ABSTRACT

HUANG, JIN. An Empirical Analysis of Adaptability to Climate Change and Risk in Forest Management. (Under the direction of Professor Robert C. Abt).

This dissertation provides a quantitative analysis of the adaptability in forest management to future risks using existing data describing pine growth and management across a range of conditions in the southern U.S. Future risks include gradual climatic change, catastrophic events, price and yield risks. The adaptive options considered include rotation ages, thinning ages, thinning intensity and frequency, planting density and stand stocking. Using a bio-economic model approach, two empirical yield models based on U.S. Forest Service FIA data are integrated with an extended Faustmann and a Real Options optimization models respectively. Simulation results are obtained across risk categories and model types. Marginal and joint effects of risk are derived and comparisons between different integrated models are made. Forest managers' optimal decisions in response to risk are found to be sensitive to the set of adaptive options. The "standard" optimal rotation results do not necessarily hold if stand density control and thinning options are considered. The impacts of discrete catastrophic events on forest management adaptation and welfare are found to be more important than the gradual climate change impact. Gradual climate change within the range of Hadley 3 scenarios does not lead to significant changes in optimal rotation age, stand density or thinning ages but the change in forest rents may be significant. Depending on the impact of climate change on agriculture rent, we would expect more adaptations at the extensive margin (land use change) than the intensive margin (silvicultural intensity).

An Empirical Analysis of Adaptability to Climate Change and Risk in Forest Management

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
In partial fulfillment of the
Requirements for the degree of
Doctor of Philosophy

Forestry

Raleigh, North Carolina

May, 2008

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DEDICATION

This dissertation is dedicated to my dearest mother, Yanan Li. My appreciation to her is far beyond words. I hope I can live up to her expectation. I would like to put some Chinese here so that my mom can read them.

我最亲爱的妈妈，我要把我的博士毕业论文献给您以表达我对您深深的感谢。 谢谢您孜孜不倦的教诲和鼓励！您是世界上最伟大的妈妈！

BIOGRAPHY

I was born and grown in Chengdu, a lovely city in the southwest of China. After culminating the high school education in 1998, I headed north to Beijing Forestry University where I completed a Bachelor degree in Forest Economics and Management in July 2002. From there I ventured to North Carolina State University in Raleigh, NC, US to pursue my graduate studies leading to a Master in Statistics and a Ph.D. in Forest Economics that ended in May 2008.

ACKNOWLEDGMENTS

I would like to express my appreciation to all people who have advised, supported, and encouraged me during my Ph.D. study. In particular, I want to express my deep gratitude to my advisor Dr. Bob Abt for his consistent patience and guidance. I am also grateful to IIASA, a research institute in Austria for the YSSP opportunity. Three months maybe short but it benefits a lot to my research and experience. I wish to extend my heart-felt thanks to Michael Obersteiner and Jana Szolgayova for their great help with my research project.

I know I have a wonderful Advisory Committee which plays an important role in my Ph.D. program. I would like to offer my thanks to my committee members: Dr. Sujit Ghosh for his guidance and suggestions; Dr. Barry Goodwin for his support and considerate advice and Dr. Brian Murray for his interest and constructive criticism. In addition, I also want to acknowledge Bobby Huggett, Michael Roberts and Wolfram Schlenker and Georg Kindermann.

Finally I want to thank my family and friends in Chengdu, Beijing and Raleigh---my mom, my boyfriend Jianhong, my roommate Feng, my tailor officemates and many others. I would never have finished without their physical, emotional, and spiritual support.

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Chapter 1

Introduction

In recent years the related topics of climate change, energy security, and renewable energy sources have dominated popular and scientific examinations of future resource management. Much of this research has focused on the impacts on, and potential responses of, agriculture to climate change. It has been recognized that climate change has the potential to affect agriculture and forest ecosystems and the risks associated with discrete events like fire and hurricanes. Together with volatility in energy markets, development of new renewable energy technologies, and the potential development of carbon markets as a mitigation strategy, the future resource management environment is likely to be more volatile. To study how resource management is likely to change, it is important not only to understand the direct impact of climate on resource yields, but also the economics of management in this riskier environment. This requires a bio-economic modeling approach.

In the U.S. South, forests cover most of the landscape, support an important industry and have a significant role both as a carbon sink and a source of biofuels. Over half of the pine harvest in the South comes from pine plantations. The stands cover a variety of sites, ownerships, and management intensities. Most work on climate change and forestry, however, has focused on the biological impacts on natural ecosystems at a landscape level (e.g., McGuire et al., 1995; VEMAP, 1995; Prasad and Iverson, 1999-ongoing), or site specific experiments (e.g., Butnor et al., 2003; Oren et al., 2004; Palmroth et al., 2005). Economic studies tend to focus on aggregate market responses (e.g., Perez et al., 1997; Sohngen and Mendelsohn, 1998; Abt and Murray, 2001; Irland et al., 2001), or the impact of carbon markets on the optimal rotation age (e.g., Romero, 1998; Gong and Kristrom, 1999; Benitez and Obersteiner, 2006). Some of these economic impact analyses consider market adaptation and land management adaptation to climate change and associated risks. However discussions about when, where and how to incorporate adaptation into forest management has been limited (Ogden and Innes, 2007).

The early studies in forest management were based on an approach developed by Faustmann (1849) and generally ignored both market and biological risk factors (e.g., Faustmann, 1849; Morgan, 1974; Hyde, 1980; Jackson, 1980; Chang, 1983; Graham-Tomasi, 1983). As the importance of risk analysis has been recognized, researchers started to incorporate risk into the forest management decision-making studies. Many of them examined the price and growth risk (e.g., Lembersky and Johnson, 1975; Norstrom, 1975; Lohmander, 1987; Newman et al., 1985; Brazee and Mendelsohn, 1988; Haight et al., 1995; Kaya and Buongiorno, 1987; Buongiorno, 2001; Rollin, 2005). There is limited literature on catastrophic risk. Reed (1984) and Amacher et al. (2005a) looked at the fire risk in an extended Faustamnn framework. Haight et al. (1995) applied Reed's model to study hurricane risk. In addition, some others studied the risk preference of forest managers (e.g., Valsta , 1992; Gong, 2005).

A more recent literature using the Real Options (RO) approach to model risk response has emerged (e.g., Morck et al., 1989; Thomson , 1992; Insley, 2002). This approach recognizes that the manager has the ability to respond to unexpected changes in the future management environment. However most of the previous RO literature focuses on the harvesting option facing price/yield risks. There are few studies that examine other management options or catastrophic risks.

Past studies in forest management have been based on the assumption that the climate remains relatively stable throughout a forest's life. Relative to annual crops which have been extensively studied, climate change has the potential to affect forest management within two or three timber crop rotations. This makes it important to understand forest management flexibility to ameliorate climate impacts.

Only a few authors have linked climate change to forest management decision making. Spittlehouse (2005) and Ohlson et al. (2005) provided qualitative analysis of integrating climate change adaptation into decision making. Johnston and Williamson (2005) quantitatively linked a climate sensitive forest ecosystem process model with Reed's model to study optimal rotation age under climate change and fire risk. They assumed fixed stumpage prices over time and did not consider other adaptive measures.

This dissertation builds on previous climate change and risk analysis literature to study forest management adaptation to climate change and other risks using existing data describing pine growth and management across a range of conditions in the southern US. In this context, current variation in forest management provides a way to model adaptation to the potential risks and climatic changes.

One of the primary objectives of this dissertation is to provide a quantitative analysis of the adaptability in forest management to future risks. Future risks include gradual changes in the climate as well as potential changes in related discrete phenomena like fires and hurricanes. These risks have the potential to interact with variation in yields and prices associated with any longterm investment like forestry. The adaptive measures being studied include changing rotation ages, thinning ages and planting density, controlling thinning intensity, thinning frequency and stand stocking/density.

Another objective of this dissertation is to investigate whether climate sensitivity of forest growth can be detected in the Forest Inventory and Analysis (FIA) database[1]. Prasad and Iverson (1999-ongoing) used the FIA database to describe natural species migrations, but as far as I know, no one has used this database to characterize the response of managed forest species to climate.

The third objective is to compare the two optimization frameworks, the Faustmann and Real Options (RO) frameworks. The well known Faustmann model has been used to solve forest management and investment problems for over a century (Newman, 2002). Limitations in the Faustmann approach have also long been recognized and the framework has been extended to deal with some of these limitations.

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[1] FIA data will be described in Chapter 4

The Real Options approach quantifies the impact and value of dynamic flexibility in forest management decisions. While the RO approach has theoretical advantages in valuation, it requires an exhaustive and sophisticated analysis of options over time. Using empirical biological response functions, this dissertation compares optimal management strategies and the associated valuation of the forestry enterprise from the two approaches.

After reviewing the previous literature on risk and climate change analysis, chapters 3 and 4 examine the methodology and databases employed respectively. Chapter 5 presents the results. Chapter 6 relates the results to the dissertation objectives and discusses implications for future work.

Chapter 2

Literature Review

2.1 The Faustmann Model and Extensions

The study of optimal forest management has a long history that can be traced back to Faustmann (1849). This seminal paper had a profound impact on subsequent work in forest management. The established net present value (NPV) method and the well-known Faustmann formula have been widely used in forestry management and investment. As expressed in equation (2.1), the model assumes that the forest manager maximizes the profit by choosing an optimal rotation age.

$$NPV = MAX_T \frac{(P \cdot V(T) - C) \cdot e^{-rT}}{(1 - e^{-rT})} \tag{2.1}$$

NPV is the maximized net present value at the optimal rotation T,
P is the price of timber,
C is the planting related costs,
$V(T)$ is the volume harvested,
r is the discount rate.

Thus the optimal rotation age is determined by solving the first order condition (FOC) of equation (2.1).

$$P \cdot V^{'}(T) = r(P \cdot V(T) - C) + r \cdot \frac{(P \cdot V(T) - C) \cdot e^{-rT}}{1 - e^{-rT}} \tag{2.2}$$

The FOC indicates that NPV is maximized when the marginal benefits of waiting another year to harvest (the left-hand side of 2.2) are equal to the marginal costs of waiting another year (the right-hand side of 2.2).

The Faustmann model is a steady-state and deterministic model which assumes constant prices with no risk or uncertainty. These assumptions have limited the empirical applications of this model. Forest managers operate in an uncertain world where they encounter risk in many diverse forms: Economic market fluctuations (price risk), variation in tree growth, catastrophic risk and changing climate. As the importance of risk and uncertainty analysis has been recognized, there has been an increased focus on these issues and Faustmann's model has been extended.

2.1.1 Price and Growth Risk

In the earlier extended Faustmann studies, the impacts of timber price change on forest management were examined by conducting comparative statics analysis (e.g., Morgan, 1974; Hyde, 1980; Jackson, 1980; Chang, 1983; Graham-Tomasi, 1983). The stochastic price and growth were not studied until the late 1980's (e.g., Lembersky and Johnson, 1975; Norstrom, 1975; Lohmander, 1987; Newman et al., 1985; Brazee and Mendelsohn, 1988; Haight et al., 1995; Kaya and Buongiorno, 1987; Buongiorno, 2001; Rollin, 2005). I summarize three methods that are commonly used in the previous literature for incorporating the price and growth risk.

The first and most common approach is the Markov Decision Process (MDP) Model (e.g., Lembersky and Johnson, 1975; Norstrom, 1975; Kaya and Buongiorno, 1987; Buongiorno, 2001; Rollin, 2005). MDP models generalize Faustmann's approach by recognizing that future stand states and prices are known only as probabilistic distributions. These probabilistic distributions are described in a matrix of transition probabilities. Each matrix element is the probability that the system moves from one state to another between t and $t+1$. The objective function is the expected long-term discounted value of returns. The theory of Markovian decision processes shows that the best decision depends only on the current stand-market state, independently of how it was reached (Buongiorno, 2001).

For the empirical application of MDP model, the key is to define the states and compute the transition probabilities. State definitions may involve biological as well as economic variables. For example, Lembersky and Johnson (1975) used number of trees and average diameter to define the state of even-aged stands, and four levels of autocorrelated prices for market states. Lin and Buongiorno (1998) used basal area, tree size, and species to characterize the states of uneven-aged stands, and two levels of white noise prices. Buongiorno (2001) used the stand volume. The transition probabilities between system states are often computed by stochastic simulations, based on growth and econometric models (Kaya and Buongiorno, 1987). A decision is an action (e.g., tree removal or planting) that causes the system to move from one state to another, thus changing the transition probabilities between states.

$$E(NPV) = MAX_{u_t} E \sum_{t=1}^{\infty} [R(X_t, u_t) \cdot \beta^t | X_0] \tag{2.3}$$

Equation 2.3 is a general form for MDP model, where X_t designates the system state at t, which instead of being deterministic is now a random variable; u_t is the decision at time $t = 1, 2, ...$; R is the immediate return from the decision given a particular state; and β is the discount factor $\beta = (1 + r)^{-T}$, where r is the interest rate, and T is the number of years between decisions.

As the Faustmann model gives the optimal rotation in addition to the maximized NPV, the solution of the MDP gives simultaneously the best decision and the stand value, given the initial state followed by the optimum decision policy. Numerical solutions may use successive approximation or linear programming (see Buongiorno, 2001). It is a fundamental result of the MDP analysis that the optimum policy is invariant over time and is tied only to the current system state. The Faustmann model is a special case of MDP where the transition probabilities between system states are all equal to one.

While the MDP method has become a standard in the forest economics literature for incorporating ecological and market risks into management decisions, this approach works only in a discrete world (discretization of the state space) and is difficult to apply in systems with many stochastic variables.

Brazee and Mendelsohn (1988) and Forboseh et al. (1996) used the asset sale model to analyze the effects of price risk on timber harvesting policy. The objective is also to maximize the expected NPV (see equation 2.4 and 2.5) but instead of choosing optimal rotation the forest manager is assumed to choose a reservation price at each age so that current revenue would be equal to the expected net present value of revenue from delaying harvest. And the harvesting policy is to cut when current price is above the reservation price, otherwise the forest manager should wait another year.

$$\begin{aligned} E(NPV) &= MAX_{P_{m,t}}\{-C + R_1 \cdot e^{-r\cdot 1} + F(1)R_2 \cdot e^{-r\cdot 2} + F(1)F(2)R_3 \cdot e^{-r\cdot 3} \\ &\quad + \cdots + F(1)F(2)\cdots F(Z-1)R_Z \cdot e^{-r\cdot Z}\} \end{aligned} \tag{2.4}$$

where C is planting costs, $F(t)$ is the probability that a tree is left standing at age t, R_t is the expected value in year t given a reservation price $P_{m,t}$, and Z is the oldest age the owner is willing to allow before harvesting. Further, R_t can be expressed in equation 2.5.

$$R_t = \int_{P_{m,t}}^{\infty} (p \cdot V(T) + E(W)) \cdot f(p)dp \tag{2.5}$$

where $f(p)$ is the probability of price p occurring that year, V(T) is the volume function and E(W) the the expected value of bare land. The first element of this payoff is the expected revenue in the first period from selling the standing timber and the second element in the expected payoff is the present value of bare land.

Limitations of this approach include the need for a known price distribution process. Brazee and Mendelsohn (1988) assumed a normal distribution which is not typical since many analyses suggest that the price process should be modeled as a geometric Brownian motion or mean-reverting process. Second, rotation age, thinning and other decision variables are not included. This limits the scope for modeling adaptation to risks. Third, with this asset sale model, yield risk is not considered.

Liang et al. (2006) proposed a bootstrapping method to simulate forest stand growth, timber prices and interest rates. Compared with many other optimizing models (e.g., MDP model), he argued that the distribution-free bootstrapping method would make it easier to incorporate risk in many variables.

2.1.2 Catastrophic Risk

Catastrophic risks are less studied than price or growth risks. Reed (1984) is probably the first to look at the impact of fire risk on the optimal rotation age. He extended the Faustmann formula by modeling the fire as a Poisson process (jump process). Thus the time between stand destruction, by fire or by harvesting, is a random variable (X) with a mixed distribution. For $0 \leq X < T$, where T is the rotation age, X is distributed exponentially with cumulative distribution function $(1 - e^{-\lambda t})$, where λ is the parameter of the Poisson process representing the average occurrence rate of fire per period. Therefore the probability that the stand is destroyed by fire before reaching the rotation age is $(1 - e^{-\lambda T})$. And the probability that the stand is "destroyed" by harvesting instead of fire is $e^{-\lambda T}$. The fire-risk-adapted Faustmann model is shown in equation (2.6).

$$E[NPV] = MAX \frac{E(e^{-rX}Y)}{1 - E(e^{-rX})} \tag{2.6}$$

where Y is a vector of profits and r is the discount rate.

The FOC of equation (2.6) reveals that the effect of fire risk on rotation age is the same as that of an increase in the discount rate by an amount equal to the average fire occurrence rate (λ). The presence of the fire risk effectively adds a premium to the risk-free time-preference rate determined exogenously. The effect is to shorten the rotation age. Reed also extended his model to consider timber salvage and a nonhomogeneous Poisson process.

Reed's paper is fundamental in studying the impact of catastrophic risk on forest management. But it is limited by its focus on one dimension of adaptation.

Amacher et al. (2005a,b) improved and extended Reed's model in several aspects. First, they added three new decision variables in addition to the rotation age, i.e. planting density, the level of intermediate fuel treatment and the stand age at which intermediate treatment is undertaken. Second, Reed assumed that fire protection affects the probability of fire occurrence but not the volume of timber salvaged in the event of fire. Amacher et al. relaxed this assumption by setting up a relationship between prevention efforts and the volume of timber salvaged after a fire. Third, the authors used a simulation method rather than solving the first order conditions, making the approach more applicable to empirical modeling.

Amacher et al. (2005a) found that rotation age may not decrease when preventive measures are considered. The rotation age declines monotonically with fire risk only if the fire occurrence rate rises with stand age. Most striking are the results for their "full prevention" model, in which the landowner chooses the level and timing of intermediate treatment along with planting density and rotation age. In this model, rotation ages are consistently larger than the Faustmann rotation ages and invariably rise as fire risk increases.

Amacher et al. (2005b) further estimated the value of information under fire risk. They identified three types of information a landowner needs. The first is the relationship between the average fire occurrence rate and stand age. The second is the magnitude of the fire occurrence rate. Third, the landowner must understand the relationship between fuel reduction and fire loss. The value of information is the difference in the maximum present value of rents with and without accurate information. They concluded that information is most valuable to a landowner who does not undertake fuel treatment. The value of information about the magnitude of fire risk is also more than twice as high when the landowner underestimates fire risk, rather than overestimating it. For a landowner who undertakes fuel treatment with incorrect assumptions about fire risk, the asymmetry between overestimating and underestimating fire risk and efficacy of fuel reduction is even more pronounced.

However Amacher's studies have the following limitations. First, they assumed a single timber price, i.e. they didn't specify different classes of timber products. Timber prices normally depend on the timber size. Bigger trees are more valuable. Ignoring this aspect may affect the simulation results. Secondly, the volume (yield) function used in their studies is hypothetical, which is based on some theoretical assumptions (e.g., concavity). Therefore their yield model may not capture real-world effects. Third, they assumed that the non-homogenous fire risk parameter λ depends on stand age only. Other factors such as stand density and climate change could also affect the magnitude of λ.

In addition to studying fire risk, Haight et al. (1995) applied Reed's model framework to hurricanes. Their empirical study was designed to determine the effects of age-dependent damage risk, salvage proportion, and degree of initial stand damage on the relationship between a stand's expected present value (EPV) and harvest age. The damaging storm is modeled as a nonhomogeneous Poisson process and the derived EPV formula is same as Reed (1984). The authors found that age-dependent damage risk and stocking reduction have the greatest impact on the relationship between EPV and rotation age. However this study shares the weakness of Reed's in that only a rotation age response is considered.

2.2 Real Options Framework

Professor Stewart Myers coined the term "real options" at the MIT Sloan School of Management in 1977. A real option is the right, but not the obligation, to undertake some business decisions. For example, the opportunity to cut a stand of trees is a real option. A real option is similar in nature to an American call option. But in contrast to financial options, a real option is not often tradable, e.g., the forest manager cannot sell the right to cut the trees to another party, only he can make this decision.

2.2.1 Real Options Framework v.s. Faustmann Framework

Although the traditional Faustmann model has been improved in several ways as described above, there are some limitations that lie in the nature of the Faustmann-type NPV rule. The most important one is probably the static feature of this approach. The flexibility of intertemporal management actions are not taken into account. Whether the forest manager maximizes NPV or EPV, this approach considers a single decision pathway with fixed outcomes. This path is set at the very beginning of the planning period and the forest manager has no ability to adapt over time. Given that the future is unknown and the forest manager has several options to adapt to the changes, this limitation may be significant in forestry. Even if the manager updates the analysis as new information becomes available, which is common, sub-optimal decisions may result under the traditional approach as shown below. The real options approach correctly values choices that maintain flexibility.

In this section, the real options approach is introduced with a simple harvest decision example which shows the basic difference between the two approaches. The following example is a modified version of Chladna (2007).

Consider a forest manager who owns an acre of land and wants to decide whether to harvest the planted loblolly pine this year (strategy A) or wait and harvest later (strategy B). The current merchantable growing stock volume is 1500 cubic feet per acre, and its yearly growth rate has been estimated at 3%. For simplicity I assume that the timber price is the only source of uncertainty. The current price is \$3.5/cu ft and the next year it will either increase to \$4.5/cu ft or decrease to \$2.5/cu ft with equal probability. After the first year all the uncertainty about the timber price is resolved and the price will increase at a constant rate of 5% per year. It takes one year to harvest the stand completely with harvest cost being \$2.5/cu ft, paid up-front and increasing at the rate of 8% per year. The risk-free interest rate is 5% per year.

To examine the forest manager's decision-making, let us first calculate the Faustmann-type NPV for strategy A, to harvest today.

$NPV_0^{Faust,A} = 1500(\frac{(2.5+4.5)/2}{1.05} - 2.5) = \$1250$

Now consider strategy B which delays the harvest for one year, but assumes that the decision about future plans must be taken today.

- In the "up-state" (that is, when price increases), the NPV of next year is

  $NPV_{1,up}^{Faust,B} = 1500 \times 1.03 \times (\frac{4.5 \times 1.05}{1.05} - 2.5 \times 1.08) = \$2781$

- In the "down-state", the NPV is

  $NPV_{1,down}^{Faust,B} = 1500 \times 1.03 \times (\frac{2.5 \times 1.05}{1.05} - 2.5 \times 1.08) = \$-309$

  The NPV in the current year is

  $NPV_0^{Faust,B} = \frac{(NPV_{1,up}^{Faust,B} + NPV_{1,down}^{Faust,B})/2}{1.05} = \$1177 < NPV_0^{Faust,A}$

From the above calculation strategy A seems to be optimal. However this conclusion may be incorrect because the Faustmann-type valuation ignores the flexibility to wait and keep open the opportunity not to harvest in case the price goes down.

We now apply the real options (RO) valuation to take into account the option to wait. The RO-type NPV of strategy A is the same as that of Faustmann-type NPV because there is no further information we could obtain if the decision is to harvest today. However the RO valuation can include dynamic adaptation for strategy B. Taking advantage of new information in the next year leads to different results. To be specific harvest only occurs if the price goes up, that is $NPV_{1,up}^{RO,B} = \$2781$, but $NPV_{1,down}^{RO,B} = 0$. Then the NPV at current year is

$NPV_0^{RO,B} = \frac{(NPV_{1,up}^{RO,B}+NPV_{1,down}^{RO,B})/2}{1.05} = \frac{(2781+0)/2}{1.05} = \$1324$

According to the RO valuation, the optimal strategy is to postpone the decision for one year and decide afterwards based on market price.

This example shows the static nature of Faustmann-type models. The inflexibility to adapt dynamically leads to underestimation of the NPV and may lead to an inferior decision. This example also shows the importance of the option to wait to obtain new information. The value of waiting is simply the difference between the two NPVs.

2.2.2 Application to Forest Management

From the above example we see that forest management decisions (harvesting in the previous case) can be treated as real options. The theory of the RO was probably first introduced into forestry by Miller and Voltaire (1983),Brock and Rothschild (1984), and Brock et al. (1988). In general, these earlier studies focused on theoretical implications of the problem of uncertainty in harvesting decisions, using stylized analytical models with closed-form solutions to show how optimal harvest rules and asset values can be determined when timber price, P, follows a process of geometric Brownian motion (GBM), given by:

$$dP = \mu P dt + \sigma P dz \tag{2.7}$$

where μ is the constant drift rate,
σ is the constant variance rate,
dz is the increment of a Wiener process, i.e., $dz = \epsilon_t \sqrt{t}$ and ϵ_t is $N(0,1)$ and $E(\epsilon_t \epsilon_s) = 0$, for $t \neq s$.

Clarke and Reed (1989) and Reed and Clarke (1990), building on the previous studies, demonstrated that over a single forest rotation, if the price follows GBM and harvesting costs are ignored, then a barrier rule can be specified for the optimal cutting time. The barrier rule is in terms of optimal cutting age for age-dependent growth in wood volume, and optimal cutting size, for size-dependent growth. Neither depends on the absolute level of timber prices. Given stochastic prices, the choice of the optimal time to harvest a stand of trees represents a real option similar to an American call option. Clarke and Reed's assumption of GBM prices and the exclusion of harvesting and management costs allow the analytic solution of the real option and lead to the price-independent harvesting rule. This is analogous to valuing an American call option on a dividend-paying stock with a zero exercise price. Once harvesting and management costs are explicitly included, the option can no longer be solved analytically or be independent of price.

Using the Clarke and Reed results, but incorporating land rent costs as deterministic, Yin and Newman (1997) compared the optimal harvest time where growth and price are stochastic with what would be prescribed by Faustmann or maximum sustained yield rules. In reality land rent should reflect the value of the bare land, which would equal the expected discounted net benefit from optimally managing the timber stand forever. Thus land rent should be endogenous, determined jointly with the value of the harvesting opportunity, although this considerably complicates the analysis.

Thomson (1992) provided an example of one of the earlier uses of the RO approach in a forestry application. Thomson solved his model using a lattice method (a binomial tree) to determine land rent endogenously assuming stumpage prices follow GBM. He compared stand value and rotation ages (as a function of price) with a fixed price Faustmann model.

Morck et al. (1989) brought insights from financial real options methods to their model more explicitly. They used a contingent claims approach to determine the optimal harvesting rate for a firm with a ten year lease on a mature forest. This is a problem of inventory management where growth in inventory is assumed to follow Brownian motion with a drift, and timber prices are assumed to follow GBM process.

Some later studies also examined the optimal harvesting problem under mean reverting (MR) timber prices (Plantinga, 1998; Insley, 2002; Insley and Rollins, 2005). Particularly, Insley (2002) contrasted the implication of GBM and MR process of timber prices on harvesting decisions in the single rotation framework by using a dynamic programming approach. Her paper demonstrated that the assumption about the stochastic timber prices can make a significant difference to the valuation of the stand of trees and optimal cutting time. She provided numerical examples to compare GBM assumption with MR process and found that for prices below the mean, the MR process implies an option value higher than that of GBM. The paper by Insley and Rollins (2005) extended the work in Insley (2002) to an ongoing rotations framework under MR timber prices with bare land value determined endogenously. They analyzed forest stand value by postulating stochastic timber prices and deterministic wood volume.

Alvarez and Koskela (2004) analyzed the impact of the stochastic mean-reverting interest rate process on the optimal rotation age under risk aversion. The authors found that higher interest rate volatility increases the optimal rotation age while higher risk aversion decreases the optimum. But Alvarez and Koskela (2004) used a conventional, time-additive, expected utility approach to consider the risk aversion. Epstein and Zin (1991) argued that expected utility approach is not able to separate the intertemporal substitution and risk aversion and thus leads to modeling deficiency. As a remedy to the deficiency, Epstein and Zin (1991) proposed a non-expected utility model. However disentangling of risk aversion from intertemporal substitution has been a problem in the empirical literature. The difficulties lie in the choice of utility functional forms and the estimation of the time preference and substitution parameters.

There are several other studies that apply the RO approach to forest management. Conrad (1997) and Forsyth (2000) calculated the minimum amenity value needed to preserve old growth forest when amenity value is stochastic. Reed (1993) modeled both revenue and amenity value as stochastic variables following GBM. Saphores et al. (2000) examined the impact of jumps on the harvesting decision. Haight and Holmes (1991) considered the policy implications of assuming prices follow a driftless random walk compared to mean reversion. Saphores (2003) focused on the optimal

2.2.3 Characterizing the Timber Price Process

The assumption of the timber price process is crucial for the RO analysis. As shown above, much of the previous literature assumed GBM for the timber price without explicit testing. Insley (2002) argued that the GBM assumption embodies some unrealistic implications for the behavior of real commodity prices. She found that option value and optimal rotation age are significantly different under the mean reversion (MR) assumption compared to GBM assumption. However it is difficult to conclude definitively that the price of any particular commodity exhibits MR process or possesses a unit root and hence is a nonstationary GBM (Insley and Rollins, 2005).

A number of studies have examined the statistical properties of stumpage prices in various markets and have obtained mixed results. Several studies have examined pine sawtimber stumpage prices in the southern United States. Haight and Holmes (1991); Hultkrantz (1993); Yin and Newman (1995, 1996, 1997) all found evidence that supports stationary, autoregressive models. Prestemon (2003) extended the data series used in Hultkrantz (1993), and Yin and Newman (1996) and improved the statistical tests used. He found that most of the monthly series contain nonstationary as well as stationary components and that quarterly prices are closer to pure nonstationary processes. Brazee et al. (1999) tested price series for pine and hardwood in Virginia and found that the unit root hypothesis is rejected for the former, but not for the latter. Hultkrantz (1995) examined the behavior of timber rents in Sweden over a seventy-nine year time span and accounted for a structural break in the price level using a Perron test. He rejected the unit root hypothesis for his data series.

The choice of price process in modeling the optimal harvesting decision will continue to be the subject of ongoing research. A challenge of resource economists is to develop models and solution algorithms that handle various assumptions regarding price, depending on the circumstances of a particular market (Insley and Rollins, 2005).

2.2.4 Solution Techniques for Real Options Model

As seen from the previous literature, the RO model can be solved using different methods. Binomial lattice is one of the most popular methods due to an intuitively clear representation of the decision-making process. A binomial lattice model has been first introduced by Cox et al. (1979). A basic idea of this method is a discrete-time approximation of the continuous stochastic underlying process (e.g., timber price process). This method is not applicable to all processes but it is suitable for GBM. Assume that during each time interval $\triangle t$ the stochastic process S_t either goes up to uS_t or down to dS_t. The probability of an up-movement is p. Figure 2.1 shows the first movement. The resulting structure is a binomial tree.

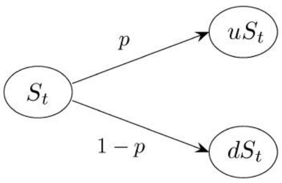

Figure 2.1: A one-step representation of the stochastic movement under binomial lattice model.

The second solution technique is known as partial differential equation method. This method is often used for financial options. However it cannot be directly applied to real options, except for the simplest cases where only a single option exists. To be specific, the partial differential equation describes the behavior of the system only until the first action is taken. This is in particular sufficient for financial options (e.g., for American call or put option) since options of this kind typically cease to exist after they are exercised and one just needs to exercise them optimally. Unfortunately, the case for real options is more complex and the direct transformation into a partial differential equation is not appropriate if we deal with compound real options.

The third one I summarize here is the Monte Carlo Simulation method. In options valuation, Monte Carlo simulations have not been considered to be appropriate for pricing American-type options (see Hull, 1988). Simulation is a powerful tool to analyze European-type options where no early exercise is possible. However, for

American-type options one has to estimate the expected values, which depend on future events. Nonetheless, during the last decade several authors have attempted to propose an efficient method for approximation of conditional expected values using the corresponding empirical average, derived from simulations. In order to utilize the Monte Carlo simulations one typically uses the dynamic programming method and Bellman equation and simulates conditional expected values in each time step. In other words, one combines the dynamic programming backward moving in time with expected value simulations forward moving in time. A general disadvantage of Monte Carlo simulations approach is a relatively large amount of simulations needed to obtain a sufficiently reliable expected value approximation, possibly making this approach computationally intractable. However, recently, mainly due to the ideas related to Longstaff and Schwartz (2001), Monte Carlo simulations have become a promising tool for these problems. For instance, they can handle problems of higher dimension (e.g., Gamba, 2003) or problems modeled by non-Brownian types of underlying processes. Simulations show promise for analysis of not only financial options but of real options as well.

As stated above dynamic programming is used for applying Monte Carlo simulation method. Dynamic programming is a very general tool for dynamic optimization, and is particularly useful in treating uncertainty. It breaks an entire sequence of decisions into just two components: the immediate decision, and a valuation function that encapsulates the consequences of all subsequent decisions, starting with the position that results from the immediate decision (Dixit and Pindyck, 1994). If the planning horizon is finite, the value in the terminal time period (the last period) is first determined. This value then provides the valuation appropriate to the penultimate decision. That, in turn, serves for the decision two stages from the end, and so on. One can work backwards all the way to the initial condition. Computation is difficult but advances in computing hardware and software have made it quite feasible. If the planning horizon is infinite, what might seem like an even more difficult calculation is simplified by its recursive nature: each decision leads to another problem that looks exactly like the original one. This not only facilitates numerical computation, but also often makes it possible to obtain a theoretical characterization of the solution, and sometimes an analytical solution itself (Dixit and Pindyck, 1994).

2.3 Climate Change Impacts and Adaptation

It has been shown that increasing greenhouse gas in the atmosphere will lead to global warming[1]. This change in climate will affect the ecosystems all around the world since the ecosystems are sensitive to temperature, precipitation and carbon dioxide. The impacts could include productivity changes, species migration, and changes in the frequency and intensity of catastrophic events like hurricanes and wildfire. These impacts will have direct and indirect market consequences. For example, climate change will affect forest growth rates and risk of plantation failure. The impact of these changes on profits will depend on the manager's ability to adapt. Therefore it is important to incorporate the climate change impact as well as the various risks (as reviewed in the previous sections) into forest management analyses. Previous studies have not focused on how forest managers can best respond to this new risk environment.

2.3.1 Economic Impact Studies of Climate Change on Agriculture and Forestry

A number of economic approaches have been applied to assessing the climate change impact on agriculture. A simple taxonomy of these methods is to classify them as either a linked-process model or a reduced-form model approach.

A linked-process model approach uses models from several disciplines to measure the consequences of climate change. For example, the approach may start by using crop simulation models to obtain yield changes under climate change. This general approach thus directly incorporates the effects of climate change on yield. The crop simulation model can also include the specific farm-level adaptation activities such as switching crops and changing planting date. After measuring crop yield changes under different climate scenarios (e.g., from GCM forecasts), the yield estimates can

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[1] Intergovernmental Panel on Climate Change (IPCC) (2001).

then be inputs to the economic models to estimate changes in acreage, supply and market clearing prices and so on by crop or/and by region. The economic models seek to either minimize costs or maximize consumer and producer welfare subject to the climatic and other constraints. A key assumption of this approach is that producers', consumers' and livestock feeders' etc. adaptation would proceed as modeled and that the simulated climate effects are accurate (McCarl et al., 2001). This approach has been applied at the state level by Kaiser et al. (1993), at the regional level by Easterling et al. (1993), and at the national level by Adams et al. (1998).

An alternative approach is a reduced form model approach that is based on observed differences in agricultural production and climate between regions. This approach attempts to draw inferences about how cooler regions might adopt practices of warmer regions if climate were warmed. A key assumption is that farmers will be both able and willing to adopt the farming practices of the farmers in warmer regions.

Mendelsohn et al. (1994) were probably the first to apply the reduced form model approach to agriculture. They examined the relationship between agricultural land values and climate using county-level data in the United States. Mendelsohn et al. (1994) referred to their procedure as the Ricardian approach because of its focus on land values. It is based on the theory that in a competitive market, land value is measured by the present value of expected net revenues that are derived from the most economically efficient management and land use. The Ricardian approach is essentially a hedonic model of farmland pricing, based on the notion that the value of a tract of land capitalizes the discounted value of all future profits or rents that can be derived from the land. Specifically, the Ricardian approach uses regression techniques to estimate the effects of various climate, economic, environmental factors on farmland values. It sidesteps the problems of understanding explicit crop and farmer responses to climate by implicitly assuming that the biophysical and economic adjustments imposed by climate change will be made automatically (an assumption that can be confirmed today by examining crops and behaviors in warmer regions), a fact common to all reduced form models.

For studying the welfare and market effects, the reduced form model may have some advantages over the linked process model because the structural changes and farmer responses are implicit in the reduced form model, freeing the analyst from the burdens of both collecting huge biological databases and estimating the effects of climate change on particular region-specific crops and farmer responses. Conversely, if our focus is the farmer's responses and adaptation, the linked process model maybe a stronger candidate. In addition, the reduced form model approach ignores likely changes in output and input prices that result from changes in production. Since market price changes are not measured, effects on consumers are not captured. Another weakness of this approach lies in the assumption that farmers will automatically know how and when to respond to climate changes, which is a problematic assumption in practice (Adams et al., 1998).

Climate Change Impact Analysis in Forestry Sector

A limited number of studies have examined potential economic impacts of climate change on the forest sector. As summarized in McCarl et al. (2001), economic models generally predict that, under future expected climate change without yield or price risk, total U.S. forest inventories will increase, timber harvests will increase, and product prices will decrease relative to an assumed stable climate.

Binkley (1988) was probably the first to link the ecological effects of climate change on boreal forests with a timber model. But market effects were not predicted. Later Joyce et al. (1995) linked the TEM[2] biogeochemical cycle model to the TAMM-ATLAS[3] model to project how U.S. timber markets would adapt to changes in forest production under climate change. Perez et al. (1997) use the same ecological and climate models as Joyce et al. (1995) in a global analysis. They assumed climate change would stimulate increased net primary production and found that as a consequence timber became more abundant, less expensive with corresponding higher consumption levels. They concluded that U.S. would benefit from all climate change scenarios examined. A limitation of this study is that adaptation was ignored and forest management actions were treated as external to the analysis.

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[2] TEM is short for Terrestrial Ecosystem Model.

[3] TAMM-ATLAS is short for Timber Assessment Market Model-Aggregate Timberland Analysis System.

Callaway et al. (1994) applied an early version of FASOM[4] together with climate and ecological models to examine a doubled CO2 equilibrium climate. Their study estimated how harvests could shift over time, along with changes in tree planting investment, as part of the dynamic adjustment of markets and capital stocks to global warming. The study used timber demand information from the USDA Forest Service's Resources Planning Act (RPA) Assessment data base and modeling systems (see Adams and Haynes, 1996) and resource information similar to that used in the Joyce et al. (1995) study.

Sohngen and Mendelsohn (1998) linked a dynamic model of U.S. timber markets with a large-scale biogeographic model. This application provided more information on dynamic adjustment of markets and resources than the Perez et al. (1997) study, although it also assumed a doubling of CO2 to an equilibrium level that leads to steady state biogeographical results. The market model employed in this study was less complex than the FASOM model used by Callaway et al. (1994), containing less regional and ownership detail. Similar to Perez et al. (1997), Sohngen and Mendelsohn found that climate change expanded long run timber supply under all scenarios.

Abt and Murray (2001) provided integrated assessment to model the adjustments of timber and land markets in the south U.S. to the Hadley II climate change scenario. The adjustments they considered include changing levels and distribution of harvest across ownerships, forest types and age classes in the South. They found that differences in species response and ownership characteristics influence both the level and distribution of market responses. Murray et al. (2001) showed that how climate change would affect land use change between forestry and agriculture by applying the impacts of climate-induced changes in forest and agricultural economic rents to a model of land allocation for the Southeastern U.S.

As reviewed above, most past studies in the forest sector used a linked process model approach. But they focused on timber markets and did not pay much attention to another important aspect of economic impacts i.e. how would forest managers adapt to the climate change by changing their behaviors such as harvesting time,

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[4] FASOM is short for Forest and Agricultural Sector Optimization Model.

planting density and thinning actions?

This dissertation takes a different bio-economic approach. Rather than using process models of the ecological sensitivity to climate, I link spatially explicit panel data on loblolly pine yield with historical climate data to analyze species sensitivity to temperature and precipitation. These results provide an empirically derived basis for modeling forest management adaptability to climate change.

2.3.2 The Role of Adaptation to Climate Change

Following the IPCC, a broad definition of adaptation is any adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities[5]. Sir Nicholas Stern in The Stern Review wrote "Adaptation is the only way to deal with the unavoidable impacts of climate change to which the world is already committed". Adaptation refers to a variety of responses aimed at reducing adverse impacts or at taking advantage of opportunities created by novel conditions related to climate change(McCarthy et al., 2001). As the importance of adaptation has been recognized in national and international policy debates, it is also receiving increasing attention in academic research.

In the forestry sector, the ecosystem adaptation has been studied using ecological models. Neilson (1995) uses biogeography models to simulate the geographic distribution of ecosystems through analysis of an ecosystem's response to ecophysiological constraints imposed by climatic conditions, and to limitations in basic resources such as water, light, and nitrogen. These models show how the distribution of ecotypes changes from one equilibrium state to another, though they cannot indicate the condition of those systems (Winnett, 1998). McGuire et al. (1995) applied biogeochemistry models to simulate ecosystem productivity and carbon storage over time. This kind of models can estimate the condition of the ecosystem but cannot show distribution of the different ecosystems over landscape. VEMAP (1995) linked biogeography models with biogeochemistry models to project both the distribution and condition of ecotypes arising once climate changes have equilibrated. Prasad and Iverson (1999-

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[5] Intergovernmental Panel on Climate Change (IPCC)(2001), Chapter 18

ongoing) have been statistically modeling potential change in habitat for common tree species in the eastern United States. They initially developed DISTRIB around regression tree analysis, a new statistical tool at that time and they were among the first to use it extensively for ecological queries.

As reviewed in the previous subsection, there are many economic impact analyses of climate change on agriculture and forestry. Some of them addressed market adaptation to climate change, where human being's adaptive actions are either ignored or included as external factors.

Krankina et al. (1997); Goff et al. (2005); Spittlehouse (2005); Ohlson et al. (2005) suggested that adaptation is also important in forest management and adaptive measures can and should be applied to managing natural resources, especially to those human-managed forests/plantations, in order to moderate harmful impacts of climate change. Some adaptive measures are identified in these qualitative studies, such as change of harvest decision, improving tree species (fire resistant and drought resistant), change of land uses, change of planting dates and choice of planting sites and so on. Goff et al. (2005) qualitatively examined adaptive capacity of forest management to climate change and the associated fire risk. They proposed and assessed adaptation options such as salvage logging, regeneration enhancement and prescribed burning and so on. The authors called for quantitative studies using integrative approaches.

Unfortunately there are only a few studies which quantitatively linked climate change to forest management adaptation. Lindner (2000) used a forest gap model to investigate the decision making in managed forests under climatic change. However their only adaptive action was to switch species. Species switching is likely to be optimal at the extensive margin of current species distribution or with significant climate change. Intensive margin options like optimal rotation age, thinning, planting density and salvage logging are not studied.

Johnston and Williamson (2005) linked a forest model with an economic model to explore the effects of climate change on future stand yields, future area burned and optimal rotation age. They first projected the future forest productivity using a forest ecosystem process model that is sensitive to climate and other environmental factors. They extended the Faustmann model developed by Reed (1984) to obtain soil expectation value and optimal rotation age. However one limitation of their study is that a constant stumpage price is assumed over time. In addition, they only examined the optimal rotation age. Other management options were not studied.

Chapter 3

Methods

I use a bio-economic modeling approach to examine the forest manager's adaptation to climate change and other risks by integrating forest yield models with economic models. Two methods are used to model forest yield. The "simple" yield model assumes that forest yield is determined by stand status (stand age and density) and the surrounding environment (site characteristics, geographic regions and climate). This method provides a direct test of whether a significant climate influence on forest yield can be statistically derived. Since the FIA database provides data at a regional level (e.g., county level) it does not include individual stand dynamics and intermediate silvicultural treatments. A set of individual stand dynamics assumptions are introduced to create a "dynamic" model of stand growth parameterized by FIA data. With the "simple" yield model the climate impact is directly measured. In the "dynamic" yield model, climate impacts are estimated through their influence on site productivity.

The management responses to estimated climate impacts and other risks are examined using two optimization frameworks; the extended Faustmann (EF) and Real Options (RO) frameworks. The EF model extends Reed's and Amacher's models by including yield risk, price risk and climate change in addition to fire risk. The RO model takes both price and fire as stochastic processes and applies dynamic programming and Monte Carlo simulation to solve for the optimal management schedules.

3.1 Forest Growth and Yield Modeling

Forest management decisions require information on the growth of trees over time and how it is affected by silvicultural options and site conditions. Climate change has recently emerged as an environmental condition worthy of study. Three approaches to estimate climate impacts are summarized. Intensive experiments have been conducted to determine how tree growth responds to environmental influences. The Ameriflux network focuses on modeling carbon dynamics in response to climate and other stressors (Law, 2007). Ameriflux sites exist on managed pine stands, but their focus is on providing data to enhance carbon dynamics in process models.

The process model approach simulates the growth of stands in terms of the underlying physiological process. For example PnET and Forest-BGC have been applied to broad forest ecosystems that include both managed and natural components. An application focused on managed plantations is Landsberg et al. (2001) which calibrated a simple process model with managed loblolly pine data from one location.

Prasad and Iverson (1999-ongoing) provide an example of the third approach. They used FIA data to empirically describe natural species migration based on the distribution of ecosystems across different climate zones. This empirical approach could provide insight into the natural migration of loblolly pine with climate change, but it does not consider the implications for managed stands.

Traditional empirical growth and yield models that focus on site and silvicultural interactions take either a forest stand or individual tree approach. Stand level models either represent volume directly as a function of age and site characteristics or model average stand parameters (e.g., average or dominant height, average diameter, basal area, stocking, etc.) as a function of age, site characteristics(Ambrose, 1997). Single tree models, in contrast, represent the growth of individual trees and synthesize the entire stand by aggregating representative individuals (Philip, 1983).

I use the FIA database to empirically capture variation in managed stands across the South. In this section, I first introduce a “simple” yield model. It can be described as an empirical stand-level model which uses a flexible functional form to fit the FIA data. Next I present the “dynamic” yield model, which starts with modeling an individual tree. The individual tree model is then extended to the stand level by incorporating assumptions about stand dynamics.

3.1.1 The “Simple” Yield Model

The “simple” yield model (SYM) is a stand-level forest model where climate variables are introduced directly into the model. The growing stock volume (GSV) per acre is modeled as a function of stand age, stand density, site slope, site productivity index, region dummies and three climate variables. The model can be expressed as follows:

$$\log V_i = f_i(A, D, L, SI, Reg) + g_i(MAXT, MINT, PPT) + \varepsilon_i \tag{3.1}$$

where V_i is the GSV per acre on the ith plot,
$f(\cdot)$ represents parametric relationship (linear),
$g(\cdot)$ represents nonparametric relationship (smooth function),
A is stand age,
D is stand density,
L is site slope,
SI is site index,
Reg is the region dummies,
$MAXT, MINT, PPT$ represent average annual maximum temperature, minimum temperature and precipitation respectively,
ε_i is assumed to be an independent and identically distributed (*iid*) random variable[1] that follows a normal distribution with mean 0 and variance σ^2, i.e. $\varepsilon_i \overset{iid}{\sim} N(0, \sigma^2)$.

Equation 3.1 is a partially linear model (PLM) which has both parametric and non-parametric components. Climate variables are included as a non-parametric component. The major advantage of PLM over linear model (LM) is that PLM allows flexible specification of the dependence of the response on the covariates by using the smooth functions. A non-linear relationship between climate and growth, as suggested by previous literature, can be captured by PLM. Another reason why PLM is

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[1] In section 5.1 residual analysis is conducted to test if ε_i behaves like an *iid* variable.

chosen is based on statistical criteria such as AIC, R-square and statistical significance (p-value), e.g., PLM yields lower AIC than LM.

To model the non-parametric component, the type of smooth function needs to be chosen. The candidates include thin plate regression splines, cubic regression spline, and tensor product (te). Each of them has its advantages and disadvantages (see Table 3.1). Tensor product is chosen mainly due to its ability to capture the interaction of quantities measured in different units (temperature and precipitation). In addition, it yields smaller AIC than plate regression splines and cubic regression spline for this problem. Table 3.1 lists the features of different smooth functions[2].

To transform the estimation of $logV$ to V, the following formula is used:

$$\hat{V} = e^{\hat{\sigma^2}/2} \cdot e^{\widehat{\log V}}$$

where $\hat{\sigma^2}$ is simply the unbiased estimator of the variance of the error process, σ^2.

Since $\hat{V}$ is transformed using the mean function of Equation 3.1, it represents the deterministic yield. In order to take yield risk into account, the deterministic yield is turned into a stochastic one by adding random shocks, ω_i, which leads to

$$V_i = \hat{V}_i + \omega_i \tag{3.2}$$

The stochastic shock can be obtained by using the bootstrapping method. First a pool of residuals are obtained by calculating $V - \hat{V}$ for each observation. Then the stochastic shock is drawn randomly, with replacement, from the pool of the residuals each time when the simulation is conducted.

3.1.2 The “Dynamic” Yield Model

The “dynamic” yield model (DYM) starts with estimating the growth of one “typical” tree in the forest using the often applied Richards function (see Richards, 1959). It is a flexible S-shaped mathematical function. The basic form of Richards function can be written as:

$$v_i = a \cdot e^{b \cdot \ln^2 \frac{A_i}{c}} \tag{3.3}$$

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[2] This table is a revised version of Table 5.1 and Table 5.2 in Wood (2006). For more discussion about different types of smooth functions, please refer to Chapter 4 and 5 of Wood (2006).

Table 3.1: Smooth Bases

Smooth Function	Advantages	Disadvantages
Thin plate regression splines	Can smooth w.r.t any number of covariates.	Computationally costly for large data sets.
	Can select penalty order. No 'knots' and some optimality properties.	Not invariant to covariate rescaling. Not good for smooth interactions of quantities measured in different units.
Cubic regression spline	Computationally cheap.	Can only smooth w.r.t. one covariate.
	Directly interpretable parameters.	Knot based.
Tensor product	Invariant to linear rescaling of covariates	Not invariant to rotation of covariate space.
	Good for smooth interactions of quantities measured in different units.	Apart from scale invariance, not much supporting theory.
	Computationally inexpensive	

where v_i is the average GSV per tree on plot i,

A_i is the stand age on plot i ,

a, b and c are the parameters to be estimated.

Parameter a can be interpreted as the maximum value of the GSV per tree (in cubic feet). b is the shape parameter and c represents the age associated with maximum volume.

Equation (3.3) can be revised to include the influence of site productivity (*pdt*) on the growth.

$$v_i = (a_1 + a_2 \cdot pdt) \cdot e^{(b_1+b_2 \cdot pdt)\cdot \ln^2 \frac{A_i}{c_1+c_2 \cdot pdt}} \tag{3.4}$$

Equation 3.5 assumes that climate influences the tree's growth via site productivity. Climate is described by a long-term historical average in maximum temperature, minimum temperature and precipitation. However due to the unavailability of soil or other inherent site characteristics at the FIA plot level, Equation 3.5 can not be directly estimated. Since soil fertility can be considered as a static site parameter which is not influenced by climate (Lindner et al., 1997), I can instead measure the change in site productivity induced by climate change (Equation 3.6). Then the estimated change in site productivity is used to predict how the yield/growth of the tree is affected by climate change.

$$pdt = h_1(climate) + h_2(soil) \tag{3.5}$$

where $h_1(\cdot)$ and $h_2(\cdot)$ represent non-parametric functions,
soil represents the soil and other inherent site characteristics.

$$\Delta pdt = h_1(climate_2) - h_1(climate_1) \tag{3.6}$$

where $climate_1$ is the current climate,
$climate_2$ is the future climate scenario.

The single tree growth model must be modified to reflect competitive conditions with a stand. For example, if there is only a single tree on a stand, it will grow fast because of ample space, water, sunlight and nutrients. This single tree is called an open-grown tree. On the contrary, a tree surrounded by other trees will grow slower due to competition for space, sunlight, and nutrients. "Stocking degree" is used to describe such surrounding conditions. Stocking degree is defined as the ratio of observed trees per acre to maximum trees per acre. When the stocking degree is close to 0, the stand is at open-grown status. If the stocking degree is close to 1, it is a full stocked stand. As the trees grow, the stand capacity will become smaller as the trees get bigger. Maximum trees per acre is an estimate of the largest number of living trees the stand can sustain. It is an unobserved quantity but it can be estimated by constructing the self-thinning line (see Reinecke, 1933). This line describes the relationship between stocking and tree size over time. Because of the competition, weaker trees start to die and the forest self-thins. With the self-thinning line, maximum trees per acre can be estimated if the GSV per tree is known. Then the stocking degree is calculated to adjust the estimated volume from equation 3.4. Finally this adjusted tree-level model is extended to the stand-level given a planting density. Details and estimation results are reported in Section 5.2.2.

3.2 Economic Model Framework

In order to examine forest management decisions in the presence of various risks (yield risk, price risk, fire risk and climate change), the yield models developed in the previous section are imported into the economic model framework. As mentioned previously, two optimization frameworks are used, the extended Faustmann (EF) and the Real Options (RO) frameworks. The RO method may have theoretical superioriry over EF model but RO is more difficult to implement in practice. In this dissertation, I apply both methods to test whether they lead to different management decisions or valuations. Thus applying the two types of yield models into the two optimization frameworks produces four potential combinations (see Table 3.2). Model SYM-EF and DYM-RO are our focus since they represent the fewest implicit assumptions and the highest adaptive potential respectively. Model SYM-RO and DYM-EF allow us to examine the sensitivity of our results to the two yield and optimization methods.

Table 3.2: Model Framework

SYM-EF: SYM→ EF	**DYM-RO: DYM → RO**
SYM-RO: SYM→ RO	DYM-EF: DYM → EF

3.2.1 Extended Faustmann Model

Model Setup

In this subsection, I introduce the extended Faustmann model that uses the "simple" yield model for yield estimates (SYM-EF). Suppose the forest manager's objective is to maximize the expected NPV in the presence of risks. Yield risk is taken into account using equation 3.2. Prices can be modeled similarly. The market prices of trees depend on the size usually measured as diameter at breast height dbh (4.5ft). Prices also vary over time due to market fluctuations. The stochastic prices can be expressed by

$$P(dia) = f(dia) + e \tag{3.7}$$

where P represents the stumpage price, which is the price paid to the forest manager for standing timber,

dia stands for diameter of the tree and is a function of stand age and density,

e represents the random shock on the price and $e \sim N(0, \sigma_P^2)$.

Following Reed (1984), the occurrence of forest fires is assumed to follow a Poisson process with parameter λ. This parameter represents the possibility of the fire occurrence in a given year, which is also referred to as the average fire occurrence rate. The cause of the forest fire can be lightning, arson or wildfire originating from elsewhere. If λ is constant, the fire process follows a homogeneous Poisson distribution. Otherwise it is a non-homogenous Poisson process. Particularly in the non-homogenous case, Reed (1984) and Amacher et al. (2005a) considered the nonhomogenous parameter λ as a function of stand age only. I extend their work and model λ as a function of both stand age and stand density, i.e. $\lambda = f(A, D)$. As commonly assumed forest fires are more likely to happen on a denser forest stand, i.e. $\frac{\partial\lambda(\cdot)}{\partial D} > 0$. The relationship between $\lambda(\cdot)$ and stand age is more complicated. If it is a top-down or crown fire, older trees may be ignited easier than younger trees because of the flourishing crown, i.e. $\frac{\partial\lambda(\cdot)}{\partial A} > 0$. In contrast, if it is a bottom-up or ground fire, smaller trees may get fire with bigger probability, i.e. $\frac{\partial\lambda(\cdot)}{\partial A} < 0$. All these situations will be examined and the details about fire risk functions are described in Section 5.4.1 and in Table 5.5.

Define a random variable $X_i, (i = 1, 2, \cdots)$ as time between stand "destructions", by fire, hurricane or by harvesting. This is a problem of modeling "life time" or "time until failure" and X_i is commonly modeled using the exponential distribution. Based on Reed (1984), the cumulative distribution function (*cdf*) of X_i is

$$F(X;D) = \begin{cases} 1 - e^{-m(X;D)} & \text{if } X < T \\ 1 & \text{if } X \geq T \end{cases}$$

where $m(X;D) = \int_0^x \lambda(t;D)dt$ is the aggregate level of fire risk,

T is the rotation age.

The probability density function (*pdf*) of X can be easily obtained :

$$f(X;D) = \begin{cases} \lambda(X;D) \cdot e^{-m(X;D)} & \text{if } X < T \\ e^{-m(T;D)} & \text{if } X = T \end{cases}$$

Assume the planting cost consist of a fixed cost (e.g., the site preparation cost) and a variable cost (e.g., the seedling purchase cost). The cost of planting on burned land is lower than that on unburned land because of less soil preparation is required (Waldrop, 1997; Dubois et al., 2001). If the forest fire happens before the harvest, it only incurs costs and the net return at time X is

$$\pi_f = -c_0 - c_1 \cdot D \qquad \text{if } X < T$$

where π_f represents the net return if fire happens before the harvest,

c_0 is the fixed costs,

c_1 is the planting cost per tree on burned land.

If the fire happens after the harvest, the forest manager's net return at time X is

$$\pi_{nf} = P \cdot V - c_0 - c_2 \cdot D \qquad \text{if } X > T$$

where π_{nf} represents the net return if no fire happens before the harvest,

P and V are given in Equation 3.7 and 3.2 respectively,

c_2 is the planting cost per tree on unburned lands.

Combining the above information on price, yield, costs and fire risk and following Reed (1984), the expected net present value (ENPV), can be derived as follows given an interest rate r:

$$\begin{aligned}
ENPV &= E\left\{\sum_{n=1}^{\infty} e^{-r(X_1+X_2+\cdots+X_n)}\pi_n\right\} \\
&= \sum_{n=1}^{\infty} E(e^{-r(X_1+X_2+\cdots+X_{n-1})}) \cdot E(e^{-rX_n}\pi_n) \\
&= \sum_{n=1}^{\infty}\prod_{i=1}^{n-1} E(e^{-rX_1}) \cdot E(e^{-rX_n}\pi_n) \\
&= \frac{E(e^{-rX}\pi)}{1-E(e^{-rX})} \\
&= \frac{\int_0^T \lambda(X;D)\cdot e^{-m(X;D)}\cdot e^{-rX}\pi_f dX + e^{-m(T;D)}\cdot e^{-rT}\cdot \pi_{nf}}{r\cdot\int_0^T e^{-m(X;D)-rX}dX}
\end{aligned}$$

The forest manager's objective is to maximize the ENPV by choosing optimal rotation age T^* and density D^*, i.e.

$$MAX_{\{T,D\}}\frac{\int_0^T \lambda(X;D)\cdot e^{-m(X;D)}\cdot e^{-rX}\pi_f(X,D)dX + e^{-m(T;D)}\cdot e^{-rT}\cdot \pi_{nf}(X,D)}{r\cdot\int_0^T e^{-m(X;D)-rX}dX} \tag{3.8}$$

The first-order conditions for Equation 3.8 are complicated.Therefore simulations are conducted in Section 5.4 to solve for the optima.

For Model DYM-EF where the DYM is imported into the EF framework, thinning is included as an adaptive action in addition to final harvesting. In silviculture, thinning is the intermediate harvest aimed primarily at controlling the growth of stands by adjusting stand density or species composition. The Faustmann-type NPV is calculated for each possible combination of stand age and thinning age(s). The optimal NPV is chosen and the corresponding optimal stand age and thinning age(s) are identified.

3.2.2 Real Options Model

Model Setup

In this section DYM is imported into the RO framework (DYM-RO in Table 3.2) to determine the optimal forest management schedules. The essential property of real options lies in the decision-maker's ability to utilize all information available at the time when the decision is made. This is especially true when random sources are present. The decision-maker (the forest manager in this analysis) does not need to make the optimal decision about future actions right now. Instead, he/she can wait to observe the behavior of the random source value and decide accordingly. This implies that the decision-maker operates on basis of a series of local optima rather than a global optimum and thus can adapt dynamically to risky events. This idea is expressed by the Bellman's principle of optimality (see *pp.*100 in Dixit and Pindyck, 1994). Therefore in the RO framework, the forest manager's decision process can be described by Equation 3.9, also known as the Bellman equation.

$$F_t(Z_t, S_t) = MAX_{u_t}\{\pi(Z_t, u_t, S_t) + \frac{E(F_{t+1}(Z_{t+1}, S_{t+1}, u_{t+1}|t, Z_t, S_t))}{(1+r)}\} \tag{3.9}$$

where t stands for time,
Z_t is the forest stand state at t, including stand age and thinning status,
S_t is the stochastic process (e.g., The fire and price process),
u_t is the action taken at t, i.e. thin, cut or wait,
$\pi(Z_t, u_t)$ is the immediate profit,
r is the discount rate.

Suppose the current status of the forest stand is Z_t and the current realization of the stochastic process (e.g., fire and price) is S_t, $F_t(Z_t, S_t)$ represents the expected net present value at time step t of all the cash flows when the forest manager makes all decisions optimally from this point (t) onwards. Z_t is a vector of the state variables, which includes the stand age and thinning status. Thinning status is described by thinning frequency and thinning age(s). Once Z_t is observed, the stand growing stock volume and average size/diameter at time t are also known from the yield model. At any period t, the current value of state variables (Z_t) is known, but future values Z_{t+1},$Z_{t+2}, \cdots$ are random variables. For instance, the current stand age is 10, but next year the stand age could be 0 if forest fire happens and damages the stand. Suppose the process is Markov, that is all the information relevant to the determination of the probability distribution of future values is summarized in the current state Z_t and is independent of past states.

Equation 3.9 splits the decision sequence into two parts, the immediate period and the entire continuation beyond that. At each period t, the forest manager has three managerial actions (u_t): to thin, harvest or continue waiting. The forest manager's objective is to maximize $F_t(Z_t, S_t)$ at each time step by choosing the optimal managerial action u_t. Once he/she chooses one action at current time period, he/she gets an immediate profit flow π. Continuation value as described in the second term of Equation 3.9 is an expected value because the future states are random from the perspective of current period and is obtained through the probability distribution of future states conditional on current states and action taken. It is the computation of the conditional expectation that shows how dynamic adaptation is made.

The optimization problem in formulation (3.9) can be solved by stochastic dynamic programming combined with the Monte Carlo simulation method. I first value $F(T, S_T, Z_T)$ at terminal time T (Terminal condition) and then go on backwards until time 0. At each backward step the key is to compute conditional expectations. Thus the backward calculation provides all the optimal actions for all possible combination of states. Then forward-moving Monte Carlo simulations are conducted to determine the real management schedules.

When using the SYM as the input to the RO framework, the only difference in the model setup is the specification of the state variables. Stand age and density become the state variables. Stand density is assumed to be fixed over time because the SYM does not capture stand dynamics and thus planting density is equal to the stand density over time.

Fire Risk

Fire risk is modeled similar to that described above. The occurrence of forest fires is assumed to follow a Poisson process with parameter λ. The probability of fire occurrence in a given year is $1 - e^{-\lambda}$ and with probability $e^{-\lambda}$ there is no fire that year.

More attention is given to the non-homogenous λ case, where λ is a function of stand age and density. Thinning, therefore, has an additional role in the RO model. It is not only a silvicultural treatment but also a fuel treatment to reduce fire risk. Figure 3.1 shows an example of the λ setup where λ is specified in equation 3.10 with $t_0 = 0.01, t_1 = 0.6$ and two thinnings are included. Note that when thinning is conducted, there is a drop in the fire risk.

$$\lambda(A, D) = \frac{t_0 \cdot D + t_1 \cdot (50 - A)}{2500} \tag{3.10}$$

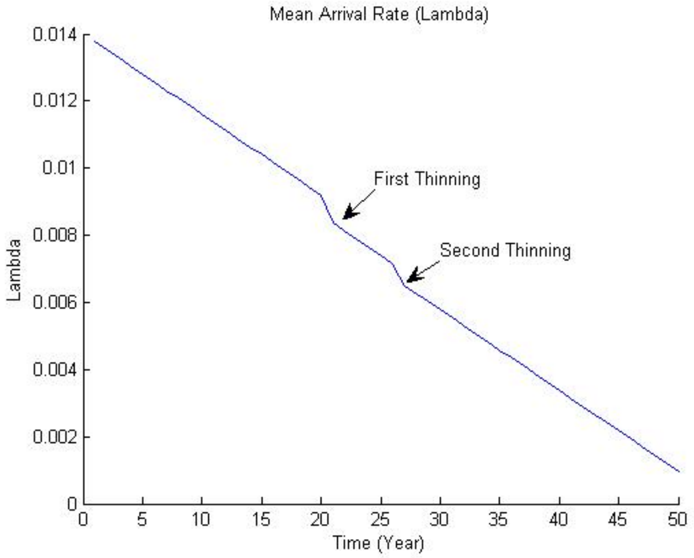

Figure 3.1: Setup of Fire Risk Parameter

When the forest fire happens, it is assumed that it damages the whole stand but the forest manager can conduct salvage cuttings to recover the values of the salvageable trees. The salvageable proportion of the stand depends on stand density at the time fire happens (See Table 5.5). The assumed salvage function indicates that fewer trees can be salvaged on a denser stand. This implies thinning can also increase the salvageable proportion. Alternative salvage assumptions are possible.

Price Risk

Price risk is composed of two parts as described above. In general terms, suppose the stumpage price, P, follows some known stochastic process that is given as:

$$dP = a(P,t)dt + b(P,t)dw \tag{3.11}$$

where the drift term, $a(P,t)$, and the volatility term, $b(P,t)$, are known nonrandom functions and dw is the increment of a Wiener process.

As described in section 5.3, Geometric Brownian Motion (GBM) and Mean-Reversion Process (MRP) are the two most commonly used assumptions for timber prices and they are the special cases of expression 3.11. The expressions for GBM and MRP are listed in equation 3.12 and 3.13 respectively.

$$dP = \mu P dt + \sigma P dz \tag{3.12}$$

where μ is the constant drift rate,
σ is the constant variance rate,
dz is the increment of a Wiener process, i.e., $dz = \epsilon_t \sqrt{t}$ and ϵ_t is $N(0,1)$ and $E(\epsilon_t \epsilon_s) = 0$, for $t \neq s$.

$$dP = \eta(M - \ln P)P dt + \sigma P dw \tag{3.13}$$

where M is the long-run equilibrium level (or the long-run mean price which the prices tend to revert to),
η is the speed of reversion,
Other terms have the same meaning as the GBM.

To test which hypothesis is more appropriate, real price data from Timber Mart South[3] were analyzed using Dickey-Fuller unit root test. By Ito's lemma it is known

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[3] Price data are described in Chapter 4.

that if stumpage prices follow a GBM, then the logarithm of the prices will follow a simple Brownian motion with a drift. Let P_t be stumpage prices at period t, and p_t be the logarithm of prices at t. If P_t can be characterized by equation 3.12, then p_t will be described as

$$dp_t = (\alpha - \frac{1}{2}\sigma^2)dt + \sigma dw \tag{3.14}$$

To test whether p_t follows a Brownian motion process with a drift, equation 3.14 must be approximated in discrete time. This can be done as follows:

$$p_t - p_{t-1} = (\alpha - \frac{1}{2}\sigma^2)\Delta t + \sigma\epsilon_t\sqrt{\Delta t} \tag{3.15}$$

where ϵ_t is a normally distributed random variable with a mean of 0 and standard deviation of 1. A unit root test is performed to determine whether the log of real stumpage prices from TMS behaves like a random walk with a drift, since Brownian motion is the limit of a random walk as $\Delta t \rightarrow 0$. Let $c_1 = (\alpha - \frac{1}{2}\sigma^2)\Delta t$, and $e_t = \sigma\epsilon_t\sqrt{\Delta t}$. Equation 3.15 can be re-written to Equation 3.16.

$$p_t - p_{t-1} = c_1 + c_2 p_{t-1} + e_t \tag{3.16}$$

The Dickey Fuller test of whether p_t follows a random walk with a drift requires running the regression and test $H_0 : c_2 = 0$ v.s. $H_1 : c_2 < 0$. If the null hypothesis can't be rejected, the data support the GBM assumption. Otherwise the data suggest the prices follow a MRP. The results from the Dickey Fuller test along with parameter estimation is reported in section 5.3.

Chapter 4

Study Area and Data

4.1 Study Area

The study area includes the twelve states in the southeastern United States as shown in Figure 4.1. The Southern forest resource covers more than 200 million acres or 56 percent of the Southern land area[1]. Almost 90 percent of these forestlands are privately owned.

The South contributes about 55 percent to the total U.S. harvest and has about one-half of the total industrial forest plantations in the world (Cubbage and Abt, 1998). Over half of the southern pine harvest comes from the 40 million acres of plantations. Corporate owners control nearly 60 percent of the private plantations and currently provide about 70 percent of private harvest. In Figure 4.1, the shaded area shows the native range of loblolly pine, but loblolly pine has been planted in a much wider area in a variety of climate zones with varying levels of management intensity.

The climate over the south U.S. is mostly humid and warm with long hot summer and mild winter. Information about historical temperature and precipitation in the South is summarized in Table 4.1.

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[1] Southern Perspectives, Volume 3, Number 2, Summer 1999

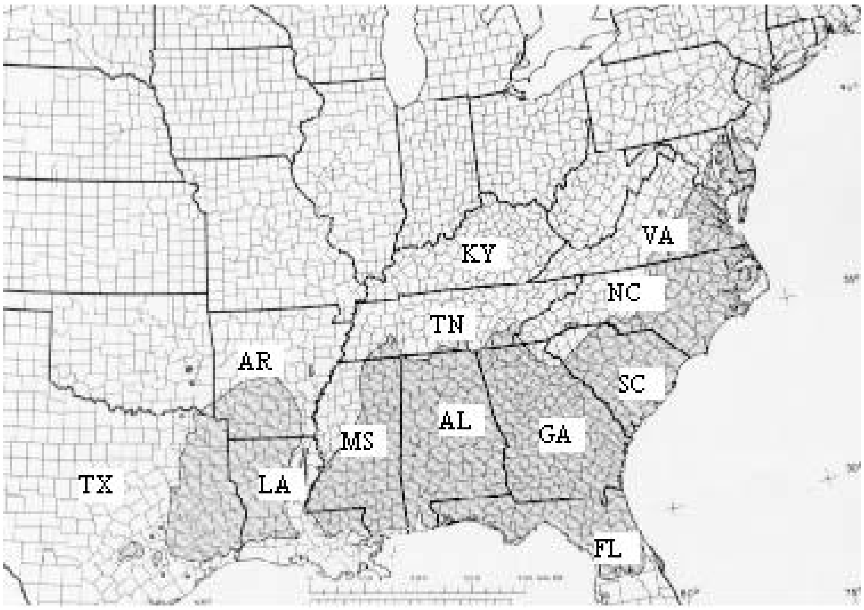

Figure 4.1: The native range of loblolly pine

4.2 Data

This section describes the primary data source and data analysis. The forest yield-related data are obtained from USDA Forest Service plot surveys. Stumpage price data are from Timber Mart-South price surveys. Climate data include historical data and future climate scenarios. Historical climate data are downloaded from the PRISM[2] website. Climate scenarios are based on Hadley 3 models. Data processing and analysis are conducted using SAS software.

4.2.1 Forest Yield-related Data

The source of the raw forest data are the Forest Inventory and Analysis (FIA) Database. The FIA Database has a uniform data structure for forestry inventories. It contains extensive data on forest and site attributes such as stand age, stocking status, species, diameter, site index and so on.

FIA data are collected periodically on permanent plots across the South. The

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[2] PRISM is short for "Parameter-elevation Regression on Independent Slopes Model"

survey plots are randomly located, and the forested plots are field measured for tree attributes as well as site characteristics. Using standard forest measurement techniques, the height, diameter and quality of each tree is recorded. These values are then “expanded” to a per acre level by estimating the number of trees per acre of this type and size[3].

Generally, there are nine data tables in the FIA Database. I use three of them for this study: the Condition Table, the Tree Table and the Plot Table. The latest-year (2004 or 2005) raw FIA data are downloaded for the target states (the 12 southern states of US) and is then imported into SAS. Mississippi State is excluded because of large range of missing data. I first merge the condition, tree and plot table and choose planted loblolly pine only (i.e. Natural forests are excluded). Then I calculate the merchantable growing stock volume per acre and number of trees per acre on the loblolly pine plantations. Plot level data are also obtained for stand age, stocking status, average stand diameter and site productivity. A total of 3683 forested plots for loblolly pine are used and Table 4.1 summarizes some descriptive statistics.

4.2.2 Climate Data

Historical Climate Data

Spatially explicit climate data are required to link historical and projected climate to tree growth by county. The “Parameter-elevation Regression on Independent Slopes Model” (PRISM) is widely regarded as one of the best interpolation procedures (http://www.ocs.oregonstate.edu/prism/index.phtml). PRISM uses point data, a digital elevation model (DEM), and other spatial data sets to predict weather outcomes on 2.5 × 2.5 mile grids across the contiguous United States and generate estimates of annual, monthly and event-based climatic elements that are GIS compatible. I use three climate variables, annual average maximum temperature, minimum temperature and precipitation in the 25-year time series (1980-2004). The national climate data (map) downloaded from the PRSIM website are imported into ArcMap

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[3] More detailed information about the FIA database can be found on http://www.ncrs2.fs.fed.us/FIADatamart/fiadatamart.aspx

Table 4.1: Descriptive statistics for loblolly pine

Variables	Description(units)	Mean	std	Minimum	Maximum
V	Growing stock volume per acre (cubic feet)	1340.26	1050.94	1.43	9351.01
A	Stand age (years)	18.7	7.93	1	45
d	Stand density (number of trees per acre)	389	348.90	6	4012
L	Site slope (angle)	5.7	7.24	0	155
dia	Average diameter (inch)	7.51	2.21	1.83	19.90
SI	Site productivity class (Bigger number indicates less productive site.)	3.8	0.99	1	6
$MAXT$	Average maximum temperature (Celsius)	23.75	1.43	17.80	27.47
$MINT$	average minimum temperature (Celsius)	10.82	1.53	5.00	15.81
PPT	Precipitation (mm)	1308.18	135.19	976.62	1759.15

for conversion from ASCII to raster. A point shape file is then created by first converting a polygon dataset of southeastern U.S. counties to a raster with a grid size of 2.5 × 2.5 mile and then converting the raster into points. Next, the climate data from the first step are extracted to the points created in the second step by using the spatial analyst tools in ArcGIS. The created dbs file containing the climate data and geographic information is then imported into SAS. From these data I calculate the 25-year annual average of maximum temperature, minimum temperature and precipitation at county level for the eleven southeastern states. Each county's climate data are the area-weighted averages of all PRISM grids that cover the forest land. Finally, the county level climate data are attached to the plot-level forest yield-related data obtained in the previous subsection. The descriptive statistics for the climate data on the 3683 loblolly pine plots are presented in Table 4.1.

Future Climate Scenarios

Future climate change data were obtained from Drs. Roberts and Schlenker[4]. These are the latest climate change scenarios from the Hadley 3 model[5]. Hadley 3 model is the climate change model that will form the basis for the next report by the Intergovernmental Panel on Climate Change (IPCC). Monthly model output is obtained for both minimum and maximum temperatures under four major emission scenarios (A_1, A_2, B_1, and B_2) for the years 1960-2099. Each scenario rests on different assumptions about population growth and availability of alternative fuels, among other factors (Nakicenovic, 2000).

Climate changes are estimated as follows[6]. At each of 216 Hadley grid nodes covering the United States, the predicted difference is found in monthly mean temperature for 2020- 2049 (medium-term), 2070-2099 (long-term), and historic averages (1980-2004). Next, the predicted change in monthly minimum and maximum temperature at each 2.5×2.5 mile PRISM grid is calculated as the weighted average of the monthly mean change in the four surrounding Hadley grid points, where the weights are proportional to the inverse squared distance and forced to sum to one. The predicted monthly mean change in temperature is obtained at the county level as described for the historical data. Annual mean change for each county is then calculated. In the final step, I add the predicted changes in annual mean minimum and maximum temperatures for each county to the historical climate data. An analogous approach is applied to precipitation. Predicted changes in the medium term for the different climate scenarios are summarized in Table 4.2.

As can be seen from Table 4.2, the prediction for maximum temperature is most conservative under the Hadley 2 IS92a scenario. The Hadley 3 A_1 scenario predicts the largest increase in the mean maximum temperature and minimum temperature. Precipitation change has more spatial variation. Under each scenario, the change in precipitation is not monotonic. Some counties gain more rainfall while others become

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[4] Dr. Roberts is Economic Research Service, USDA. Dr. Schlenker is from Department of Economics and School of International and Public Affairs, Columbia University.

[5] http://www.metoffice.com/research/hadleycentre/

[6] For more detailed information, see Schlenker and Roberts (2006).

drier. Only the B_2 scenario indicates a decrease in the mean precipitation across the South. Among the other four scenarios, $IS92a$ predicts the largest increase in the mean precipitation.

Table 4.2: Descriptive statistics Climate Scenarios

Climate Variables& Scenarios	Mean($^{\circ}C$ or mm)	std	Min($^{\circ}C$ or mm)	Max($^{\circ}C$ or mm)
$\Delta MAXT$(IS92a)	0.67	0.14	0.48	1.07
$\Delta MAXT$(A_1)	1.99	0.28	1.08	2.68
$\Delta MAXT$(A_2)	1.89	0.20	1.08	2.26
$\Delta MAXT$(B_1)	1.84	0.26	1.10	2.47
$\Delta MAXT$(B_2)	1.66	0.36	0.70	2.42
$\Delta MINT$(IS92a)	1.03	0.12	0.73	1.30
$\Delta MINT$(A_1)	1.96	0.11	1.24	2.22
$\Delta MINT$(A_2)	1.64	0.11	1.17	1.84
$\Delta MINT$(B_1)	1.75	0.10	1.16	1.93
$\Delta MINT$(B_2)	1.40	0.20	0.79	1.82
ΔPPT(IS92a)	87.39	33.11	−0.18	182.09
ΔPPT(A_1)	59.25	57.78	−51.84	166.15
ΔPPT(A_2)	29.93	15.11	−29.84	78.89
ΔPPT(B_1)	54.99	51.79	−86.64	156.04
ΔPPT(B_2)	−15.54	34.96	−118.15	76.54

4.2.3 Price and Cost

The stumpage price data are from the monthly and quarterly surveys of Timber Mart-South (TMS). The stumpage price is the price paid to the forest manager for standing timber. TMS provides standard forms for reporting market activity to a broad cross section of the timber industry, both companies and individuals, who are actively engaged in the day to day operation of selling and buying timber on the stumpage and delivering to yards and mills. From these reports, over each quarter, the data are sorted out and tabulated to arrive at high and low groupings of price ranges. Then simple average is obtained for each state, area, and product. Quarterly stumpage prices from TMS are used for the three products across the south U.S. (See below). In addition, biomass value is also included for the stumpage that is even smaller than the pulpwood size.

- Biomass at a d.b.h. less than 4 inches;
- Pulpwood (PW) at a d.b.h. of 4 to 9 inches;
- Chip-n-saw (CNS) at a d.b.h of 9 through 11 inches;
- Sawtimber (ST) with a d.b.h greater than 11 inches.

Table 4.3 lists the stumpage prices by product classes. These are discrete prices. I use the information in Table 4.3 to fit a smooth curve of the price as a function of diameter for use in the extended Faustmann model. The discrete prices may be appropriate to use for an individual tree because as an individual tree grows it moves between size classes in discrete steps. However a stand of trees will have a distribution of diameters for any given age. As the stand ages, some proportion of the trees will enter the large size class first and it may take several years for all of the trees to move to a higher value product. Thus a continuous value (price) function would reflect this smoother transition to a higher value product.

Table 4.3: Product Prices

	Biomass value	Pulpwood	Chip-N-Saw	Sawtimber
Price/ton	\$1	\$6.42	\$25.8	\$40.97

In addition to using the price function, the RO model also needs historical price information in order to capture the stochastic price movement over time. The quarterly price data (1980-2007) from TMS are used. Real prices are obtained by using the producer price indexes (PPI) for all commodities as the deflator and thus all prices are in real 1982 year dollars. Figure 4.2 provides an example using prices for chip-n-saw . The price series in the figure, both nominal prices and real prices exhibit a little upward trend except over the past decade that is characterized by periods of significant volatility.

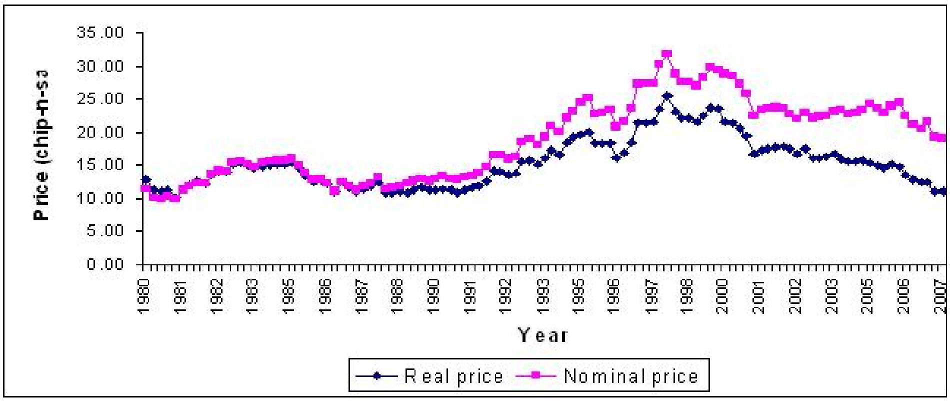

Figure 4.2: Time Series Price Data for Chip-N-Saw (Real prices vs. Nominal prices)

Planting costs on both burned and unburned land are assumed to be linear in planting density. Per-acre costs of establishing loblolly pine on burned and unburned land is based on the current practice of loblolly pine plantations. The cost on burned land is lower than that on unburned land because less soil preparation is required (Waldrop, 1997; Dubois et al., 2001). As listed in Table 5.5, the cost function includes fixed and variable cost. The fixed cost represents the site preparation cost and the variable cost depends on how many trees are planted. Harvesting costs are not included because stumpage prices of standing trees are considered. Thinning costs are assumed to reduce stumpage value from thinning by 10%.

4.2.4 Fire Data

In the non-homogenous case, we need information on how $\lambda(\cdot)$ varies with stand age and density ideally, however such quantitative information is not available. Coarse-scale spatial data from U.S. Forest Service indicate that fires arrive on average every 0-35 years in the southern U.S. (Schmidt et al., 2002). Similar data for 37 counties in northern Florida suggest that the average annual risk of fire was 1% during 1981-2001. These general fire data can provide a basic idea about the magnitude of the fire risk in the south U.S. I choose values for the parameters of fire risk function (t_0 and t_1) so that the simulated fire risk from the stochastic fire process is consistent with these empirical data.

Chapter 5

Results

The estimation results of the SYM and DYM are reported and explained in section 5.1 and 5.2 respectively along with a sensitivity analysis using different sets of climate data. Section 5.3 shows the estimation for the price models. Simulations are then conducted and the optimization results are reported in Section 5.4.

5.1 The "Simple" Yield Model

5.1.1 Estimation Results

The partially linear model (PLM) shown in (Equation 3.1) is our full model which includes stand age, density, site characteristics, climate variables and region variables (Mountain, Piedmont, Coastal plain and Delta region). It is fitted using the GAM function in the R language. The regression results are listed in Table 5.1. The adjusted R-square is 0.565. Stand age, age squared, density, density squared, slope and site index are all significant at a 1% level. Climate variables represented by te(MAXT,MINT,PPT) are significant at a 10% level. The region dummies are not significant. One reason could be the distribution of plantations. Among the 3683 observations, 67% of them are located in the Coastal Plain (Reg1), 25% in the Piedmont (Reg2), 7% in the Mountain (Reg3) and 1% in the Delta Region (Reg4). An alternative explanation is that the climate variables explain most of the regional variation.

Table 5.1: Regression Results for The "Simple" Yield Model (Full Model)

Variable	Coefficient	Std. Error	t-value	p-value
Constant	3.0153	0.1105	27.28	< 0.001
A (stand age)	0.3501	0.0076	46.29	< 0.001
A^2	-0.0057	0.0002	-33.57	< 0.001
D (hundred trees/acre)	0.1135	0.0091	12.52	< 0.001
D^2	-0.0046	0.0004	-11.4	< 0.001
L (slope)	-0.0054	0.0022	-2.435	0.01
SI (site index)	-0.2046	0.0148	-13.82	< 0.001
Reg2 (Piedmont)	-0.0443	0.0420	-1.053	0.29
Reg3 (Mountain)	0.0411	0.0740	0.5548	0.58
Reg4 (Delta)	0.0381	0.1243	0.3062	0.76
Variable (non-parametric)	estimated df	chi.sq	p-value	
te(MAXT,MINT,PPT)	9	42.277	0.09	
Adjusted R^2	0.565			
$\hat{\sigma^2}$	0.745			

Without the regional dummies, the significance of the climate variables increases to 7% level and the adjusted $R^2 = 0.566$. Thus I will proceed with the reduced form model as expressed in Equation (5.1).

$$\begin{aligned}\widehat{\log V} &= \underset{(27.44)}{3.014^b} + \underset{(46.28)}{0.349^b}A - \underset{(-33.52)}{0.0057^b}A^2 + \underset{(12.58)}{0.113^b}D - \underset{(-11.45)}{0.0046^b}D^2 - \underset{(-2.59)}{0.0056^b}L \\ &\quad -\underset{(-13.86)}{0.205^b}SI +^c \underset{(\chi^2=42.87)}{te(MINT, MAXT, PPT)} \qquad (5.1)\end{aligned}$$

Where figures in the parentheses are t ratios or χ^2
^{b}significant at 1% level, ^{c}significant at the 10% level

Holding other factors fixed, the average GSV/acre would increase as the stand ages until $A = 30.6$ then GSV/acre would goes down as the stand gets older. Similarly the average GSV/acre increases with stand density until it reaches 1228 trees/acre. The marginal effects of site productivity index (SI)[1] and site slope (L) on the average GSV/acre are that the GSV is lower on poorer or steeper sites.

In the above PLM regression, the error process is assumed to be an uncorrelated process with mean zero and constant variance.To examine the validity of the

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[1] Higher values of SI represent lower quality sites.

assumption, residual analysis is conducted. Let e denote the residual process, then $e = logV - \widehat{\log V}$. The zero mean assumption is violated if there is lack of fit. It is obvious that the expectation of the error will not be 0 if the fitted model is incorrect. To identify lack of fit, a residual plot is used where residuals are plotted against the predicted values of the dependent variable. The residual plot can also be used to check whether the variance is constant. The residual plot (see Figure A.1 in the Appendix) presents a random pattern generally indicating that heterogenous variance is not a concern. Therefore it is reasonable to assume that the error process has a zero mean and constant variance.

$$d\hat{i}a = 5.29 + 0.16A - 0.21D \tag{5.2}$$

The average diameter of the stand is assumed to be a function of stand age and stand density. Both explanatory variables are highly significant and the adjusted R^2 is 0.57. Equation (5.2) shows the estimation results, which are intuitive and reasonable. The ceteris paribus effect of stand age on the average diameter is that the trees are larger on older stands. When holding stand age fixed, the diameter is smaller on denser stands.

5.1.2 The SYM Response to Climate

The relationship between the mean function of $\log V$ and climate variables can be viewed in Figure 5.1 and 5.2. From different angles, the two 3-D graphs in Figure 5.1 show the yield response of loblolly pine to maximum temperature and precipitation. The vertical axis is the logarithm of the merchantable growing stock volume ($logV$). It is shown that when PPT is in the relatively low range, the yield will decrease nonlinearly as $MAXT$ goes up (RHS graph). But when PPT is relatively high, an increase in the $MAXT$ could make the tree more productive (LHS graph). This is reasonable because increases in temperature can stimulate carbon uptake and thus increase plant respiration and photosynthesis. But temperature-induced drought stress can disproportionately affect the growth of the tree and limit carbon uptake. This result is consistent with the findings of Barber et al. (2000).

The yield response to $MINT$ and PPT is presented in Figure 5.2. In the LHS graph, it is clear that the yield rises as both $MINT$ and PPT increase from low levels. But when PPT and $MINT$ are high, the yield starts to decrease as it becomes wetter and hotter. The RHS graph shows the same relationship but from a different angle.

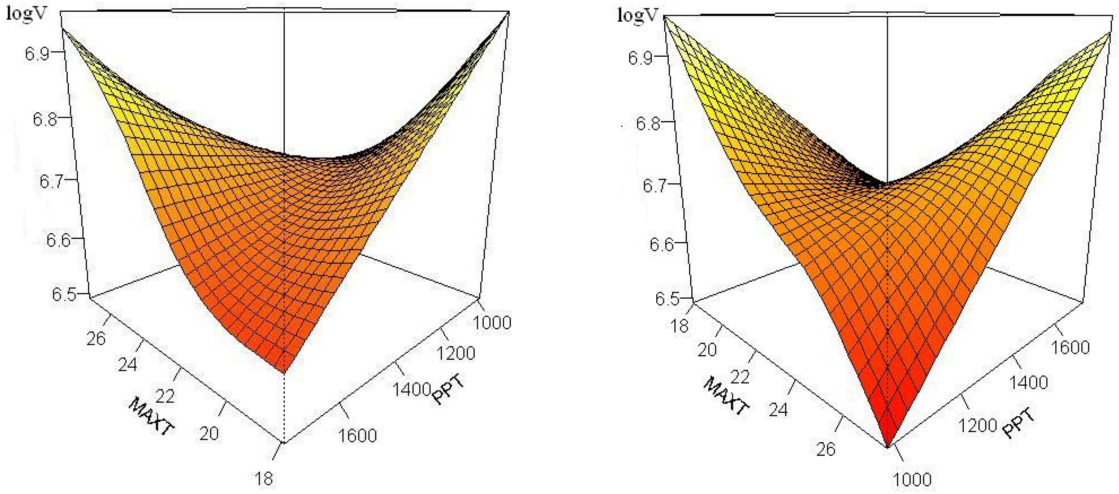

Figure 5.1: Loblolly pine yield response to climate (MAXT & PPT)

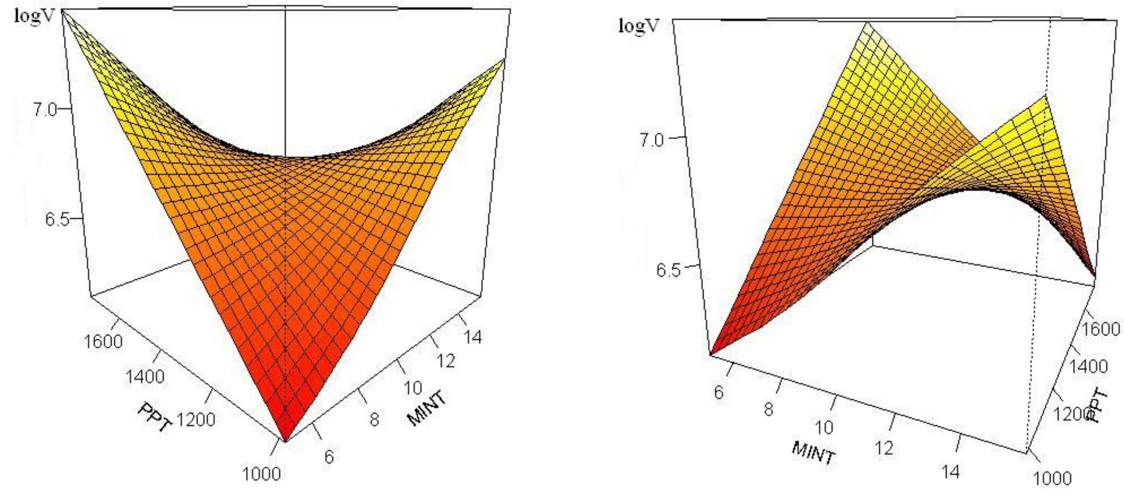

Figure 5.2: Loblolly pine yield response to climate (MINT & PPT)

Using different values of climate variables, the yield sensitivity to climate can be examined. Figure 5.3 shows the yield curves under various climate conditions when other variables are fixed. Note that these yield curves show significant decreases in volume after age 30. They include the effect of past silvicultural treatments. The decrease in volume is probably due to thinning rather than mortality or decreased growth. In the LHS graph, the precipitation is fixed at an average level of 1308mm. As the temperature increases, the yield first increases and then falls. The RHS graph shows the sensitivity to precipitation when fixing the $MAXT = 23.85°C, MINT = 10.82°C$. The yield becomes bigger as the precipitation increases. These graphs show the quantitative impact is relatively small. Note that the slope of the yield curves change when the climate changes. For economic optimization the change in slope may be more important than the change in level.

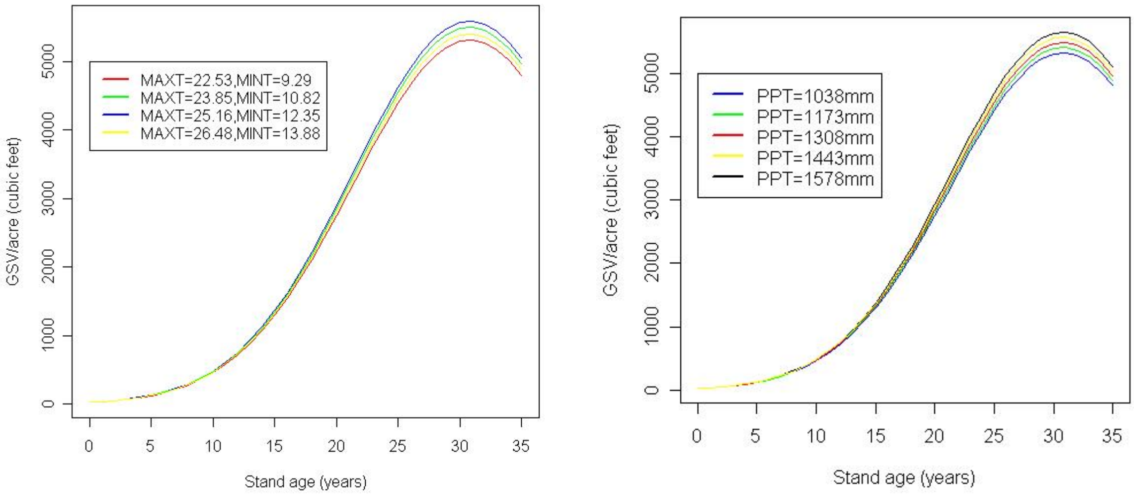

Figure 5.3: SYM Sensitivity to Climate

5.2 The Dynamic Yield Model

5.2.1 Parameter Estimation

Using the same data points, equation (3.4) is fitted using nonlinear least squares in the R language. The estimation results are listed in Table 5.2. All parameters are significant at 0.001 level and the signs on the parameters match expectations: a_2 is positive indicating that the GSV (growing stock volume) is higher on better sites; c_2 is negative, indicating that the age associated with maximum volume of loblolly pine will increase as the site quality gets worse. This is because that the growth rate is lower on poorer sites.

Table 5.2: Coefficient Estimation (An "Typical" Tree)

Coefficients	Estimate	Std. Error	t-value	p-value
a_1	21.99	3.014	7.294	< 0.001
a_2	0.19	0.02	8.586	< 0.001
b_1	-0.63	0.06	-10.337	< 0.001
b_2	-0.002	4.67e-04	-3.998	< 0.001
c_1	108.40	7.590	14.284	< 0.001
c_2	-0.15	0.035	-4.332	< 0.001

The results in Table 5.2 can be viewed graphically. For each level of site productivity, the average GSV per tree is plotted against the age as shown in Figure 5.4. The shape of curves given by the Richard's functional form is the standard shape for growth curve of the tree. As site productivity increases, the curve shifts up indicating faster growth and higher yields.

5.2.2 Growth Adjustment by Stocking Degree

The yield estimation using the GSV curve (Figure 5.4) doesn't consider the tree's surrounding conditions. As stated in Section 3.1.2 the relationship between stocking and yield must be estimated. First the self-thinning line is estimated using all the observations on the full-stocked stands in our dataset (the small circles in Figure

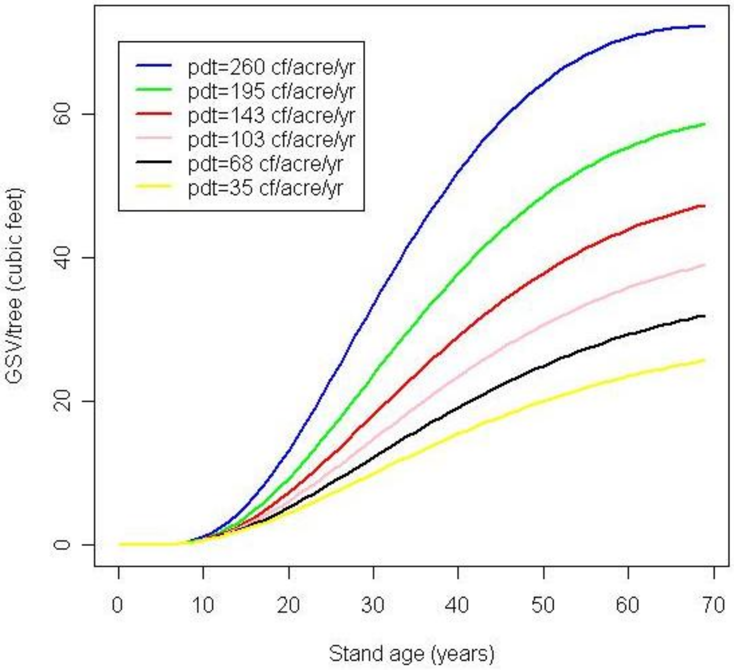

Figure 5.4: GSV Curve by Site Productivity

5.5). The solid line is the estimated self-thinning line. The slope of the line is $-3/2$ following Reinecke's 2/3 power law (Reinecke, 1933).

When the average GSV per tree is known, the maximum trees per acre is calculated from the self-thinning line. The stocking degree can then be easily obtained by dividing observed trees per acre by the maximum trees per acre. Next the average stocking degree is calculated across all the stands in our dataset. According to this average stocking degree, the estimated average GSV per tree is adjusted to its open grown status and the incremental curve for an open grown tree is developed (Figure 5.6). The incremental curve shows the growth rate of an open grown loblolly pine.

5.2.3 Extending the One-tree Model to Stand Level

Recall that the stand yield not tree yield is the input to the bio-economic model. Combining information from the self-thinning line and the incremental curve (Figure 5.5 and Figure 5.6), the dynamic growth path of an acre of forest is simulated, given

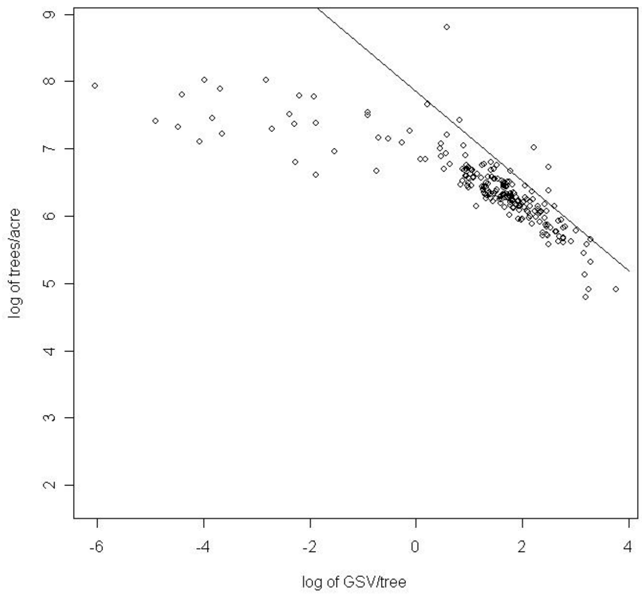

Figure 5.5: Self-thinning Line

a planting density. For example, if a forest manager plants 500 loblolly pines on an acre of land, the GSV is 0 when stand age is 0 and the self-thinning line gives the maximum capacity of the land as infinity. From the incremental curve the growth of an average tree during the first year is calculated. Next based on competition we adjust the per tree volume and sum the adjusted yield of the individual tree to obtain the stand level yield at age 1. The above calculation is repeated to get the stand yield at other ages. Note that as the trees grow, the maximum capacity of the stand may fall below the planting density, meaning the stand reaches the full stocked status. This maximum trees per acre is then used as the stand density to calculate the stand level volume.

Thinning or final harvest can also be included in the growth path. Figure 5.7 provides an example, where the thinnings are conducted at age 21 and 27 respectively.

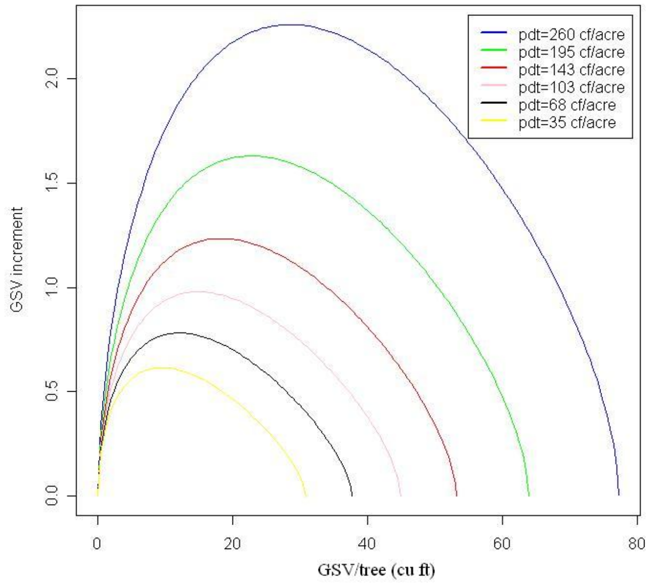

Figure 5.6: GSV Increment by Site Productivity

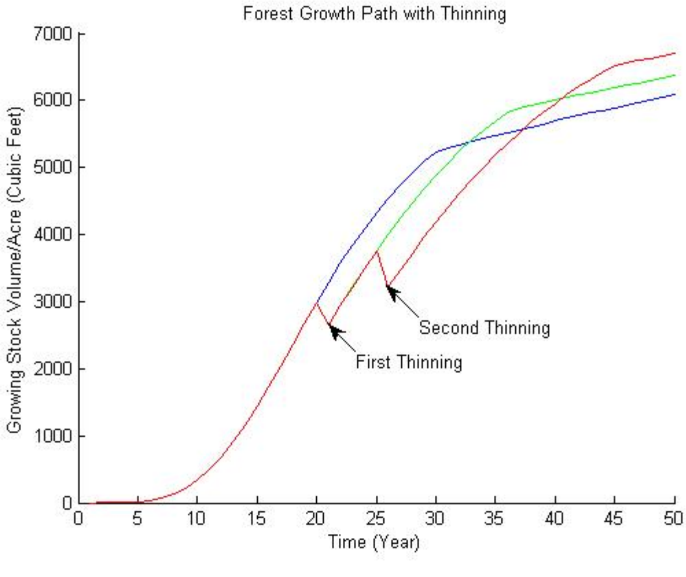

Figure 5.7: Dynamic Growth Path with Thinning

5.2.4 Estimation of the Diameter

In the dynamic yield model, the diameter of an average tree is estimated as a function of the growing stock volume per tree, using the same FIA data set. The functional form is listed in Table 5.5. All the coefficients are significant at 0.001 level. The adjusted R-square of the regression is 0.8636. The fitted curve is shown in Figure 5.8.

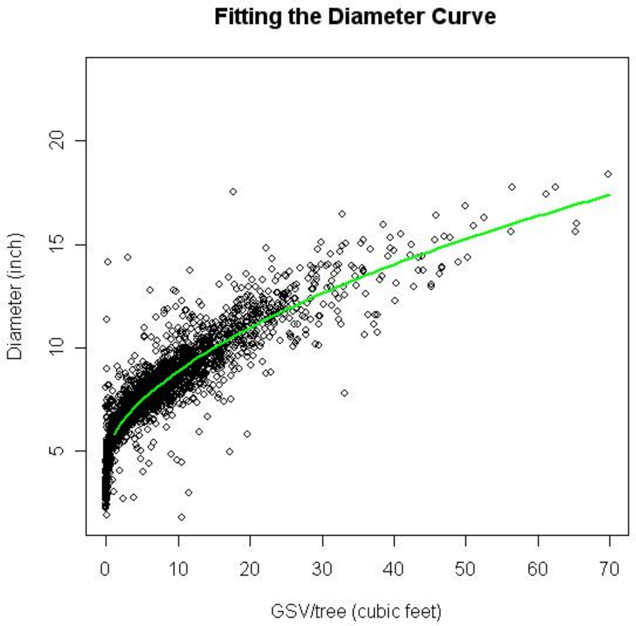

Figure 5.8: The Relationship between Diameter and GSV/tree

5.2.5 The DYM response to Climate

As discussed in Section 3.1.2, the climate influences the growth of the tree through site productivity. A non-parametric model is used to estimate Equation 5.3. Specifically the smooth function "te" is used (see description in Section 3.1.1 and Table 3.1). Figure 5.9 shows the results from estimating Equation 5.3, which gives an idea of the direction of climate impact on the site productivity. But recall that the estimation from Equation 5.3 is not used directly because soil characteristics are not accounted for. Instead the estimation of change in *pdt* is used for examining the climate change impact.

$$pdt = te(MAXT, MINT, PPT) \tag{5.3}$$

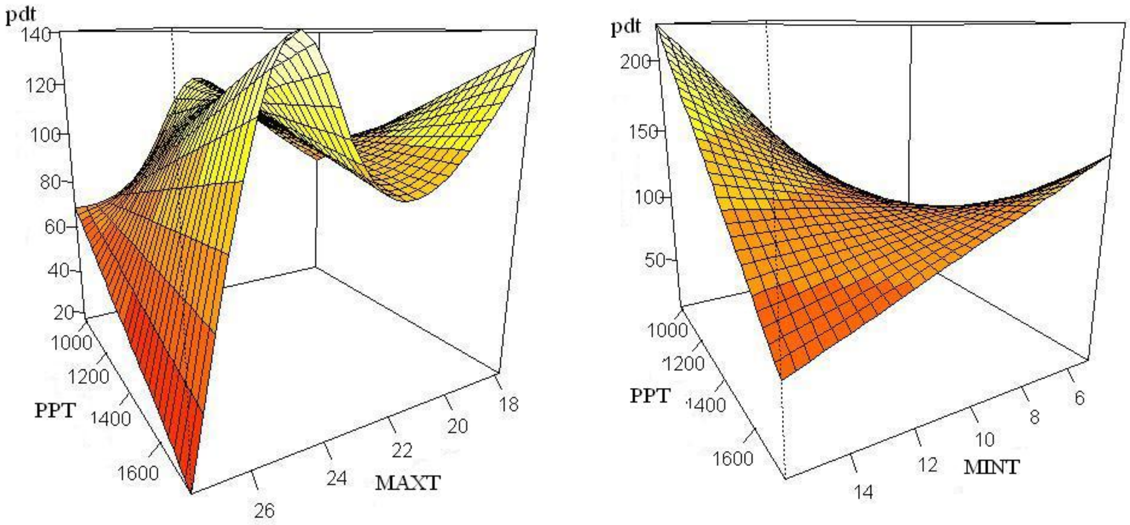

Figure 5.9: Relationship between Site Productivity and Climate Variables

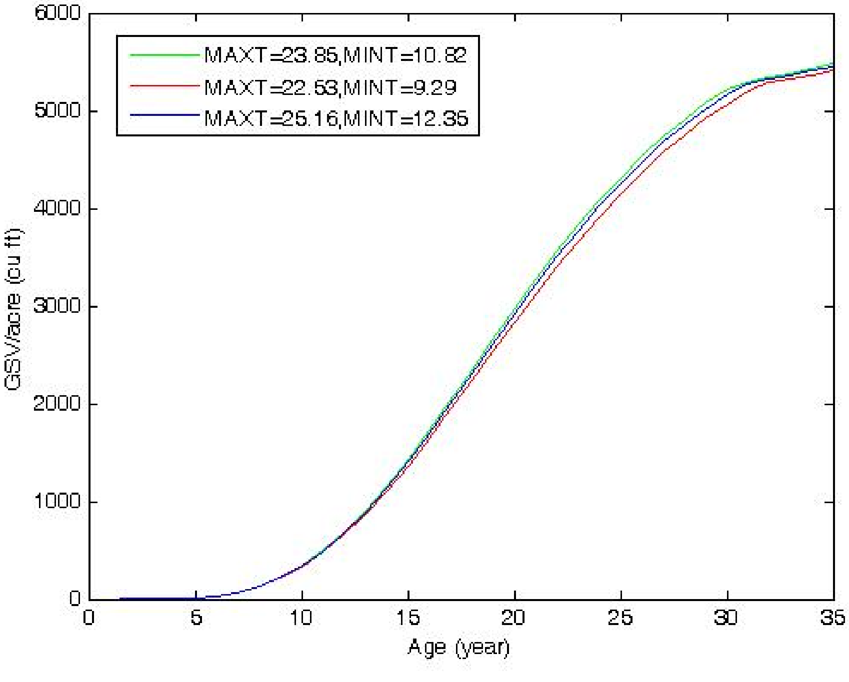

Figure 5.10: DYM Sensitivity to Climate

The same sensitivity analysis is conducted for DYM. Figure 5.10 shows a similar pattern as Figure 5.3, which indicates that the two types of the yield model generate consistent results. The yield of loblolly pine increases until some temperature threshold. DYM predicts a lower threshold than SYM.

5.3 Results from the Price Models

Two aspects of the stumpage prices are considered. The first is the deterministic part where prices depend on the diameter of the tree. The other aspect is the stochasticity of the prices. I provide two ways to capture price stochasticity. For the EF framework, probabilistic simulation is used to randomly draw the prices from a known distribution. For the RO framework the time series price data from Timber Mart-South are used to model the price movement over time as GBM or MRP.

Recall that discrete prices by product are obtained from Timber Mart-South[2]. In order to convert discrete prices into a continuous function I estimate a simple relationship between price and diameter. The coefficient estimation is shown in Table 5.5 and is plotted in Figure 5.11. The coefficient is highly significant and the adjusted R^2 is 0.998.

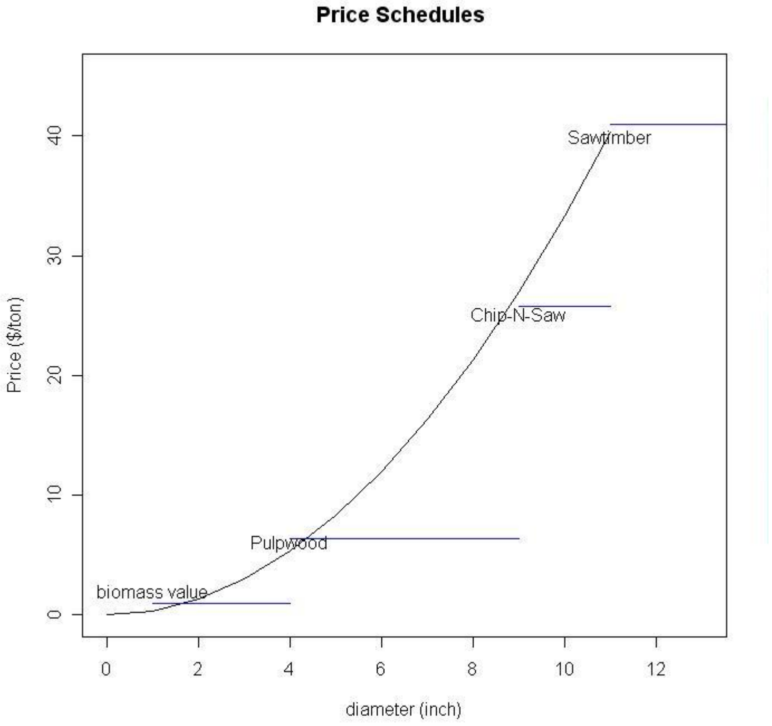

Figure 5.11: Price Function

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[2] Details are in Section 4.2.3

In Section 3.2.1 the random shock on the price was introduced, $e \sim N(0, \sigma_P^2)$. The mean square error (MSE) from the above regression provides an unbiased estimate for σ_P^2. Thus $\hat{\sigma_P^2} = 1.157$. When running the simulation for the EF model, the price shock will be randomly drawn from the normal distribution with a mean of 0 and variance of 1.157.

In the RO framework, prices are typically modeled as GBM or MRP as reviewed in Section 5.3. I first model the time series quarterly real prices for chip-n-saw product. As described in Section 3.2.2, the issue of whether the price process follows GBM or MRP is the same as asking if $c_2 = 0$ in Equation 3.16 using the "Dickey-Fuller" test. The SAS ARIMA procedure is used to perform this test.

Table 5.3 lists the results from the Dickey Fuller test. In the "Single Mean" line, $Pr < Tau = 0.7257 > 0.05$, indicating that it fails to reject the null hypothesis that $c_2 = 0$ and that the data support the assumption of GBM.

Table 5.3: Dickey-Fuller Unit Root Tests

Type	Rho	$Pr < Rho$	Tau	$Pr < Tau$	F	$Pr > F$
Zero Mean	−0.0748	0.6642	−0.33	0.5633		
Single Mean	−2.8447	0.6715	−1.07	*0.7257*	0.60	0.9214
Trend	−1.3889	0.9818	−0.45	0.9845	1.00	0.9675

Next the drift and volatility parameters of the GBM price process are estimated, i.e. μ and σ in Equation 2.7. Using the logarithm of P_t format, p_t, $(\mu - \frac{1}{2}\sigma^2)$ can be estimated as the average values of $p_t - p_{t-1}$. The estimate for σ is simply the standard deviation of $p_t - p_{t-1}$. This can also be done using PROC ARIMA, which gives the estimates for μ and σ as 0.00035 and 0.0034 respectively. The autocorrelation check for white noise indicates that we fail to reject the null hypothesis that the residual is white noise. Table A.1 in Appendix Appendix A shows the results of white noise check. Quarterly estimates were converted to annual ones by multiplying 4 to $\hat{\mu}$ and $\hat{\sigma}$.

After obtaining the estimated prices for chip-n-saw, an adjustment factor (adj) is used to capture the prices for other products.

$$adj = \frac{0.333 \cdot dia^2}{25.8}$$

Where the numerator is from the regression results of the price function described above, dia is the average diameter for other products and the denominator is the average price for chip-n-saw product.

5.4 Results from the Integrated Models

Combining the estimation results from the above sections with the optimization models, I conduct simulations to examine the forest management adaptation to climate change and other risks. Various cases are simulated for the four integrated models, SYM-EF, SYM-RO, DYM-RO and DYM-EF. I start with the base case where no climate change or any other risk is present. Then fire risk, climate change, yield and price risk are added sequentially to examine the marginal and joint effects on an optimal forest manager's behavior and welfare[3]. Table 5.4 lists descriptions for all the cases along with the section in which each case is located. For SYM-EF and DYM-RO, most cases are examined since they are the benchmark models. The SYM-RO and DYM-EF models allow for tests of how sensitive results are to model specification. They also serve as logical links between SYM-EF and DYM-RO. The results of Case 1, 2, and 6 are reported for these two. A real interest rate of 0.04 is used throughout the analysis. Table 5.5 lists the estimated functions and parameter values used in the simulation.

5.4.1 SYM-EF

SYM-EF integrates SYM with the Faustmann framework. The objective of the forest manager is to manage loblolly pine to maximize the net present value. Case 1 is the base case where no climate change or any other risk is considered. The average historical values of the climate variables are used. There are two sub-cases. One is the

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[3] For the producer, welfare and profitability are considered equivalent.

Table 5.4: List of Cases

Case Description	SYM-EF	SYM-RO	DYM-RO	DYM-EF
C1: Base w/o any risk	5.4.1	5.4.2	5.4.3	5.4.4
C2: Fire risk sensitivity	5.4.1	5.4.2	5.4.3	5.4.4
C3: Climate sensitivity	5.4.1		5.4.3	
C4: Climate scenario & Fire risk	5.4.1		5.4.3	
C5: Price/yield risk only	5.4.1	5.4.2	5.4.3	
C6: Price/yield risk & fire risk	5.4.1	5.4.2	5.4.3	5.4.4
C7: Price/yield risk w/ climate change	5.4.1			
C8: Price/yield risk & fire risk & climate change	5.4.1		5.4.3	

Table 5.5: Functional forms and base values of parameters used in simulation

Type	Function and parameter values
Average fire occurrence rate	Constant occurrence rate: $\lambda = \frac{t_a}{50}$ Increasing occurrence rate: $\lambda = \frac{t_0 \cdot D + t_1 \cdot A}{2500}$ Decreasing occurrence rate:$\lambda = \frac{t_0 \cdot D + t_1 \cdot (50-A)}{2500}$
Planting costs ($/acre)	Damaged land: $C_1 = 300 + 0.05 \cdot D$ Undamaged land: $C_2 = 300 + 0.08 \cdot D$
Diameter (Inch)	SYM: $dia = 5.29 + 0.16A - 0.21D$ DYM: $dia = 5.84 + 0.63 \cdot lnv + 0.14 \cdot lnv^2 + 0.06 \cdot lnv^3 + 0.01 \cdot lnv^4$
Price ($/ton)	$P = 0.333 \cdot dia^2$
Timber salvage (Ratio)	$sa = 0.9936 \cdot (1 - e^{-200/D})$
Discount rate (r)	$r = 0.04$

traditional Faustmann case where rotation age is the only management decision and stand density is fixed at 500 trees per acre. The second row of Table 5.6 represents the other sub-case where the forest manager can choose stand density in addition to rotation age. Table 5.6 shows that when stocking is considered as a decision variable, the forest manager would be better off by planting more trees and harvesting a little later.

Case 2 examines the optimal management and welfare when fire risk is present. Three scale parameters, t_0, t_1 and t_a are introduced in the fire risk function as shown in Table 5.5. Since they enter the function multiplicatively, changes in them are

Table 5.6: Case 1 of SYM-EF (Base case)

Case	T^*	D^*	EPV^*
One decision variable	29.00	500(fixed)	2012
Two decision variables	29.18	686	2051

directly and linearly related to changes in the average fire occurrence rate. Thus a doubling of t_0 (t_1) results in a doubling of the average occurrence rate for each stand density (age). For the decreasing case, fire occurrence rate decreases as the stand ages and the rate of decrease is controlled by t_1. For the increasing case, occurrence is positively related to age and is also controlled by t_1. For both falling and rising cases, the occurrence rate is an increasing function in stand density, thus an increase in t_0 results in steeper slope on stand density. For the constant occurrence case, an increase in t_a increases fire occurrence equally across all ages and stand densities.

Table 5.7: Case 2.1 of SYM-EF: Fire Risk Sensitivity (decreasing occurrence)

t_0	t_1	T^*	EPV^*
1	0.6	28.71	1608
3	0.6	28.47	1459
5	0.6	28.22	1317
7	0.6	27.98	1182
1	0.6	28.71	1608
1	1.5	28.36	1170
1	2.5	27.91	737
1	4.5	26.86	15

Table 5.7 shows the one-decision-variable case using a decreasing fire occurrence. The presence of fire risk lowers the rotation age relative to the base case. The reduction becomes larger as t_0 or t_1 increases, and ranges from 0.3 to 2.2 years. These results mirror the simulation results obtained by Reed (1984); Amacher et al. (2005a). The last column in the table shows that expected profits fall dramatically as the fire occurrence rate rises.

But when density control is included (Table 5.8), the optimal rotation age no longer declines monotonically with t_0. In both decreasing and increasing occurrence

Table 5.8: Case 2.2 of SYM-EF: Fire Risk Sensitivity

Fire occurrence Rate	t_0	t_1	T^*	D^*	EPV^*
Decreasing	1	0.6	28.76	593	1617
	3	0.6	28.47	422	1464
	5	0.6	28.35	253	1369
	7	0.6	28.42	88	1324
	1	0.6	28.80	593	1617
	1	1.5	28.40	570	1174
	1	2.5	27.93	534	737
	1	4.5	26.81	412	18
Increasing	1	1	28.19	614	1668
	1	2	27.43	607	1437
	1	4	26.02	592	1064
	1	5	25.36	585	913
	1	1	28.19	614	1668
	2	1	28.03	533	1582
	5	1	27.80	286	1407
	8	1	27.95	42	1342
Constant occurrence	$t_a = 1$		27.99	658	1276
	$t_a = 2$		26.73	617	678
	$t_a = 3$		25.42	553	213

cases, the optimal rotation age falls and then rises as t_0 increases. The forest manager can engage in loss prevention by lowering stand density instead of lowering rotation age.

Figure 5.12 compares the percentage of profit losses for the one-decision-variable and two-decision-variable cases using decreasing occurrence rate. The two curves diverge as fire risk increases. The role of additional adaptive actions becomes more important at higher risk levels.

The results across different fire occurrence schedules can be compared. But the results are comparable only if the value of m^* (the aggregate fire risk from time zero to the optimal rotation age) is approximately the same for the corresponding fire occurrence schedules. Not comparing in this manner would make it difficult to

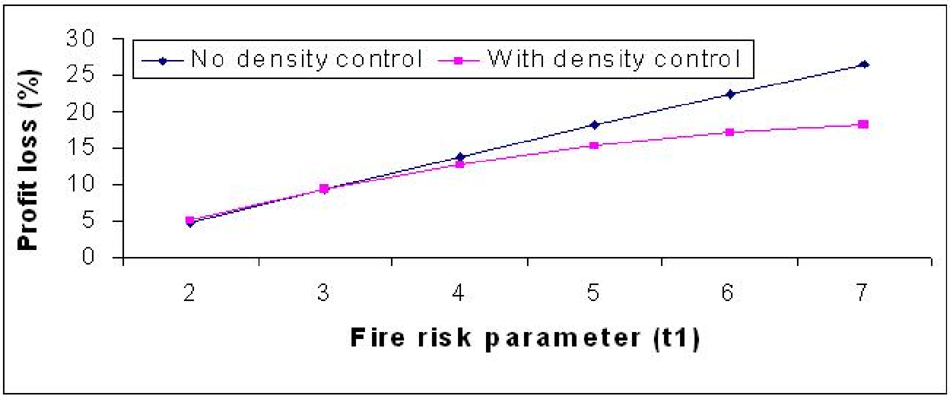

Figure 5.12: The Role of Adaptation

Table 5.9: Results Comparison across Fire occurrence Rates

Fire occurrence Rate	t_0	t_1	T^*	D^*	EPV^*	m^*
Decreasing	1	0.6	28.76	593	1617	0.31
Increasing	5	1	27.80	286	1407	0.31
Decreasing	3	0.6	28.47	422	1464	0.39
Increasing	1	2	27.43	607	1437	0.37
Decreasing	1	1.5	28.40	570	1174	0.67
Increasing	1	5	25.36	585	913	0.70
Decreasing	1	2.5	27.93	534	737	1.07
Constant	$t_a = 2$		26.73	617	678	1.07
Increasing	1	4	26.02	592	1064	0.60
Constant	$t_a = 1$		27.99	658	1276	0.57

attribute changes in the optimal decision variables to changes in the shape of the occurrence path alone; changes would also be due to differences in the m^*. Table 5.9 pairs up the results based on the value of m^*. The optimal rotation age is always larger for decreasing occurrence rate than for the increasing occurrence rate and constant occurrence rate. A decreasing occurrence rate implies that the expected marginal cost of continuing a rotation falls over time due to the decreasing fire risk, thus inducing the forest manager to choose a higher rotation age. Similarly, the optimal rotation is shorter using the increasing occurrence than using the constant occurrence. An increasing occurrence rate implies that the expected marginal net benefit of waiting to harvest falls more rapidly as a stand ages than when the fire occurrence rate is constant.

Table 5.10 shows how would a forest manager respond to the perturbed climate optimally (Case 3). As can be seen, the climate perturbation has little impact on optimal rotation and stand density. This is due to the small impact of gradual climate change on the forest yield (see Figure 5.3). At an average level of precipitation, a moderate increase in average temperature would benefit the forest manager. When the temperature increase becomes relatively large, the expected profit goes down. When fixing the average temperature, an increase in the precipitation (in the range of 1038mm to 1578mm) improves profitability.

Table 5.10: Case 3 of SYM-EF: Climate Sensitivity

MINT	MAXT	PPT	T^*	D^*	EPV^*
9.29	22.53	1308	29.20	685	1977
10.82	23.85	1308	29.18	686	2051
12.35	25.16	1308	29.18	686	2089
13.88	26.48	1308	29.19	685	2014
10.82	23.85	1038	29.20	685	1986
10.82	23.85	1173	29.19	685	2018
10.82	23.85	1308	29.18	686	2051
10.82	23.85	1443	29.18	686	2084
10.82	23.85	1578	29.17	686	2116

In Case 4, I examine optimal forest management and welfare under the future climate scenarios from Hadley 3 model[4]. Previous literature suggests that there is a causal link between gradual climate change and disturbances such as fires and hurricanes (Kurz et al., 1995; Peng and Apps, 1999; Calzadilla et al., 2005). The change in temperature and precipitation can influence the occurrence, timing, frequency, duration, extent, and intensity of the disturbances (Baker, 1995). Forest fire disturbance has been recognized as a regime that is highly sensitive to possible future climate change (Peng and Apps, 1999). Flannigan and Van Wagner (1991) used General Circulation Models (GCMs) and determined that fire danger would increase by nearly 50% across Canada with climate warming.

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[4] Description is in Section 4.2.2

Table 5.11: Case 4 of SYM-EF: Future Climate Scenario

Region	Climate Scenario	T^*	D^*	EPV^*
Coastal Plain	Current	28.82	588	1379
	A_1	28.87	584	1226
	A_2	28.85	586	1285
	B_1	28.86	585	1255
	B_2^*	28.75	566	1262
Mountain	Current	28.87	585	1247
	A_1	28.85	586	1292
	A_2	28.85	586	1287
	B_1	28.85	586	1290
	B_2^*	28.78	564	1195

Recall that the Hadley B_2 scenario predicts warmer and dryer climate in the future. In this dissertation a 20% increase in fire occurrence rate is associated with the Hadley B_2 to create a B_2^* scenario. For the other three Hadley scenarios which predict warmer and wetter future climate, the fire risk is fixed at the default level ($t_0 = 1, t_1 = 0.6$). I ran the simulations for different regions using local climate data and site characteristics.

Generally, Table 5.11 shows that the profitability in the coastal plain may decrease in the future climate scenarios. The loss is largest under A_1 scenario ($153/acre or 11%) and mildest under A_2 scenario ($94/acre or 7%). However there is almost no impact on the optimal rotation and stand density except for B_2^* scenario. Since fire risk is assumed to increase by 20% under B_2^* scenario, the stand density and rotation age both decrease to adapt to the higher fire risk.

In contrast, there is some potential for economic gains in the mountain area because the future climate increases yield in that area. But these positive effects are offset by higher fire risk in the B_2^* scenario. Accordingly the optimal rotation and stand density decline.

The impact of climate change will vary with site conditions across the South. I have shown that changes by physiographic region are significantly different. This technique could be used to examine responses by other spatial criteria, e.g., state, county, or latitude.

Case 5-8 repeated the simulations above but added stochastic yield and price. Recall that yield stochasticity is included using bootstrapping and price is assumed to follow a normal distribution. Figure 5.13 and 5.14 show the comparison between case 6 (price/yield risk & fire risk) with case 2 (fire risk only). In Figure 5.13 the left y-axis and the bars represent stand density. The right y-axis and the lines represent expected present value. As can be seen, the EPV of case 6 is lower than that of case 2 at each fire risk level, indicating that adding price/yield stochasticity decreases profitability. Facing such uncertain future prices and yields, the forest manager would adapt by producing a larger quantity of timber to offset the effects of yield and price risk. Figure 5.14 shows that the impact on optimal rotation age is small and mixed. Similar results are found for other stochastic price/yield cases and detailed results are listed in Table B.1 through B.4 in the Appendix.

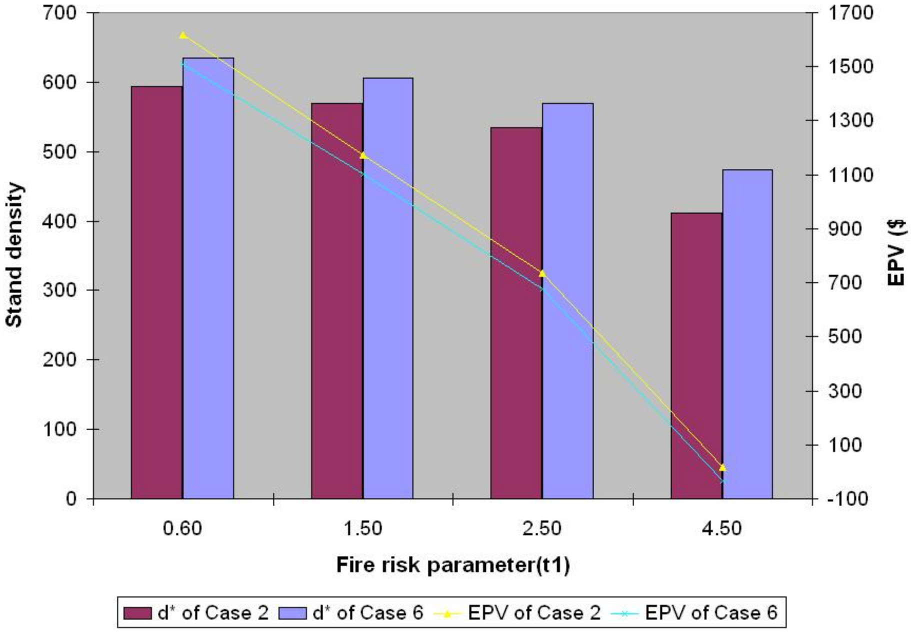

Figure 5.13: Impact of stochastic yield and price on stand density and profitability

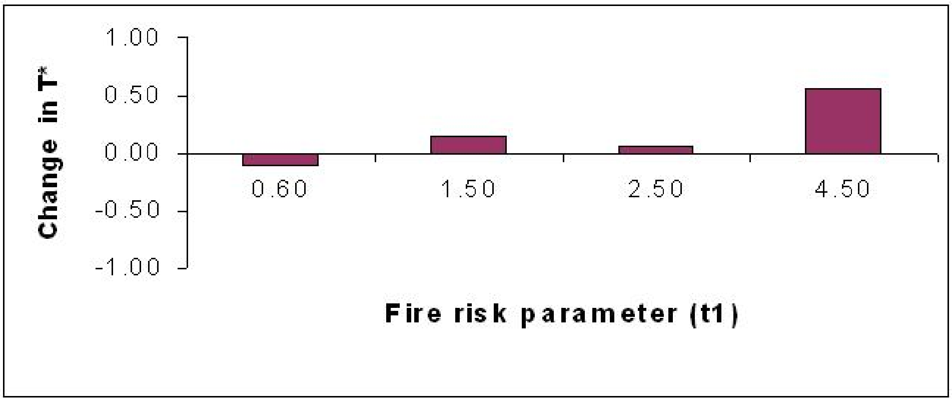

Figure 5.14: Impact of stochastic yield and price on optimal rotation age(Case 6 v.s. Case 2)

5.4.2 SYM-RO

The second integrated model being examined is SYM-RO where SYM is imported into RO framework. As stated in Section 3.2.2, stand density needs to be assumed as fixed over time because SYM does not capture the stand dynamics. Recall that this model is used to examine the sensitivity of the results to different optimization criteria.

Four cases are simulated for SYM-RO: no risk (Case 1), decreasing fire risk only (Case 2), price risk only (Case 5), and price risk with decreasing fire risk (Case 6). The results are listed in Table 5.12 and 5.13. The number in the parenthesis is the standard deviation.

Table 5.12: Case 1 and 2 of SYM-RO (decreasing occurrence)

t_0	t_1	T^*	D^*	$EPV^*(std)$
0	0	29	654	2053(0)
1	0.6	29	561	1651(536.6)
3	0.6	28	388	1495(556.3)
5	0.6	28	220	1407(502.6)
7	0.6	28	57	1347(449.9)
1	1.5	28	531	1216(721.4)
1	2.5	28	495	814(744.2)
1	4.5	27	366	134(717.6)

Table 5.13: Case 5 and 6 of SYM-RO (decreasing occurrence)

t_0	t_1	$T^*(std)$	D^*	$EPV^*(std)$
0	0	29.58(0.60)	660	2420(1758.1)
1	0.6	29.27(0.59)	560	1881(1608.7)
3	0.6	29.08(0.58)	380	1606(1326.6)
5	0.6	28.75(0.62)	130	1479(1244.9)
7	0.6	28.83(0.71)	50	1352(1220.8)
1	1.5	28.86(0.63)	530	1394(1515.9)
1	2.5	28.29(0.57)	490	926(1370.1)

Comparing Table 5.12 with 5.13 shows that the mean EPV is higher and optimal rotation age is longer in Table 5.13. This is reasonable because Table 5.13 incorporates the stochastic prices as a GBM. In the RO modeling, the decision maker can observe the behavior of the stochastic source dynamically. This may increase the marginal benefit of waiting and thus induce the forest manger to harvest later. As can be seen from the comparison of the two tables, the gain in EPV decreases as the fire risk increases. Fire risk and stochastic prices seem to have opposite effects on EPV. When fire risk goes too high, the negative effect from fire risk dominates the positive effect from stochastic prices.

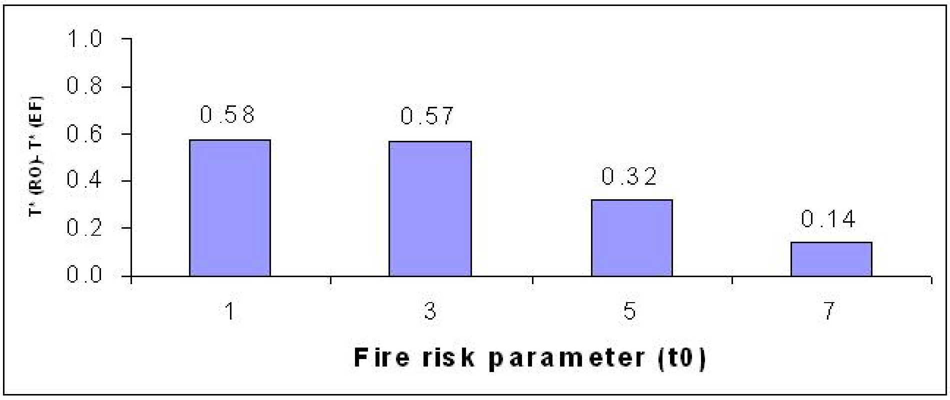

Figure 5.15: Comparison of optimal rotation between SYM-EF and SYM-RO

Some comparisons are made between SYM-EF and SYM-RO to test the sensitivity of these results to the optimization criteria. Figure 5.15 and 5.16 plot the

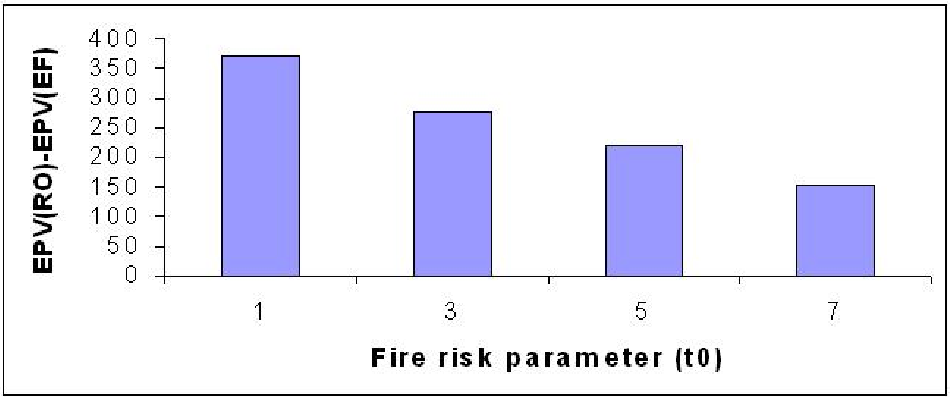

Figure 5.16: Comparison of expected profit between SYM-EF and SYM-RO

case 6 (stochastic price w/ fire risk) of both models. From the above figures, we can observe that the EPV is larger and optimal rotation is longer from SYM-RO than that from SYM-EF. Waiting would be more valuable in the RO framework and thus induces the forest manager to lengthen the rotation age. The Faustmann model would potentially underestimate the expected profit because it does not incorporate intertemporal adaptation to future events. As fire risk increases the difference in EPV becomes smaller because the effect of fire risk dominates at high risk level of fire.

Another obvious difference between SYM-EF and SYM-RO is the effect of stochastic prices. Assuming the stochastic prices to follow a normal distribution in the Faustmann framework reduces optimal expected profits. Modeling the prices as a GBM in the RO framework benefits the forest manager. Two explanations are possible. One lies in the static nature of the Faustmann method. Thus forest managers could not take intertemporal dynamic adaptations. The second is the assumption about the price process. The normal distribution assumption implies that prices fluctuate around the mean while GBM has a drift term. Although the estimated drift is a small positive number, it still implies a possible upward path for the prices. Delaying timber harvest when the price goes up results in higher profits. But note that although the presence of stochastic prices in the RO framework leads to higher expected profits, it also produces larger standard deviations.

5.4.3 DYM-RO

DYM-RO is one of the two benchmark models. It integrates the DYM with the RO framework to optimize forest management and welfare in the presence of various risks. The forest manager is assumed to seek optimal management decisions to maximize the value function (i.e. Equation 3.9). By default planting density, thinning intensity and site productivity are assumed to be 500 trees/acre, 0.2 and 143 cu ft/acre/year respectively.

Table 5.14: Case 1 of DYM-RO (Base case)

Case	T^*	$thin1^*$	$thin2^*$	EPV^*
One decision variable	28	na	na	1702
With thinning	36	21	26	2250

Table 5.15: Case 2.1 of DYM-RO: Fire Risk Sensitivity

t_0	t_1	T^*	$EPV^*(std)$
0.01	0.6	27	1279(541.0)
0.05	0.6	27	1039(642.2)
0.1	0.6	26	710(710.2)
0.2	0.6	24	271(711.1)
0.01	1.5	27	897(679.6)
0.01	2.5	26	462(752.2)
0.01	4.5	24	-131(707.7)

Table 5.14 lists the results for Case 1 where no risk is present. The first row shows the one-decision-variable case where neither thinning nor post-fire salvage is assumed. When thinning becomes a management option, the forest manager has the flexibility to choose thinning age(s) and thinning frequency in addition to rotation age. The salvagable proportion after fire is assumed to depend on stand density (see Table 5.5). As can be seen, the optimal rotation age is 8 years longer if thinning is conducted and the corresponding EPV is much higher. The value of thinning is simply the difference of the two EPVs. Therefore even in the absence of any risk, thinning can benefit the forest manager. This result is consistent with typical silviculture on pine plantations in the southern U.S.

In case 2, fire risk is incorporated in the same manner as in SYM-EF. Table 5.15 lists the results for one-decision-variable case. The presence of fire risk lowers the optimal rotation age. The reduction becomes larger as the average fire occurrence rate increases. The expected profit drops sharply as fire risk increases.

Table 5.16: Case 2.2 of DYM-RO: Fire Risk Sensitivity

Fire occurrence rate	t_0	t_1	T^*	$thin1^*$	$thin2^*$	$EPV^*(std)$
Decreasing	0.01	0.6	36	21	26	1790(625.8)
	0.05	0.6	35	21	26	1515(727.7)
	0.1	0.6	35	21	26	1142(858.7)
	0.2	0.6	34	21	26	557(929.8)
	0.01	1.5	36	21	26	1329(815.3)
	0.01	2.5	36	21	26	868(922.2)
	0.01	4.5	35	21	26	39(937.6)
Increasing	0.01	1	34	21	26	1834(574.5)
	0.01	2	33	21	26	1585(651.9)
	0.01	4	31	21	26	1192(739.5)
	0.01	5	31	21	26	918(772.2)
	0.1	1	34	21	26	1197(807.2)
	0.2	1	33	21	26	643(869.0)
	0.3	1	31	15	21	184(826.9)
Constant	$t_a = 1$		34	21	26	1409(785.1)
	$t_a = 2$		33	21	26	671(852.5)
	$t_a = 3$		32	21	26	165(862.0)

Table 5.16 presents the results of Case 2, where management flexibility is extended to include thinning treatment, assuming that forest managers can choose to thin once or twice. In silviculture, thinning is the intermediate cuttings that are aimed primarily at controlling the growth of stands by adjusting stand density or species composition. In this model thinning has an additional role in reducing fire risk because the average occurrence rate of fire (λ) is decreasing as stand density declines. The value of the thinned trees are assumed to be reduced by 10%, due to thinning costs. The RO model searches for the optimal thinning frequency, thinning age and final harvest year for forest managers to maximize their value functions. Thinning intensity is first

set at 0.2, i.e. 20% of the trees on the stand are removed during thinning treatment. The first thinning is assumed to occur after year 15 and the spacing between the two thinnings should be at least 5 years.

Table 5.16 shows that as the average fire occurrence rate increases, the optimal rotation age is either unchanged or decreases slightly. Two thinnings are optimal in the fire risk range examined. The thinning ages are robust across all fire risk rates (first thin at year 21 and second thin at 26) except for the increasing occurrence with $t_0 = 0.3, t_1 = 1$. The thinning ages decrease to 15 and 21 in that case, which indicates that high risk of fire has the potential to lower thinning ages as well.

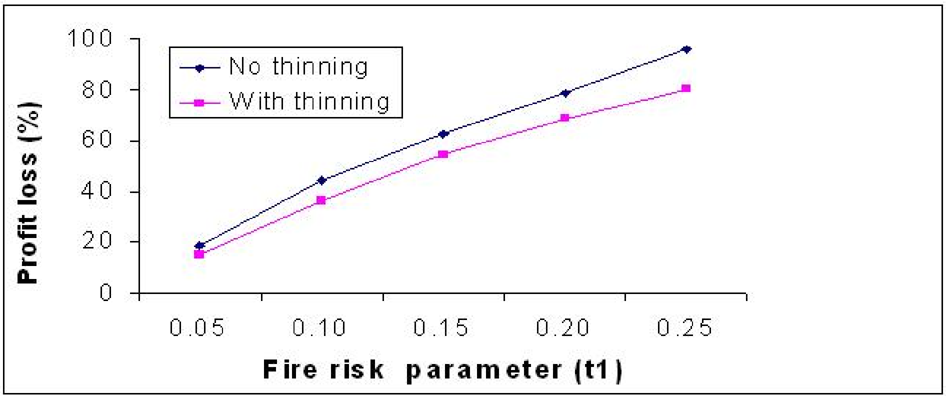

Figure 5.17: The Role of Adaptation (Thinning)

Examining the optimal rotation age more closely and comparing the decreasing occurrence case in Table 5.16 with Table 5.15, we can observe that the rotation age decreases as fire risk increases in both tables but the variation in rotation ages is smaller with thinning than it is in the no-thinning case. Forest managers can adapt to fire risk by conducting thinning in addition to lowering the rotation age when thinning is considered as a management option.

To study the role of thinning in the presence of fire risk, I plot the percentage of mean profit loss versus the fire risk level. Figure 5.17 shows that the red line (no thinning) is always above the blue one. At each fire risk level, forest managers would lose less if they conduct thinning. More importantly, the two curves diverge as fire risk increases. This implies that thinning becomes even more important at higher levels of fire risk.

Table 5.17: Sensitivity to thinning intensity

Intensity	T^*	$thin1^*$	$thin2^*$	$EPV^*(std)$
0.2	36	21	26	1790(625.8)
0.25	38	21	26	1933(604.1)
0.3	40	21	27	2005(616.8)
0.35	41	21	29	2022(618.1)
0.4	40	21	30	1991(625.3)
0.45	40	21	33	1962(617.8)

Thinning intensity and planting density are the other management options that are included as parameters rather than endogenous decision variables. Table 5.17 and 5.18 present the sensitivity analyses on these two parameters. t_0 and t_1 are fixed at a relatively low level ($t_0 = 0.01$ and $t_1 = 0.6$).

As shown in Table 5.17 the optimal rotation age and expected profit both first rise and then fall as the thinning intensity increases. More intensive thinning could have three effects: (1) The stand volume decreases more immediately, (2) The trees left on the stand grow faster and (3) fire risk is lowered (since stand density is lowered further). When thinning intensity increases from a low level, the second and third effects may dominate the first effect, increasing the profitability and rotation age. But if the intensity goes too high, the first effect would dominate and thus lowers the profit and rotation age. The timing of first thinning is not affected but the second thinning is delayed, which is intuitive. The results in Table 5.17 suggest that the optimal thinning intensity is 35%.

To test if this optimal thinning intensity holds under a different fire risk level, I ru n the simulations using a relatively high risk level ($t_0 = 0.1$, $t_1 = 0.6$). Table B.5 in the Appendix show the same pattern. The optimal thinning intensity is 0.35 in both fire risk scenarios.

Similar sensitivity analysis is conducted on planting density to find the optimal decision. Table 5.18 lists five choices of planting density, ranging from 400 trees/acre to 600 trees/acre. A thinning intensity of 35% is used. The simulation relusts show that at the current level of fire risk ($t_0 = 0.01, t_1 = 0.6$), it is optimal to choose 550

Table 5.18: Sensitivity to planting density

Planting density	T^*	$thin1^*$	$thin2^*$	$EPV^*(std)$
400	39	24	31	1892(595.6)
450	40	23	30	1999(596.7)
500	41	21	29	2022(618.1)
550	41	21	27	2029(624.7)
600	40	21	26	1998(660.6)

trees per acre. At a relatively high fire risk ($t_0 = 0.1, t_1 = 0.6$), the optimal planting density is reduced to 500 trees per acre (see Table B.6 in the Appendix).

Table 5.19: Case 4 of DYM-RO: Simulation Results under Future Climate Scenarios

Region	Climate Scenario	T^*	$thin1^*$	$thin2^*$	$EPV^*(std)$
Coastal Plain	Current	37	21	26	1514(521.3)
	A_1	37	21	26	1446(492.8)
	A_2	37	21	26	1396(516.1)
	B_1	37	21	26	1403(505.8)
	B_2^*	36	21	26	1356(520.8)
Mountain	Current	37	21	26	1423(486.2)
	A_1	36	21	26	1591(552.6)
	A_2	36	21	26	1591(539.4)
	B_1	36	21	26	1598(523.6)
	B_2^*	36	21	26	1454(569.8)

In Case 4 of DYM-RO, the impact of climate change and associated fire risk on forest management and welfare are simulated as in SYM-EF with similar results (Table 5.24). In the mountain area, the simulated optimal rotation age under future climate scenarios is 1 year shorter and there is no change in the thinning ages. But profits increase consistently under A_1, A_2 and B_1, which is consistent with the results of SYM-EF. For the B_2^* scenario, the DYM-RO predicts a slight gain even though a 20% higher fire risk is associated with this scenario. Recall that Flannigan and Van Wagner (1991) predicted about 50% increase in fire risk across Canada with climate warming. If the future risk in the South also increases this much, the positive effects of gradual climate change would likely be more than offset by the negative effects of fire risk.

For the Coastal Plain, the simulation results of DYM-RO show that the largest profit loss occurs under the B_2^* (\$158/acre) which is about 10%. The current climate in the Coastal Plain is warm and a warmer and drier future climate decreases yield. A higher fire risk would also lower expected profits. The optimal rotation under the B_2^* scenario is shorter.

Table 5.20: Case 5 of DYM-RO (Price risk only)

Case	$T^*(std)$	$thin1^*(std)$	$thin2^*(std)$	$EPV^*(std)$
One decision variable	38.90(9.81)	na	na	1602(1670.2)
Two decision variables	36.4(1.17)	21(0.07)	26(0.07)	2366(1890.7)

Case 5 examines the impact of GBM stochastic prices without fire risk. Table 5.20 compares the no-thinning with thinning case. The optimal rotation age in the no-thinning case is even longer than that with thinning, but note that the standard deviation of the optimal rotation age is much higher in the no-thinning case. Figure 5.18 shows the distribution of the optimal rotation under both cases. In the no-thinning case (the RHS graph) the majority of the optimal rotation ages occur at either age 28 or age 48. This may be due to the nature of the GBM price process. The price data from Timber Mart-South suggest a non-stationary GBM with a very small drift and a relatively large variance. Without thinning the optimal rotation choice is driven by expected value increase relative to the interest rate. With high price variance these results could be volatile. With thinning the manager can better control the value increase of the stand.

To test if the results of the no-thinning case are sensitive to the volatility term, I conducted additional simulations with smaller variance, i.e. $\sigma = 0.05$ instead of 0.117. Figure 5.19 shows that the optimal rotation falls in the range of 27-30. Lower price risk decreases the variance of the rotation age.

The simulated results under case 5 and 1 are compared in Table 5.21 (thinning included). The table shows that the optimal rotation age is longer and the expected profit is higher when stochastic prices are present. This is as expected since the essential property of the RO is the decision-maker's ability to utilize all information available at the time when the decision is taken. The forest manager would wait to

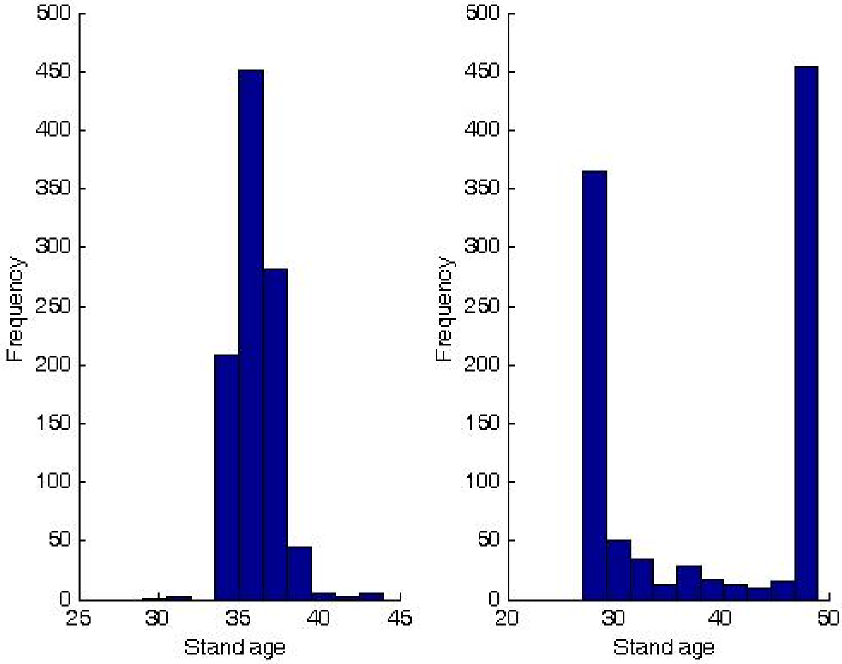

Figure 5.18: The Distribution of Optimal Rotation with (LHS graph) and without (RHS graph) thinning

Table 5.21: Comparison of Case 5 and Case 1 of DYM-RO (Thinning included)

Case	$T^*(std)$	$thin1^*(std)$	$thin2^*(std)$	$EPV^*(std)$
C1: Thinning w/o risk	36	21	26	2250
C5: Thinning w/ price risk	36.4(1.17)	21(0.07)	26(0.07)	2366(1890.7)

observe the prices in the future and decide accordingly. The optimal EPV in case 5 has a very large variance. This is probably due to the nature of the price process again, which leads to some extreme values (see Figure 5.20). But the majority of the simulation results fall in the reasonable range.

As seen from the above analyses, the effect of fire risk alone would shorten the rotation age while the presence of stochastic prices would lengthen it. Case 6 incorporates both fire risk and price risk. The results are presented in Table 5.22 and 5.23. In Table 5.22, note that there is a big drop in the optimal rotation age when

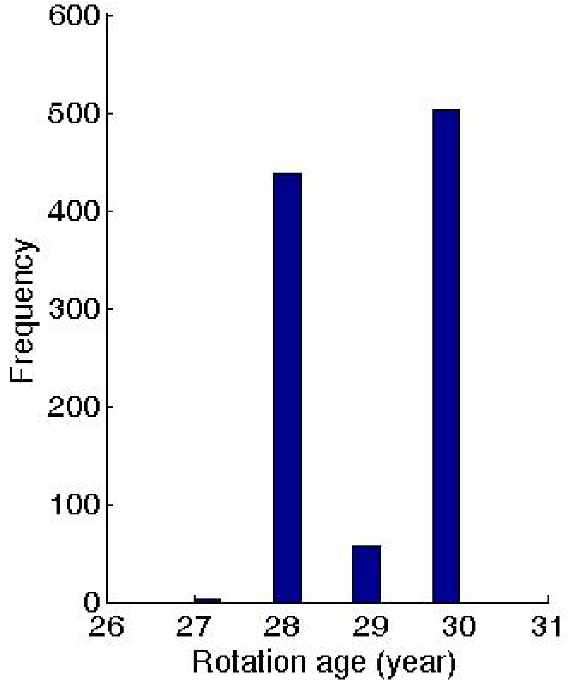

Figure 5.19: The distribution of optimal rotation age at lower price risk (No-thinning case)

Table 5.22: Case 6.1 of DYM-RO: Fire Risk Sensitivity with Stochastic Prices

t_0	t_1	$T^*(std)$	$EPV^*(std)$
0.01	0.6	38.96(9.76)	1222(1573.3)
0.1	0.6	37.98(10.22)	697(1354.6)
0.2	0.6	28.37(2.06)	426(1163.7)
0.01	1.5	38.64(10.00)	811(1322.7)
0.01	2.5	38.11(10.24)	559(1328.9)
0.01	4.5	27.91(1.89)	-12(1056.4)

the fire risk increases to a very high level. The large fire risk would make the waiting potentially costly and leading early harvest. Thus we don't observe the long rotations noted earlier in the RHS graph of Figure 5.18.

Table 5.23 incorporates thinning and presents the sensitivity analysis with fire risk using decreasing, increasing and constant occurrence rates. The results show similar patterns as the fire-risk-only case (Case 3 in Table 5.16). The difference is

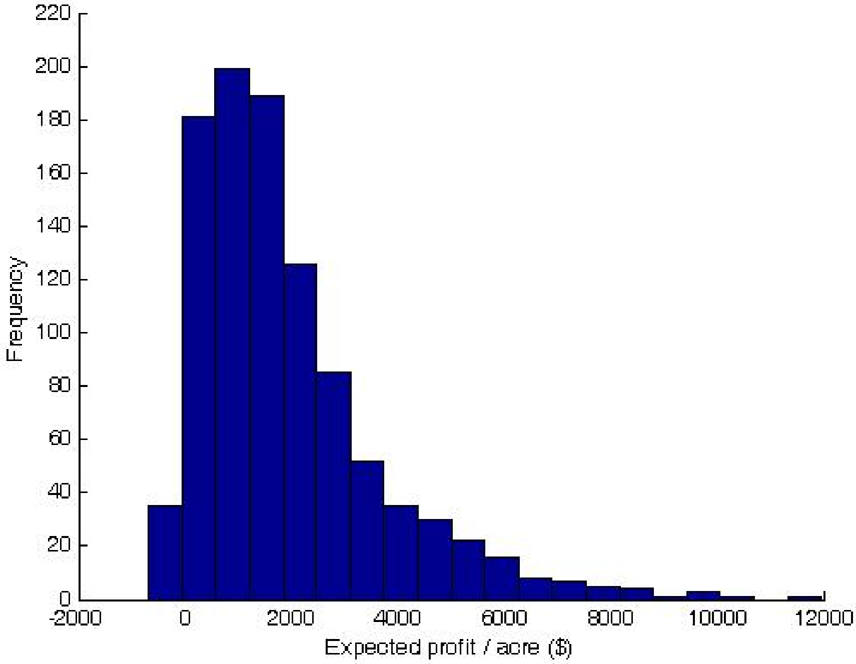

Figure 5.20: The Distribution of Expected Profit (Case 5 with thinning)

that the optimal rotation is longer and expected profit is higher when stochastic price is present.

Unlike Table 5.22, a big drop in rotation age is not observed in Table 5.23. Rather the change in the rotation age is smooth. This again indicates that thinning option helps to reduce the variation in rotation age.

Case 8 simulates the future management and welfare under the four Hadley climate scenarios when stochastic prices are present. Again the results show similar pattern as Case 4 (climate scenario w/o price risk) except that the optimal rotation, thinning ages and expected profit are all higher, as expected.

5.4.4 DYM-EF

The DYM-EF is the last integrated model examined in this dissertation, which combines the DYM and the Faustmann framework. It enables us to investigate the sensitivity of the results to the two yield and optimization methods.

Table 5.23: Case 6.2 of DYM-RO: Fire Risk Sensitivity with Stochastic Price

Fire Occurrence	t_0	t_1	$T^*(std)$	$thin1^*$	$thin2^*$	$EPV^*(std)$
Decreasing	0.01	0.6	36.45(1.37)	21	26	1964(1842.9)
	0.1	0.6	35.77(1.43)	21	26	1313(1693.6)
	0.2	0.6	35.00(1.59)	21	26	649(1387.1)
	0.01	1.5	36.39(1.49)	21	26	1460(1683.1)
	0.01	2.5	36.64(2.09)	21	26	1012(1550.8)
	0.01	4.5	36.46(2.47)	21	26	216(1513.7)
Increasing	0.01	1	34.92(1.12)	21	26	1875(1683.1)
	0.01	2	33.66(1.10)	21	26	1709(1686.4)
	0.01	4	31.75(0.94)	21	26	1290(1558.8)
	0.01	5	31.08(0.97)	21	26	1063(1353.1)
	0.1	1	34.84(1.14)	21	26	1401(1719.6)
	0.2	1	33.78(1.23)	21	26	779(1453.6)
	0.3	1	31.73(1.27)	21	26	346(1209.1)
Constant	$t_a = 1$		34.99(1.39)	21	26	1553(1745.1)
	$t_a = 2$		33.60(1.29)	21	26	808(1336.6)
	$t_a = 3$		32.25(1.11)	21	26	412(1246.2)

Table 5.24: Case 8 of DYM-RO: Future Climate Scenario with Stochastic Price

Region	Climate	$T^*(std)$	$thin1^*(std)$	$thin2^*(std)$	$EPV^*(std)$
Coastal Plain	Current	37.40(1.76)	21.01(0.10)	26.01(0.10)	1567(1526.6)
	A_1	38.16(2.00)	21.26(0.45)	26.26(0.45)	1539(1570.8)
	A_2	37.65(1.80)	21.12(0.32)	26.12(0.33)	1598(1576.5)
	B_1	37.82(1.82)	21.14(0.35)	26.14(0.35)	1452(1545.4)
	B_2^*	37.82(1.65)	21.08(0.27)	26.08(0.28)	1428(1522.2)
Mountain	Current	38.04(2.05)	21.05(0.36)	26.15(0.36)	1441(1443.7)
	A_1	37.08(1.57)	21.01(0.07)	26.01(0.09)	1805(1736.7)
	A_2	37.26(1.65)	21.01(0.09)	26.01(0.10)	1607(1666.5)
	B_1	37.32(1.45)	21.02(0.14)	26.02(0.14)	1756(1805.8)
	B_2^*	37.66(1.92)	21.02(0.13)	26.02(0.13)	1554(1558.1)

Table 5.25- 5.29 cover the results for Case 1, 2 and 6. The optimal rotation age is 5-7 years longer when thinning is included and the corresponding EPV is also higher. As fire risk increases, both the optimal rotation ages and thinning ages decrease and

the expected profits drop sharply as well.

Table 5.25: Case 1 of DYM-EF (Base case)

Case	T^*	$thin1^*$	$thin2^*$	EPV^*
One decision variable	28	na	na	1976
With thinning	35	15	20	2216

Table 5.26: Case 2.1 of DYM-EF: Fire Risk Sensitivity (decreasing occurrence)

t_0	t_1	T^*	EPV^*
0.01	0.6	27	1547
0.1	0.6	25	966
0.2	0.6	23	590
0.01	0.6	27	1547
0.01	1.5	26	1088
0.01	2.5	25	742
0.01	4.5	23	352

Table 5.27: Case 2.2 of DYM-EF (decreasing occurrence)

t_0	t_1	T^*	$thin1^*$	$thin2^*$	EPV^*
0.01	0.6	33	16	21	1641
0.1	0.6	31	15	20	1145
0.2	0.6	29	15	20	794
0.01	1.5	32	16	21	1208
0.01	2.5	31	15	20	857
0.01	4.5	28	15	20	35

Some comparisons are made across the different integrated models. First, DYM-EF is compared with SYM-EF (see Table 5.30). For the one decision variable case, the results from the two models are comparable. This again indicates that the two yield models produce consistent results.

Another similarity is the effect of normally distributed prices. In both models, the presence of stochastic prices reduces the expected profit but the impact on optimal rotation age is mixed. The possible explanations have been provided in Section 5.4.2.

Table 5.28: Case 6.1 of DYM-EF: Fire Risk Sensitivity with Stochastic Prices (One decision variable and decreasing occurrence)

t_0	t_1	$T^*(std)$	$EPV^*(std)$
0.01	0.6	27(1.73)	1472(42.9)
0.1	0.6	24.92(1.59)	920(29.4)
0.2	0.6	23.34(1.39)	562(20.6)
0.01	1.5	25.9(1.74)	1036(32.4)
0.01	2.5	24.88(1.68)	706(22.1)
0.01	4.5	23.31(1.42)	333(11.8)

Table 5.29: Case 6.2 of DYM-EF (Two decision variables and decreasing occurrence)

t_0	t_1	$T^*(std)$	$thin1^*(std)$	$thin2^*(std)$	$EPV^*(std)$
0.01	0.6	33.43(1.64)	15.56(0.83)	21.47(1.31)	1590(22.9)
0.1	0.6	31.14(1.5)	15.48(0.75)	21.29(1.17)	1082(17.9)
0.2	0.6	29.23(1.46)	15.45(0.69)	21.20(1.06)	750(13.3)
0.01	1.5	32.04(1.6)	15.52(0.77)	21.37(1.2)	1112(16.2)
0.01	2.5	30.45(1.57)	15.49(0.76)	21.21(1.14)	736(11.7)
0.01	4.5	27.75(1.46)	15.41(0.68)	21.08(1.07)	347(6.1)

Table 5.30: Comparison of SYM-EF and DYM-EF (Case 1)

Case	T^*	EPV^*
Case 1 of SYM-EF	29	2012
Case 1 of DYM-EF	28	1976

The other comparison is between DYM-RO and DYM-EF. The simulated optimal rotations from both models are much longer if thinning is conducted and the corresponding expected profits are higher. A closer look at case 2 of both models (see Figure 5.21) shows that the optimal rotations are much longer in the DYM-RO model and the difference becomes larger as fire risk increases, indicating the RO modeling has stronger potential to adapt to risk than the Faustmann model. Figure 5.22 shows that the EPV from the DYM-RO model is consistently larger than that from the DYM-EF model and the difference decreases as fire risk increases, as is found in the comparison between SYM-EF and SYM-RO (Figure 5.16).

These results provide a comprehensive assessment of forest management under

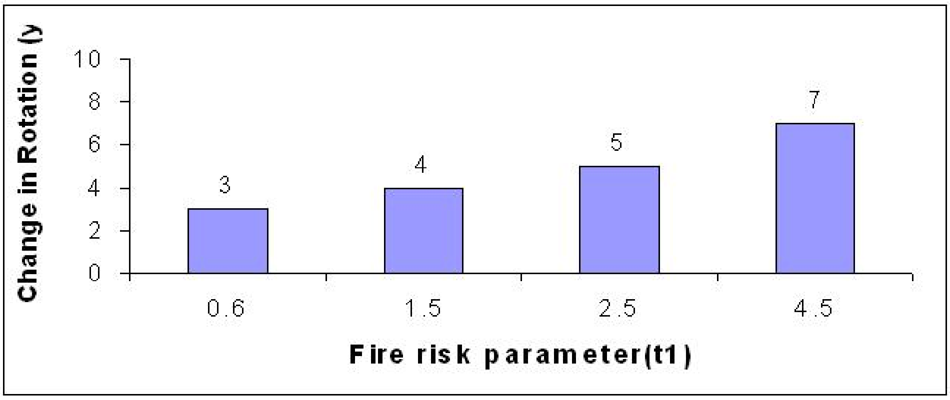

Figure 5.21: Comparison of optimal rotation between DYM-EF and DYM-RO

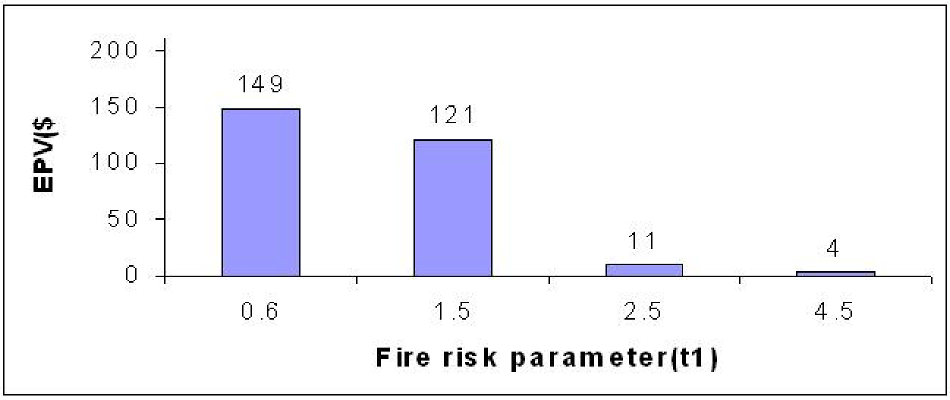

Figure 5.22: Comparison of expected profit between DYM-EF and DYM-RO

risk. This study has extended the literature quantifying marginal and joint risk effects. It expands both the types or risk considered and the set of adaptive responses. Sensitivity of the results to yield models and optimization frameworks are also investigated. Chapter 6 synthesizes the risk results and the comparative strengths of the modeling approaches.

Chapter 6

Conclusions

I used integrated bio-economic models to examine forest management adaptation to climate change and other risks along with the consequent welfare effects. Various results across risk categories and approaches are obtained. In this chapter, I first summarize the results by risk factors and model types. Following that are some general conclusions and discussion of opportunities for further research.

6.1 Summary by Risk Factors

Marginal Effects of Fire Risk

The simulation results from our integrated models reveal that the forest management adaptability to fire risk depends on: (1) the relationship between fire occurrence rates and stand age, and (2) the parameters of fire risk function (t_0, t_1 and t_a). For the one-decision-variable case where rotation age is the only decision the forest manager can make, the results are qualitatively equivalent to those in the existing literature. Specifically, I find that the optimal rotation age is smaller than in a traditional Faustmann model, with the optimal rotation declining as fire risk increases. The largest reduction in rotation age are observed when the average fire occurrence rate increases with stand age, and the smallest when it decreases with stand age.

These reductions in rotation age do not necessarily occur when density control is added as an additional adaptive option. In both decreasing and increasing occurrence cases, I find that the optimal rotation age no longer declines monotonically with t_0; instead it falls and then rises as t_0 increases. The optimal stand density consistently falls as fire risk increases. The forest manager's ability to vary stand density results in higher expected profits, especially when the average fire occurrence rate is high.

When thinning becomes an adaptive option, I find that the variation in the optimal rotation age is smaller than in the no-thinning case. The forest manager can adapt to the fire risk by conducting thinning in addition to lowering the rotation age. Thinning also effectively reduces the profit loss and the role is more important at a higher risk level. The optimal thinning intensity is 0.35 and is insensitive to level of risk. But the optimal planting density decreases as fire risk increases.

Gradual Climate Change Impact

The use of non-parametric methods to estimate climate influence on forest growth and yield is shown to be promising, especially for capturing the non-linear relationship between climate and yield. The yield models, both SYM and DYM, show a small but statistically significant climate impact on loblolly pine growth using FIA data. The sensitivity analysis with climate variables show that moderate increase in the mean temperature or precipitation is beneficial but too much heat may lower forest yield.

The results from the integrated models show that the impact of climate change will vary with site conditions across the South. It has been shown that changes in welfare by physiographic region are significantly different but forest management adaptation to climate change is weak. This technique could be used to examine responses by other spatial criteria, e.g., state, county, or latitude.

Marginal Effects of Price/Yield Risk

When price risk is present in the form of GBM in the RO framework, the forest manager would adapt by lengthening the rotation age because the expected marginal benefit of waiting is greater than marginal costs. This adaptation results in higher expected average profits but much larger variance in the expected profits. Comparing the thinning with no-thinning case, I find that thinning helps to reduce the standard deviation of the optimal rotation age especially when price risk is high.

If yield stochasticity is included by using bootstrapping and price is assumed to follow a normal distribution in the EF framework, the effects are to decrease profitability and increase stand density. The impact on optimal rotation age is mixed.

Joint Risk Effects

When higher fire risk is associated with climate scenario B_2, the welfare loss in the Coastal Plain is bigger and the gain the mountain area may disappear. The adaptive response is to lower rotation age and stand density but the thinning schedules are not affected.

When fire risk and price risk are both present in the RO framework, they work in opposite directions, i.e. fire risk decreases the optimal rotation age and profits while stochastic prices increase them. But when the fire risk increases to a very high level, the forest manager would harvest early even though the price may go up in the future, i.e. the effects of fire risk dominate. In addition, a big drop in the optimal rotation age is observed when fire risk increases to a high level if thinning is not conducted. The change in optimal rotation age is smooth when thinning is incorporated. This again shows that thinning reduces the variance in rotation age.

In the Faustmann framework, the presence of both fire and price/yield risks would decrease profitability, optimal rotation and stand density since the two types of risks work in the similar directions and fire risk has a stronger impact than price/yield risk.

6.2 Summary across Model Types

Four integrated models are developed and compared, i.e. SYM-EF, SYM-RO, DYM-RO and DYM-EF. I find that SYM and DYM provide comparable yield inputs to the optimization frameworks. Although the climate impacts are built in differently (direct way in SYM and indirect way in DYM), the climate impacts on loblolly pine yields are consistent across the two yield models.

The RO framework maybe more appropriate to model management adaptations to risk than Faustmann framework. The adaptive actions are treated as real options and have option values. For example, waiting is more valuable in the RO modeling and therefore the optimal rotation age is consistently longer in the RO than in Faustmann framework. This also leads to higher expected profits. However the use of dynamic programming to solve the RO model has dimensionality problems for large scale simulations.

6.3 General Conclusions and Discussion

This analysis considers a variety of risk factors using two yield models and two optimization frameworks. Looking across risk categories and approaches, some general conclusions are evident.

First I find that results are sensitive to the set of adaptive options being considered. For example, the "standard" optimal rotation results in response to risk do not necessarily hold if stand density and thinning options are included. This implies that the dynamic yield model approach which provides more options is more appropriate to model adaptation. This richer choice set, however, comes at a cost of more implicit biological assumptions on stand dynamics.

The gradual climate change within the range of Hadley scenarios doesn't lead to significant change in optimal rotation age, stand density or thinning ages. But the change in forest rents may be significant. Depending on the impact of climate change on agricultural rent, we would expect to see more adaptations at the extensive margin (land use change) than the intensive margin (silvicultural intensity).

The impacts of discrete catastrophic events on forest management adaptation and welfare are more important than the gradual climate change impact. There are two components that need further research. Many qualitative studies suggested a causal link between extreme events and gradual climate change. Given the importance of these events in terms of adaptive strategies and profitability it is important that future research provides better quantitative estimates of the link between fire risk and climate change.

Similarly, some studies indicate that silvicultural actions can influence fire risk. My research shows that the forest management adaptation and welfare are sensitive to the fire risk parameters, but the relationship between stand characteristics and fire risk was assumed. Therefore it is important to better quantify this relationship through further silvicultural research.

The important impact of fire (and probably hurricanes) on forest management and profitability could have policy implications. In the South, fire suppression is the responsibility of the state government. Amacher et al. (2005a) suggested that a better understanding of silviculture and fire risk may lead to a reallocation of funding priorities. My research implies that this may be especially important with climate change. A better quantitative understanding of fire risk could also allow market responses (e.g., insurance) to provide better signals for adapting management.

The approach used here has provided important new insights into the impact of risk and climate change on forest management. Using this approach a variety of additional factors could be considered in future work. Modeling climate impact on yields could be expanded to include genetic gains, CO_2 fertilization and imposition of long range climate forecasts. Interest rates and the appropriate way to measure cumulative weather impacts should also be examined. Refinements of risk modeling could include an analysis of joint distributions. For example if market risk is increased by climate risk, the joint effects could be significant. Relaxing the assumption of risk neutrality and sensitivity of the results to the form of the utility function is planned for future extensions of this work. The joint distributions of climate risk, fire risk, hurricane or flooding, and pests could also be important variables in determining optimal strategies.

Given the long time scale implied by climate change adaptation, the set of management options could be expanded. Genetic modification of species or species switches are also possible. Initial examination of other pine species were inconclusive due to data limitations, but given the yield effects simulated under the Hadley scenarios, it is unlikely that substitution for loblolly pine will be extensive. Further, these yield impacts may be more than offset by the historical yield increases due to genetics.

The potentially more important risk due to related catastrophic events, however, is unlikely to have a technological fix in the near future.

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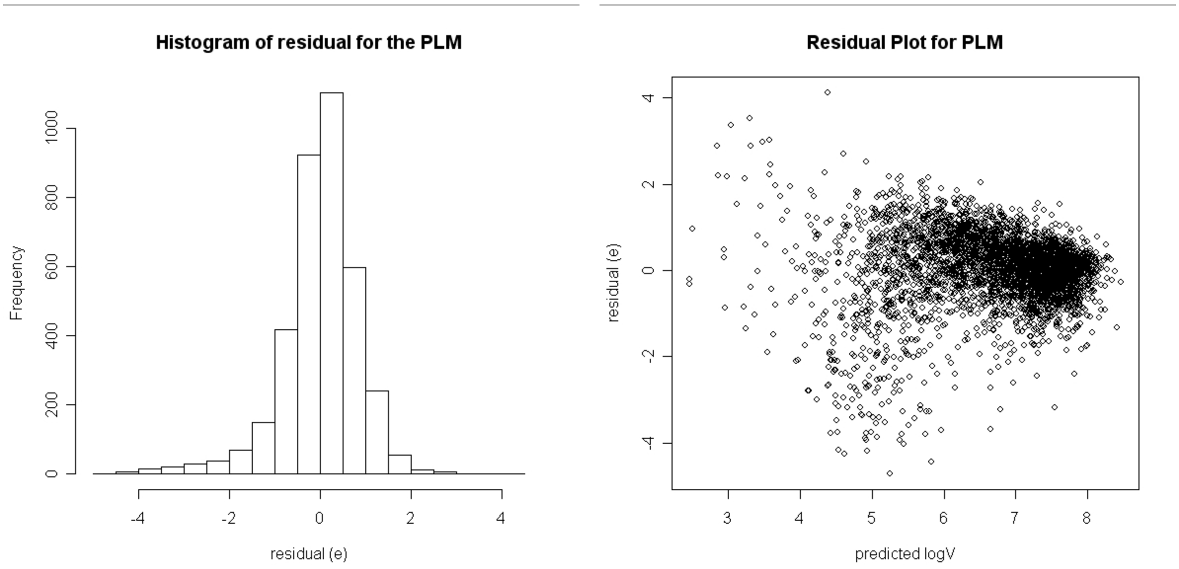
Appendices

Appendix Appendix A

Residual Analysis


Histogram of residual for the PLM

Residual Plot for PLM

Figure A.1: Residual Plots

Table A.1: Autocorrelation Check for White Noise

Lag	Chi-square	DF	$Pr > Chi - square$
6	8.66	6	0.1938
12	13.92	12	0.3060
18	15.56	18	0.6230
24	18.91	24	0.7570

Appendix Appendix B

More Results

Table B.1: Case 5 of SYM-EF

Case	T^*	d^*	EPV^*
One decision variable	29.14(0.26)	500(fixed)	1897(260.2)
Two decision variables	29.17(1.30)	711(63)	1939(279.3)

Table B.2: Case 6.1 of SYM-EF: Fire Risk Sensitivity with Stochastic Yield and Price

t_0	t_1	T^*	EPV^*
1	0.6	28.82(0.31)	1521(225.5)
3	0.6	28.60(0.33)	1376(206.5)
5	0.6	28.37(0.37)	1236(196.5)
7	0.6	28.14(0.40)	1106(185.0)
1	0.6	28.82(0.32)	1518(225.5)
1	1.5	28.51(0.36)	1090(181)
1	2.5	28.08(0.44)	678(145.2)
1	4.5	28.08(0.42)	-22(92.8)

Table B.3: Case 6.2 of SYM-EF: Fire Risk Sensitivity with Stochastic Yield and Price

Fire Occurrence Rate	t_0	t_1	T^*	d^*	EPV^*
decreasing occurrence	1	0.6	28.69(1.74)	635(104)	1509(271.6)
	3	0.6	28.32(2.40)	482(150)	1329(307.8)
	5	0.6	28.51(2.70)	305(165)	1260(281.1)
	7	0.6	28.69(1.30)	17(174)	1201(295.8)
	1	1.5	28.55(0.74)	606(95)	1101(188.7)
	1	2.5	27.99(3.38)	569(226)	678(258.0)
	1	4.5	27.37(1.72)	473(163)	-32(115.4)
increasing occurrence	1	1	28.17(2.03)	637(109)	1560(318.8)
	1	2	27.51(1.95)	598(106)	1348(369.8)
	1	4	26.18(0.91)	585(82)	1007(188.8)
	1	5	25.17(3.93)	593(183)	829.55(337.8)
	2	1	28.00(2.31)	551(116)	1447(391.5)
	5	1	27.89(4.85)	389(270)	1116(1383.7)
	8	1	28.14(1.24)	136(179)	1245(313.9)
Constant occurrence	$t_a = 1$		27.97(2.01)	685(73)	1183(264.8)
	$t_a = 2$		26.73(1.95)	611(210)	605(187.3)
	$t_a = 3$		25.77(1.17)	582(98)	173(108.9)

Table B.4: Case 7 of SYM-EF: Climate Sensitivity with Stochastic Yield and Price

MINT	MAXT	PPT	T^*	d^*	EPV^*
9.29	22.53	1308	29.16(1.41)	709(64)	1876(297.6)
10.82	23.85	1308	29.17(1.30)	711(63)	1939(279.3)
12.35	25.16	1308	29.21(1.11)	710(60)	1977(331.2)
13.88	26.48	1308	29.18(1.37)	711(62)	1902(350.6)
10.82	23.85	1038	29.17(1.50)	711(65)	1871(301.7)
10.82	23.85	1173	29.18(1.28)	710(63)	1910(285.8)
10.82	23.85	1308	29.15(1.42)	709(63)	1944(201.2)
10.82	23.85	1443	29.19(1.12)	711(63)	1980(275.2)
10.82	23.85	1578	29.21(0.94)	710(62)	2009(266.3)

Table B.5: DYM-RO: Sensitivity to thinning intensity $t_0 = 0.1, t_1 = 0.6$

Intensity	T^*	$thin1^*$	$thin2^*$	EPV^*
0.2	35	21	26	1150(831.7)
0.25	37	21	26	1262(867.3)
0.3	49	21	26	1266(894.5)
0.35	40	21	26	1404(873.0)
0.4	39	21	28	1384(875.8)
0.45	39	21	31	1372(851.8)

Table B.6: DYM-RO: Sensitivity to planting density $t_0 = 0.1, t_1 = 0.6$

Planting density	T^*	$thin1^*$	$thin2^*$	EPV^*
400	39	23	31	1315(852.3)
450	39	21	27	1383(856.9)
500	40	21	26	1404(873.0)
550	41	21	26	1300(901.4)
600	40	21	26	1233(962.6)