Strategic Forest Management Planning Under Uncertainty Due to Fire

by

David W. Savage

A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy Graduate Program in Forestry Faculty of Forestry University of Toronto

© Copyright by David W. Savage 2009
Abstract

Strategic Forest Management Planning Under Uncertainty Due to Fire

Doctor of Philosophy
Faculty of Forestry
University of Toronto

2009

Forest managers throughout Canada must contend with natural disturbance processes that vary over both time and space when developing and implementing forest management plans designed to provide a range of economic, ecological, and social values. In this thesis, I develop a stochastic simulation model with an embedded linear programming (LP) model and use it to evaluate strategies for reducing uncertainty due to forest fires. My results showed that frequent re-planning was sufficient to reduce variability in harvest volume when the burn fraction was low, however, as the burn fraction increased above 0.45%, the best strategy to reduce variability in harvest volume was to account for fire explicitly in the planning process using Model III. A risk analysis tool was also developed to demonstrate a method for managers to improve decision making under uncertainty.

The impact of fire on mature and old forest areas was examined and showed that LP forest management planning models reduce the areas of mature and old forest to the minimum required area and fire further reduces the seral area. As the burn fraction increased, the likelihood of the mature and old forest areas satisfying the minimum area requirements decreased. However, if the seral area constraint was strengthened (i.e., the right hand side of the constraint was increased) the likelihood improved. When the planning model was modified to maximize mature and old forest areas, the two fixed harvest volumes (i.e., 2.0 and 8.0 M. m$^3$/decade) had
much different impacts on the areas of mature and old forest when the burn fraction was greater than 0.45%.

Bootstrapped burn fraction confidence intervals were used to examine the impact of uncertain burn fraction estimates when using Model III to develop harvest schedules. I found that harvest volume bounds were large when the burn fraction was ≥0.45%. I also examined how the uncertainty in natural burn fraction (i.e., estimates of pre-fire suppression average annual area burned) estimates being used for ecosystem management can impact old forest area requirements and the resulting timber supply.
Acknowledgements

I would like to thank my supervisor Dr. David L. Martell for his constant support and encouragement, especially through tough times over the last 5 years. His high expectations required me to develop skills and knowledge that will serve me well throughout my career. I would also like to thank Dr. Jay Malcolm, Dr. Marie-Josée Fortin, and Dr. Daniel Frances who served on my thesis committee and provided thorough reviews of the thesis chapters and advice over the course of my time at the University of Toronto.

Financial support and data for my research was provided by NSERC, the Sustainable Forest Management Network, Tembec Inc., Spatial Planning Systems, Ontario Ministry of Natural Resources, and Alberta Sustainable Resource Development.

Mike Wotton a great friend and mentor provided me with an equal dose of professional and personal advice and truly helped me succeed in my PhD. I wouldn’t have survived without the technical support and friendship of Jason Myers who’s programming help and advice on research objectives constantly challenged me to define my work and improve my research. Patrick James and Robert Kruus are great friends who challenged my ideas and were always ready for a visit to the GSU.

I would also like to thank The Tommy, Wenbin, Mariam, Ana, Justin, Doug, Fletcher and Kelsy, all members of the firelab who provided great insight and conversations about our research and beyond. Harry and Ed at the GSU supplied me with a small amount of financial support (but mostly increased my debt) but more importantly provided a great environment for discussion and socializing.

I would also like to thank Doug Woolford for providing me with the LaTex thesis template used to assemble and format this thesis.
Finally, I would like to thank my family for their constant emotional (and sometimes financial) support throughout this long ordeal. My wife Jacqueline never doubted I would finish and my baby daughter Lilly kept me from finishing earlier (only by a couple of months). My mom and sister pushed me to keep moving ahead and my dad and Caiden who never got to see me finish, I love you all. I also want to thank Jacqueline’s large family for their constant support and encouragement.
## Table of Contents

Abstract ii

Acknowledgements iv

List of Tables x

List of Figures xi

1 Introduction 1
   1.1 Forest Management .................................................... 1
      1.1.1 Forest Management Planning Under Uncertainty Models ... 3
   1.2 Risk and Uncertainty in Forest Management Planning ......... 8
   1.3 Thesis Model Development ............................................. 9
      1.3.1 Linear Programming Forest Management Planning Models .. 11
      1.3.2 Fire Simulation Model ........................................... 12
      1.3.3 Simulation of Area Burned and Forest Management ....... 14
      1.3.4 Study Area: A Representative Hypothetical Forest ....... 16
   1.4 Research Objectives and Brief Chapter Overviews .......... 19

2 The Evaluation of Two Risk Mitigation Strategies for Dealing with Fire-Related Uncertainty in Timber Supply Modelling 22
   2.1 Introduction .......................................................... 22
      2.1.1 Study Objectives ................................................. 26
   2.2 Methods ............................................................... 26
      2.2.1 Study Area Description ........................................... 26
2.2.2 Forest Management Planning Model .................................. 27
2.2.3 Stochastic Forest Fire Model .......................................... 30
2.2.4 Modelling Annual Area Burned ........................................ 32
2.2.5 Modelling Forest Growth and Yield .................................... 33
2.2.6 Simulation of Forest Management Planning, Harvesting and
    Burning ........................................................................... 34
2.2.7 Experimental Design ...................................................... 37
2.2.8 Harvest Volume Distribution and Risk Analysis to Determine
    the Long-term Sustainable Harvest Volume ................................. 40

2.3 Results .............................................................................. 41
  2.3.1 Preliminary Experiment ................................................ 41
  2.3.2 Main Experiment ........................................................... 43

2.4 Discussion .......................................................................... 53

2.5 Conclusion .......................................................................... 57

3 An Evaluation of Strategies for Dealing with Uncertainty Due to
  Fire When Managing Two Forest Seral Stages .............................. 58
  3.1 Introduction ....................................................................... 58
    3.1.1 Study Objectives ........................................................ 61
  3.2 Methods ............................................................................. 62
    3.2.1 Study Area Description ................................................ 62
    3.2.2 Forest Management Planning Model ............................... 64
    3.2.3 Stochastic Forest Fire Model .......................................... 69
    3.2.4 Modelling Annual Area Burned ..................................... 69
    3.2.5 Modelling Forest Growth and Yield ................................. 69
    3.2.6 Simulation of Forest Harvesting and Forest Fires ............... 70
    3.2.7 Study Design ............................................................... 71
    3.2.8 Examining the Variability in Mature and Old Forest Area ... 74
3.3 Results ................................................................. 75
  3.3.1 Strategy 1: Ignore Fire in the Planning Process .......... 75
  3.3.2 Strategy 2: Account for Fire in the Planning Process ..... 76
  3.3.3 Strategy 3: Increase Mature and Old Forest Area ....... 81
  3.3.4 Strategy 4: Maximized Mature and Old Forest Area ..... 81
  3.3.5 Bootstrapped Confidence Intervals Examining the Number of Replications ............................................. 86

3.4 Discussion .......................................................... 86

3.5 Conclusion .......................................................... 91

4 Assessing Uncertainty in Area Burned Estimates in the Boreal Forest and their Potential Impact on Forest Management Planning 92
  4.1 Introduction .......................................................... 92
    4.1.1 Study Objectives ............................................... 94
  4.2 Methods ............................................................ 96
    4.2.1 Calculating Burn Fraction ..................................... 96
    4.2.2 Study Area Description ....................................... 96
    4.2.3 Using Historical Area Burned Data to Develop Confidence Intervals ......................................................... 97
    4.2.4 Burn Fraction and Harvest Volume Trade-off Curve ........ 98
    4.2.5 Simulating Area Burned to Estimate Annual Burn Fraction Confidence Intervals ............................................. 99
    4.2.6 Estimating Burn Fraction Confidence Intervals Using Simulated Area Burned Data ........................................ 101
    4.2.7 Examining the Uncertainty in Natural Burn Fraction Estimates and its Potential Impact on Harvest Volume .......... 102
    4.2.8 Development of a Graphical Tool to Estimate Burn Fraction Confidence Intervals ........................................ 104
4.3 Results ................................................................. 105
  4.3.1 Burn Fraction and Harvest Volume Trade-off Curve with Boot-
strapped Confidence Intervals ........................................... 105
  4.3.2 A Comparison of the Simulated and Bootstrapped Confidence
Intervals ................................................................. 105
  4.3.3 Assessing the Potential Impact of Natural Burn Fraction Un-
certainty on Old Forest Area and Timber Supply .................. 107
  4.3.4 A Graphical Tool for Estimating Burn Fraction Confidence In-
tervals ................................................................. 110
4.4 Discussion ............................................................ 112
  4.4.1 Uncertainty in Burn Fraction Estimates and their Impact on
Forest Management Planning ............................................. 112
  4.4.2 Factors Influencing Burn Fraction Estimation .................... 115
4.5 Conclusion ............................................................. 116

5 Research Summary and Further Discussion 117
  5.1 Summary of Research Results ......................................... 117
    5.1.1 Limitations of the Modelling Approach Used in this Thesis ... 120
  5.2 Research Applications ................................................ 122
    5.2.1 Application: Dealing with Uncertainty in Forest Management
Planning ................................................................. 122
    5.2.2 Application: Predicting the Impact of Decades with High Area
Burned on Timber Supply ................................................ 123
    5.2.3 Application: Managing Mature and Old Forest Areas ............ 123
  5.3 Future Research ....................................................... 124

Appendix 1 - Glossary of Terms 127

Literature Cited 130
List of Tables

2.1 Fire regime modelling parameters for four burn fraction regions in Ontario collected over the period 1960 to 2004. ........................................... 33
2.2 Experimental design factors and levels. .................................................. 38
3.1 The combination of objective functions and constraints used in each strategy. ......................................................................................... 73
4.1 Fire occurrence rates from four burn fraction regions in Ontario and based on historical fire data from the period 1960 to 2004. .............. 99
4.2 Fire size distribution parameters based on historical fire data for the period 1960 to 2004 from four burn fraction regions in Ontario. .... 101
4.3 Simulation modelling parameters used to develop natural burn fraction confidence intervals. ................................................................. 103
List of Figures

1.1 A conceptual diagram showing the arrangement of arcs and nodes for a single forest type with four age classes over three time periods. . . . 12

1.2 A flow chart which illustrates the simulation process including harvest planning, harvest implementation, burning, and re-planning activities. 15

1.3 A map of Ontario showing the four burn fraction regions, the Romeo Mallette Forest, and fire management zone boundaries. . . . . . . . . 17

1.4 a) Initial forest age class distribution used in each replication of the simulation modelling from the Romeo Mallette Forest in northeastern Ontario. b) A jack pine growth and yield curve from the Romeo Mallette Forest in northeastern Ontario (Source: Anonymous (2002)). 18

2.1 Annual area burned from 1960 to 2004 in the intensive and measured fire management zones of Ontario. . . . . . . . . . . . . . . . . . . . . . 23

2.2 A flow chart illustrating the simulation process including harvest planning, harvesting, burning, and re-planning activities. . . . . . . . . 36

2.3 A comparison of the volume harvested in the preliminary experiment for the four burn fraction regions for scenarios in which fire was accounted for and ignored in the planning process. . . . . . . . . . . 42

2.4 A box and whisker plot showing the sensitivity of harvest volume distributions to 1000 simulation replicates in the ‘extreme’ burn fraction region scenario in which the strategy was to ignore fire in the planning process. Each panel shows the precision of the $5^{th}$, $10^{th}$, $25^{th}$, and $50^{th}$ percentile measures of the harvest volume distribution. . . . . . . . . . . 43
2.5 A comparison of histograms showing the average decadel harvest volume in the ‘extreme’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. ........................................ 44

2.6 A comparison of histograms showing the average decadel harvest volume in the ‘high’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. .................................................. 46

2.7 A comparison of the volume harvested in the ‘extreme’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. ...................... 47

2.8 A comparison of the volume harvested in the ‘high’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. ...................... 48

2.9 The minimum planned harvest volume survival function (1-ECDF) was plotted against the minimum harvest volume to illustrate the probability of achieving the minimum harvest volume over 200 years in the ‘extreme’ and ‘high’ burn fraction regions for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. ................. 49

2.10 A comparison of scatterplots that show the relationship between the decade of highest area burned and the percentage change in harvest volume in the next decade for the ‘extreme’ burn fraction region. .................. 51

2.11 A comparison of scatterplots that show the relationship between the decade of highest area burned and the percentage change in harvest volume in the next decade for the ‘high’ burn fraction region. ............ 52
3.1 a) Initial forest age class distribution used in each replication of the simulated management of the Romeo Mallette Forest in northeastern Ontario. b) A jack pine growth and yield curve for the Romeo Mallette Forest in northeastern Ontario (Source: Anonymous (2002)).

3.2 A comparison of the mature and old forest areas (%) in strategy 1 (ignored fire in the planning process) for the four burn fraction regions.

3.3 A comparison of the harvest volume (m$^3$/decade) variability in strategy 1 (ignored fire in the planning) over 200 years for the four burn fraction regions.

3.4 A comparison of the mature and old forest areas (%) in strategy 2 (fire accounted for in the planning process) for the four burn fraction regions.

3.5 The minimum planned seral area survival function (1-ECDF) was plotted against the minimum average mature and old forest areas (from 1000 replications) to illustrate the probability of achieving the minimum required area (i.e., 10%) over the last 100 years of a 200 year simulation period in the four burn fraction regions for strategies 1 and 2 (whether or not to account for fire in the planning process).

3.6 A comparison of the harvest volume (m$^3$/decade) variability in strategy 2 (fire accounted for in the planning process) over 200 years in the four burn fraction regions.

3.7 The minimum planned seral area survival function (1-ECDF) was plotted against the minimum average mature and old forest areas (from 1000 replications) to illustrate the probability of achieving lower bounds of 10%, 12%, 14%, 16%, 18%, and 20% in the planning model over the last 100 years of a 200 year simulation period in the four burn fraction regions for strategy 3 (increased area of mature and old forest).
3.8 A comparison of the mature and old forest areas (%) in strategy 4 (maximized mature and old forest area) with a fixed harvest volume equal to 2.0 M. m$^3$/decade for the four burn fraction regions. Each panel in the plot represents a combination of a burn fraction region and a seral stage. ...................................................... 83

3.9 A comparison of the mature and old forest areas (%) in strategy 4 (maximized mature and old forest area) with a fixed harvest volume equal to 8.0 M. m$^3$/decade for the four burn fraction regions. Each panel in the plot represents a combination of a burn fraction region and a seral stage. ...................................................... 84

3.10 The minimum seral area survival function (1-ECDF) was plotted against the minimum average mature and old forest area (from 1000 replications) to illustrate the probability of achieving the minimum required area (i.e., 10%) area over the last 100 years of a 200 year simulation period in the four burn fraction regions for strategy 4 (maximized mature and old forest area). ...................................................... 85

3.11 A box and whisker plot showing the sensitivity of old forest area (%) distributions to 1000 simulation replicates in the ‘high’ burn fraction region for strategy 4 (2.0 M. m$^3$/decade). Each panel shows the precision of the 5$^{th}$, 10$^{th}$, 25$^{th}$, and 50$^{th}$ percentile measures of the old forest area distribution. ...................................................... 87

4.1 A map of Ontario showing the four burn fraction regions, two published natural fire regime study areas, and the fire management zone boundaries. 97
4.2 a) Bootstrapped confidence intervals were developed for the four burn fraction regions using historical area burned data from the period 1960 to 2004. b) A trade-off curve showing the relationship between burn fraction and harvest volume was developed using the Model III forest management planning model.

4.3 Confidence intervals developed from simulated area burned data and confidence intervals developed from bootstrapped historical area burned data from the period 1960-2004, were compared for the four burn fraction regions.

4.4 A comparison of natural burn fraction confidence intervals generated from simulated area burned data for two study areas in northeastern and northwestern Ontario.

4.5 The inverse of the natural burn fraction confidence intervals from two study sites in northeastern and northwestern Ontario were used as the mean forest age in the exponential age class distribution to determine the proportion of old forest area that would be required to meet ecosystem management objectives.

4.6 The estimated harvest volume (M. m$^3$/decade) using old forest area constraints developed from the natural burn fraction confidence intervals for two natural burn fraction studies in Ontario.

4.7 A graphical tool for estimating relative confidence interval range as a percentage of the burn fraction based on the fire occurrence rate (fires/million ha/year) and the number of years of area burned data.
Chapter 1

Introduction

1.1 Forest Management

Forest management has changed a great deal in the last 50 years. It has evolved from a focus on one single objective, resource extraction, to providing a suite of forest values to society. Sustained yield management was the dominant forest management paradigm in the province of Ontario from the 1940s to the 1960s with the goal of providing a constant sustainable flow of timber volume. Throughout the 1970s and 1980s, the management of multiple forest values became more important in many jurisdictions across North America (Adamowicz and Veeman, 1998). However, in Ontario it wasn’t until 1994 when the Crown Forest Sustainability Act (Crown Forestry Sustainability Act, R.S.O. 1994, c. 25) was enacted that forest management formally shifted from sustained yield management to an ecosystem management approach with the goal of sustainable forest management. The National Forest Strategy (CCFM, 2008) defined sustainable forest management as: “Management that maintains and enhances the long-term health of forest ecosystems for the benefit of all living things while providing environmental, economic, social, and cultural opportunities for present and future generations.”

To evaluate and facilitate the implementation of sustainable forest management, criteria and indicators (C&I) have been developed. The criteria are a set of forest conditions, characteristics, or processes that can be assessed to meet the goals of sustainable forest management. The indicators are measurable elements which either influence or are influenced by the forest and how it is managed and are evaluated
periodically to assess the impacts of management (Prabhu et al., 1999). The C&I framework stresses: (1) the maintenance of natural processes, (2) the provision of social, economic, and ecological values, (3) the participation of an informed public, and (4) an adaptive framework that is flexible to changing knowledge (CCFM, 2003). Under sustainable forest management timber harvesting should not diminish the productive capacity of the forest (CCFM, 1995) or limit the long-term flow of benefits to current and future generations (CCFM, 2003).

Sustainable forest management plans can provide a broad spectrum of ecological, economic, and social values to society. However, uncertainty concerning forest ecosystem processes is significant and can influence the achievement of these objectives. In Ontario, the area disturbed by forest fires is highly variable over both time and space, and can have a range of impacts on forests (Martell, 1994). As well, other natural disturbance processes such as insect infestations and windthrow can occur at a variety of spatial and temporal scales with variable levels of intensity. These natural disturbance processes are a source of great uncertainty for forest managers tasked with satisfying sustainable forest management objectives. This thesis will investigate how uncertainty concerning forest fires impacts timber supply and two seral stage forest types which are ecologically important.

Sustainable forest management objectives and methods are constantly evolving as science advances our understanding of ecological, economic, and social values of the forest resource. Holling (1978), Walters (1986), and Lee (1993) produced influential pieces of research that describe adaptive ecosystem management whereby management actions and policies can be treated as hypotheses, the results of which are then monitored and evaluated to inform managers for the development of subsequent management actions and policies. To implement an adaptive management process, there are three major components: (1) the development of dynamic models which are used to make predictions of the consequences of alternative policies, (2) the design of man-
agement experiments to evaluate alternative policies (Holling, 1978; Walters, 1986), and (3) the results of management experiments are used to inform policy changes and modify subsequent management actions (Stankey et al., 2005). A simple form of adaptive forest management has always been practiced by managers that typically use a cycle of planning, implementation, and re-planning. This thesis will use the cycle of re-planning to evaluate several strategies for dealing with uncertainty due to fire.

1.1.1 Forest Management Planning Under Uncertainty Models

1.1.1.1 Stand-level Planning Models

At the stand-level Martell (1980) examined the impact of fire on the optimal rotation age and found that as the risk of fire increased, the optimal rotation age decreased. Routledge (1980) confirmed this result but also investigated the impact of salvage logging and found that with a high proportion of the volume recovered through salvage logging, the rotation age could be increased by 1 or 2 years to maximize profit. Two other strategies for dealing with fire at a stand-level were investigated and included using a modified interest rate to account for fire losses (Reed, 1984) and using a “fire adjusted, volume rotation curve” (Reed and Errico, 1985). Although stand-level forest rotation models are relatively simple to formulate and solve, when used in planning, they prescribe the harvest of all stands beyond the planned rotation age and the harvest of young stands as soon as they reach their optimal rotation age. Such harvesting rules can create a highly variable flow of timber volume and may not be compatible with industrial capacity demands (Martell, 1994). Although stand-level forest rotation models are rarely used to develop forest management plans, it is important to understand their behaviour because some aspects of the stand-level prescription can be observed in forest-level planning models which are used to develop sustainable forest management plans.
1.1.1.2 Landscape-level Planning Models

To overcome some of the drawbacks of stand-level rotation models and to account for the shifting focus from stand-level management to landscape-level management, Johnson and Scheurman (1977) described two of the earliest (and most well known) strategic forest management planning models that aggregated stands spatially and temporally into age class-forest type units. The models are identified as Models I and II in the forest management planning literature. These models can be used to develop optimal harvesting and silviculture plans by allocating pre-defined treatment activities (e.g., harvesting and regeneration) to specified aspatial treatment units at specified times. These two models are usually formulated as linear programming models which maximize harvest volume or net present value. Uncertainty due to natural disturbance can be incorporated in Model II (Davis et al., 2000) but the structure requires that a large number of forest management and disturbance outcomes be pre-defined (e.g., when to harvest, the time between harvests, and the area burned in different time periods), creating a difficult task for managers. As an alternative, Garcia (1984) proposed a strata based forest management planning model with subsequent formulations developed by Reed and Errico (1986) and Gunn and Rai (1987) that can deal with uncertainties such as natural disturbance. Boychuk and Martell (1996) refer to this network model as Model III in the forest management planning literature. In the ecological literature, Model III type formulations are often referred to as a Leslie population matrix models (Williams, 1989). In Model III the expected or average annual burn fraction can be used to model area burned deterministically along with harvest and regeneration. Model III is sometimes referred to as a “mean value” model because fire is assumed to burn some “known” average area during each time period. Reed and Errico (1986) suggested that in forest planning, managers use their model in a cycle of planning, implementation, and then re-planning, Gunn (1991) characterized this type of planning cycle as a rolling planning horizon.
approach and suggested it may be a good strategy for dealing with uncertainty in forest management planning. In an uncertain environment, some decisions will be made before stochastic events occur while others will be made in response to such events. Decisions made in response to the stochastic events are referred to as recourse decisions (Jensen and Bard, 2003). Chappelle and Sassaman (1968), Armstrong et al. (1984), McQuillan (1986), Reed and Errico (1986), Armstrong (2004), and Peter and Nelson (2005) have used rolling planning horizon frameworks to evaluate planning model performance and to determine sustainable harvest volumes in uncertain environments.

Gassman (1989) and Boychuk and Martell (1996) used stochastic programming models to examine the effects of explicitly modelling fire as a stochastic process (as opposed to a deterministic mean value process). They used a penalty term in the objective function to moderate the deviation in harvest level through time. Boychuk and Martell (1996) found that if the penalty term increased, the harvest volume decreased along with variability in the harvest volume, showing that to provide a long-term stable timber supply a reduction in harvest volume was required. The “mean value” model is a good approximation of the stochastic programming model developed by Boychuk and Martell (1996) (i.e., the optimal solutions it produces are similar to those produced by a stochastic programming model in forests with fire losses that are characteristic of those observed in Ontario) and because of the simpler deterministic model structure, it is much easier to solve (i.e., they take much less time to solve) than stochastic programming models.

Landscape models can also be spatially explicit and can incorporate patch adjacency and road access decision-making into the planning or spatial processes such as fire and forest succession. These models are typically developed as either mathematical programming models or simulation models. Spatial planning models are usually formulated as a mixed-integer programming (MIP) model and are constrained by ad-
Jacency relationships between patches (Baskent and Keles, 2005). These models are very difficult to solve and as a result “good” solutions are usually developed using meta-heuristic techniques such as simulated annealing (see for example Lockwood and Moore (1993)) or tabu-search (see for example Murray and Church (1995)) algorithms. Simulation modelling approaches have also been used extensively to model harvesting and landscape processes such as natural disturbance and succession (Xi et al., 2009). One of the benefits of using spatial models is that the impacts of spatial processes (e.g., harvesting, natural disturbance and other ecological processes) on the forest landscape can be evaluated using spatial metrics. Alternatively, spatial models can be very difficult to parameterize and may require large amounts of computing time, as a result achieving statistically significant numbers of replications may be difficult.

1.1.1.3 Hierarchical Planning

Forest management planning occurs over a range of spatial and temporal scales. Anthony (1965) developed a hierarchical planning framework in which decisions are categorized into one of three levels: strategic, tactical, and operational. Silver and Peterson (1985) and Gunn (1991) summarized Anthony’s work and used several categories of activity to distinguish the three decision levels. The planning problem characteristics that Gunn (1991) presented to distinguish between the levels were: the objective, planning horizon, level of management, scope, source of information, level of detail, degree of uncertainty, and degree of risk. In a forest management context, strategic planning occurs over long time horizons (e.g., 200 years) using spatially and temporally aggregated data and is usually subject to a high degree of risk and uncertainty. Tactical planning occurs over medium time horizons (e.g., 5-20 years) using data that exhibits some degree of aggregation but also more spatial and temporal detail than at the strategic level. Operational planning is conducted over short
time horizons (e.g., days, weeks, months to 1 year) using detailed data with the least amount of uncertainty (e.g., less change in planning problem parameters between when the plan is developed and when it is implemented) (Gunn, 1991). Decisions and information should flow among levels, informing the planning in the level above and below in an iterative process (Weintraub and Davis, 1996).

The province of Ontario has structured their planning process using a hierarchical framework similar to the one described by Gunn (1991). The Strategic Forest Management Model (SFMM) (Davis and Martell, 1993) is an aspatial planning model that uses aggregated data and provides a long-term schedule of forest harvesting and silviculture (OMNR, 2007). SFMM is a variant of Model III (Reed and Errico, 1986; Davis and Martell, 1993; Boychuk and Martell, 1996). Recently the Ontario government approved the use of a spatial planning system, Patchworks (Spatial Planning Systems, 2009), as well. As a hierarchical system SFMM develops long-term plans that account for several types of uncertainty including: natural disturbance, regeneration, succession, and the efficacy of management treatments. Information from SFMM is passed to Patchworks to guide the spatial allocation of stands for harvest which may include objectives for road access and the patch size distribution (Spatial Planning Systems, 2009). Hierarchical planning systems have also been investigated in other jurisdictions such as Wisconsin, where Gustafson et al. (2006) used an LP forest management planning model and a spatial simulation model to produce spatially explicit harvest allocations. These models were used to assess differences in spatial habitat characteristics for a set alternative plans in a national forest. Since, much of the uncertainty accounted for in forest management planning (e.g., natural disturbance, regeneration, and succession) is incorporated at the strategic planning phase, planning at the strategic level will be the focus of this research.
1.2 Risk and Uncertainty in Forest Management Planning

Uncertainty and risk have been formally investigated and discussed in an economic context for almost 90 years (Knight, 1921). In their review of risk and uncertainty, Samson et al. (2009) indicated that these two terms may be considered to be equivalent or separate concepts depending on the field (to which, I might add, the context) in which they are used (e.g., engineering, operations research, or finance). In the situation in which uncertainty and risk were considered equivalent, Samson et al. (2009) found that the common elements between several definitions were: “... they assume that uncertainty follows a distribution, or a set of distributions giving rise to a joint distribution, which helps quantify the uncertainties that they define as risk.” In this thesis, I assume uncertainty can be characterized in the form of uncertain input parameter estimates for distributions or processes of interest, while risk involves the probability of an event occurring multiplied by an estimate of the loss associated with that event occurring.

Each individual has a different attitude or risk preference, their preference can be classified into one of three broad categories that include: risk averse, risk neutral, and risk seeking (Loomba, 1978). To illustrate the differences between the three risk attitudes, Clemen (1996) used a simple example where an individual is forced to play a game where there is a probability of 0.5 that s/he will win $500 and an equal probability that s/he will lose $500. The expected monetary value of the gamble is $0. An individual that is willing to pay a small amount to prevent losing $500 is risk averse, an individual that is willing to pay to play the game (e.g., a person that likes to gamble or play the lottery) is risk seeking, and an individual that maximizes the expected value of $0 is risk neutral.

In forest management planning, uncertainty is widespread and influences all aspects of the planning. Eid (2000) found that uncertainty concerning forest inventory attributes at the stand-level can have significant impacts on final harvest decision
making. At the landscape level, processes such as fire (Van Wagner, 1983; Reed and Errico, 1986; Martell, 1994; Boychuk and Martell, 1996), insects (Hennigar et al., 2007), windthrow (Gardiner and Quine, 2000), and climate change (Lexer et al., 2000; Lindner et al., 2000) can cause great difficulties for managers attempting to provide a sustainable flow of economic, ecological, and social values to society. Conversely, risk is often overlooked and rarely incorporated into formal forest management planning procedures (Gadow, 2000). Gardiner et al. (2008) investigated the risk of windthrow and recognized that losses are not only economic but can also be measured in terms of ecological changes, damage to infrastructure, and loss of life. Gadow (2000) indicated that to manage risk within an uncertain environment that risk analysis, evaluation, and management must be quantified using formal procedures. Kangas and Kangas (2004) provided a thorough review of techniques for dealing with uncertainty and risk in forest management planning. In this thesis, I develop a risk analysis tool that managers can use to determine the minimum harvest volume per decade that they would expect over a 200 year planning horizon given their risk preference. This approach was also used to develop minimum area risk plots for mature and old forest seral stages.

1.3 Thesis Model Development

To model the impact of uncertain fire disturbances on timber supply and the areas of mature and old forest, there are many modelling options. There are 2 main requirements of the model used for this thesis, it must: 1) create harvest schedules subject to restrictions on timber and ecological objectives, and 2) stochastically disturb the forest age class distribution based on parameters from four burn fraction regions. As well, the model must satisfy the thesis objectives outlined below in Section 1.4.

To achieve the first requirement a number of planning models were examined including ones that use simulation modelling and mathematical programming tech-
niques to perform harvest allocations. Linear programming (a subset of mathematical programming) is a formal resource allocation methodology that can be used to optimize a linear objective function subject to linear equality and linear inequality constraints (Winston, 2003). It was developed by economists and operational researchers more than 60 years ago (see, for example, Dantzig (1949)) and has been used extensively in forestry for almost 60 years (Martell, 2007). LP was chosen for this study because of its widespread use in forestry and its ideally suited to the resource allocation problems being examined. Another decision in developing the model was whether or not it should be spatial? Spatial planning models were examined as one option for the scheduling of harvesting and regeneration activities. However, because of computational limitations in solving mixed-integer programming problems and the need to perform many simulation runs to properly characterize the variability in harvest volume and the areas of mature and old forest (Objective 1), an LP model was chosen to ensure computing time was not a limiting factor. As well, one of the strategies being evaluated was whether or not to account for fire in the planning process (Objective 2), Model III is a well known LP forest management planning model and is commonly used for that purpose.

The second requirement of the model was to disturb the age class distribution based on parameters from four burn fraction regions in Ontario. Podur et al. (2009) found that the area burned in Ontario followed a compound Poisson distribution, providing the probability distribution of the number of fires each year is Poisson and the sizes of the individual fires each year have some distribution. For a discussion of how the compound Poisson distribution is used by actuarial scientists in loss modelling see Panjer and Willmot (1992). In this thesis I chose to model area burned based on a compound Poisson distribution. To model the annual area burned using the Poisson distribution and fire size distributions I assumed that there was no correlation between the number of fires in a given year and the area burned. In a recent study,
Ter-Mikaelian et al. (2009) found a weak correlation (0.316) in the number of fires and the area burned in northeastern Ontario and used a similar approach in their own study.

For this thesis, I develop a stochastic fire simulation model with an embedded forest management planning model and use it in a hypothetical forest management unit to evaluate strategies for dealing with uncertainty due to disturbances when managing for timber supply and an ecological objective. In chapters 2 and 3, the fire and forest management planning models were incorporated in a rolling planning horizon framework and in chapter 4 the models were used separately in the analysis. The models and modelling approaches are discussed in these three chapters but will be reviewed here to provide readers, some of whom may not be familiar with linear programming and simulation modelling techniques, with an overview of what was done and the potential significance of my findings.

1.3.1 Linear Programming Forest Management Planning Models

LP forest management planning models generally maximize net present monetary value (i.e., $) or harvest volume (i.e., m³) in the objective function, while at a tactical or operational planning scale the objective function might be formulated to minimize operating costs. Constraints in a strategic model may provide for an even or constant flow of harvest volume over time, minimum or maximum area for certain age classes, or budgetary restrictions on silviculture spending.

Model III’s flexible arc and node network structure, where nodes represent the area in age class $a$, at the start of time period $t$, allows uncertain disturbance processes like fire to be incorporated in planning relatively easily (Figure 1.1). The nodes are connected via arcs through which area “flows” between nodes (e.g., how much area of each age class and forest type will be harvested and/or burned during each time period). The initial forest age class distribution is specified for all age classes in the
Figure 1.1: A conceptual diagram showing the arrangement of arcs and nodes for a single forest type with four age classes over three time periods.

first period. A specific proportion (i.e., burn fraction) of the total area in each age class and period is “burned” and transferred to a burn node\(^1\) (the horizontally hatched nodes in Figure 1.1). A proportion of the unburned area in the node is then harvested and transferred to the harvest node (the vertically hatched nodes in Figure 1.1) with the remaining undisturbed area transferred to (i.e., growing into) the next age class in the next period. The area disturbed by fire and harvesting is then transferred to the first age class in the next period. My forest management planning model was implemented using ILOG’s OPL Development Studio modelling language and solved using the CPLEX (ILOG, 2007) solver running on Windows and Unix platforms.

1.3.2 Fire Simulation Model

Annual area burned was modelled as a two-stage stochastic process using a fire occurrence model and a fire size distribution model. Cunningham and Martell (1973)

\(^1\) Although this proportion can vary by age class, forest type, and over time, I chose to use a constant burn fraction for all age classes, cover types, and periods for my study.
showed it was reasonable to assume that the probability distribution of the number of people-caused forest fires that occurred in their study area in northwestern Ontario each day is Poisson with an expected value that increases as the forest dries. Since the sum of Poisson distributed random variables is also Poisson (Ross, 1989), it is reasonable to assume that annual fire occurrence in a designated area is also Poisson. The probability distribution of the number of fires in a study area each year was therefore assumed to be Poisson with an expected value of $\lambda$ fires per year.

Fire size distributions on forest landscapes have been studied extensively around the world (see, for example, Cui and Perera (2008) for a comprehensive literature review). In the boreal forest, the observed frequency distribution of fire sizes that escape initial attack resembles the probability distribution of the power law family of distributions (Cui and Perera, 2008). The exponential and Pareto distributions are the most common distributions from the power law family that are used to model fire sizes. The exponential distribution has been used by several authors to model fire sizes in the United States and Canada (Baker et al., 1991; Baker, 1995; Li et al., 1999). Cumming (2001) used log transformed fire sizes to fit a truncated exponential distribution for an 86,000 km$^2$ study area in northeastern Alberta. His analysis showed that when the exponential distribution was used, the predicted probability of large fire sizes was too high and that an upper truncation point was required to prevent extreme events that had a low probability of occurrence (i.e., fires that burn the entire landscape). Schoenberg et al. (2003) showed that a tapered Pareto distribution fit fire sizes well in California. Both Cumming (2001) and Schoenberg et al. (2003) used a lower truncation point to eliminate a large proportion of small fires that have little impact on the forest and prevent a good fit of the power law distributions.

My estimates of $\lambda$ (i.e., average number of fires/year) and $\mu$ (i.e., average fire size) were based on historical fire data from the province of Ontario for the period 1960
to 2004. Annual area burned was modelled by first randomly drawing the number of fires that occurred each year from a Poisson distribution. Then for each simulated fire occurrence, a final fire size was randomly drawn from either the exponential, truncated exponential, or tapered Pareto distributions. The simulated fire sizes were then summed to produce an annual area burned value.

1.3.3 Simulation of Area Burned and Forest Management

My integrated simulated managed forest model has three main components: (1) an embedded LP forest management planning model (i.e., Model III), (2) a stochastic fire occurrence and fire size model, and (3) a forest growth and yield model (Figure 1.2). The simulation model first initiates in step 1, then in step 2, performs the 1000 replications by looping through steps 3 to 10. In step 3, the forest management planning model (i.e., Model III) creates an aspatial, 200 year forest harvest plan that stipulates how much area will be harvested by each age class, forest type stratum in each period. The first decade of the forest management plan is then implemented in the simulated forest in step 4 by harvesting 1/10 of the prescribed harvest area from each age class allocated by the planning model. In step 5, for each year, if the volume harvested by the simulation model is less than the volume scheduled by the planning model (e.g., if fires have reduced the area of an age class below the area prescribed for harvest by the forest management planning model), the contingency planning heuristic starts harvesting the oldest age class down to the youngest age class until the missing volume has been produced or the minimum operability age precludes more harvesting.

Contingency planning is common in Ontario and is used to substitute for previously allocated timber volume that is unavailable at the time of harvest (e.g., due to fire or blowdown) (OMNR, 2004). In each scenario, contingency planning was available as a form of recourse when the actual harvest volume in any particular year
Figure 1.2: A flow chart which illustrates the simulation process including harvest planning, harvest implementation, burning, and re-planning activities.
falls below the harvest volume scheduled by the forest management planning model. In step 6, the stochastic fire occurrence and fire size models were used to calculate an annual burn fraction which was then used to burn all age classes equally and reset the area burned to age 1. Once all the harvesting and burning was completed, the simulation model in step 7 decided whether to (1) proceed to the next year with the existing plan (2) re-plan the harvest, or (3) finish the current replication at year \(200\). If the simulation run proceeds to the next year with the existing plan or the harvest schedule was re-planned, the model proceeds to step 8 where the forest age was incremented by 1 year and year \(j\) was incremented by 1. When year 200 was reached in step 9, all 200 years of simulated harvest and burn data were written to a file and the simulation model either continued to the next replication (replication \(i\) was incremented by 1 in step 10) or the simulation was stopped.

1.3.4 Study Area: A Representative Hypothetical Forest

To evaluate the strategies in this thesis, a representative hypothetical forest was created from a GIS forest inventory. The purpose for using a representative hypothetical forest was not to model strategies on an actual forest landbase but to provide “some” realism for the real focus of this study which was strategy evaluation. It is fairly common in operations research studies for simplified data sets to be used when conducting controlled experiments using models. An unaltered forest inventory was obtained for the Romeo Mallette Forest (RMF) in northeastern Ontario, Canada (Figure 1.3). This data set was simplified by re-classifying all of the stands to jack pine (\textit{Pinus banksiana} Lamb.), the addition of multiple species and the associated natural processes would likely contribute little to my strategy evaluation objective. The initial age class distribution from the RMF was used because it was considered to be representative of

---

2. Note that this flow chart was representative of the modelling process in chapter 2 and was modified slightly in chapter 3 because of minor differences in the implementation of the models.
Figure 1.3: A map of Ontario showing the four burn fraction regions, the Romeo Mallette Forest, and fire management zone boundaries.

The conditions that a manager could potentially face in an Ontario management unit (Figure 1.4). The bi-modal age class distribution was likely created by increased harvesting over the last 30 to 40 years. As well, I used a jack pine growth and yield function from the RMF (Anonymous, 2002). The area of this forest, excluding water and non-productive forest is 520,306 ha.

Because Ontario has a highly variable burn fraction that varies longitudinally from east to west, and one of the objectives was to evaluate the strategies under different levels of fire activity, four regions representing a gradient in burn fraction from east to west were selected (Figure 1.3). The four burn fraction regions (BFR) from east to west will be referred to as ‘low’, ‘moderate’, ‘high’, and ‘extreme’. The province of Ontario was until recently divided into 3 fire management zones; the in-
Figure 1.4: a) Initial forest age class distribution used in each replication of the simulation modelling from the Romeo Mallette Forest in northeastern Ontario. b) A jack pine growth and yield curve from the Romeo Mallette Forest in northeastern Ontario (Source: Anonymous (2002)).

tensive, measured, and extensive zones. All fires in the intensive zone are aggressively suppressed to protect communities, property, and natural resources. In the measured zone all fires are subject to initial attack, but if they escape initial attack, they are subject to an escaped fire situation analysis and suppressed if necessary. Extensive zone fires are monitored and suppressed if they threaten public safety or isolated values in the north (Martell and Sun, 2008). The ‘low’, ‘moderate’, and ‘high’ BFRs are located in the intensive fire management zone which is currently subject to forest management planning, while the ‘extreme’ BFR is located in the extensive zone where no forest management is currently underway. The ‘extreme’ BFR was chosen for two reasons. Firstly, the Ontario government is considering issuing Sustainable Forest Licences (SFL) in that region and managers will be required to deal with the high area burned. Secondly, under climate change scenarios, the burn fraction throughout the managed forest is expected to increase with larger more frequent fires (Flannigan and Van Wagner, 1991; Flannigan et al., 2005).
1.4 Research Objectives and Brief Chapter Overviews

The three main chapters in this thesis have several common objectives that link both the research related to forest management planning under uncertainty and the methods for evaluating and managing forests given such uncertainty. The following objectives underpin and link the elements of research described in the following chapters.

1. To quantify the variability in timber supply, mature and old forest areas and area burned,
2. To evaluate strategies for dealing with the impact of forest fires on timber supply and mature and old forest areas,
3. To develop risk analysis tools to improve decision-making in a stochastic environment,
4. To evaluate the impact of a range of burn fractions on the strategies examined,
5. To provide insight into the impact of using LP based forest management planning models when managing timber supply and mature and old forest areas.

To achieve these objectives, in chapter 2 I developed an aspatial landscape fire simulation model with an embedded LP forest management planning model and used it to evaluate two risk mitigation strategies for dealing with fire-related uncertainty in timber supply modelling. The first strategy examined the impact using three static re-planning intervals (1, 5, and 10 years) and two dynamic re-planning intervals where re-planning was re-initiated after 1.5% and 2.5% of the area of the landscape was burned since the previous re-planning point. The second risk mitigation strategy I examined deals with the decision of whether or not to explicitly account for fire in planning, in my case, by using Model III with the deterministic burn fraction.

Chapter 3 builds on chapter 2 by using the same fire and forest management planning model to investigate four strategies for dealing with the uncertain impacts
of fire on an ecological objective. The ecological objective examined in this study managed for mature and old forest areas and was selected because these two seral stages are ecologically important, easily measured, and impacted by both human and natural disturbance. The four strategies that were examined were: (1) whether or not to ignore fire in the planning process by using a burn fraction of 0 in Model III, (2) whether or not to account for fire in the planning process by using the estimated burn fraction in Model III, (3) whether or not to strengthen the lower bound in the planning model by increasing the minimum required area (i.e., the right hand side of the constraint), and (4) whether or not the mature and old forest areas should be maximized in the objective function with the harvest volume constrained to two fixed harvest targets of 2.0 and 8.0 M. m$^3$/decade. In both chapters 2 and 3, the strategies were evaluated in four burn fraction regions that vary with respect to the level of fire activity (i.e., the burn fraction varies) to investigate the extent to which the amount of fire impacts the performance of a particular strategy. As well, in both chapters, data from the simulation runs were used to develop risk analysis survival functions that could be used for decision-making under uncertainty.

In chapter 4 I examined the impact of uncertainty concerning burn fraction estimates on timber supply management (m$^3$/decade). Bootstrapping was first used to develop burn fraction confidence intervals from annual area burned data for the period 1960 to 2004. A trade-off curve was then developed to show the relationship between burn fraction and timber supply using a Model III forest management planning model (similar to Figure 3 found in Martell (1994)). The bootstrapped burn fraction confidence intervals were then input into the forest management planning model and the corresponding harvest volumes were calculated for the upper and lower bounds and were presented on the trade-off curve. Then using historical area burned data from the same period to estimate fire occurrence rate and fire size distribution parameters from four burn fraction regions, a fire simulation model was used
to estimate simulated confidence interval ranges. The simulated and bootstrapped confidence intervals were then compared to determine whether it was reasonable to model area burned using the simulation model.

The natural burn fraction (i.e., the pre-fire suppression area burned) and exponential age class distribution (see Van Wagner (1978)) are often used to estimate the proportion of old forest area required on the landscape to meet ecosystem management objectives (Bergeron et al., 1999). However, confidence intervals for natural burn fractions are rarely developed and presented, and the uncertainty concerning their estimates may have significant implications for timber supply management. I used the stochastic fire simulation model developed earlier in this study (i.e., because it provided reasonable area burned estimates) to develop natural burn fraction confidence intervals for two published estimates of the natural burn fraction from Ontario (Suffling et al., 1982; Bergeron et al., 2001). The upper and lower bounds of the natural burn fraction confidence intervals were then used as input parameters in the exponential distribution to estimate the proportion of old forest area required on the landscape to meet the objectives of one particular ecosystem management approach (Bergeron et al., 2004). The estimates of old forest area were then used as constraints in the Model III forest management planning model to evaluate the impact of uncertainty in natural burn fraction estimates on timber supply (m³/decade). A graphical tool was developed for managers who want to incorporate burn fraction confidence intervals in their planning. This tool provides the relative confidence interval ranges as a percentage of the burn fraction using the fire occurrence rate and the sample period length. In the final chapter, the results of each study were summarized, potential management applications were outlined, some of the limitations of the approach were discussed, and future work in this research area was described.
Chapter 2

The Evaluation of Two Risk Mitigation Strategies for Dealing with Fire-Related Uncertainty in Timber Supply Modelling

2.1 Introduction

Forest managers are responsible for developing long-term sustainable forest management plans that are designed to achieve a variety of timber and non-timber objectives. However, uncertainty about the occurrence of natural disturbances (e.g., fire, insects, and windthrow) can cause difficulty in achieving these objectives. For example, in the province of Ontario, over an area of 473,399 km$^2$, the annual area burned was highly variable ranging from 9 to 6,232 km$^2$ between 1960 and 2004 (Figure 2.1). Approximately 96.9% of the fires were <200 ha in size, however, these fires only accounted for about 3% of the area burned while the remaining 97% of the area burned resulted from a few large fires (Stocks et al., 2002).

One of the components of a forest management plan provides managers with a schedule of harvesting and regeneration activities which are expected to result in the achievement of a set of stated objectives. However, these long-term plans are rarely implemented beyond the first period (e.g., 5 or 10 years) of the plan before a new plan is created. In an uncertain environment, some decisions will be made and implemented before stochastic events occur while others will be made in response to such events. Decisions made in response to stochastic events are referred to as recourse decisions (Jensen and Bard, 2003). In a management framework, this pattern of planning, implementation, and then re-planning is referred to as using a rolling planning horizon.
Changes to the forest landscape, marketplace, or policy make recourse decisions important. The cycle of re-planning allows managers to adapt their plans to changing conditions rather than continuing the implementation of an infeasible or sub-optimal plan (Gunn, 1991). Studies by Chappelle and Sassaman (1968), Armstrong et al. (1984), McQuillan (1986), Reed and Errico (1986), Armstrong (2004), and Peter and Nelson (2005) have used rolling planning horizon frameworks to evaluate model performance and to determine sustainable harvest volumes in uncertain environments.

In Ontario’s current forest management planning manual, the re-planning interval has recently changed from 5 to 10 years. However, significant changes to the forest or marketplace can trigger the re-planning process after 5 years (OMNR, 2004).
In the province of Alberta, natural disturbances that exceed 2.5% of the landscape area initiate the re-planning process (ASRD, 2006), although, the planning manual provides no rationale for using this level of disturbance to initiate re-planning. The re-planning interval may be an important factor in mitigating uncertainty in timber supply due to fire.

Decision support systems have been used for almost 60 years to aid in the planning of forest management activities (Martell, 2007). Johnson and Scheurman (1977) presented two strata based forest management planning models that use linear programming to create optimal harvest and silviculture plans by allocating pre-defined treatment activities to specified aspatial treatment units comprised of aggregations of stands with similar attributes (e.g., age, cover type, and productivity). These models are referred to in the literature as Models I and II. Uncertainty due to natural disturbance can be incorporated in these models (Davis et al., 2000), however, the structure would require a large number of forest management and disturbance outcomes be pre-defined, creating a difficult task for managers. A third strata based forest management planning model was first proposed by Garcia (1984) with subsequent formulations developed by Reed and Errico (1986) and Gunn and Rai (1987). Boychuk and Martell (1996) refer to this as Model III in the literature. The network structure of Model III has many similarities to the structure of a Leslie population matrix model (Williams, 1989). Model III’s flexible structure allows uncertainty to be incorporated as a deterministic equivalent (i.e., in the form of an average) of a stochastic process such as forest regeneration, succession, or natural disturbance. Model III is therefore sometimes referred to as a “mean value” model.

In an early study by Van Wagner (1983), harvesting and fire were modelled as deterministic processes, both disturbing the same proportion of the landscape each year. His results showed that harvest volume was insensitive (i.e., did not vary from period to period) to natural disturbance when the harvest level was reduced below
the optimum harvest level. Reed and Errico (1986) extended this work using Model III to account for fire losses by assuming a constant burn fraction (i.e., the average annual area burned expressed as a proportion of the landscape size) which burned the same proportion of forest each period and had the effect of reducing the available harvest volume or the annual allowable cut. To examine the impact of forest fire processes on timber supply, Gassman (1989) and Boychuk and Martell (1996) used stochastic programming models to explicitly model fire as a stochastic process, as opposed to a deterministic mean value process. They used a penalty term in the objective function to control the deviation in harvest level through time. Boychuk and Martell (1996) found that if the penalty term increased, the harvest volume decreased along with variability in the harvest volume. This result illustrated that to provide a long-term stable timber supply under uncertainty, a reduction in harvest volume was required. The “mean value” model solutions are good approximations of the solutions to the stochastic programming model developed by Boychuk and Martell (1996) (i.e, the optimal solutions it produces are similar to those produced by a stochastic programming model in forests with fire rates that are characteristic of those observed in Ontario) and because of the deterministic structure, it is much simpler to solve than stochastic programming models.

Armstrong (2004) and Peter and Nelson (2005) also developed models to examine timber supply uncertainty and they also found similar results that indicated reductions in harvest volume were required to ensure long-term sustainability. The debate among managers of whether or not to account for fire losses in their planning is still ongoing across Canada. The decision of whether or not to account for natural disturbance can be complicated when the disturbance rate is low. Martell (1994) found that at low burn fractions the impact of fire on jack pine (Pinus banksiana Lamb.) timber supply in the boreal forest region of Ontario was minimal, while at higher levels of 1.5%, the reduction in timber supply could be approximately 35%.
His study did not examine the variability in timber supply through time created by stochastic fires.

2.1.1 Study Objectives

The focus of this study was the evaluation of strategies for dealing with uncertainty in timber supply due to fire. I used a stochastic fire simulation model and an embedded forest management planning model (Model III) in a hypothetical forest management unit to evaluate two risk mitigation strategies. Model III was chosen for this study because it explicitly accounts for fire in the planning process and LP is the predominant technique for harvest scheduling in Canada. The re-planning interval was the first strategy examined with three static re-planning intervals of 1, 5, and 10 years, along with two dynamic re-planning intervals where re-planning was initiated when the cumulative area burned since the previous re-planning point exceeded 1.5% or 2.5% of the landscape size. A second strategy examined whether or not to account for fire in the planning process by using either the observed burn fraction (i.e., account for fire in the planning process) or by using a burn fraction of 0 (i.e., ignore fire in the planning process) as an input to Model III. Since, previous research suggested the amount of fire may be an important factor in determining the effectiveness of a particular strategy, these strategies were evaluated in four burn fraction regions with burn fractions that ranged from 0.0172 to 1.78%.

2.2 Methods

2.2.1 Study Area Description

To evaluate the strategies in this study, a representative hypothetical forest data set was constructed from a GIS inventory of the Romeo Mallette Forest in northeastern Ontario, Canada. For a description of the location of the initial unaltered forest
inventory, the four burn fraction regions, the age class distribution, and the growth and yield function, please see Figures 1.3 and 1.4 in Section 1.3.4 (Page 16) of the Introduction.

2.2.2 Forest Management Planning Model

Long-term forest management plans were developed to maximize harvest volume over the planning horizon subject to a set of constraints using Model III. The constraints required an even-flow of harvest volume for all periods throughout the planning horizon. A terminal volume constraint was also used to prevent the “end of world” scenario that would allow the planning model to liquidate the growing stock in the final period. The terminal volume was based on the growing stock volume that would be present in a forest managed using the biological rotation age (i.e., stands are harvested according to the maximum mean annual increment, thus creating a fully regulated forest over time). When modelling forest management and natural disturbance in a simulated environment, the terminal volume constraint may become infeasible during a simulation run. For example, if a large fire burned much of the forest, there may not be sufficient growing stock volume to satisfy the terminal volume constraint, rendering the model infeasible. If the model was infeasible, a volume deficit decision variable was assigned the missing volume (i.e., up to the lower volume bound), the deficit decision variable was then multiplied by the penalty term to reduce the objective function. Since the penalty was only activated when a growing stock volume deficit existed, the model would produce feasible harvest plans that did not reduce the objective function whenever possible. I felt that using a penalty term in the objective function was realistic given that managers would be required to deal with the current condition of their management unit and would attempt to achieve the desired conditions in subsequent periods through continued planning and implementation. In the forest management planning model, a period was defined as
10 years. The model was written in ILOG’s OPL Development Studio, a modelling environment used to solve mathematical programming models and were solved using CPLEX (ILOG, 2007) on a Windows operating system.

2.2.2.1 Model III Formulation

The objective function was structured to maximize the volume harvested over T time periods (i.e., 10 years) in the planning horizon (Eq. 2.1).

Maximize $\sum_t VolumeCut_t - DeficitTermVol \times P$, \hspace{1cm} (2.1)

where $VolumeCut_t$ was the total volume harvested at the start of period $t$. $DeficitTermVol$ was the terminal volume deficit (i.e., the amount of volume by which the actual terminal volume was less than the “required” volume) not satisfied in period T. T is the number of time periods in the planning horizon and $t$ denotes the time period; $t = 1,2,\ldots,T$. $P$ was a large penalty term.

The following constraints were used:

The initial area was assigned to each age class decision variable at the start of period 1 (Eq. 2.2).

$Area_{at} = InitialArea_a \quad \forall \, a, t = 1 \hspace{1cm} (2.2)$

where $Area_{at}$ was the area in age class $a$, at the start of period $t$. $InitialArea_a$ was the initial area in age class $a$ (at the start of the planning horizon); A was the number of age classes; $a$ denotes age class; $a = 1,2,\ldots,A$. Forest age was classified into discrete age classes with $a = 1$ if $0 \leq$ age $\leq 10$, $a = 2$ if $10 <$ age $\leq 20$, ..., $a = 18$ if age $> 170$. The total area of the three possible states of an age class in a particular time period was summed (i.e., undisturbed, cut, or burned) for each age class and time period.
Area_{at} = UnDisturbedArea_{at} + CutArea_{at} + BurnArea_{at} \quad \forall \ a, t \quad (2.3)

where UnDisturbedArea_{at} was the area not harvested or burned in age class \( a \), at the start of period \( t \). CutArea_{at} was the area harvested in age class \( a \), at the start of period \( t \). BurnArea_{at} was the area burned in age class \( a \), at the start of period \( t \). The area cut in each period is summed (Eq. 2.4).

TotalCutArea_{t} = \sum_{a} CutArea_{at} \quad \forall \ t \quad (2.4)

where TotalCutArea_{t} was the total area harvested during period \( t \). The area burned in each age class and time period was calculated (Eq. 2.5).

BurnArea_{at} = BurnFraction \times Area_{at} \quad \forall \ a, t \quad (2.5)

where BurnFraction was the burn fraction (i.e., average annual area burned) applied to age class \( a \), at the start of period \( t \) before harvesting had occurred. The area burned in each period was summed (Eq. 2.6).

TotalBurnArea_{t} = \sum_{a} BurnArea_{at} \quad \forall \ t \quad (2.6)

where TotalBurnArea_{t} was the total area burned at the start of period \( t \). Undisturbed area was transferred from one age class and period to the next age class and period, except for the youngest and oldest age classes and the first period (Eq. 2.7).

Area_{at} = UnDisturbedArea_{(a-1)(t-1)} \quad 2 \leq a \leq A - 1, \ t > 1 \quad (2.7)

Undisturbed area from age class \( A - 1 \) was transferred to the oldest age class along
with undisturbed area from the oldest age class in the previous period (Eq. 2.8).

\[ Area_{At} = UnDisturbedArea_{A(t-1)} + UnDisturbedArea_{(A-1)(t-1)} \forall \ t > 1 \]  

(2.8)

Disturbed area from the previous period was transferred to the first (youngest) age class in the next period (Eq. 2.9).

\[ Area_{1t} = TotalCutArea_{t-1} + TotalBurnArea_{t-1} \quad \forall \ t \geq 1 \]  

(2.9)

The volume cut in each age class was summed for all time periods (Eq. 2.10).

\[ VolumeCut_t = \sum_a Volume_a \times CutArea_{at} \quad \forall \ t \]  

(2.10)

where \( Volume_a \) was the volume (\( m^3/ha \)) of age class \( a \). The harvest volume between periods must be equal (Eq. 2.11).

\[ VolumeCut_{t-1} - VolumeCut_t = 0 \quad t > 1 \]  

(2.11)

The growing stock at the start of the last period must be greater than or equal to the terminal volume requirement (Eq. 2.12).

\[ \sum_a Area_{at} \times Volume_a + DeficitTermVol \geq TerminalVolume \quad t = T \]  

(2.12)

where \( TerminalVolume \) is the required growing stock volume at the start of time period \( T \).

### 2.2.3 Stochastic Forest Fire Model

Most forest fires that occur in Ontario are suppressed before they can grow to a large size because of efficient detection networks and initial attack by fire fighting crews.
These small fires have little or no impact on timber supply (Martell, 1994). The small proportion of fires that do escape initial attack can grow to a large size and have a range of impacts on timber supply. These large fires were the focus of this study and were defined as burned areas $\geq 25$ ha in size.

2.2.3.1 Fire Occurrence Model

Cunningham and Martell (1973) showed it was reasonable to assume that the probability distribution of the number of people-caused forest fires that occur in a study area each day is Poisson. Since the sum of Poisson distributed random variables is also Poisson (Ross, 1989), it is not unreasonable to assume that annual fire occurrence in a designated area is also Poisson. The probability distribution of the number of fires in a BFR each year is shown in Equation 2.13.

$$P(x) = \frac{\lambda^x \exp^{-\lambda}}{x!}$$  \hspace{1cm} (2.13)

where $\lambda$ is the average number of people and lightning caused fires per year. Fire occurrence was modelled as a two-stage process where the total number of fires each year was selected from a Poisson distribution in the first stage. In the second stage, each fire was classified as an escaped or contained fire by generating a random number from a uniform distribution $(0,1)$, if the random number was less than the probability of escape, the fire had escaped initial attack and a fire size was randomly generated.

2.2.3.2 Fire Size Model

Cumming (2001) fit the logarithm of fire sizes to a truncated exponential distribution using data from an 86,000 km$^2$ study area in northeastern Alberta. His analysis showed that the exponential distribution over-estimated the occurrence of very large fire sizes and that a truncation point was required to prevent extreme events that had a low probability of occurrence (i.e., fires that burn the entire landscape). For
this study, the truncated exponential distribution was chosen to model fire sizes and was fit to historical data from 1960 to 2004 using maximum likelihood estimation in R (Table 2.1) (Ihaka and Gentleman, 1996). The fire size distribution was truncated from below using my escaped fire size threshold (i.e., ≥ 25 ha) and from above using a maximum fire size that was estimated using a method described in Hannon and Dahiya (1999). The cumulative distribution function of the truncated exponential is shown in Equation 2.14.

\[
F_{Xt}(x) = \frac{1 - \exp(-x/\sigma)}{1 - \exp(-\beta/\sigma)} \quad (25 \leq x \leq \exp^\beta \times 25)
\]

where subscript \( t \) indicates truncation, \( \sigma \) was a scale parameter and \( \exp^\beta \times 25 \) was the upper truncation point. Fire sizes were initially log transformed and divided by 25 (i.e., minimum fire size) to estimate the distribution parameters, they were untransformed while modelling annual area burned.

### 2.2.4 Modelling Annual Area Burned

The annual area burned was modelled using the fire occurrence (i.e., \( \lambda \) and fires size distribution models described above and were parameterized using historical area burned data from the period 1960 to 2004 (Table 2.1). For example, for each year, the total number of fires was generated from the Poisson distribution. Then for each fire that escaped initial attack, a fire size was generated from the truncated exponential distribution. All fire sizes in a given year were then summed to calculate the total annual area burned for that year and finally, the simulated area burned values were divided by the landscape size to produce an annual burn fraction value. The annual area burned was modelled independently of what was harvested and burned in previous years. To model area burned using the fire occurrence and the final fire size models, I assumed that the fire occurrence rate and final fire size were independent.
Table 2.1: Fire regime modelling parameters for four burn fraction regions in Ontario collected over the period 1960 to 2004.

<table>
<thead>
<tr>
<th>Burn Region</th>
<th>Max Fire Size (ha)</th>
<th>Max Average Annual Fire Occurrence Rate ($\lambda^*$)</th>
<th>Proportion of Fires that Escape Initial Attack</th>
<th>Burn Fraction</th>
<th>$\sigma$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>'Low'</td>
<td>36,054</td>
<td>8.55</td>
<td>0.0432</td>
<td>0.017%</td>
<td>1.114</td>
<td>7.274</td>
</tr>
<tr>
<td>'Moderate'</td>
<td>37,937</td>
<td>9.43</td>
<td>0.0428</td>
<td>0.134%</td>
<td>2.913</td>
<td>7.325</td>
</tr>
<tr>
<td>'High'</td>
<td>113,083</td>
<td>15.38</td>
<td>0.0330</td>
<td>0.448%</td>
<td>3.574</td>
<td>8.417</td>
</tr>
<tr>
<td>'Extreme'</td>
<td>140,067</td>
<td>3.47</td>
<td>0.3551</td>
<td>1.780%</td>
<td>4.963</td>
<td>8.631</td>
</tr>
</tbody>
</table>

*All fire occurrence rates were expressed in terms of the average number of fires per 520,306 ha. per year (the area of the Romeo Mallette Forest Size).

2.2.5 Modelling Forest Growth and Yield

The forest inventory ranged in age from 1 to 180+ (i.e., an upper collector age), with the area in each forest age tracked throughout the simulation run. The forest ages and areas were incremented by 1 year after each simulated year. It is common in this type of study for the data to be structured using 10 year age classes (e.g., Armstrong (2004)), where the age class is incremented by 1 age class every 10 years. When using re-planning intervals of <10 years, the inventory must be structured (i.e., the width of the age class) and updated to an interval less than the re-planning interval, otherwise the age class distribution would not reflect the most recent disturbances and the planning model would not be providing recourse opportunities to respond to the new fire disturbances. Therefore, an assumption was made that the inventory was continually updated on an annual basis to reflect current human and natural disturbances. The yield curve used to model the age volume relationship was from a jack pine cover type in the Romeo Mallette Forest (Anonymous, 2002) (Figure 1.4 in the Introduction).
2.2.6 Simulation of Forest Management Planning, Harvesting and Burning

The simulated managed forest model has three main components: 1) an embedded linear programming (LP) forest management planning model, 2) a stochastic fire occurrence and fire size model, and 3) a forest growth and yield model. These three components were used in a rolling planning horizon framework to evaluate strategies for dealing with the uncertain impacts of fire on timber supply. The Python scripting language (Python Software Foundation, 2005) was used to program the fire simulation model, initiate the OPL implementation of the LP planning model, and controlled the transfer of data between the simulation and planning models. Harvesting and burning were modelled annually for a total of 200 years for each simulated replicate. It was felt that from a forest management policy perspective, 200 years was sufficient to observe the impact of the forest management strategies given the initial starting conditions. A total of 1000 replications were run for each scenario in this study. Armstrong (2004) used 1000 replications with a similar model and then examined the sensitivity of the shape of the harvest volume distributions to the number of replications selected. He found that 1000 replications was quite precise in almost every case when estimating the 5th, 10th, 25th, and 50th percentiles of the harvest volume distributions. This same procedure was repeated in this study using a bootstrapping technique to estimate the precision of the harvest volume distributions. From the 1000 replications, 1000 random replicates were selected with replacement. The 5th, 10th, 25th, and the 50th percentiles were then calculated from the 1000 random replicates. This process was then repeated 10,000 times to develop a sampling distribution for each of the percentiles measured. The four percentile estimates were then plotted using box and whisker plots to describe their precision.
2.2.6.1 Contingency Planning

Contingency planning is a common type of recourse that allows forest managers in Ontario to substitute unallocated timber volume for previously allocated volume that is unavailable at the time of harvest (e.g., due to fire or blowdown) (OMNR, 2004). In each scenario, contingency planning was available as a form of recourse when the volume harvested by the simulation model in any particular year fell below the harvest volume scheduled by the forest management planning model (i.e., there was not enough area in an age class to fully implement the harvest plan produced by the LP planning model). The contingency planning heuristic started at the oldest age class and harvested sequentially younger age classes down to the minimum operability limit or until all of the missing volume was replaced.

To illustrate the simulation process, a flowchart was developed to describe each step in the simulation of fire and forest management (Figure 2.2).

1. Initiate the simulation model,

2. Loop over steps 3 to 11 for each replication,

3. Use Model III to develop a 200 year harvest schedule,

4. The first decade of the harvest schedule was implemented by attempting to harvest 1/10 of the area from each age class allocated,

5. If the volume harvested by the simulation model in a given year was less than the volume scheduled by the planning model (e.g., if fires reduced the area of an age class scheduled for harvest below the area prescribed for harvest by the forest management planning model), the contingency planning heuristic started harvesting the oldest age class down to the youngest age class until the missing volume was replaced or the minimum harvest age was met,
Figure 2.2: A flow chart illustrating the simulation process including harvest planning, harvesting, burning, and re-planning activities.
6. The stochastic fire occurrence and final fire size models were used to model the annual burn fraction which was then used to burn all age classes equally and reset the age of the area burned to year 1, at the start of the next year,

7. If year $j$ was not a re-planning point, continue the simulation with the existing plan, if year $j$ was a re-planning point then re-plan the harvest, or if year $j$ was equal to 200 finish the simulation run,

8. If the simulation model continued with the existing plan, grow the forest by 1 year and increment year $j$ by 1,

9. If re-planning occurred, grow the forest by 1 year and increment year $j$ by 1,

10. If year $j$ equalled 200 then write all 200 years of simulated harvesting and burning data to a file, if replication $i$ was less than 1000, continue to the next replication, otherwise stop the simulation model,

11. If replication $i$ was less than 1000, increment $i$ by 1, and continue the next 200 year simulation run.

2.2.7 Experimental Design

The simulation study was designed and executed in two stages to limit the experimental size of the study (Table 2.2). The preliminary experiment examined all four burn fraction regions (BFR) and whether or not to account for fire in the planning process. Fire was accounted for in the planning process by using the observed burn fraction from each of the four BFRs in Model III, while fire was ignored in the planning process by using a burn fraction of 0 in Model III. The re-planning interval for the preliminary study was 10 years. The results from the preliminary experiment were used to design a larger main experiment to examine the interaction of the two
risk mitigation strategies (i.e., whether or not to account fire in planning process and the re-planning interval).

Table 2.2: Experimental design factors and levels.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Factors</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preliminary</td>
<td>Whether or not to Account for Fire in the Planning Process</td>
<td>1. Ignore Fire</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Account for Fire</td>
</tr>
<tr>
<td></td>
<td>Burn Fraction Region</td>
<td>1. ‘Low’ (BF = 0.0172%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. ‘Moderate’ (BF = 0.134%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. ‘High’ (BF = 0.448%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. ‘Extreme’ (BF = 1.78%)</td>
</tr>
<tr>
<td>Main</td>
<td>Whether or not to Account for Fire in the Planning Process</td>
<td>1. Ignore Fire</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Account for Fire</td>
</tr>
<tr>
<td></td>
<td>Re-planning Interval</td>
<td>1. 1 year</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. 5 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. 10 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Dynamic - 1.5%*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5. Dynamic - 2.5%*</td>
</tr>
<tr>
<td></td>
<td>Burn Fraction Region</td>
<td>1. ‘High’ (BF = 0.448%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. ‘Extreme’ (BF = 1.78%)</td>
</tr>
</tbody>
</table>

*The cumulative area burned since the previous re-planning point.

The main experiment had three factors: 1) burn fraction region, 2) whether or not to account for fire in the planning process, and 3) the length of the re-planning interval. For this study, each combination of the three factors will be referred to as a scenario. A total of 20 scenarios were investigated in the main experiment. A variance reduction technique (Law and Kelton, 2003) was used to reduce the variability in the harvest volume among scenarios. The random number generator in the fire model was seeded to generate identical lists of annual burn fractions for each of the scenarios within a specific BFR, consequently the differences in harvest volume were a direct
result of the management strategies and not an artifact of the random fires that “burned” the landscape.

2.2.7.1 Experimental Factors Examined

The main experiment focused on the ‘high’ and ‘extreme’ BFRs because they experience the most variability in harvest volume. Both BFRs are found in northwestern Ontario, however, the ‘high’ BFR is in a region currently subject to forest management, while the ‘extreme’ BFR is not. The ‘extreme’ BFR was chosen for two reasons. Firstly, the Ontario government is considering issuing Sustainable Forest Licences (SFL) in that region and managers will be required to deal with the elevated level of area burned that is common there. Secondly, with climate change, the burn fraction throughout the managed forest is expected to increase with larger more frequent fires (Flannigan et al., 2005; Flannigan and Van Wagner, 1991). By modelling these strategies in the ‘extreme’ BFR, their effectiveness under a changing climate can be evaluated.

The decision of whether or not to account for natural disturbance in the planning process is still being debated by forest managers. In Ontario, expected fire losses are incorporated in strategic forest planning (OMNR, 2004) with the effect of reducing the harvest rate, while other provinces across Canada rely on a strategy of re-planning to deal with uncertainty due to fire. This study examined the impact of accounting for fire in the planning process (i.e., by using the observed burn fraction in Model III) vs. ignoring fire in the planning process (i.e., by using a burn fraction of 0 in Model III).

In this study the re-planning interval was considered to be the time between subsequent forest management plans. Five re-planning intervals were evaluated, in-

1. Note that harvesting, silviculture, and fire itself can influence subsequent fire regimes but such interactions are at best poorly understood and beyond the scope of this research.
cluding three static and two dynamic intervals. Static re-planning intervals occurred
on a regular time interval of 1, 5 and 10 years and were selected to represent a high
frequency re-planning interval (i.e., 1 year) and a standard re-planning interval (i.e., 5
or 10 years) found across Canada (OMNR, 2004; ASRD, 2006). Dynamic re-planning
does not follow a predictable 5 or 10 year re-planning interval but instead occurs
whenever some forest attribute has been altered beyond a specified threshold. Re-
planning was initiated when the cumulative area burned in the forest management
unit exceeded 1.5% or 2.5% of the forest area since the previous re-planning point.

2.2.8 Harvest Volume Distribution and Risk Analysis to Determine the
Long-term Sustainable Harvest Volume

For each scenario examined, boxplots of harvest volume (m$^3$/decade) were developed
to describe its distribution through time. The centre line represents the median, the
box represents the 25th and 75th percentiles, the end of the whiskers represent the
10th and 90th percentiles, the points represent the 5th and 95th percentiles and the
“+” signs represent the minimum and maximum values.

I also developed a risk analysis tool to demonstrate to managers, a method for
incorporating uncertainty into their decision-making using the probability of achieving
a minimum harvest volume over time. To produce the graphical risk analysis plot,
the annual harvest volume was summed over 10 years for each of the 20 decades in
a simulation run, this produced a vector of 20 total harvest volumes from which the
decade with the minimum total harvest volume was then selected. Given the set of N
ordered data points, $X_1, X_2, ..., X_N$ the empirical cumulative distribution function
of the minimum harvest volume was defined in Equation 2.15.

$$F_n(x) = \frac{\text{number of } X_i's \leq x}{n} \quad (2.15)$$
To simplify the interpretation of the risk analysis plots, they were graphed as one minus the empirical cumulative distribution function (1-ECDF), which I refer to as the minimum planned harvest volume survival function. For example, if a manager wanted a specific volume for their mill they could determine the probability of achieving that volume as the minimum harvest volume over a 200 year horizon. They could then adjust the minimum harvest volume (i.e., increase or decrease it) until the probability of achieving that minimum volume corresponded with their risk preference. This method for developing risk analysis plots was adapted from Armstrong (2004) and Peter and Nelson (2005).

2.3 Results

2.3.1 Preliminary Experiment

The preliminary experiment showed that the harvest volume in all four burn fraction regions (BFR) exhibited little variability over time for scenarios in which the strategy was to account for fire in the planning process (Figure 2.3). This was also the case for the ‘low’ and ‘moderate’ BFRs for scenarios in which fire was ignored in the planning process, however, in the ‘high’ and ‘extreme’ BFRs, the harvest volume was quite variable if fire was ignored in the planning process. The harvest volume for the ‘moderate’ BFR was approximately 13.5 m³/decade, while the ‘low’ BFR was approximately 14.0 m³/decade. In the ‘extreme’ and ‘high’ BFRs for scenarios in which fire was ignored in the planning process, the harvest volume ranged from 3.5 to 13.5 M. m³/decade and from 8.0 to 13.5 M. m³/decade, respectively.

To examine the sensitivity of the harvest volume distributions to the number of replicates, a bootstrapping technique was used to estimate the precision of the 5th, 10th, 25th, and 50th percentiles (Figure 2.4). The results from the ‘extreme’ BFR scenario in which fire was ignored in the planning process was used to estimate the
Figure 2.3: A comparison of the volume harvested in the preliminary experiment for the four burn fraction regions for scenarios in which fire was accounted for and ignored in the planning process. Panels A-H show the different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the simulated planning process, and the re-planning interval which was fixed at 10 years. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels A, C, E, F, G, and H, the symbols are not visible because of low variability in harvest volume.
Figure 2.4: A box and whisker plot showing the sensitivity of harvest volume distributions to 1000 simulation replicates in the ‘extreme’ burn fraction region scenario in which the strategy was to ignore fire in the planning process. Panels A-D show the precision of the 5th, 10th, 25th, and 50th percentile measures of the harvest volume distribution. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, and the points represent the 5th and 95th percentiles. Note: In panels A, B, C, and D, the symbols are not visible because of high precision in estimating the harvest volume percentiles.

The variance in harvest volumes were quite small for the four percentiles measured in all 20 decades modelled, indicating that these estimates were quite precise. For this study 1000 replications was sufficient to estimate the harvest volume distributions.

2.3.2 Main Experiment

2.3.2.1 Average Harvest Volume

The average harvest volume (m$^3$/decade) was calculated for each replication in the ‘extreme’ BFR scenarios and were plotted as histograms (Figure 2.5). For scenarios in
Figure 2.5: A comparison of histograms showing the average decadal harvest volume in the ‘extreme’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold.

which the strategy was to account for fire in the planning process (i.e., the observed burn fraction from the ‘extreme’ BFR was used in Model III), the distribution of
average harvest volumes was centred on 6 M. m$^3$/decade and showed little variability. In contrast, the scenarios in which fire was ignored in the planning process (i.e., a burn fraction of 0 was used in Model III) showed high variability in the distribution of harvest volumes with the values ranging from approximately 7 to 12 M. m$^3$/decade. The average harvest volume was approximately 9 M. m$^3$/decade. The histograms of average harvest volume (m$^3$/decade) from the ‘high’ BFR showed a similar trend to the average harvest volumes in the ‘extreme’ BFR (Figure 2.6). However, the average harvest volumes for scenarios in which fire was accounted for in the planning process were approximately 11.5 M. m$^3$/decade and scenarios in which fire was ignored in the planning process were approximately 13 M. m$^3$/decade. The average harvest volumes for both strategies were much closer than the ‘extreme’ BFR.

### 2.3.2.2 Distribution of Harvest Volume Through Time

In the ‘extreme’ BFR, the harvest volume distributions showed little variability in scenarios in which fire was accounted for in the planning process with harvests of approximately 6 M. m$^3$/decade in all five re-planning intervals (Figure 2.7). The harvest volume for scenarios in which fire was ignored in the planning process ranged from approximately 3.5 to 13.5 M. m$^3$/decade in all five re-planning intervals, however, the range increased marginally as the re-planning interval increased.

The ‘high’ BFR showed a similar pattern of harvest volume variability as the ‘extreme’ BFR, however, the variability in the harvest volume distribution was much lower in the ‘high’ BFR (Figure 2.8). For scenarios in which fire was accounted for in the planning process, the harvest volume was approximately 12.0 M. m$^3$/decade. For scenarios in which fire was ignored in the planning process, the harvest volume distributions ranged from 10.0 to 14.0 M. m$^3$/decade. In both BFRs, the re-planning interval appeared to have a marginal impact on the variability in the harvest volume distributions.
Figure 2.6: A comparison of histograms showing the average decadal harvest volume in the ‘high’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold.

2.3.2.3 Risk Analysis Plots for Determining the Minimum Harvest Volume

The minimum planned harvest volume survival function (1-ECDF) was produced from 1000 replications to show the probability of achieving a minimum harvest volume in
Figure 2.7: A comparison of the volume harvested in the ‘extreme’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. Panels A–J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels A, C, E, G, and I, the symbols are not visible because of low variability in harvest volume.
Figure 2.8: A comparison of the volume harvested in the ‘high’ burn fraction region for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels A, C, E, G, and I, the symbols are not visible because of low variability in harvest volume.
Figure 2.9: The minimum planned harvest volume survival function (1-ECDF) was plotted against the minimum harvest volume to illustrate the probability of achieving the minimum harvest volume over 200 years in the ‘extreme’ and ‘high’ burn fraction regions for scenarios in which fire was accounted for and ignored in the planning process with a range of re-planning intervals. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold.

the ‘extreme’ and ‘high’ BFRs (Figure 2.9). For scenarios in which fire was accounted for in the planning process, the survival functions reached a maximum harvest volume
threshold of 6.0 and 12.0 M. m$^3$/decade for probabilities <0.8 for the ‘extreme’ and ‘high’ BFRs, respectively. The minimum planned harvest volume survival function for the scenarios in which fire was ignored in the planning process ranged from 2.0 to 9.0 M. m$^3$/decade in the ‘extreme’ BFR and from 6.0 to 14.0 M. m$^3$/decade in the ‘high’ BFR. As the re-planning interval increased, the survival functions moved to the left (i.e., decreasing minimum harvest volume) showing the marginal benefit of the re-planning strategies. To illustrate the use of this plot, example lines were added to panels E and F in Figure 2.9 to show that the probability of achieving a harvest volume of 5.0 M. m$^3$/decade (panel E, ‘extreme’ BFR) was approximately 0.83 and 0.22 when fire was accounted for and ignored in the planning process, respectively. In the ‘high’ BFR for a harvest volume of 10.0 M. m$^3$/decade (panel F) the probability of achieving this minimum harvest volume was approximately 0.97 when fire was accounted for in the planning and 0.78 when fire was ignored in the planning process.

2.3.2.4 The Impact of High Fire Decades on Short-term Timber Supply

To examine the impact of high fire decades on timber supply, the decade with the highest area burned in each replicate was identified and the percentage change in harvest volume in the next decade was calculated. Only the last 100 years of each simulation run were used in the analysis to reduce the impact of the starting age class distribution on the results. These plots illustrate the potential for the two risk mitigation strategies to deal with extreme area burned in the short-term. In the ‘extreme’ BFR, the area burned ranged from 10% to more than 60% of the landscape over the last 100 years of the planning horizon (Figure 2.10). In scenarios in which fire was accounted for in the planning process, extreme fire decades showed less change in harvest volume in the following decade than scenarios in which fire was ignored in the planning process. In some cases, the harvest volume increased in the next decade, especially when fire was ignored in the planning process. The largest range of harvest
Figure 2.10: A comparison of scatterplots that show the relationship between the decade of highest area burned and the percentage change in harvest volume in the next decade for the ‘extreme’ burn fraction region. Each point shows what was observed in one of the 1000 replications and the dotted line shows where no change in harvest volume was observed. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold.

volume changes occurred when the re-planning interval was 10 years. In the ‘high’ BFR, the area burned ranged from 0 to approximately 45% of the landscape (Figure
Figure 2.11: A comparison of scatterplots that show the relationship between the decade of highest area burned and the percentage change in harvest volume in the next decade for the ‘high’ burn fraction region. Each point shows what was observed in one of the 1000 replications and the dotted line shows where no change in harvest volume was observed. Panels A-J show different scenarios with the panel title indicating the burn fraction region, whether fire was accounted for or ignored in the planning process, and the re-planning interval or burn threshold.

2.11). The percent change in harvest volume in the ‘high’ BFR followed a pattern similar to that which was observed in the ‘extreme’ BFR but with smaller harvest
volume changes due the lower area burned. In all scenarios that ignored fire in the planning process, a downward trend in harvest volume can be observed as the area burned increased, however, this relationship was highly variable. In all scenarios in which fire was ignored in the planning process, a large reduction in harvest volume was observed in many of the replications.

2.4 Discussion

This study provided insight into important questions about the impacts of uncertainty in area burned on timber supply and the effectiveness of two risk mitigation strategies: (1) frequent re-planning and, (2) whether or not to account for fire in planning process. Fire was accounted for the planning process by using the observed burn fraction from each of the BFRs in Model III to deterministically model fire along with harvesting and regeneration, while fire was ignored in the planning process by using a burn fraction of 0 in Model III. In the ‘moderate’ and ‘low’ BFRs, fire had little impact on the variability in harvest volume distributions regardless of whether or not fire was accounted for in the planning process (Figure 2.3). The static and dynamic re-planning intervals had little impact on variability in the harvest volume distributions in either the ‘extreme’ or ‘high’ BFRs indicating that for burn fractions greater than 0.45% (i.e., ‘high’ BFR), re-planning alone was not an adequate strategy to reduce variability in harvest volume (Figures 2.5, 2.6, 2.7, 2.8, 2.9, 2.10, and 2.11). The dynamic re-planning thresholds produced results that were similar to the static re-planning intervals which suggested that the use of a disturbance threshold to re-initiate forest management planning was not a necessary strategy to reduce uncertainty concerning timber supply in forests similar to those that I studied. Although re-planning alone was not an effective strategy to reduce uncertainty due to fire, it is an important feature of the adaptive management cycle which requires new knowledge to be integrated into policy and practice (Stankey et al., 2005). Using a
re-planning interval of 10 years would reduce the cost associated with more frequent re-planning intervals while ensuring that new science is incorporated in the planning.

The results of this study showed that depending on the risk preference of the forest manager, the best strategy could be either to account for or ignore fire in the planning process. The scenarios that accounted for fire in the planning process were able to produce a stable timber supply with little variability over time by reducing the harvest volume (Figures 2.7, 2.8, and 2.9). This result is consistent with the conjecture by Reed and Errico (1986) that the mean value model in a rolling planning horizon framework would be sufficient to deal with uncertainty due to fire. These scenarios would be ideal for a manager who was risk averse and wanted a long-term predictable harvest volume. The scenarios in which fire was ignored in the planning process would appeal to a forest manager who was risk seeking (Figures 2.7, 2.8, and 2.9). In these scenarios a manager is able to harvest more volume than scenarios that accounted for fire in the planning process, however, the results showed that the chance of the harvest volume declining to a low level in the short-term was high. These results are similar to those reported by Armstrong (2004). For burn fractions >0.45%, forest managers should expect to see some variability in harvest volume over time but the best strategy will depend on a managers risk preference. The determination of a sustainable harvest volume is the solution to a risk management problem (Dempster and Stevens, 1987), while Armstrong (2004) noted that the only certain long-term harvest volume is 0.

Regardless of their risk preference, forest managers will need to justify their chosen strategy because both accounting for fire and ignoring fire in the planning process have benefits and costs. The tradeoff between the two strategies are: a low average harvest volume with low variability in harvest volume over time (i.e., account for fire in the planning) vs. high average harvest volume with high variability in harvest volume over time (i.e., ignore fire in the planning) (Figures 2.5 and 2.6). In
in this study, the average harvest volume results differed from those reported by Boychuk and Martell (1996), who found that as the harvest volume was reduced to produce a more constant harvest flow (i.e., by increasing the penalty term) over time, the expected average harvest volume increased. The differences in the results stem from the formulation of the objective functions in the two planning models, I maximized harvest volume, while Boychuk and Martell (1996) maximized net present value.

When Boychuk and Martell (1996) reduced the harvest volume to create a stable harvest flow, the age classes being harvested were closer to the biological rotation age than the economic rotation age and thus produced more volume than the younger age classes. In this study as the harvest volume was reduced to account for fire in the planning process, older age classes beyond the biological rotation age were harvested first and thus produced less volume than the ones close to the biological rotation age. By changing the objective function, the average harvest volume deviated from the expected results of Boychuk and Martell (1996), which indicates that managers need to be aware of the potential impacts of different model formulations when developing forest management plans.

The risk preference of some forest managers may not lie at either end of the risk preference spectrum (i.e., risk averse or risk seeking), but instead somewhere in the middle, and those managers may want to increase the harvest volume above the Model III estimate and assume some risk. They should perform a thorough analysis given their risk preference and determine the extent to which it impacts the long-term sustainable timber supply. This study has shown that managers desiring a risk averse strategy to deal with fire should use Model III to account for fire in the planning process while developing forest management plans (Figure 2.9).

The minimum planned harvest volume survival function was developed as a risk analysis tool for managers who want to quantify the risk associated with certain minimum harvest volumes (Figure 2.9). By using the minimum planned harvest
volume, a manager who was risk averse could estimate the minimum harvest volume that would be available over the next 200 years. This plot could be expanded to show the probability of achieving the mean or median harvest volume but was not included in this study because the boxplots showing the distribution of harvest volumes over time provided a reasonable estimate of the median harvest volume for the strategies evaluated (Figures 2.7 and 2.8). As well, this plot could also be used to show the probability of achieving a specified harvest volume over different time horizons. This type of risk analysis tool could be expanded to reflect the probability of mill profitability, the impact of different market fluctuations or many other uncertain decision-making problems of interest. An important philosophical question beyond the scope of this study is how should risk be managed by foresters who are managing a public resource?

In the modelling of fire and harvesting in this study, it was assumed that managers would make recourse decisions in the form of contingency planning if volume scheduled for harvest was burned before it could be cut. This assumption was realistic given planning policies in Ontario (OMNR, 2004) and definitely reduced the variability observed in harvest volume distributions. Some of the variability in harvest volume distributions observed by Armstrong (2004) may be attributed to a lack of recourse being implemented within his planning framework.

The analysis of high fire decades was used to show the range of impacts that catastrophic disturbances can have on timber supply (Figures 2.10 and 2.11). Many of these disturbances would be difficult to anticipate and deal with given that they far exceed the expected area burned that was accounted for in the planning using Model III. In many of the simulation runs that ignored fire in the planning process, the harvest volume increased after a decade of high area burned. This increase was caused by the interaction of the age class distribution being used to develop the harvest schedule and the even-flow harvest volume constraint in the planning model.
If the age class distribution being used to develop the harvest schedule could not support a high harvest volume in the initial periods of the plan, the planning model reduced the overall harvest volume to satisfy the even-flow constraint. However, in the subsequent decade the age class distribution likely changed (e.g., due to the continued harvesting and high area burned) and the planning model was able to produce a higher harvest volume than the previous decade. This interaction caused the increase in harvest volume that I observed after the decades of high area burned. Further analysis could be done to understand the relationship between high fire years, age class distribution, and the resulting change in harvest volume.

2.5 Conclusion

The results from this study suggest that if forest managers are risk averse they should account for fire in the planning process in the boreal forest with burn fractions greater than 0.45% (i.e., the ‘extreme’ and ‘high’ BFRs). Regardless of risk preference, managers can likely ignore fire as a source of uncertainty in areas with burn fractions less than 0.45% (i.e., ‘moderate’ and ‘low’ BFRs) with little impact to the harvest volume over time. Forest managers who wish to assume some risk by increasing their harvest volume above the Model III harvest schedule need to assess the impact of the increased harvest volume to ensure that there is a high likelihood that forest sustainability will be achieved. The minimum planned harvest volume survival function developed in this study could be used by managers to aid their decision-making in an uncertain environment given a managers risk preference. Although re-planning was not effective at reducing the variability in harvest volume in the ‘extreme’ and ‘high’ BFRs, re-planning should be part of any forest management planning framework to deal with changes in science or policy. Although timber supply was the focus of this study, the simulation modelling and analysis could be applied to ecological objectives such as habitat or old growth forest.
Chapter 3

An Evaluation of Strategies for Dealing with Uncertainty Due to Fire When Managing Two Forest Seral Stages

3.1 Introduction

Forest managers must develop long-term strategic forest management plans that provide for a variety of ecological, economic, and social values. Over long time periods there is considerable uncertainty concerning the potential impact of natural disturbances (e.g., fire, insects, disease, and windthrow) and other natural processes (e.g., succession, regeneration, and growth) on forest values. Forest fires alone are a source of tremendous uncertainty for planners (Martell, 1994). For example, in the province of Ontario the annual area burned over an area of 473,399 km$^2$ between 1960 and 2004 varied from 9 to 6,232 km$^2$. Approximately 96.9% of the fires were <200 ha in size, however, these fires only accounted for about 3% of the area burned while the remaining 97% of the area burned resulted from a few large fires (Stocks et al., 2002). These large fires pose significant challenges for managers charged with the responsibility for developing long-term sustainable forest management plans.

The principles of ecosystem management can be used to guide the development of long and short-term forest management objectives at a variety of scales (Hunter, 1990). Ecosystem management is based on the assumption that if natural ecosystem structure and pattern can be created through management practices, then biodiversity can be maintained (Franklin, 1993). Hunter (1990) proposed the coarse and fine filter approach to managing both plant and wildlife species on the landscape. Under coarse filter management, a diversity of forest conditions are created on the landscape for the majority of species. Conversely, fine filter management creates species specific habitat
elements to meet special needs which were not met in the coarse filter management. This management paradigm has the potential to create landscapes with a diversity of age classes and species compositions.

The forest age class distribution has been proposed as a good coarse filter indicator of sustainable forest management (Kneeshaw et al., 2000; Fall et al., 2004) since it is influenced by both natural and human-caused disturbances (Franklin et al., 2002) and because of its relationship to many biodiversity indicators (Franklin and Forman, 1987). From an ecological perspective, stand age can be used as an indicator of structural characteristics such as the amount of downed woody debris or snags (Bergeron, 2000). With widespread harvesting and fire occurring in much of the boreal forest, critical age classes related to mature and/or old forest may be difficult to maintain on the landscape because of the time required for growth. Forests with high levels of fire activity may have a high probability of burning and therefore little forest may reach an old condition, as well, some mature and old forests are targeted for harvest because of their value to the forest products sector. The loss of these two seral stages would be detrimental to many wildlife species that are adapted to the conditions created. For example, the woodland caribou (Rangifer tarandus caribou) in Ontario, a species dependent on older forest is listed as a threatened species by the provincial government (Endangered Species Act, S.O. 2007, c. 6, Sched. 4.), human development throughout their habitat, including forest harvesting is thought to be one of the main factors for the decrease in population size (Vistnes and Nellemann, 2008).

The impact of fire and harvesting on the age class distribution has been studied extensively by Fall et al. (2004), Barclay et al. (2006), Didion et al. (2007), and James et al. (2007). They used simulation techniques to examine how the age class distribution of a forest changes under different fire cycles and forest management strategies. Fall et al. (2004) and Didion et al. (2007) examined a policy that required old forest
area objectives to be met before harvesting takes place to prevent the old forest area from being reduced below some specified minimum level. Their primary conclusion was that to achieve age class distribution objectives, the harvest volume should be reduced to account for fire losses. These conclusions were consistent with timber supply modelling studies in fire prone landscapes which showed that harvest volume should be reduced to ensure a long-term consistent timber supply (Van Wagner, 1978; Reed and Errico, 1986; Martell, 1994; Boychuk and Martell, 1996; Armstrong, 2004; Peter and Nelson, 2005).

Linear programming (LP) is commonly used to formulate aspatial forest management planning models. Garcia (1984) formulated a network based planning model, variants of which were independently developed by Reed and Errico (1986) and Gunn and Rai (1987) for forest management planning under uncertainty. In the literature this model is often referred to as Model III (Boychuk and Martell, 1996), with previous aspatial forest management planning models being labelled as Models I and II (Johnson and Scheurman, 1977). The network structure of Model III has many similarities to the structure of a Leslie population matrix model (Williams, 1989). Natural disturbance, the efficacy of management treatments, succession (OMNR, 2007) and many other uncertain processes can be incorporated deterministically in the planning model. In the case of fire, the burn fraction (i.e., average annual area burned expressed as a proportion of the landscape size) is a parameter in the planning model and is used to account for fire losses by deterministically modelling the average area burned in each age class and time period before area is allocated for harvest. Martell (1994) showed how as the burn fraction increased, the harvest volume decreased. The objective function in a forest management planning LP model can be structured to maximize or minimize any measurable economic, ecological or social value\(^1\). When these types of models are simplified to maximize timber yield or net present value

\(^1\) That can be expressed as a linear function of the decision variables.
(i.e., age class or habitat constraints are absent), the planning model tends to generate solutions that produce fully regulated forests with an equal area in each age class over time.

Gunn (1991) suggested that frequent re-planning using LP models was a good strategy for dealing with uncertainty in timber supply management. The cycle of re-planning is often referred to as using a rolling planning horizon framework and involves the creation of an initial forest management plan, followed by the implementation of the first one or two periods of that plan after which a new plan is developed. The iterative cycle of planning and implementation provides recourse opportunities to managers who need to adjust their plans in response to stochastic events that “disrupt” their plans (Jensen and Bard, 2003). The rolling planning horizon framework is commonly used in forest management planning, in part, because LP models have a finite planning horizon. Chappelle and Sassaman (1968), Armstrong et al. (1984), McQuillan (1986), Reed and Errico (1986), Armstrong (2004), and Peter and Nelson (2005) have used the rolling planning horizon framework with forest management planning models to evaluate model and constraint structure, as well as strategies for dealing with uncertainty in timber supply. All of these studies, examined the long-term sustainability of timber supply under uncertainty. However, since the management of ecological objectives has become an equally and sometimes more important component of sustainable forest management in some areas, I investigated the potential impact of using the rolling planning horizon framework to deal with fire related uncertainty when managing ecological objectives in forest management planning.

3.1.1 Study Objectives

A stochastic simulation model with an embedded Model III forest management planning model was used to evaluate four strategies for dealing with the uncertain impact
of fire on ecological objectives. Since my primary objective was to develop and test a methodology for investigating the uncertain impact of a natural disturbance process on an ecological objective in the forest management planning, I chose to focus on mature and old forest areas because they are ecologically valuable, easily measured, and impacted by both human and natural disturbances. In all of the strategies evaluated, mature and old forest areas were constrained separately in the LP planning model to lower and upper bounds of 10% and 40% of the total area of the landscape, respectively. The four strategies that were evaluated were: (1) fire was ignored in the planning process (by using a burn fraction of 0 in Model III), (2) fire was accounted for in the planning process (by using the observed burn fraction from the region of interest in Model III), (3) the lower bound constraints on mature and old forest area were strengthened by increasing the minimum required area from 10% to 12%, 14%, 16%, 18%, and 20% (increasing the right hand side of the constraint) in the forest management planning model, to produce five sets of simulation runs, and (4) mature and old forest areas were maximized in the objective function with harvest volume constrained to a fixed harvest volume target of either 2.0 or 8.0 M. m$^3$/decade. The four strategies were examined in four representative burn fraction regions across Ontario which represent a range of potential burn fractions or fire activity levels.

### 3.2 Methods

#### 3.2.1 Study Area Description

The initial age class structure for each replication of this simulation study was taken from an inventory of the Romeo Mallette Forest in northeastern Ontario, Canada (Figure 3.1). The bi-modal age class distribution was likely created by increased harvesting over the last 30 to 40 years and this initial age class distribution is representative of the type of conditions that a manager would face in that management
Figure 3.1: a) Initial forest age class distribution used in each replication of the simulated management of the Romeo Mallette Forest in northeastern Ontario. b) A jack pine growth and yield curve for the Romeo Mallette Forest in northeastern Ontario (Source: Anonymous (2002)).

Unit. The focus of this study was the evaluation of strategies for dealing with the uncertainty of fire and since the modelling of multiple species and the associated natural processes would likely contribute little to my primary objectives, all forest stands were assumed to be jack pine (*Pinus banksiana* Lamb.) to simplify growth and yield and succession modelling. Forest stands experience a series of developmental stages as they grow from seedlings to old forest: pre-sapling stage (e.g., approximately 0 to 10 years of age), sapling stage (e.g., approximately 10 to 30 years of age), immature stage (e.g., approximately 30 to 70 years of age), mature stage and finally the transition to an old stand of trees. Mature and old forest areas were managed in this study as two separate seral stages and were measured independently to determine the effectiveness of the strategies being investigated. I defined mature forest as jack pine 71 to 110 years of age. The Ontario Ministry of Natural Resources (OMNR) defines jack pine greater than 110 years of age growing in northeastern Ontario on ecosite 2 as old growth forest (Uhlig et al., 2003). For this study, old forest was defined as jack
pine greater than 110 years of age.

Because Ontario has a highly variable burn fraction that occurs in a longitudinal east-west gradient, four burn fraction regions (BFR) from across Ontario were selected (Figure 1.3). For a description of the four burn fraction regions and why they were selected please see Section 1.3.4 (Page 16).

3.2.2 Forest Management Planning Model

A long-term forest management planning model was formulated (i.e., Model III) which maximized either harvest volume or mature and old forest areas over the planning horizon, subject to a set of constraints. For this study, several objective function and constraint combinations were used to evaluate the strategies being examined. Constraints were formulated to regulate the flow of harvest volume through time and to impose upper and lower bounds on the areas of mature and old forest on the landscape. Two types of harvest flow constraints were used in this study, the first of which was an even-flow constraint that ensured the harvest volume was constant over the planning horizon, although the harvest volume could change in subsequent decades after re-planning. The second harvest constraint fixed the harvest volume at a constant level (i.e., 2.0 or 8.0 M. m$^3$/decade) for all decades, regardless of the age class distribution. These two fixed harvest volume targets were chosen to represent a low and high mill demand because the level of fire activity (i.e., the four BFRs) will have very different sustainable harvest levels depending on the amount of area burned. The lower and upper bounds on mature and old forest area in the planning model were selected to be 10% and 40%, respectively. Although it was unlikely that both mature and old forest areas would have identical lower and upper bound ranges in the four BFRs, this range was chosen to facilitate the comparison of strategies.

When modelling forest management and natural disturbance in a simulated environment, the mature forest area, old forest area and fixed harvest volume con-
constraints in the LP model may become infeasible during a simulation run. For example, if a large fire burned much of the old forest area, there may not be sufficient area to satisfy the lower bound constraint, rendering the model infeasible. To prevent an infeasible LP model from stopping a simulation run, an area or volume deficit decision variable was assigned the missing area or volume (i.e., up to the lower area or volume bound), the deficit decision variable was then multiplied by a penalty term to reduce the objective function. Since the penalty was only activated when an area or volume deficit existed, the model would produce feasible harvest plans that did not reduce the objective function whenever possible. The penalty term for mature and old forest areas was 100,000 times higher than the harvest volume penalty term. The two seral stages were assumed to be equally valuable on the landscape and were given equal weights to ensure that a direct comparison of the impacts of the LP model could be made between the two seral stage areas under the 4 levels of fire activity and 4 strategies evaluated. There were no units associated with the penalty terms and they were selected to ensure that the planning model gave preference to the mature and old forest area constraints given the focus of this study. The sensitivity of the planning model to differences in the harvest volume and seral stage penalty terms was not investigated because it was beyond the scope of this study but could provide important information for managers dealing with trade-offs in harvest volume and mature and old forest areas. I felt that the inclusion of a penalty term in the objective function was realistic given that managers would be required to deal with the current condition of their forest management unit and attempt to achieve the desired conditions in subsequent periods through continued re-planning and implementation. The alternative would be to formulate and solve a stochastic programming model which would not be tractable given the structure and size of the forest management planning problem. In the forest management planning model a period was defined as 10 years. The model was written in ILOG’s OPL Development Studio, a modelling
environment that can be used to formulate mathematical programming models and was solved using CPLEX (ILOG, 2007).

3.2.2.1 Model III Formulation

Objective function #1 was used to maximize the volume harvested over T time periods in the planning horizon (Eq. 3.1)

Maximize \( \sum_{t} VolumeCut_t - \sum_{t} DeficitMatureFor_t \times P_1 - \sum_{t} DeficitOldFor_t \times P_1 - \sum_{t} DeficitVolume_t \times P_2 \) (3.1)

where \( VolumeCut_t \) was the total volume harvested at the start of period \( t \). \( DeficitMatureFor_t \) was the mature forest area deficit (i.e., the amount of area by which the actual mature forest area was less than the “required” area) not satisfied at the start of period \( t \). \( DeficitOldFor_t \) was the old forest area deficit not satisfied at the start of period \( t \). \( DeficitVolume_t \) was the volume deficit not satisfied to meet the fixed harvest volume at the start of period \( t \). \( T \) was the number of time periods in the planning horizon and \( t \) denotes the time period; \( t = 1, 2, \ldots, T \). \( P_1 \) and \( P_2 \) were large penalty terms with \( P_1 \) being 100,000 times larger to ensure that the seral stage constraints were met before the harvest constraints.

Objective function #2 was used to maximize the sum of mature and old forest areas
over T time periods in the planning horizon (Eq. 3.2).

\[
\text{Maximize } \sum_t \text{MatureForest}_t + \text{OldForest}_t \\
- \sum_t \text{DeficitMatureForest}_t \times P_1 \\
- \sum_t \text{DeficitOldForest}_t \times P_1 \\
- \sum_t \text{DeficitVolume}_t \times P_2
\]

(3.2)

where \(\text{MatureForest}_t\) was the area of mature forest at the start of period \(t\). \(\text{OldForest}_t\) was the area of old forest at the start of period \(t\).

The objective functions were maximized subject to a set of constraints. The constraints which specify how area was transferred from one age class and period to another were identical for Chapters 2 and 3. For a description of these common constraints please see Section 2.2.2.1 (Page 28), Equations 2.2 to 2.10 in Chapter 2. Most of the constraints presented below were unique to this study. The area in age classes 8 to 11 was summed to determine the total area of mature forest on the landscape at the start of period \(t\) (Eq. 3.3).

\[
\text{MatureForest}_t = \sum_{8 \leq a \leq 11} \text{UnDisturbedArea}_{at} \quad \forall t
\]

(3.3)

The area in age classes greater than or equal to 12 were summed to determine the total area of old forest on the landscape at the start of period \(t\) (Eq. 3.4).

\[
\text{OldForest}_t = \sum_{a \geq 12} \text{UnDisturbedArea}_{at} \quad \forall t
\]

(3.4)

The harvest volume between periods must be equal (Eq. 3.5).

\[
\text{VolumeCut}_{t-1} - \text{VolumeCut}_t = 0 \quad t > 1
\]

(3.5)
The volume harvested in each period must equal the fixed harvest volume (Eq. 3.6).

\[ \text{VolumeCut}_t + \text{DeficitVolume}_t = \text{FixedHarvestVolume} \quad \forall t \]  
(3.6)

where \( \text{FixedHarvestVolume} \) was the specified harvest volume target for all periods.

The mature forest area must be greater than or equal to the lower bound of the mature forest requirement (Eq. 3.7).

\[ \text{MatureForest}_t + \text{DeficitMatureFor}_t \geq \text{MatureForestAreaLower} \quad \forall t \]  
(3.7)

where \( \text{MatureForestAreaLower} \) was the minimum mature forest area. The old forest area must be greater than or equal to the lower bound of the old forest requirement (Eq. 3.8).

\[ \text{OldForest}_t + \text{DeficitOldFor}_t \geq \text{OldForestAreaLower} \quad \forall t \]  
(3.8)

where \( \text{OldForestAreaLower} \) was the minimum old forest area. The mature forest area must be less than or equal to the upper bound of the mature forest requirement (Eq. 3.9).

\[ \text{MatureForest}_t - \text{DeficitMatureFor}_t \leq \text{MatureForestAreaUpper} \quad \forall t \]  
(3.9)

where \( \text{MatureForestAreaUpper} \) was the maximum mature forest area. The old forest area must be less than or equal to the upper bound of the old forest requirement (Eq. 3.10).

\[ \text{OldForest}_t - \text{DeficitOldFor}_t \leq \text{OldForestAreaUpper} \quad \forall t \]  
(3.10)
where $OldForestAreaUpper$ was the maximum old forest area.

### 3.2.3 Stochastic Forest Fire Model

Most forest fires that occur in Ontario are contained before they escape initial attack by fire fighting crews (i.e., grow to a large size) because of efficient detection networks. These small fires have little or no impact on timber supply (Martell, 1994). The small proportion of fires that do escape initial attack (defined here as fires $\geq 25$ ha. in size) can have a range of impacts on the forest landscape and were the focus of this study.

#### 3.2.3.1 Fire Occurrence Model

For a description of the fire occurrence model please see Section 2.2.3.1 (Page 31) in Chapter 2.

#### 3.2.3.2 Fire Size Model

For a description of the fire size model please see Section 2.2.3.2 (Page 31) in Chapter 2.

### 3.2.4 Modelling Annual Area Burned

For a description of how annual area burned was modelled using the fire occurrence and fire size models, please see Section 2.2.4 (Page 32) in Chapter 2. As well, the input parameters used to model annual area burned can be found in Table 2.1 (Page 33).

### 3.2.5 Modelling Forest Growth and Yield

The forest inventory was structured as a vector of age classes that ranged from 1 to 18 with each age class representing 10 years. The oldest age class was an upper
collector age class where forest area accumulated if it was not disturbed. The forest age class-areas were incremented by 1 age class every 10 years when the re-planning occurred. The yield curve used to model the age volume relationship was from a jack pine cover type in the Romeo Mallette Forest (Figure 3.1).

3.2.6 Simulation of Forest Harvesting and Forest Fires

The simulated managed forest model has three main components: (1) an embedded LP forest management planning model, (2) a stochastic fire ignition and fire size model, and (3) a forest growth and yield model. These three components were used in a rolling planning horizon framework to evaluate strategies for dealing with uncertain fire activity on mature and old forest areas. For a description of the modelling process, simulation length, number of replications, and implementation of the model please see Section 2.2.6 (Page 34) in Chapter 2.

3.2.6.1 Contingency Planning

For a description of what contingency planning is and how it was used in this thesis, please see Section 2.2.6.1 (Page 35) in Chapter 2. This study was focussed on developing strategies to deal with the impact of fire on mature and old forest areas, as a result the contingency planning heuristic was modified to deal with the mature and old forest area objectives.

For each year that contingency planning was used, the algorithm first determined the amount of mature and old forest area that was available for harvest given that lower bound constraints were an important aspect of the management strategy. The contingency planning heuristic started at the oldest age class and harvested the available mature and old forest areas, if the lower bound area was reached and further volume was required, the contingency heuristic stipulated that younger age classes
would be harvested until the minimum harvest age was reached or the missing volume was replaced.

To illustrate the simulation process, a flowchart was developed to describe each step in the process of modeling forest planning, harvesting, and burning (Figure 2.2, Page 36, in Chapter 2). One minor difference between this study and the one described in Chapter 2 was the structure of the forest inventory. In this study forest area was stored in 10 year age classes with a total of 18 age classes. Because re-planning was only occurring on a 10 year interval, the forest was grown by 1 age class during the re-planning years (see step 9 in Figure 2.2). The remainder of the simulation process was identical between this study and Chapter 2.

3.2.7 Study Design

This simulation study was designed to examine four forest management planning strategies to determine the extent to which they reduce the impact of fire on mature and old forest areas. Mature and old forest areas were treated as independent seral stages in this study and were constrained separately in the forest management planning model. The four strategies investigated in this study were:

- **Strategy 1 (Ignored Fire in the Planning Process - IFP)** - Harvest volume was maximized, mature and old forest areas were each constrained to a lower and upper bound of 10% and 40% of the landscape area (i.e., $10\% \leq \text{mature forest} \leq 40\%$ and $10\% \leq \text{old forest} \leq 40\%$), respectively. Fire was ignored in the planning process by using a burn fraction of 0 in Model III.

- **Strategy 2 (Accounted for Fire in the Planning Process - AFP)** - Harvest volume was maximized, mature and old forest areas were each constrained to a lower and upper bound of 10% and 40% of the landscape area, respectively. Fire was accounted for in the planning process by using the observed burn fraction from each of the four BFRs in Model III.
• Strategy 3 (Increased Mature and Old Forest Area - IMOF A) - Harvest volume was maximized and the lower bound constraints for mature and old forest areas were each strengthened by increasing the minimum required area (i.e., increasing the right hand side of the constraint) in the planning model from 10% to 12%, 14%, 16%, 18%, and 20%. For each lower bound constraint area, a total of 1000 replications was performed (i.e., the same number of replications as the other three strategies). The upper bound in the planning model was 40%. A second feature of this strategy was that fire was accounted for in the planning process by using the observed burn fraction from each of the four BFRs in Model III.

• Strategy 4 (Maximized Mature and Old Forest Area - MMOFA) - Mature and old forest areas were maximized, mature and old forest areas were each constrained to a lower and upper bound of 10% and 40% of the landscape area, respectively. The harvest volume was constrained to equal two fixed target levels of 2.0 and 8.0 M. m$^3$/decade.

Strategy 1 (IFP) examined the impact of ignoring fire in the planning process when managing mature and old forest areas. Fire was ignored in the planning process by using a burn fraction of 0 in Model III. Strategy 2 (AFP) investigated the impact of accounting for fire in the planning process when managing mature and old forest areas by using the observed burn fraction from each of the four BFRs in Model III. In Ontario, expected fire losses are incorporated in forest management planning (OMNR, 2004) with the effect of reducing the harvest rate using Model III (OMNR, 2007), however, in other jurisdictions the debate about whether or not to account for fire is still ongoing. Strategy 3 (IMOFA) examined whether or not to strengthen the lower bound constraints for mature and old forest areas by increasing the minimum required area from 10% to 12%, 14%, 16%, 18%, and 20%. The lower bounds for mature and old forest areas were each increased at the same rate (i.e., both seral stages were run with lower bounds of 10%, then 12%, then 14%, up to 20%). By adding a “buffer” to
the lower bound, the likelihood of satisfying the true policy stipulated (as opposed to the right hand side value of the LP model constraints) minimum required area should increase.

In Strategy 4 (MMOFA), the objective function of the planning model was modified to maximize mature and old forest areas while harvest volume was constrained to equal two fixed targets (i.e., 2.0 and 8.0 M. m$^3$/decade). The two fixed harvest levels were selected to investigate the impact that a high and low fixed harvest volume would have on the areas of mature and old forest in the four BFRs. By modifying the objective function to maximize mature and old forest areas, the objective of the forest management planning model switched from timber harvesting to the growth and conservation of mature and old forest areas (subject to an upper bound constraint) and therefore better reflects ecosystem management goals. In the forest management planning model, each strategy used a different combination of objective function and constraints, the combinations of objective function and constraints can be found in Table 3.1.

Table 3.1: The combination of objective functions and constraints used in each strategy.

<table>
<thead>
<tr>
<th>Objective Function and Constraints</th>
<th>Equations used for Strategies:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1, 2, &amp; 3</td>
</tr>
<tr>
<td>Objective Function</td>
<td>Eq. 3.1</td>
</tr>
<tr>
<td>Harvest Flow</td>
<td>Eq. 3.5</td>
</tr>
<tr>
<td>Mature Forest</td>
<td>Eq. 3.7</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.9</td>
</tr>
<tr>
<td>Old Forest</td>
<td>Eq. 3.8</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.10</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.2</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.6</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.7</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.9</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.8</td>
</tr>
<tr>
<td></td>
<td>Eq. 3.10</td>
</tr>
</tbody>
</table>

A variance reduction technique (Law and Kelton, 2003) was used to reduce the variability in mature and old forest areas among the strategies investigated. The random number generator in the fire model was seeded to generate identical lists of annual burn fractions for each of the strategies within a BFR. The differences in
mature and old forest areas were consequently a direct result of the management strategies and not an artifact of the random fires.

### 3.2.8 Examining the Variability in Mature and Old Forest Area

For each strategy examined, boxplots of mature and old forest areas and harvest volume (m$^3$/decade) were developed to describe their distribution through time. The centre line represents the median, the box represents the 25$^{th}$ and 75$^{th}$ percentiles, the end of the whiskers represent the 10$^{th}$ and 90$^{th}$ percentiles, the points represent the 5$^{th}$ and 95$^{th}$ percentiles and the “+” signs represent the minimum and maximum values.

A risk analysis tool was developed to demonstrate to managers, a method for incorporating uncertainty into decision-making when determining the probability of achieving a minimum area of either mature or old forest. To produce the graphical risk plot, the annual areas of mature and old forest were averaged over 10 years for each of the 20 decades in a simulation run to produce a vector of 20 average mature and old forest areas from which the decade with the lowest average mature and old forest areas was then selected. A total of 1000 average minimum mature and old forest area values were found in the 1000 replications. Given the set of N ordered data points, $X_1, X_2, ..., X_N$ the empirical cumulative distribution function of the average minimum mature and old forest area was defined in Equation 3.11.

$$F_n(x) = \frac{\text{number of } X_i \text{'s} \leq x}{n} \quad (3.11)$$

To simplify the interpretation of the risk analysis plots, they were graphed as one minus the empirical cumulative distribution function (1-ECDF), this plot was referred to as the minimum planned seral area survival function. For example, a manager could determine the probability of the old forest area declining below a minimum required area of 10%. A manager would find 10% area on the x-axis and then using the
old forest area survival function would find the corresponding probability. For each survival function developed, only the last 100 years of each simulation results were used to minimize the likelihood that the initial starting conditions (e.g., low area of old forest in the initial age class distribution) would affect the comparison of strategies. Some strategies may increase the areas of mature and old forest over the modelling horizon and a low initial old forest area may conceal the benefits or drawbacks of a particular strategy being examined. This method for developing survival functions curves was adapted from Armstrong (2004) and Peter and Nelson (2005).

3.3 Results

3.3.1 Strategy 1: Ignore Fire in the Planning Process

The results from strategy 1, in which fire was ignored in the planning process (IFP), showed that the within decade variability of mature and old forest areas were influenced by the area burned (Figure 3.2). The variability in mature and old forest areas was highest in the ‘extreme’ BFR and lowest in the ‘low’ BFR. In all four BFRs the mature and old forest areas quickly declined to their lower bound area (i.e., 10%) after decade 5 and in many simulations they fell below the minimum area requirement. The mature and old forest areas were allowed to fall below the minimum area requirement of 10% because of the penalty term in the objective function of the planning model.

The harvest volume in strategy 1 showed high variability in the ‘extreme’ and ‘high’ BFRs with volumes ranging from approximately 2.0 to 12.0 M. m$^3$/decade (Figure 3.3). In the ‘moderate’ BFR, the variability in harvest volume increased through time and ranged from approximately 8.0 to 12.0 M. m$^3$/decade during the last 5 decades of the simulated study period. The area burned in the ‘low’ BFR was not sufficient to produce variability in the harvest volume.
Figure 3.2: A comparison of the mature and old forest areas (%) in strategy 1 (ignored fire in the planning process) for the four burn fraction regions. Panels A-H show a combination of burn fraction regions and seral stages. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Mature forest was 71 - 110 years of age and old forest was >110 years of age. Note: In panels C, D, E, F, G, and H, the symbols are not visible because of low variability in the area of mature and old forest.

3.3.2 Strategy 2: Account for Fire in the Planning Process

The mature and old forest areas in strategy 2, in which fire was accounted for in the planning process (AFP), showed a similar trend to strategy 1 (Figure 3.4). However,
Figure 3.3: A comparison of the harvest volume (m$^3$/decade) variability in strategy 1 (ignored fire in the planning) over 200 years for the four burn fraction regions. Panels A-D show the four burn fraction regions. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels C and D the symbols are not visible because of low variability in the harvest volume.

The within decade variability of the extreme mature and old forest areas was much greater with strategy 2 and the boxplots showed the minimum area requirement of 10% was satisfied for a large number of the simulation runs.

The minimum planned seral area survival function was used to compare the probability of achieving the minimum areas of mature and old forest in strategies 1 and 2 (Figure 3.5). In general, the probability of achieving the minimum mature and old forest areas was lower in strategy 1 than strategy 2. In the ‘extreme’ BFR for strategy 1 (i.e., fire ignored in the planning process), the probability of mature and old forest areas being reduced to 0 was approximately 0.4 and 0.1, respectively. As the burn fraction decreased (e.g., the range of ‘moderate’ and ‘low’ BFRs), the survival functions moved to the right demonstrating that the probability of achieving
<table>
<thead>
<tr>
<th>Decade</th>
<th>Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td></td>
</tr>
</tbody>
</table>

**Area (%)**

**Decade**

Figure 3.4: A comparison of the mature and old forest areas (%) in strategy 2 (fire accounted for in the planning process) for the four burn fraction regions. Panels A-H show a combination of burn fraction regions and seral stages. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the wiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Mature forest was 71 - 110 years of age and old forest was >110 years of age. Note: In panels E, F, G, and H, the symbols are not visible because of low variability in the area of mature and old forest.

The minimum areas of mature and old forest was higher than in the ‘extreme’ and ‘high’ BFRs.
Figure 3.5: The minimum planned seral area survival function (1-ECDF) was plotted against the minimum average mature and old forest areas (from 1000 replications) to illustrate the probability of achieving the minimum required area (i.e., 10%) over the last 100 years of a 200 year simulation period in the four burn fraction regions for strategies 1 and 2 (whether or not to account for fire in the planning process). Panels A-H show a combination of burn fraction regions and seral stages. The solid line shows the survival function for the strategy that accounted for fire in the planning, the dashed line shows the strategy that ignored fire in the planning, the dash-dotted line was the lower bound in the planning model (10%), and the dotted line demonstrates how a manager would use this plot to determine the probability of a minimum of 8% of the landscape existing in a mature and old forest condition. Mature forest was 71 - 110 years of age and old forest was >110 years of age.
The harvest volume in strategy 2 showed high variability in the ‘extreme’ BFR with many of the 25th percentiles (i.e., box) intersecting with 0 (Figure 3.6). The

![Figure 3.6](image)

Figure 3.6: A comparison of the harvest volume (m$^3$/decade) variability in strategy 2 (fire accounted for in the planning process) over 200 years in the four burn fraction regions. Panels A-D show the four burn fraction regions. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels C and D the symbols are not visible because of low variability in the harvest volume.

‘high’ BFR showed increasing variability through time with the highest variability in decades 17-20 ranging from approximately 5 to 10 M. m$^3$/decade for the 2.5th and 97.5th percentiles. In the ‘moderate’ and ‘low’ BFRs the harvest volume varied little through time and was approximately 11.5 and 12 M. m$^3$/decade, respectively. The area burned in the ‘moderate’ and ‘low’ BFRs was not sufficient to create significant variability in the harvest volume.
3.3.3 Strategy 3: Increase Mature and Old Forest Area

In strategy 3, the simulated management model was run with lower bounds of 10%, 12%, 14%, 16%, 18%, and 20% to investigate the extent to which an increase in the minimum required mature and old forest areas would increase the likelihood of satisfying the minimum desired area of 10% (Figure 3.7). The minimum planned seral area survival functions showed the probability of achieving the minimum desired areas of mature and old forest for six different lower bound levels. In the ‘extreme’ BFR, the probability of satisfying the minimum desired areas of mature and old forest (i.e., 10%) was approximately 0, even with a lower bound of 20%. As the burn fraction decreased, the probability of achieving the minimum mature and old forest area increased. In the ‘high’ BFR, if a manager wanted to increase the likelihood that the mature and old forest areas did not decline below 10%, a lower bound of 14% area should be used in the planning model. In the ‘moderate’ and ‘low’ BFRs, the results showed that a lower bound in the planning model of 12% and 10% respectively, would be sufficient to ensure that the minimum required areas were achieved.

3.3.4 Strategy 4: Maximized Mature and Old Forest Area

In strategy 4, the areas of mature and old forest were maximized with harvest volume constrained to equal a fixed level of 2.0 and 8.0 M. m$^3$/decade. With a fixed harvest volume equal to 2.0 M. m$^3$/decade, the ‘extreme’, ‘high’, and ‘moderate’ BFRs showed high within decade variability (Figure 3.8). In the ‘extreme’ BFR, approximately half of the simulation runs (i.e., median line in boxplot) satisfied the minimum required areas of mature and old forest, while in the other three BFRs the areas of mature and old forest were above the minimum required area. For the ‘high’, ‘moderate’, and ‘low’ BFRs, the mature and old forest areas were above the maximum area of 40% in many of the simulation runs. As well, in all four BFRs, the areas of mature forest were generally lower than the area of old forest.
Figure 3.7: The minimum planned seral area survival function (1-ECDF) was plotted against the minimum average mature and old forest areas (from 1000 replications) to illustrate the probability of achieving lower bounds of 10%, 12%, 14%, 16%, 18%, and 20% in the planning model over the last 100 years of a 200 year simulation period in the four burn fraction regions for strategy 3 (increased area of mature and old forest). Panels A-H show a combination of burn fraction regions and a seral stages. Each solid line in a panel shows a different lower bound area of 10%, 12%, 14%, 16%, 18%, and 20%. The dash-dotted line shows the lower bound area in the planning model. Mature forest was 71 - 110 years of age and old forest was >110 years of age.

The within decade variability of mature and old forest areas was smaller for a fixed harvest volume of 8.0 M. m$^3$/decade than a fixed harvest volume of 2.0 M. m$^3$/decade (Figure 3.9). In the ‘extreme’ and ‘high’ BFRs, the areas of mature and
Figure 3.8: A comparison of the mature and old forest areas (%) in strategy 4 (maximized mature and old forest area) with a fixed harvest volume equal to 2.0 M. m³/decade for the four burn fraction regions. Panels A-H show a combination of burn fraction regions and seral stages. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Mature forest was 71 - 110 years of age and old forest was >110 years of age. Note: In panels E, F, G, and H, the symbols are not visible because of low variability in the area of mature and old forest.

old forest were below the minimum required area of 10% in many of the simulations. As the fixed harvest volume increased from 2.0 to 8.0 M. m³/decade, the within
Figure 3.9: A comparison of the mature and old forest areas (%) in strategy 4 (maximized mature and old forest area) with a fixed harvest volume equal to 8.0 M. m³/decade for the four burn fraction regions. Panels A-H show a combination of burn fraction regions and seral stages. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Mature forest was 71 - 110 years of age and old forest was >110 years of age. Note: In panels E, F, G, and H, the symbols are not visible because of low variability in the area of mature and old forest.

decade variability decreased and the overall amount of mature and old forest areas decreased.
The minimum planned seral area survival functions were compared for the two fixed harvest volumes in strategy 4 (Figure 3.10). In general, the survival function for mature forest was reduced to the minimum required area and in some cases went
below 10% (i.e., the ‘extreme’ and ‘high’ BFRs). As well, in the ‘extreme’ BFR both the survival functions for mature and old forest areas showed that the probability of achieving a minimum area of 10% was very low. In the ‘high’, ‘moderate’ and ‘low’ BFRs, a fixed harvest volume target equal to 2.0 M. m$^3$/decade showed a high probability of achieving the minimum areas of old forest, while for a fixed harvest volume equal to 8.0 M. m$^3$/decade the probability of achieving the minimum area of old forest was high in only the ‘moderate’ and ‘low’ BFRs.

### 3.3.5 Bootstrapped Confidence Intervals Examining the Number of Replications

To examine the sensitivity of the old forest area distributions to the number of replicates, non-parametric bootstrapping was used to estimate the precision of the 5$^{th}$, 10$^{th}$, 25$^{th}$, and 50$^{th}$ percentiles (Figure 3.11). The results from strategy 4 in the ‘high’ BFR with a fixed harvest volume target equal to 2.0 M. m$^3$/decade was used to estimate the precision. The distribution of old forest area values were quite small for the four percentiles measured in all 20 decades modelled, indicating that these estimates were quite precise. For this study 1000 replications was sufficient to estimate the distributions of mature and old forest areas.

### 3.4 Discussion

This study investigated the use of four strategies for reducing the uncertainty in area burned and its impact on mature and old forest areas. Mature and old forest areas were chosen because they are ecologically valuable, easily measured, and are impacted by both natural and human-caused disturbance. The variability in the areas of mature and old forest was observed for each strategy and minimum planned seral area survival functions were developed to determine the probability of achieving the minimum required areas of mature and old forest over a 200 year planning horizon.
Figure 3.11: A box and whisker plot showing the sensitivity of old forest area (%) distributions to 1000 simulation replicates in the ‘high’ burn fraction region for strategy 4 (2.0 M. m$^3$/decade). Panels A-D show the precision of the 5th, 10th, 25th, and 50th percentile measures of the old forest area distribution. The centre line represents the median, the box represents the 25th and 75th percentiles, the end of the whiskers represent the 10th and 90th percentiles, the points represent the 5th and 95th percentiles and the “+” signs represent the minimum and maximum values. Note: In panels A, B, C, and D, the symbols are not visible because of high precision in estimating the old forest area percentiles.

In general, as the burn fraction increased the within decade variability of mature and old forest areas increased (Figures 3.2, 3.4, 3.8, and 3.9). This variability may create some difficulty for managers who want to predict the impact of management activities over long time horizons. During the optimization process in an LP forest management planning model, resources being constrained within the model (e.g., mature and old forest areas) will often be forced to the extremes of the lower or upper bounds. For example, in strategies 1, 2 and 3 (i.e., harvest volume was maximized) the mature and old forest areas were reduced to the lower bound in the first 5 to 6 periods and in some cases the area fell below the lower bound of 10% (Figures 3.2, 3.4, 3.8, and 3.9). This indicates that age classes beyond the optimum rotation age may be difficult to
maintain at or above the minimum required area in the presence of fire when using a standard LP forest management planning model, especially if managers choose to continue harvesting in areas with burn fractions that are comparable to the ‘extreme’ and ‘high’ BFRs.

In the ‘moderate’ and ‘low’ BFRs, fire had little impact on the mature and old forest areas, whether the strategy was to account for fire or not (Figures 3.2, 3.4, 3.8, and 3.9), this result was consistent with those reported by Martell (1994) who found similar results for impacts on timber supply. However, in the ‘extreme’ and ‘high’ BFRs, using strategy 1 (i.e., ignored fire in the planning process) resulted in a lower probability of satisfying the minimum required area than strategy 2 which accounted for fire in the planning process. In the ‘high’ BFR, strategy 2, which accounted for fire in the planning was not a sufficient strategy to satisfy the minimum required areas of mature and old forest.

By strengthening the lower bound constraints for mature and old forest areas in strategy 3 (i.e., an increase in the right hand side of the area constraints from 10 to 14%), the likelihood of satisfying the minimum required areas increased (Figure 3.7). Although none of the strategies were effective at providing the minimum required areas of mature and old forest in the ‘extreme’ BFR, forest managers practicing ecosystem management principles in regions with very high burn fractions (e.g., the ‘extreme’ BFR) would likely not be required to provide much old forest due to the short fire cycle and the low probability that old forest would occur naturally.

In strategy 4 the areas of mature and old forest were maximized subject to a fixed harvest volume targets equal to 2.0 or 8.0 M. m$^3$/decade. This strategy was somewhat comparable to simulation studies that evaluate the impacts of fire and harvesting (Van Wagner, 1983; Fall et al., 2004; Didion et al., 2007; James et al., 2007) using a stochastic fire model and specified harvest rate. This study showed that depending on the fixed harvest volume selected, the mature and old forest areas will
vary over time due to initial starting conditions but will eventually reach an equilibrium range. In general, if the fixed harvest volume target was low, the mature and old forest areas accumulated due to a lack of disturbance, especially in the ‘moderate’ and ‘low’ BFRs (Figure 3.8). Alternatively, if the fixed harvest volume target was high, the mature and old forest areas would decline to the lower bound (Figure 3.9). In strategy 4, because harvest volume was constrained to a fixed level and mature and old forest areas were being maximized, the fixed harvest volume constraint was satisfied first with the area remaining used to maximize the area of mature and old forest. Forest or parks managers using LP planning models should understand that forest values which are treated as constraints will be satisfied before the forest values being optimized are maximized. Strategy 4 clearly showed that the volume harvested had the most significant impact in determining the areas of mature and old forest. These strategies show that the appropriate harvest volume will be a function of the risk that a manager is willing to assume, given that they may not achieve their desired minimum areas of mature and old forest. In other studies the objective functions have been modified to better achieve ecological objectives such as the maximization of the expected plant population for the conservation of a threatened species under climate change (Hof et al., 1999) or the minimization of a cost function related to total habitat area and habitat density for reserve design (Possingham et al., 2000; Rayfield et al., 2008).

Although the harvest volume produced by each strategy was not the focus of this study, it is worthwhile to note that they do provide an indication of the difficulty that managers would face in providing a constant flow of timber, especially in regions with burn fractions similar to the ‘high’ to ‘extreme’ BFRs (Figures 3.3 and 3.6). The variability in harvest volume was not assessed for strategies 3 and 4 because strategy 3 would have a similar pattern of variability to strategy 2 but with lower harvest volumes. In strategy 4, the 2.0 M. m³/decade fixed harvest volume target
would have been constant with little variability, except in the ‘extreme’ BFR. While
the 8.0 M. m$^3$/decade fixed harvest volume would show high variability in both the
‘extreme’ and ‘high’ BFRs, based on the variability observed in strategies 1 and 2.
These results demonstrate that managers need to be cautious when setting the fixed
harvest target because it impacts not only the variability in the areas of mature and
old forest but also the variability in harvest volume which can have implications for
meeting mill capacity demands.

Holling and Meffe (1996) suggested that one goal of resource management was
to reduce natural variability in systems to improve predictability and stability, with
the objective of greater product yield. They termed this type of management as
“Command and Control”. As part of such management, an attempt is made to
reduce extreme events and control the composition of the system. The LP forest
management planning model in this study exhibited some of this behaviour when it
reduced the mature and old forest areas to the lower bound. Ludwig et al. (1993) in a
review paper, argued in favour of reducing natural resource extraction below so called
“optimum” levels. They discussed the collapse of several ocean fisheries that were
managed under maximum sustained yield principles without a clear understanding
of the range of natural variability of the systems or the population dynamics. The
results from this study show a similar trend where a high harvest target (i.e., 8.0 M.
m$^3$/decade) reduced the areas of mature and old forest to the lower bound, while a low
harvest target (i.e., 2.0 M. m$^3$/decade) produced a surplus of mature and old forest,
especially in the ‘high’, ‘moderate’ and ‘low’ BFRs (Figures 3.8 and 3.9). A reduction
in harvest volume or the modification of mature and old forest area constraints may
provide greater flexibility in the future for changes in science, policy, and social values
and increase the likelihood that forest sustainability is being acheived.
3.5 Conclusion

The strategies examined in this study highlight several significant implications of using LP forest management planning models in an uncertain planning environment. If the objective function maximizes harvest volume, it may be difficult to maintain the minimum required mature and old forest areas in the presence of fire, especially if the burn fractions >0.45% (i.e., ‘extreme’ and ‘high’ BFRs) and the seral stage areas are at their lower bound already. Increasing the lower bound areas of mature and old forest by strengthening the constraints may improve the likelihood of these two seral stages satisfying minimum required areas. A modification of the objective function (i.e, maximized mature and old forest areas) to better represent ecosystem management objectives did not ensure that the minimum seral stage areas would be satisfied (e.g., the ‘high’ BFR with a fixed harvest target of 8.0 M. m3/decade). These results indicate that the selection of the fixed harvest target was very important in determining the extent to which the seral stage area requirements were satisfied and may require a great deal of analysis if managers choose to maximize mature and old forest area in their planning. In general, any planning strategy used in forest management should ensure that there is a high likelihood that sustainable forest management objectives will be achieved in the long-term.
Chapter 4


4.1 Introduction

In the province of Ontario, forest fire activity can vary significantly over both time and space (Martell, 1994). Across northern Ontario from east to west the burn fraction ranged from 0.01214 to 0.351115% (Martell and Sun, 2008) and for the period 1960 to 2004 over an area of 473,399 km\(^2\), the annual area burned varied from 9 to 6,232 km\(^2\) (see Figure 2.1 in Chapter 2, Page 23). The majority of fires were small (e.g., <200 ha) and accounted for only about 3% of the area burned while the remaining 97% of the area burned was accounted for by a relatively small number of large fires (Stocks et al., 2002). This variability poses significant challenges to forest managers who must account for potential fire losses when they make decisions over long planning horizons.

The average annual burn fraction (i.e., the average annual area burned expressed as a proportion of the landscape size) has been used extensively as a performance measure to evaluate fire suppression effectiveness (Ward et al., 2001; Martell and Sun, 2008), and to compare past, current, and predicted future fire regimes (Bergeron et al., 2004, 2006). It is also used by forest management planners to assess the potential impact of fire on timber supply, when they determine the annual allowable cut (Martell, 1994). Forest managers use the burn fraction to deterministically model area burned along with harvesting and regeneration in linear programming (LP) forest management planning models. Martell (1994) developed a trade-off curve to describe
the relationship between burn fraction and harvest volume, as the burn fraction increased, the harvest volume decreased. He found that with small burn fractions of 0.5% the reduction in harvest volume was approximately 15%, however, with a burn fraction of 1.5%, the reduction in harvest volume was approximately 35%. Although the burn fraction is widely used in forest management, forest managers rarely recognize the uncertainty in their burn fraction estimates.

The natural burn fraction (i.e., the pre-fire suppression estimate of burn fraction), or its inverse (often referred to as the fire cycle), is commonly used by those that advocate ecosystem management (e.g., Bergeron et al. (2004)), to provide insight into the proportion of young, mature and over-mature forest that might occur under natural conditions (Franklin, 1993; Gauthier et al., 1996). Ecosystem management is based on the assumption that if natural ecosystem structure and pattern can be created through management practices, then biodiversity can be maintained (Franklin, 1993). Van Wagner (1978) predicted that a landscape subject to stochastic fire would develop an exponential age class distribution with an average age corresponding to the inverse of the burn fraction. For a thorough discussion of the exponential distribution and its relationship to the forest age class distribution see Boychuk et al. (1997).

Bergeron et al. (1999, 2002) used the exponential age class distribution along with the fire cycle or mean forest age (i.e., inverse of the natural burn fraction) to develop a multi-cohort forest ecosystem management system that creates landscapes with varying stages of forest development from young to old. The natural burn fraction can be estimated using various methods including dendrochronology (Fritts and Swetnam, 1989; Bergeron et al., 2001; Girardin et al., 2006), fire scar mapping of trees (Reed and Johnson, 2004), time since fire mapping (Johnson and Gutsell, 1994; Reed, 2000; Bergeron et al., 2001), lake sediment sampling (Hallett and Walker, 2000), and stochastic landscape simulation modelling (Perera et al., 2003). However,
the uncertainty associated with natural burn fraction estimates generated using these methods may have significant implications for forest management planning and timber supply.

Fire simulation models developed from parameterized statistical distributions can be used to model annual area burned and to develop simulated burn fraction confidence intervals. Studies modelling area burned have used the lognormal distribution (Armstrong, 1999) and compound Poisson distribution (Podur et al., 2009). When using the compound Poisson distribution to model area burned, a fire size distribution must be selected to model the sizes of individual simulated fires that burn during a given year. Fire size distributions have been investigated extensively in forest landscapes around the world (see Cui and Perera (2008)). In the boreal forest, the observed frequency distribution of the sizes of fires that escape initial attack by fire crews resembles the probability distribution of the power law family of distributions (Cui and Perera, 2008). The exponential and Pareto distributions are the most common distributions from the power law family that have been used to model fire sizes. The exponential distribution has been used by several authors to model fire sizes in the United States and Canada (Baker et al., 1991; Baker, 1995; Li et al., 1999), while the truncated exponential distribution was fit to log transformed fire sizes in northeastern Alberta. Schoenberg et al. (2003) showed that a tapered Pareto distribution fits California fire sizes well. These studies show that fire size distributions can be represented by a variety of power law distributions and the most appropriate distribution may depend on the geographic location of the fire regime.

4.1.1 Study Objectives

In this study I first used a hypothetical forest and an LP forest management planning model to reproduce the burn fraction and harvest volume trade-off curve from Martell (1994). Then using historical annual area burned data from the period 1960 to 2004,
I developed bootstrapped confidence intervals for four burn fraction regions (BFR) in Ontario and used them and the forest management planning model to determine the corresponding upper and lower bounds on the harvest volume on the trade-off curve. This plot showed the uncertainty in harvest volume that would result from uncertainty in burn fraction estimates. An aspatial simulation model was then developed and parameterized using fire occurrence rate and fire size distribution models from historical data for the same period and four BFRs. Using the bootstrapped confidence intervals and confidence intervals developed from the simulation model, I compared the upper and lower bounds to determine whether it was reasonable to use the simulation model to develop burn fraction confidence intervals.

I then used the simulation model to develop 95% confidence intervals for two natural burn fraction estimates from the published literature (Suffling et al., 1982; Bergeron et al., 2001). When estimating the confidence intervals, the number of years of area burned data will influence the confidence interval range, therefore, the confidence intervals were developed with the number of years of area burned data ranging from 5 to 200 years. The upper and lower bounds of the natural burn fraction confidence intervals were then used with the exponential age class distribution to find the corresponding upper and lower bounds for the area of old forest, which would be required to meet ecosystem management objectives. Finally, the upper and lower bounds of the old forest area (i.e., for both Suffling et al. (1982) and Bergeron et al. (2001) study sites) were used as minimum area constraints in the LP forest management planning model to examine the impact that uncertainty in natural burn fraction estimates from Ontario would have on the available harvest volume (e.g., m$^3$/decade) from a hypothetical forest.

As well, given the uncertainty concerning which fire size distribution to use when simulating the annual area burned, three distributions were considered: exponential, truncated exponential, and tapered Pareto. I also developed a graphical tool that
can be used by forest managers who wish to incorporate burn fraction confidence intervals in their planning. This tool provided estimates of the relative confidence interval ranges as a percentage of the burn fraction using the fire occurrence rate and the number of years of area burned data as inputs.

4.2 Methods

4.2.1 Calculating Burn Fraction

The expected burn fraction of a region is the expected annual area burned, expressed as a proportion of the size of the region as depicted in Equation 4.1.

\[
\text{Expected Burn Fraction} = \frac{\lambda \times \mu}{A} \tag{4.1}
\]

where \( \lambda \) is the average number of fires per year, \( \mu \) the average fire size, and \( A \) is the size of the region. The burn fraction is also sometimes referred to as the burn rate (Bergeron et al., 2004, 2006) or the annual proportion burned (Boychuk et al., 1997). The estimates of \( \lambda \) and \( \mu \) were based on historical fire data from the period 1960 to 2004 for the four BFRs.

4.2.2 Study Area Description

This study used the same burn fraction regions as Chapter 2 (described in Section 1.3.4 on page 16 of the Introduction), however, two natural burn fraction study sites from the published literature (Suffling et al., 1982; Bergeron et al., 2001) were also used (Figure 4.1). As well, a simple hypothetical forest of jack pine (\textit{Pinus banksiana} Lamb.), 1 M. ha in size was used to study the potential impact of uncertain burn fraction estimates on harvest volume. The age class distribution of the hypothetical forest was exponential and corresponded to a fire cycle of 1000 years (i.e., a burn
fraction of 0.1%), which might be expected in a landscape with a managed fire regime in the province of Ontario (Martell and Sun, 2008).

4.2.3 Using Historical Area Burned Data to Develop Confidence Intervals

Non-parametric bootstrapping was used to develop confidence intervals from historical area burned data from the four BFRs for the period 1960 to 2004. For each bootstrapped sample, I randomly selected 45 years of area burned data with replacement (i.e., some years could be selected more than once) and the average burn fraction was calculated from the 45 year sample, this process was repeated 10,000 times. Using this sampling distribution of burn fractions (i.e., 10,000 bootstrapped burn fraction sam-
ples), the average, $2.5^{th}$ and $97.5^{th}$ percentiles were used to calculate 95% confidence intervals for the burn fraction estimates in the four BFRs.

### 4.2.4 Burn Fraction and Harvest Volume Trade-off Curve

The burn fraction and harvest volume trade-off curve from Martell (1994) was developed using an LP forest management planning model (i.e., the Model III formulation which is described below) and the age class distribution from the hypothetical forest. The harvest volume was calculated for burn fractions that ranged from 0 to 1.5%. Then using the bootstrapped confidence intervals, the corresponding upper and lower bounds on the harvest volumes were calculated using the forest management planning model.

#### 4.2.4.1 Forest Management Planning Model

For a detailed description of the forest management planning model please see Section 1.3.1 in Chapter 1 (Page 11).

#### 4.2.4.2 Linear Programming Formulation

The objective function maximized the volume harvested over $T$ time periods in the planning horizon (Eq. 4.2).

$$\text{Maximize } \sum_{t} VolumeCut_t$$

where $VolumeCut_t$ was the total volume harvested at the start of period $t$. $T$ was the number of time periods and $t$ denotes the time period; $t = 1, 2, ..., T$. The objective function was maximized subject to a set of constraints. The constraints in this study which control the transfer of area from one age class and period to another were identical to constraints in Chapter 2 and can be found in Equations 2.2 to 2.11 (Page 28). Most of the remaining constraints presented here were unique to this study.
The area in age classes greater than or equal to 12 was summed to determine the total area of old forest in period $t$ and must be greater than or equal to the amount of old forest area required to meet ecosystem management objectives (Eq. 4.3).

$$\sum_{a \geq 12} Area_{at} \geq RequiredOldForest \quad \forall \ t \quad (4.3)$$

where $RequiredOldForest$ was the area of old forest required in each period to meet ecosystem management objectives.

### 4.2.5 Simulating Area Burned to Estimate Annual Burn Fraction Confidence Intervals

#### 4.2.5.1 Modelling Fire Occurrence

For a description of how fire occurrence was modelled, please see Section 2.2.3.1 (Page 31) in Chapter 2. The fire occurrence rates for this study can be found in Table 4.1.

**Table 4.1:** Fire occurrence rates from four burn fraction regions in Ontario and based on historical fire data from the period 1960 to 2004.

<table>
<thead>
<tr>
<th>Burn Fraction Region</th>
<th>Average Annual Fire Occurrence Rate*</th>
<th>Proportion of Fires That Escape Initial Attack</th>
<th>Average Annual Escaped Fire Occurrence Rate($\lambda$)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>‘Extreme’</td>
<td>6.67</td>
<td>0.355</td>
<td>2.379</td>
</tr>
<tr>
<td>‘High’</td>
<td>29.57</td>
<td>0.033</td>
<td>0.978</td>
</tr>
<tr>
<td>‘Moderate’</td>
<td>18.13</td>
<td>0.042</td>
<td>0.774</td>
</tr>
<tr>
<td>‘Low’</td>
<td>16.44</td>
<td>0.043</td>
<td>0.708</td>
</tr>
</tbody>
</table>

*All fire occurrence rates were expressed in terms of the number of fires per million ha per year.
4.2.5.2 Modelling Fire Size

Historical fire size data collected in the four BFRs for the period 1960 to 2004 was used to fit three distributions using maximum likelihood estimation in R (Ihaka and Gentleman, 1996). The three distributions were truncated from below (i.e., fires $\geq 25$ ha) to reflect the emphasis on large fires that escape initial attack and because they account for the majority of area burned. The cumulative distribution function (cdf) of the exponential distribution is depicted in Equation 4.4.

$$F(x) = 1 - \exp(-\mu x) \quad (25 \leq x \leq \infty) \quad (4.4)$$

For a description of the truncated exponential distribution please see Section 2.2.3.2 (Page 31) in Chapter 2, the cdf is shown in Equation 2.14.

The cdf of the tapered Pareto distribution is depicted in Equation 4.5.

$$F(x) = 1 - \left(\frac{a}{x}\right)^{\sigma} \exp\left(\frac{a - x}{\theta}\right) \quad (a \leq x \leq \infty) \quad (4.5)$$

where $a$ is the lower truncation point and $\theta$ is the taper point.

The fire size distributions were fit using maximum likelihood estimation and the estimated parameters can be found in Table 4.2. The exponential, truncated exponential and tapered Pareto distributions do not produce identical mean fire sizes. To compare the simulated burn fraction confidence intervals produced by the three fire size distributions, the mean fire sizes of the three distributions should be the same.

The mean fire size of the exponential distribution was equal to the observed mean fire size from the historical fire data and was not adjusted. However, the scale parameters from the truncated exponential and tapered Pareto distribution were adjusted using a simple binary search. The binary search started with an initial scale parameter and simulated 100 million fires and calculated the mean. A new scale parameter was then systematically chosen, fire sizes were simulated, and a new mean fire size calculated.
This process was repeated until the scale parameter produced an estimate of the mean fire size that was within 1% of the observed mean fire size from the historical data. The truncation and taper points from the two distributions were not adjusted.

Table 4.2: Fire size distribution parameters based on historical fire data for the period 1960 to 2004 from four burn fraction regions in Ontario.

<table>
<thead>
<tr>
<th>Burn Fraction Region</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>( \beta )</th>
<th>( \sigma )</th>
<th>( \theta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>‘Extreme’</td>
<td>5531</td>
<td>3.68</td>
<td>8.631</td>
<td>0.269</td>
<td>29672</td>
</tr>
<tr>
<td>‘High’</td>
<td>4301</td>
<td>3.39</td>
<td>8.417</td>
<td>0.344</td>
<td>39526</td>
</tr>
<tr>
<td>‘Moderate’</td>
<td>1600</td>
<td>2.73</td>
<td>7.325</td>
<td>0.393</td>
<td>12766</td>
</tr>
<tr>
<td>‘Low’</td>
<td>269</td>
<td>1.16</td>
<td>7.274</td>
<td>0.860</td>
<td>18142</td>
</tr>
</tbody>
</table>

4.2.5.3 Modelling Area Burned

For a description of how annual area burned was modelled using the fire occurrence and fire size models, please see Section 2.2.4 (Page 32) in Chapter 2. The process of modelling annual area burned was repeated over \( n \) years, for \( r \) replications, to create three \( r \times n \) matrices of annual area burned values for the three fire size distributions. A total of 10,000 replications were performed for each set of simulation runs, however the number of years modelled varied depending on the problem being examined.

4.2.6 Estimating Burn Fraction Confidence Intervals Using Simulated Area Burned Data

Using the three \( r \times n \) matrices of annual area burned values, 95% confidence intervals were developed with the number of years of area burned data ranging from 5 to 200 years. For example, to construct the confidence interval with 5 years of area burned data, the 5 year average burn fraction was calculated using the simulated area burned data from years 1-5. The process of calculating 5 year averages was then repeated for each replication. This produced a sampling distribution of 10,000
average burn fraction estimates from the 5 years of fire data. The average, 2.5<sup>th</sup> and 97.5<sup>th</sup> percentiles were calculated from the sampling distribution. The number of years of area burned data was then incremented by 1 year and a new average burn fraction was calculated for each replication along with new confidence intervals. This process of generating confidence intervals for a range of years of area burned data was repeated for each of the three fire size distributions examined.

### 4.2.7 Examining the Uncertainty in Natural Burn Fraction Estimates and its Potential Impact on Harvest Volume

To evaluate the impact that uncertainty in natural burn fraction estimates has on forest management, two natural burn fraction estimates from the published literature were chosen (Suffling et al., 1982; Bergeron et al., 2001) and compared in a hypothetical forest. The simulation model was used first used to develop confidence intervals for the two natural burn fraction estimates with the number of years of area burned data used to calculate the burn fraction ranging from 5 to 200 years. The method for developing the confidence intervals can be found in Section 4.2.6 of this study. In historical studies of natural fire regimes, the historical fire occurrence rate and fire size distribution are difficult to determine because data on individual fires are either incomplete or not available for studies that span several hundred years (see Bergeron et al. (2006) for a list of long-term fire history studies in eastern Canada). For any particular natural burn fraction estimate, a large number of fire occurrence rate and mean fire size combinations could produce the observed burn fraction. Historical lightning fire data for the period 1960 to 2004 showed the average number of fires ≥25 ha in size was 2.078 fires/M. ha/year in the northeastern Ontario and 7.778 and fires/M. ha/year in the northwestern Ontario. These historical fire occurrence rates would likely be somewhat different than the fire occurrence rates that occurred over the period of the natural burn fraction estimates. Therefore, this study used four
plausible combinations of fire occurrence rate and mean fire size in the simulation model to produce the natural burn fractions reported by Suffling et al. (1982) and Bergeron et al. (2001) (Table 4.3).

The upper and lower bounds of the natural burn fraction confidence intervals were inverted (i.e., the mean forest age was calculated) and used as the input parameter for the exponential distribution, to determine the amount of old forest area that would be required on the landscape to meet ecosystem management objectives. The Ontario Ministry of Natural Resources (OMNR) defines jack pine $>110$ years of age in northwestern Ontario as old growth forest (Uhlig et al., 2003). A threshold of 110 years was used to determine the amount of old forest from the cumulative distribution function of the exponential distribution. Finally, the corresponding upper and lower bounds on the old forest area were used as minimum area constraints in the forest management planning model to examine the long-term impact of uncertain natural burn fraction estimates on harvest volume ($\text{m}^3$/decade). For all three steps in this analysis the confidence intervals and upper and lower bounds were developed with the number of years of area burned data ranging from 5 to 200 years.

Table 4.3: Simulation modelling parameters used to develop natural burn fraction confidence intervals.

<table>
<thead>
<tr>
<th>Potential Fire Regimes</th>
<th>Northwest† Burn Fraction = 1.92%</th>
<th>Northeast‡ Burn Fraction = 0.58%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Annual Fire Occurrence Rate*</td>
<td>Average Annual Fire Occurrence Rate*</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>19,200</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>3840</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>1920</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>960</td>
</tr>
</tbody>
</table>

*All fire occurrence rates were expressed in terms of the number of fires per million ha. per year
†see Suffling et al. (1982)
‡see Bergeron et al. (2001)
4.2.8 Development of a Graphical Tool to Estimate Burn Fraction Confidence Intervals

Forest managers are often required to make decisions that rely on the burn fraction (e.g., when accounting for fire in the planning process using Model III). However, developing burn fraction confidence intervals using bootstrapping or simulation techniques may be difficult for managers not familiar with these methods. I developed a graphical tool that managers can use to help construct confidence intervals using the fire occurrence rate and the number of years of area burned data for a particular landscape. This tool provided the relative confidence interval range as a percentage of the burn fraction being examined and was therefore, applicable to a broad range of burn fractions found in the boreal forest. For example, if the burn fraction estimate was 1.0% and the fire occurrence rate and the number of years of area burned data indicated a relative confidence interval range of 20%, the confidence interval ranged from 0.8% to 1.2%. To build the graphical tool, confidence intervals were first developed from simulated area burned data for fire occurrence rates that ranged from 0.1 to 100 fires/M. ha/year and with the number of years of area burned data ranging from 5 to 1000 years. Although it was unlikely that the historical fire record (i.e., number of years of area burned data) would be 1000 years in length, this number of years of area burned data was chosen to demonstrate how much data was required to achieve a relative confidence interval range that was <10% when the fire occurrence rate was low. The exponential distribution was used to model fire sizes for the graphical tool because it was relatively easy to parameterize compared with either the truncated exponential or tapered Pareto distributions. By using the exponential distribution, the burn fraction variance estimates were smaller than other fire size distributions, thus providing a conservative estimate of the confidence interval range. Using the simulated confidence intervals for each fire occurrence rate, the number of years of area burned data was found where the confidence intervals were within
the upper and lower bounds of \( \pm 10\% \), \( \pm 20\% \), \( \pm 30\% \), \( \pm 40\% \), and \( \pm 50\% \) of the mean burn fraction estimate. A plot was then created showing the relationship between the number of years of area burned data and fire occurrence rate for the five relative confidence interval bounds.

4.3 Results

4.3.1 Burn Fraction and Harvest Volume Trade-off Curve with Bootstrapped Confidence Intervals

Using historical area burned data from the period 1960 to 2004, bootstrapped confidence intervals were developed (panel a, Figure 4.2). A trade-off curve was then developed using the forest management planning model which showed the relationship between burn fraction and harvest volume when fire was deterministically modelled along with harvesting and regeneration (panel b, Figure 4.2). In the trade-off curve, the burn fraction ranged from 0 to 1.5\% and showed that the harvest volume ranged from approximately 14 to 21 M. m\(^3\)/decade. The reduction in harvest volume with a burn fraction of 1.5\% was approximately 34\%. Because the burn fraction confidence intervals increased as the burn fraction increased, the range of harvest volume upper and lower bounds also increased. In the ‘extreme’ and ‘high’ BFRs, the harvest volume upper and lower bounds ranged from approximately 10 to 18 M. m\(^3\)/decade and from 16 to 21 M. m\(^3\), respectively.

4.3.2 A Comparison of the Simulated and Bootstrapped Confidence Intervals

Simulated and bootstrapped burn fraction confidence intervals were developed for the four BFRs to assess the extent to which they provide consistent variance estimates (Figure 4.3). The two methods provided similar variance estimates, for the ‘high’,
Figure 4.2: a) Bootstrapped confidence intervals were developed for the four burn fraction regions using historical area burned data from the period 1960 to 2004. b) A trade-off curve showing the relationship between burn fraction and harvest volume was developed using the Model III forest management planning model. The bootstrapped confidence intervals were then input into the forest management planning model and the upper and lower bound on the harvest volume were calculated.

‘moderate’, and ‘low’ BFRs, which was expected given that both sets of confidence intervals were calculated from the same number of fires. As well, the bootstrapped confidence interval range corresponded better with the truncated exponential and tapered Pareto fire size distributions than the exponential distribution, which under estimated the variance. For the ‘extreme’ BFR, the bootstrapped confidence intervals over-estimated the width of the simulated confidence intervals. The similar variance estimates between the two confidence interval development methods indicate that the simulation model likely provided reasonable estimates of the burn fraction confidence intervals.
Figure 4.3: Confidence intervals developed from simulated area burned data and confidence intervals developed from bootstrapped historical area burned data from the period 1960-2004, were compared for the four burn fraction regions. To determine the impact of the fire size distribution when modelling area burned and estimating confidence intervals, three distributions were chosen and compared.

4.3.3 Assessing the Potential Impact of Natural Burn Fraction Uncertainty on Old Forest Area and Timber Supply

The simulated natural burn fraction confidence intervals developed for northwestern Ontario exhibited a larger absolute range than the natural burn fraction confidence
Figure 4.4: A comparison of natural burn fraction confidence intervals generated from simulated area burned data for two study areas in northeastern and northwestern Ontario. Since no estimate of the fire occurrence rate was available because of the methods used to estimate the natural burn fraction, four plausible fire occurrence rates were examined in the modelling of area burned.

Intervals for northeastern Ontario (Figure 4.4). The lowest fire occurrence rate of 1 fire/M. ha/year had the largest confidence interval range of the 4 fire occurrence rates modelled. The natural burn fraction confidence intervals for fire occurrence rates of 5, 10, and 20 fires/M. ha/year were clustered closely together. Using 25 years as a reasonable number of years of area burned data for comparison in northwestern Ontario, the confidence intervals ranged from 0.99% to 3.08% and 1.68% to 2.17%, for 1 and 20 fires/M. ha/year, respectively. In northeastern Ontario, the burn fraction confidence intervals ranged from 0.291% to 0.928% for a fire occurrence rate of 1 fire/M. ha/year, while the confidence intervals ranged from 0.509% to 0.654% for a fire occurrence rate of 20 fires/M. ha/year.

Using the inverse of the natural burn fraction confidence intervals as the mean forest age in the exponential distribution, the proportion of old forest area was calculated (Figure 4.5). In general, as the natural burn fraction increased, the proportion
Figure 4.5: The inverse of the natural burn fraction confidence intervals from two study sites in northeastern and northwestern Ontario were used as the mean forest age in the exponential age class distribution to determine the proportion of old forest area that would be required to meet ecosystem management objectives. Since no estimate of the fire occurrence rate was available because of the methods used to estimate the natural burn fraction, four plausible fire occurrence rates were examined in the modelling of area burned.

of old forest area decreased. Using the upper and lower bounds that correspond to 25 years of area burned data for comparison purposes, the proportion of old forest area with a fire occurrence rate of 1 fire/M. ha/year ranged from 0.03 to 0.33 in the northwest region. While in the northeast region for the same fire occurrence rate, the proportion of old forest area ranged from 0.35 to 0.72.

The upper and lower old forest area bounds were then used as minimum area constraints in the forest management planning model to examine the impact on harvest volume (m$^3$/decade). In the northwestern Ontario with 25 years of area burned data, the harvest volume ranged from 14.9 to 20.3 M. m$^3$/decade, with a mean of 18.8 M. m$^3$/decade for a fire occurrence rate of 1 fire/M. ha/year. In the northeastern Ontario the harvest volume ranged from 7.1 to 14.4 M. m$^3$/decade, with a mean of 11.4 M. m$^3$/decade for a fire occurrence rate of 1 fire/M. ha/year (Figure 4.6).
4.3.4 A Graphical Tool for Estimating Burn Fraction Confidence Intervals

A graphical tool was developed to assist managers in estimating the relative burn fraction confidence interval range based on the fire occurrence rate and the number of years of area burned data (Figure 4.7). Confidence intervals were first developed using simulated area burned data for a range of fire occurrence rates and numbers of years of area burned data. Then using the confidence intervals, the number of years of area burned data were found which corresponded to the relative burn fraction ranges (i.e., ±10%, ±20%, ±30%, ±40%, and ±50%). The relationship between fire occurrence rate and the number of years of area burned data was then plotted for the relative confidence interval ranges. To illustrate the use of this plot for managers, the fire occurrence rate and the number of years of area burned data from the ‘high’ BFR
Figure 4.7: A graphical tool for estimating relative confidence interval range as a percentage of the burn fraction based on the fire occurrence rate (fires/million ha/year) and the number of years of area burned data. Fire size was modelled using the exponential distribution. To illustrate the use of this plot for a manager, they would first find the region (i.e., the relative confidence interval width) where the fire occurrence rate and the number of years of area burned data intersect. They would then calculate the confidence intervals from the burn fraction and relative confidence interval width based on the equation presented. The fire occurrence rate (i.e., 0.978 fires/million ha/year) and number of years of area burned data (i.e., 45 years) from the ‘high’ BFR are presented on the plot as an example.
4.4 Discussion

4.4.1 Uncertainty in Burn Fraction Estimates and their Impact on Forest Management Planning

The burn fraction is used in forest management planning models to account for fire losses when scheduling harvest and regeneration activities (Martell, 1994). The bootstrapping of historical area burned data demonstrated a relatively easy method for developing burn fraction confidence intervals and showed that the impact of uncertainty in burn fraction estimates can be significant when managers plan the harvest allocation (panel b, Figure 4.2). When using the exponential age class distribution as part of an ecosystem management approach, I showed that a decreasing burn fraction resulted in an increase in the area of old forest. Burn fraction estimates that are near the upper bound of the confidence interval can cause over-harvesting (i.e., because less old forest area is required on the landscape), which has serious implications for ecosystem health and biodiversity, while estimates near the lower bound of the burn fraction confidence interval can cause sub-optimal use of forest resources.

The results also showed that uncertainty in natural burn fraction estimates can have a significant impact on the amount of old forest area and hence the harvest volume (Figures 4.5 and 4.6). Under the traditional sustained yield management paradigm, the retention and production of old forest area was not considered. When managing primarily for timber, an increase in burn fraction results in a decrease in timber supply because a greater proportion of the landscape was being disturbed by fire. This study has demonstrated that if managers were to use the ecosystem management approach described by Bergeron et al. (2004), an increase in burn fraction would result in an increase in timber supply (Figure 4.6), a seemingly counter-intuitive result that differs dramatically from those presented by Martell (1994). The reason of course, is that a low burn fraction calls for a much higher proportion of the
landscape to be in an old forest condition and results in a reduction in harvest volume in order to achieve the desired age class distribution (Figure 4.5). The requirement to maintain or increase old forest area on the landscape has a much greater impact on timber supply than the area disturbed by fire.

Boychuk et al. (1997) and Armstrong (1999), examined whether boreal age class distributions would achieve an exponential distribution when subjected to stochastic forest fires as proposed by Van Wagner (1978). Their results showed that in any single realization of their simulated forests, the age class distribution was not exponential, however, when the distributions from all of the replications were averaged, they appeared to follow an exponential distribution. Several other studies in the United States have found similar results where the age class distribution did not reach an equilibration state (Romme, 1982; Baker, 1989a,b). Two of the underlying assumptions with the exponential age class distribution (Van Wagner, 1978) is that area burned was constant between years and that fires were not correlated in time or space. This assumption does not hold in many parts of the boreal forest (Boychuk et al., 1997) and perhaps should discount the exponential distribution as the target age class distribution for ecosystem management. The results from this study suggest that managers need to be cautious when implementing ecosystem management (i.e., especially when using an exponential age class distribution) because uncertain estimates of old forest area can have significant impacts on timber supply, which can influence economic and social aspects of sustainable forest management (Figure 4.4).

In their estimates of the natural burn fraction, Suffling et al. (1982) and Bergeron et al. (2001) did not estimate the fire occurrence rate, as a result, four possible fire occurrence rates were chosen and used to develop natural burn fraction confidence intervals. Historical fire data from the period 1960 to 2004 was used to determine average lightning fire occurrence rates of 7.778 and 2.078 fires/M. ha/year in northwestern and northeastern Ontario, respectively. Although these lightning fire occurrence rates
were not collected over the same time period as the natural burn fraction studies, they
do provide an estimate of lightning fire frequency for the areas of interest. In north-western Ontario the natural burn fraction confidence intervals will be smaller due to
the relatively high fire occurrence rate in comparison to northeastern Ontario (Figure
4.4). These results could have significant implications for forest managers required
to estimate the proportion of old forest area on the landscape. In Ontario, approximately 16% (i.e., 5.4 M. ha) of the landscape is considered old growth forest across all
species types (OMNR, 2006). The old forest area in many forest management units in
Ontario would not be adequate to meet the old forest area requirements predicted by
the natural burn fractions investigated in this study. In Ontario, forest managers will
need to make trade-offs between ecological and economic objectives, that is, managers
will likely be required to reduce harvest volumes or reduce the amount of old forest
area below what is predicted by the exponential age class distribution, but what is
certain is that not all stakeholders will be satisfied.

When comparing differences in burn fraction among fire history studies, forest
managers should be cautious about drawing conclusions about observed differences
in burn fractions. Armstrong (1999) found that in Alberta, two estimates of the burn
fraction which differed by a factor of 4 (i.e, 0.5% and 2.0%) from the same region
were statistically the same when the number of years of area burned data was less
than 230 years. Bergeron et al. (2006) compared natural burn fractions estimates
from ten fire history studies throughout Quebec with current burn fraction estimates
and found that decreases in area burned could be used to assist forest managers
in achieving ecosystem management objectives. Depending on the fire occurrence
rate in the regions examined, the natural burn fraction estimates may have large
confidence interval ranges and should be used with caution when developing ecosystem
management objectives that will have significant impacts to economic or social values.
4.4.2 Factors Influencing Burn Fraction Estimation

Previous authors have argued that with an increase in spatial scale (i.e., landscape extent) the variance in burn fraction estimate should decrease (Simard, 1976; Reed and Errico, 1986; Johnson and Gutsell, 1994) as a result of higher fire occurrence rates. Simard (1976) also suggested that the burn fraction distribution would approach the expected burn fraction for very large landscapes. Boychuk et al. (1997) found that the burn fraction did indeed converge to the expected value for large landscapes when the cells being burned were assumed to be independent. This study confirmed the results from Boychuk et al. (1997) and found that as the number of fires modelled increased (e.g., by increasing the number of years of area burned data or by increasing the fire occurrence rate), the confidence interval range decreased (Figure 4.4).

The graphical tool developed in this study constitutes a simple method that forest managers can use to estimate burn fraction confidence intervals for their management unit (Figure 4.7). However, managers should be aware that the graphical tool was developed using the exponential distribution to represent the fire size distribution and will provide lower variance estimates (i.e., narrower confidence intervals) than other fire size distributions. My results indicate that managers working in regions with low fire occurrence rates and high burn fractions will observe high variance in their burn fraction confidence intervals. The forest management plans in these regions may under- or over-estimate the burn fraction which can increase or decrease the risk that the manager will not be able to meet harvest volume requirements.

The comparison of bootstrapped vs. simulated confidence intervals illustrated the relative ease of developing confidence intervals using historical area burned data and demonstrated that the two techniques provided similar variance estimates (Figure 4.3). The results showed that the simulated confidence intervals for the exponential fire size distribution were narrower than those produced using the truncated exponential and tapered Pareto fire size distributions. If historical fire size data exists for
a region, then managers should use this data to develop either truncated exponential, tapered Pareto, or some other variant of the power law family of distributions.

4.5 Conclusion

The confidence intervals developed for the burn fraction and harvest volume trade-off curve showed that uncertainty in burn fraction estimates can create challenges for managers who want to account for fire in their planning by using the burn fraction in Model III. Managers interested in incorporating uncertainty in their burn fraction estimates can use relatively easy techniques such as bootstrapping of historical area burned data or using the graphical tool developed in this study to find the relative confidence intervals based on the fire occurrence rate and the number of years of area burned data. The results also showed that natural burn fraction estimates can have significant implications for forest management planning and timber supply. Managers should be cautious when using the exponential age class distribution to determine forest characteristics for ecosystem management (i.e., old forest area objectives) because the underlying assumptions of the exponential age class distribution may only apply to a narrow range of conditions not typically found in the boreal forest. As with any management framework, when practicing ecosystem management, trade-offs in timber supply and ecological objectives will undoubtedly be required to achieve forest sustainability.
Chapter 5

Research Summary and Further Discussion

This thesis addresses questions related to the evaluation of strategies for dealing with uncertainty due to fire when managing flammable forest landscapes for timber supply and an ecological objective. Depending on the level of fire activity and a manager's risk preference, the best strategy may change. The annual area burned in Ontario is both spatially and temporally variable (Martell, 1994). Temporal variability was incorporated in this study by modelling annual area burned as a stochastic process defined over time, while spatial variability was examined by investigating the impact of fire on four burn fraction regions (BFR) that vary with respect to their average annual area burned. In chapters 2 and 3, risk analysis tools were developed and used to demonstrate one method for evaluating strategies and to provide insight into the potential effectiveness of each strategy that was investigated. As well, I investigated the impact of using uncertain natural burn fraction estimates when determining old forest area requirements and their overall impact on timber supply. The results of this research can be used by forest managers to reduce the impact of fire and other natural disturbances in their plans when managing for a broad range of forest values.

5.1 Summary of Research Results

In chapter 2, two strategies for dealing with uncertainty in timber supply due to fire were evaluated. The results showed that the best strategy to reduce variability in harvest volume over time was to account for fire in the planning process by using Model III with an appropriate estimate of the annual burn fraction. This strategy would be used by a manager who is risk averse, while a manager who is risk seeking...
may choose a strategy that provides more harvest volume but with some variability over time (e.g., a strategy that ignores fire in the planning process). The minimum planned harvest volume survival function could be used to predict the probability of achieving a minimum harvest volume in each decade over a 200 year planning horizon. Re-planning alone as a strategy to deal with fire was shown to be ineffective at reducing the variability in harvest volume, especially in areas that experience burn fractions similar to the ‘extreme’ and ‘high’ BFRs. However, re-planning remains an essential aspect of the adaptive management cycle to ensure that new science and policy can be integrated into forest management plans over time. As well, the results showed that in regions with burn fractions similar to the ‘moderate’ and ‘low’ BFRs, potential fire losses can be ignored when carrying out strategic planning because the area burned is at sufficiently low levels. Forest managers could use these risk analysis tools to determine the timber volume capacity for a new mill to ensure it is compatible with sustainable timber harvest flows from the flammable forests that feed it.

Forest managers are required to develop plans that manage for a variety of ecological objectives (e.g., age class, wildlife habitat, or downed woody debris). Chapter 3 builds on the previous chapter by examining strategies for dealing with the impact of fire on mature and old forest areas. I chose to investigate the impact of fire on mature and old forest areas because they are ecologically valuable, they are impacted by both fire and harvesting, and they can be easily measured. The strategies I examined varied with respect to whether or not: (1) to account for fire in the planning, (2) to strengthen the lower bound constraints for the mature and old forest areas by increasing the minimum required area in the planning model, and (3) modify the planning models to maximize mature and old forest areas while constraining harvest volume flow to a constant rate. The results showed that linear programming (LP) forest management planning models will produce strategic forest management plans that will result in the areas of mature and old forest being reduced to the lower bound
and stochastic fire may further reduce the seral area. Accounting for fire during the planning process does improve the likelihood of satisfying the minimum required areas of mature and old forest. However, in regions with burn fractions greater than the one observed in the ‘high’ BFR a buffer in the lower bound constraint of the planning model should be used. Burn fractions similar to the ‘moderate’ and ‘low’ BFRs had little impact to the areas of mature and old forest, while in the ‘extreme’ BFR, managers will have a difficult time maintaining any level of old forest.

The last strategy, (i.e., maximized mature and old forest areas) was evaluated at two fixed harvest volumes (i.e., 2.0 and 8.0 M. m$^3$/decade). My analysis of this strategy revealed that when the harvest volume was reduced to the lower fixed harvest volume, a surplus of mature and old forest areas were available in the ‘high’, ‘moderate’ and ‘low’ BFRs, while at the high fixed harvest volume it would be difficult to maintain mature and old forest areas in the ‘extreme’ and ‘high’ BFR. The minimum planned seral area survival functions were developed as a risk analysis tool that managers can use to assess the probability of achieving mature and old forest area objectives.

In chapter 4, bootstrapping statistical methods were used to develop confidence intervals from historical area burned data from the period 1960 to 2004 and were then input into the Model III forest management planning model to calculate the corresponding upper and lower bounds on the harvest volume. These results showed that managers wishing to account for fire in their planning could expect high variance in burn fraction estimates in areas with similar burn fractions to the ‘high’ and ‘extreme’ BFRs.

A stochastic fire simulation model was then used to develop confidence intervals for two natural burn fraction estimates from the published literature (Suffling et al., 1982; Bergeron et al., 2001). The upper and lower confidence interval bounds were then used to calculate the amount of old forest area from the exponential distribution,
the old forest area was then incorporated in the forest management planning model as a constraint. The results showed that uncertainty concerning the confidence interval estimates can impact the estimate of old forest area and therefore, the amount of timber volume available for harvest (m³/decade). As well, this study demonstrated that when using the ecosystem management methods described by Bergeron et al. (2004), an increase in the burn fraction will result in an increase in the harvest volume. This result seems counter intuitive and differs dramatically from those presented by Martell (1994) because of the impact of old forest area constraints (that were not considered by Martell 1994) on timber production. With a low burn fraction a much higher proportion of a natural landscape will be in an old forest condition and a reduction in harvest volume is required to achieve the desired age class distribution. Managers requiring burn fraction confidence intervals could use the graphical tool developed in chapter 4 to estimate the confidence interval range based on the fire occurrence rate and sample size (i.e., number of years of area burned data).

5.1.1 Limitations of the Modelling Approach Used in this Thesis

I made several assumptions while modelling forest management and fire processes. In the forest management planning model, I assumed a constant flow of harvest volume over time (i.e., an equal harvest volume among all periods). Although, companies rarely harvest an equal amount of volume each year because of economic factors, provinces such as Ontario still have an even-flow policy that requires harvest volume to change a maximum of ±10% among periods. Using an even-flow harvest volume constraint will reduce the overall harvest volume (especially in the early periods) to produce an equal volume among periods, while Ontario’s policy would allow a higher initial volume to be harvested in the early periods, with the harvest volume reducing over time. Another type of harvest flow constraint known as a non-declining flow constraint (which is used in some provinces) requires the harvest volume in period $t$
to be ≤ period \( t+1 \). This constraint usually produces similar results to the even-flow harvest constraint when a terminal volume constraint is used in the planning model (which was used in chapter 2). Overall, the use of an even flow constraint likely impacted harvest volumes observed somewhat but given the harvest flow policies of most provinces this assumption was not unreasonable.

The simulation model developed in this thesis used a simplified forest inventory with a single forest type so that succession modelling could be ignored. In Ontario, little quantitative data exists on forest successional processes and many forest management planning models use expert opinion derived successional transitions. To incorporate succession in this thesis would have required many assumptions to be made, which may have obscured the impacts to timber supply and mature and old forest areas that were observed. The assumption of a collector age class where old forest area accumulated over the planning horizon, likely resulted in an over-estimate of the amount of old forest area in the forest management planning model because these stands would eventually die and revert to an early seral stage. However, this technique for modelling forest age classes is common in LP forest management planning models (e.g., see Boychuk and Martell (1996)).

During the simulation of stochastic fires, the annual burn fraction was applied to all age classes equally. Although anecdotal evidence from some fire managers may suggest that old age classes burn more often, the published literature does not provide convincing evidence that forest fires preferentially burn one age class over another. If forest fires do burn old forest more often, then the modelling in this thesis would be under-estimating the amount of mature and old forest areas burned and over-estimating the amount of young seral stages burned. Given the possibility of preferential burning of old forest, the risk analysis plots showing the probability of achieving the minimum required mature and old forest areas may be optimistic and in fact managers may have an even harder time providing these two seral stages on
the landscape.

5.2 Research Applications

5.2.1 Application: Dealing with Uncertainty in Forest Management Planning

My research findings have significant implications for forest management planning and how forest managers deal with uncertainty. Gunn (1991) suggested that frequent re-planning in the form of a rolling planning horizon was a good strategy for dealing with uncertainty. The results from chapter 2 indicate that re-planning can be used to deal with uncertainty providing the burn fraction is low enough (e.g., ‘moderate’ and ‘low’ BFRs). These results have implications for regions where fire is ignored in the planning and managers rely on re-planning to account for fire losses. If a forest manager is risk averse, they should be accounting for fire losses to increase the likelihood of a long-term constant flow of timber volume. One problem with moving from a strategy that ignores fire to one which accounts for fire in the planning process is the resulting decrease in the harvest volume. This decrease is evident in the ‘extreme’ and ‘high’ BFRs and would cause short term problems for mills that have high timber volume demands, however, ignoring high fire rates will ultimately lead to unsustainable harvest flows and dramatic reductions in harvest levels. The current global recession has caused many mills to close due to the significant decrease in demand for timber products. With the closure of mills and the need to re-structure the Canadian forest products industry, this might be an opportune time to deal with planning deficiencies by revising planning policies and implementing new strategies that increase the likelihood of achieving desired objectives.
5.2.2 Application: Predicting the Impact of Decades with High Area Burned on Timber Supply

In chapter 2, I examined the impact of extreme fire years on harvest volume, the decade with the highest area burned was found and the percentage change in harvest volume in the next decade was calculated. This analysis provided an indication of how harvest volume changes after high fire years. Research on the occurrence of extreme fire sizes (Beverly and Martell, 2005) and the annual area burned modelling (Armstrong, 1999; Podur et al., 2009) could be combined with the results of this study to predict the impacts of large fires or fire years on timber supply and the probability of their occurrence. With an expected increase in larger more frequent fires in the managed part of the boreal forest due to climate change (Flannigan and Van Wagner, 1991; Flannigan et al., 2005), analysis that looks at future risks of increased fire to timber supply would be beneficial to managers. By combining these types of analyses managers can assess the probability of mill ending events.

5.2.3 Application: Managing Mature and Old Forest Areas

Managers attempting to provide a broad range of economic, ecological, and social values need to understand the potential impacts of using their preferred planning system. The results presented in chapter 3 showed that mature and old forest areas may be reduced to the lower bound through the process of planning and implementation and may be further reduced due to stochastic fire disturbance. LP forest management planning models are used in most provinces throughout Canada to develop sustainable plans in areas with great uncertainty. Although these types of models are useful, managers should be cautious about allowing mature and old forest areas to be reduced to minimum required levels. Sustainable forest management is: “Management that maintains and enhances the long-term health of forest ecosystems for the benefit of all living things while providing environmental, economic, social, and cultural opportuni-
ties for present and future generations." (CCFM, 2008). The LP forest management planning model behaviour observed in chapter 3, showed that managers need to implement strategies that look beyond simply accounting for fire in the planning process to ensure true forest sustainability is achieved.

5.3 Future Research

The research completed in this thesis provides a starting point for several directions of future inquiry. To achieve sustainable forest management goals in an uncertain environment fire and forest managers need to work together to achieve a range of landscape objectives. Martell (1994) examined the problem of integrating fire and forest management planning and discussed the trade-off between area burned and timber supply. His analysis could be extended to include ecological objectives (e.g., mature and old forest areas). The model developed in this thesis could be combined with a fire management planning model, where fire management decisions impact area burned and thus the volume available for harvest. Managers would then be able to develop landscape goals for area burned with an understanding of the impacts to timber supply variability. Using this type of model, policies that allow prescribed natural fires to burn for ecological benefits could be assessed. As well, other types of natural disturbance such as insects or blowdown should be examined for future inclusion in forest management planning models.

The risk analysis tools described in this thesis were developed to demonstrate one method for managers to integrate risk into their planning. Managers could produce a suite of survival functions depending on the ecological, economic and social values which are important to their planning. As well, risk tools could be developed for different hierarchical planning levels (i.e., tactical or operational) to address planning objectives. Although these risk analysis tools might prove difficult to develop,
managers may consider decisions which incorporate uncertainty to be an improvement over traditional deterministic decision-making methods they generally use.

The research presented in this thesis examined several strategies for dealing with the potential uncertain impact of fire on timber supply and mature and old forest areas. Future research must focus on developing new strategies for dealing with uncertainty and should examine the extent to which re-planning is effective at dealing with uncertainty at tactical and/or operational planning levels. As well, government and industry should examine the extent to which regional wood supply agreements (i.e., those that expand the wood shed) can be used to deal with uncertainty (Patritch et al., 2008). Regional wood supply agreements allow companies to share wood and the risk of large catastrophic disturbances, to ensure a long-term consistent flow of volume. Finally, with spatial forest management planning becoming a priority for government and industry, strategies to deal with spatial issues must be developed.

An area with an abundance of research opportunities is the impact that economic uncertainty has on forest management planning. In Ontario, the policy is to develop forest management plans with an even-flow of harvest volume (i.e., ±10% between periods) over time. In reality, product demand and price are constantly changing and the even-flow harvest regulation does not allow companies to increase production in “good” times to take advantage of economic opportunities. However, in “bad” times companies will often reduce production and lay-off workers. Allowing production to increase and decrease does have problems related to determining what the maximum sustainable harvest volume should be (i.e., a short-term surge cut), as well as social issues related to communities and workers. A policy that allows companies to increase production during good economic times might attract more investment in the forest products industry, which is required if this sector is to be sustainable in the long-term.

Finally, with the interest from industry, government, and other stakeholders in
developing spatial forest management plans, strategies to deal with uncertainty need to be developed. Although current planning frameworks (i.e., hierarchical planning) incorporate uncertainty due to natural disturbance at the strategic planning level, small scale uncertainties at the tactical and operational planning levels can still cause great difficulties for managers. Researchers interested in spatial planning under uncertainty will need to tackle a set of very complex problems which are exacerbated by computational limitations. Managers need strategies that can be easily implemented at a low cost and are effective in reducing the uncertainty they face in managing the forest landscape.
Appendix 1 - Glossary of Terms

**Age Class Distribution** - The classification of continuous stand or tree ages into a discreet classification of typically 5 or 10 years. For example, in a 10 year age class, trees of 0-10 years would be age class 1, 11-20 years would be age class 2, etc.

**Biological Rotation** - The optimal biological rotation occurs at the age when the mean annual increment (i.e., gross merchantable volume/rotation age) of tree growth is maximized.

**Burn Fraction** - The average annual area burned expressed as a proportion of the landscape size.

**Contingency Planning** - This planning is a common type of recourse that allows forest managers in Ontario to substitute previously allocated timber volume that is unavailable at the time of harvest (e.g., due to fire or blowdown) for other unallocated timber volume (OMNR, 2004).

**Economic Rotation** - The optimal economic rotation is the rotation that maximizes the soil expectation value usually expressed on a per ha basis. The soil expectation value is the net present value calculated over an infinite number of forest rotations.

**Ecosystem Management** - This management is based on the assumption that if natural ecosystem structure and pattern can be created through management practices, then biodiversity can be maintained (Franklin, 1993).

**Fire Occurrence Rate** - The average number of fires in a year expressed in terms of a given landscape size.

**Fire Size Distribution** - A statistical model of fire sizes, typically based on the power law family of distributions (Cui and Perera, 2008).
Growth and Yield Curve - An empirical model of tree volume growth over time and usually expressed on a per ha basis.

Harvest Scheduling Model - A planning model used to schedule harvest and regeneration activities. These models can be aspatial or spatial and can be formulated as simulation or optimization models.

Hierarchical Planning - A system for decision making where decisions are divided among three levels: strategic, tactical, and operational planning. The three levels of decision making can be distinguished by the objective, planning horizon, level of management, scope, source of information, level of detail, degree of uncertainty, and degree of risk (Gunn, 1991). Information should flow among the three levels constraining the decisions in the levels above and below.

Linear Programming (LP) - A technique used to optimize a linear objective function subject to linear equality and linear inequality constraints (Winston, 2003).

Model III - A forest management planning model with a network structure (i.e., nodes and arcs) that can be used to plan harvesting and regeneration activities. The flexible Model III structure allows uncertain processes such as natural disturbance, regeneration, and succession to be incorporated in the planning.

Natural Burn Fraction - An estimate of the pre-fire suppression annual area burned expressed as a proportion of the landscape size and is often estimated using dendrochronology, fire scar mapping of trees, time since fire mapping, lake sediment sampling, or stochastic landscape simulation modelling.

Planning Horizon - The time period over which the linear programming forest management planning develops a plan of harvesting and regeneration activities. Typically the planning horizon is 200+ years in Canada.

Re-planning Interval - The number of years between subsequent forest management plans. Static re-planning occurs on a regular basis (e.g., 5 or 10 years), while dynamic re-planning occurs when an exogenous factor triggers the re-planning (e.g., when the
cumulative area burned over time exceeds 1.5% of the landscape size since the previous re-planning point).

**Risk** - The probability of an event occurring multiplied by the loss (e.g., monetary value, ecological impact, or loss of human life) associated with that event.

**Silviculture** - The art and science of establishing trees, stands and/or forests and includes controlling the growth, composition, and forest health to meet forest managers or societies needs.

**Simulation Modelling** - The act of abstracting a system to model key processes and interactions to gain insight into system behaviour or predict system outcomes. Simulation models can be deterministic or stochastic. Stochastic simulation models typically use parameterized input distributions to represent uncertain processes.

**Stand** - A spatial grouping of trees with similar age, composition, and site productivity. Many other site factors can also be used to determine stand groupings.

**Sustainable Forest Management** - The Canadian National Forest Strategy (CCFM, 2008) defined sustainable forest management as: “Management that maintains and enhances the long-term health of forest ecosystems for the benefit of all living things while providing environmental, economic, social, and cultural opportunities for present and future generations.

**Uncertainty** - This term is used to indicate uncertain estimates used as input parameters for distributions or processes of interest.
Literature Cited


James, P.M.A, M.-J. Fortin, A. Fall, D. Kneeshaw, and C. Messier. 2007. The effects of spatial legacies following shifting management practices and fire on boreal forest age structure. Ecosystems. 10:1261-1277.


