# RECONSTRUCTING THE HISTORICAL FREQUENCY OF FIRE:

# A MODELING APPROACH TO DEVELOPING AND TESTING METHODS

by

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## Abstract

Fire is a prevalent natural disturbance in most of British Columbia's forest ecosystems. Recently, scientists and forest managers have recognized the important role fire plays in regulating forest ecosystems and maintaining biodiversity. In response, B.C. Government initiatives propose to use an ecosystem's historical disturbance dynamics for guiding forest management. Gaining an understanding of the methods used to estimate historical fire frequency, along with the limitations of these methods, and the sources of uncertainty and magnitude of bias in such estimates, will be critical for developing such ecosystem-based management objectives.

In Chapter 2, I review the published fire history literature, focusing particularly on the methods, underlying models, and calculations used to estimate historical fire frequency. This review is presented as an interactive tutorial, to aid a novice reader gain an understanding of some of the more difficult aspects of fire frequency reconstruction and interpretation. Some sample pages and a description of the tutorial are provided along with instructions on how to obtain the complete package.

All fire history studies rely on a series of inferences based on a set of physical evidence left by fire. This physical evidence contains inherent errors, most often of unknown magnitude. In addition, other errors are introduced when a researcher samples this evidence to create a data set, and estimates the history of fire occurrence from this data set. In Chapter 3, I present a methodology for quantifying the level of confidence that should be placed in an estimate of historical fire frequency made from tree-ring based fire interval data. In this approach, I use a spatial simulation model of the fire regime to generate synthetic fire histories. I propose and use new techniques to model the formation and survivorship of fire evidence in the tree-ring record. These models introduce errors into the synthetic fire histories based on the types of errors thought to be present in the physical data. Finally, a spatial model of fire history sampling is used to simulate errors introduced by the researcher.

I use Monte Carlo simulation to derive a confidence interval for the empirical estimate of fire frequency made in a recent fire history study. The results indicate that it is possible to reliably estimate historical fire frequency from fire interval data. However, the greatest source of uncertainty in this estimate is the probability with which fire evidence is formed in the tree ring record. This source of error has received little attention in the literature, and so I conclude by recommending that this problem be given serious study. In the mean time, I recommend that researchers minimize this source of uncertainty by collecting samples from several trees at each sampling point in the landscape.

## Acknowledgments

I would like to thank Brigitte Dorner for her helpful insights and infinite patience; Ken Lertzman for his constant inspiration and encouragement; and my brother, Andrew Fall, for all of his help with SELES and the trickier bits of math — they each deserve much credit for this work, except for the errors, which are all mine. In addition, this project would not have been possible without the case study data set on which it is based. I thank Emily Heyerdahl for bravely submitting her Dugout Creek data to the tortures of my analyses, and give her all the credit for designing and carrying out such an excellent empirical fire history study. This research was supported by a Natural Sciences and Engineering Research Council Post-Graduate Scholarship (NSERC PGS A), and grants from Forest Renewal British Columbia.

# Table of Contents

## List of Tables

## List of Figures

# Chapter 1: Background and Problem Definition

## *The relevance of fire regimes to resource management*

> *"The more that managed forests resemble the forests that were established from natural disturbances, the greater the probability that all native species and ecological processes will be maintained." (B.C. MoF 1995)*

Fire is a prevalent natural disturbance in most of British Columbia's forest ecosystems (British Columbia Ministry of Forests 1995, Bunnell 1995, Andison 1996, Daigle 1996, DeLong and Tanner 1996, Parminter 1998). In many forests, recurring fires dominate the disturbance regime, and the effects of these fires shape the system's configuration (species composition, age and canopy structure, distribution of habitat types, etc.) and drive many aspects of the system dynamics (nutrient cycling, successional trajectories, etc.) (Heinselman 1973, Johnson 1992, Agee 1993, British Columbia Ministry of Forests 1995, Parminter 1998). The spatial and temporal patterns of fire in many Western North American forests have been radically altered in the past century by a combination of changing climate, land clearing, livestock grazing and fire suppression (e.g., Heinselman 1973, Madany and West 1983, Romme and Despain 1989, Johnson et al. 1990, Masters 1990, Mladenoff et al. 1993, Swetnam 1993, Heyerdahl 1997).

Recently, scientists and forest managers have recognized that these changes in fire regime often result in undesirable effects on the species and communities that have adapted to the forests and fire regimes of the previous centuries (Hansen et al. 1991, Agee 1993, Forest Ecosystem Management Assessment Team (FEMAT) 1993, Bunnell 1995). This developing awareness of the important roles fire plays in regulating forest ecosystems and maintaining biodiversity is creating new challenges for managers who wish to use an ecosystem's natural dynamics for guiding management (Agee and Johnson 1988, Hansen et al. 1991, Forest Ecosystem Management Assessment Team (FEMAT) 1993, Hunter 1993, Swanson et al. 1993, Bunnell 1995, Johnson et al. 1995, DeLong and Tanner 1996, Duinker and Euler 1997, Fule et al. 1997, Lertzman et al. 1997). B.C. Government initiatives, such as the Forest Practices Code (FPC) Biodiversity Guidebook, and the

Clayoquot Sound Scientific Panel (CSSP), are evidence of a move towards this type of ecosystem-based management in B.C. (British Columbia Ministry of Forests 1995, Scientific Panel for Sustainable Forest Practices in Clayoquot Sound 1995).

Gaining an understanding of the historical fire regime and range of natural variability with which forest ecosystems have evolved will be critical for developing ecosystem-based management objectives (Swanson et al. 1993, Johnson et al. 1995, DeLong and Tanner 1996, Duinker and Euler 1997, Fule et al. 1997, Lertzman et al. 1997, Parminter 1998). For example, in order to develop effective objectives and strategies to restore or maintain "natural" (historic or desired) conditions in parks and wilderness areas, managers will often need to understand how the historical fire regime shaped the landscape. In addition, managers of smaller, conservation-oriented reserves (usually called ecological reserves in B.C.) will need to know whether these systems will remain stable over time, and thus serve their purpose, in the presence, or absence, of a particular fire regime. Forest health managers will also require knowledge about the relationship between fire and outbreaks of insects or pathogens, to determine appropriate fire and pest management strategies. Even recent initiatives in timber management use historical fire regimes as models for anthropogenic disturbances (Forest Ecosystem Management Assessment Team (FEMAT) 1993, British Columbia Ministry of Forests 1995, Scientific Panel for Sustainable Forest Practices in Clayoquot Sound 1995, Duinker and Euler 1997).

In B.C., the FPC Biodiversity Guidebook (British Columbia Ministry of Forests 1995) establishes target seral stage distributions for all landscapes managed for timber in the province. These targets are designed to reflect the seral stage distributions of "natural," or pre-industrial, forests, and are thus based on an estimate of historical disturbance frequencies. To determine the target distribution from the estimate of historical disturbance frequency, the Biodiversity Guidebook makes use of a common model of fire frequency and age-class structure (the negative exponential model, discussed in Chapter 2). While the usefulness of this model is currently being questioned by some fire researchers (Lertzman et al. 1998, Andison pers. comm.), others are applying it to

guide forest management. For example, recent research within the B.C. Ministry of Forests (MoF) Nelson Region makes use of this and other fire frequency models to argue for increased harvest levels in the region (Pollack et al. *in prep.*). Clearly, forest managers require at least a basic understanding of the models, assumptions, and implications of the various methods used to reconstruct historical fire frequency. In addition to understanding how an estimate of historical fire frequency was derived, they will also require information about the historical range of variability, along with some measure of the uncertainty in these estimates. These requirements form the primary motivation for my project.

### *Key factors driving fires and fire regimes*

A *fire regime* describes the general, long-term pattern of fire occurrence and effects in an ecosystem. Individual fires are commonly described by both their physical characteristics, called fire behaviour (e.g., fire line intensity, rate of spread, etc.), and by their ecological effects (e.g., proportion of trees killed, depth of burn, etc.; Rothermel 1972, Johnson 1992, Agee 1993, Whelan 1995). Similarly, fire regimes may also be described by their physical characteristics (e.g., fire frequency, mean fire extent, etc.), and by their ecological effects (e.g., typical fire severity, influence on species composition and competitive advantage, etc.; Heinselman 1973, Barrett et al. 1991, Bergeron 1991, Johnson 1992, Agee 1993, Heyerdahl 1997). However, while individual fires are of limited duration and occur over a discrete, identifiable spatial area, a fire regime summarizes the cumulative, typical, or statistical characteristics and effects of many fires occurring over *some larger region of space and time*. This definition raises an important point — whereas the spatio-temporal domain of an individual fire has a physical definition (e.g., the fire burned for 10 days over an area of 1000 ha.), the spatio-temporal domain used to define a fire regime is largely determined by the observer. This point has significant implications for the interpretation of historical fire regimes because the conclusions that a researcher draws from a fire history will be greatly influenced by the spatio-temporal domain chosen for the study (Lertzman et al. 1998).

The key factors driving the behaviour of individual fires are well understood. These variables include fire weather (wind speed and direction, temperature, and relative humidity); topography (elevation, slope, and aspect), and fuels (fuel load, size, moisture content, and continuity) (Johnson 1992, Agee 1993, Whelan 1995, Pyne et al. 1996). In fact, given a set of values for these variables, the behaviour of many fires can be predicted with some accuracy (Rothermel 1972, Keane et al. 1990, Green et al. 1995, Finney 1996). The effects of any particular fire are largely a function of the fire's behaviour, coupled with the pre-fire state of the ecosystem (i.e., depth of duff layer, status of seed banks, etc.). In general, the effects of fire on soils, hydrology, wildlife and vegetation, both at the individual and community level, are also fairly well understood (Keane et al. 1990, Johnson 1992, Agee 1993, Whelan 1995, Turner et al. 1997). However, considerable heterogeneity in both the physical environment during the fire and in vegetative responses after the fire generally result in effects that are quite variable and thus more difficult to predict accurately (Agee 1993, Huff 1995, Turner et al. 1997).

The characteristics of a fire regime, on the other hand, are primarily determined by climate (Johnson 1992, Agee 1993, Whelan 1995), although other larger scale physical

mechanism has interesting implications since it indicates that there may be a feedback interaction between the vegetation type and the fire regime (Parminter 1998). The fire regime is also often primarily responsible for determining the age structure of the vegetation (Johnson 1979, Huff 1995). Other attributes of the forest affected by the fire regime include the landscape patch-size distribution, the availability, adjacency, and connectivity of different habitat types through time, nutrient cycling, productivity, and the physical properties of the soil, including the depth of the organic layer, and erosion potential (Heinselman 1973, Stark 1977, Eberhard and Woodard 1987, Dyrness et al. 1989, Hansen et al. 1991, Ruggerio et al. 1991, Agee 1993, Turner et al. 1994, Bunnell 1995, DeLong 1997, Parminter 1998). The degree of variability in the fire regime and heterogeneity in the system will play a large part in determining the stability of each of Hafir08pthdire ofo

1. In areas with low-severity, stand-maintaining fires, fires may kill a portion of the cambium on some trees, while not killing the tree itself. This creates a scar on the tree, which can be dated dendrochronologically (Madany et al. 1982, McBride 1983). A single tree may record many such fire events, and the distribution of intervals between fire events can be used to derive an estimate of the fire frequency (Agee 1993, also see Chapter 2).

Similar methods have also been used to characterize the typical spatial *extent* of fires. Using "time-since-fire" methods, the annual percent burned (the average proportion of the study area burned each year) can be estimated from the frequency measure (Johnson and Gutsell 1994). In conjunction with an estimate of the average number of fires per year, this estimate can be used to derive a mean fire extent, but will not yield a distribution of fire extents (see Chapter 2). On the other hand, various methods have been used to reconstruct the extent of individual fires directly from fire scar data (e.g., Morrison and Swanson 1990, Heyerdahl 1997). These reconstructions can then be used to estimate the distribution of fire extents over time for the study area.

The *magnitude* of fire is likely the most heterogeneous of the three primary fire regime parameters. It is variable both between different fires and within a single fire event (Romme and Despain 1989, Morrison and Swanson 1990, DeLong and Tanner 1996). In addition, while evidence of fire occurrence may remain for centuries, evidence of the fire's intensity is most often obscured in a relatively short period. Thus, the historical magnitude of fire is usually described qualitatively (e.g., surface fire vs. crown fire) from anecdotal evidence or written historical record. To my knowledge, no quantitative methods for deriving a measure of the magnitude of historical fire have been developed to date. For the purposes of my study, a "fire" must be severe enough to potentially scar or kill a tree. Historical fires of lower severity cannot be detected and are thus excluded from analysis. Other than this observation, I will not deal with fire magnitude further.

**Sources of uncertainty in estimates of historical fire frequency and extent**

All fire history studies rely on a series of inferences based on a set of physical evidence left by fire. This evidence includes even-aged, post-fire regeneration cohorts (e.g., Johnson 1979, Masters 1990); anomalies in the tree-ring structure of individuals, such as suppression-release radial growth signals and fire scars (e.g., Kilgore and Taylor 1979, Heyerdahl 1997); and charcoal, found in both soil (e.g., Gavin et al. 1996, Gavin et al. 1997) and lake sediments (e.g., Cwynar 1987, Long et al. 1997). All of these sources of physical evidence contain inherent errors, often of unknown magnitude. In addition, other errors are introduced when a researcher samples this evidence to create a data set, estimates the history of fire occurrence from this data set, and makes inferences about the historical fire regime from this history.

Both dominant methods for reconstructing fire history, time-since-fire and fire-interval, yield estimates of fire frequency and extent with some level of uncertainty. In applying time-since-fire methods, this uncertainty is primarily a result of substantial heterogeneity in forest systems and variability in fire regimes, which violate the assumptions of the method and models (Lertzman et al. 1998). In particular, many studies indicate that landscape age structure cannot be assumed to be temporally stable (Romme 1982, Baker 1989, Sprugel 1991, Turner et al. 1993, Andison 1996, Cumming et al. 1996). In addition, spatial and temporal autocorrelation and variability in the extent and timing between fires can introduce a substantial error to fire frequency estimates derived from age-class distributions (Boychuk et al. 1997, Lertzman et al. 1998). Compounding these problems, the difficulty in detecting and accurately aging small, old stands may cause the disturbance frequency to be overestimated (Finney 1995).

In the case of reconstructions from fire scars, uncertainty is primarily due to our inability to detect all past fires. A historical fire may go undetected for several reasons:

- a fire may fail to leave a record in every location it burned (i.e., did not produce a fire scar);
- a severe fire may erase the evidence of previous fires; or
- the sampling scheme may be insufficient to detect all fires that did leave a record.

While an intensive survey may be done to estimate the error introduced by the sampling scheme (e.g., Morrison and Swanson 1990), the level of uncertainty introduced by deficiencies in the physical data are difficult to assess from the fire history data itself. In other areas of ecology, replication and time-series analysis may be used to estimate errors or noise in the physical evidence of a process. However, a fire historian cannot use replication (i.e., each forest landscape is unique), and, of course, there is no way of ever knowing, and thus making a comparison with, the true, long-term fire history for an area.

While there has been a great deal of fire history research, both theoretical (e.g., Johnson and Van Wagner 1985) and empirical (e.g., Agee 1991), it is often difficult to compare values for the primary fire regime parameters between study areas because methods for data collection and analysis are not consistent among investigators. This problem largely arises because the appropriate methods and measures vary for different forests types and disturbance regimes. However, there is also little consensus amongst investigators as to the particular methods and set of measures that should be derived to

gain access to some of the more difficult aspects of this literature. Some sample pages from this tutorial are provided in this document, with the complete, interactive tutorial is available on diskette, or on the World Wide Web at **www.rem.sfu.ca/frstgrp/**.

The tutorial starts with some basic definitions and an introduction to the concept of fire frequency. This portion of the tutorial is intended to give the reader some understanding of how the occurrence of fire over time translates into fire frequency. It covers the types of evidence typically employed in analyses of fire frequency, along with a description of how these data are used to build models of fire frequency. The introduction also includes a map of the tutorial, to aid the reader in finding particular sections, a glossary of commonly used terminology, and a bibliography, which serves as an introduction to the literature on fire frequency reconstruction.

The primary subject material is structured as a set of individual, but related, sub-tutorials, each on a particular model or method used in fire frequency analyses. For example, the first tutorial covers the Natural Fire Rotation (NFR) method, as presented by Heinselman (1973). This tutorial presents Heinselman's data for the Boundary Waters Canoe Area and demonstrates how the NFR is computed. The reader can compute the NFR over different time periods.

The next tutorial introduces a Poisson model of fire occurrence. It describes the underlying assumptions of this model and explains why the model is so important for fire frequency analysis. Two interactive pages allow the reader to control a random Poisson process. The outcomes of this random Poisson process are then analyzed as fire occurrences over space on one page and as fire occurrences over time on the other. These data are then transformed into a measure of frequency to demonstrate the relationship between the Poisson process as a model of fire occurrence, and the computation of fire frequency.

two estimates of fire frequency, using different methods, can be derived from the same data set. Included is an interactive section that demonstrates, and alerts the reader to the presence of, some of the scale dependent properties of fire interval data.

The fourth sub-tutorial presents the negative exponential and Weibull models of fire frequency. This tutorial includes an interactive section that allows the reader to examine the equations and graphs for these two models, and to see the effect of changing the model parameters on the shape of the distributions. The final sub-tutorial presents a

- developed a spatial model to simulate field sampling of fire evidence;
- estimated the parameters for the fire occurrence and fire evidence survivorship models from the Dugout Creek fire history data;
- ran a Monte Carlo simulation of the Dugout Creek fire regime, to produce multiple synthetic realizations of fire histories that could have resulted from this fire regime.
- produced realistic, synthetic fire history data sets, by applying the fire evidence formation, survivorship, and sampling models to these synthetic fire histories.
- analyzed these synthetic fire history data sets to quantify a confidence interval for the original estimate of fire frequency; and
- performed sensitivity analyses that vary the fire evidence formation and sampling models to determine the magnitude of effect on the confidence interval for each factor.

The results indicate that the sampling protocol applied in Dugout Creek was sufficient to provide a reliable estimate of the historical fire frequency. The results also clearly demonstrate that the greatest source of uncertainty in this estimate is the probability with which fire evidence is formed in the tree ring record. This is an aspect of fire interval analyses that has received little attention, and so I conclude by recommending that this problem be given serious study. Until a better understanding of these mechanisms exists, I recommend that researchers minimize this source of uncertainty by collecting records from several fire scarred trees at each sample point to create a more complete record of fire occurrence.

# Chapter 2: An Introductory Tutorial on Common Methods for Determining Fire Frequency

## *Introduction*

The purpose of this chapter is to present a clear and comprehensive description of common methods for computing historical fire frequency. This chapter is structured as an interactive tutorial, programmed in Excel 5.0 for Windows. Some sample pages of the tutorial are provided below and the complete, interactive tutorial is available on diskette, or on the World Wide Web at **www.rem.sfu.ca/frstgrp/**. The following topics are covered in the tutorial:

- An introduction to fire regimes, fire frequency, the evidence and data used to estimate fire frequency, measures of fire frequency, and fire frequency models, including a glossary and bibliography.
- A tutorial on the Natural Fire Rotation method for estimating fire frequency.
- A tutorial on the Poisson model of fire frequency.
- A tutorial on the Fire Return Interval method for estimating fire frequency.
- A tutorial on potential pitfalls of working with Fire Interval Data.
- A tutorial on the Negative Exponential and Weibull Fire Frequency Models.
- A tutorial on the Fire Cycle method for estimating fire frequency.

## *Motivation and Scope*

I was originally motivated to produce this tutorial because I found it difficult to compare different methods for computing fire frequency presented in the literature. I also found that working with these published data sets in a consistent framework helped me to grasp some of the concepts and computations involved in estimating historical fire frequency. While the tutorial covers only a single aspect of fire history reconstruction (i.e., the mechanics of computing fire frequency), I hope that it will serve to make this portion of the science accessible to others who do not make it their career. In this section I will further outline the objectives, relevance, and scope of the tutorial.

I have two primary objectives for this tutorial:

1. to review the published fire history literature and determine the methods, underlying models, and calculations being used, along with the statistical and ecological assumptions and interpretations being made in fire frequency reconstructions; and
1. to synthesize and convey this material in a format that will help a novice reader understand what has been done, how it was done, and why it was done that way.

It is important to note that this tutorial is not meant to advocate any particular method, nor is it meant to propose new or emerging approaches to fire frequency reconstruction. It is simply a review of published material that is meant to help aid comprehension of that material.

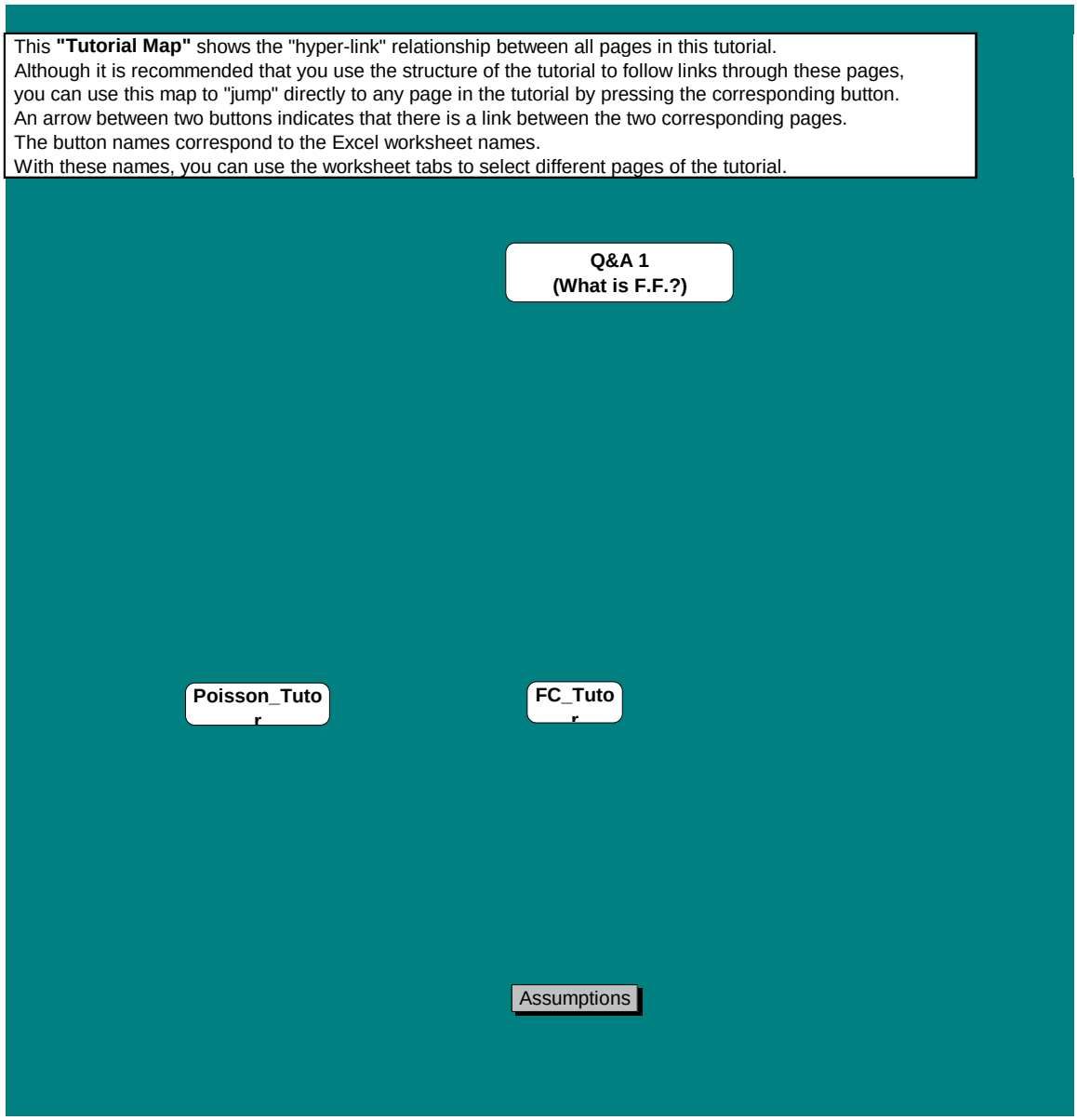
This tutorial is particularly relevant at this time in B.C. because of new initiatives and projects underway at the Ministry of Forests. In particular, the Forest Practices Code Biodiversity Guidebook (British Columbia Ministry of Forests 1995) uses a rough fire cycle analysis employing the negative exponential fire frequency model to estimate the seral stage distributions required to meet biodiversity objectives. Any forest manager who wishes to understand how these distributions were derived, and to evaluate the applicability of this model, needs to have a clear understanding of the fire cycle method, the negative exponential model, and their assumptions and interpretation. A project currently underway in the Nelson Forest Region provides a good example (Pollack et al. *in prep.*). The authors of that study use a fire cycle analysis based on the Provincial forest cover maps (the FIP/SEG database) and, based on this analysis, suggest that the seral stage requirements for the region should be altered and the Annual Allowable Cut (AAC) for the region should be increased. It is very important that the people who will review this material and make decisions about these proposed changes should have access to a clear presentation of the underlying models that were used in the original analysis.

Finally, the scope of this tutorial is limited to the computation of fire frequency. An understanding of these computations is only one of the many tools and skills required to reconstruct a fire history. In this respect, it would be useful to include e CPro frequency tutorial within a larger package of fire ecology and fire behaviour tutorials.

However, for the time being it is important to keep in mind that the scope of this tutorial is limited, and that it is designed only to provide access to understanding fire frequency analyses. The tutorial is not sufficient to equip people with all the tools they would require to *undertake* a fire frequency analysis.

### *Example Tutorial Pages*

The following ten sample pages are representative of the material contained in the interactive tutorial. These ten pages were selected to complement references to this material in Chapter 3. Each sample page has been scaled to fit on one paper page, and thus do not reflect the actual text size in the tutorial (all actual text is in 12 point font).


This "Tutorial Map" shows the "hyper-link" relationship between all pages in this tutorial.
Although it is recommended that you use the structure of the tutorial to follow links through these pages,
you can use this map to "jump" directly to any page in the tutorial by pressing the corresponding button.
An arrow between two buttons indicates that there is a link between the two corresponding pages.
The button names correspond to the Excel worksheet names.
With these names, you can use the worksheet tabs to select different pages of the tutorial.
Q&A 1
(What is F.F.?)
Poisson_Tutor
FC_Tutor
Assumptions

*An Introductory Tutorial on:*

End Tutorial

## Common Methods for Determining Fire Frequency

The purpose of this tutorial is to present a set of methods commonly employed to compute measures of historical fire frequency. These methods, as published in the literature, are sometimes difficult to understand. In addition, there is no single source where all of these methods, with worked examples, are presented together so they can be compared. This tutorial relies primarily on a worked example of each method (taken from the literature and worked up in an MS-Excel spreadsheet where possible). Each example is accompanied by a description of the procedures and models used by the method. The tutorial is intended only as a first step in understanding these methods, procedures, and models. More formal, detailed literature (see bibliography) should be consulted before undertaking any fire frequency analysis. Please read the cautionary note on using these tutorials...

Read Cautionary Notes...

Before proceeding, you will require some basic information about fire frequency. If you need to brush up, detailed answers are provided to the following questions:

- What is Fire Frequency?
- What evidence and data is available to estimate Fire Frequency?
- What measures are used to represent Fire Frequency?
- What is a Fire Frequency model?

Also, see the glossary for definitions of terms used in discussing fire frequency.

Look at Glossary...

**The rest of the tutorial presents four methods for estimating fire frequency:**

- An intuitive approach that does not use formal models is the ***Natural Fire Rotation*** method. — Run NFR Tutorial
- An introduction to the statistical models used in other methods is the ***Poisson*** model. — Run the Poisson Tutorial
- A statistical approach that relies on the number of years, or interval, between fires is the ***Mean Fire Interval*** method; — Run the MFI Tutorial
- An more complex statistical modeling approach that relies on the current forest age-class distribution is the ***Fire Cycle*** method; — Run Fire Cycle Tutorial

**Each method is presented as a tutorial with the following format:**

1) Give an overview of the method, the type of data required, any important distributions, and any relevant models.
2) Present the data set that will be used to work through this method.
3) Graph the data to reveal the relevant distributions.
4) Fit a statistical model (distribution) to the empirical data.
5) Explain the interpretation of the model and relevant measures of fire frequency.
6) Set out the assumptions, strengths, and limitations of the method.

A Conceptual Diagram of Fire Recurrence over Time

Time-Since-Fire Data
(For this data we look only at the 1990 map)

| Current Year | Fire Year | Area in 1990 | Time-Since- | Percent of total |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |

Fire Interval Data
(For this data we look at the sampling points A, B, C,& D through time)

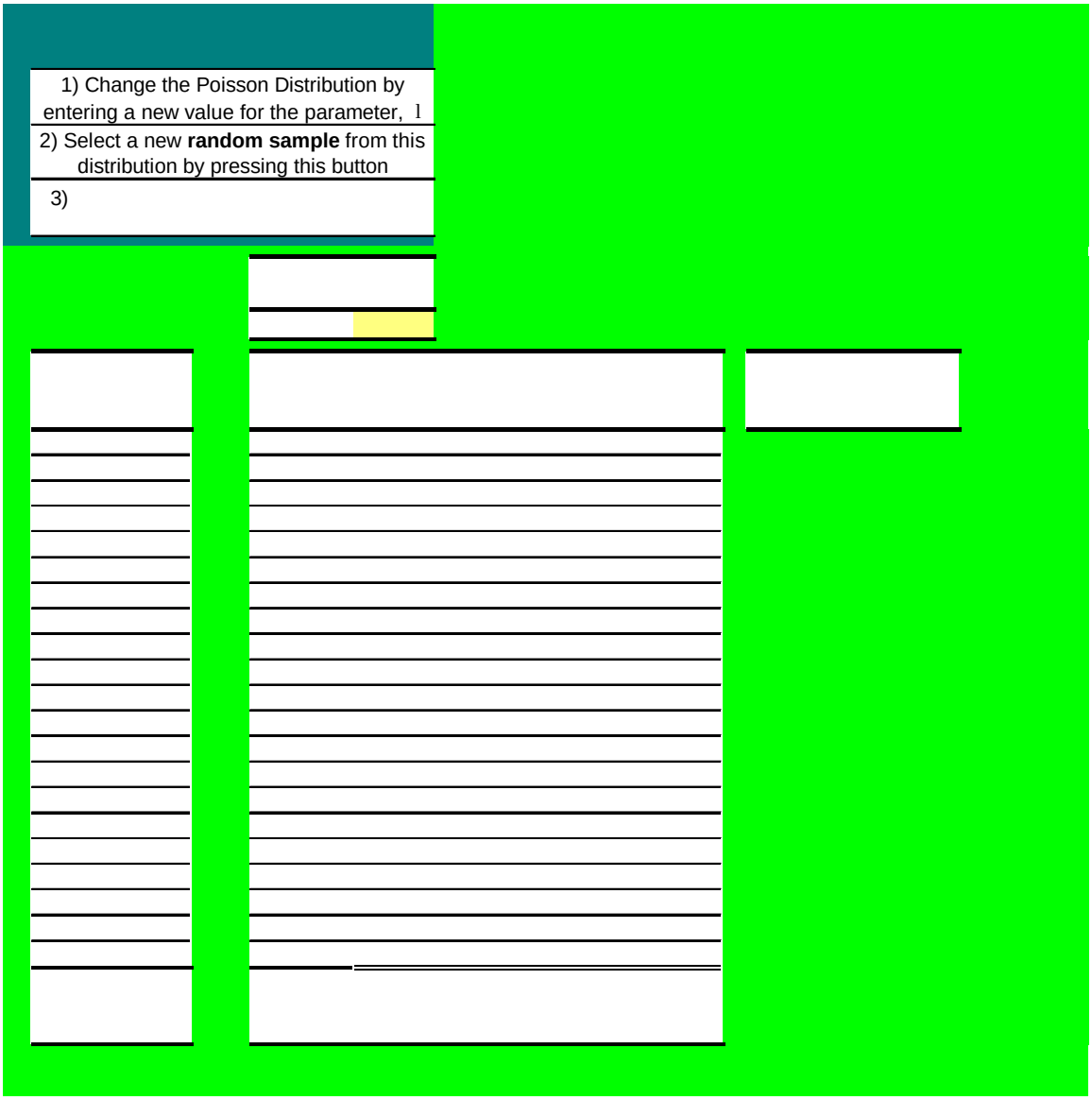
| Data | Data | Data | Data |
|---|---|---|---|
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |

***Fire over Time as a Poisson Process***

***Abstract Concept:***

If the occurrence of fire over time is a Poisson process, then the number of fires occurring in time periods of equal length, ***t,*** should have a Poisson distribution with parameter $\lambda t$! Furthermore, if the numbers of fires in each period are independent, then the distribution of

An Overview of the Poisson Process


1) Change the Poisson Distribution by entering a new value for the parameter, l
2) Select a new **random sample** from this distribution by pressing this button
3)

***Method Name:*** Mean Fire Interval Method

***References:*** Agee (1993, ch.4), Grissino-Mayer (1995), Heyerdahl and Agee (1996)

***Abstract Concept:***

We have an area with relatively frequent fires and an extensive record of past fires. The dates of multiple fires are recorded in individual tree ring records (e.g. as fire scars) throughout the study area. We would like to know how many years, on average, between fires at any given point in the study area. The statistical population we are interested in is the complete inventory of fire intervals at every point in the area. If we knew this, we could fit a distribution to the intervals and compute the average interval between fires for the area, or the *mean fire interval*.

To obtain the data for this method we take a random sample of fire intervals across the study area and use this sample to estimate the fire frequency for the whole study area. Fire interval data are usually derived from evidence of fire found in tree-ring records. The tree-ring sections must be collected in the field and then prepared, and cross-dated in the lab.

***Basic Method:***

I. Select a set of randomly located, equal sized "sample plots". Collect a complete inventory of fire dates for each plot (the plot's "fire chronology").

II. For each plot, compute the fire intervals from this fire chronology. Pool the fire intervals from all plots to construct a composite fire interval histogram (distribution of fire intervals).

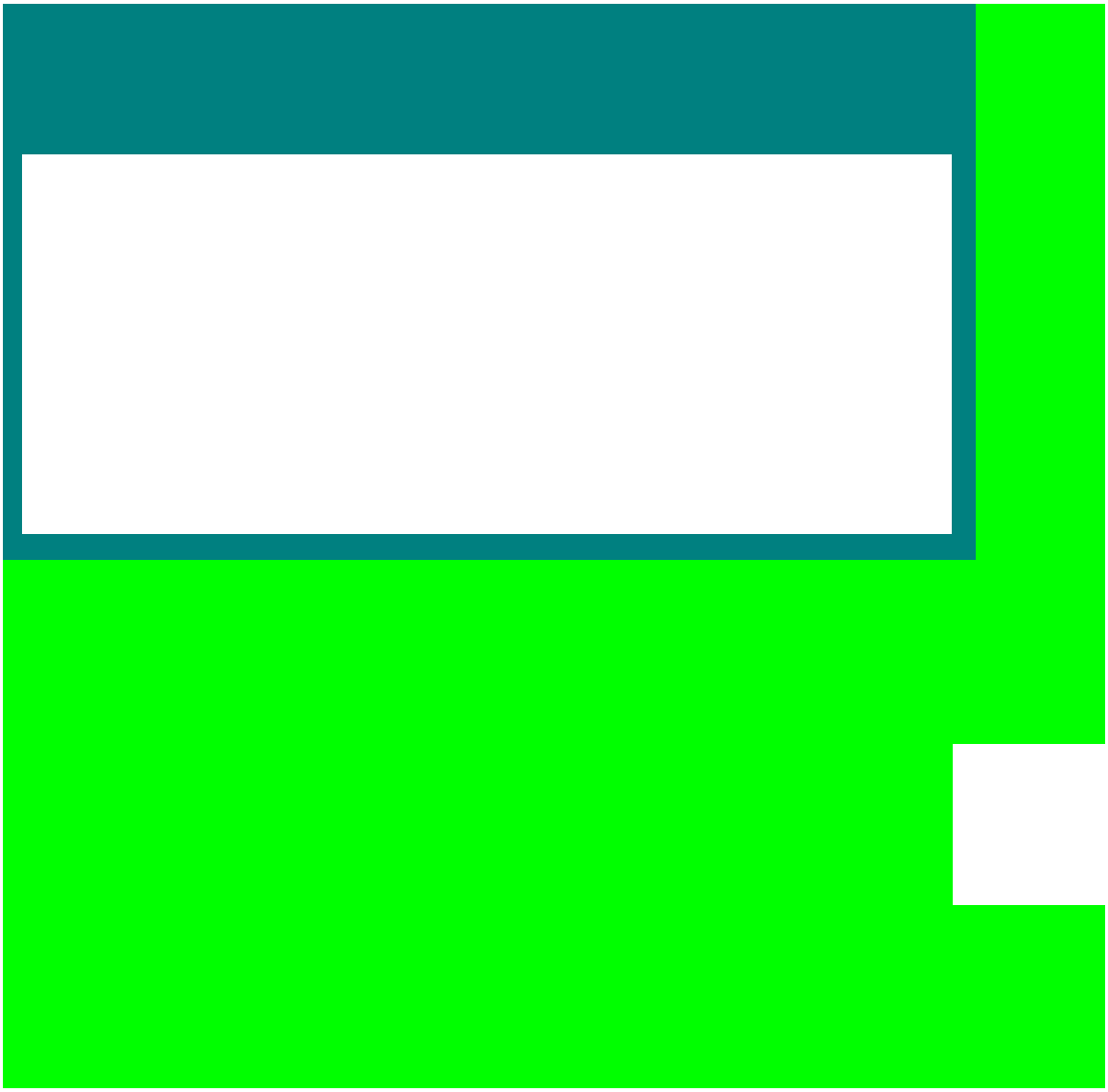
III. Graph the fire interval distribution as: t x f(t)

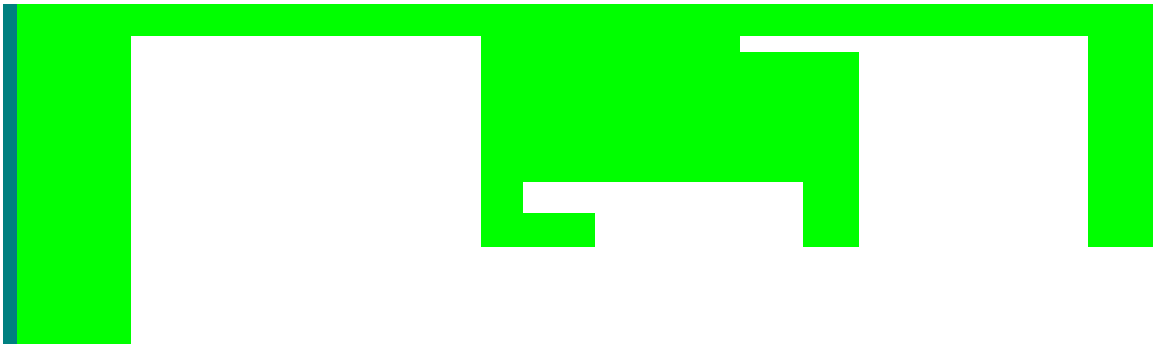
IV. [where t=interval in years; f(t)=Proportion of occurrences of that interval in the composite fire interval histogram.

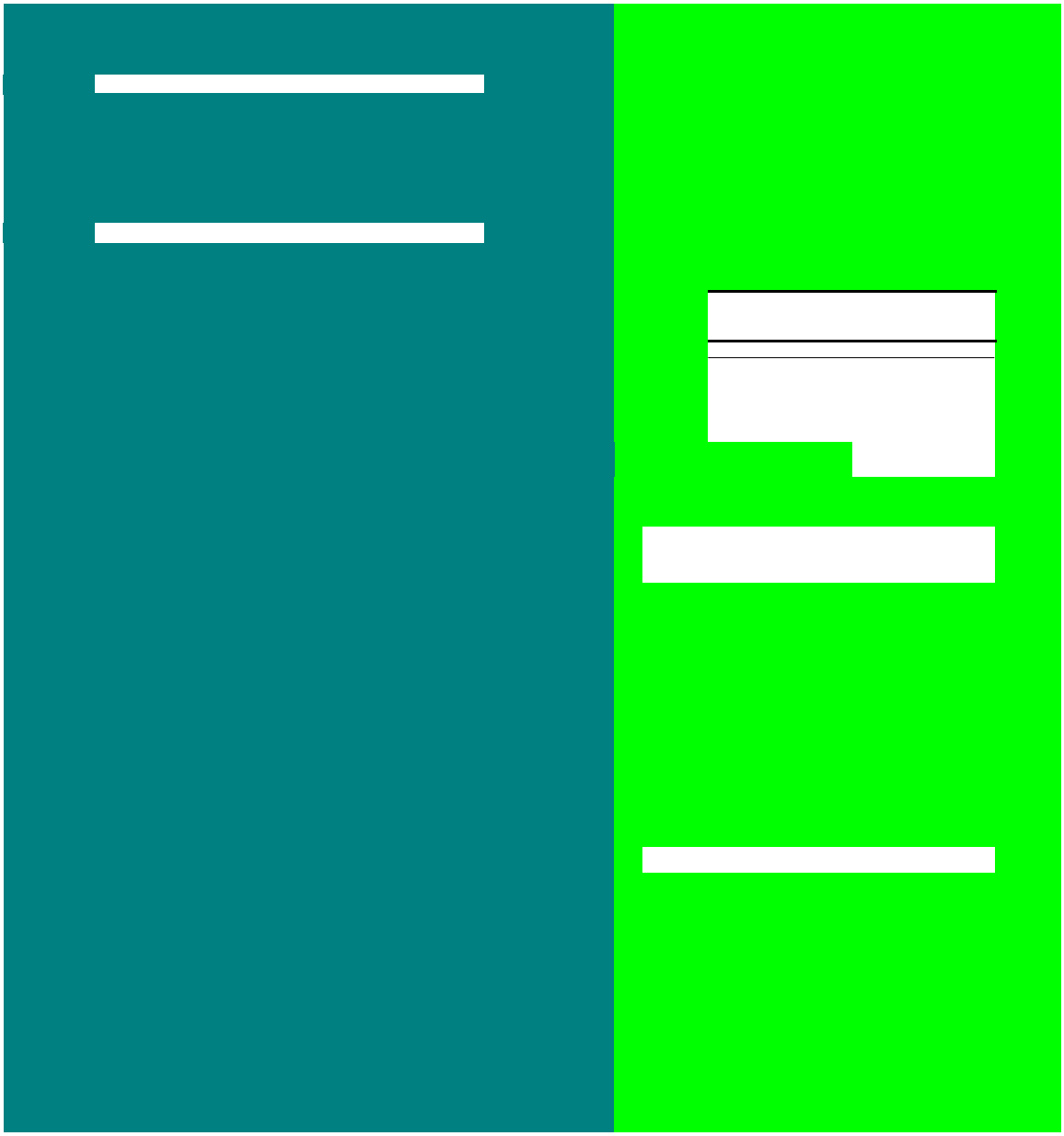
V. Fit a theoretical model to the fire interval distribution:

Common models used are: the empirical (approx. Normal) and Weibull. Each of these models has a probability density function, f(t), which is fit to the fire interval distribution.

The data may require spatial or temporal subdivision of data to get significant fit. The model will only give a good fit in spatio-temporal







**<< Previous Page : Model Interpretation**

## Assumptions, Strengths and Limitations of the Mean Fire Interval Method:

The following items should be considered before selecting the mean fire interval method, and fully accounted for when interpreting the results of a fire interval analysis.

***Strengths:***

The main advantage of this method is that it works directly with a series of fire dates at each location. This has several important implications:

- The researcher is able to fit the fire interval distribution (from the fire frequency model)

# Chapter 3: Testing Methods for Estimating Fire Frequency from Fire Interval Data

## *Introduction*

All studies of fire history rely on a series of inferences based on a set of physical evidence left by fire. In forests where the fire regime is dominated by frequent, low-severity fires, the physical evidence of fire occurrence is usually limited to anomalies in the ring structure of individual trees, such as fire scars, where patches of cambium have been

In this chapter, I develop an approach to assessing the uncertainty in estimates of fire frequency derived from fire interval data. The foundation of this approach is a model of fire frequency, based on the statistical characteristics of fire regimes often described in fire history studies, coupled with a simple, spatial model of typical fire history sampling schemes. In addition, I propose statistical models of fire scar formation and survivorship. Using these models, I construct a series of computer simulations, based on a fire history study in Oregon's Blue Mountains (Heyerdahl and Agee 1996, Heyerdahl 1997). These simulations are used to create synthetic fire interval data sets similar to those collected in the fire history study. Analyses of these synthetic data sets are, in turn, used to determine the level of uncertainty that we should expect in the original estimates of fire frequency for the study area. A sensitivity analysis of the model parameters provides an indication of the most important factors contributing to this uncertainty.

**Sources of uncertainty in estimates of historical fire frequency derived from fire interval data**

Trees are not perfect recorders of fire. While the mechanisms of fire scarring are fairly well understood in the laboratory (e.g., Gutsell and Johnson 1996), little is known about the probability of a fire scar forming in the field. A low-severity fire sometimes kills a portion of the cambium at the base of a tree, without killing the tree itself. As this wound heals, a "fire scar" is formed in the tree-rings that can be accurately dated using dendrochronology (Stokes and Smiley 1968, Madany et al. 1982, McBride 1983). There is some evidence that the probability of a fire initially scarring a previously unscarred tree is very low (personal communication Peter Impara). Once a tree has been scarred, however, the thinner bark covering this scar makes the tree more susceptible to being scarred again by a subsequent fire (see references in Gutsell and Johnson 1996). Thus, fire history researchers generally sample multiply scarred trees to reconstruct the occurrence of fire over time (e.g., Arno and Sneck 1977, Kilgore and Taylor 1979, Grissino-Mayer 1995, Heyerdahl 1997, Riccius 1998). These multiply scarred trees are often referred to as "recorder trees", but little is known about the susceptibility of these trees to scarring,

and thus recording the occurrence of successive fires. In this study, I assume that trees with more than one scar will record some, but not necessarily all, subsequent fires.

Two key issues arise from the previous discussion that have important implications for this study. First, the probability of a tree recording a fire (i.e., forming a fire scar) for the first time is different from the probability of the tree recording subsequent fires. For simplicity, I assume in this study that there are an adequate number of recorder trees distributed across the landscape at all times. With this assumption, each fire that occurs has a similar opportunity to leave a record of its occurrence. Since a fire history sampling scheme will concentrate on these recorder trees, we need only be concerned with the probability that a previously scarred tree records a fire. However, this raises the second issue — the probability that a previously scarred tree will actually record the occurrence of a particular fire is most often unknown. While many researchers assume this probability is less than one, few have attempted to estimate its actual value (e.g., Dietrich 1980, Arno and Petersen 1983, Agee 1993). Note that fire evidence can never be recorded unless there was a fire (barring the misinterpretation of non-fire related tissue damage). Thus,

variability in fire frequency, or to detect all fires that did leave a record. While a spatially intensive survey may be employed to estimate the error introduced by the sampling scheme (e.g., Morrison and Swanson 1990), the degree of uncertainty introduced by deficiencies in the physical data is difficult to assess from the fire history data itself.

## *Models and Methods*

I built two computer simulation models to manufacture synthetic fire interval data sets similar to the empirical data sets typically collected and used to reconstruct fire history for a low-severity fire regime. The first model simulates a low-severity fire regime and records the dates and locations of all fires that burned during the simulation. The second model censors and samples this complete synthetic fire record. It simulates the formation and survival of fire scars in the tree-ring record and then sub-samples this record based on a fire history sampling strategy. Together, these two models produce a "synthetic fire history" data set that can be analyzed in an identical manner to an empirical fire interval data set (Figure 1).

These two models use probability functions to capture the variability apparent in the system. Using Monte Carlo simulation to generate a number of "replicate" fire histories, I derive an estimate of the expected variability and bias in fire frequency measures computed from the simulated system and sampling strategy. The following subsections describe in detail the development of these models.

### REFR -- A Spatially Explicit, Stochastic Fire Regime Simulation Model

*Fire regime models* should be distinguished from *fire models*. The latter are generally mechanistic models concerned with predicting the behaviour and/or effect of fire over a discrete period of time, for a fixed set of fuel and weather conditions (e.g., Rothermel 1972, Keane et al. 1990, Finney 1996). By contrast, fire regime models are generally stochastic, and more concerned with the potential range of long term spatial and temporal dynamics, given a general range of vegetative and climatic conditions (e.g., Baker 1992, Boychuk et al. 1997). Efforts to incorporate the mechanistic details of a fire

model into a larger scale fire regime model are underway, but the data requirements and computational overhead involved make this challenging (McKenzie et al. 1996).

Here, I propose a simple fire regime model based on statistical distributions that are often described in empirical fire history studies. The key aspect of this model is that it reproduces the long-term, statistical characteristics of the fire regime under study. The foundation of this model lies in the relationship between fire extent and fire frequency, described by equation 1.

$$\boldsymbol{MFRI} = (\boldsymbol{R}$$

I constructed a computer simulation of the Return-Extent Fire Regime (REFR) model, above, using SELES (Fall and Fall 1998). REFR is a raster-based, spatially explicit, stochastic simulation model. The parameters for the model can be estimated from empirical fire-interval data sets. Each of these parameters generally represents a set of ecological and physical processes acting at a particular scale. While these processes are not modeled directly, their composite influence on the fire regime is captured by a simple function or probability distribution. The REFR requires 4 such composite parameters:

1. The ***Return Time (RT)*** parameter specifies the distribution of intervals between fire years in the study area, or the "*area frequency*" (*sensu* Agee 1993). This parameter is highly scale dependent (see Chapter 2 or Agee 1993) and the data used to estimate its value must be matched with the scale of the model. The *RT* is driven by large-scale processes responsible for the occurrence of fire through time. This parameter may be thought of as the frequency of fire-conducive weather, or ignition sources, on an annual scale.
1. The ***Event Extent (EE)***

related to spatial heterogeneity in the fuel, topography, or canopy structure, in addition to the specific behaviour of the fire event, such as spotting or crowning.

Figure 2 shows a conceptual diagram of the REFR simulation model. The time-since-fire is stored for each cell in the model. When a fire burns in a cell, the time and location of the fire is recorded, and the time-since-fire for that cell is reset to zero. During the simulation, the parameters described above are treated as independent, random variables, where the value of the variable is drawn from the specified distribution whenever it is required. Ignition locations and fire spread directions are chosen at random. This gives us a simple starting point, however it is important to keep in mind that in the real system these parameters may be inter-dependent and the behaviour of fire may be dependent on the time-since-last-fire. While it is possible to construct a SELES model that incorporates these interactions, I use only the simple case in this project.

REFR produces a complete, spatially referenced record of fire occurrence for the duration of the simulation. This synthetic record of fire occurrence is called the "Complete Event Record" in Figure 1. I used this complete record to verify the REFR model by reconstructing the realized Return Time and Event Extent distributions for a number of different simulation scenarios. I then compared these realized distributions to the original input model parameters to verify that the model was behaving correctly.

**EVA -- a Stochastic Model of Error Sources in Fire History Data**

The EVA model employs two sub-models to construct a realistic, synthetic data set from the complete event record produced by REFR (Figures 1 and 3). The complete event record is considered an *ideal fire record* because from it we can obtain a complete list of fire years for any point on the landscape, or a complete list of locations burned for any given fire year. However, this is not the record available to a fire ecologist in the field. In reality, the length of the fire record is limited by the period covered in the tree ring record. Furthermore, some fires fail to leave evidence (e.g., a fire scar) at every location they burned. I constructed a stochastic model of these processes to *degrade* the ideal fire record. A second model samples this degraded record based on a specified

sampling strategy, to yield a synthetic data set similar to the empirical one. Figure 3 shows a conceptual diagram of these two EVA sub-models, each of which is described in more detail below.

***A Model of the Formation and Survival of Fire Evidence in the Tree-Ring Record***

The "EVA Fire Record Degradation" sub-model removes a sub-set of the fire dates from the ideal record produced by REFR (Figure 3). Two composite parameters are required for this sub-model. The "survivorship function", ***S***, specifies the distribution of survival times, *into the past*, for individual tree ring records of fire. Note that this function *does not* describe the expected time a newly created record will survive into the future. Rather, it describes the expected number of years that a fire record will extend *into the past*. This function can be estimated from the distribution of ages, in years before present, of the oldest scar on each fire history sample. The "fire scar recording rate", $\boldsymbol{p_r}$, specifies the probability that evidence of a fire will be recorded in the tree ring record (e.g., probability of a fire scar forming on a previously scarred tree). I have been unable to locate any studies or methods that might be used to estimate this parameter. Thus, I developed a method based on the same principles used to estimate population sizes in animal ecology using mark-recapture methods (e.g., Krebs 1989). This method uses the relationship between the number of trees sampled at a point and the total number of unique fire years identified on all such samples to estimate the total number of fires that burned at that point over the period common to all samples. The proportion of fires recorded by each tree yields an estimate of the fire scar recording rate for that tree. A second method, based on the same relationship, directly yields a single estimate of the fire scar recording rate averaged over all samples. See appendix B for a derivation of these two methods.

### *A Model of the Fire Interval Sampling Strategy*

The "EVA Fire History Sampling" sub-model simulates the data collection and analysis stages of a fire history study (Figure 3). The three parameters for this sub-model describe the sampling strategy. The "*sampling density*" specifies the number of sample sites at which fire records will be collected, while the "*sample layout*" specifies how these sample sites are distributed in space (i.e., randomly vs. systematically). Together, these two parameters are used to build a list of cells in the REFR raster to serve as sampling sites. Note that the size of each cell in the REFR raster must be the same as the size of the sample sites! A third parameter, $\boldsymbol{N_t}$, specifies the number of trees to be sampled at each sample site.

The EVA model treats each cell in the REFR raster as a potential fire history sampling site, with $\boldsymbol{N_t}$ recorder trees on each site. Initially, each of these recorder trees contains the ideal or complete fire record for its site. These complete records are then degraded independently, based on the probability functions defined for the evidence survivorship, $\boldsymbol{S}$, and the fire scar recording rate, $\boldsymbol{p}_r$. In other words, for each recorder tree, a length of record is randomly selected from $\boldsymbol{S}$, and all fire dates older than this are removed from that tree's record; each of the remaining fire dates is removed from the tree's record with a probability of 1- $\boldsymbol{p}_r$. The set of fire dates that remain form the record of fire for each recorder tree. The fire dates from all $\boldsymbol{N_t}$ trees on a sample site are then pooled to form the synthetic record of fire for that site. This record represents the best possible history of fire available to the field ecologist. A spatial sample of this synthetic fire record yields the synthetic data set for the model run (Figures 1 and 3). This synthetic data set can then be analyzed in a manner equivalent the analysis of the original empirical fire history data set (e.g., the point fire frequency for the simulation might be estimated from the synthetic data set). Note that this model assumes that all fire evidence is dated correctly. No provisions are made for errors introduced by mis-dating fires, or mis-interpreting non-fire related scars. (See Chapter 2, or Gara et al. 1986, Agee 1993, for details on these avoidable sources of error.)

### *Case Study -- A model for Dugout Creek.*

A recent fire history study at Dugout Creek, in Oregon's Blue Mountains, (Heyerdahl and Agee 1996, Heyerdahl 1997) provided me with an ideal data set with which to develop a case study for these methods. The rigorous methods used to collect and analyze these data made it very appropriate as a basis for a trial of this methodology. In this section, I describe the Dugout Creek study area, the fire history data set for the area, and the data modelling necessary to derive the REFR and EVA model parameters from this data set. I then use these models of the Dugout Creek fire regime and sampling strategy to answer the following questions:

1. Are the fire regime parameters reconstructed from the original data internally consistent (i.e., can we reasonably expect to replicate the reconstructed fire regime with a model parameterized from the empirical fire history data)?
1. What is the expected range of variability in the fire regime over time?
1. What degree of confidence should be placed in the point frequency estimate computed from the original data?
1. What factors have the largest influence on our confidence in the parameter estimates?
1. Was the sampling design used to collect the fire history data optimal?

The Dugout Creek study area is approximately 21,000 acres (51,900 ha) and is located in an area with gentle topography and predominantly dry ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) forests. These forests historically experienced a low-severity, stand-maintaining fire regime (Heyerdahl and Agee 1996, Heyerdahl 1997). The fire history sampling was conducted in 72 one acre plots distributed in a regular pattern over the study area. In each plot, an average of three fire scarred trees were sampled. The fire scars were crossdated and fire years from all trees on the same one acre plot were pooled together to give the history of fire for that plot. The 255-year period from 1645 to 1900 was deemed be fairly homogeneous, with respect to fire frequency, and to have a sufficiently rich record of fire to allow further analysis. This "period of reliability" is used for all the data modelling described below. These data

provide an estimate of the point fire frequency (mean fire return interval or MFRI) during this period for the study area, by way of the Fire Interval Method outlined in Chapter 2.

**Simulating the Dugout Creek Fire Regime**

This section describes the data modelling that was undertaken to parameterize the REFR model for the Dugout Creek fire regime. Because the REFR model is a realization of the temporal Poisson process described in Chapter 2 (Poisson Models), I first needed to determine if the recurrence of fire over time in Dugout Creek could be modeled as such. I constructed a histogram of the number of fires per decade (Figure 4). A Chi-squared

Finally, I used maps of the historic fires (Heyerdahl and Agee 1996) to estimate the emergent spatial heterogeneity in fire behaviour. The distribution of ***Event Openings*** shows that in almost 70% of the fire years the burned area represented a single, large, contiguous patch. To simplify the model, only one opening was created per fire event. I do not expect this to significantly affect the results. In addition, a qualitative assessment of the shape of the individual fires was used to estimate an appropriate value for the ***Fire-Shape-Complexity*** parameter. The value selected results in fires that are similar in shape to those reconstructed for Dugout Creek — not simple squares, but not highly convoluted either.

The parameters described above (estimated parameters, $\mathbf{A_0}$, in Figure 1) provide the complete specification for the REFR model. One-hundred replicates of this fire regime model were run on a landscape of 140 x 150 (= 21,000) one acre cells, to approximate the size and shape of the empirical study area. This landscape was homogeneous with respect to fire occurrence and spread, because the gentle topography at Dugout Creek was thought to have little influence on these processes. Each replicate was run for 500 years, with year 500 representing 1994; and the 255 year period from year 151 to year 406 representing the period of reliability for Dugout Creek, 1645 to 1900. Each of these 100 replicates is one instance of the stochastic process defined by the REFR model. Similarly, the empirical history of fire occurrence could be considered a single instance of the stochastic process defined by the fire regime acting at Dugout Creek. If we assume that the REFR model yields a reasonable representation of variability in this fire regime, then the 100 simulation replicates provide a means for studying its statistical properties (i.e., we can interpret the variability exhibited by the 100 simulation replicates as an estimate of the expected variability in the natural system). For most of the analyses described in the *Results* section, the complete fire records from the 100 replicate histories are sub-sampled using the EVA models described below.

**Simulating the Dugout Creek Fire History Sampling**

This section describes how the EVA model was parameterized for the Dugout Creek fire history study. The parameters for the fire history sampling sub-model were easily obtained directly from the sampling strategy used in Dugout creek. In the real study, an average of three fire scarred trees were sampled in each plot. Although the actual number of trees sampled varied from two to five per plot, in the model exactly three trees are sampled in each plot. This provides the same number of samples, but they are distributed slightly differently across space. In the model, fire scarred trees are distributed evenly across space, all have equal probability of recording fires, and all have the same survivorship function. Since these assumptions may or may not hold true in reality, it is possible that the different sampling intensity at each site in the empirical study either

rejected the null hypothesis that the survivorship data were drawn from this distribution ($p>0.9$ for both tests). This theoretical function can now be interpreted as giving the probability that a randomly drawn sample tree will have recorded fires for at least X years.

Fortunately, the structure of the sampling strategy used at Dugout Creek also allowed me to estimate $\boldsymbol{p}_{\mathbf{r}}$, the probability that a recording tree would record a subsequent fire. Specifically, both methods for estimating $\boldsymbol{p}_{\mathbf{r}}$ require that multiple trees be collected at a single site. In the first method, the fire dates on each recorder tree are treated as a random sample from the "population" of years in which fire burned the site. A Schnabel mark-and-recapture calculation (Krebs 1989) is used to estimate the size of this population (i.e., the number of fires that burned on the site over the period of study). An estimate of $\boldsymbol{p}_{\mathbf{r}}$ can then be derived for each tree on the site by dividing the number of fires recorded on the tree by the number of fires that burned on the site. This calculation was performed for each tree on each of the 72 sites sampled at Dugout Creek. Figure 9a shows the distribution of proportion of fires recorded by each sample tree along with the MLE normal distribution fit to this data. Only sites where at least 10 fires burned are included in this graph, to avoid spurious values caused by extremely small sample sizes.

In the second method, I rely more directly on the relationship between the number of trees sampled on a site, $t$, and the total number of unique fire dates observed from those trees, $U_t$. Note that the number of new unique fire dates detected (and add to $U$) with each new tree sampled will decrease until all the fires that burned the site are detected, after which no new fire dates are added with any additional sample trees. This relationship

(via least-squares) to the empirical data, $G_t$, for Dugout Creek. See Appendix B for a complete development and derivation of these two methods.

To my knowledge, neither of these two methods has been tried before, and the results need to be empirically tested. Thus, the parameter value $\hat{p}_r$ cannot be assumed robust, yet it is a critical parameter for the EVA model. While it is encouraging (if not somewhat expected) that both methods yield the same estimate, $\hat{p}_r$ =0.56, I use the estimate $\hat{p}_r$ as a "best guess" only.

**Summary of REFR and EVA model parameter values for Dugout Creek:**

The Return-Extent Fire Regime model was parameterized as follows:

- Model size, $A$ = 140 x 150 = 21,000 one acre cells (homogeneous landscape)
- Return-Time is drawn from an Exponential histogram: $p$(RT) = Exp(RT; $\lambda$)

  $p$(time to next fire is $x$ years, where $x$=1,2,3,...) = Exp($x$; 3.68) =

  $e^{-(x-1)/\lambda} - e^{-x/\lambda}$ where $\lambda = \frac{-1}{\ln(1 - 1/3.68)}$ (see Appendix A)

- Event-Extent is drawn from a Weibull distribution: $p$(EE) = w(EE; $\alpha$, $\beta$)

  *xp .02-0.142,22.8.6*

- Probability of a tree recording a fire is assumed to be constant for all trees:
  $p$(individual tree recording a particular fire) = 0.56
- Number of trees per sampling plot, $N_t = 3$
- Sampling density = 72 one acre plots
- Sample layout = uniform

I use the 100 synthetic fire history data sets that result from this "Base Case" sampling scenario to answer questions about the quality of the empirical MFRI estimated for Dugout Creek (Figure 1). A few notes of caution are warranted: I have assumed that the parameters reconstructed from the empirical data set, and subsequently used to parameterize REFR, are a fairly good approximation of the true fire regime parameters. An inadequate empirical sample or a mis-match between the scale of the sampling design and the scale of the true fire regime, for example, would generate misleading results. I have also assumed that the EVA model incorporates into the synthetic samples all of the important sources of error and bias present in the empirical sample. If the errors in the synthetic samples are not distributed similarly to those in the empirical sample, then the measures of uncertainty that I propose tell us little about the quality of the empirical observations.

To answer other questions about the expected variability in the fire regime, the relative importance of various sources of uncertainty, and the adequacy of the sampling design, I use a number of other sampling scenarios. The EVA parameters for each of these other scenarios are listed in Table 1. The "Complete" scenario yields the complete fire record (Figure 1) over the 255 period of study, for all 21,000 cells with no sub-sampling. This record can be used to compute the true fire frequency realized for each of the replicate simulations. The three "Spatial" sampling scenarios yield similar complete, un-degraded records for a subset of 36, 72, and 144 of the model cells. These records can be used to determine the impact of different sampling densities in isolation from other sub-sampling mechanisms. The remainder of the scenarios vary the value of a single parameter while holding the value of all other parameters equal to those of the "Base Case" scenario. The "BaseCase36" and "BaseCase144" scenarios vary the number of sample sites (from

72 sites collected in the Base Case, to 36 and 144 sites respectively). The "RecRate.25", "RecRate.75", and "RecRate1" scenarios vary the fire scar recording rate (probability of a fire scarring a previously scarred tree). These scenarios use a recording rate of 0.25, 0.75, and 1 respectively, as compared to the Base Case value of 0.56. In the "Trees1", "Trees2", and "Trees4" scenarios one, two, and four trees, respectively, are collected at each of the 72 sample sites, as opposed to the three trees collected at each site in the Base Case scenario. These eight scenarios form a sensitivity analysis for the results of the analysis on the Base Case scenario.

Each of these scenarios takes its samples from the same set of 100 replicate simulations, at the same sampling locations, over the same 255 year period. Thus, any differences between the samples is purely an artifact of the sub-sampling mechanisms employed. It is the magnitude of these differences that allows me to determine the relative importance of each individual source of uncertainty.

Three other sampling scenarios were run over an extended temporal period. The "CompleteLong", "SpatialLong", and "BaseCaseLong" scenarios are identical to the Complete, Spatial72, and Base Case scenarios described above, except that the temporal extent of the record is 500 years, as opposed to 255 years in all the other scenarios. These scenarios allow us to examine the effect of the limited temporal extent of the period of study in isolation from other factors.

**Table 1. Parameters for the EVA sub-sampling models discussed in the text. Each sub-sampling model is applied to the same 100 replicate Complete fire records produced by the Monte Carlo runs of the REFR model (see Figure 1).**

| EVA Sampling Scenario | Years in Period | # Sample Sites | Trees per Site | Probability of Recording | Evidence Survivorship |
|---|---|---|---|---|---|
| Complete | 255 | 21,000 | - | 1 | 100% |

Table 2 gives the summary results for each scenario. For example, the first row in Table 2 presents the results for the "Complete" scenario, which express the "true" MFRI's realized over the 255 year period of study for the 100 replicate simulations. The left-hand portion of the table shows that the replicate with the highest point fire frequency (Min. MFRI) realized a MFRI of about 11 years, while the replicate with the lowest point fire frequency (Max. MFRI) has a MFRI of just over 20 years. The average "true" realized MFRI over all 100 replicates is 14.7 years with a standard deviation of 2.22 years. Geary's test for normality fails to reject that the MFRI's over the 100 replicates may be drawn from a normal distribution -- in other words, the MFRI's for the 100 replicates appear to be distributed normally about the mean. The right-hand side of the table yields a similar set of descriptive statistics for the bias in the MFRI estimates for each scenario. Because the "Complete" scenario represents the true MFRI for each replicate, there is no bias in this scenario. However, the fifth row of Table 2 gives the results for the "Base Case" scenario, and shows that the bias in the MFRI estimates from the Base Case samples range from one to just over six years. The average bias over all replicates in this scenario is about two and a half years with a standard deviation of 0.81 years. Geary's test for normality does reject that the biases are distributed normally ($p<0.05$), and an examination of the biases for this scenario confirms that the distribution is actually skewed to the right of the mean (see Figure 13).

The "Mean MFRI" and "Mean bias" columns of Table 2 are discussed extensively in the following sections. All of the sampling scenarios started with the same 100 replicate fire histories represented by the "Complete" scenario. Thus, differences in average MFRI between scenarios are attributable solely to the sub-sampling mechanisms employed by the scenario. The average difference between the MFRI estimate from a sampling scenario and the true MFRI from the "Complete" scenario yields the "Mean bias" for the scenario. The magnitude of this bias indicates the relative impact of the scenario's sub-sampling mechanisms on our ability to accurately reconstruct the fire history.

**Table 2. Results from the different sampling scenarios described in Table 1. MFRI = point mean fire return interval. Bias = estimated(MFRI) - true(MFRI). Mean and StdDev columns give the average and standard deviation over 100 replicates, while Max and Min give the maximum and minimum value that occurred for a single replicate. Geary's Z is a test statistic, where |Z| ³ 1.96 rejects the hypothesis that the data are normally distributed, at the a=0.05 level. The full distribution of MFRI's for the 100 replicates (CompleteLong, Complete, and Base Case scenarios) is shown in Figure 11. The full distribution of biases for the 100 replicates (Base Case, RecRate, and Trees scenarios) are shown in Figures 14 and 15.**

| Sampling Scenario | Min. MFRI | Max. MFRI | Mean MFRI | StdDev MFRI | Geary's Z | Min. bias | Max. bias | Mean bias | StdDev (bias) | Geary's Z |
|---|---|---|---|---|---|---|---|---|---|---|
| **Complete** | 10.9 | 20.7 | **14.7** | 2.2 | 0.8 | 0.0 | 0.0 | **0.0** | 0. | - |
| **Spatial72** | 10.9 | 20.7 | **14.7** | 2.3 | 0.9 | -0.4 | 0.7 | **0.0** | 0.1 | -4.1 |
| **Spatial36** | 11.1 | 20.8 | **14.7** | 2.3 | 1.1 | -0.7 | 0.6 | **0.0** | 0.2 | -2.3 |
| **Spatial144** | 11.0 | 20.6 | **14.7** | 2.2 | 0.9 | -0.2 | 0.3 | **0.0** | 0.1 | 1.2 |
| **Base Case** | **12.4** | **26.9** | **17.1** | **2.7** | **-0.2** | **1.1** | **6.2** | **2.4** | **0.8** | **-2.5** |

**Consistency of fire regime parameters**

From equation 1, we would expect that the empirical MFRI at Dugout Creek should be roughly equal to 15.10 years [mean(*RT*)/mean(*EE*) * *A* = 3.68 years / 5,170 acres * 21,213 acres). The actual empirical mean point fire return interval for the 255 year period 1645 to 1900 is 15.02 years (computed from 991 fire intervals collected at 72 sites). Furthermore, a Weibull model fit to the fire interval distribution yields a MLE MFRI of 15.09 years (Figure 10a). If these three estimates of MFRI were not similar, it would indicate that the *ReturnTime*, *EventExtent*, and *MFRI* parameters were not internally consistent, and thus at least one of them was in error. For Dugout creek, these three estimates of the MFRI are virtually identical (given the precision of the data), and thus suggest that *RT* and *EE* form a consistent set of parameters with which to model the

this value should be regarded as significant evidence for an increasing hazard of burning function operating at Dugout Creek.

Many of the synthetic fire histories also exhibited a skewed and/or leptokurtic point fire interval distribution, similar to the empirical distribution for Dugout Creek. For example, Figure 10 shows both the empirical and a synthetic point fire interval histogram. Both histograms exhibit a similar shape and degree of variability, and both have a modal value close to 10 years. However, the expected shape of the fire interval distribution under a constant hazard of burning is negative exponential (Van Wagner 1978, Johnson and Van Wagner 1985, Johnson and Gutsell 1994). Because the hazard of burning is

conditions over a very long period (or a very large area), the MFRI for a system should converge to that of the generating processes, which in the case of our simulation model is a Poisson process with a MFRI of 15 years. However, even when averaged over 500 years (more than 30 fire rotations!) and 21,000 sample locations, the MFRI still shows substantial variability among the 100 replicate simulated landscapes (Table 2 and Figures 11 and 12). As the period examined (or size of the study area) is reduced, this apparent variability in the MFRI among replicates increases.

Figure 11 depicts this scale effect clearly, with the distribution for the CompleteLong scenario (MFRI is averaged over 500 years, 21,000 sites) exhibiting less variance than that for the Complete scenario (where the MFRI is averaged over about half the number of years). This increasing variance would continue as we reduced the temporal extent of our observations. On the other hand, over very long periods, we'd expect that every replicate would converge to a MFRI of 15 years, with little variance among replicates.

The variance introduced by the temporal scale of the observations has important implications because it implies that substantially different *historical* MFRI's can arise from the same set of generating processes (where by *historical* I simply mean those reconstructed over some finite region of space and time). Figures 11 and 12 show this effect clearly — substantial differences are apparent between replicate synthetic histories, although each was created by an identical generating process. Thus, investigators should avoid the temptation to infer a difference in the processes driving the fire regime based solely on a finding of significant difference between two fire interval distributions (see also Lertzman et al. 1998). Such an inference would be inappropriate, for example, when comparing two periods, because the observed difference indicates only that the *historical* occurrence of fires differed between periods, not necessarily that the fire regime changed. An analysis of variance between replicates from the same scenario illustrates this cautionary point clearly (Table 3). While each of the 100 replicate fire interval distributions was driven by an identical process, it is not difficult to find statistically significant differences between them. In fact, even a very small difference between the

means of two distributions may result in a significant difference (e.g., Run39 vs. Run85 in Table 3

Although the synthetic FID's exhibited a fairly wide range of shapes (Figure 12), they almost all differed from the empirical FID for Dugout Creek in one respect. The maximum interval in the synthetic FID's tended to be much longer than the maximum

While the Poisson process that drives the simulated fire regime in the REFR model is admittedly simplistic, the variability it exhibits may serve as a first estimate of the expected range of variability for the processes driving the fire regime at Dugout Creek. Based on the variability exhibited by my model of Dugout Creek, the particular historical sequence of fires observed at Dugout Creek is one of a fairly wide range that could have been generated by the physical fire regime, and, conversely, could have been generated by a number of distinct fire regimes. Thus, the observed sequence of fire may be typical for the processes acting at Dugout Creek, as we have assumed, or it may represent the tail of the distribution and not the average behaviour of these processes. Due to the limited temporal extent of any tree-ring record, and/or the limited period over which the driving processes can be assumed to be relatively stable (Masters 1990, Johnson and Larsen

question is intractable, I have instead asked "what set of observed MFRI estimates could result from a given fire regime?" The REFR model described above is the "given fire regime", and the 100 replicates of the Base Case sampling scenario yields a "set of observed MFRI estimates". The errors in these synthetic observations are given by the MFRI bias (Table 2). If we assume that the errors in the synthetic observations are distributed similarly to those in the empirical observation, then the average synthetic error approximates the expected error in the empirical observation (see notes of caution in the *parameter summary* section above!). Furthermore, the range into which 95% of the synthetic errors fall yields a measure of how likely it is that the error in the empirical estimate also falls within that range. Since this range gives us a measure of confidence in the empirical observation, I will refer to it as the 95% confidence interval.[1]

To compute a 95% confidence interval for the empirical MFRI estimate for Dugout Creek, I constructed the distribution of biases in the Base Case MFRI estimates. The bias for each synthetic sample is computed by subtracting the true MFRI for the simulation (calculated from the Complete record) from the estimated MFRI (calculated from the sub-sampled "Base Case" record). The distribution of biases for the Base Case sample appears to be a skewed or truncated normal distribution (Figure 13; Geary's test

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[1] More formally:
Define $A_{nature}$ as the true value of parameter $A$ in nature;
$A_{empirical}$ as the empirically estimated parameter value;
$A_{synthetic}$ as the true value of parameter $A$ for the synthetic fire histories;
$A_i$ as the parameter value estimated from synthetic fire history *i;* and
$B_{empirical} = A_{empirical} - A_{nature}$ as the true bias in the empirical estimate of $A$.
Given the set $\{A_i \mid i=1..N_r\}$, then the bias in each synthetic estimate is $B_i = A_i - A_{synthetic}$, and the expected bias in any synthetic estimate is $\overline{B} = \sum B_i / N_r$ . If we assume that the errors in $A_i$ are distributed similarly to those in $A_{empirical}$, then the expected bias in the empirical estimate of $A$

for normality rejects that the biases were drawn from a normal distribution, $p<0.05$). The mean bias was 2.4 years with a standard deviation of 0.8 (Base Case in Table 2). The range into which 95% of the MFRI biases fall is [1.1 , 4.0] (Figure 13). I use this range, coupled with the empirical estimate of the MFRI at Dugout Creek, 15 years, to compute a 95% confidence interval for the true MFRI at Dugout Creek of 11 to 13.9 years, with an expected value of 12.6 years.

Given the number of assumptions made in these analyses, and the range of natural variability exhibited by the system, this magnitude of bias is quite reasonable and, I suspect, most researchers would be pleased with such a result. However, for critical applications of the Dugout Creek study (e.g., the development of a conservation plan for an endangered species that is fire dependent) it may be important to consider that there is a 1 in 100 chance that the empirical MFRI estimate may be biased by 40% or more (e.g., the MFRI estimate for Run82 was biased by 6 years). While providing an absolute measure of confidence in the empirical MFRI estimate for Dugout Creek, this analysis has broader consequences because it can be used to quantify the relative magnitude of a number of sources of uncertainty that have likely had a more substantial impact on other fire history studies.

**Primary sources of uncertainty in fire history studies**

To determine the primary sources of uncertainty in the estimates of fire regime parameters, I performed a sensitivity analysis on the EVA sampling model. Table 1 shows the parameter settings for the different sub-samples used in the sensitivity analysis. In each case, the sub-sample proceeds as for the Base Case, except that one parameter of interest is varied about its Base Case value. The following results simply examine the effect of varying each EVA parameter on the bias and uncertainty in the reconstructed MFRI, as compared to the Base Case scenario.

*Sampling Density*

I ran two scenarios to determine the effect of varying sampling density. While the Base Case scenario had 72 plots (1 plot per 295 acres), the BaseCase36 and BaseCase144

scenarios had half and twice that density of plots, respectively. Although I expected the sample size to influence the amount of variance in the MFRI estimates, in fact varying the sampling density had little effect (Table 2). This insensitivity likely arises because the fires tended to be much larger than the spacing between sample points (mean fire size = 5,170 acres). Thus, even at half the sampling density (1 plot per 590 acres), most fires are still sampled adequately. Note that sampling density is usually defined, as it is here, with respect to the size of the landscape. When designing a sampling strategy, it would be more useful to think about the density with respect to typical fire size (which, of course, is usually unknown before sampling begins). I expect that reducing sampling density to a degree that is low with respect to the typical fire size (e.g., one plot per *X* acres, where *X* is the average fire size) would have a significant influence on the estimate of fire frequency.

*Evidence Survivorship*

While I did not run any scenarios that varied the parameters of the evidence survivorship function, two of the scenarios demonstrate that it did not have a direct impact

plays an indirect role in censoring the fire history by primarily determining the period of reliability (see section on "Temporal Censoring" below).

It is useful to note that the RecRate1 scenario, where "evidence survivorship" is the sole censoring mechanism, is the only scenario that introduced a negative mean bias into the MFRI estimate (i.e., the MFRI tended to by underestimated; Table 2). This underestimation occurs because long intervals are more "susceptible to mortality", and are thus underrepresented in the sample. In other words, a record of fire is more likely to begin following (or end just prior to) a long interval, simply because there are more years in a long interval than a short one.[2] This effect is present in all the sampling scenarios, it is just overwhelmed by the positive bias introduced from other sources. If the size of the longer intervals approaches or exceeds the temporal extent of the period of study, these longer intervals will not be detected. While evidence survivorship plays an insignificant role in the Dugout case study, it will be a critical factor in study areas where fire intervals are long relative to the period of analysis, or in studies that attempt to make inferences about the fire frequency outside the period of reliability.

*Temporal Censoring*

While the "evidence survivorship" parameter did not play a direct role in influencing the MFRI estimate at Dugout Creek, it plays a substantial indirect role by limiting the temporal extent of the analysis. As discussed above, temporal censoring of the fire history introduces both variability and a bias into measurements of fire frequency. For example, differences between the Complete and CompleteLong scenarios indicate that the MFRI's realized over 255 years exhibit a higher variance than those computed over 500

[2] Consider a short interval of $S$ years and a long interval of $L$ years. If the probability that a fire record will begin is equal in each of the $N=S+L$ years, then the probability that it will begin in the long interval is $L/N$, and in the short interval, $S/N$. The probability $L/N$ is greater than $S/N$ because $L > S$, and thus it is more likely that the record will begin during the long interval. This is an oversimplification of the process of fire record establishment, but it seems likely that these statistical properties should hold in any case. Because the interval preceding the start of a fire record is not known and not included in

years (Figure 11; $s^2$=4.9 vs. s

scenario, all fires at each site are recorded ($p_r$ =0.25, 0.75, and 1.0 respectively; Table 1). The RecRate.25 samples exhibited, by far, both the largest bias and variance between replicates of any of the scenarios. By contrast, the RecRate.75 samples exhibited the lowest bias and variance of all scenarios that applied some record degradation (Table 2 and Figure 14). The RecRate1 scenario shows that the bias introduced from all sources other than the recording rate is very small (Table 2 and Figure 14). These results suggest that the magnitude of bias and uncertainty in a fire history study is highly dependent on the true value of $p_r$. For example, if the recording rate at Dugout is 0.25 rather than 0.56, then it is very likely that the MFRI estimate of 15 years may be out by a factor of two or more (Max. MFRI estimate = 42 years in RecRate.25 scenario; Table 2).

Further research is required to determine if the estimate, $\hat{p}_r$ =0.56, is sound, and what range of values constitutes a reasonable confidence interval for the estimate. In addition, the

MFRI because two true short intervals are removed from the FID in addition to one false long interval being added. For any recording rate, $p_r > 0.5$, a sample of at least two trees has a reasonable chance of detecting most fires. Because the parameter $N_t$ is under the control of the researcher, multiple trees should always be sampled at each site if one wishes to reconstruct the history of fire with greatest certainty.

**Evaluating the Sampling Design**

In terms of simply estimating fire frequency, the sampling design employed at Dugout Creek was close to optimal, although a small improvement might have been possible, in theory and with hindsight. Reducing the sampling density made very little difference to the bias in the MFRI estimate (BC36 scenario, Table 2), and so I assume that an empirical sample of 36 plots with 4 trees sampled at each plot would yield a result similar to that of the Trees4 scenario (mean bias in MFRI estimate = 1.47 years; Table 2). Thus, assuming a fixed budget (in terms of number of trees sampled), a less biased MFRI estimate likely would have resulted from a strategy that sampled more trees per plot at fewer plots. In reality, this may not have been feasible (e.g., there may not have been a suitable number of recorder trees available at each site), nor desirable from the perspective of achieving the other objectives of the study (e.g., more accurate estimates of fire extent).

**The Effect of Fire Frequency on Fire Frequency Estimates**

Holding everything else constant, the frequency of fire itself has a direct impact on the magnitude of both the bias and uncertainty in the estimates of MFRI. This effect occurs because, over the same period, an area with lower fire frequency (higher MFRI) will simply have fewer fire intervals, and thus a lower $N$, for the MFRI calculation. Thus, a decrease in fire frequency has an effect very similar to that of reducing the period of analysis, discussed above. Because each of the 100 replicate fire histories in my study realized a slightly different fire frequency over the 255 year period of analysis, I was able to examine this effect over the limited range of fire frequencies covered by the replicates. Figure 16 shows the relationship between MFRI and the bias in the Base Case estimate of

MFRI. The regression between MFRI and bias is significant (correlation coefficient $R^2 = 0.27$, N =100, $p < 0.001$), indicating that such a relationship can be identified even over the limited range examined. Further analysis of this relationship over a wider range of conditions may yield some general principles about the uncertainty in fire frequency estimates that could help guide fire history researchers. It is also worth noting that the variance in bias, and thus uncertainty in the MFRI estimate, also appears to increase with MFRI (examine the magnitude of deviation of the data points from the trend line Figure 16). Although this relationship was not formally tested, it makes sense both intuitively (variance usually increases with increasing mean), and for some of the reasons discussed above under temporal censoring.

## *Conclusions*

The results of this study indicate that there are a number of techniques that fire researchers can employ to minimize the bias in their estimates of historical fire frequency. A number of important considerations also arose that have direct implications for forest managers who wish to use the results of a fire history study to guide their management actions. In the following sub-sections, I make a set of specific recommendations that highlight the important points of my results for each of these two groups. In addition, I review the plethora of outstanding questions related to testing fire history methods raised by my analyses.

### *Recommendations for Fire History Researchers*

The case study for Dugout Creek shows that it is possible to reconstruct the historical frequency of fire from fire interval data with some precision. However, the sensitivity analysis of the EVA model indicates that a sampling design that is insufficient or not well matched with the scale of the fire regime can produce very inaccurate results. Two features of the Dugout Creek sampling design substantially reduced the bias in the empirical MFRI estimate — the collection of multiple samples of the fire record at each point and the use of an iterative approach in determining the sampling density. These two

approaches have not been consistently applied in studies of fire history from fire interval data.

While it may be difficult to determine the exact probability with which fire is recorded in the tree-ring record, there is little doubt that this probability is, in general, substantially less than one. The error introduced by the fire recording rate is inherent in the physical data, and thus not under the control of the researcher. However, the collection of samples from multiple recorder trees at each sample site in Dugout Creek not only allowed me to estimate the fire recording rate, but also compensated for the errors introduced by it, and thus played a key role in minimizing bias in the empirical MFRI estimate. I strongly recommend that in all studies of fire history from fire interval data, researchers should sample multiple trees at each sampling point. The size of a "point" on the landscape (e.g., one acre at Dugout Creek) must be large enough to encompass several fire scarred trees, yet small enough that it can be assumed to be acting as a single unit with respect to fire occurrence.

Another strong feature of the sampling strategy applied at Dugout Creek was its use of an iterative approach — data analysis from the first field season was used to re-design the sampling strategy for subsequent seasons. In general, the budget for a study will, to some extent, pre-determine the number of samples that can be taken. A pilot study should be used to help determine how to best allocate these samples across space. The goal of such a pilot study should be to gain an estimate of the spatial scale and heterogeneity of the fire regime, along with an estimate of the probability with which trees record the passage of fire (see Appendix B for details). This information can then be used to determine a plot density compatible with the typical fire extent, and the number of trees that need to be sampled in each plot to achieve an acceptable level of certainty in the results. At Dugout Creek, the results from the first season indicated, quite correctly, that the investigator should reduce plot density and sampled a wider area in subsequent field seasons (Emily Heyerdahl, personal communication).

Finally, temporal censoring, due to the limited lifespan of fire evidence, plays a key role in increasing the variance apparent in the fire interval distribution. Fire history

researchers will find themselves in a dilemma, caught between wanting to expand the temporal period of analysis (to reduce the variance in their MFRI estimate), yet needing to restrict the temporal period of analysis such that they have an adequate sample at each spatial location over the entire period. The choice of period of analysis is further complicated if the processes driving fire regimes are hypothesized to have changed over the period of study (Johnson and Gutsell 1994, Lertzman and Fall 1998). This is a difficult problem for which I have no direct recommendations, other than to select a period of analysis by objective criteria that are sensible for the type of question being asked.

*Implications for Management*

It will be difficult to formulate timber harvesting objectives based on low-severity, stand-maintaining disturbance regimes because the fires that characterize these regimes tend to remove the unmerchantable trees, while leaving most of the mature trees intact. The Biodiversity Guidebook (British Columbia Ministry of Forests 1995) designates the Interior Douglas Fir and Ponderosa Pine Biogeoclimatic zones as Natural Disturbance Type 4 (NDT4). According to this designation, "frequent, stand-maintaining fires" dominate the disturbance regime in these forests (see p. 39 of Biodiversity Guidebook).

Furthermore, the range of variability in NDT4 systems makes the traditional approach of working with mean disturbance intervals questionable. My research demonstrates that these forests experience a wide range of inter-fire intervals, across both space and time. This variance is likely as important to the ecology as the mean, because it promotes a diversity of species and vegetative responses to fire. This diversity may, in turn, allow these ecosystems to adapt to a change in fire regime (e.g., brought on by a change in climate). The Biodiversity Guidebook recognizes this point by emphasizing seral stage distributions rather than a fixed rotation period. However, there have been many difficulties interpreting the meaning of the seral stage distributions in the Biodiversity Guidebook, and, in practice, variability is not being implemented across the landscape — each forest block is being operationalized with the mean (John Nelson, personal communication). More research is required to determine how to best base a management strategy on a low-severity fire regime, and how to incorporate variation into the forest operations.

My finding that there may be an increased hazard of burning with time-since-fire, or that severe fires may ensue after long periods without fire has important fire management implications for Dugout Creek, in which only two significant fires have burned since 1900. The role of fire suppression in increasing fuel loads and thus the potential for large, catastrophic fires is well documented in the literature and deserves serious consideration by forest managers.

*Future Research*

My analyses raised a number of interesting questions and novel applications for the modelling framework that I developed for this project. This framework could easily be applied to other study areas, and could also be used to:

- determine the cause of the skew and kurtosis common in the synthetic point fire interval distributions and relate this effect to hazard of burning function in models of fire frequency (e.g., Weibull);
- determine the optimal sampling density with respect to typical fire size;

- determine the minimum period of reliability with respect to the mean and/or longest fire intervals, required to adequately reconstruct fire frequency ;
- generate the expected range of variability for two reconstructed fire regimes to yield a measure of variance that can be used to test for differences between two fire regimes.
- simulate a fire regime on a heterogeneous landscape and/or changes in fire regime over time to determine effectiveness of methods in detecting these differences;
- develop methods for recognizing empirical samples that may be extremely biased by analyzing a set of synthetic samples that are outliers on the MFRI bias distribution for common characteristics;

As a final note, it may be possible to derive an analytic relationship between the probability of recording, the number of trees in each sample, and the expected bias in the MFRI estimate, holding all else equal (e.g., MFRIbias = *f*(MFRIestimate, RecRate, TreesPerSample)). As a first approximation, the models described herein could be used to generate an "empirical" approximation of such a function. Having such a function would greatly assist researchers in designing optimal sampling strategies, and estimating the bias in their reconstructed estimates of fire regime parameters, without having to resort to the Monte Carlo analyses conducted in this project.

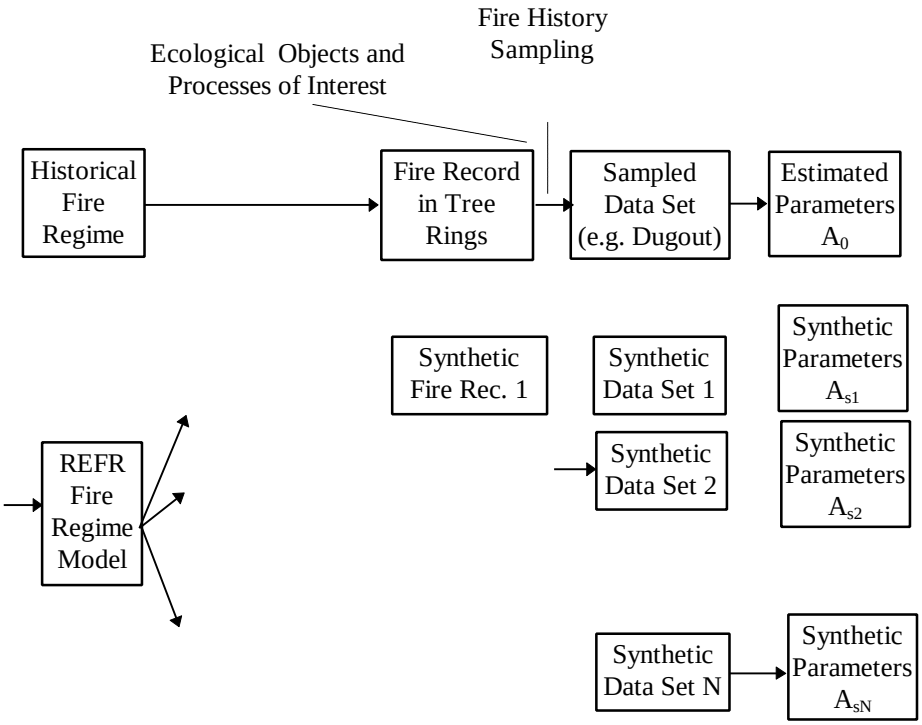



**Figure 1. Conceptual diagram for the project. Each box in this diagram represents some object of study. The arrows should be read as "produces via" the mechanism specified for the arrow. The empirical fire history study is depicted above the heavy dashed line. Through a set of ecological and physical processes, the fire regime leaves evidence of fire occurrence in the tree rings. A researcher samples this evidence to create an empirical fire history data set. This data set is, in turn, used to estimate the parameters of the fire regime, $A_0$ . The models used in this project are shown below the heavy dashed line. The empirical parameters, $A_0$ , are used in the REFR model to simulate the fire regime and produce a synthetic realization of fire occurrence. The EVA model then censors and samples this complete record to yield a synthetic data set similar to the empirical one. Synthetic parameters $A_{si}$ (i=1..N) may be derived by the same methods used to derive $A_0$ . These synthetic parameter estimates may then be used to form a confidence interval for the empirical estimate, $A_0$ .**

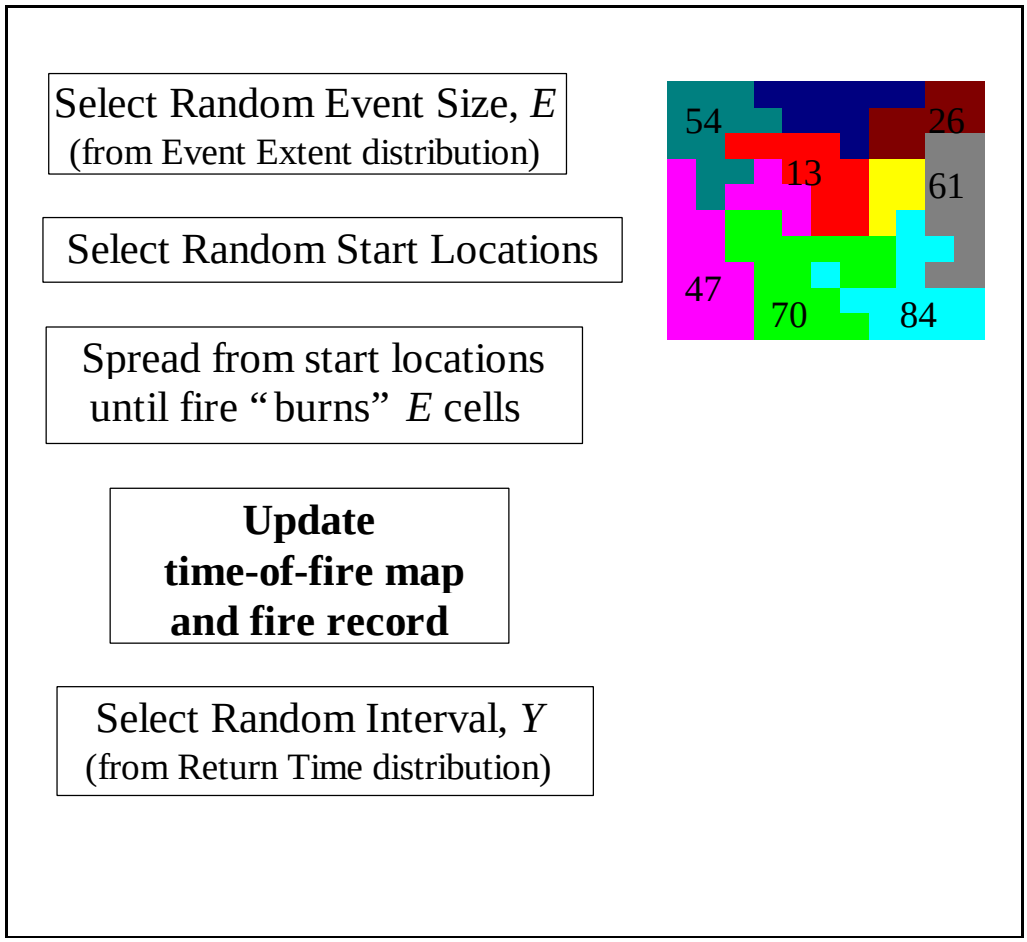



**Figure 2. Conceptual diagram of REFR simulation. When the simulation starts, the time of the first fire year is selected from the Return Time distribution (Figure 5). When a fire year occurs, a fire size is selected from the Event Extent distribution (Figure 6). A random start location is chosen for the fire, and it spreads out from this cell until it burns the number of cells required by its Extent. The time until the next fire year is then selected from the Return Time distribution. The complete record of all cells burned by each fire is the "Complete Event Record" in Figure 1. (A map of time-of-last-fire is also kept but not used in this project.)**

**Figure 3. Conceptual diagram of EVA model. Both the uncertain states of nature and the sampling options are parameters for this model. The "Complete Event Record" is produced by the REFR fire regime model (Figure 2). The EVA record degradation sub-model introduces errors into this record based on the types of error thought to be present in the physical data. The EVA fire history sampling sub-model then selects a sub-sample of the spatial locations to simulate data collection by the fire history researcher.**

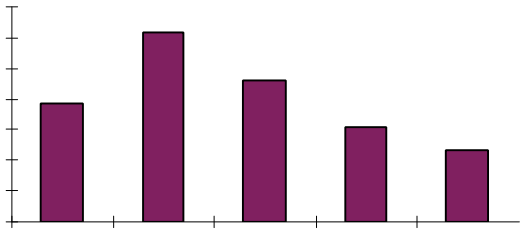


**Figure 4. The distribution of fire years per decade at Dugout Creek between 1645 and 1900. The Maximum Likelihood Poisson distribution is also shown. Note that 2.69 fires per decade translates into approximately 3.7 years between fires (10/2.69 @ 3.7).**

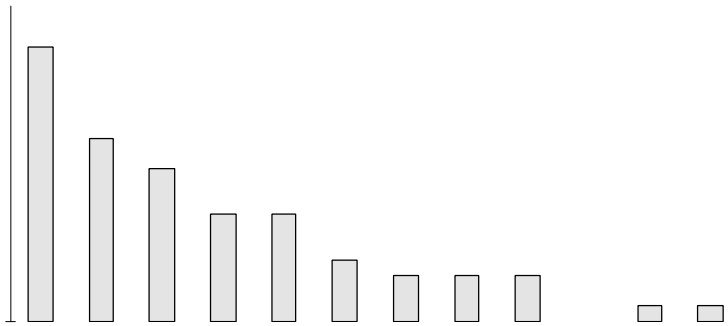


**Figure 5. Distribution of intervals between fire years at Dugout Creek between 1645 and 1900. The Maximum Likelihood negative exponential distribution is also shown. Random numbers are selected from this "Return Time" distribution in the REFR simulation to determine the time to next fire year on the landscape (Figure 2).**

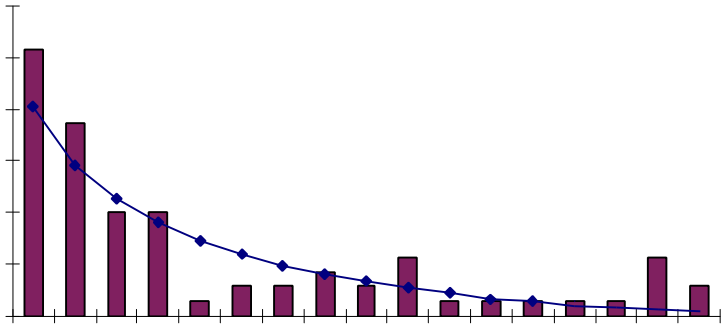


**Figure 6. The distribution of fire extents at Dugout Creek between 1645 and 1900. The Maximum Likelihood Weibull distribution is also shown. Random numbers are selected from this "Event Extent" distribution in the REFR simulation to determine the spatial extent of each fire event (Figure 2).**

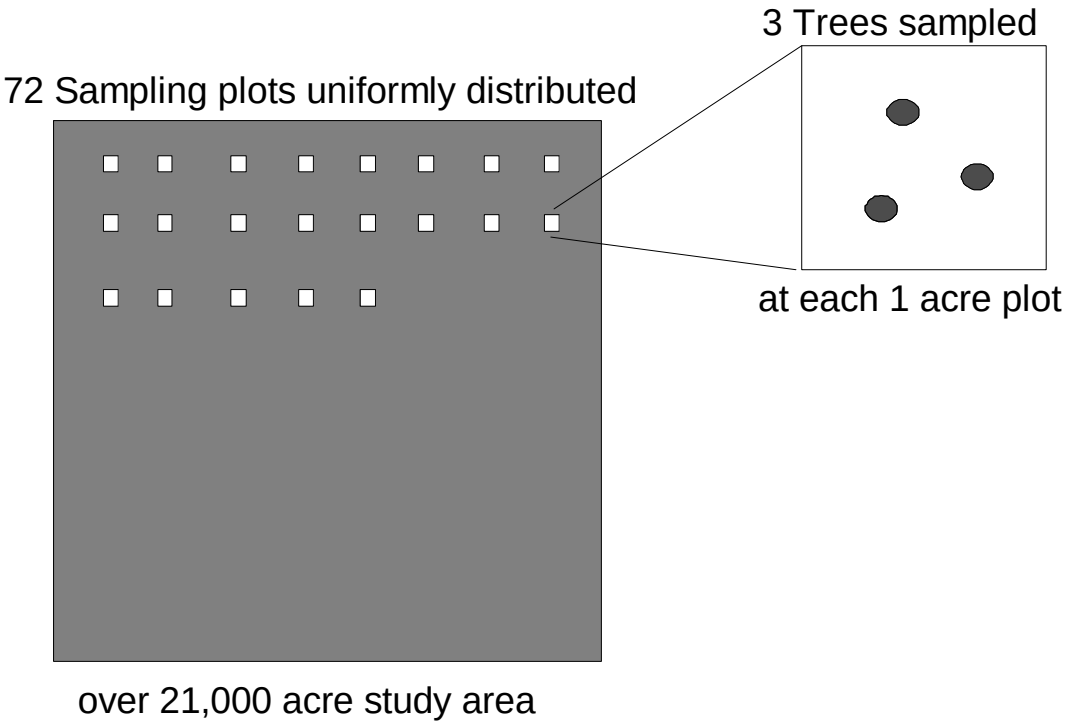



**Figure 7. Sampling design used in the EVA sampling model (Figure 3). The inset on the lower right shows the approximate layout of plots in empirical study at Dugout Creek for comparison.**

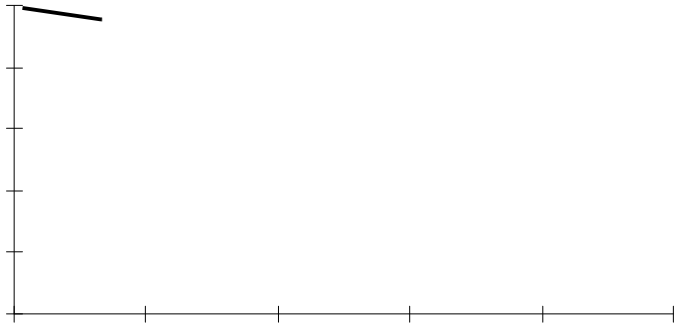


**Figure 8. The cumulative distribution of survival times for fire evidence at Dugout Creek. The Maximum Likelihood Weibull survivorship model is also shown. Random numbers are selected from this distribution in the EVA record degradation sub-model to truncate the synthetic complete fire records (Figure 3).**

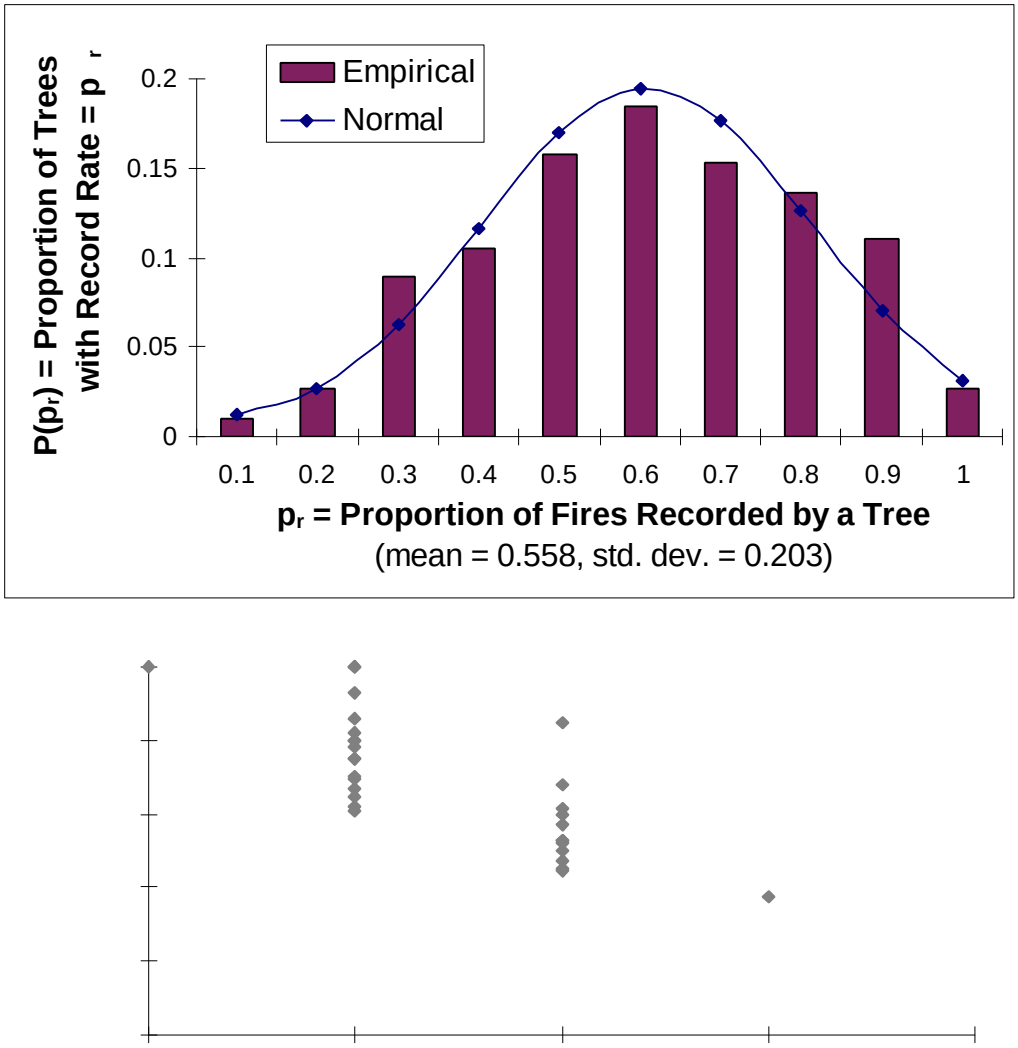



**Figure 9. (a) The proportion of fires recorded by trees sampled at Dugout Creek; and (b) the function G(t) fit to the empirical estimate $G_t$ for all Dugout Creek sample sites (see Appendix B). In (a), only those sets of trees with at least 10 total fires in their common period of record are included, yielding N=190 sets. In (b), all 72 sites are included, but there are fewer sites where four and five trees shared a common period (i.e., there were few sites where $G_4$ and $G_5$ could be estimated). Thus, the least-squares fit function, G(t), is most heavily influenced by $G_2$ and $G_3$.**

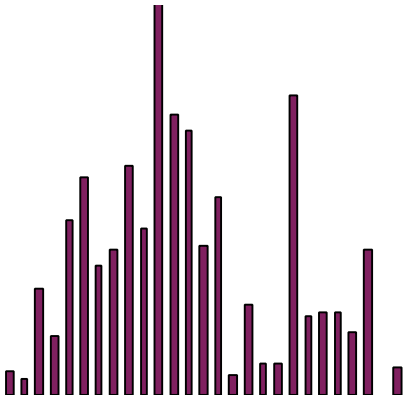


**Figure 10. Point fire interval distributions for (a) the empirical data set for Dugout Creek and (b) the synthetic Base Case scenario replicate Run73.**

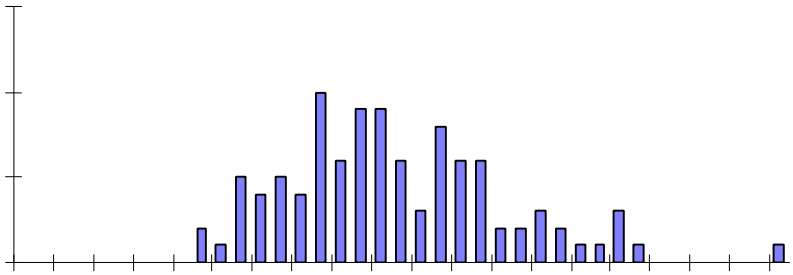


**Figure 11. Distribution of mean fire return intervals (MFRI) resulting from 100 replicates of the CompleteLong (a), Complete (b), and Base Case (c) scenarios. None of these distributions were rejected as being normal by Geary's Z (p>0.4 in all cases).**

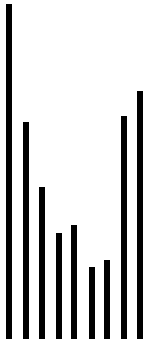


**Figure 12. Synthetic point fire interval histograms from three of the 255 year replicates. Each graph shows the Complete interval histogram (grey bars) and the reconstructed interval distribution from the Base Case sampling scenario for the same replicate (black bars), along with the MLE Weibull distribution fit to the Base Case distribution (rejected with p<=0.01 in**

**each case). Also shown are the number of point intervals in the sample (N), the mean and maximum point interval in the sample, and the proportion of intervals not shown on the graph (> 64 years, the maximum interval found at Dugout). The MLE Weibull parameters and the Kolmogorov-Smirnov goodness of fit test values for each replicate are also given.**

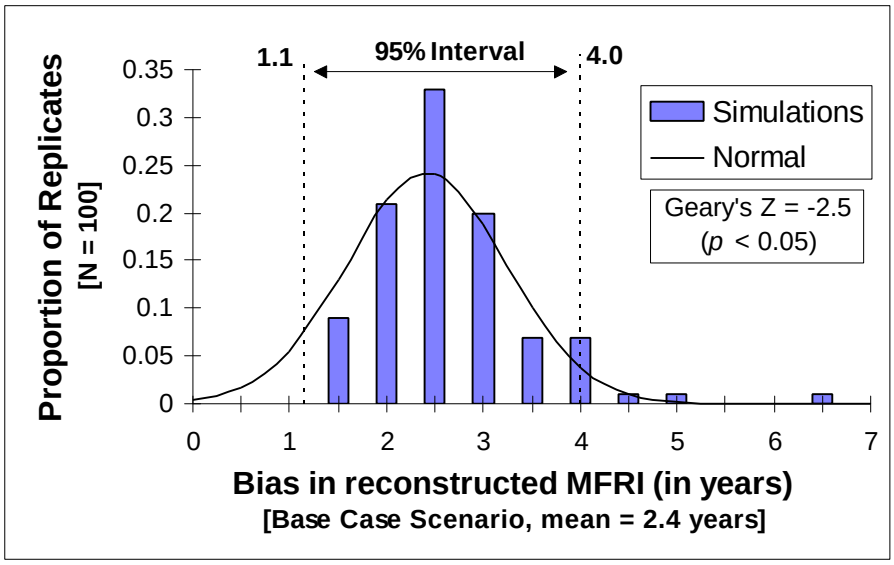



**Figure 13. Distribution of biases in the estimates of MFRI for the 100 replicates of the Base Case scenario, showing the 95% interval for the histogram. Note that this is slightly different (skewed right) from the 95% interval for MLE normal distribution.**

**Figure 14. Distribution of biases in MFRI estimates for 100 replicates of the EVA sampling scenarios that vary the probability of recording fire evidence. A perfect estimate has a bias of zero. The wider the distribution, the higher the uncertainty resulting from samples of this type. The further the distribution's mean is shifted from zero, the greater the expected bias from samples of this type. (An approximation to the MLE normal is also shown for each scenario. See Table 2 for the exact mean, standard deviation, and significance of fit.)**

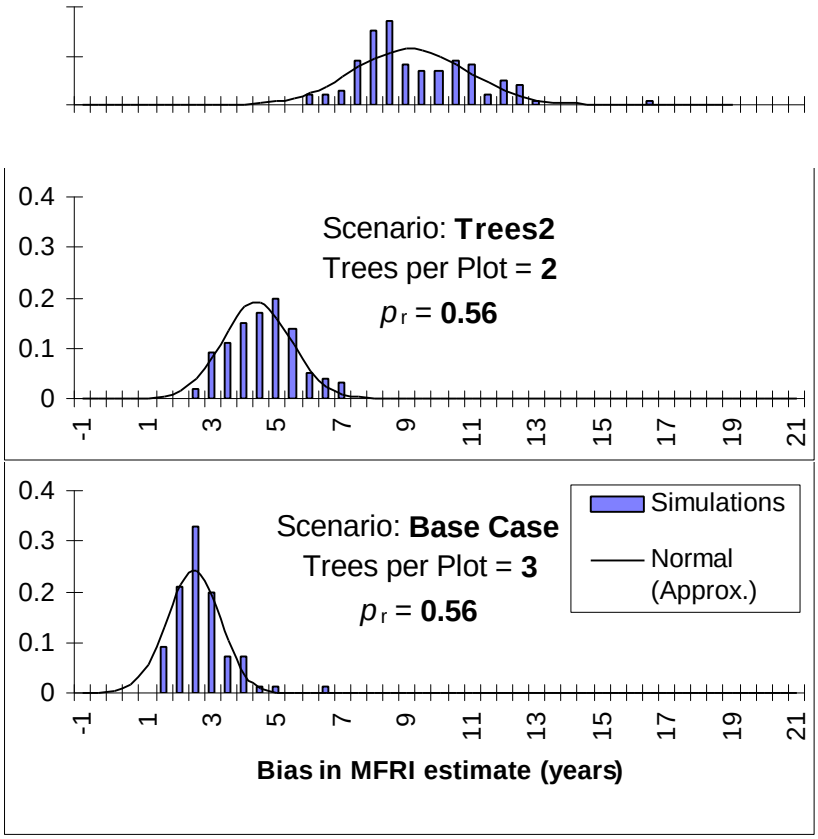



**Figure 15. Distribution of biases in MFRI estimates for 100 replicates of the EVA sampling scenarios that vary the number of trees collected at each plot. A perfect estimate has a bias of zero. The wider the distribution, the higher the uncertainty resulting from samples of this type. The further the distribution's mean is shifted from zero, the greater the expected bias from samples of this type. (An approximation to the MLE normal is also shown for each scenario. See Table 2 for the exact mean, standard deviation, and significance of fit.)**

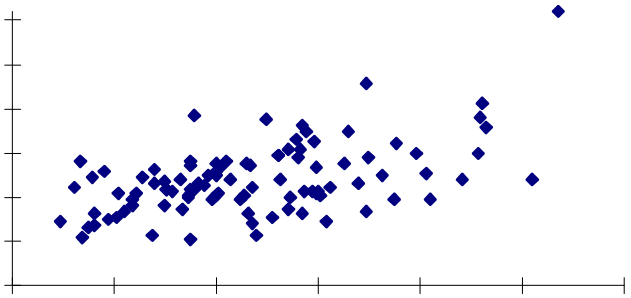


**Figure 16. Correlation between the true MFRI and the magnitude of bias in the MFRI estimate. The true MFRI is computed from the Complete sample, over 255 years, for each of the 100 replicates. The MFRI estimate is computed from the Base Case samples. The bias is the difference between the true and estimated MFRI. While there is a substantial amount of variation, the trend itself is significant (N=100, $R^2$=0.27, F=35.8, p<0.001).**

# Appendix A

### *Transforming an exponential distribution into a histogram*

There is a complication with using an exponential distribution to represent the Return Time parameter, RT. The empirical return times are discrete integers and never have a value less than one, due to the resolution of tree ring data. Thus, the complete histogram of return times forms a probability mass function (pmf) with mean μ:

$h(x;m) = \mathrm{P}(\mathrm{X} = \mathrm{x}) =$ proportion of RT intervals equal to x years [ x = 1,2,3,...]

The expected value of $h$(x) is:

$$\mathrm{E}(h(x)) = \sum_{x=1}^{\infty} x * h(x) = \mu \qquad \text{(A1)}$$

The probability distribution used to represent RT in the simulation, $p$(x), should have the same properties as $h$(x) — that is it returns integer values >=1 with the same shape and expected value, E($p$(x))=μ. Although the exponential model is suggested by the Poisson process and gives a good fit to $h$(x) (i.e. it is the correct shape), it is a continuous probability density function (pdf) with mean λ, defined on [0<=x<=∞]:

$$p(x;\ l) = \frac{1}{l}\ e^{-x/l} \quad \text{for } x >= 0 \qquad \text{(A2)}$$

Two questions arise: first, what is the best method to fit the continuous exponential model p(x; λ) to the discrete pmf $h$(x; μ)?; and second, how can we draw random integer values on [1, ∞] from p(x; λ

$$l = \frac{-1}{\ln(1 - 1/m)} \qquad \textit{(see proof at end)} \quad \text{(A5)}$$

With λ defined as in A5, we get the MLE pmf fit to the empirical pmf :

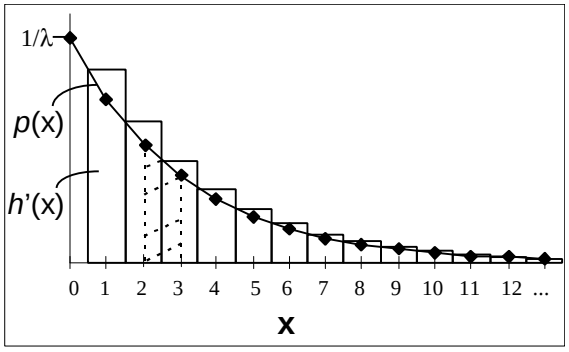
$$h'(x;m) = \int_{x-1}^{x} \frac{1}{l}\, e^{-x'/l} dx = e^{-(x-1)/l} - e^{-x/l} \quad \text{[for x=1,2,3...] (A6)}$$

We can select random values from *h*'(x) during the simulation, and the resulting RT distribution will have an expected shape and mean of that of the empirical distribution.

**Proof:** $l = \frac{-1}{\ln(1 - 1/m)}$

We defined the pdf, *h*'(x), such that: $\mathrm{E}(h'(x)) = \mu = \sum_{x=1}^{\infty} x * \mathrm{P}(\mathrm{X} = \mathrm{x})$,

where P(X=x) = the proportion of intervals of size x, which is the area under the histogram bar x (see figure).




We note that for each integer *i*, an exponential pdf, *p*(x; λ) defines:

$$A_i = \int_{i-1}^{i} \frac{1}{l} e^{-x/l} \quad \text{[i=1,2,3,...]}$$

where $A_i$ is the area under *p*(x) on the interval (i-1, i) (see figure).

We require *p*(x; λ) such that $A_x$ = P(X=x). To obtain the desired λ, we simply substitute P(X=x) = $A_x$ in the first equation above, and solve the equality:

$$\mu = \sum_{i=1}^{\infty} i * A_i$$

$$= \sum_{i=1}^{\infty} i * \int_{i-1}^{i} \frac{1}{l} e^{-x/l}$$

$$= \sum_{i=1}^{\infty} i * \left( e^{-(i-1)/l} - e^{-i/l} \right)$$

$$= \left( e^{-0/l} - e^{-1/l} \right) + \left( 2e^{-1/l} - 2e^{-2/l} \right) + \left( 3e^{-2/l} - 3e^{-3/l} \right) + \ldots$$

$$= \sum_{x=0}^{\infty} e^{-x/l}$$

$$= \sum_{x=0}^{\infty} \left( e^{-1/l} \right)^x \qquad \left[ \text{Sum of a geometric series } \sum_0^{\infty} \mathrm{r}^{\mathrm{x}} = \frac{1}{1 - \mathrm{r}} \right] \Rightarrow$$

$$\mu = \frac{1}{1 - e^{-1/l}}$$

$$e^{-1/l} = 1 - \frac{1}{m}$$

$$-1/l = \ln(1 - 1/\mu)$$

$$l = \frac{-1}{\ln(1 - 1/\mu)}$$

# Appendix B

## *Computing the probability of a fire scar forming*

**Application problem:**

- Given a set of *T* trees on a site, that were all fire recorders for a period of *Y* years, yielding a list of fire years recorded by each tree over the period,
- assume that for each fire year in the period, the whole site burned;
- assume that in each of *N* fire years during the period, each tree acted as an independent recording device to record the fire with some unknown probability, $p_r$.
- We would like to know the values of *N* and $p_r$.

**Equivalent counting problems to derive an estimate of *N*:**

In the case where *T* = 2, this problem is very similar to a classic counting problem (adapted from Constantine 1987):

- Persons *A* and *B* independently proofread a book (all errors are assumed to be independent and equally likely to be found).
- Person *A* finds *a* errors and *B* finds *b* errors, with *c* errors spotted by both *A* and *B*.
- What is the number of errors, *N*, in the book?

The solution is fairly simple and intuitive:

⇒ Note that the probability *A* finds a randomly selected error is *a/N*, and for *B* it's *b/N*.

⇒ The number of errors found by both will be, on average, (*a/N*)* *b* [because *A* should find approximately *a/N* of those errors found by *B*].

⇒ Thus, we solve *c* @*a/N* * *b* for *N* and get: ***N* @*a*b* / *c***

Ecologists may recognize this solution as the Petersen method for estimating population abundance using the mark-and-recapture technique. In this case, *a* is the number of individuals caught and marked in the first capture, *b* is the number of individuals caught in the second capture, and *c* is the number of marked individuals, re-

captured in the second capture (Krebs 1989). ***N @a*b / c*** gives us an estimate of the total population size. We may also calculate a confidence interval for *N* (see Krebs 1989).

For the application problem, *a* is the number of fire years recorded on tree *A* over the period *Y*, *b* is the number of fire years recorded on tree *B* over the same period, and *c* is the number of fire years recorded by both *A* and *B*. ***N @a*b / c*** gives us an estimate of the total number of fire years for the site, over the period *Y*.

In fact, there may be more than two sample trees on a site (i.e., $T > 2$). In this case, the Schnabel mark-and-recapture method (Krebs 1989) serves as an appropriate model. This method simply treats the *T* samples as a series of Petersen samples, and estimates the population size with a weighted average of Petersen estimates:

$$N \cong \frac{\sum_{t=1}^{T}\left(C_t * M_{t-1}\right)}{\sum_{t=1}^{T} R_t}$$

where $C_t$ is the total number of fire years recorded by tree *t* (e.g., $C_A = a$),
$M_{t-1}$ is the number of unique fire years in the pooled record of *t*-1 trees, and
$R_t$ is the number of "re-captured" fire years on the $t^{th}$ tree (already in $M_{t-1}$).

**Estimating a value for $p_r$, the probability of recording a fire:**

It is possible to use the estimate of *N*, above, to derive an estimate of $p_r$ for each tree, $\hat{p}_t$, by simply dividing by *N* the number of fires recorded by the tree during the period *Y* (e.g., $\hat{p}_t \cong C_t / N$). Because different trees cover different periods, each tree, *t*, may have several different estimates of $\hat{p}_t$, so the final value of $\hat{p}_t$ would actually be a weighted average of these estimates.

In contrast, the following method derives $p_r$ directly, without relying on *N*. Although the derivation below uses only trees from a single site and period, as above, the final curve fitting may be done using the values from any number of sites and/or periods. This method yields a single, "average" value of $p_r$ for all trees and periods included in the computation, rather than a separate probability, $\hat{p}_t$, for each tree, *t*.

**Problem Development:**

- Define

**Assumptions:**

Both of the methods described above make two key assumptions that are most likely not borne out in nature. Empirical studies will be required to determine how adversely departures from these assumptions in nature affect the results:

1. Each tree is assumed to act as an independent recorder. This assumption will not hold if, for example, a fire burns in such a way that it scars more trees in one area than it does in some other area (i.e., the rate of fire scarring is spatially autocorrelated).
2. Each fire is assumed to have an equal probability of being recorded. This assumption will not hold if, for example, one fire burns in such a way that it scars fewer trees than another fire (i.e., the rate of fire scarring varies among fire years).

A third assumption that must be carefully controlled for during

**Proof : $f(t) = 1 - (1-p)^t$**

We require a function $f(t) \cong f_t$ , where $f_t = M_t / N$ , the proportion of fires found after the $t^{th}$ tree is examined.

Let $p$ = the probability that a tree will record any given fire year.

Then $f_{t+1} @ f_t + p(1- f_t)$

If $f(t) @ f_t$ then $f(0) = 0$, and $f(t+1) = f(t) + p(1-f(t))$

Which yields: $f(t) = p\sum_{i=0}^{t-1}(1-p)^i$ for $t \geq 1$, and 0 otherwise.

Proof by induction:

$$f(1) = f(0) + p(1- f(0)) = p = p(1-p)^0 = p\sum_{i=0}^{0}(1-p)^i$$

Assume $f \quad 3.il174174(1f \quad )$

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