	39	25,701	496	26,197
Block 2	125	9	216	519	735
Block 3	104	48	21,958	558	22,516
Block 4	75	19	2,884	525	3,409
Block 5	136	29	16,052	507	16,559
Sample Site Total	582		8,359,566	301,666	8,661,232

Table 22 Summary of Forest Management Outcomes by the Hypothetical Forest Manager Whose Risk Tolerance Level τ = 0.7

	Size	**Initial Stand Age**	**Total Cash Position**	**Standing Timber Value**	**Total**
Block 1	142	39	25,701	496	26,197
Block 2	125	9	654	519	1,173
Block 3	104	48	20,708	496	21,204
Block 4	75	19	7,135	260	7,395
Block 5	136	29	18,692	508	19,200
Sample Site Total	582		8,962,274	275,479	9,237,753

Table 23. Summary of Forest Management Outcomes by the Hypothetical Forest Manager Whose Risk Tolerance Level τ = 0.9

	Size	**Initial Stand Age**	**Total Cash Position**	**Standing Timber Value**	**Total**
Block 1	142	39	30,191	496	30,687
Block 2	125	9	5,860	850	6,710
Block 3	104	48	20,708	496	21,204
Block 4	75	19	10,897	610	11,507
Block 5	136	29	22,348	929	23,277
Sample Site Total	582		11,029,883	400,360	11,430,243

Chapter 6. Discussion and Conclusion

Forestry, by its nature, is a long-term investment. Given the extended growing period, trees are exposed to multiple forms of risks and uncertainties, especially the timber price uncertainty. Therefore, throughout a long investment cycle, properly managing a forest should involve an adaptive decision-making process to respond to potential risks and uncertainties in a timely fashion. Besides, to reflect an individual’s attitude toward uncertainty, risk preference should be considered along with risk itself when designing a decision-making approach involving uncertainties. Existing studies addressing the risk preference issue in the forest management field focus more on measuring the impact of risk preference on certain management decisions. However, there lacks a comprehensive picture showing how varying risk preferences affect the forestland valuation and forest management outcomes (Couture, Cros, and Sabbadin 2016, Buongiorno, Zhou, and Johnston 2017). In addition, the methods used to quantify risk preferences are either inexplicit or difficult to implement. For a long time, there lacks a meaningful way to link the adaptive forest management decision-making approach with a practical method to measure forest managers’ risk preferences explicitly.

This dissertation is meant to fill this gap. In this dissertation, a behavior-based model is developed to measure individual forest manager’s risk preferences through their management behaviors. Based on this model, I construct an adaptive harvest decision-making approach using the level of risk tolerance to incorporate varying risk preferences across different forestland managers. Numerical simulations demonstrate the impact of varying risk preferences on the forest management outcomes under different scenarios. Furthermore, a case study was also conducted, which provides a practical guide of using this method to carry out adaptive forest management and presents more empirical evidence to support the theoretical analyses.

In detail, the numerical simulations demonstrate that, for a certain range of risk tolerance levels, the adaptive harvest decision-making approach developed in this dissertation outperforms both the reservation price strategy and the classical Faustmann approach. This result implies that a properly selected risk management strategy may bring additional benefit to forestland owners if price uncertainty persists. More importantly, evidences are showing that a certain level of risk tolerance could lead to the highest average LEV, regardless of how market conditions change. As shown in the sensitivity analyses, this finding is valid for all market conditions that I have included in this study. The results of sensitivity analyses reveal that a forestland owner should be more risk-seeking during the low-interest rate period because of the low cost of carrying the timber asset, while one should be more risk-averse if the interest rate rises. Furthermore, choosing a proper level of risk preference is more important to a forestland owner if the market volatility is large. In fact, a properly chosen, relatively risk-seeking strategy is preferred in the highly volatile market because it may bring a considerable risk premium to forestland owners. Conversely, the impact of risk preference on forest management will be relatively weak if the stumpage price does not fluctuate too much or is even close to a constant level.

In addition to numerical simulations, this dissertation also includes a case study using the LSU Lee Memorial Forest as the sample site. This case study is meant to showcase practical applications the behavior-based model developed in this dissertation into adaptive forest management and examine the impact of risk preferences on forest management outcomes in a real-world scenario. The empirical results of this case study are largely consistent with that of numerical simulations, which again validated the theoretical framework established in this dissertation. Specifically, for a certain range of risk tolerance levels, the final total value position increases as the risk tolerance level rise. For a 584-acre sample site, a better risk management strategy eventually brings more than $2 million final value position over a 30-year management period. This result is more than enough to reiterate that a proper risk management strategy is the key to the success of forest management under uncertainties.

Overall, the adaptive harvest decision-making approach constructed in this dissertation enables the forestland owners to incorporate their risk preferences into the harvest decision-making process in response to potential price risk. Numerical simulations and practical case studies both show the advantages of this approach. In addition to building an adaptive forest management methodology, this dissertation creates a behavior-based approach to measure risk preference. This approach allows us to directly observes the forest manager's risk preference from their behavior response to given price situations. Compared to existing methods to measure risk preference, the behavior-based model developed in this dissertation provides a direct measure of an individual forest manager's risk preference. In other words, the risk tolerance level of an individual forest manager can be measured explicitly by answering relevant situational questions on a survey questionnaire.

Before this behavior-based forest management model, there is no meaningful way to survey the risk preferences of forest managers explicitly. For example, under the utility function framework, the risk preferences cannot be measured precisely in practice as utility is not something that one can observe directly. Therefore, beyond the optimal harvest age, this behavior-based model may have wide usage across many disciplines as long as a practical, observable measurement of individual forestland manager's risk preference is needed. For instance, one application of this method is to address the economy of scale issues in Forestry. In general, trees grow in similar patterns among landowners, but large landowners usually can achieve better management outcomes. A question may be raised as to whether large-scale forestland owners can achieve better forest management outcomes because they can tolerate more risks (i.e. more risk-seeking) than small-scale landowners so that they can capture the risk premiums. Obviously, answering such a question requires precise measurement of the risk preferences across different types of forestland owners in a practical survey, which was impossible before the invention of this behavior-based model.

As an initial exploration to apply this behavior-based model in adaptive forest management, the level of risk tolerance for a forestland owner is assumed to be constant over the length of rotation in this dissertation. However, forestland owners are very unlikely to keep their risk preferences unchanged over time. In fact, they might be more risk-seeking at the initial stage while becoming more risk-averse as the trees grow larger since the speed of tree growth has slowed down. Therefore, it will be very interesting to explore the impact of risk preference on forest management behavior and forestland valuation under a varying risk preference scheme.

In addition, the behavior-based model developed in this dissertation relies on an essential assumption that the stumpage price follows a certain distribution with finite mean and variance, i.e. it is a mean-reverting process. However, price behavior varies across regions in the world. For instance, Hultkrantz, Andersson, and Mantalos (2014) found that the real price of timber stumpage is a mean-reverting process in Sweden after World War II. On the contrary, Parajuli and Chang (2015) found that the Louisiana southern pine real stumpage price does not really have a long-term mean, i.e. follows a diffusion process. Obviously, due to the restrictive assumption, the approach proposed in this dissertation is not capable of addressing risk preference issues if the stumpage price is not a mean-reverting process.

I believe that risk and risk preferences are like two sides of the same coin, and one should always consider them together. There is much room for legitimate debate as to whether the stumpage price follows a certain distribution, or whether the risk preference of a person or an organization will vary over time. But this dissertation, through a behavior-based model, has guided us through what has been the terra incognita of practically incorporating varying risk preferences into the adaptive forest management.

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References

Amacher, Gregory S., Markku Ollikainen, and Erkki Koskela. 2009. *Economics of Forest Resources*: The MIT Press.

Andersson, Mats, and Peichen Gong. 2010. "Risk preferences, risk perceptions and timber harvest decisions: an empirical study of nonindustrial private forest owners in Northern Sweden." *Forest Policy and Economics* 12 (5):330-339.

Bentley, William R, and Roger D Fight. 1966. "A zero interest comparison of forest rent and soil rent." *Forest Science* 12 (4):460-460.

Bentley, William R, and Dennis E Teeguarden. 1965. "Financial maturity: a theoretical review." *Forest Science* 11 (1):76-87.

Brazee, and Mendelsohn. 1988a. "Timber harvesting with fluctuating prices." *Forest Science* 34 (2):359-372.

Brazee, J Richard., and Mendelsohn. 1988b. "Timber harvesting with fluctuating prices." *Forest Science* 34 (2):359-372.

Brazee, Richard J, and Erwin Bulte. 2000. "Optimal harvesting and thinning with stochastic prices." *Forest Science* 46 (1):23-31.

Brazee, Richard, and Robert Mendelsohn. 1988c. "Timber harvesting with fluctuating prices." *Forest Science* 34 (2):359-372.

Buongiorno, Joseph, Mo Zhou, and Craig Johnston. 2017. "Risk aversion and risk seeking in multicriteria forest management: a markov decision process approach." *Canadian Journal of Forest Research* 47 (6):800-807.

Burnes, E., E. Thomann, and E. C. Waymire. 1999. "Arbitrage-free valuation of a federal timber lease." *Forest Science* 45 (4):473-483.

Chang, Sun Joseph. 1998. "A generalized Faustmann model for the determination of optimal harvest age." *Canadian Journal of Forest Research* 28 (8):652-659.

Chang, Sun Joseph, Rodney L Busby, PR Pasala, and Daniel J Leduc. 2005. "VB merch-lob: A growth-and-yield prediction system with a merchandising optimizer for planted loblolly pine in the west Gulf region." *Res. Pap. SRS-35. Asheville, NC: US Department of Agriculture, Forest Service, Southern Research Station. 18p.* 35.

Chang, Sun Joseph, and Peter Deegen. 2011. "Pressler's indicator rate formula as a guide for forest management." *Journal of Forest Economics* 17 (3):258-266.

Chladna, Zuzana. 2007. "Determination of optimal rotation period under stochastic wood and carbon prices." *Forest Policy and Economics* 9 (8):1031-1045.

Clarke, Harry R, and William J Reed. 1989. "The tree-cutting problem in a stochastic environment: the case of age-dependent growth." *Journal of Economic Dynamics and Control* 13 (4):569-595.

Cochrane, John Howland. 2005. *Asset Pricing: Revised Edition*: Princeton University Press.

Couture, Stéphane, Marie-Josée Cros, and Régis Sabbadin. 2016. "Risk aversion and optimal management of an uneven-aged forest under risk of windthrow: A Markov decision process approach." *Journal of Forest Economics* 25:94-114.

Cox, John C, Stephen A Ross, and Mark Rubinstein. 1979. "Option pricing: A simplified approach." *Journal of Financial Economics* 7 (3):229-263.

Di Corato, L., A. Gazheli, and C. J. Lagerkvist. 2013. "Investing in energy forestry under uncertainty." *Forest Policy and Economics* 34:56-64.

Duku-Kaakyire, Armstrong, and David M. Nanang. 2004. "Application of real options theory to forestry investment analysis." *Forest Policy and Economics* 6 (6):539-552.

Faustmann, Martin. 1849. "Berechnung des wertes welchen waldboden sowie noch nicht haubare Holzbestände für die waldwirtschaft besitzen." *Allgemeine Forst-und Jagd-Zeitung* 15 (1849):7-44.

Feliciano, Diana, Laura Bouriaud, Elodie Brahic, Philippe Deuffic, Zuzana Dobsinska, Vilem Jarsky, Anna Lawrence, Erlend Nybakk, Sonia Quiroga, Cristina Suarez, and Andrej Ficko. 2017. "Understanding private forest owners' conceptualisation of forest management: Evidence from a survey in seven European countries." *Journal of Rural Studies* 54:162-176.

Gaffney, M Mason. 1957. *Concepts of financial maturity of timber and other assets*. Raleigh, North Carolina: Department of Agricultural Economics, North Carolina State College.

Gjolberg, Ole, and Atle G. Guttormsen. 2002. "Real options in the forest: what if prices are mean-reverting?" *Forest Policy and Economics* 4 (1):13-20.

Gong, Peichen. 1998. "Risk preferences and adaptive harvest policies for even-aged stand management." *Forest Science* 44 (4):496-506.

Gong, Peichen, Mattias Boman, and Leif Mattsson. 2005. "Non-timber benefits, price uncertainty and optimal harvest of an even-aged stand." *Forest policy and economics* 7 (3):283-295.

Gong, Peichen, and Karl-Gustaf Lofgren. 2008. "Impact of risk aversion on the optimal rotation with stochastic price." *Natural Resource Modeling* 21 (3):385-415.

Gould, Ernest M. Jr. 1960. "Fifty years of management at the Harvard forest." *Bull. Harv. Forest* (29):30.

Haight, Robert G., and Thomas P. Holmes. 1991. "Stochastic price models and optimal tree cutting: results for loblolly pine." *Natural Resource Modeling* 5 (4):423-443.

Hardie, Ian W, Julie N Daberkow, and Kenneth E McConnell. 1984. "A timber harvesting model with variable rotation lengths." *Forest Science* 30 (2):511-523.

Heaps, Terry. 1981. "The qualitative theory of optimal rotations." *Canadian Journal of Economics*:686-699.

Hultkrantz, Lars, Linda Andersson, and Panagiotis Mantalos. 2014. "Stumpage prices in Sweden 1909–2012: testing for non-stationarity." *Journal of Forest Economics* 20 (1):33-46.

Insley, Margaret. 2002. "A real options approach to the valuation of a forestry investment." *Journal of Environmental Economics and Management* 44 (3):471-492.

Insley, Margaret, and Kimberly Rollins. 2005. "On solving the multirotational timber harvesting problem with stochastic prices: a linear complementarity formulation." *American Journal of Agricultural Economics* 87 (3):735-755.

Johansson, Per-Olov, and Karl-Gustaf Löfgren. 1985. *The economics of forestry and natural resources*: Basil Blackwell Ltd.

Kaya, Ismail, and Joseph Buongiorno. 1987. "Economic harvesting of uneven-aged northern hardwood stands under risk: A markovian decision model." *Forest Science* 33 (4):889-907.

Laakkonen, Anu, Rebekah Zimmerer, Tanja Kähkönen, Teppo Hujala, Tuomo Takala, and Jukka Tikkanen. 2018. "Forest owners' attitudes toward pro-climate and climate-responsive forest management." *Forest Policy and Economics* 87:1-10.

Lembersky, Mark R, and K Norman Johnson. 1975. "Optimal policies for managed stands: an infinite horizon markov decision process approach." *Forest Science* 21 (2):109-122.

Lien, G., S. Størdal, J. B. Hardaker, and L. J. Asheim. 2007. "Risk aversion and optimal forest replanting: a stochastic efficiency study." *European Journal of Operational Research* 181 (3):1584-1592.

Lin, Ching-Rong, and Joseph Buongiorno. 1998. "Tree diversity, landscape diversity, and economics of maple-birch forests: Implications of Markovian models." *Management science* 44 (10):1351-1366.

Lohmander, Peter. 1987. "Pulse extraction under risk and a numerical forestry application." *Systems Analysis and Modelling Simulation* 5 (4):339-354.

Louisiana Department of Agriculture and Forestry. 2019. "Louisiana timber and pulpwood production, various issues." http://www.ldaf.state.la.us/forestry/reports/.

Lunnan, Anders, Erlend Nybakk, and Birger Vennesland. 2006. "Entrepreneurial attitudes and probability for start-ups—an investigation of Norwegian non-industrial private forest owners." *Forest Policy and Economics* 8 (7):683-690.

McConnell, K. E., J. N. Daberkow, and I. W. Hardie. 1983. "Planning timber production with evolving prices and costs." *Land Economics* 59 (3):292-299.

Newman, D. H. 2002. "Forestry's golden rule and the development of the optimal forest rotation literature." *Journal of Forest Economics* 8:5-27.

Norstrøm, Carl J. 1975. "A stochastic model for the growth period decision in forestry." *The Swedish Journal of Economics* 77 (3):329-337.

Pagnoncelli, Bernardo K., and Adriana Piazza. 2017. "The optimal harvesting problem under price uncertainty: the risk averse case." *Annals of Operations Research* 258 (2):479-502.

Parajuli, Rajan, and Sun Joseph Chang. 2015. "The softwood sawtimber stumpage market in Louisiana: market dynamics, structural break, and vector error correction model." *Forest Science* 61 (5):904-913.

Pressler, MR. 1860. "Aus der holzzuwachlehre (zweiter Artikel) allgemeine forst und jagd zeitung 36: 173–191." *Translated by W. Löwenstein and JR Wirkner (1995) as "For the comprehension of net revenue silviculture and the management objectives derived thereof" in Journal of Forest Economics* 1 (1):45-87.

Shaffer, R. M., Jr. 1984. "Valuation of certain long-term timber cutting contracts." *Forest Science* 30 (3):774-787.

Sharpe, William F. 1964. "Capital asset prices: A theory of market equilibrium under conditions of risk." *The journal of finance* 19 (3):425-442.

Susaeta, Andres, and Peichen Gong. 2019a. "Economic viability of longleaf pine management in the Southeastern United States." *Forest Policy and Economics* 100:14-23.

Susaeta, Andres, and Peichen Gong. 2019b. "Optimal harvest strategy for even-aged stands with price uncertainty and risk of natural disturbances." *Natural Resource Modeling*.

Tahvonen, Olli, and Markku Kallio. 2006. "Optimal harvesting of forest age classes under price uncertainty and risk aversion." *Natural Resource Modeling* 19 (4):557-585.

Tee, James, Riccardo Scarpa, Dan Marsh, and Graeme A. Guthrie. 2014. "Forest valuation under the New Zealand emissions trading scheme: A real options binomial tree with stochastic carbon and timber prices." *Land Economics* 90 (1):44-60.

Thomson, Thomas A. 1991. "Financial maturity: a binomial options pricing approach." 1991 Symposium on Systems Analysis in Forest Resources, Asheville, North Carolina.

Thomson, Thomas A. 1992. "Optimal forest rotation when stumpage prices follow a diffusion process." *Land Economics* 68 (3):329-342.

Trigeorgis, Lenos. 1996. *Real options: Managerial flexibility and strategy in resource allocation*: MIT press.

Yin, Runsheng. 2001. "Combining forest-level analysis with options valuation approach: A new framework for assessing forestry investment." *Forest Science* 47 (4):475-483.

Yin, Runsheng, and David Newman. 1995. "Optimal timber rotations with evolving prices and costs revisited." *Forest Science* 41 (3):477-490.

Yin, Runsheng, and David. Newman. 1997. "When to cut a stand of trees." *Natural Resource Modeling* 10 (3):251-61.

Zhou, Mo, and Joseph Buongiorno. 2006. "Forest landscape management in a stochastic environment, with an application to mixed loblolly pine–hardwood forests." *Forest Ecology and Management* 223 (1-3):170-182.

Zhou, Mo, and Joseph Buongiorno. 2019. "Optimal forest management under financial risk aversion with discounted Markov decision process models." *Canadian Journal of Forest Research* 49 (7):802-809.

Zinkhan, F. Christian. 1991. "Option pricing and timberland's land-use conversion option." *Land Economics* 67 (3):317-325.

Vita

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