ADAPTIVE MANAGEMENT OF MIXED-SPECIES HARDWOOD FORESTS UNDER RISK AND UNCERTAINTY

by

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ABSTRACT

Forest management involves numerous stochastic elements. To sustainably manage forest resources, it is crucial to acknowledge these sources as uncertainty or risk, and incorporate them in adaptive decision-making. Here, I developed several stochastic programming models in the form of passive or active adaptive management for natural mixed-species hardwood forests in Indiana. I demonstrated how to use these tools to deal with time-invariant and time-variant natural disturbances in optimal planning of harvests.

Markov decision process (MDP) models were first constructed based upon stochastic simulations of an empirical forest growth model for the forest type of interest. Then, they were optimized to seek the optimal or near-optimal harvesting decisions while considering risk and uncertainty in natural disturbances. In particular, a classic expected-criterion infinite-horizon MDP model was first used as a passive adaptive management tool to determine the optimal action for a specific forest state when the probabilities of forest transition remained constant over time. Next, a two-stage non-stationary MDP model combined with a rolling-horizon heuristic was developed, which allowed information update and then adjustments of decisions accordingly. It was used to determine active adaptive harvesting decisions for a three-decade planning horizon during which natural disturbance probabilities may be altered by climate change.

The empirical results can be used to make some useful quantitative management recommendations, and shed light on the impacts of decision-making on the forests and timber yield when some stochastic elements in forest management changed. In general, the increase in the likelihood of damages by natural disturbance to forests would cause more aggressive decisions if timber production was the management objective. When windthrow did not pose a threat to mixed

hardwood forests, the average optimal yield of sawtimber was estimated to be 1,376 ft^3/ac/acre, while the residual basal area was 88 ft^2/ac. Assuming a 10 percent per decade probability of windthrow that would reduce the stand basal area considerably, the optimal sawtimber yield per decade would decline by 17%, but the residual basal area would be lowered only by 5%. Assuming that the frequency of windthrow increased in the magnitude of 5% every decade under climate change, the average sawtimber yield would be reduced by 31%, with an average residual basal area slightly around 76 ft^2/ac. For validation purpose, I compared the total sawtimber yield in three decades obtained from the heuristic approach to that of a three-decade MDP model making *ex post* decisions. The heuristic approach was proved to provide a satisfactory result which was only about 18% lower than the actual optimum.

These findings highlight the need for landowners, both private and public, to monitor forests frequently and use flexible planning approaches in order to anticipate for climate change impacts. They also suggest that climate change may considerably lower sawtimber yield, causing a concerning decline in the timber supply in Indiana. Future improvements of the approaches used here are recommended, including addressing the changing stumpage market condition and developing a more flexible rolling-horizon heuristic approach.

CHAPTER 1. INTRODUCTION

1.1 Uncertainty, Risk, and Planning

There is generally a confusion between what we call "uncertainty" and what we consider as "risk". In engineering, uncertainty and risk are interchangeably used to represent an event with an unknown outcome. In finance, risk is defined as the probability of monetary loss in an investment choice. In economics and management sciences, however, there exist a rigorous distinction between the two terms. Risk is an uncertainty when we know or can gauge the chances of occurrence of a particular event (Knight 1921). For example, the probability of landing heads in a coin toss is 50% when flipping an unaltered coin. In contrast, uncertain events are those to which you cannot assign such probabilities for their chances of happening (Knight 1921). For instance, *who is going to be the next president of the United States*? *When will COVID-19 end*? *Where is climate change leading us*? Can we assign accurate probabilities to such events like we do with a coin toss? No, because these events have many factors involved and not all of them are fully understood or completely observable. As a result, attaching a reliable estimate of the probability to such an event is impossible.

In the context of forest management, the attendant ecological and economic systems are highly complex and consist of numerous uncertain or risky elements, such as climate change, natural disturbances (e.g., wildfire, windthrow, insect outbreak), market volatility, and changing social acceptability of silvicultural/forest management treatments (Liang et al. 2006). These elements are present in the decision-making of forest management, thus affecting the potential financial income and ecosystem services provided by the forests. Loosely speaking, time-invariant natural disturbances and timber price fluctuations can be viewed as risk, whereas uncertainty includes climate change, policy changes, people's perceptions, etc. However, it is important to keep in mind that risk and uncertainty are not two completely distinct sets (Figure1.1). As we gain more knowledge about uncertainty, it may become risk; risk can become uncertainty if it is, directly or indirectly, influenced by uncertainty.

Figure 1.1. A conceptual diagram illustrating the relationship between risk and uncertainty in forest management.

Incorporating uncertainty and risk in decision-making or planning is a crucial aspect in sustainable management of forests. Planning is developing a strategy to optimize the objective of a given problem and/or to avoid undesirable outcomes. Planning involves establishing certain processes and policies at each stage of decision-making. However, uncertainty or risk creates multiple possible outcomes with differing known and unknown probabilities. Hence, planning under uncertainty and risk are far more complicated when decisions result in multiple outcomes, compared to planning for a single deterministic outcome.

Nevertheless, real-world opportunities for desirable outcomes only exist in the face of genuine uncertainty (Knight 1921). Nowhere does that statement resonates more clearly as in the scenario of forest management. Deterministic models rarely predict real-world scenarios. Only through stochastic models, which include risk and uncertainty, can we come to reasonable conclusions which are practical and robust.

1.2 Forest Planning and Management

Planning for a very complex system like forests is not a simple task. In this thesis, forest planning and forest management are used interchangeably, both referring to the management and allocation of forest resources to achieve certain objectives. In a broad sense, forest management/planning integrates all the biological, social, economic, and other factors that affect management decisions about the forest (Leuschner 1984). Until the 1990s, most countries had implemented forest planning under the principle of "sustainable yield" which aimed for long-term timber yield that did not vary considerably year-to-year. Currently, the prevailing principle is "sustainable forest management" which has the explicit goal to manage forests to satisfy the social, economic, and ecological needs of humans without compromising the needs of future generations (Tittler et al. 2001). Hierarchical planning strategies is one of the methodologies used to help achieve the goals of sustainable forest management. These strategies are developed to address complex planning problems that have many different objectives covering different spatial and temporal scales comprising three layers (Figure 1.2) are: (1) Strategic planning, (2) Tactical planning, and (3) Operational planning (Boyland 2003).

Figure 1.2. Forest Management Plan Hierarchy (adapted from Boyland 2003).

Each level in this hierarchy addresses different requirements of planning, from allocation of resources to efficient resource allocation and, finally, to linking required activities to achieve objectives set at higher planning levels.

Strategic planning is a long-term planning which could deal with a period ranging from multiple decades to an infinite horizon. The infinite planning horizon is often used to take future generations into account for long-term sustainable flow of timber and provision of ecosystem services. Strategic planning is commonly done across large spatial extents (landscape, state, national, and international). Strategic planning sets up a general direction of reaching the objectives rather than specifying how or when these objectives are achieved. There are multiple phases of strategic planning, including assessment of current situation, planning guided by the assessments, revision of plans through public inputs, and monitoring (Boyland 2003).

Tactical planning comes next in the hierarchy. This focuses on how to best structure forest-related activities. Tactical-level plans are shorter than strategic plans in terms of time frames, usually lasting between a few years to decades. Tactical planning involves informing the landowner of specific needs and requirements. Activities in this stage include development of silvicultural prescriptions and harvest scheduling for a landscape (Boyland 2003, Alvarez et al. 2020).

Operational planning is the lowest level of planning in the hierarchy and it deals with the stand or tract level. Operational planning details activities at fine temporal scales, days or weeks. For example, operational plans are needed to schedule the work force and machinery needed for each harvest unit at a tactical level (Boyland 2003, Alvarez et al. 2020).

The disintegration of a plan into multiple levels provides not only reduces complexity but also, to some degree, mitigates uncertainty and risk. The objectives and planning horizons differ with each level to address the differing types and magnitudes of risk and uncertainty that arise at each level. At the operational level, risk and uncertainty are low as compared to that at the tactical level. Risk and uncertainty are often the highest in strategic planning due to long time horizons and large spatial scales (Anthony 1965, Gunn 2003, IPCC 2014, Kunreuther et al. 2014).

1.3 Adaptive Management and Climate Change

"Adaptive management promotes flexible decision-making that can be adjusted in the face of uncertainty and risk as outcomes from management actions and other events become better understood" (National Research Council 2004, Williams et al. 2009). Adaptive management involves a continual learning process (Waiters 1986) and tries to reduce the uncertainties that are present in the system by enhancing scientific knowledge. Adaptive management is not a trial and error process; instead, it emphasizes learning-while-doing (Figure 1.3). The “true measure of adaptive management is in how well it helps meet environmental, social, and economic goals, increases scientific knowledge, and reduces tensions among stakeholders” (Williams et al. 2009).

Figure 1.3. Graphical representation of Adaptive Management (adapted from National Research Council, 2004).

The ambiguity in the definition of adaptive management has caused confusion in implementation in practice. As a result, policy makers, managers and stakeholders often develop their own unique definitions and expectations (National Research Council 2004). Hence, it is important to understand the true definition to be able to implement it in a more satisfactory manner. The key distinction in adaptive management is between active and passive forms of adaptive decision-making (Williams 2011). The primary difference between the two is to what degree they emphasize on reducing the uncertainty (Williams 2011). “Active adaptive management actively pursues the reduction in uncertainty through management interventions, whereas passive adaptive management focuses on resource objectives, with learning a useful but unintended byproduct of decision-making" (Walters 1986, Williams 2011). However, active adaptive management is mathematically difficult to formulate.

Adaptive management strategy is central to sustainable forest management because of the presence of uncertainty and risk in the growth and the future structure of forests (Holling 1978, Walters 1986). Not only is adaptive forest management theoretically superior to non-adaptive management (Alonso-Ayuso et al. 2011, Veliz et al. 2015), its advantage is also proven in practice (Zhou et al. 2008). However, the methods for finding the solutions are extremely limited for adaptive forest management due to the complexity in forest ecosystem, as well as the multi-dimensional risk and uncertainty involved. In this thesis, I define adaptive forest management as setting certain objectives and reaching those objectives through analytical and empirical approaches so the optimal decisions can adapt to risk and uncertainty and improve efficiency in planning forest resources.

Climate change is a major uncertainty that is involved in forest management. Alteration of climate has naturally occurred over the course of earth's history, but the changes during the last 50-100 years have accelerated at a significant pace, mostly induced by anthropogenic forces (Wuebbles et al. 2016). Many lines of evidence show that the human interactions through the emission of greenhouse gases is the primary reason for increasing temperatures (Wuebbles et al. 2016, IPCC 2013, IPCC 2014).

Here, the big question is "*By how much*?" We can get an almost accurate weather forecast just by using a mobile app, but predicting the climate for the future, even if it is near, is an extremely difficult task, even with a suite of highly sophisticated tools such as, general circulation models (GCM's), earth system models (ESM's), earth system models of intermediate complexity (EMIC's), and regional climate models (RCM's) (Flato et al. 2014) . Significant improvements have been made to these tools to enhance the forecasting accuracy, especially of the temperature, but enormous uncertainty remains. As a result, the path of climate change is best described as scenarios with no certain probabilities. Examples of such scenarios are the four Representative Concentration Pathway (RCP, Van Vuuren et al. 2011) and the IPCC AR5 (Mastrandrea et al. 2011). As one can safely assume, there is a far greater difficulty in predicting for the distant future than for the short-term. It involves numerous factors, such as the choice of life style, policy stringency, heat distributions in oceans, the quantity of solar energy that earth receives, and the changes in atmospheric structure (Wuebbles et al. 2016), to name a few. Consequently, when we consider the future climate, it is wrong to assume that the climate change will follow a constant pattern so that we only consider one single pathway that would eventually happen. Therefore, the uncertainty in climate change should be analyzed using a wide variety of time-dependent scenarios that are modeled to predict various elements, such as, human population, global temperatures, resource production, etc., that will be effected due to climate change (Hayhoe et al. 2017).

Mounting evidence has shown that climate change not only changes forest growth worldwide (e.g. Battles et al. 2008, McMahon et al. 2010, Ma et al. 2016), but also alters natural disturbance patterns (e.g., Flannigan et al. 2000, Kurz et al 2008, Seidl et al. 2017) which are traditionally viewed as a type of risk in forest management. With tremendous difficulty in predicting the changes in the frequency and magnitude of natural disturbance patterns induced by climate change, the task of sustainable forest management is daunting. Mathematically, the difficulty lies in working with an open, nonstationary system, in contrast to a closed, stationary one, so analytical solutions are most of the time nonexistent. Practically, predictions of the probability of natural disturbances under the influence of uncertain climate change are often merely educated guesses that could potentially be misleading and causing undesirable consequences. Adaptive management can help to minimize these.

1.4 Objectives

The overarching goal of my thesis is to develop an adaptive optimization framework to find best or close-to-best forest management strategies at the tactical level, subject to occurance of some natural disturbances the probability of which may be altered over time due to climate change. Other types of risk and uncertainty are not considered here. This framework is applied using natural mixed-species hardwood forests located in Indiana. The type of risk under consideration is time-invariant natural disturbances (Zhou and Buongiorno 2004), i.e., the frequency and impact assumed to remain constant over time, whereas the type of uncertainty under consideration is windthrow which may become more frequent due to climate change. Based on an empirical growth and yield model for the study region (Ma et al. 2016, Wang et al. 2020), I first developed a stochastic growth model for the mixed-species forest type and then compared a passive adaptive forest management model with an active adaptive management heuristic model, both to maximize the expected harvested volume of hardwood sawtimber. My specific objectives are to:

1. Determine the optimal forest management decision only considering risk;
2. Determine the near-optimal forest management decision considering both risk and uncertainty; and
3. Describe the decisions, timber yields, and stand structures in different scenarios.

These results will illustrate the potential productivity of hardwood forests under adaptive management. Moreover, the optimal decision table derived from the first objecttive can be used to make management recommendations for those landowners prioritizing timber production. In addition, the explorative heuristic framework developed here allows for future development of active adaptive management models under climate change.

CHAPTER 2. LITERATURE REVIEW

2.1 Forest Growth and Yield Models

Forecasting the change in forest dynamics is critical for forest management (Shifley et al. 2017). Over the past century, the modeling tools needed to assist decision-making in forest management have become more and more quantitative, and comprehensive of numerous factors that have an impact on forest change (Mladenoff 2005, Mladenoff and Baker 1999). Forest growth and yield models have a history of over 200 years, starting from the pure stand yield tables (Paulsen and Führer 1795, Cotta 1821) to the more sophisticated and complex models that are present now, such as LANDIS (Mladenoff 2004, Wang et al. 2014) and Forest Vegetation Simulator (FVS, Crookston et al. 2005, Reinhardt and Crookston, 2003). Today's models can be classified based on the following analytical and structural properties:

1) process vs. empirical models;
2) tree-level vs. stand-level models;
3) distance-dependent vs. distance-independent models; and
4) deterministic vs. stochastic models.

2.1.1 Process vs. empirical models

Process models "simulate the dependence of growth on a number of interacting processes, such as photosynthesis, respiration, decomposition, and nutrient cycling" (Peng 2000). Generally speaking, for process models, plot measurement data are less important than data of environmental factors, such as temperature, light, and nutrients, in developing these complex models. In general, process models are useful tools for ecological studies but are difficult to apply in forest management, especially in optimal harvesting scheduling, due to the lack of prediction accuracy at the small scale.

Empirical models are derived from forest measurement and inventory data. In this type of modeling, forest structure and environmental/site factors, such as basal area, number of trees, and site index, are used in the regression functions to predict future growth and yield of forest stands. Although suitable for the purpose of quantitative forest management due to the relatively accurate prediction, empirical models have limited use for ecological studies especially over a long term and for an extended geographical scale. There also exists a hybrid framework combining both approaches to obtain results which might be able to overcome the shortcomings of both (e.g. Kimmins 1990).

2.1.2 Tree-level vs. stand-level models

These two models differ by the prediction unit, either the individual tree (or group of trees with same characteristics) or a population/stand of trees. Individual tree-level models simulate the growth and yield of individual trees and then adds them up to get the stand-level values. Tree-level models generally are less accurate than stand-level models as prediction errors accumulate while summing individual simulations. However, tree level approaches are more flexible in that stand composition and structure can be finely tuned to match on-the-ground measurements, thereby allowing predictions of stand growth in a wide array of mixed-species stands.

Stand-level models utilize characteristics of tree- and stand-level data to simulate the growth and yield of a whole stand. Normally, they cannot capture spatial information between trees, such as crown dynamics and planting patterns, into account. The majority of the stand-level models are empirical models (Mladenoff and Baker 1999). A widely-used type of stand-level models are matrix growth models which describe the movement of trees between different size classes with growth matrices. Liang and Picard (2013) provide a comprehensive review of such models. The deterministic growth model used in this study (Ma et al. 2016, Wang et al. 2020) for constructing the optimization models belongs to this class.

2.1.3 Distance-dependent vs. distance-independent models

Tree-level models can be further classified into two distinct groups (Bruce and Wensel 1987): (1) distance-dependent (Newnham and Smith, 1964, Monserud and Ek, 1974), where the location of every tree is required to explicitly state the interactions of the subject tree with the neighboring trees, and (2) distance-independent models (e.g., Shugart and DC 1977, Shugart 1984), where the spatial location is not needed and the interactions between the trees are estimated by an averaging procedure over the space (Picard and Franc 2001, Picard et al. 2001, Kokkila et al. 2006). In the latter group, it is assumed that there is no connection between spatial patterns formed by trees (Moeur 1993), and the volume of wood, a variable of interest that results from the growth process. On the contrary, in distance-dependent models, there is a reciprocal action between these two (Picard et al. 2001).

2.1.4 Hybrid Models

Hybrid forest growth models are developed by integrating elements from process-based and empirical growth models. With climate change becoming a factor in forest growth and decision-making, this inclusion of environmental factors along with the inputs and outputs from empirical models suitable for forest management in hybrid models has attracted considerable attention (Mäkelä 2009). These hybrid models can be divided into three basic types : (1) hybridized empirical growth models with process-elements as sub models (e.g.,Woollons et al.1997, Weiskittel et al. 2010) ; (2) hybridized process-based growth models with empirical elements as sub models (Running and Coughlan 1988, Kimmins et al. 1990, Landsberg and Waring 1997, Chertov et al. 1999, Valentine et al. 2000); (3) "Genuine hybrid models", the potential growth is derived from empirical data/functions, improved by using a system of process-based functions or sub models (Mäkelä 2009). The 'GAP' family belongs to this last group of hybrid models (Mäkelä 2009). 'GAP' models are considered to be the most famous growth models and are among the first attempts to model mixed-species forest growth (e.g. Acevedo et al. 1995, Fischlin et al. 1995, Jorritsma et al. 1999, Larocque et al. 2011). In essence, Gap models are a special category of tree-level distance-based modeling, as "they define and keep track of individual trees competing and growing in a restricted area, the gap" (Botkin et al. 1972, Shugart 1984, Porté and Bartelink 2002). Even though more flexible than stand-level models, Gap-models heavily rely on descriptive relationships (Porté and Bartelink 2002).

2.1.5 Deterministic vs. stochastic models

Deterministic models yield the same result in repeated simulations because no elements of uncertainty and risk are considered, unless uncertainty in the model parameters are considered. In contrast, stochastic models will generate different results in every repetition because of the presence of randomness. The stochastic models can often be derived from deterministic models by including stochastic elements either in additive or multiplicative form (Landsberg *et al.* 2001). As Higgins et al. (1997) point out, deterministic models of forest growth can be unreliable because "small environmental disturbances can considerably alter the dynamics of deterministic biological mechanisms." Generally speaking, stochastic models more realistically depict the growth of forests as these disturbances can be taken into consideration in simulations. As demonstrated in Zhou and Buongiorno (2004), a deterministic stand-level model of mixed-species forests in the southern pine region predicts that in the long run, shade-intolerant species will be entirely replaced by more shade-tolerant species, since little openings are created without disturbances. In contrast, the stochastic counterpart of the same model predicts the co-existence of both shade-tolerant and -intolerant species. Fortin and Langevin (2012) show that at the tree level, a stochastic model also produces better predictions than a deterministic one.

2.2 Optimizing Forest Management

Rigorous mathematical modeling and programming can efficiently identify novel and optimal plan for forest management. Models can simulate the forest growth and compare alternative management regimes, providing the information on the potential consequences and tradeoffs among alternatives, but only optimization can the identify the alternative that best achieves all goals of management (Dykstra 1984). Operations research has been widely used to help decision makers act optimally, given model forms and parameters. Optimization methods can be categorized based on the implementation modes and models they are used with, either deterministic or stochastic.

2.2.1 Deterministic Optimization Methods

Deterministic forest growth models can be optimized using deterministic methods. Mathematical programming and/or deterministic optimization handles decision-making problems with certain outcomes. Lin et al. (2012) provide a thorough review of this approach's application in engineering and management. Deterministic optimization dominates the literature of forest planning at all three hierarchical levels (e.g. Field 1973, Nelson and Brodie 1990, Hof, J.G. and Joyce 1993, Troncoso and Garrido 2005, de-Miguel et al 2014).

Linear programming, a deterministic method, is used to obtain an optimal solution to a management goal(s), where management constraints or resource limitations are depicted in the form of linear functions. Linear programming is used in various fields, such as manufacturing, transportation, energy, telecommunication, and human resources, and has widely been used in forest management since the early 1960s. An early application on the uneven-aged forest management was Rorres (1978). Buongiorno and Michie (1980) used linear programming to maximize the net present value (NPV) of periodic harvests by determining the sustained-yield of alternative management regimes. The method allowed for the joint determination of optimum harvest, cutting cycle, residual stock, and diameter distribution. Lu and Buongiorno (1993) presented a mixed-species growth model for uneven-aged stands and maximized NPV of harvests by using linear programming.

Most constraints, however, are not simple linear tradeoffs. Non-linear programming can then be used to solve the optimization. Similar to the linear programming, non-linear programming is also composed of an objective and general constraints, but at least one of them are described by non-linear function. This makes non-linear programming intrinsically much harder to optimize. There have been several applications of non-linear programming in forest management. For example, Adams and Ek (1974) determined the optimal sustainable distribution of trees by diameter class for a given initial stocking level using non-linear programming. Roise (1986) formulated a non-linear program for stand optimization and compared three non-linear programming techniques and a discrete dynamic programming approach, concluding that the non-linear programming optima was more favorable than the discrete dynamic programming optima. Buongiorno et al. (1994) used non-linear programming to optimize the economic returns and tree-diversity as management objectives.

2.2.2 Stochastic Optimization Methods

In general, optimization of forest management regimes is carried out by assuming that there is a certainty in the outcomes of management activities, even though these outcomes are universally recognized to be uncertain (Brumelle et al. 1990). Optimization based on stochastic models provides a robust management plan that acknowledges uncertainty and risk. Stochastic optimization is not straightforward and, under certain circumstances, may not lead to a tractable mathematical solution. Like deterministic methods, there are several stochastic methods available that can be tailored to the specific optimization problem.

Stochastic programming is useful when the outcome is probabilistic, but there is inherent risk and uncertainty in the system. Hense, this mathematical approach can be a good candidate for developing robust forest management models that are resilient to the challenges posed by climate change, natural disturbance, and other forms of risk and uncertainty. Stochastic programming is categorized in a few different ways. One common way is to group the methods by the number of stages involved in the planning: two-stage stochastic optimization and multi-stage stochastic optimization, the latter mathematically more complex (Shapiro and Philpott 2007). Multiple-stage approaches can be further divided according to the length of the planning horizon: finite and infinite. For all stochastic programming problems, a decision is made at each stage of the planning process and affects the instant and future rewards. Stochastic programming has abundant applications in the field of management science (e.g., Escudero et al. 1993, Bakir and Byrne 1998, Huang 2005, Kazemi Zanjani et al. 2007), supply chain (Nagar and Jain 2008, Shabani et al. 2014) and scheduling (Duffuaa and Al-Sultan 1999, Benisch et al. 2004).

There exist ample applications of stochastic programming in the forestry context. For instance, Garcia-Gonzalo et al. (2016) use a scenario optimization approach to handle forest planning under climate change. Lohmander (2007) discusses three stochastic optimization approaches for adaptive forest planning: dynamic programming, scenario tree optimization, and a simulation-optimization method. Eyvindson and Kangas (2014) propose a stochastic goal programming approach for forest planning. Besides forest planning, stochastic programming also finds applications in forest production planning. Alonso-Ayuso et al. (2018) utilize multi-stage stochastic integer programming model to analyze decision-making under uncertainty in wood selling prices and demand. Shabani et al.(2014) develop a two-staged stochastic programming model to deal with the uncertainty of monthly biomass supply in the supply chain for a forest biomass power plant.

One particular class of stochastic programming approaches is Markov decision process (MDP, Puterman 2014). This process offers “a rigorous and practical way of developing optimum management strategies, given multiple sources of risk” (Buongiorno and Zhou 2015). The major advantage of using MDP is that one can effectively address multiple types of risks that are present in the forest system. MDPs also can simplify complex systems and make optimizations easier as compared to other stochastic programming methods (Insley and Rollins 2005). MDPs are, in essence, passive adaptive optimization models, as they provide optimal decisions that change with respect to the state of the system under consideration (Zhou and Buongiorno 2008).

Early applications of MDPs in forest management include Lembersky and Johnson (1975) and Lembersky (1976). Examples of using MDP for uneven-aged forests are Kaya and Buongiorno

(1987) for economic objectives, Lin and Buongiorno (1998, 1999a, 1999b) for combined economic and ecological objectives, and Zhou and Buongiorno (2006) for landscape-level objectives. Recent developments of MDPs for forest management include Zhou and Buongiorno (2011) which expands the types of risk in forest management by including stochastic interest rates, Buongiorno et al. (2018) which integrates goal programming and MDP, and Zhou and Buongiorno (2019) which considers the risk-attitude of decision makers.

One major limitation of MDPs is the hurdle of including uncertainty. Although there exist a few methods in the MDP family (e.g. Williams and Young 2007), dealing with partially unknown thus, to some degree, uncertain systems, they are far less developed than their certainty counterpart. In addition, they are impractical for large forest management problems. Thus, although an ideal candidate for forest management under risk, the MDP cannot directly be applied to adaptive forest management under uncertainty. The only exception of using the MDP for uncertainty in forest planning is Zhou (2015) which deals with uncertainty in climate policy by recognizing different scenarios of carbon prices in the MDP framework.

2.2.3 Rolling Horizon

One important consideration in applying stochastic programming in forest management is choosing the appropriate planning period. With future uncertainty, long forest management planning horizons can lead to less reliable estimates and potentially erroneous decisions. On the other hand, sustainable forest management aims at long-term benefits for the future generations, so only considering the immediate and short-term benefits are insufficient, potentially preemptively depleting resources.

A relatively simple solution to this conundrum is use of a “rolling horizon” heuristic approach, a technique predominantly used in production planning where there is uncertainty in demand or production capacity (e.g. Bookbinder and H'ng 1986, Li and Ierapetritou 2010). Rolling horizons are based on the assumption that the information about an uncertain event only arrives after a certain period of time. Forecasting to obtain the information ahead of time is either high costly or impossible (Sethi and Sorger 1991). Planning for a long period based on the information far ahead in time thus can lead to erroneous decision. The rolling-horizon approach dissect the long planning period into multiple short-period and “roll” the decision-making window as the information about the near future becomes available. Decisions are revised at each stage of the problem within the rolling horizon and the optimization is based on the uncertainty realized so far (Ahmed et al. 2003). Figure 2.1 below illustrates the rolling-horizon approach with a two-period window. The green rectangles represented the current stage when decisions need to be made for both the current and the next stage (red rectangles).

To my best knowledge, no quantitative active adaptive framework exists for optimal forest management under future climate uncertainty. The work presented here will be the first to provide such a framework by integrating a well-established passive adaptive framework, the MDP model, with a flexible planning heuristic, rolling horizon.

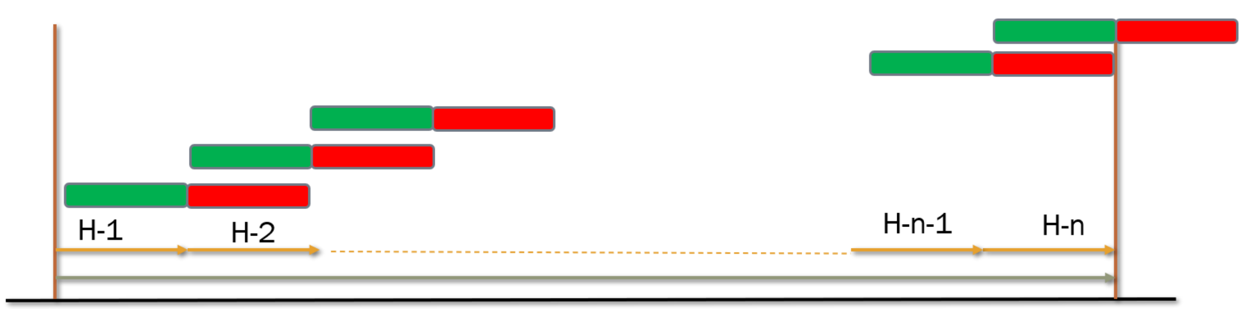

Figure 2.1. An illustration of the rolling horizon approach with a two-period window for a long planning period.

CHAPTER 3. METHODOLOGY

3.1 Motivations for the proposed methods

A two-stage approach is particularly attractive in the context of forest management for two main reasons: it greatly reduces the complexity of the optimization problem; it reduces the uncertainty in planning because the farther into the future, less reliable is the prediction of uncertainty induced by climate change. At the same time, long-term planning considering future generations is of paramount importance. Thus, it is essential to develop a technique that instead of directly dealing a lengthy problem involving uncertainties, divides the problem into multiple short-period problems. At each stage, the realized information of the immediate future will be updated and help make better decisions for the next period. This technique shines bright because, when planning for a long period, forecasting or assigning the probability distribution to the possible future outcomes becomes exceedingly difficult or expensive. This is true especially when we are dealing with multiple decades of forest planning under uncertainty. Any assumptions or forecasts become more and more unreliable as the planning period lengthens. In these cases, a rolling horizon heuristic combined with an efficient stochastic optimization approach such as the MDP becomes a go-to approach. The reason is that the decision maker is no longer dealing with a long planning period with unrealistic possibilities, but shorter periods of time in each of which the planning can be done with a relatively better foresight. With the arrival of new information, the stochastic model will be updated and so will the optimal decisions for the next short period.

3.2 Markov Decision Process

An Markov decision process (MDP) model consists of four components (Figure 3.1): (1) state variables (S), (2) decision set (A), (3) transition probabilities (P), and (4) expected rewards (R). The state variables are the unique stand states describing the condition a forest is in, usually represented by the density of certain species-size combinations; the decision set consists of the possible management actions for each state; the transition probabilities represent the change of the forest condition due to growth and disturbances in a pre-defined length of period; and the expected rewards are the immediate expected returns (timber return or ecosystem services) from forest management actions.

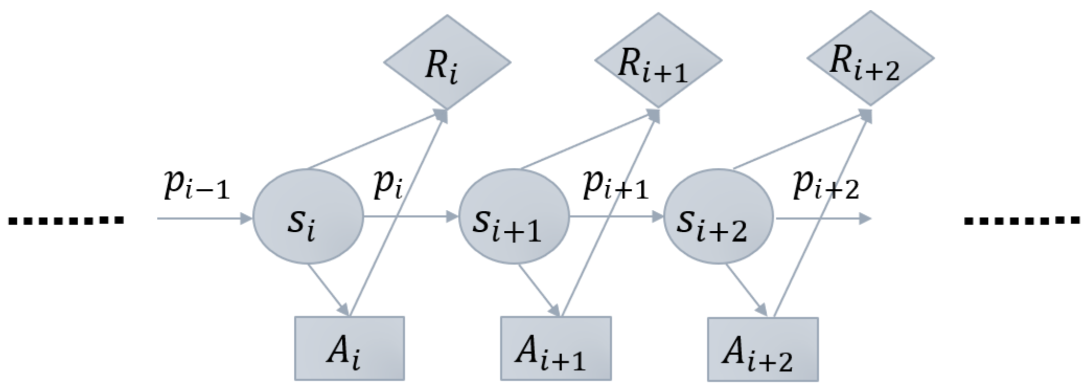

Figure 3.1. A diagram illustrating the component and structure of an MDP model.

3.2.1 States Variables

State variables are the representations of the forest stands, as defined based on the basal area of trees in predefined size classes and species combination. For this case study, there were six species/size classes defined as follows:

1. Oak pulpwood (DBH ≤ 12 inches);
2. Oak sawtimber (DBH>12 inches);

3. Maple pulpwood (DBH ≤ 12 inches);
4. Maple sawtimber (DBH >12 inches);
5. Other species pulpwood (DBH ≤ 12 inches); and
6. Other species sawtimber (DBH >12 inches).

For each of the six species/size classes, the basal area can be either *low* (L) or *high* (H). The allocation of *low* or *high* to each class was based on the basal area threshold, the derivation of which is described in §3.11.

With six classes, state of the forest stand can be represented as a string of six digits (e.g. LL HL HH) where each digit refers to either *low* (L) or *high* (H) basal area of each species/size class listed above. Altogether, there will be 64 (2^6) unique possible stand states for this analysis.

3.2.2 Defining forest states

Here, the forest condition is represented by the basal area of the six classes defined above. To determine the level of L and H for each class, I use the stocking condition of a forest stand as my guide. In forestry, a stocking chart outlines the relationship between basal area, number of trees per acre, and the quadratic average diameter of the tree (Gingrich 1967). The stocking condition of a forest stand is usually categorized into three levels: (1) Understocked, stands with the growing space not being utilized effectively (the space below B-line); (2) Fully stocked, stands with trees occupying the growing space effectively and still having an ample space for new trees to develop (the space between B-line and A-line); (3) Overstocked, stands with trees occupying the entire growing space and suppressing the new growth (the space above B-line). Gingrich (1967) has developed the upland hardwoods stocking chart for different (small and large) average diameters (Figure 3.1 and Figure 3.2), which is used for the forest type that I am focusing on to find the stocking levels. The chart is easy to use if one has both the basal area of the stand and the number of trees in it. The point of intersection of basal area and number of trees represents the stands present stocking level. For example, a plot with 900 small-diameter trees and 60 ft^2/acre basal area from Figure 3.1 is estimated it to be fully stocked.

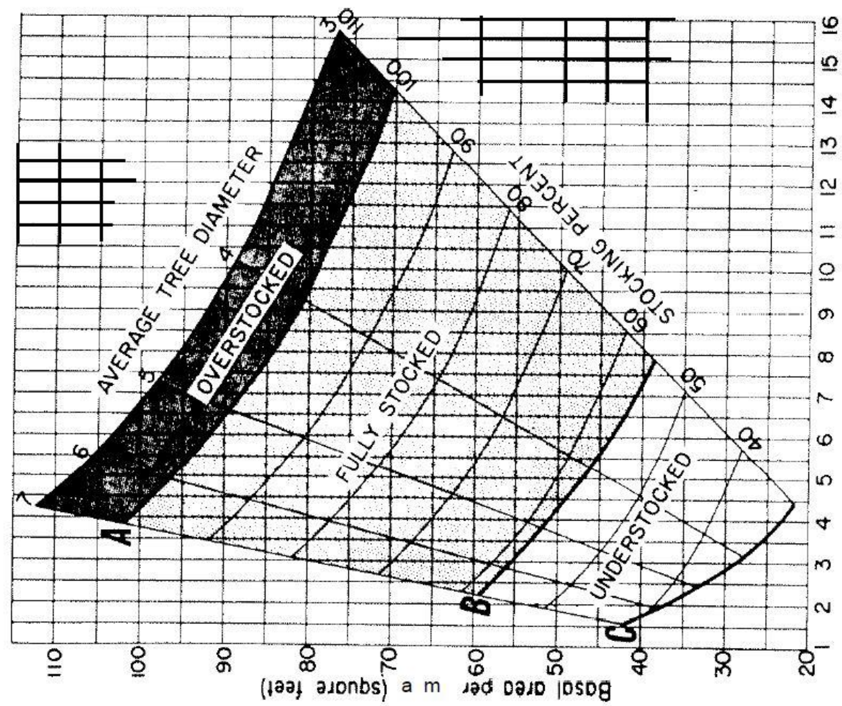

Figure 3.2. Stocking charts of upland hardwoods for smaller diameter trees (Gingrich 1967)

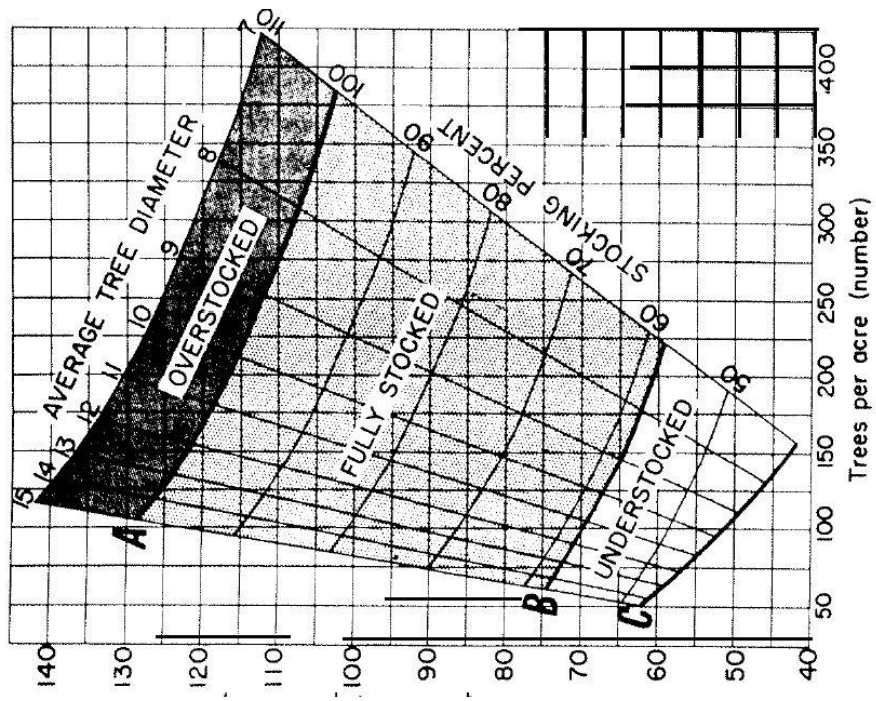

Figure 3.3. Stocking charts of upland hardwoods for larger diameter trees (Gingrich 1967)

To find the stocking level of Indiana’s forests in order to define the threshold for *low* and *high* basal areas in the MDP model, I obtained plot-level forest inventory data in Indiana, collected from 2010-2019, from the Forest Inventory and Analysis (FIA) database (Gray et al. 2012). The total number of sample plots were 2,242. Using the stocking chart in Gingrich (1967), we categorized each plot as fully stocked (n = 623 or 27.7%), overstocked (n = 959 or 42.7%) or understocked (n = 660 or 29.4%). For all the plots at each stocking level, the mean basal areas corresponding to the six species-size classes were calculated (Table 3.1). In particular, across all fully-stocked plots, the average basal area for oak pulpwood, oak sawtimber maple pulpwood, maple sawtimber, other species pulpwood and other species sawtimber was 8.1, 16.4, 8.2, 6.9, 22.8, 20.1 ft^2/ac, respectively. These values were used as the thresholds for determining the level of basal area, *low* (L) and *high* (H) in the corresponding species-size classes. Hence, all fully stocked and overstocked stands were *high* (H), whereas understocked stands were *low* (L). Based on these thresholds, the 2,242 sample plots were classified into different stand states, and the probability of an Indiana forest stand falling in one of the 64 states was calculated (Table 3.2).

Table 3.1. Mean basal areas of the Forest Inventory and Analysis plots at different stocking levels in Indiana from 2010 to 2019.

Stocking level	No. of plots	**Basal area (ft^2/acre)**					
		Oak Species		Maple Species		Other Species	
		Pulpwood	Sawtimber	Pulpwood	Sawtimber	Pulpwood	Sawtimber
Overstocked	959	9.3	29.8	12.4	12.0	32.1	40.0
Fully stocked	623	8.1	16.4	8.2	6.9	22.8	20.1
Understocked	660	3.2	5.2	3.1	3.2	10.7	7.8

Table 3.2. Definition and numerical code of stand states of the MDP model, and the number of sample plots (N) in each stand state. The total number or sample plots were 2,242.

Stand state	Code	N	Stand state	Code	N
LL LL LL	1	234	HL LL LL	33	73
LL LL LH	2	83	HL LL LH	34	13
LL LL HL	3	109	HL LL HL	35	55
LL LL HH	4	124	HL LL HH	36	62
LL LH LL	5	70	HL LH LL	37	4
LL LH LH	6	37	HL LH LH	38	5
LL LH HL	7	9	HL LH HL	39	7
LL LH HH	8	29	HL LH HH	40	8
LL HL LL	9	52	HL HL LL	41	15
LL HL LH	10	42	HL HL LH	42	9
LL HL HL	11	24	HL HL HL	43	26
LL HL HH	12	57	HL HL HH	44	14
LL HH LL	13	68	HL HH LL	45	7
LL HH LH	14	81	HL HH LH	46	8
LL HH HL	15	24	HL HH HL	47	7
LL HH HH	16	61	HL HH HH	48	11
LH LL LL	17	77	HH LL LL	49	84
LH LL LH	18	35	HH LL LH	50	17
LH LL HL	19	28	HH LL HL	51	47
LH LL HH	20	45	HH LL HH	52	37
LH LH LL	21	18	HH LH LL	53	9
LH LH LH	22	10	HH LH LH	54	0
LH LH HL	23	8	HH LH HL	55	8
LH LH HH	24	7	HH LH HH	56	9
LH HL LL	25	31	HH HL LL	57	48
LH HL LH	26	39	HH HL LH	58	22
LH HL HL	27	15	HH HL HL	59	23
LH HL HH	28	31	HH HL HH	60	15
LH HH LL	29	31	HH HH LL	61	19
LH HH LH	30	48	HH HH LH	62	5
LH HH HL	31	10	HH HH HL	63	13
LH HH HH	32	20	HH HH HH	64	5

3.3 Transition Probabilities

Transition probabilities define the proportion of stands that transition from state to another, generally because of growth, harvests, natural disturbances or other factors. To derive these probabilities, first, a non-linear stochastic tree growth model for this forest type was used to take into account some time-invariant natural disturbances. Once the transition probabilities were calculated, they were further modified to include the frequency of windthrow, another source of time-invariant risk. In §4.3, the probability of windthrow was changed to mimic time-variant disturbances, thus an uncertainty.

Here, the first type of time-invariant risk due to natural disturbances was assumed to be represented by the residuals of a deterministic growth model of mixed-species hardwood forests in Indiana (Ma et al. 2016, Wang et al. 2020). The model has the following form:

$$\boldsymbol{y}_{t+1} = \boldsymbol{G}_t(y_t) + \boldsymbol{R}_t + \varepsilon_t \tag{3.1}$$

where $\mathbf{y}_t = [y_{ijt}]$ represents the number of live trees per ha of species i and diameter class at time t. $\mathbf{G}_t$ is a state- and time-dependent transition matrix describing the change of structured population between t and $t+1$. $\mathbf{R}_t$ is a column vector containing the recruitment/ingrowth between t and $t+1$ and ε is a vector of random errors. All the species in the region were classified into seven species groups: White oak (WO), Red oak (RO), Black walnut (BW), Black cherry (BC), Maple (MP), Soft wood (SW), Other Angiosperms (OA), and seventeen diameter classes: each at 5 cm increments, with two exceptions being the first class, with an increment of 4.46 cm and the last classes, with an open range starting from 82 cm and above.

For each of the sample plots that were measured twice from 2010 to 2019, the number of trees at the first inventory was used as the initial condition in the deterministic model to predict the number of trees at the second inventory. Then, the prediction was subtracted from the actual number of trees at the second inventory to determine the residuals:

$$\hat{\boldsymbol{e}}_{t+n} = \boldsymbol{y}_{t+n} - \hat{\boldsymbol{y}}_{t+n} \tag{3.2}$$

Here $\mathbf{y}_{t+n}$ was the observed number of trees at the second inventory and $\hat{\mathbf{y}}_{t+n}$ was the number predicted by the deterministic model (3.1), n representing the number of years between the two inventories. In theory, if the growth model is valid, these residuals should follow a white-noise process, randomly distributed with an expected value of zero and a constant standard deviation.

Figure 3.1 below shows the mean and 95% confidence interval of the residuals by species groups, and size classes. In general, the residuals were centered around zero for all species groups and sizes. There existed some outliers, e.g., in other species (OA), and size class 1, but the overall patterns of the residuals appeared to be satisfactory.

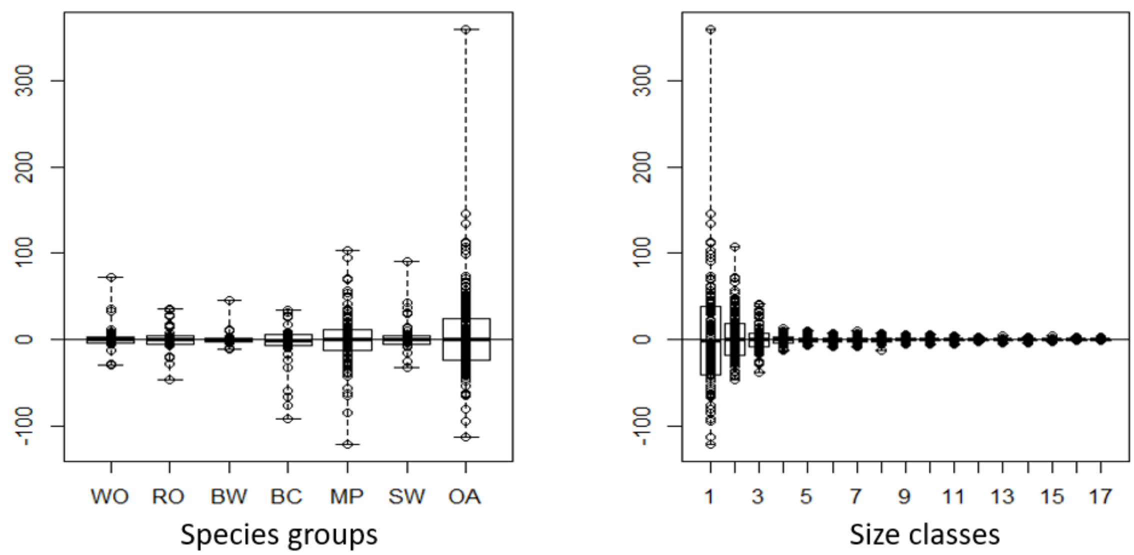

Figure 3.4. Boxplot of residuals by species groups (left) and size classes (right).

These residuals were first divided by the number of years between the two inventories. Then, the annualized residuals were used during the bootstrapping simulations to mimic time-invariant disturbances other than the windthrow. Bootstrapping simulations are obtained by the following process: at each step (year) of the simulation, a residual was randomly drawn from the set of all the residuals with replacement and then added the predicted values of the deterministic model, truncated at zero because negative numbers of trees are not possible.

This stochastic growth model was then used to directly estimate transitional probabilities between stand states. For each stand state (see Table 3.1), a random FIA plot categorized in that state was selected as the initial condition, $\mathbf{y}_t$, in the growth model. The plot was then projected for 10 years, $\mathbf{y}_{t+10}$, and re-categorized into a stand state. Repeating this process 1000 times with random plot selections, 10-year transition probabilities from that state to all 64 states were determined. In total, 64,000 repetitions were performed across all stand states.

Although the bootstrapping method accounts for time-invariant stochastic shocks, the second stochastic element, i.e., windthrow, was ignored. Within Indiana, windthrow has been the most typical and destructive natural disturbance (Gardiner et al. 2013, Cox et al. 2017, Kabrick et al. 2017). I assumed that the windthrow occurs randomly and independent of one another over the area considered with a probability of h (here, h=10%) per decade, an estimate based on Runkle (1982, 1998), and that the destruction caused by this will take any stand state to the stand state LL LL LL, i.e., low basal area in all six classes. Thus, the probability that one stand state moves from state i to state LL LL LL in one decade is increased from $p(\text{LL LL LL} \mid i)$ to $p'(\text{LL LL LL} \mid i)$, where

$$p'(\text{LL LL LL} \mid i) = p(\text{LL LL LL} \mid i) \times (1+h) \tag{3.3}$$

All the other probabilities will be adjusted to

$$p'(i' \mid i) = p(i' \mid i) \times (1-h) \qquad \text{for } i' \neq \text{LL LL LL} \tag{3.4}$$

The transition probability matrix with both elements of stochasticity is shown in the appendix.

3.4 Decision sets and Expected rewards

A decision, here in the forest management model, is taking one stand state to another by cutting some of the trees or not cutting any trees and remaining in the same state. A decision set contain all the possible decisions for all states defined in the state space. For example, for state HL LH LL, the possible decisions include not doing anything, cutting it to LL LH LL, cutting it to

LL LL LL, and cutting it to HL LL LL. It is infeasible to cut it to LH LH LL. Hence, the decision sets only contain the possible harvesting decisions for each stand state. For simplicity, a decision for a specific stand state is represented by the code of the stand state (see Table 3.1) that resulted from that decision. For instance, the decision of cutting HL LH LL to LL LH LL could be represented by Code 5.

The timber volume generated by a decision and the residual basal area only depend on the current stand state and the decision. The expected values corresponding to each level of basal area (*low* and *high*) in six species/size classes are presented in Table 3.4. The expected harvested volume in each class was equal to the difference between the average volume of the current stand state and that of the post-harvest stand state. The expected residual basal area, i.e., the basal area that was expected to remain after the harvest, was the average expected basal area of the post-harvest state itself.

Table 3.3. Expected Basal area by tree class and basal area level

Basal area level	**Basal area (ft^2/acre)**					
	Oak Species		Maple Species		Other Species	
	Pulpwood	Sawtimber	Pulpwood	Sawtimber	Pulpwood	Sawtimber
low	5.97	12.16	5.18	4.26	14.87	15.17
high	16.07	46.07	15.52	16.42	35.50	44.05

Table 3.4. Expected Volume by tree class and basal area level

Basal area level	**Volume (ft^3/acre)**					
	Oak Species		Maple Species		Other Species	
	Pulpwood	Sawtimber	Pulpwood	Sawtimber	Pulpwood	Sawtimber
low	96.13	246.85	79.29	86.16	205.12	320.80
high	257.39	903.14	235.81	334.84	516.03	937.16

3.5 Optimization of MDP models

The initial step of developing the MDP will be used to progress towards finding the optimal policies that satisfy certain management objectives, under different circumstances. Since I only considered risk and uncertainty in natural disturbances, no volatility in stumpage price was taken into account. Stumpage prices, however, fluctuate significantly over time. Using the stumpage price at one point in time, for instance, in 2019, does not give an accurate estimate of the net present value of timber income. Therefore, I didn't optimize for the NPV in this thesis. Instead, my focus was on optimizing the expected harvested volume of timber. Because there is no pulpwood market in the State of Indiana, I only considered the harvested volume of sawtimber (> 12 inches). The following models can be easily adapted to maximize other objectives, such as the total basal area, as well as the volume or basal area of certain species groups. Including multiple objectives in the MDP model is also straightforward which I will show in the following section.

3.5.1 Linear programming model for the expected criterion

The expected value of a criterion is a function of the steady-state probabilities, i.e., the average value of a criterion over the long term. The management objective can be to maximize the harvested volume or to maximize the residual basal area on average for an infinite planning horizon, assuming that transition probabilities remain constant over time. A linear programming model is formulated for the MDP model to optimize the expected average value of a criterion of interest in the long run, presented below.

$$Max \qquad \sum_{i} \sum_{k} R(i,k) y(i,k)$$

Subject to,

$$\sum_k y(i',k) - \sum_i \sum_k y(i,k) p(i'|i,k) = 0 \qquad \text{for} \quad i' = 1, \ldots \ldots \ldots \ldots, 64$$

$y(i,k) \geq 0$ for $i = 1, \dots \dots \dots \dots, 64$

$\sum_i \sum_k y(i,k) = 1$

(3.5)

where R(i, k) is the corresponding reward associated with the current state *i* and making decision *k*. y(i,k) is the expected steady-state probability in state *i* and making decision k. $p(i'|i,k)$ is the probability of finding a stand in state *i'* at *t*+1 after starting in state *i* and making decision *k*.

In this formulation, the expected reward, R(i,k), can be change to either the expected volume of harvest or the expected residual basal area of a stand in state *i* and making decision *k* depending the criterion that is being optimized. The first set of constraints represented in the above linear programming formulation keeps the probability of each stand state steady over time (steady-state probability). The second set of constraints make sure that the decision variable is non-negative. The third constraint expresses that the decision variables here are in fact probabilities and all of them add up to one, meaning that the total probabilities of all stand states equal to one.

To consider multiple objectives, the following constraints can be added to Model 3.3,

$$C(i,k)y(i,k) \geq C \quad (3.6)$$

to represent that a minimum threshold of other criterion of interest needs to be met. For instance, if we use $C(i,k)$ to denote the residual basal area of making decision k in state *i*, the new model maximizes the total harvested volume of sawtimber while keep the residual basal area above a given value, thus achieving multiple objectives.

3.5.2 Non-stationary MDP (NMDP) with rolling horizon

Below a mixed integer linear programming formulation is provided for a two-stage forest decision-making model when future transition probability is only known for the first stage. This two-stage model was then integrated with a rolling-horizon heuristic approach for every decade as the new information about the probability of time-variant disturbances arrives. Figure 3.4 illustrates the conceptual structure of this adaptive decision-making process. This heuristic approach only requires information of the nearest future, but still takes sustainability into account by always looking one step ahead. In particular, one can assign specific values to β over time to represent the relative importance of the future to the present, thus reflecting differing sustainability principles.

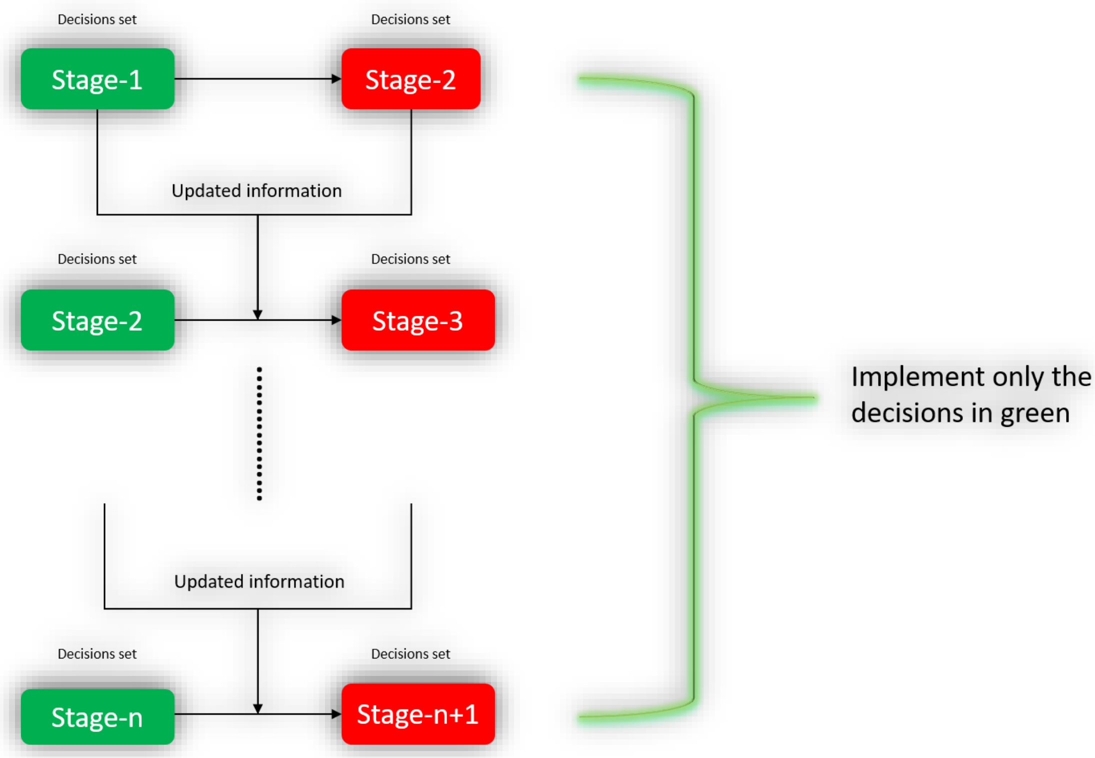

Figure 3.5. Illustration of the heuristic approach used in combination with the non-stationary Markov Decision Process Model as an adaptive management strategy.

This procedure applies to the situations when forecasting is too expensive, inaccurate, or simply impossible. For instance, the windthrow probability, assumed to be 10% per decade, may only be valid for the next decade. An accurate estimate for the probability, say, in 2050 or 2100, may be too expensive or infeasible to obtain. The MDP model for infinite horizon was modified to a two-stage model that allows information updating, shown below:

$$Max \quad \sum_{t=1}^{2} \sum_{i} \sum_{k} R_t(i,k) y_t(i,k)$$

Subject to,

$\sum_k y_1(i,k) = s_1(i)$ for $i = 1, \ldots, 64$

$s_2(i) = \sum_j s_1(j) p_1(j|i, d_1(i,k))$ for $i = 1, \ldots, 64$

$\sum_k y_2(i,k) = s_2(i)$ for $i = 1, \ldots \ldots \ldots \ldots, 64$

$\sum_k d_t(i,k) = 1,$ for $i = 1, \ldots \ldots \ldots \ldots, 64$

$\sum_i s_1(i) = 1$

$d_t(i,k) \geq y_t(i,k)$ for all *i*, *k* and *t*

$d_t(i,k) \in \{0,1\}$ for all *i*, *k* and *t*

$y_t(i,k) \geq 0$ for all *i*, *k* and *t*

(3.7)

where $y_t(i,k)$ represents the expected probability of spending time in state *i* and making decision *k* at stage *t*. $s_1(i)$ is the stand distribution at stage 1, set to be the same across all 64 states. $d_t(i,k)$ is the binary decision variable and takes the value of one when the decision *k* is optimal for state *i* at stage *t*. $p_1(j|i, d_1(i,k))$ is the decision-transition probability at stage 1 and calculated as:

$$p_1(j|i, d_1(i,k)) = \sum_k p_1(j|i,k) d_1(i,k) \quad (3.8)$$

The stand distribution as a result of the decision made in stage 1 is $\{s_2(i)\}$. At the beginning of stage 2, the transition probability, $p_2(j|i,k$ becomes known. Consequently, instead of implementing the best decision for stage 2 that is determined at stage 1, i.e., $d_2(i,k)$, the decision maker adjusts the decision-making model presented above by setting $\{s_1(i)\}$ equal to $\{s_2(i)\}$ and $p_2(j|i, d_1(i,k))$ as $p_1(j|i, d_1(i,k))$ to derive the optimal actions for stages 2 and 3. The resulting best decision for stage 2 is then implemented, whereas at the beginning of stage 3, the decision-making model is updated again and the best decision for stage 3 is re-calculated. The procedure can be updated for as many stages as possible, but at each stage, only one mixed integer linear programming problem is solved, making it easy to implement in practice. To implement multiple-objective management, Equation 3.6 could be added to the model while changing $y\,(i,k)$ to $y_t(i,k)$.

Using the approaches described in this and the previous sections, I optimized the harvested volume of sawtimber in the following scenarios:

1) Infinite planning horizon when only considering time-invariant natural disturbances simulated by bootstrapping. This applies to the situation in which windthrow poses little to no threat to forest growth. It also serves as a benchmark to illustrate how the optimal decision varies with different types of risk and uncertainty forests face.
2) Infinite planning horizon when considering both the disturbances in scenario 1 and constant probabilities of windthrow. This scenario provides practical management recommendations to Indiana landowners whose forests are subject to natural disturbances including windthrow.
3) A three-decade planning horizon when the probability of windthrow increasing over time. This was an exploratory analysis demonstrating the heuristic approach proposed in the thesis. This planning period was chosen because it was a reasonable management length for a typical private nonindustrial landowner, although the actual length of ownership varies significantly in practice. Expanding it to long planning periods is straightforward. Granted, some consequences of implementing the decisions were not directly comparable

to those with an infinite planning horizon. For instance, the residual basal area was specific for the planning stage, different from the long-run expected basal area. Nevertheless, the average sawtimber yield over the three decades was comparable to the long-run average yield per decade.

In the third scenario, the two stages that were optimized in each period/decade as depicted in the Figure 3.3. were: 1, 2; 2, 3; and 3, 4. Both time-invariant natural disturbances and windthrow were considered in the model. I assumed that the probability of windthrow was expected to increase by 5% every decade, for the demonstration of this optimization method. In other words, the windthrow probability was 10, 15, and 20 percent in periods 1, 2 and 3, respectively, but they only became known at the beginning of the corresponding period. For instance, at the beginning of Period 1 when the optimal decision was to be made for both stages, only the 10% probability of windthrow was known for sure. The windthrow probability in period 4 or beyond was irrelevant after the planning ended. Hence, the third period of the optimization was run with the same assumption that the 4^{th}-period transition probabilities were still unknown. In addition, I explored a two-objective management problem that maximized the harvested sawtimber volume while maintaining the basal area above the level of basal area in Scenarios 1 and 2, respectively. All optimizations were carried out with *What's best*® 16, a spreadsheet-based solver made by LINDO® (Lindo, 2018).

CHAPTER 4. RESULTS

4.1 Optimization Results of Scenario One

Table 4.1 lists the optimal decision for each stand state by maximizing the harvested sawtimber volume, the before-harvest and after-harvest steady-state probability of each stand state under this management along with several other stand parameters, such as total residual basal area and total harvested volume. There were only three stand states which had before-harvest steady-state probabilities over five percent, HH HH HH (38.1%), HH HL HH (28.4%), LH HH HH (11.8%). And only two stand states with after-harvest steady-state probabilities that were over five percent, LL HL HL (86.7%) and HL LL HL (8.2%). They all had both pulpwood and sawtimber of other species category along with pulpwood oak species and sawtimber of maple species. The average residual basal area was 88.8 ft^2/ac and it falls in the fully-stocked category. The volume of harvested sawtimber was 1,376 ft^3/acre per decade on average and the policy only required harvesting of 115.12 ft^3/acre of pulpwood per decade on average, which accounts for only around 8% of total harvested volume.

Table 4.1 Decisions, steady state probabilities, and consequences of maximizing volume of sawtimber harvest considering only natural disturbances.

Stand state	Decision	Before-harvest Steady-state probability (%)	Post-harvest Steady-state probability (%)
LL LL LL	-	0	-
LL LL LH	-	0	0.3
LL LL HL	-	0	0.9
LL LL HH	3	0.1	-
LL LH LL	-	0	1
LL LH LH	5	0	-
LL LH HL	-	0	1.5
LL LH HH	7	0.1	-
LL HL LL	-	0	-
LL HL LH	-	0	-
LL HL HL	-	0	86.7
LL HL HH	11	0	-
LL HH LL	-	0	-
LL HH LH	5	0	-
LL HH HL	11	0	-
LL HH HH	11	0.5	-
LH LL LL	-	0	-
LH LL LH	2	0	-
LH LL HL	3	0	-
LH LL HH	3	0.8	-
LH LH LL	-	0	-
LH LH LH	5	0.1	-
LH LH HL	7	0	-
LH LH HH	7	1.4	-
LH HL LL	-	0	-
LH HL LH	2	0.3	-
LH HL HL	11	0	-
LH HL HH	11	4.6	-
LH HH LL	-	0	-
LH HH LH	5	0.4	-
LH HH HL	11	0.1	-
LH HH HH	11	11.8	-

Table 4.1. Cont'd.

Stand state	Decision	Before-harvest Steady-state probability (%)	Post-harvest Steady-state probability (%)
HL LL LL	-	0	0.2
HL LL LH	33	0	-
HL LL HL	-	0	8.2
HL LL HH	35	0	-
HL LH LL	5	0	-
HL LH LH	5	0	-
HL LH HL	35	0	-
HL LH HH	35	0.2	-
HL HL LL	-	0	0.7
HL HL LH	41	0.1	-
HL HL HL	11	0	-
HL HL HH	11	0.4	-
HL HH LL	-	0	-
HL HH LH	5	0	-
HL HH HL	11	0.1	-
HL HH HH	11	0.9	-
HH LL LL	33	0	-
HH LL LH	33	0.2	-
HH LL HL	35	0.4	-
HH LL HH	35	3.4	-
HH LH LL	5	0	-
HH LH LH	5	0	-
HH LH HL	35	0.1	-
HH LH HH	35	4.1	-
HH HL LL	41	0.1	-
HH HL LH	41	0.5	-
HH HL HL	11	0.9	-
HH HL HH	11	28.4	-
HH HH LL	5	0.2	-
HH HH LH	5	0.3	-
HH HH HL	11	0.9	-
HH HH HH	11	38.1	-
Basal area (ft^2/ac/decade)		88.18	
Total Harvested Volume (ft^3/ac/decade)		1491.12	
Sawtimber harvest (ft^3/ac/decade)		**1376.00**	
Pulpwood harvest (ft^3/ac/decade		115.12	

4.2 Optimization Results of Scenario Two

Similarly, the planning period was set as infinite and the same linear programming model 3.4 was used, except that the transition probability matrix contained the 10-percent probability of windthrow. Table 4.2 lists the optimal decision for each stand state by maximizing the harvested sawtimber volume, the before-harvest and after-harvest steady-state probabilities of each stand state under this management, along with several other stand parameters, such as total residual basal area and total harvested volume. There were in total five stands which had before-harvest steady state probabilities over five percent, HH HH HH (25.9%) , HH HL HH (21.5%), LL LL LL (10.1%), HH LL HH (7.9%), and LH HH HH (7.6%). Four stands with after-harvest steady-state probabilities over 5%, LL LL LL(10.7%), LL LH LL(9.5%), LL HL HL(61.7%), and HL LL HL(13.6%) The three stand states with high steady-state probabilities in the policy without considering windthrow were also present here with high steady-states probabilities as well. As a result of windthrow, the expected residual basal area and harvested sawtimber volume were lowered by 5% and 17% respectively, the exact values of which were at 83.12 ft^2/acre and 1138.60 ft^3/acre per decade, respectively, compared to the policy without considering the windthrow. The most distinctive consequence of windthrow on forest structure is that there was higher probability of the stand state being LL LL LL in this scenario, namely, 10.1%, which explained the dip in the optimal value and residual basal area.

An observation of both management policies was that, although for 55 out of 64 states, the decisions were the same whether or not windthrow was taken into consideration, for the other nine states, in general, when windthrow was a threat, the decision was more aggressive, removing some large trees before losing them to windthrow. For instance, for state LH LL LH, the best decision without windthrow was doing nothing, whereas with windthrow was to cut it to state LL LL LL, by reducing the basal area of large sawtimber trees in the other-species category. There were 5 such instances where the decision state was to cut it to LL LL LL when windthrow was a threat. Comparing the consequences of following the optimal decisions in each scenario illustrates that a 10% per-decade windthrow threat, on average, reduced the periodic yield of sawtimber by 17%, although it only reduced the total basal area by 5%, implying that most loss occurred for large trees. Also, the steady-state probability of state LL LL LL has increased from 0 to 10.1% due to the inclusion of windthrow disturbance.

Table 4.2. Decisions, steady-state probabilities, and consequences of maximizing volume of sawtimber harvest considering catastrophes in addition to the disturbances.

Stand state	Decision	Before-harvest Steady-state probability (%)	Post-harvest Steady-state probability (%)
LL LL LL	-	10.1	10.7
LL LL LH	1	0.1	-
LL LL HL	-	0	1.5
LL LL HH	3	0.1	-
LL LH LL	-	2.4	9.5
LL LH LH	5	1.8	-
LL LH HL	-	0	1.5
LL LH HH	7	0.1	-
LL HL LL	-	0	-
LL HL LH	-	0	-
LL HL HL	-	0	61.7
LL HL HH	11	0	-
LL HH LL	5	0	-
LL HH LH	5	0	-
LL HH HL	11	0	-
LL HH HH	11	0.4	-
LH LL LL	1	0.2	-
LH LL LH	1	0.1	-
LH LL HL	3	0	-
LH LL HH	3	1.4	-
LH LH LL	5	2.2	-
LH LH LH	5	0.9	-
LH LH HL	7	0	-
LH LH HH	7	1.4	-
LH HL LL	1	0	-
LH HL LH	1	0.2	-
LH HL HL	11	0	-
LH HL HH	11	3.1	-
LH HH LL	5	0.2	-
LH HH LH	5	0.3	-
LH HH HL	11	0.1	-
LH HH HH	11	7.6	-

Table 4.2. Cont'd.

Stand state	Decision	Before-harvest Steady-state probability (%)	After-harvest Steady-state probability (%)
HL LL LL	-	0.1	0.6
HL LL LH	33	0.1	-
HL LL HL	-	0	13.6
HL LL HH	35	0	-
HL LH LL	5	0.5	-
HL LH LH	5	0.2	-
HL LH HL	35	0	-
HL LH HH	35	0.1	-
HL HL LL	-	0	0.5
HL HL LH	41	0.1	-
HL HL HL	11	0	-
HL HL HH	11	0.3	-
HL HH LL	5	0	-
HL HH LH	5	0	-
HL HH HL	11	0.1	-
HL HH HH	11	0.6	-
HH LL LL	33	0.1	-
HH LL LH	33	0.3	-
HH LL HL	35	0.4	-
HH LL HH	35	7.9	-
HH LH LL	5	0.5	-
HH LH LH	5	0.2	-
HH LH HL	35	0.2	-
HH LH HH	35	5	-
HH HL LL	41	0.1	-
HH HL LH	41	0.3	-
HH HL HL	11	1.1	-
HH HL HH	11	21.5	-
HH HH LL	5	0.1	-
HH HH LH	5	0.2	-
HH HH HL	11	1	-
HH HH HH	11	25.9	-
Basal area (ft^2/ac/decade)		83.12	
Total Harvested Volume (ft^3/ac/decade)		1224.64	
Sawtimber harvest (ft^3/ac/decade)		**1138.60**	
Pulpwood harvest (ft^3/ac/decade)		86.04	

4.3 Optimization Results of Scenario Three

The results obtained from a combination of Non-stationary MDP (NMDP) and rolling-horizon heuristic are presented in Tables, 4.3 through 4.6. We only implemented the decisions in green in every period which here were the first- stage decisions for each period (Table 4.3). The total reward was the sum of all of the first-stage rewards, i.e., the harvested sawtimber volume, over the entire three periods. Table 4.3, contain the results of the first-stage decisions of the three periods, all implemented. The last columns of these tables provide the stand state distribution after the first-stage decisions which were fed into the next period as the initial condition, as discussed in §3.4.2.

The results obtained for Period 1 show that the optimal expected sawtimber volume was 714.03 ft^3/ac/decade and the residual basal area was 77.88 ft^2/ac. For Period 2 and Period 3, the expected harvested volumes of sawtimber were 1,115.47 and 1,170.47 ft^3/ac/decade, respectively. The expected residual basal areas were 80.29 and 70.89 ft^2/ac, respectively. It is clear that the residual basal area was decreasing but the expected harvested volumes of sawtimber was consistently increasing between the periods. Over all three periods, the average harvested volume of sawtimber was 999.99 ft^3/ac/decade while the average basal area was 76.35 ft^2/ac, both much lower than those in the first two scenarios. This shows that the increasing occurrence of windthrow would decrease both yield and density significantly. One distinctive feature of the decisions implemented at the second and third period was that larger trees were always cut, whereas in the first period there were several instances where the larger trees were retained.

Table 4.4 presents the results for the second stage of every period when the second-stage probabilities were still unknown at the time of decision-making. The results suggest that at every period, the best decisions for the 2nd stage were to cut the trees down to stand state LL LL LL, or cut the majority larger of the trees. This was reasonable as the decisions at stage two of every period were to remove the remaining sawtimber in the forest in order to maximize the total harvested volume of sawtimber in two decades. However, we do not implement these decisions (coded in red in Figure 3.3), as the actual transition probabilities in the second stage of each period only became known after the first stage ended.

Tables 4.5 and 4.6 present the short-term stand state distribution after every stage of decision-making. Table 4.5 contains the results for first stages of three periods, thus the actual distribution. Table 4.6 contains the results for second stages of first and second periods. The stand distribution after second stage of third period cannot be calculated as the transition probabilities of the fourth period were assumed to be unknown. As it can be clearly seen in the results that the stand state distribution obtained for the state LL LL LL has been increasing consistently with the increase in windthrow frequency for every decade. The distribution of the stand state with the highest basal area (HH HH HH), on the other hand, has been steadily declining, from 14% to 2%, also suggesting increasing windthrow damages to forest stands.

Table 4.3. Decisions and consequences of maximizing volume of sawtimber harvest at stage-1 of all three periods of Non-stationary MDP optimization.

Stand state	Decision at stage-1 and period-1	Decision at stage-1 and period-2	Decision at stage-1 and period-3
LL LL LL	-	-	1
LL LL LH	1	1	1
LL LL HL	-	-	3
LL LL HH	3	3	3
LL LH LL	-	1	1
LL LH LH	5	1	1
LL LH HL	-	3	3
LL LH HH	7	3	3
LL HL LL	1	-	-
LL HL LH	1	-	-
LL HL HL	-	-	-
LL HL HH	11	11	11
LL HH LL	5	1	1
LL HH LH	5	1	1
LL HH HL	11	11	11
LL HH HH	11	11	11
LH LL LL	1	1	1
LH LL LH	1	1	1
LH LL HL	3	3	3
LH LL HH	3	3	3
LH LH LL	5	1	1
LH LH LH	5	1	1
LH LH HL	7	3	3
LH LH HH	7	3	3
LH HL LL	1	1	1
LH HL LH	1	1	1
LH HL HL	11	11	11
LH HL HH	11	11	11
LH HH LL	5	1	1
LH HH LH	5	1	1
LH HH HL	11	11	11
LH HH HH	11	11	11

Table 4.3. Cont'd

Stand state	Decision at stage-1 and period-1	Decision at stage-1 and period-2	Decision at stage-1 and period-3
HL LL LL	-	-	-
HL LL LH	33	33	33
HL LL HL	-	-	-
HL LL HH	35	35	35
HL LH LL	33	33	33
HL LH LH	33	33	33
HL LH HL	35	35	35
HL LH HH	35	35	35
HL HL LL	-	-	-
HL HL LH	41	41	41
HL HL HL	11	11	11
HL HL HH	11	11	11
HL HH LL	41	41	41
HL HH LH	41	41	41
HL HH HL	11	11	11
HL HH HH	11	11	11
HH LL LL	33	33	33
HH LL LH	33	33	33
HH LL HL	35	35	35
HH LL HH	35	35	35
HH LH LL	33	33	33
HH LH LH	33	33	33
HH LH HL	35	35	35
HH LH HH	35	35	35
HH HL LL	41	41	41
HH HL LH	41	41	41
HH HL HL	11	11	11
HH HL HH	11	11	11
HH HH LL	41	41	41
HH HH LH	41	41	41
HH HH HL	11	11	11
HH HH HH	11	11	11
Basal area (ft^2/ac/decade)	77.88	80.29	70.89
Total Harvested Volume (ft^3/ac/decade)	753.75	1140.44	1221.21
Sawtimber harvest (ft^3/ac/decade)	**714.03**	**1115.47**	**1170.47**
Pulpwood harvest (ft^3/ac/decade)	39.72	24.97	50.74

Table 4.4. Decisions and consequences of maximizing volume of sawtimber harvest at stage-2 of all three periods of Non-stationary MDP optimization (These decisions are not to be implemented)

Stand state	Decision at stage-2 and period-1	Decision at stage-2 and period-2	Decision at stage-2 and period-3
LL LL LL	-	-	1
LL LL LH	1	1	1
LL LL HL	1	-	3
LL LL HH	1	3	3
LL LH LL	1	1	1
LL LH LH	1	1	1
LL LH HL	3	3	3
LL LH HH	1	3	3
LL HL LL	-	-	-
LL HL LH	-	-	-
LL HL HL	-	-	11
LL HL HH	1	11	11
LL HH LL	9	9	9
LL HH LH	9	9	9
LL HH HL	1	11	11
LL HH HH	3	11	11
LH LL LL	1	1	1
LH LL LH	1	1	1
LH LL HL	3	3	3
LH LL HH	3	3	3
LH LH LL	1	1	1
LH LH LH	1	1	1
LH LH HL	1	3	3
LH LH HH	3	3	3
LH HL LL	1	9	9
LH HL LH	1	9	9
LH HL HL	11	11	11
LH HL HH	11	11	11
LH HH LL	1	9	9
LH HH LH	9	9	9
LH HH HL	11	11	11
LH HH HH	3	11	11

Table 4.4. Cont'd

Stand state	Decision at stage-2 and period-1	Decision at stage-2 and period-2	Decision at stage-2 and period-3
HL LL LL	1	-	33
HL LL LH	33	33	33
HL LL HL	-	-	35
HL LL HH	35	35	35
HL LH LL	33	33	33
HL LH LH	1	33	33
HL LH HL	1	35	35
HL LH HH	1	35	35
HL HL LL	1	1	41
HL HL LH	9	41	41
HL HL HL	11	-	43
HL HL HH	41	43	43
HL HH LL	41	41	41
HL HH LH	9	41	41
HL HH HL	3	43	43
HL HH HH	9	43	43
HH LL LL	33	33	33
HH LL LH	1	33	33
HH LL HL	3	35	35
HH LL HH	35	35	35
HH LH LL	33	33	33
HH LH LH	33	33	33
HH LH HL	35	35	35
HH LH HH	35	35	35
HH HL LL	9	41	41
HH HL LH	1	41	41
HH HL HL	35	43	43
HH HL HH	11	43	43
HH HH LL	1	41	41
HH HH LH	1	41	41
HH HH HL	33	43	43
HH HH HH	11	43	43
Basal area (ft^2/ac/decade)	74.39	74.16	68.37
Total Harvested Volume (ft^3/ac/decade)	1187.91	1170.47	1079.78
Sawtimber harvest (ft^3/ac/decade)	**1076.81**	**1170.47**	**1079.78**
Pulpwood harvest (ft^3/ac/decade)	111.10	0.00	0.00

Table 4.5. Short term stand state distributions after stage-1 of all the three periods of Non-stationary MDP optimization.

Stand state	Stand-distribution after 1st-stage of period-1 (%)	Stand-distribution after 1st-stage of period-2 (%)	Stand-distribution after 1st-stage of period-3 (%)
LL LL LL	0.10	0.15	0.20
LL LL LH	0.00	0.00	0.00
LL LL HL	0.00	0.00	0.00
LL LL HH	0.00	0.00	0.00
LL LH LL	0.03	0.02	0.04
LL LH LH	0.02	0.02	0.03
LL LH HL	0.00	0.00	0.00
LL LH HH	0.00	0.00	0.00
LL HL LL	0.00	0.00	0.00
LL HL LH	0.00	0.00	0.00
LL HL HL	0.00	0.00	0.00
LL HL HH	0.01	0.00	0.00
LL HH LL	0.00	0.00	0.00
LL HH LH	0.00	0.00	0.00
LL HH HL	0.00	0.00	0.00
LL HH HH	0.01	0.00	0.00
LH LL LL	0.00	0.00	0.00
LH LL LH	0.00	0.00	0.00
LH LL HL	0.00	0.00	0.00
LH LL HH	0.02	0.05	0.00
LH LH LL	0.02	0.02	0.04
LH LH LH	0.01	0.01	0.03
LH LH HL	0.00	0.00	0.00
LH LH HH	0.01	0.03	0.02
LH HL LL	0.00	0.00	0.00
LH HL LH	0.00	0.00	0.00
LH HL HL	0.00	0.00	0.00
LH HL HH	0.02	0.01	0.00
LH HH LL	0.00	0.00	0.00
LH HH LH	0.00	0.00	0.30
LH HH HL	0.00	0.00	0.00
LH HH HH	0.04	0.02	0.03

Table 4.5. Cont'd

Stand state	Stand-distribution after 1st-stage of period-1 (%)	Stand-distribution after 1st-stage of period-2 (%)	Stand-distribution after 1st-stage of period-3 (%)
HL LL LL	0.00	0.00	0.00
HL LL LH	0.02	0.01	0.00
HL LL HL	0.00	0.00	0.00
HL LL HH	0.00	0.00	0.00
HL LH LL	0.01	0.00	0.01
HL LH LH	0.01	0.00	0.00
HL LH HL	0.00	0.00	0.00
HL LH HH	0.00	0.00	0.00
HL HL LL	0.00	0.00	0.00
HL HL LH	0.00	0.00	0.00
HL HL HL	0.00	0.00	0.00
HL HL HH	0.01	0.00	0.00
HL HH LL	0.00	0.00	0.00
HL HH LH	0.00	0.00	0.00
HL HH HL	0.00	0.00	0.00
HL HH HH	0.00	0.00	0.00
HH LL LL	0.01	0.00	0.00
HH LL LH	0.05	0.02	0.01
HH LL HL	0.00	0.00	0.00
HH LL HH	0.10	0.28	0.02
HH LH LL	0.01	0.01	0.01
HH LH LH	0.02	0.01	0.09
HH LH HL	0.00	0.00	0.00
HH LH HH	0.06	0.11	0.04
HH HL LL	0.02	0.00	0.00
HH HL LH	0.03	0.00	0.00
HH HL HL	0.01	0.01	0.00
HH HL HH	0.12	0.10	0.01
HH HH LL	0.03	0.00	0.00
HH HH LH	0.04	0.00	0.07
HH HH HL	0.01	0.01	0.00
HH HH HH	0.14	0.08	0.02

Table 4.6. Short term stand state distributions after stage-2 of all the periods 1 and 2 of Non-stationary MDP optimization.

Stand state	Stand-distribution after 2nd-stage of period-1 (%)	Stand-distribution after 2nd-stage of period-2 (%)
LL LL LL	0.15	0.20
LL LL LH	0.00	0.00
LL LL HL	0.00	0.00
LL LL HH	0.00	0.00
LL LH LL	0.08	0.03
LL LH LH	0.06	0.03
LL LH HL	0.00	0.00
LL LH HH	0.00	0.00
LL HL LL	0.00	0.00
LL HL LH	0.00	0.00
LL HL HL	0.00	0.00
LL HL HH	0.01	0.00
LL HH LL	0.00	0.00
LL HH LH	0.00	0.00
LL HH HL	0.00	0.00
LL HH HH	0.01	0.00
LH LL LL	0.01	0.00
LH LL LH	0.00	0.00
LH LL HL	0.00	0.00
LH LL HH	0.00	0.00
LH LH LL	0.07	0.03
LH LH LH	0.03	0.03
LH LH HL	0.00	0.00
LH LH HH	0.00	0.02
LH HL LL	0.00	0.00
LH HL LH	0.00	0.00
LH HL HL	0.00	0.00
LH HL HH	0.02	0.00
LH HH LL	0.01	0.01
LH HH LH	0.00	0.11
LH HH HL	0.00	0.00
LH HH HH	0.04	0.05

Table 4.6. Cont'd

Stand state	Stand-distribution after 2nd-stage of period-1 (%)	Stand-distribution after 2nd-stage of period-2 (%)
HL LL LL	0.00	0.00
HL LL LH	0.01	0.00
HL LL HL	0.00	0.00
HL LL HH	0.00	0.00
HL LH LL	0.02	0.01
HL LH LH	0.01	0.00
HL LH HL	0.00	0.00
HL LH HH	0.00	0.00
HL HL LL	0.00	0.00
HL HL LH	0.00	0.00
HL HL HL	0.00	0.00
HL HL HH	0.01	0.00
HL HH LL	0.00	0.00
HL HH LH	0.00	0.00
HL HH HL	0.00	0.00
HL HH HH	0.00	0.00
HH LL LL	0.00	0.00
HH LL LH	0.02	0.01
HH LL HL	0.00	0.00
HH LL HH	0.03	0.02
HH LH LL	0.02	0.01
HH LH LH	0.01	0.08
HH LH HL	0.00	0.01
HH LH HH	0.02	0.07
HH HL LL	0.00	0.00
HH HL LH	0.00	0.01
HH HL HL	0.01	0.00
HH HL HH	0.14	0.03
HH HH LL	0.00	0.01
HH HH LH	0.00	0.11
HH HH HL	0.01	0.00
HH HH HH	0.13	0.07

Table 4.7 presents the results obtained when two management objectives were considered, which were to maximize the harvested sawtimber volume while maintaining a minimum residual basal area, using the formulation in §3.5.2. Evidently, Scenario 3 is equivalent to no constraint on the level of residual basal area and led to the highest timber yield under its specific circumstance. As the basal area threshold increased from zero to 83.12 ft^2/ acre (the average level in Scenario 2), and to 88.18 ft^2/acre (the average level in Scenario 1), the total timber yield in three decades dropped, as expected. The biggest impact was on the timber yield in the first decade, decreasing by up to 35%, because less harvests were needed for trees to grow so the basal areas in the subsequent decades could be maintained at the same level as before. There was a slight decline in the timber yields and third decades. Thus, the opportunity cost of maintaining a higher and stable residual area over time was represented by the reduction in the total timber yield.

Table 4.7. Comparison of maximum sawtimber yield for different minimum thresholds of the residual basal area for three periods of planning.

	Period 1	Period 2	Period 3	Total
		No constraint on basal area		
Yield (ft^3/acre)	714.03	1115.47	1170.47	2999.97
		Basal area >83.12 ft^2/acre		
Yield (ft^3/acre)	627.85	1137.81	1170.22	2935.88
		Basa area >88.18 ft^2/acre		
Yield (ft^3/acre)	527.58	1095.49	1075.31	2698.38

CHAPTER 5. DISCUSSION

The major contribution of this study was an active adaptive framework in the form of a two-stage non-stationary MDP combined with a rolling-horizon heuristic that mitigates uncertainty in windthrow damage. In theory, this approach should lead to a satisfactory result that is close to the actual optimum, because it is similar to a greedy optimization algorithm which finds a locally optimal decision at each stage of the decision-making. A greedy algorithm works best for problems that satisfy the property of "optimal substructure" (Helman et al. 1993). A problem is deemed to to have this property if a global optimum can be constructed from optimal solutions of its subproblems. MDP models satisfy this property (Puterman 2014), thus the adaptive approach was expected to work well here. To further validate the approach, I extened the two-stage model to a three-stage model, assuming that the same windthrow probabilies were known ahead of time. Thus, the model solved for *ex post* optimal decisions. It was found that the actual optimal sawtimer yield was 122.7 ft^3/acre/year. Recall that the heuristic approach generated a yield of 100 ft^3/acre/year, only 18% lower. This was deemed a satisfactory result, in terms of the performance of the optimization heuristic, because the knowledge on the future might be either impossible or too expensive to attain, or have a questionable accuracy.

A direct quantitative comparison of the optimization results from the three scenarios to the findings made by the previous studies (e.g., Roach and Gingrich 1968, Dale 1972, Hilt and Dale 1989) was not meaningful because these existing estimates of timber yield were mostly for even-aged oak stands based on yield tables or different deterministic growth models. In addition, the thinning was usually implemented infrequently with the goal of harvesting all trees at the end of the rotation. Our model, on the other hand, dealt with mix-species, uneven-aged forest structure and required so clear cut, hence most realistically resembling the situtaion nonindustrial private forest (NIPF) landowners face (Amacher et al., 2004, Tönisson 2013). Even so, the literuature, in general, suggests that frequent or heavy thinning reduces density and improves sawtimber yield (e.g., Roach and Gingrich 1968, Dale 1972, Hilt and Dale 1989), thus in agreement with our findings qualitatively. The only relatively comparable study also uses a 10-year thinning schedule for even-aged upland oak stands and estimates that the removed timber per decade ranges from about 1,700 to 3,800 ft^3/ac, depending on the age at the time of thinning (Gingrich 1971). Comparing to these estimates, the estimate of timber yield ranging from about 1,000 to over 1,300 ft^3/ac per decade for mixed hardwood forests appeared plausible. And also further evaluation of the management model in this study can be conducted by using Forest Vegetation Simulators(FVS) to make projections and comparing the results obtained through these models which are used to predict forest stand dynamics.

It is important to note that this study was based on several strong assumptions. A key assumption made when constructing the MDP model was that the mean basal area of fully-stocked stands represented the threshold for the decision: only when the basal area of the corresponding tree class exceeded the threshold, a harvesting action was allowed. Because of the lack of harvests by NIPF landowners in Indiana due to landowners' higher priority for nontimber objectives such as recreation (Ross-Davis and Broussard 2007), the basal areas of forest stands in the state are in general very high, as shown in Table 3.1. Defining the threshold this way, thus, could result in a threshold much higher than what is used in practice by foresters. Consequently, the residual basal area after thinning would be much higher than the desired level. A possible remedy was to define the threshold based on the FIA plots that fall in the neighborhood of the B-line on the stocking chart.

Another assumption was that the expected reward was the difference in the average volumes between pre- and post-harvest states. In reality, the stand structures could be drastically different even if they were all represented by the same stand state. Thus, the variablity in timber yield associated with one state-decision pair could be high. One way to address this was to calculate the standard deviation of the average volume corresponding to the *low* or *high* basal area during boostrapping simulations and then use the information to construct an interval for the timber yield of each state-decision pair. This interval can be used in a variant of the classic MDP model presented here, namely, MPD with imprecise parameters (Givan et al. 1997, White and El-Deib 1986), to determine the optimal harvesting decision. In this study, I also assumed that every decision was economically feasible, i.e., the value of the sawtimber volume harvested would at least equate to the costs of harvesting. In reality, to harvest some states may not be the case, thus the decision would not be carried on. Consequently, the optimal timber yield may be an overestimate of what would have been achieved. To improve this in the future, one could estimate the economic value of each state-decision pair and eliminate those economically infeasible ones.

A couple of assumptions used in the stochastic simulation of forest growth may have also impacted the results shown here. The residuals of the deterministic growth model were assumed to represent white-noise disturbances. However, the actual residuals were slightly skewed to the left or right for some of species groups and size classes (Figure 3.1). Furthermore, the stochastic simulations were truncated at zero, skewing the overall stochastic prediction to the right, likely causing the predicted basal area and volume higher than the actual levels. I also assumed that windthrow caused damages to forest that were not captured by the residuals. However, windthrow may have occurred on some of the FIA plots from 2010 to 2019, but went undetected due to the long temporal gap between re-measurements (Schroeder et al. 2014). A better estimate of the impacts of windthrow or other disturbances on forest stands could be achieved by combining FIA and remote sensing data such as LANDSAT (Reams et al. 2010, Schroeder et al. 2014). It is not clear to what extent these assumptions jointly affected the stochastic simulation results. If the impacts were substantial, the accuracy of the estimated transition probabilities and rewards would become questionable. Future studies need to carefully re-examine these assumptions and use the improved forest inventory data that better captured the disturbances.

The results from the three specific scenarios chosen in this study have a few important impliations for forest landowners, both public, and private, and managers. Evaluating different sources of risk in forest management and considering them in optimal decision-making are critical, as suggested by the comparison between the results obtained from the first two scenarios. Disturbances, such as windthrow, not only affect the best management strategy but also the outcome in terms of yield and residual basal area. A 10%-per-decade risk of windthrow would decrease the yield per decade by 17%, resulting in a moderate drop in the timber return. Scenario three, despite represening a hypothetical case that may never be realized, suggests that the decisions for some stand states changed once the windthrow frequency was altered. Hence, forest management plans need to be updated frequently to reflect new knowledge of climate change and the impacts on forests so adjustments to management strategies can be made in time. This applies to both public and NIPF landowners. Indiana's state strategic plan and assessment, the Indiana Forest Action Plan, is updated every decade. A more frequent or flexible examination of the forest condition and re-evaluation of the management plan could better mitigate climate change impacts and safeguard forest resources against potential damages caused by disturbances. However, this would incur a higher cost, which the landowners may not be willing to pay. Financial or technical assistance provided by federal or state programs may help alleviate this problem.

The results also suggest that frequent harvest/thinning of hardwood forests could, to some degree, mitigate the potential loss due to windthrow and ensure a stable flow of timber for landowners, especially if multple objectives were considered in the decision-making process. Nevertheless, the supply of timber from nonindustrial private forests (NIPFs) in Indiana was expected to decline even if the near-best strategies were to be implemented, as shown by the lower average yield of timber per decade in Scenario 3. This could be a concern for hardwood producers in the state who rely heavily on local resources for manufacturing timber products.

The study outlined in this thesis could be improved in the following ways. Only two sources of risk and uncertainty were considered here, ignoring other types of stochastic elements, such as ice storms, that threaten forests in Central hardwood region (Hart et al. 2015, Kabrick et al. 2017). If reliable estimates of these hazards could be obtained and used in the optimzation models, the resulting decision tables would be of much higher practical value to landowners and managers in the state. I did not consider market fluctuations during the planning period. Extending the current model to include such information would be very valuable as it would guide harvesting decisions based on changes in the market condition, potentially helping landowners greatly enhance their financial return from timber. The market condition could be represented by different market states representing various levels of stumpage prices. Another extension of high practical value was to consider timber quality in the optimzation model. If one can quantify the proportion of veneer- and prime-grade trees for each stand state, the optimzation was then straightforward. On the techinical side, a more definitive algorithm other than the heuristic used here may further push the result to the optimum. In particular, the method could be improved by allowing a flexible rolling horizon instead of a fixed one. Information rarely arrives at fixed intervals. A flexible horizon acting upon the arrival of new information would help make timely adjustments of management and enhance the quality of decisions.

In conclusion, a novel decision-making framework was developed allowing passive or active adaptive forest management under risk and uncertainty. Using the framework, it was found that for the mixed-species hardwood forests in Indiana, the estimated average optimal yield of sawtimber was 1,376 ft^3/ac/decade, and the residual basal area was 88 ft^2/ac, when the windthrow was not considered as a threat. The two would decline by 17% and 5%, respectively, when a 10 percent per decade probability of windthrow was assumed. When the windthrow frequency was assumed to increase in the magnitude of 5% every decade under climate change, the optimal values of average sawtimber yield and residual basal area would drop by 31% and 14%, respectively. Despite some assumptions that may have impacts on the model quality, quantitative and qualitative comparisons to the literuature suggest that the results appeared plausible. Decision tables that linked optimal or near-optimal harvesting actions to specific forest conditions were generated for mixed-species central hardwood forests, which could be useful for forest managers to guide their field practices. This study provided important management implications to both public and NIPF landowners: frequent monitoring of forest resources and flexible planning were important in the face of climate change impacts.

APPENDIX A. TRANSITION PROBABILITIES

The below transition probabilities table was calculated by the method described in §3.3. The 4th decimal point was kept due to the addition of the 10% windthrow(ref. formulation 3.3.).

Table A.1. Stand transition probabilities within a decade

Code	Stand state	Transition probability
1	LL LL LL	1(0.1135), 2(0.0108), 5(0.2232), 6(0.1638), 13(0.0045), 14(0.0027), 17(0.0198), 18(0.0135), 21(0.1998), 22(0.0747), 25(0.0009), 29(0.0189), 30(0.0081), 33(0.0054), 34(0.0027), 37(0.0441), 38(0.0198), 45(0.0018), 49(0.0072), 50(0.0027), 53(0.0441), 54(0.0135),58(0.0009), 61(0.0027), 62(0.0009)
2	LL LL LH	1(0.1),2(0.0135),4(0.0441),6(0.0099),8(0.0369),12(0.009),14(0.0018),16(0.0063, 18(0.0396), 20(0.108), 22(0.0207), 24(0.0765), 26 (0.0198), 28(0.0351), 30(0.0117), 32(0.0252), 34(0.0117), 36(0.0405), 38(0.0036), 40(0.018), 42(0.0009), 44(0.0144), 46(0.0009), 48(0.0063), 50(0.0225), 52(0.1368), 54(0.0126), 56(0.0513),58(0.0189),60(0.0747),62(0.0063),64(0.0225)
3	LL LL HL	1(0.1), 3(0.0126),4(0.045),7(0.0108),8(0.0369),11(0.0153),12(0.1143), 15(0.0243), 16(0.0837), 19(0.0054), 20(0.0324),23(0.0117),24(0.0045), 27(0.0225), 28(0.1008),31(0.0243), 32(0.045), 35(0.0081), 36(0.0162), 39(0.0036), 40(0.0027), 43(0.018),44(0.0909), 47(0.0117),48(0.0225), 51(0.009), 52(0.0108),55(0.0027), 56(0.0054), 59(0.0234), 60(0.0576), 63(0.0099), 64(0.018)
4	LL LL HH	1(0.1), 26(0.0009), 30(0.0009), 34(0.0081), 38(0.0009), 42(0.0018), 44(0.0018), 46(0.0018),48(0.0009), 50(0.1188), 52(0.1242), 54(0.0603), 56(0.0486), 58(0.1467), 60(0.2178), 62(0.0684), 64(0.0981)
5	LL LH LL	1(0.1), 20(0.0999), 24(0.0486), 52(0.5328), 56(0.2124), 60(0.0027), 64(0.0036)
6	LL LH LH	1(0.1), 6(0.4887), 8(0.0027), 14(0.0018), 22(0.2988), 24(0.0027), 30(0.0045), 38(0.0612), 40(0.0018), 54(0.0369), 56(0.0009)
7	LL LH HL	1(0.1), 8(0.0045), 16(0.0018), 20(0.0036), 23(0.0018), 24(0.0774), 28(0.0027), 31(0.0054), 32(0.0801), 40(0.0063), 47(0.0009), 48(0.0027), 51(0.0027), 52(0.0252), 55(0.0144), 56(0.207), 59(0.0027), 60(0.0378), 63(0.0225), 64(0.4005)
8	LL LH HH	1(0.1), 8(0.4491), 16(0.0297), 24(0.279), 32(0.0369), 40(0.063), 48(0.0009), 56(0.0342), 64(0.0072)
9	LL HL LL	1(0.1), 5(0.0009), 9(0.1503), 10(0.1206), 13(0.1197), 14(0.045), 25(0.1602), 26(0.0747), 29(0.0855), 30(0.0171), 41(0.0459), 42(0.018), 45(0.0045), 46(0.0036), 57(0.0324), 58(0.0126), 61(0.0081), 62(0.0009)
10	LL HL LH	1(0.1), 2(0.0207) , 6(0.0387) , 10(0.0504) , 14(0.0846) , 18(0.0459) , 22(0.0891) , 26(0.2106) , 30(0.2412) , 34(0.0036) , 38(0.0027) , 42(0.018) , 46(0.0081) , 50(0.0054) , 54(0.0135) , 58(0.0441) , 62(0.0234)
11	LL HL HL	1(0.1) , 12(0.0009) , 16(0.0045) , 20(0.0063) , 22(0.0009) , 24(0.0126) , 26(0.0027) , 28(0.0468) , 30(0.0036) , 31(0.0009) , 32(0.1197) , 40(0.0018) , 42(0.0009) , 44(0.0027) , 47(0.0009) , 48(0.009) , 50(0.0009) , 51(0.0027) , 52(0.0153) , 56(0.0315) , 58(0.0036) , 59(0.0027) , 60(0.252) , 62(0.0009) , 63(0.0045) , 64(0.3717)

12	LL HL HH	1(0.1) , 10(0.0063) , 12(0.1305) , 14(0.0018) , 16(0.1377) , 26(0.0009) , 28(0.1521) , 30(0.0009) , 32(0.1314) , 44(0.1035) , 48(0.0441) , 58(0.0018) , 60(0.1206) , 64(0.0684)
13	LL HH LL	1(0.1), 13(0.0927) , 14(0.0855) , 15(0.0477) , 16(0.0387) , 26(0.0009) , 29(0.1188) , 30(0.0711) , 31(0.0558) , 32(0.0279) , 45(0.0468) , 46(0.0378) , 47(0.0486) , 48(0.0216) , 57(0.0018) , 61(0.0801) , 62(0.036) , 63(0.0612) , 64(0.027)
14	LL HH LH	1(0.1) , 8(0.0009) , 14(0.3015) , 16(0.0027) , 22(0.0009) , 30(0.2043) , 32(0.0036) , 46(0.2169) , 48(0.0036) , 62(0.162) , 64(0.0036)
15	LL HH HL	1(0.1) , 13(0.0009) , 14(0.0009) , 15(0.2061) , 16(0.1719) , 31(0.1791) , 32(0.0981) , 47(0.09) , 48(0.045) , 63(0.0783) , 64(0.0297)
16	LL HH HH	1(0.1), 16(0.351) , 32(0.2106) , 48(0.2061) , 64(0.1323)

Code	Stand state	Transition probability
17	LH LL LL	1(0.1) , 21(0.0657) , 22(0.0324) , 29(0.0387) , 30(0.0144) , 49(0.0009) , 53(0.2601) , 54(0.108) , 55(0.0018) , 56(0.0009) , 61(0.2457) , 62(0.1287) , 63(0.0009) , 64(0.0018)
18	LH LL LH	1(0.1) , 18(0.0072) , 20(0.0027) , 22(0.1179) , 24(0.0531) , 26(0.0216) , 28(0.0108) , 30(0.2061) , 32(0.1593) , 50(0.0099) , 52(0.0009) , 54(0.0315) , 56(0.0261) , 58(0.0171) , 60(0.0171) , 62(0.0999) , 64(0.1188)
19	LH LL HL	1(0.1) , 17(0.0018) , 18(0.0054) , 19(0.0072) , 20(0.0189) , 23(0.0072) , 24(0.0162) , 49(0.0108) , 50(0.0324) , 51(0.1845) , 52(0.3555) , 53(0.0054) , 54(0.0045) , 55(0.1017) , 56(0.1386) , 58(0.0009) , 59(0.0027) , 61(0.0018) , 62(0.0018) , 64(0.0027)
20	LH LL HH	1(0.1) , 20(0.1773) , 24(0.1143) , 32(0.0018) , 52(0.4446) , 56(0.1575) , 60(0.0027) , 64(0.0018)
21	LH LH LL	1(0.1) , 6(0.0018) , 18(0.0027) , 21(0.0936) , 22(0.3024) , 23(0.0018) , 24(0.0036) , 29(0.0207) , 30(0.0711) , 32(0.0027) , 38(0.0018) , 49(0.0018) , 50(0.0018) , 53(0.072) , 54(0.2133) , 55(0.0018) , 56(0.0018) , 58(0.0018) , 61(0.0261) , 62(0.072) , 63(0.0027) , 64(0.0027)
22	LH LH LH	1(0.1) , 5(0.0009) , 6(0.0072) , 7(0.0009) , 8(0.0054) , 21(0.0216) , 22(0.2088) , 23(0.0216) , 24(0.2286) , 29(0.0009) , 30(0.0216) , 31(0.0018) , 32(0.0288) , 37(0.0009) , 38(0.0027) , 40(0.0009) , 53(0.0054) , 54(0.0936) , 55(0.0189) , 56(0.18) , 61(0.0036) , 62(0.0135) , 63(0.0045) , 64(0.0279)
23	LH LH HL	1(0.1) , 22(0.0036) , 23(0.0135) , 24(0.3348) , 30(0.0027) , 31(0.0126) , 32(0.3366) , 55(0.0018) , 56(0.0837) , 63(0.0027) , 64(0.108)
24	LH LH HH	1(0.1) , 20(0.0207) , 22(0.0009) , 23(0.0009) , 24(0.3132) , 28(0.0072) , 31(0.0009) , 32(0.0603) , 52(0.054) , 54(0.0009) , 56(0.3141) , 60(0.018) , 64(0.1089)
25	LH HL LL	1(0.1) , 14(0.0018) , 25(0.0144) , 26(0.0765) , 29(0.1098) , 30(0.297) , 31(0.0009) , 32(0.0036) , 46(0.0018) , 57(0.0315) , 58(0.0963) , 60(0.0009) , 61(0.0765) , 62(0.1854) , 63(0.0027) , 64(0.0009)
26	LH HL LH	1(0.1) , 30(0.5976) , 32(0.0036) , 58(0.0009) , 62(0.2961) , 64(0.0018)
27	LH HL HL	1(0.1) , 16(0.0009) , 20(0.0009) , 24(0.0009) , 28(0.045) , 31(0.0009) , 32(0.0927) , 48(0.0018) , 51(0.0009) , 52(0.0009) , 56(0.0063) , 59(0.0018) , 60(0.3393) , 64(0.4077)
28	LH HL HH	1(0.1) , 22(0.0009) , 26(0.2187) , 28(0.1746) , 30(0.1287) , 32(0.1017) , 58(0.0873) , 60(0.1359) , 62(0.0216) , 64(0.0306)

29	LH HH LL	1(0.1) , 13(0.0009) , 21(0.0279) , 22(0.0306) , 24(0.0018) , 29(0.1044) , 30(0.1224) , 31(0.0018) , 32(0.0054) , 46(0.0009) , 53(0.0432) , 54(0.0378) , 55(0.0009) , 56(0.0009) , 61(0.2421) , 62(0.2628) , 63(0.0099) , 64(0.0063)
30	LH HH LH	1(0.1) , 30(0.7974) , 62(0.1026)
31	LH HH HL	1(0.1) , 29(0.0009) , 31(0.2736) , 32(0.243) , 63(0.2259) , 64(0.1566)
32	LH HH HH	1(0.1) , 16(0.0108) , 32(0.8001) , 48(0.0009) , 64(0.0882)

Code	Stand state	Transition probability
33	HL LL LL	1(0.1) , 33(0.0144) , 34(0.1179) , 35(0.0009) , 36(0.0144) , 37(0.0072) , 38(0.0504) , 39(0.0009) , 40(0.0081) , 46(0.0009) , 49(0.0396) , 50(0.3654) , 51(0.0099) , 52(0.0549) , 53(0.0378) , 54(0.1485) , 55(0.0027) , 56(0.0207) , 57(0.0018) , 58(0.0009) , 62(0.0018) , 64(0.0009)
34	HL LL LH	1(0.1) , 34(0.0693) , 36(0.0279) , 38(0.0486) , 40(0.0171) , 42(0.1107) , 44(0.0828) , 46(0.072) , 48(0.0405) , 50(0.0522) , 52(0.0207) , 54(0.0315) , 56(0.0117) , 58(0.1386) , 60(0.0783) , 62(0.0558) , 64(0.0423)
35	HL LL HL	1(0.1) , 36(0.0009) , 40(0.0009) , 44(0.0027) , 51(0.018) , 52(0.1296) , 55(0.0126) , 56(0.0477) , 59(0.0621) , 60(0.4158) , 63(0.0459) , 64(0.1638)
36	HL LL HH	1(0.1) , 8(0.0009) , 20(0.0018) , 36(0.1881) , 40(0.0873) , 48(0.0009) , 52(0.4302) , 56(0.1854) , 60(0.0027) , 64(0.0027)
37	HL LH LL	1(0.1) , 37(0.0018) , 38(0.0018) , 39(0.0018) , 40(0.0009) , 49(0.0018) , 50(0.0018) , 51(0.0036) , 52(0.0009) , 53(0.2916) , 54(0.1737) , 55(0.2772) , 56(0.1116) , 61(0.0126) , 62(0.0045) , 63(0.0117) , 64(0.0027)
38	HL LH LH	1(0.1) , 38(0.0414) , 46(0.0081) , 48(0.0009) , 50(0.0009) , 54(0.5445) , 56(0.0261) , 62(0.2673) , 64(0.0108)
39	HL LH HL	1(0.1) , 39(0.0009) , 40(0.009) , 47(0.0027) , 48(0.018) , 51(0.0018) , 52(0.0054) , 55(0.0063) , 56(0.1035) , 59(0.0009) , 60(0.0036) , 63(0.0585) , 64(0.6894)
40	HL LH HH	1(0.1) , 37(0.0009) , 40(0.0009) , 48(0.0027) , 54(0.0162) , 55(0.0009) , 56(0.2709) , 62(0.0333) , 64(0.5742)
41	HL HL LL	1(0.1) , 41(0.0009) , 46(0.0027) , 57(0.1323) , 58(0.2079) , 61(0.2421) , 62(0.3123) , 63(0.0009) , 64(0.0009)
42	HL HL LH	1(0.1) , 26(0.0009) , 30(0.0018) , 42(0.0153) , 44(0.0009) , 46(0.0432) , 58(0.2331) , 60(0.0054) , 62(0.5814) , 64(0.018)
43	HL HL HL	1(0.1) , 40(0.0009) , 51(0.0063) , 52(0.2025) , 55(0.0063) , 56(0.2511) , 59(0.009) , 60(0.2214) , 63(0.0108) , 64(0.1917)
44	HL HL HH	1(0.1) , 42(0.0117) , 44(0.0252) , 46(0.0081) , 48(0.0171) , 58(0.1422) , 60(0.4554) , 62(0.063) , 64(0.1773)
45	HL HH LL	1(0.1) , 13(0.0009) , 18(0.0009) , 21(0.0081) , 22(0.009) , 25(0.0018) , 26(0.0045) , 29(0.027) , 30(0.0414) , 38(0.0009) , 45(0.0036) , 46(0.0018) , 49(0.009) , 50(0.009) , 53(0.036) , 54(0.0441) , 56(0.0009) , 57(0.0342) , 58(0.0693) , 61(0.2358) , 62(0.3564) , 63(0.0027) , 64(0.0027)
46	HL HH LH	1(0.1) , 46(0.0009) , 61(0.0027) , 62(0.8946) , 64(0.0018)

47	HL HH HL	1(0.1) , 8(0.0009) , 16(0.0009) , 24(0.0009) , 32(0.0036) , 40(0.0126) , 47(0.0009) , 48(0.0153) , 55(0.0018) , 56(0.1674) , 63(0.0063) , 64(0.6894)
48	HL HH HH	1(0.1) , 8(0.0027) , 16(0.0009) , 20(0.0009) , 24(0.0036) , 28(0.0009) , 32(0.0153) , 36(0.0009) , 40(0.009) , 44(0.0018) , 48(0.0162) , 51(0.0009) , 52(0.0054) , 54(0.0009) , 56(0.1359) , 58(0.0009) , 59(0.0009) , 60(0.0531) , 62(0.0045) , 63(0.0045) , 64(0.6408)

Code	Stand state	Transition probability
49	HH LL LL	1(0.1) , 49(0.3348) , 50(0.207) , 51(0.0621) , 52(0.027) , 53(0.1629) , 54(0.0675) , 55(0.0225) , 56(0.0099) , 57(0.0027) , 61(0.0036)
50	HH LL LH	1(0.1) , 49(0.0009) , 50(0.4995) , 52(0.1242) , 54(0.2223) , 56(0.0468) , 58(0.0027) , 62(0.0036)
51	HH LL HL	1(0.1) , 51(0.0036) , 52(0.0108) , 55(0.0099) , 56(0.0909) , 59(0.0072) , 60(0.072) , 63(0.0594) , 64(0.6462)
52	HH LL HH	1(0.1) , 18(0.0216) , 20(0.0216) , 22(0.0261) , 24(0.0459) , 26(0.0216) , 28(0.036) , 30(0.0189) , 32(0.0423) , 50(0.0306) , 51(0.0009) , 52(0.0828) , 54(0.0432) , 56(0.0801) , 58(0.0621) , 60(0.1593) , 62(0.0531) , 64(0.1539)
53	HH LH LL	1(0.1) , 6(0.0018) , 14(0.0009) , 21(0.0018) , 22(0.0018) , 24(0.0009) , 29(0.0018) , 30(0.0018) , 37(0.0045) , 38(0.0081) , 45(0.0027) , 46(0.0045) , 53(0.1044) , 54(0.1665) , 55(0.0009) , 56(0.0027) , 61(0.1971) , 62(0.3915) , 63(0.0027) , 64(0.0036)
54	HH LH LH	1(0.1) , 54(0.6408) , 55(0.0009) , 56(0.2241) , 62(0.0261) , 64(0.0081)
55	HH LH HL	1(0.1) , 50(0.0027) , 51(0.0054) , 52(0.0045) , 53(0.09) , 54(0.2178) , 55(0.1575) , 56(0.4158) , 61(0.0018) , 62(0.0018) , 63(0.0009) , 64(0.0018)
56	HH LH HH	1(0.1) , 49(0.0009) , 50(0.0198) , 52(0.0027) , 53(0.0009) , 54(0.5319) , 55(0.0018) , 56(0.2331) , 58(0.0009) , 62(0.0792) , 63(0.0009) , 64(0.0279)
57	HH HL LL	1(0.1) , 61(0.0396) , 62(0.8487) , 63(0.0018) , 64(0.0099)
58	HH HL LH	1(0.1) , 18(0.0018) , 22(0.0027) , 24(0.0009) , 26(0.0252) , 28(0.0009) , 30(0.0252) , 32(0.0009) , 50(0.0189) , 52(0.0009) , 54(0.0153) , 58(0.5094) , 60(0.0207) , 62(0.2664) , 64(0.0108)
59	HH HL HL	1(0.1) , 8(0.0027) , 16(0.0009) , 24(0.0027) , 28(0.0009) , 32(0.0072) , 36(0.0009) , 40(0.0045) , 48(0.0072) , 51(0.0009) , 52(0.0279) , 56(0.1053) , 60(0.2115) , 64(0.5274)
60	HH HL HH	1(0.1) , 52(0.0063) , 56(0.0054) , 58(0.0063) , 60(0.4563) , 62(0.0009) , 64(0.4248)
61	HH HH LL	1(0.1) , 53(0.0117) , 54(0.099) , 55(0.0009) , 56(0.0072) , 61(0.0486) , 62(0.6714) , 63(0.0054) , 64(0.0558)

62	HH HH LH	1(0.1) , 57(0.0009) , 58(0.0072) , 62(0.8451) , 64(0.0468)
63	HH HH HL	1(0.1) , 53(0.0027) , 54(0.0009) , 55(0.0036) , 56(0.0063) , 61(0.0522) , 62(0.0414) , 63(0.4797) , 64(0.3132)
64	HH HH HH	1(0.1) , 50(0.0009) , 53(0.0018) , 54(0.0567) , 55(0.0009) , 56(0.0243) , 58(0.0009) , 60(0.0009) , 61(0.0054) , 62(0.4104) , 63(0.0072) , 64(0.3906)

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