Modeling Forest Growth, Yield, and Wildlife Habitat in the Lake States

A Dissertation
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Alan R. Ek, Advisor

May 2013

Acknowledgements

So many individuals deserve recognition at the culmination of over a decade of post-secondary education. Above all of them, however, is my personal Lord and Savior, Jesus Christ, to Whom belongs complete credit and thanks for this milestone and the ones to come.

I cannot adequately thank my advisor, Alan Ek, for his guidance, input, advice, generosity, care, and friendship throughout my graduate journey. I could not ask for a better mentor than him. Very special thanks to the members of my committee, Thomas Burk, Anthony D'Amato, and Gary Oehlert, for their thoughtful advice and suggestions during my graduate experience.

My family has shown unequivocating support throughout my educational pursuits. Most of all, I would like to thank my best friend and wife for her companionship and patience through the latter days of this work. I love you so dearly. Thanks to my son for brightening my nights after long days. I cannot express sufficient thanks to my parents, Ken and Kathy, for the innumerable exhortations, counsels, prayers, and love I have depended upon for the duration of my education. I would not be here if it were not for you. And thanks to my parents-in-law, Rick and Cindy, for their persistent encouragement and refreshment.

Several mentors and peers played an important role as I progressed through my undergraduate and graduate education. Special thanks to John Marshall for his guidance and introducing me to Forest Biometrics and one of the field's brightest, Nick Crookston. The foresight, patience, and care of Nick positioned me to succeed in graduate school and beyond. Thanks to Andrew Robinson for guiding a naive undergraduate toward an exceptional graduate education. Additional thanks to Grant Domke for helping me understand the bigger picture and to Peter Dieser III, Justin Pszwaro, and Janelle Schnadt for excellent conversations ranging from faith to biometrics to basketball. And finally, thanks to all my friends and compatriots in 101B – "The Pride of Green Hall."

Many individuals, agencies, and funding sources deserve thanks for assistance with the different chapters. For chapter two, the authors would like to specifically thank Dr. Mark H. Hansen, formerly of the Northern Research Station, U.S. Forest Service for his considerable help in forming the dataset of remeasured plots and the Forest Inventory and Analysis (FIA) program for the use of their data in this project. Funding for this research was provided by the Forest Resources Interagency Information Cooperative (IIC), funded by the State of Minnesota and the University of Minnesota, Department of Forest Resources. Also, a special thanks to Dr. Anthony D'Amato and Grant M. Domke, University of Minnesota, Department of Forest Resources, for their numerous constructive suggestions.

The authors would also like to thank Dr. Lee Frelich for his advice during the development of chapter three and Peter Dieser III for his constructive comments and suggestions regarding earlier versions of the wildlife model. Thanks to the Forest Vegetation Simulator help staff for assistance and cooperation with chapter four. Finally, for chapters three through six, the authors give special thanks to FIA for the use of their data and to the Department of Forest Resources, University of Minnesota and the IIC for funding these projects.

Dedication

This dissertation is dedicated to my Lord and Savior Jesus Christ. As my life and work are sourced in Him, so the results of both are to His glory. In addition, I dedicate this effort to my family: Tammy, Andrew, and the future little people. And finally to my parents, Ken and Kathy.

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Chapter 1

Introduction

Forestry modeling efforts in the Lake States region (Michigan, Minnesota, and Wisconsin) have produced or applied statistical models for a variety of phenomena, from empirical yield models (e.g., Walters and Ek 1993; Dixon and Keyser 2008) to process models (e.g., Aber and Federer 1992) to forest succession models (e.g., Pastor and Post 1986). However, several gaps remain, including representation of intensive forest management and estimates of wildlife habitat response to forest practices. This dissertation seeks to assist in filling these gaps. The following paper does not represent one comprehensive project, but rather a collection of individual studies that examined and/or modeled various aspects of forest dynamics. Descriptions of these projects follow.

Chapter two compares several datasets from the Forest Inventory and Analysis unit of the U.S. Forest Service for similar utility when developing empirical yield models. In the context of fitting basal area models, the results indicated little practical difference between datasets from different time periods and different sample sizes when used for fitting the models. In addition, several candidate yield models and fitting methods were compared for their applicability and stability over time. These comparisons suggest one model behaves slightly better than the others ($B = b_1 S^{b_2}(1 - \exp(-b_3 A))$, where B = basal area, S = site index, and A = stand age) and that nonlinear mixed-effects fitting procedures are preferred for their potential to improve model projections. This article was published in Forest Ecology and Management, Vol. 262(2), Zobel, J.M., Ek, A.R., and Burk, T.E., Comparison of Forest Inventory and Analysis surveys, basal area models, and fitting methods for the aspen forest type in Minnesota,188-194, Copyright Elsevier (2011).

Chapter three describes efforts toward development of a forest wildlife habitat model. The Wildlife Habitat Indicator for Native Genera and Species (WHINGS) represents the next iteration of the wildlife model from the Generic Environmental Impact Statement (GEIS) for Minnesota (Jaakko Pöyry Consulting, Inc. 1992a). Building off of an extensive literature review, professional expertise, and previous modeling efforts, WHINGS allows forest managers and policy makers to analyze the effects of proposed management scenarios on forest wildlife habitat during an environmental review. In addition, the model can aid the establishment of wildlife management objectives and practices during forest plan development and can estimate current site specific wildlife habitat conditions that will influence timber management. This research proposed several updates to the current habitat suitability index methodology used in the model. A case study demonstrates an application of the model to three 100 year harvest scheduling projections. This work is in preparation for Forest Ecology and Management or similar journal. The authors include John M. Zobel and Alan R. Ek.

Chapter four creates a managed and intensively managed stand version of the Lake States variant of the Forest Vegetation Simulator (LS-FVS). The potential gains from intensive management have been poorly quantified in the Lake States, due to inadequate data and models. However, economic considerations and recent sustainable harvest level research has necessitated quantification and modeling of the increased individual tree growth in intensively managed stands. The FIA database provided the data for model development, and the work focused on updating the large tree diameter growth model in LS-FVS. However, the lack of available managed stand data in the Lake States necessitated defining managed stand subdatasets from FIA data. Results show that using FIA variables for stand treatment and pure/full stocking proved effective at parsing out stands managed using multiple and few stand entries, respectively. Intensively managed stands were defined as those experiencing frequent, varied stand treatments, and an upper percentile of growth ($\geq 90^{th}$ quantile) adequately characterized this intensive management for all species. Updating the current growth model involved determining the model underestimated growth of trees in the newly defined managed stands. After removing the inherent bias in the model, the observed mean undergrowth was converted to an individual tree growth multiplier that increases growth to observed levels. This work is in preparation for Forest Ecology and Management or similar journal. The authors include John M. Zobel and Alan R. Ek.

Chapter five seeks to evaluate the model proposed in chapter four. Evaluation statistics included mean error, standard deviation of the errors, and mean percent error. Ultimately, the level of acceptable error will depend on the user. Still, evaluation procedures for the managed and intensively managed stand version of the LS-FVS growth model showed that errors in diameter growth projections were similar to those found during the validation of the current model. Thus, nearly all species/diameter class combinations had reasonable model errors relative to previous validation efforts. In addition, diameter dependent height growth appeared reasonable, with no egregious violations of typical height/diameter relationships. This work is in preparation for Forest Ecology and Management or similar journal. The authors include John M. Zobel and Alan R. Ek.

Chapter six modified an existing volume yield curve (Walters and Ek 1993) to more accurately represent the entire life of an even aged forest stand (i.e., single cohort). This study made the assumption that across the life of the stand, accumulated stand mortality equals accumulated stand growth (i.e., stand mortality eventually reaches 100%). From among several proposed model forms, a symmetric curve based on an underlying basal area model proved superior. The curve first follows the existing yield model, then departs toward an asymptote at half of an empirically determined maximum stand age, before retreating back down the curve to reach zero yield at maximum age. Conversion of the basal area yield to volume yield follows the equation found in Walters and Ek (1993). In addition, the study provides a modified version of the model for ease of implementation and a mortality yield model. Forest managers and planners tasked with estimating yield (or yield loss) from extended rotations can now obtain more realistic projections for older stands than those given by typical yield models. This work is in preparation for the Northern Journal of Applied Forestry or similar journal. The authors include John M. Zobel, Alan R. Ek, and Tim O’Hara.

Chapter 2

Comparison of Forest Inventory and Analysis surveys, basal area models, and fitting methods for the aspen forest type in Minnesota

John M. Zobel, Alan R. Ek, and Tom E. Burk

The Forest Inventory and Analysis (FIA) unit of the U.S. Forest Service has collected, compiled, and made available plot data from three measurement periods (identified as 1977, 1990, and 2003, respectively) within Minnesota. Yet little if any research has compared the relative utility of these datasets for developing empirical yield models. This paper compares these and other subdatasets in the context of fitting a basal area (B) yield model to plot data from the aspen (*Populus tremuloides* Michx.) forest type. In addition, several models and fitting methods are compared for their applicability and stability over time. Results suggest that the three parent datasets, along with their subdatasets, provide very similar three parameter B yield model prediction capability, but as model complexity increases, variability in coefficient estimates increases between datasets. The absence of data for older aspen stands and the inherent noise within B data prevented the exact determination of an overall best model. However, the model $B = b_1 S^{b_2}(1-\exp(-b_3 A))$ with site index (S) and stand age (A) as predictors was found consistently among the highest in precision and stability. Additionally, nonlinear least squares and nonlinear mixed-effects fitting procedures produced similar model fits, but

the latter is preferred for its potential to improve model projections. The results indicate little practical difference between datasets from different time periods and different sizes when used for fitting the models. Additionally, these results will likely extend to other states or regions with similar remeasurement data on aspen and other forest types, thus facilitating the development of other ecological models focused on forest management.

2.1 Introduction

For many years the U.S. Forest Service has collected inventory data on Minnesota's forests via the Forest Inventory and Analysis (FIA) program. This data has been made available online and includes the last three completed surveys, corresponding to the years 1977, 1990, and 2003, respectively. Each survey required 4-5 years of field work, with the survey date indicating the year of completion. Through the years, the various datasets have provided researchers with a source of forestry data representative of all Minnesota. In particular, Walters and Ek (1993) utilized the 1977 survey data to develop a system of linked yield models for basal area, density, and merchantable volume, among others, for 14 forest types in Minnesota.

As time passes and more data becomes available, questions arise as to the utility, similarity, and compatibility of the datasets for yield model building. For example, the sampling methodology was revised before each subsequent survey in an attempt to improve data quality, usefulness, and efficiency. In addition to methodological changes, possible physical differences between the three surveys include the size, representative quality, and scope of each dataset; the inherent weather during the years prior to measurement; and the stand treatments conducted since the last survey. Typical users often utilize only the most recent available data, for obvious reasons. However, in the context of model building, the methodological changes should theoretically have little effect on parameter estimates. Still, the physical differences may produce varying model fits. Therefore, this paper asks three questions related to the FIA data available for Minnesota: (1) which dataset (or subdataset or combination of datasets), if any, has the most utility/reliability for building yield models, specifically an aspen (*Populus tremuloides* Michx.) basal area (B) yield model; (2) which B model fits the best with respect to the available data (including all three surveys collectively) and best extrapolates per the usual assumptions; and (3) which fitting method yields the most credible parameter estimates across measurement periods. The answers to these questions will likely have relevance for other states or regions with similar remeasurement data on aspen and other forest types, thus facilitating the development of other ecological models focused on forest management.

Criteria for determining the optimal dataset, model form, and fitting method involves comparing coefficient estimates, fit statistics (root mean square error (RMSE) and R^2), plotted curves, and/or residual plots from the following: (1) the same model fit to each dataset, (2) each model fit using the same dataset, and (3) the same model derived via each fitting method and the same dataset. Determining the best model form also includes evaluating the theoretical properties (both statistical and ecological) of each form.

2.2 Methods

2.2.1 Data

The parent datasets compared in this study were all obtained from the FIA online database (see http://199.128.173.17/fiadb4-downloads/datamart.html). Due to constant improvements in the sampling scheme and information collected, several differences exist between the 1977/1990 and 2003 surveys. For example, the first two surveys used a variable radius, 10-point cluster plot design, sampled on a periodic basis (each decade) (Leatherberry et al., 1995). The survey completed in 2003 used a fixed radius, 4-subplot design, with 20% of the plots in the State measured per year, with all the plots being measured in five years (FIA, 2008). Other changes in 2003 included the further breakdown of plots into conditions and updates to the forest type determination algorithm to include more types. However, across all three surveys, the plot layout encompassed roughly the same area, approximately one acre (see LaBau et al. (2007) for graphical representations of both designs). Many plots have been revisited during all three measurement periods, but many have also been either retired or introduced as new plots in the subsequent surveys. In 1990, numerous undisturbed plots were not actually revisited, but characterized via projection with the STEMS growth model (Belcher et al., 1982; Leatherberry et al., 1995).

At the time of this study, the online database included all inventory information for Minnesota dating back to the 1977 periodic inventory through the annual measurements in 2007. The database contained three completed surveys (i.e., a complete measurement of all FIA plots across Minnesota) and 80% of the most recent survey (completed in 2008, but not yet fully processed). This study focused on the three completed surveys and subsets of these datasets (subdatasets) as described below (CON1-CON4).

2.2.1.1 CON1

Through considerable assistance from the U.S. Forest Service Northern Research Station's FIA staff, 5,141 plots were identified that had been measured in all three surveys (excluding projected plots but including nonforest plots), of which 378 maintained an aspen forest type across periods (see Table 2.1). This dataset is referred to as CON1 ("constraint one").

However, even with the availability of the remeasurement data in CON1, B yield instead of B growth was modeled for several reasons. First, FIA remeasurement data represents a broad range of stand conditions, from undisturbed to heavily managed, and differs considerably from research plot data. Additionally, the majority of FIA plots show signs of some interruption in the usual growth patterns. Thus most plots have modest value for modeling growth, but are useful for describing yield. Second, the aspen forest type has by far the most observations (plots) in every FIA survey in Minnesota. However, extending this research to the other forest types considered in Walters and Ek (1993) will encounter much smaller sample sizes, often too sparse to create precise yield (or growth) models without grouping data from various measurement periods. Finally, yield measurements/estimates often provide starting conditions for growth models, and thus developing yield models will aid the implementation of growth models if and when they become available.

Table 2.1. Aspen datasets considered in this study and their sample sizes.

Constraint[a]	Survey Completion Year			Total[b]
	1977	1990	2003	
CON1	378	378	378	1,134
CON2	585	585	585	1,755
CON3	652	706	653	n/a
CON4	3,417	4,410	1,564	n/a

[a] CON1 = remeasured plots that remain aspen across all periods

CON2 = remeasured plots that start aspen, but may have changed type over time

CON3 = aspen plots determined independently within each survey from among remeasured plots

CON4 = aspen plots determined independently within each survey from all plots

[b] Total = all three surveys combined

2.2.1.2 CON2-CON4

We defined additional datasets based on alternative constraints: CON2 – the set of remeasured plots that start as aspen in 1977, but were allowed to maintain or change their forest type in one or both of the next two surveys; CON3 – the set of aspen plots that were determined independently within each survey from among the collection of *remeasured* plots; CON4 – the set of aspen plots that were determined independently within each survey from among the collection of *all* plots. In other words, we followed individual plots through time in CON1 and CON2, with each constraint defining a dataset with the same number of plots in each survey year (see Table 2.1). For CON3 and CON4, we applied a cross sectional approach, with each constraint defining a unique (and different) number of plots in each survey year.

Table 2.1 provides all sample sizes and Table 2.2 gives basic descriptions of the datasets under the first and last constraints (the summary statistics for CON2 and CON3 roughly resemble those from CON1). Note that without disturbance, the sequential survey datasets under CON1 should have mean ages roughly 10 years apart, a fairly constant mean site index, and increasing mean basal area. However, the summary statistics in Table 2.2 do not follow this pattern, suggesting the influence of management actions, natural disturbance, sampling distribution changes, or even measurement inconsistencies on the within plot values (e.g., annual rings in aspen trees are notoriously difficult to read, thus making age determination problematic). Note this observed influence relates to the first question of this study regarding the utility of the different datasets.

In an attempt to provide adequate comparison of the FIA surveys, subdatasets were defined as every combination of dataset (CON1 – CON4) and measurement period (1977, 1990, 2003), in addition to the CON1 and CON2 totals (i.e., all years combined), providing a total of 14 datasets for examination. These datasets were compared for their ability to produce similar B model performance (i.e., in terms of parameter values, fit statistics, and predictions). In addition, the diversity among the datasets allows us to investigate B model stability over time and under various conditions. Model stability (or lack of it) is important for model usage, since this characteristic embodies sampling error and changes in the environmental factors that influence growth and subsequently yield. However, this stability may only tell a partial story. Other influences on B yield, such as the age class distribution of plots, might change considerably. Also, the model used to estimate B may tend to force a stable model form, and thus the strength of conclusions drawn from consistent model fits may be limited.

Table 2.2. Summary statistics for stand age (years), site index (m), and basal area ($m^2\ ha^{-1}$) in datasets under CON1 and CON4, separated by survey year (and combined survey years (Total)).

Const.	Statistic	Stand Age				Site Index				Basal Area			
		1977	1990	2003	Total	1977	1990	2003	Total	1977	1990	2003	Total
CON1	Mean	33.6	33.9	37.4	35.0	20.3	21.0	19.7	20.3	2.7	2.6	2.9	2.8
	Median	35	31	37	35	20.4	21.2	19.8	20.4	2.6	2.6	3.0	2.7
	St. Dev.	20.8	22.7	21.3	21.7	3.5	3.0	3.4	3.3	1.5	1.5	1.5	1.5
	Min	1	0	1	0	11.0	13.4	4.9	4.9	0	0	0	0
	Max	129	136	100	136	30.2	29.0	30.5	30.5	7.6	7.3	7.4	7.6
	n	378	378	378	1,134	378	378	378	1,134	378	378	378	1,134
CON4	Mean	37.3	40.9	38.7	39.2	20.3	20.7	19.1	20.3	2.8	2.9	2.8	2.9
	Median	40	44	40	42	20.4	20.7	19.2	20.4	2.7	2.9	2.8	2.8
	St. Dev.	19.5	23.8	24.4	22.5	3.5	3.3	3.6	3.5	1.5	1.6	1.6	1.6
	Min	1	0	0	0	7.0	5.8	4.9	4.9	0	0	0	0
	Max	129	232	230	232	30.2	30.2	30.5	30.5	8.0	16.7	9.6	16.7
	n	3,417	4,410	1,564	9,391	3,417	4,410	1,564	9,391	3,417	4,410	1,564	9,391

2.2.2. Models

Two primary B yield models were considered in this study (equations 2.1 and 2.2), along with three variations of equation 2.1:

$$B = b_1 S^{b_2} A^{b_3} \tag{2.1}$$

$$B = b_1 S^{b_2} (1 - \exp(-b_3 A)) \tag{2.2}$$

$$B = b_1 S^{b_2} A^{b_3} - A^{b_4} \tag{2.3}$$

$$B = b_1 S^{b_2} A^{b_3} - b_4 A \tag{2.4}$$

$$B = b_1 S^{b_2} A - b_3 A^{b_4} \tag{2.5}$$

where B = stand basal area (m^2 ha^{-1}) for all trees with diameter at breast height (dbh) > 2.413 cm or > 2.54 cm, depending on the survey year, S = stand site index (m) (base age = 50 years; see FIA (2008)), and A = stand age (years). Models (2.1)-(2.5) are hereafter referred to as M1 – M5, respectively. M1 comes directly from Walters and Ek (1993), where this equation was used to project B in aspen stands, along with 13 other common forest types in Minnesota. The variations of M1 (M3-M5) were conjectured in an attempt to find a model that expressed a decline in B as an aspen stand moved into older ages, primarily due to mortality and successional processes (Pothier et al. 2004; Schwalm 2009). However, very little FIA data is currently available in the older age classes to observe this trend. M2 resembles the exponential model discussed by Grosenbaugh (1965) and was selected for its asymptotic property. Ultimately, these five model forms were chosen for their empirical elasticity and simplicity of structure, ensuring ease of use during model applications. All stand variable data for fitting these models came directly from the FIA database and were subject to FIA definitions (see FIA (2008) for further details).

Models M1 and M2 were fit to all 14 datasets, and M3 – M5 were fit to a portion of the datasets (due to the similarity of additional fits). Overall, the models provide a range of B curves for determining the most empirically appropriate model and an avenue for comparing the various datasets through exploring model consistency.

2.2.3 Fitting Methods

Since the candidate models all had nonlinear forms, two nonlinear methods were selected to fit the models, including nonlinear least squares (NLS or GNLS) and nonlinear mixed-effects (NLME). The difference between NLS and GNLS relates to the error structure of the model, with NLS typically assuming constant variance and independent errors, whereas GNLS allows for non-constant variance and/or correlated errors. M1 and M2 were fit using NLS to all constraint/survey combinations, and the three model variations were fit using NLS to a subset of these 12 datasets.

CON1 defined a parent dataset that follows specific aspen plots over all three measurement periods. This facilitated the use of a hierarchical (multilevel) fitting approach (e.g., NLME) with two levels, a base level (a plot/survey combination) and a group level (a plot). Many studies within forestry have used this fitting approach (Budhathoki et al. 2008; Calegario et al. 2005; Garber and Maguire 2003; Gregoire and Schabenberger 1996; Hall and Bailey 2001; Hall and Clutter 2004; Yang et al. 2009, among others). The hierarchical fitting methodology allows specified model parameters to vary by group (typically referred to as random effects) through being modeled themselves. In effect, each plot was allowed to have its own unique parameter value(s), with all parameters described by a linear model with no predictor. The NLME approach fits both the parameter models and the overall model simultaneously while accounting for the within group and between group variability. This method produces essentially the same results as the NLS approach when no group parameters are modeled. When using NLME to fit all five models, every model parameter was in turn allowed to vary and in some cases two varied together.

An advantage to using a hierarchical approach is an increased overall sample size (through combining the measurement periods), which may help to reduce or mitigate the negative effects of unmet regression assumptions resulting from small datasets. However, use of all the remeasurement data may lead to the presence of autocorrelation between model residuals. Therefore, the models were fit with and without adjustment for autocorrelation to observe its presence and magnitude (note that this correlation differs from that between model parameters, which quantifies how the parameters vary together and depends on the model form, not the data). For more information on hierarchical modeling approaches, see Gelman and Hill (2007). The statistical package R and the basic function nls and the functions nlme and gnls (from package "nlme") were used to conduct all model fitting (R Development Core Team 2011).

2.3 Results and Discussion

2.3.1 Data Comparisons

For models M1 and M2, the model fits produced similar coefficients and curves (see Tables 2.3 and 2.4 and Figure 2.1). The figure shows that the B estimates remain within roughly a 0.35 m^2 ha^{-1} range throughout the duration of the projection period (150 years), suggesting considerable uniformity between datasets when used to build similar model forms. The fitting of M3 – M5 produced different coefficient estimates and quite different curves (see Tables 2.3 and 2.4 and Figure 2.1). This result is not wholly unexpected, with M3 – M5 containing a fourth parameter that not only allows B to decline at older ages, but makes the models more sensitive to variations between datasets and their extent of age class representation. Specifically, the high variability between estimates of the same M4 coefficients indicated severe instability of this model form. Further examination of M4 indicated this instability was due to ill-conditioning, with near perfect correlation between model parameters. Therefore, M4 was dropped from the final reporting. Still, for the remaining four models and across a specific range of ages, the percent differences in yield decline with age for separate fits of the same model (until extreme ages for M1 and M2 and approximately age 70 years for M3 and M5).

Table 2.3. Parameter estimates, RMSE, and R^2 for the NLS model fits to the individual surveys. Due to space limitations, only the CON1 and CON4 model fits were reported, as the CON2 and CON3 fits closely resembled those from CON1.

Model	Const.	Year	b_1	b_2	b_3	b_4	RMSE	R^2
M1	CON1	1977	0.07	0.73	0.44	n/a	1.09	0.47
		1990	0.08	0.61	0.49	n/a	1.04	0.52
		2003	0.14	0.52	0.43	n/a	1.19	0.40
	CON4	1977	0.06	0.72	0.47	n/a	1.13	0.42
		1990	0.05	0.73	0.50	n/a	1.14	0.49
		2003	0.07	0.72	0.45	n/a	1.24	0.43
M2	CON1	1977	0.60	0.63	0.04	n/a	1.08	0.48
		1990	0.88	0.51	0.04	n/a	1.01	0.54
		2003	0.88	0.50	0.05	n/a	1.18	0.41
	CON4	1977	0.55	0.67	0.04	n/a	1.13	0.41
		1990	0.58	0.67	0.03	n/a	1.13	0.50
		2003	0.55	0.66	0.04	n/a	1.24	0.44
M3	CON1	1977	1.13	0.03	1.01	1.05	1.08	0.48
		1990	1.12	0.02	1.05	1.09	1.01	0.54
		2003	1.23	0.06	0.72	0.78	1.19	0.40
	CON4	1977	0.41	0.41	0.36	0.21	1.13	0.42
		1990	1.10	0.05	0.89	0.93	1.13	0.50
		2003	1.13	0.07	0.77	0.82	1.24	0.44
M5	CON1	1977	0.25	0.12	0.15	1.17	1.08	0.48
		1990	0.27	0.10	0.16	1.15	1.01	0.54
		2003	-0.25	-0.12	-0.53	0.81	1.20	0.39
	CON4	1977	-0.35	-0.27	-0.45	0.82	1.13	0.41
		1990	-0.73	-0.07	-0.85	0.94	1.13	0.50
		2003	-0.29	-0.20	-0.48	0.82	1.24	0.43

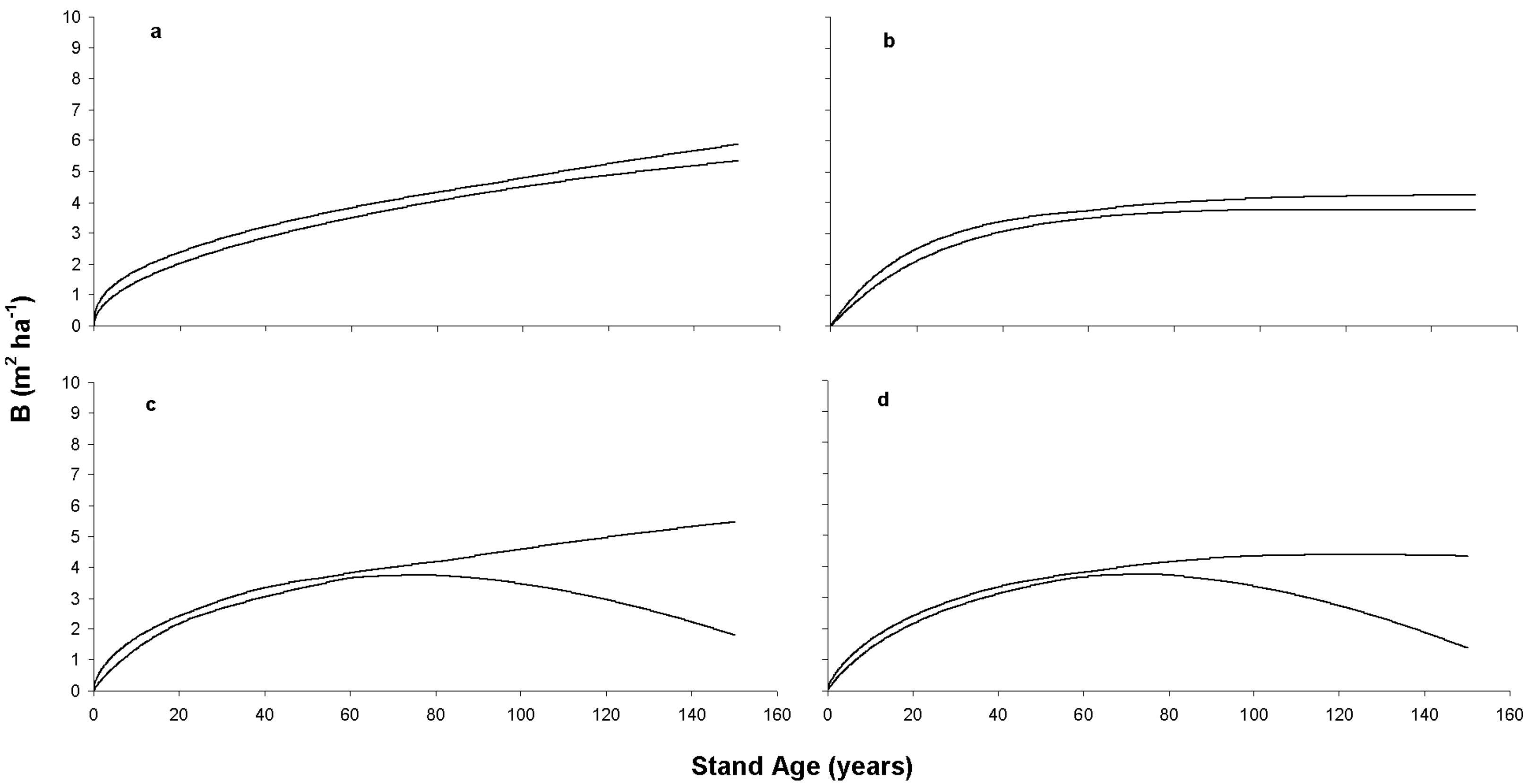

Figure 2.1. Ranges of all four aspen B yield model curves, with the upper and lower curves representing the fits with the highest and lowest projected B for a specific stand age, respectively. All projections cover 150 years with SI = 20 m. Graphs (a,b) correspond to the M1 and M2 model fits to all the constraint/survey combinations (via NLS) and the CON1/CON2 totals (via GNLS), respectively. Graphs (c,d) correspond to the M3 and M4 model fits to the CON1/survey and CON4/survey combinations (via NLS) and the CON1/CON2 totals (via GNLS), respectively.

These results suggest the methodological changes and physical differences between measurement periods do not substantially affect model fits. In particular, the choice of dataset (and its associated size) does not appear to play a significant role in model quality for any of the four models (at least up to the data deficient older age classes). Also, curve uniformity indicates the differences in weather and treatment history between the surveys have little influence on model results.

Overall, no dataset or subdataset appears to provide better performance than another. When considering aspen B yield models with three parameters and site index and stand age as explanatory variables, the choice of dataset makes little difference. However, as the models grow in complexity, the choice of dataset and the associated extent of age class representation become more important.

2.3.2 Model Comparisons

Tables 2.3 and 2.4 give the parameter estimates and the statistics RMSE and R^2 for each model fit. R^2 is simply the correlation between the fitted and actual values. As discussed above, the three parameter models (M1, M2) demonstrate greater stability over time and across datasets than the four parameter models (M3, M5). Figure 2.2 gives the combined range of all four model curves superimposed over the B data from the individual surveys under CON4. This figure shows that for a projection length within the range of data, the models differ little from one another, but as the models move past the data, the curves begin to separate and make extrapolation questionable. Unfortunately, insufficient empirical data for stands >100 years is available within these datasets to aid in the selection of the best model. In addition, B data with respect to age in FIA records is inherently noisy, also hindering the choice of a preferred model. However, upon closer inspection, the three parameter models display slightly different characteristics relative to one another (due to the variations in model form). Under M1, B increases monotonically across all ages, whereas B remains nearly constant for older ages under M2, with the curve nearing an upper asymptote.

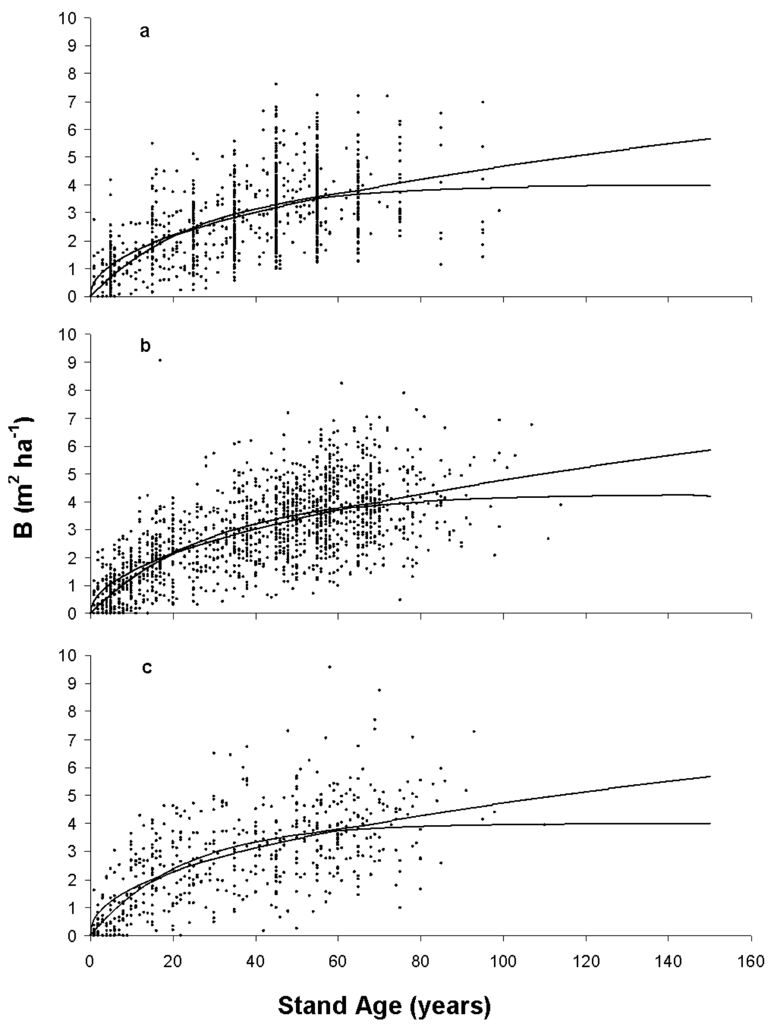

Figure 2.2. Combined range of all four aspen B yield model curves fit to the individual survey years under CON4 and superimposed over the corresponding raw data (when SI = 18.5-21.5 m). All projections cover 150 years with SI = 20 m. Graphs (a-c) correspond with the 1977, 1990, and 2003 surveys, respectively.

Note that the main objective of comparing FIA measurement periods necessitated the use of entire datasets (or subdatasets) during model fitting. Still, the relationship between the parent datasets and their subdatasets acts as a surrogate for the subsetting typically associated with model validation and evaluation of prediction capability. Additional analyses of these latter two properties were not conducted, as the results showed that a particular model fit to the various datasets and their subsets yielded similar curves, suggesting the prediction capability is roughly the same for the different fits of the same model. Also, the use of published base model forms led to the objective of determining the best *relative* model from among those considered, with less emphasis on model validation.

Aspen is a pioneer species that develops in the form of even-aged stands. Thus, these stands will decline in B as the stand moves beyond maturity and yet retains the aspen forest type (Pothier et al. 2004; Schwalm 2009). The inclusion of M3 – M5 sought to explore model forms that reduce B after some age threshold. As seen in Figure 2.1, this was only partially successful with some datasets, and again, aspen stand behavior at older ages remains to be clarified for FIA plots. Schwalm (2009) encountered this dilemma during a study on sustainable harvest levels in Minnesota, where he used FIA data and updated yield equations from Walters and Ek (1993). His proposed solution involved projecting yield via the equations until the stand reached a specified threshold, then decline yield at the same rate it increased before attaining that threshold. In essence, yield followed a symmetric, concave down curve, with an empirically defined maximum. Without observed data, this postulated solution from Schwalm (2009) may represent the most workable approach to modeling B across the life of an undisturbed and unmanaged aspen stand, or at least until the stand converts to another forest type.

The inconclusive results suggest the choice of model form will depend on the needs of the modeler and the available empirical data. Still, aspen B models with three parameters provide stable models across the FIA measurement periods within Minnesota and appear to mimic B patterns adequately for many purposes. In particular, M2 may give the best overall representation and consistency of the models considered, as this model approaches an asymptote that prevents B from increasing without bound (as discussed in Pienaar and Turnbull, 1973). Many forestry simulation models are similarly constrained, including STEMS (Belcher et al. 1982), FVS (Dixon 2002; Stage 1973), and SORTIE (Murphy 2010), among others.

As evident in Figure 2.2, all curves initiate at the origin (0,0). This would seem logical, as a stand with zero age should have zero B. However, the data also suggest that many stands have no B at very early ages and some have substantial B at young ages. Presumably, the former (and much more prevalent) are previously clearcut stands still dominated by regeneration too small to record B, and the latter are harvested stands with residual trees. Ek and Brodie (1975) described some of these dynamics in their modeling of aspen regeneration.

An average stand age for those plots with zero B was calculated at approximately 4.6 years across datasets, and thus models constrained to begin at (5,0) were fit and subsequently compared to the original model fits. Both sets of models produced essentially identical parameter estimates and fit statistics, but the constrained model curves seemed to ocularly fit the younger age data better than curves passing through the origin. The best starting age as determined by observing these curves differed little by dataset.

2.3.3 Fitting Method Comparisons

Table 2.4 gives the fixed parameter estimates, fit statistics, and estimated autocorrelation coefficient (phi) for models fit to the total CON1 data. When a random effect was included in the model, the fixed effect is simply the arithmetic mean of the unique plot coefficients. All models were fit with and without adjusting for autocorrelation (via GNLS and NLS, respectively). The data format (two remeasurements) and the fits without adjustment suggested the use of an autoregressive model (of order one, i.e., an AR(1) model) would adequately compensate for autocorrelation. Comparison of the coefficient estimates, along with the fairly high phi values, suggests a definite effect due to autocorrelation, and therefore all NLME fits accounted for this dependency between measurements. Still, the general similarity between the NLS and GNLS model fits is not surprising. The moderately large sample size (378 plots), similarity between datasets, and fixed (0,0) origin suggest any curve fit to the data will likely follow a similar path. Therefore, although accounting for autocorrelation certainly improved model fits, the extent of improvement was not overwhelming.

Table 2.4. Parameter estimates, RMSE, R^2, and estimated autocorrelation coefficient (phi) for the NLME model fits to the totaled CON1 data, along with the NLS (unadjusted for autocorrelation) and GNLS (adjusted for autocorrelation) fits. The GNLS fits resemble the NLME fits, except all parameters are fixed. Due to the NLME fits of the four parameter models being essentially identical to their respective GNLS fits, the former were excluded from the table. Also, the NLME fits with multiple random effects were only reported when they differed from their associated GNLS fits.

Model	Method	Random	b_1	b_2	b_3	b_4	RMSE	R^2	phi
M1	NLS	n/a	0.10	0.58	0.46	n/a	1.11	0.46	n/a
	GNLS	n/a	0.11	0.55	0.45	n/a	1.11	0.46	0.38
	NLME	b1	0.11	0.55	0.45	n/a	1.11	0.46	0.38
	NLME	b2	0.11	0.53	0.47	n/a	0.95	0.69	0.20
	NLME	b3	0.11	0.53	0.47	n/a	0.94	0.70	0.21
	NLME	b2,b3	0.11	0.53	0.48	n/a	0.96	0.68	0.27
M2	NLS	n/a	0.83	0.52	0.04	n/a	1.09	0.47	n/a
	GNLS	n/a	0.95	0.47	0.05	n/a	1.10	0.47	0.41
	NLME	b1	0.95	0.47	0.05	n/a	1.10	0.47	0.41
	NLME	b2	1.02	0.45	0.05	n/a	0.94	0.69	0.23
	NLME	b3	0.95	0.47	0.05	n/a	1.10	0.47	0.41
M3	NLS	n/a	1.17	0.03	0.96	1.00	1.10	0.47	n/a
	GNLS	n/a	1.18	0.02	1.02	1.06	1.11	0.47	0.42
M5	NLS	n/a	0.64	0.04	0.48	1.07	1.10	0.47	n/a
	GNLS	n/a	0.33	0.06	0.18	1.16	1.11	0.47	0.43

The different NLME and GNLS fits show little variation in fixed coefficient estimates, but for the three parameter models, modeling b_2, b_3, or both b_2 and b_3 significantly reduced RMSE (by 0.15-0.17 m^2 ha^{-1}) and increased R^2 (by 22-24%) (Table 2.4). However, calculating the same fit statistics using only the fixed coefficient estimates revealed negligible differences between the two methods.

When using NLME, the group parameter modeling yields estimates for each plot (random effects) and estimates for all the parameters across plots (fixed effects). Having coefficients for each plot does not provide the typical user with relevant information, as each estimate depends directly on the specific plot conditions and may not reflect the aspen stand of interest. Yet when the random effects improve the model fit, the fixed effects estimates from NLME more thoroughly represent the average stand conditions than general NLS. Thus, with the availability of correlated remeasurement data, the NLME fitting method is preferred when building yield models, even if the potential improvement is only modest. Still, the results suggest that the GNLS method can be used with little loss of precision.

2.4 Conclusions

This paper asked three questions regarding the FIA data available for Minnesota. (1) Concerning which dataset (or subdataset or combination of datasets) has the most utility/reliability for building a B yield model, the results suggest that every dataset considered produces remarkably similar three parameter models, indicating the choice of dataset is trivial when fitting this type of model form. As the yield models become more complex (four parameters and higher), the differences between datasets become more pronounced in the older ages (due to sparser data). (2) When determining the optimal model from among the candidate B yield models, the results indicate minimal differences between the behavior and quality of the various forms explored. Still, the three parameter models demonstrated considerable consistency across the projection range, whereas the four parameter models produced erratic behavior when extrapolated across the older ages and beyond the range of data. Among the consistent models, M2 may prove slightly more desirable, as this model form prevents B from increasing without bound. (3) Regarding which fitting procedure yields the most credible parameter estimates across measurement periods, the results showed that the NLS (or GNLS) and NLME approaches produced essentially identical model fits. Including a random effect for certain parameters in the three parameter models did lower RMSE and raise R^2, but the fixed effects estimates and their respective fit statistics changed negligibly. Still, the gains from including random effects do lead to slightly more representative models, and thus when working with remeasurement data, the NLME approach may at most yield preferred coefficient estimates over the NLS method and at least produce similar fits. These conclusions should readily transfer to other states or regions with similar remeasurement data on aspen and potentially other forest types. Also, these results should aid the development of other ecological models designed to enhance forest management.

Chapter 3

The Wildlife Habitat Indicator for Native Genera and Species (WHINGS) methodology and application in Minnesota

John M. Zobel and Alan R. Ek

The Wildlife Habitat Indicator for Native Genera and Species (WHINGS) represents the next iteration of the wildlife habitat model created for the Minnesota Generic Environmental Impact Statement. WHINGS allows forest managers and policy analysts to examine the impacts, both positive and negative, of proposed management scenarios on forest wildlife habitat during environmental review. In addition, the model can aid the synthesis of wildlife management objectives and practices during forest plan development. Further, the model can estimate current site specific wildlife habitat conditions that may influence other aspects of forest management. This research proposed several updates to the current habitat suitability index methodology used in the model. A case study for St. Louis County, Minnesota demonstrated an application of the updated model to three alternative, 100 year harvest scheduling projections. The output from WHINGS revealed differing habitat trends between harvest schedules and highlighted those species most affected by the proposed management alternatives. However, the results also illustrated the fact that any sustainable change in forest habitat will benefit some species and negatively impact others. Thus, the significance and utility of WHINGS results will depend on the user and the criteria surrounding their particular

application. Finally, WHINGS has potential to significantly reduce the time and financial burden associated with environmental review of large forest based projects in Minnesota.

3.1 Introduction

The relationship between forest management and wildlife habitat has garnered steadily increasing attention since the late 1980s. In particular, as a response to concerns over rising timber harvest rates, the state of Minnesota initiated the creation of a statewide generic environmental impact statement (GEIS) on timber harvesting and forest management (Jaakko Pöyry Consulting, Inc. 1994). The GEIS and associated technical papers addressed questions regarding the condition and sustainability of various components of local statewide ecosystems under different harvesting scenarios. When considering forest wildlife habitat, the research team quantified habitat abundance and quality using a matrix of species habitat preferences determined through literature review and personal expertise (Jaakko Pöyry Consulting, Inc. 1992a). This matrix was then summarized into habitat suitability indices (HSI) for those forest dependent species native to Minnesota. The GEIS team calculated HSI values for 136 bird species (including ruffed and spruce grouse), 22 small and medium mammals, four large mammals, and eight herptofauna (see Frelich et al. (2013) for a list of species and their habitat preferences). Changes in HSI values within the different harvesting scenarios were observed and used during the environmental impact analysis of the alternative schedules.

Ten years after the completion of the GEIS, a follow-up study assessed the accuracy of the GEIS projections, suggesting modest similarity between actual and predicted habitat conditions (Kilgore et al. 2005). Recent work by Frelich et al. (2013) updated the original habitat matrix and modified several HSI formulae to reflect the latest research on various wildlife species. Their work also sought to outline a method for rapidly assessing wildlife impacts for local (or regional) environmental impact statements within Minnesota.

This study seeks to extend the work of Frelich et al. (2013) through converting their results into a computerized version accessible to forest managers and planners. The new model, known as the Wildlife Habitat Indicator for Native Genera and Species (WHINGS), will use readily available cross-sectional data or longitudinal data (with respect to time) to compute HSI values for all included wildlife species. In addition, this research proposed several updates to the HSI methodology, including (1) conversion of the existing scale (0, ∞) to a more traditional scale (0-1); (2) replacing the linear abundance coding for birds with more representative nonlinear codes; and (3) relaxing the forest cover requirements for black bear, white-tailed deer, and moose. A case study for St. Louis County, Minnesota will exemplify the use of WHINGS when forecasting habitat trends and comparing management alternatives, thus providing opportunity for critique. The final model will allow users to reduce the time and financial commitment associated with determining wildlife impacts during an environmental review, establish wildlife management objectives and practices when developing a forest plan or related document, and estimate current site specific wildlife habitat conditions that may impact forest management.

3.2 Methods

3.2.1 Input Variables

HSI calculations follow two basic forms in WHINGS: a weighted average of abundance values (birds, small and medium mammals) and species or species group specific HSI equations (grouse, large mammals, herptofauna). The former rely upon the updated GEIS database matrix of species-habitat relationships, with abundance values organized by forest type, stand size class, and ecoregion and weighted by stand area. The latter depend on the same variables, with the addition of Minnesota county location for white-tailed deer. These variables define species specific habitat preferences (and their amount) and whether the species temporal range falls within the area of interest. Description of these variables follows below.

3.2.1.1 Forest Type

A forest type represents the predominant vegetation cover on a specified land area, often in terms of an individual tree species or a species group. Forest types typically include a variety of species, with the designated type determined by the species (one or more) comprising the majority of stocking. This approach is used by the U.S. Forest Service Forest Inventory and Analysis (FIA) program (Arner et al. 2001; Woudenberg et al. 2011). The GEIS defined its own forest types using basal area rather than stocking to simplify, yet still approximate the method used by FIA and facilitate projection of future forest type conditions (Jaakko Pöyry Consulting, Inc. 1992a; Jaakko Pöyry Consulting, Inc. 1992b). The Minnesota Department of Natural Resources (MNDNR) uses its own definitions for determining forest type (MNDNR 2012). WHINGS provides the option of using any of these three typing methods (see Appendix 1 for a forest type crosswalk between approaches).

3.2.1.2 Stand Size Class

A size class represents the predominant tree size or stage of tree development within a forest stand or landscape, e.g., seedling/sapling, poletimber, and sawtimber. The GEIS used these three size classes to maintain consistency with those used by FIA (Jaakko Pöyry Consulting, Inc. 1992a). FIA defined the three size classes based on the stocking majority of large diameter trees (≥ 11.0-in for hardwoods; ≥ 9.0-in for softwoods), medium diameter trees (≥ 5.0-in and less than large trees), or small diameter trees (< 5.0-in), with diameters measured at dbh (Woudenberg et al. 2011). However, the GEIS calculated projected size class based on stand age class and site quality, using the same dbh criteria (Jaakko Pöyry Consulting, Inc. 1992a). Likewise, some users may have difficulty determining the required size class data for their stands. Therefore, WHINGS includes an option for generating size class information from age class data (see Appendix 2 for a detailed description).

3.2.1.3 Ecoregion

For the purposes of this model, an ecoregion within Minnesota represents a collection of similar physical and biophysical characteristics as they relate to forest communities (Jaakko Pöyry Consulting, Inc. 1992a). Boundaries between the nine ecoregions identify significant shifts in ecological attributes, and wildlife population dynamics often differ between each region. Therefore, determining the ecoregion that contains the forest stand or landscape of interest is necessary for producing accurate model estimates. The GEIS uses nine broad ecoregions in Minnesota, but the U.S. Forest Service and the MNDNR further delineated these nine to define a total of 27 and 26 relevant ecoregions, respectively (Cleland et al. 2007; MNDNR 2000). WHINGS allows users to specify their preferred ecoregion definitions before using the model. See Figure 3.1 for the GEIS ecoregions and Appendix 3 for an ecoregion crosswalk between definitions.

Figure 3.1. GEIS ecoregions defined for the wildlife model (from Jaakko Pöyry Consulting, Inc. 1992a). See Cleland et al. (2007) and MNDNR (2000) for alternative and more detailed versions.

3.2.1.4 Stand Area

Stand area represents the area (in acres, hectares, or other unit) of unique divisions (i.e., stands) within the analysis unit. These divisions are defined by differences in forest type, size class, ecoregion, or county. HSI calculations use stand area as a weighting factor when combining HSI values across stands (birds, small and medium mammals), or as input values in HSI equations (grouse, large mammals, herptofauna).

3.2.1.5 Minnesota County

The county in Minnesota that contains the area of interest has significance for the white-tailed deer HSI equation. Deer have different habitat requirements depending on their location or zone in the state (see Frelich et al. (2013) for further details). WHINGS recognizes three distinct deer zones in Minnesota (see Appendix 4 for a list of the counties that define each deer zone).

3.2.2 Habitat Suitability Index (HSI)

Frelich et al. (2013) give full discussion and justification for using HSI methodology in WHINGS, which has seen much use in the wildlife research community (Terrell and Carpenter 1997; Morrison et al. 2006; USFW 1981). In summary, HSI values provide coarse measures for describing species-habitat relationships and habitat availability, with higher values indicating abundant favorable habitat for that particular species and low values indicating poor, limited habitat. However, though a species HSI value may approach an optimum, this does not guarantee the species will actually frequent the area, but only that the area represents ideal habitat for that species. Many other factors impact a species population size besides the presence of habitat (see Frelich et al. (2013) for further discussion).

HSI values are calculated using functions that incorporate species habitat preferences. In WHINGS, these calculations rely on the updated GEIS database matrix of species-habitat relationships (Frelich et al. 2013). The HSI formulae for the WHINGS species groups are given below.

$$HSI_{birds} = \left(\sum_{i=1}^{H}(AC_i * acres_i)/\sum_{i=1}^{H} acres_i\right)/\max(AC) \tag{3.1}$$

$$HSI_{grouse} = \frac{Habitat\ acres}{All\ acres} \tag{3.2}$$

$$HSI_{SMM} = (\sum_{i=1}^{H}(AC_i * acres_i)/\sum_{i=1}^{H} acres_i)/\max(AC) \tag{3.3}$$

$$HSI_{LM} = individual\ species\ weighting\ factors \tag{3.4}$$

$$HSI_{herps} = \frac{Habitat\ acres}{All\ acres} \tag{3.5}$$

where *AC* = abundance code, *acres* = acres associated with the abundance code, *H* = total number of abundance codes, *Habitat acres* = computed or actual acreage of preferred habitat, *All acres* = total acreage for entire area of interest, *SMM* = small/medium mammals, and *LM* = large mammals. See Frelich et al. (2013) for definitions of habitat acres and individual species weighting factors. The grouse and large mammal groups have individual species specific formulae, given below (see also Table 3.1 for forest type (FT) codes).

$$HSI_{RG} = \left((\overline{SIV})(FT_4) + 0.5(FT_5)\right)/FT_{all} \tag{3.6}$$

$$\text{where } SIV_i = \begin{cases} 3.125(\%\, FT_i) & if\ \%\, FT_i \leq 0.32 \\ 1 & if\ \%\, FT_i > 0.32 \end{cases}, \text{ for } i = 1, 2, 3 \tag{3.7}$$

$$HSI_{SG} = (FT_6 + FT_7 + 0.5(FT_8))/FT_{all} \tag{3.8}$$

$$HSI_{bear} = w_1 + w_2 \tag{3.9}$$

$$\text{where } w_1 = \begin{cases} 2.5(\%\, FT_9) & if\ \%\, FT_9 \leq\ 0.2 \\ 0.5 & if\ \%\, FT_9 >\ 0.2 \end{cases} \tag{3.10}$$

$$w_2 = \begin{cases} 2.5(\%\, FT_{10}) & if\ \%\, FT_{10} \leq 0.2 \\ 0.5 & if\ \%\, FT_{10} > 0.2 \end{cases} \tag{3.11}$$

$$HSI_{moose} = \begin{cases} 10(\%\, FT_{11})/3 & if\ \%\, FT_{11} \leq 0.3 \\ 1 & if\ \%\, FT_{11} > 0.3 \end{cases} \tag{3.12}$$

$$HSI_{deer_1} = \begin{cases} 10(\%\, FT_9) & if\ \%\, FT_9 \leq 0.1 \\ 1 & if\ \%\, FT_9 > 0.1 \end{cases} \tag{3.13}$$

$$HSI_{deer_{23}} = \begin{cases} 2(\%\, FT_{10} + \%\, AC_1) & if\ \%\, FT_{10} + \%\, AC_1 \leq 0.5 \\ 1 & if\ \%\, FT_{10} + \%\, AC_1 > 0.5 \end{cases} \tag{3.14}$$

$$HSI_{deer_4} = FT_{12}/FT_{all} \tag{3.15}$$

$$HSI_{wolf} = \frac{HSI_{moose}(acres_{zone_1}) + \sum_{i=2}^{4} HSI_{deer_i}(acres_{zone_i})}{\sum_{i=1}^{4} acres_{zone_i}} \tag{3.16}$$

where *RG* = roughed grouse, *SIV* = suitability index variable (Rickers et al. 1995), $\overline{SIV}$ = mean SIV, *SG* = spruce grouse, and $deer_i$ = deer zone associated with the deer HSI value.

Table 3.1. Forest type (FT) codes used in the grouse and large mammal HSI equations.

Code	Forest Type	Size Class
FT_1	Aspen	Seedling/Sapling
FT_2	Aspen	Poletimber
FT_3	Aspen	Sawtimber
FT_4	Aspen	All
FT_5	Oak, Maple-Birch	All
FT_6	Black Spruce	All
FT_7	Jack Pine	All
FT_8	Balsam Fir	All
FT_9	Aspen, Birch, Balsam Poplar	Seedling/Sapling
FT_{10}	Oak	Poletimber, Sawtimber
FT_{11}	All (except BS*, T**)	Seedling/Sapling
FT_{12}	All	Poletimber, Sawtimber
FT_{all}	All	All

* BS = black spruce; ** T = tamarack

3.2.3 Methodology Updates

The methods behind WHINGS are given in Frelich et al. (2013). However, when computerizing the model, several updates were made to assumptions and implementation procedures. These modifications increased model consistency with other HSI research and improved model accuracy and utility.

3.2.3.1 Scale

The HSI equations given above differ slightly from those in Frelich et al. (2013). These updated formulae now give unitless results between 0-1, instead of HSI values (i.e., adjusted acres) that ranged between 0-∞. Converting results to the new scale typically involved dividing the original HSI value by the maximum HSI possible. For the large mammals, the HSI formulae naturally give results in the desired scale. This new scale now maintains consistency with typical HSI applications (Beck and Suring 2009; USFW 1981; Shamberger et al. 1982).

In addition, the GEIS used the scale in Frelich et al. (2013) and reported significant projected changes in habitat quality as percent changes > 25%. A problem with this approach occurs when base HSI values are small. In this case, even a slight change in HSI yields a substantial percent change, due to the percent change formula and not necessarily the result of forest management practices. The new 0-1 scale allows for computing absolute *differences* (new HSI – old HSI) that have much better stability than percent changes and can highlight actual significant changes in habitat due to changing forest conditions.

Note that the new scale assumes roughly constant total area of the analysis unit over time. If total area increases or decreases between measurement or projection periods, the new HSI scale will not reflect the potential change in habitat availability. For example, if herptofauna habitat comprised 300 acres in time period zero, and total acreage equaled 1,000, then HSI_{herps} = 300/1000 = 0.3. However, if both habitat and total acreage decreased by 10% in time period one, then HSI_{herps} = 270/900 = 0.3. The HSI values under each period are identical. Thus, the model summarizes habitat suitability and availability *given* the overall analysis unit area remains approximately fixed. Users should consider this assumption in the interpretation of results when using the model.

3.2.3.2 Bird Abundance Codes

In the original GEIS, bird abundance values were number of pairs per 1,500 hectares (3,707 acres), a continuous value (Jaakko Pöyry Consulting, Inc. 1992a). Some less researched species were assigned a 0-5 code that represented ranges in number of pairs per 40 acres, a discrete scale. When identifying the habitat impacts of each harvesting scenario, the researchers essentially computed the percent change in acres of projected habitat to acres of original habitat, weighted by abundance values. In order to unify the scales, initial work assigned numeric codes (0-5) to specific ranges in bird abundances for well researched species, thus putting all bird species on a discrete scale (Page and Ek 2005). However, this coding is linear, whereas the abundance ranges are nonlinear. Thus, several candidate nonlinear abundance coding schemes were examined for their utility in representing the abundance ranges, as well as their similarity with the nonlinear coding used for the small and medium mammals in the GEIS (Frelich et al. 2013).

After comparison, the selected nonlinear codes used the midpoint of the abundance ranges ($new\ abundance\ code = 2\sqrt{midpoint}$), rounding each code to the nearest integer (except for the 0-1 range, which is rounded up) (see Table 3.2). This gave codes the most similar in format and methodology to those used for small and medium mammals. The WHINGS model then multiplies acres of habitat by its associated nonlinear abundance code, rather than abundance per acre as in the GEIS and Frelich et al. (2013). Comparison between the nonlinear and linear scales (not reported) showed considerable improvement in predictions using the new scale, as the previous scale tended to overestimate HSI.

Table 3.2. New bird abundance codes used in WHINGS, along with the original discrete coding, GEIS bird abundance ranges, and the corresponding range midpoints. The new coding is double the square root of the midpoints, rounded to integer values. Note that the new code for the 0-1 range is rounded up instead of down. Also, the original units for the abundance ranges were breeding pairs/1,500 hectares. In English units, this translates to pairs/3,707 acres.

Original Abundance Codes	Abundance Ranges	Range Midpoint	New Abundance Codes
0	Absent	NA	0
1	0-1	0.5	2
2	2-10	6	5
3	11-50	30.5	11
4	51-100	75.5	17
5	101-500	300.5	35

3.2.3.3 Bear, Moose, and Deer Forest Cover Requirement

Frelich et al. (2013) contains a minimum percent forest cover requirement for black bear (≥30%), moose (≥15%), and white-tailed deer (≥10% – zone 1). The latter two pertain strictly to conifer cover, since the presence of these forest types provide thermal cover during the winter months. The recommended size of analysis unit for large mammals is two by two township blocks. Summarizing stand inventory data at this level introduces complexity most forest managers cannot satisfy, or at least would rather avoid. However, when using WHINGS on a single, large analysis unit, the area of interest may not meet the cover requirement, even though some areas within the unit have sufficient cover. Therefore, WHINGS relaxes the forest and coniferous cover requirements to allow HSI calculations for any size analysis unit, provided the user employs caution when interpreting the results.

3.2.4 Case Study

In order to demonstrate the implementation of WHINGS, the model was applied to output from three harvest scheduling model projections for the forestland administered by St. Louis County (SLC), Minnesota. SLC is the second largest county east of the Mississippi River in the United States (in land area) and contains nearly 900,000 acres of county managed lands, with a large portion (~70%) classified as forestland (USDA 2010). To assist in forest planning efforts, several management scenarios were projected 100 years (20 five year cycles) using a harvest scheduling, linear programming model (REMSOFT®) and data from the Minnesota FIA 2009 inventory (Walters 1993; USDA 2010). Note that the projections were run for a subset of forestland consisting of roughly 600,000 acres.

The three alternatives include scenarios focused on (1) economic rotation ages which sought to maximize the economic return to the county and reduce the accumulated older forests to achieve age class balance; (2) custom rotation ages reflecting current county forest management; and (3) extended rotation ages that required 40% of the forest types be grown 1.5 times longer than economic rotations. Alternatives 1-3 encompass a continuum of harvest intensities, from more intensive to less, respectively. In all three scenarios, volume yield (cords) from the aspen and red pine forest types were maximized while maintaining a long-term, sustainable, even flow of the forest resource. Additional operational and environmental constraints included using practices within the framework of statewide guidelines for sustainable forest management and timber harvesting (MFRC 2005). The WHINGS model was then applied to the output from all three alternatives.

The WHINGS results provide an estimate of the habitat impacts under each scenario, relative to the initial conditions. Table 3.3 summarizes the input data at time zero for the first alternative. Note that the original data did not include ecoregion information. Since portions of four GEIS ecoregions fall within SLC, the ecoregion with the highest proportion (ecoregion four) was selected to represent the entire county. This approach appears reasonable, as the four ecoregions have similar attributes (Cleland et al. 2007; MNDNR 2000).

Table 3.3. Total forestland acreage by forest type and size class in St. Louis County, Minnesota, as used in the case study. Forest type definitions follow those used by the MNDNR. The data came from the Minnesota FIA 2009 measurement period.

Forest Type	Size Class		
	Seedling/ Sapling	Poletimber	Sawtimber
Ash	748	789	29,624
Aspen	168,606	50,401	64,400
Balsam fir	592	1,583	14,330
Birch	611	2,247	26,571
Black spruce	11,229	78,416	7,322
Eastern white pine	1,019	120	4,451
Jack pine	3,527	902	4,421
Lowland hardwoods	7	190	190
Northern white-cedar	459	31,049	7,518
Northern Hardwoods	661	1,177	11,277
Oak	78	170	170
Red pine	13,954	1,734	7,329
Tamarack	3,581	26,758	1,605
White spruce	9,318	258	1,492
Total	214,390	195,794	180,700

The WHINGS model was programmed in the Microsoft Visual Basic language and executed as functions in the R statistical package (R Development Core Team 2011), with output exported as comma delimitated files (CSV). Comparisons between projection cycles were made using absolute difference in HSI values for each species, with notable changes in habitat receiving further discussion.

3.3 Results and Discussion

For the SLC case study, Table 3.4 summarizes the potential management impact on each wildlife species group under the three alternative harvest schedules. For most species groups, each management scenario had an insignificant effect on preferred habitat (|HSI change| < 0.1). Of the 118 bird species found in GEIS ecoregion four, the alternatives with lower harvesting intensities had less overall impact, with the proportion of species experiencing significantly improved (>10%) or worsened (<–10%) habitat remaining fairly constant, regardless of scenario. For the grouse species and mammals, one medium mammal had a significant reduction in habitat (-14% in the first and second alternatives), while two small and medium mammals showed significant increases in habitat (+12% for both in the third alternative). The herptofauna fared poorly under the first management scenario, with four species experiencing significant reductions in habitat suitability (<–10%), of which three had large losses (<–20%). Compared to each other, the latter two scenarios had opposite effects, with three herptofauna having significant habitat reductions in the second alternative, but with three significant additions in the third.

Table 3.4. Number of individual species with HSI increasing, decreasing, or remaining unchanged across all 20 five-year projection periods for the three harvest scheduling alternatives for St. Louis County, Minnesota. Values based on maximum absolute difference. Results include only those species found in GEIS ecoregion four.

Species Group	**Harvest Schedule**	**Large Decrease ≥20%**	**Decrease 10-20%**	**No Change 0-10%**	**Increase 10-20%**	**Large Increase ≥20%**
Birds	Alt1	0	9	99	10	0
	Alt2	0	5	109	4	0
	Alt3	0	1	116	0	1
Grouse	Alt1	0	0	2	0	0
	Alt2	0	0	2	0	0
	Alt3	0	0	2	0	0
Small/medium mammals	Alt1	0	1	21	0	0
	Alt2	0	1	21	0	0
	Alt3	0	0	20	2	0
Large mammals	Alt1	0	0	4	0	0
	Alt2	0	0	4	0	0
	Alt3	1	1	2	0	0
Herps	Alt1	3	1	2	0	0
	Alt2	0	3	3	0	0
	Alt3	0	0	3	3	0

For every species group in Table 3.4, those species that had an increasing HSI in the first alternative generally preferred one or more forest types in the seedling/sapling stand size class, whereas those that decreased almost exclusively preferred one or more forest types in the poletimber/sawtimber size classes. The second alternative gave similar results, but with less dramatic shifts in HSI. Under the third alternative, species preferring forest types in the poletimber/sawtimber size classes showed increasing HSI values while the opposite was true for species preferring the seedling/sapling size class. As expected, these results mirrored the trends intended by each proposed harvest schedule, with the distribution of size classes moving from smaller to larger across the decreasing levels of harvest intensity.

Overall, the above findings are not unique. For all forest habitat models that relate species preferences to forest type and size class information, changing (or not changing) the landscape in some way will benefit some species and diminish others. Therefore, the actual importance and utility of these and other WHINGS results will depend on the user, the criteria surrounding their particular application, and the desired composition of species to promote on the landscape. For this case study, WHINGS facilitates comparison between harvest schedules and ultimately the selection of an alternative that best satisfies both management objectives and environmental regulations.

Importantly, the precision and accuracy of the forest inventory data and forest growth models used is well understood. However, the HSI models were developed from a necessarily coarse synthesis of species-habitat relationships that have yet to be rigorously tested. Trials such as these, therefore, may also suggest improvements to the models for the various wildlife species. Still, the difficulty in estimating population numbers and habitat use for many species complicates refining the models. Until mitigation of these issues, results from the current version of WHINGS should be viewed as instructive, but not definitive.

Further research will incorporate the current WHINGS functionality in R into a publically available Visual Basic program hosted online and an external R package. The need remains for future studies to increase the detail in WHINGS and continue updating the matrix of species-habitat relationships to reflect advances in wildlife research (see Frelich et al. 2013). The WHINGS model has great potential to aid forest and wildlife management, but only if the precision and accuracy of the component species-habitat models are well known and documented.

Chapter 4

Managed and intensively managed stand version of the Lake States variant of the Forest Vegetation Simulator

John M. Zobel and Alan R. Ek

The potential gains from intensive forest management have seldom been quantified in the Lake States (Michigan, Minnesota, and Wisconsin), due in part to inadequate data and models. However, recent economic considerations and sustainable harvest level research has necessitated quantification and modeling of the increased growth in intensively managed stands. This study sought to create a managed and intensively managed stand version of the Lake States variant of the Forest Vegetation Simulator (LS-FVS). This research concentrated on updating the large tree diameter growth model in LS-FVS using data from the U.S. Forest Service Forest Inventory and Analysis (FIA) database. However, the lack of available managed stand data in the Lake States necessitated defining managed stand subdatasets from FIA data. Results found that using FIA variables for stand treatment and pure/full stocking proved effective at parsing out stands managed using multiple and few stand entries, respectively. Intensively managed stands were defined as those experiencing a markedly higher quantity and/or frequency of stand treatments relative to managed stands. An upper percentile of growth ($\geq 90^{th}$ quantile) adequately characterized this intensive management for all species. Updating the current growth model in LS-FVS involved determining the model undergrowth (i.e., underestimate of growth) of the newly defined managed stands. After removing the inherent bias in the model, the observed mean undergrowth was converted to an individual tree growth multiplier that increases growth to observed levels for each subdataset. These growth multipliers appear consistent with expected managed and intensively managed stand behavior, and they enter the growth model as an additional parameter activated by the FVS keyword MANAGED. Evaluation of the model is deferred to another paper. Overall, the final model form provides an appropriate tool for describing individual tree level response to various management intensities.

4.1 Introduction

Throughout the history of forest management, growth and yield models have been used to provide estimates of current and future forest conditions. The breadth and quality of model forms has grown through time, from empirical yield tables (e.g., Brown and Gevorkiantz 1934; Gevorkiantz and Olsen 1955; Buckman 1962; Walters and Ek 1993) to individual tree growth models, whether based on empirical (e.g., FVS (Stage 1973; Hahn and Leary 1979)), process (e.g., PnET (Aber and Federer 1992)), hybrid (e.g., Forest 5 (Robinson and Ek 2003)), or gap (e.g., SORTIE (Pacala et al. 1993, 1996)) methodologies. Often, individual tree growth models are employed as components of stand growth simulators that include modules or processes for mortality and regeneration (e.g., FVS, SORTIE). Many growth simulators also provide capability for including management actions (e.g., thinning) during growth projections (Dixon 2002; Robinson and Ek 2003).

Historically, the vast majority of forest growth models were developed and calibrated from plot data representing natural stands (i.e., seed, sprout, or sucker origin and undisturbed and unmanaged since establishment), research plots, or a combination of unmanaged and managed stands. The Lake States (Michigan, Minnesota, and Wisconsin) variant of the U.S. Forest Service Forest Vegetation Simulator (LS-FVS) used a combination of natural stand and plantation data (Christensen et al. 1979), as did PnET (Aber and Federer 1992). SORTIE used natural stand and research plot data (Pacala et al. 1996), and Forest 5 used fit components from other growth simulators (Robinson and Ek 2003). Note that none of these models were fit to solely managed stand data, which often contain higher individual tree growth rates (though fairly similar rates of stand growth).

Without calibration to managed stand data, growth models may poorly represent individual tree growth under managed or intensively managed conditions, especially empirical models. Thus, even though some of the growth simulators allow for management actions, the tree level response to those actions will follow a trajectory consistent with those from natural stands and not realize the increased growth under management.

Few models have been calibrated using only managed stand databases. Arney (1985) published a methodology for easily adapting growth models to management conditions, and Weiskittel (2006) developed a growth model for intensively managed Douglas-fir (*Pseudotsuga menziesii* var. *menziesii*). Several FVS geographic variants include the MANAGED keyword that flags input stands as managed or not (Van Dyck and Smith-Mateja 2000). The standard growth equations then account for the estimated change in growth rates under management through the use of dummy variables (0 = unmanaged, 1 = managed). In particular, the Southern variant includes the "PLANT" (i.e., plantation) dummy variable in the potential growth equation to represent the additional growth in plantations versus natural stands (Keyser 2008).

Due to economic considerations and recent sustainable harvest level research, the need has increased for a growth model representing intensive management. The 2007 Governor's Task Force on the Competitiveness of Minnesota's Primary Forest Products Industry suggested that increasing the overall intensity and efficiency of forest management would lead to higher sustainable annual yields in Minnesota (MNDNR 2007). Ek (2007) also proposed that employing underutilized silvicultural practices and/or combinations of treatments could significantly increase forest productivity within Minnesota and presumably the region. However, the potential gains (or losses) from intensive management have not been well quantified, due to inadequate data and models.

This research sought to develop and deliver (1) a managed stand version of the existing growth model in LS-FVS (Hahn and Leary 1979) and (2) an intensively managed stand version of the same growth model. For the purposes of this study, a managed stand represents a forested stand experiencing intentional silvicultural treatment(s) to increase the accumulation rate and quality of a tree attribute relative to that achieved under natural, undisturbed conditions. An intensively managed stand refers to a forested stand experiencing a markedly higher quantity and/or frequency of silvicultural treatments or combinations of treatments than managed stands, with the intention of substantially increasing the accumulation rate and quality of a tree attribute relative to that achieved in managed stands.

Ultimately, LS-FVS will incorporate the new models into its overall framework. The choice of LS-FVS over another growth simulator resulted from the wide acceptance and familiarity of its growth model component in the Lake States, potentially leading to a rapid embracing and broad use of the managed stand version. Initial modeling efforts were concentrated on the large tree diameter growth model (trees ≥ 5.0-in diameter breast height (dbh)), as output from this model drives many other functions in LS-FVS (Dixon and Keyser 2008). Further research will consider the small tree diameter and height growth models (trees < 5.0-in dbh) and the mortality model. The final model forms will provide forest managers and scientists with an appropriate tool for describing individual tree response to various management intensities.

4.2 Methods

4.2.1 LS-FVS

During the late 1970s, researchers from the U.S. Forest Service North Central Forest Experiment Station (now the Northern Research Station) developed an individual tree, distance-independent forest growth simulator that included primary components for tree growth and mortality, but not regeneration (USDA 1979). The next iteration followed a few years later with the release of The Stand and Tree Evaluation and

Modeling System (STEMS) (Belcher 1981; Belcher et al. 1982). This version included components for regeneration and implementation of management actions. Subsequent updates of the STEMS growth model and mortality components led to the release of STEMS85 (Holdaway and Brand 1986). Continued development led to STEMS85 being packaged as the Lake States variant of The Woodsman's Ideal Growth System (LS-TWIGS) (Miner et al. 1988). LS-TWIGS provided users with a simplified personal computer version of the model and included an economics component. In 1993, LS-TWIGS was incorporated into the new Lake States variant of FVS (Bush and Brand 1995). After considerable revisions to LS-FVS in 2006, the large tree diameter growth model remains the only component of LS-TWIGS left in LS-FVS (Dixon and Keyser 2008).

The LS-FVS large tree diameter growth model has three distinct elements: a potential growth function (Hahn and Leary 1979), a competition modifier function (Holdaway 1984), and a diameter adjustment function (Holdaway 1985). The equations are given below.

$$PG = a_1 - a_2 DBH^{a_3} + a_4(SI)(CR)(DBH^{a_5}) \tag{4.1}$$

$$MOD = 1 - \exp\left(-\omega\tau\left((BAMAX/BA) - 1.0\right)^{0.5}\right) \tag{4.2}$$

$$\omega = \begin{cases} w_1\left(1 - \exp\left(-w_2(DBH/QMD)\right)\right)^{w_3} + w_4 & if DBH/QMD \geq c \\ w_4 & if\ DBH/QMD < c \text{ or } QMD = 0 \end{cases} \tag{4.3}$$

$$\tau = t_1(QMD + 1)^{t_2} \tag{4.4}$$

$$ADJ = b_1 + b_2 DBH + b_3 DBH^2 \tag{4.5}$$

$$DG = PG(MOD) + ADJ \tag{4.6}$$

where *PG* = potential diameter growth (in) for a tree, *SI* = species specific site index (ft) in the stand, *CR* = crown ratio class (decimal crown ration multiplied by ten), *MOD* = modifier value (between 0.2-1; if *MOD* < 0.2, then *MOD* = 0.2), *BAMAX* = basal area maximum (ft^2/ac) for a species, *BA* = basal area (ft^2/ac) for the stand, ω = function representing the effect of individual tree relative diameter, *QMD* = quadratic mean diameter (in) of the stand, *c* = critical value above which the function produces real values, τ = function representing the effect of stand quadratic mean diameter, *ADJ* = diameter adjustment (in), and a_1-a_5, w_1-w_4, t_1-t_2, and b_1-b_3 represent species specific model parameters. Equations adapted from Dixon and Keyser (2008) (see this publication for coefficient estimates).

4.2.2 Data

4.2.2.1 All Stands

The data for this study came from the U.S. Forest Service Forest Inventory and Analysis (FIA) database (USDA 2010). A dearth of available managed stand data in the Lake States necessitated the use of this comprehensive forest inventory that includes both unmanaged and managed stand data. Beginning in the late 1990s, FIA moved from a periodic (every 10 years) to an annual inventory design, with approximately 20% of the plots in each of the three Lake States measured every year and all plots measured every five years (an FIA cycle) (Woudenberg et al. 2011). In addition, the annual system employs a four subplot, fixed-radius ($1/24^{th}$ of an acre) design for measuring large trees (≥ 5.0-in dbh). Note that the remainder of the paper will use dbh and diameter interchangeably. Within a cycle, the annual inventories are statistically independent, with subsequent cycles representing remeasurements. This study used the two most recent complete cycles within the Lake States, as described in Table 4.1. The data were filtered to include only large trees that were alive and measured in both inventory periods, allowing for five year growth calculations. Overall, 16,259 plots and 50,223 subplots were available across the three state region, totaling 345,503 large trees with two measurements. Table 4.2 gives the summary stand characteristics for the complete dataset.

In addition, based on the objectives of this study, only the commercially important species were considered (Table 4.2). White ash (*Fraxinus Americana* L.) and black ash (*Fraxinus nigra* Marsh.) were initially investigated, but eventually dropped, due to the current and probable future decline of these species as the result of the invasive emerald ash borer (*Agrilus planipennis*).

Table 4.1. Description of the FIA database used for this study, including overall sample sizes. The number of trees refers to live trees measured in both FIA cycles, and the number of plots represents the collection of plots with at least one remeasured live tree.

State	Years	FIA Cycle	n (plots)	n (subplots)	n (trees)
Michigan	2000-2004	6	6,499	20,722	156,458
	2005-2009	7			
Minnesota	1999-2003	12	4,486	13,641	86,005
	2004-2008	13			
Wisconsin	2000-2004	6	5,274	15,860	103,040
	2005-2009	7			

Table 4.2. FIA cycle 06/12 stand summary statistics for pertinent stand characteristics for the complete Lake States FIA database of live, remeasured individual trees. All values are means, with standard deviations in parentheses. SI = site index (ft) (base age = 50-yrs), BA = basal area (ft^2/ac), QMD = quadratic mean diameter (in), and Growth = mean five year individual tree growth (in).

Common Name	**Scientific Name**	**SI**		**BA**		**QMD**		**Growth**		**n (plots)**	**n (trees)**
American basswood	*Tilia americana* L.	54	(13)	124.2	(60.8)	5.9	(2.3)	0.51	(0.42)	3,810	15,418
Balsam fir	*Abies balsamea* (L.) Mill.	45	(12)	97.3	(54.3)	5.4	(1.9)	0.32	(0.37)	1,355	9,240
Balsam poplar	*Populus balsamifera* L.	56	(14)	123.2	(58.4)	6.3	(2.4)	0.57	(0.50)	1,779	5,735
Bigtooth aspen	*Populus grandidentata* Michx.	43	(11)	111.3	(55.7)	5.4	(1.8)	0.27	(0.26)	1,995	15,116
Black spruce	*Picea mariana* (Mill.) B. S. P.	55	(11)	93.9	(47.1)	6.3	(2.1)	0.44	(0.40)	1,134	8,423
Eastern white pine	*Pinus strobus* L.	66	(12)	145.2	(60.2)	7.5	(2.4)	0.64	(0.47)	1,636	19,728
Jack pine	*Pinus banksiana* Lamb.	60	(14)	133.4	(65.3)	7.5	(3.1)	0.77	(0.67)	1,977	7,929
Northern red oak	*Quercus rubra* L.	38	(13)	183.5	(73.9)	6.1	(2.2)	0.29	(0.34)	2,262	35,995
Northern white-cedar	*Thuja occidentalis* L.	64	(11)	123.0	(49.0)	7.4	(2.8)	0.41	(0.41)	4,154	37,607
Paper birch	*Betula papyrifera* Marsh**.**	58	(13)	132.0	(59.5)	7.0	(3.0)	0.34	(0.40)	1,785	5,084
Quaking aspen	*Populus tremuloides* Michx.	57	(14)	118.2	(57.5)	6.2	(2.4)	0.30	(0.50)	3,949	15,122
Red pine	*Pinus resinosa* Ait.	57	(14)	115.5	(60.7)	5.7	(2.3)	0.47	(0.40)	875	3,456
Sugar maple	*Acer saccharum* Marsh.	70	(14)	132.4	(59.3)	6.2	(2.6)	0.68	(0.42)	1,641	8,395
Tamarack	*Larix laricina (Du Roi)* K. Koch	66	(13)	111.1	(51.9)	5.9	(2.4)	0.67	(0.44)	5,068	31,295
White oak	*Quercus alba* L.	60	(14)	118.0	(54.5)	7.9	(3.2)	0.41	(0.41)	1,353	4,833
White spruce	*Picea glauca* (Moench) Voss	64	(14)	128.9	(55.9)	7.6	(3.2)	0.69	(0.57)	2,614	10,678
Yellow birch	*Betula alleghaniensis* Britton	65	(13)	137.0	(56.5)	7.2	(2.9)	0.43	(0.60)	2,439	10,461

4.2.2.2 Managed Stands

The FIA dataset contains plots and subplots representing a variety of stand histories, from natural stands to plantations. Parsing the dataset into a managed stand subdataset proved challenging, as FIA does not include a variable that directly classifies a stand as managed. Therefore, criteria based on included variables were proposed to assist in separating out the desired data, or at least in defining a surrogate for managed stand data. The alternative approaches are discussed below.

4.2.2.2.1 Parsing Method Descriptions

4.2.2.2.1.1 Stocking Level

Stocking level has guided management since its inception. Management guides for nearly all Lake States species recommend maintaining a stand at full stocking (typically 60-100%) in order to maximize yield (e.g., Benzie 1977; Perala 1977; Sander 1977; Tubbs 1977; Myers and Buchman 1984; Johnston 1986). In other words, tend the stand to remain between the A and B lines on typical stocking charts (e.g., Ginrich 1967). Theoretically, fully stocked stands in the FIA database represent at most managed stands and at least stand conditions consistent with typical management.

FIA has its own algorithm for computing individual tree and plot level stocking (Alner et al. 2003), with four variables in the database that directly relate to stocking: all live tree stocking percent (ALSTK) and growing stock stocking percent (GSSTK), with these percents grouped to form the all live stocking code (ALSTKCD) and growing stock stocking code (GSSTKCD), respectively (Woudenberg et al. 2011). The all stocking variables represent the level of stocking based on all live trees, whereas the growing stock variables indicate the stocking level based on trees from commercially important species that satisfy certain merchantability standards. See Woudenberg et al. (2011) for further details. Since the FIA definition of growing stock appears more consistent with management, and since the stocking code variables directly represent stocking level (Table 4.3), the GSSTKCD variable was selected to identify those subplots with full stocking and collect them into a potential managed stand subdataset.

An additional constraint in this approach required that fully stocked stands have a forest type consistent with the species of interest, since most fully stocked stands have one to several minority component species. Management will likely not favor these secondary species, so using them in the analysis may not adequately represent management. Similarly, trees from species affiliated with the stand forest type should better reflect management effects.

Table 4.3. Stocking codes and description for the GSSTKCD variable in the FIA database (adapted from Woudenberg et al. (2011)).

Code	Level	Percent
1	Overstocked	100%+
2	Fully stocked	60-99%
3	Medium stocked	35-59%
4	Poorly stocked	10-34%
5	Nonstocked	0-9%

4.2.2.2.1.2 Pure Stands

Under typical management conditions, especially intensive management or in plantations, a stand will contain a one dominant species (see Domke et al. 2008). Natural stands seldom have this single species composition. Therefore, FIA plots with one dominant species (≥ 75% of the stems) can be identified via the tree list and grouped into a possible managed stand subdataset. Note that this method will likely produce more accurate results when using plot data, not subplot data. Although a subplot could be dominated by one species, the other subplots might differ in forest type, and thus the entire plot might show diversity inconsistent with managed stands.

4.2.2.2.1.3 Treatment Variable

The very definition of a managed stand often implies the application of certain prescribed management actions, including site preparation, planting, weed control, thinning, and final harvest, to name a few. Since the annualization of FIA data collection, the database contains variables that describe stand treatments that occurred since the last measurement period or within the last five years (e.g., TRTCD1) (Woudenberg et al. 2011). Those FIA subplots flagged as treated could then form a managed stand subdataset. Note that under this alternative, the collection of trees from all treated subplots will form the composite managed stand tree sample. Theoretically, residual trees of all species will benefit from improved stand conditions post treatment, regardless of the management target species. In addition, using all trees increases sample sizes relative to using only those trees within the managed forest type.

4.2.2.2.1.4 Stand Origin

For certain species or plantations, management includes artificial regeneration through plantings. The annual FIA inventories include a stand origin variable (STDORGCD) that indicates the method used to regenerate the stand (natural or artificial) (Woudenberg et al. 2011). Thus, grouping those subplots originating from direct plantings could form a potential managed stand subdataset for the appropriate species.

4.2.2.2.1.5 Constant Crown Class

Under even-aged management, the crown class for nearly all trees will remain roughly similar (as dominant or codominant), whereas unmanaged stands will likely contain a broader distribution of crown classes. The FIA database contains a crown class variable (CCLCD) that describes the crown position of individual trees (Woudenberg et al. 2011). Grouping those FIA plots with a plurality of dominant and codominant trees (≥ 75%) could represent a managed stand subdataset. Note that similar to the pure stand approach, this method would likely produce more accurate results when using plot data rather than subplot data. Although a subplot could be dominated by one crown class, the other subplots might differ in stand structure, and thus the plot might show diversity not consistent with managed stands.

Clearly, some or all of these approaches may not work for a particular species, due to substantial variety in silvicultural practices between species and among diverse site conditions. Nevertheless, some methods may have utility for different species groups based on ecological characteristics (e.g., level of shade tolerance) or management goal (e.g., sawtimber or pulpwood). In addition, combining methods may prove more successful than using a single approach. Also note that for each parsing method, the data were filtered to exclude stands thinned (or that received other treatments) during the observed growth period. Without this constraint, the reduced stocking (and improved growth) immediately following the thinning treatments could lead to artificially low growth projections. However, disturbed stands (though very few (< 6.5% of all subplots)) were not removed, as these represent natural phenomena.

4.2.2.2.2 Parsing Method Comparison

As discussed previously, the current large tree diameter growth model in LS-FVS does not pertain directly to trees in managed stands. Due to generally higher individual tree growth rates in managed stands, LS-FVS will tend to undergrow trees from managed stands relative to all stands. Therefore, the comparison of the data parsing methods involves projecting each subdataset through LS-FVS and evaluating the growth estimates against the expected model behavior for managed stands.

Unfortunately, the current version of LS-FVS tends to overgrow stands, on average (Canavan and Ramm 2000; Smith-Mateja and Ramm 2002), but may also undergrow some species (Pokharel and Froese 2008). This complicates parsing method comparisons. The output may indicate a method overgrows a species, a result inconsistent with management, when in fact the model undergrows the stand after accounting for model bias. Therefore, comparison of candidate managed stand subdatasets to expected model behavior employed the equation below:

$$\begin{aligned} MAN^*_i &= Bias_{man,i} - Bias_{all,i} \\ &= \frac{1}{n_i}\sum_{j=1}^{n_i}\left(\left(y_{man,i,j} - \hat{y}_{man,i,j}\right) - \left(y_{all,i,j} - \hat{y}_{all,i,j}\right)\right) \end{aligned} \tag{4.7}$$

where MAN^*_i = the additive model undergrowth for managed stands, *man* signifies managed stands, *all* indicates all stands, *Bias* refers to mean observed growth bias in the model, *y* = observed five year diameter growth, $\hat{y}$ = LS-FVS predicted annual diameter growth multiplied by five, i = the ith species, and j = the jth tree of the ith species. Equation 4.7 is actually comparing distributions of growth model prediction residuals when describing management and all conditions. The bias terms correspond to the center of these distributions, with the difference representing the change in predictions for managed stands. For a particular species, a positive or negative $Bias^*_{man}$ indicates improved or depressed growth, respectively. If $Bias^*_{man}$ equals zero, then LS-FVS predicts managed stands and all stands with equal accuracy. Figure 4.1 shows an example of this relationship graphically. If a parsing method adequately represents managed stand data for a species, then $Bias^*_{man}$ should be positive and notably different from zero.

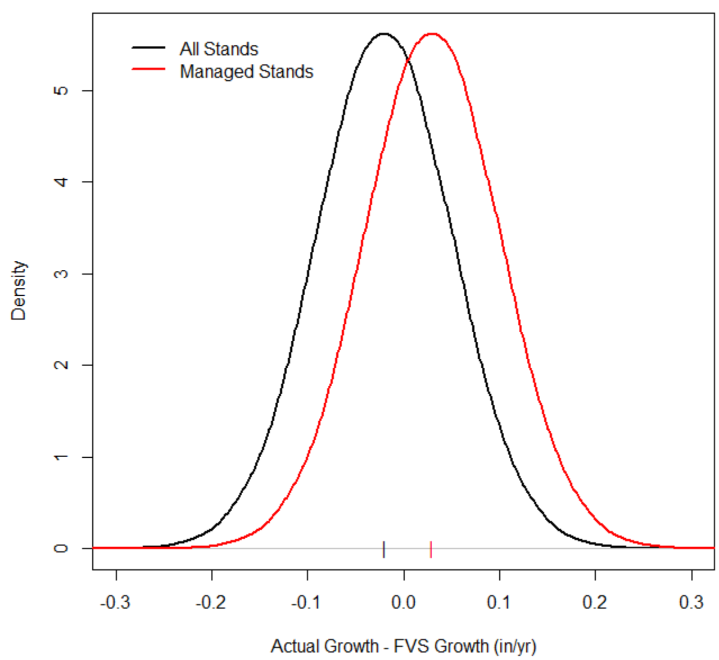

Figure 4.1. Example distributions of growth model prediction errors for all stands and managed stands. The difference between the centers of each distribution represents the increased growth in managed stands unaccounted for in the model.

4.2.2.3 Intensively Managed Stands

Intensively managed stands are defined as those stands undergoing multiple and/or combinations of treatments that markedly increase individual tree growth. Ek (2007) outlines underutilized silvicultural techniques that could significantly impact total stand yield if implemented. Examples include site preparation, active weed control, frequent thinnings, fertilization, and combinations of these and other treatments. In effect, significantly more stands entries are scheduled under intensive management than in traditional silvicultural prescriptions.

Intensive management has seen limited use in the Lake States (MNDNR 2007), leading to a dearth of intensively managed stand data. The FIA database likely contains data from intensive management, but parsing out this data is extremely challenging due to the lack of extensive management history in the plot records. Therefore, a surrogate for intensive management data was proposed that uses an upper percentile of diameter growth data to represent the increased growth under intensive management. Although upper percentile growth will not always derive from management, the growth rates are observed and thus potentially reproducible under certain management prescriptions.

Several alternatives exist for selecting the upper percentile growth data. Including a relatively large upper percentile increases sample size, but lowers mean diameter growth. Choosing a small percentile decreases sample size, but raises average diameter growth. However, the increased growth in small percentiles may result from the increased influence of extreme (though real) growth values. Ultimately, three candidate levels were proposed, including the upper 10%, 5%, and 1% of diameter growth. Note that these upper percentiles actually represent the subset of growth data greater than or equal to their associated quantiles. For example, the upper 10% of diameter growth refers to the collection of growth observations at or above the 90th quantile of diameter growth. The actual upper percentile will vary, but should remain close to the specified amount. Before using this approach, selection of the upper percentile proved challenging. After sorting the data by tree growth, the growth values of the last few trees included in the percentile were often identical to the growth value of the first few trees excluded from the percentile. In other words, growth observations were often equal before and after the specified percentage break. However, other tree characteristics and stand level attributes varied between these trees, with no clear criteria for determining which trees to include. The quantile method removed this ambiguity.

A second alternative pertained to the source dataset for the upper percentile subdataset. The upper percentile growth from all stands will likely include more extreme values that may inhibit realistic growth estimates. Also, high individual tree growth rates may occur under conditions uncharacteristic of managed stands. For example, certain trees from poorly stocked, unmanaged stands may experience rapid growth due to the lack of competition. Therefore, selecting the upper percentile from the subdataset that best represents managed stands for a particular species may provide more credible intensive management data.

4.2.3 Managed Stand Model

4.2.3.1 Form

This study considered several alternative approaches for creating a managed stand diameter growth model. Options included refitting the model to managed stand data, adding a term for management and refitting the model, estimating growth multipliers and adding them to the current model form, and creating a new growth model, among others. Determining the preferred approach was guided by previous managed stand work in other FVS variants.

The overall FVS model includes the keyword MANAGED to indicate whether a stand is managed or not (Van Dyck and Smith-Mateja 2000). Currently, five of the 20 geographic variants utilize this keyword. Three of these variants include the management effect in their large tree diameter growth model via dummy variable(s) taking values zero (unmanaged) or one (managed). For a managed stand, the increased growth is represented by the coefficient associated with the dummy variable. Specifically, two Western variants (Eastern Montana (EM) and Kookantl (KT)) added managed and unmanaged dummy variables to the model, each separately associated with the crown competition factor (CCF) variable (Keyser 2008a; Keyser and Dixon 2008). Thus, the effect of CCF (i.e., coefficient estimate) differs between managed and unmanaged stands. The KT variant also included a single dummy variable in the small tree height growth equation (again associated with CCF). However, in this equation, the dummy variable essentially indicated whether to include CCF (for managed stands) or to exclude it (for unmanaged stands). In the Southern variant (SN), a single dummy variable was added

(Keyser 2008b). The coefficient associated with this stand-alone variable increases tree growth when the dummy variable indicates management (i.e., the keyword MANAGED is activated).

Across variants, the FVS framework shows remarkable consistency in structure and component models (Dixon 2002). In order to maintain this consistency, a single parameter was added to the LS-FVS large tree diameter growth model that represents the expected additional growth under management. However, refitting the growth model with the included management parameter proved beyond the scope of this paper. Rather, this parameter acts as a growth multiplier of the existing model estimates. This approach retains the current LS-FVS growth model coefficient estimates while providing a model form readily adaptable to potential changes in the original model. Equation 4.8 gives the new model form:

$$DG^* = \big((POT * MOD) + ADJ\big) * MAN \tag{4.8}$$

where DG^* = managed stand large tree diameter growth, MAN = the additional, multiplicative individual tree growth associated with a managed stand, and the other variables are as defined earlier. In this equation, the MAN parameter is assigned a species specific growth multiplier when growing managed stands. If the stand is not managed, MAN = 1 and the growth estimates come from the current model. Ultimately, the MANAGED keyword in FVS will assign the value to MAN.

4.2.3.2 Derivation

If the LS-FVS diameter growth model were unbiased, then the mean difference between observed and estimated growth should equal zero. For managed stands, the unbiased growth model should produce biased estimates, with the average difference between actual and estimated growth greater than zero (undergrown). In practice, research has demonstrated the existence of bias in growth estimates from the current model, and thus the distribution of observed minus estimated growth for all stands will have its center different from zero (e.g., Pokharel and Froese 2008). Still, the center of this distribution for managed stand growth will be larger, with the difference representing the amount FVS undergrows managed trees. This difference is captured in equation 4.7 (see also Figure 4.1) and represents the first iteration of the MAN parameter. Adding MAN to each tree growth estimate in managed stands essentially shifts the center of the distribution of growth estimates so that the growth model will perform equally well for unmanaged and managed stands.

At this point, the MAN coefficient is additive and simply closes the gap between the bias corrected estimates of all tree and managed tree diameter growth. However, this bump in growth will likely not occur at the same rate for all trees. For example, with a constant, additive MAN parameter, the increased amount of diameter growth under management will be the same for dominant and suppressed trees, which seems unrealistic. Therefore, the MAN parameter will enter the equation as a multiplier (equation 4.8), allowing for tree specific increased growth. This necessitates converting the parameter from additive to multiplicative. Among various conversion techniques, representing MAN as a proportion of projected managed stand growth (using the current version of LS-FVS) proved the most straightforward and adequate and led to equation 4.9:

$$MAN_i = 1 + (MAN_i^* / \tilde{y}_{man,i}) \tag{4.9}$$

where i = species, MAN_i^* = the additive MAN parameter, MAN_i = the multiplicative MAN parameter, and $\tilde{y}_{man,i}$ = mean estimated five year diameter growth for the managed stand subdataset, projected using the current version of LS-FVS. Note that equation 4.9 is the percent change between five year growth estimates with and without using the additive MAN parameter when projecting managed stand subdata. The new multiplicative MAN parameter now coincides with equation 4.8. Finally, most computations described throughout this section and all model fitting were conducted in the R statistical package (R Development Core Team 2011).

4.3 Results and Discussion

4.3.1 Managed Stands

Table 4.4 lists the estimated difference in bias between the projected large tree diameter growth in the candidate managed stands subdatasets and the projected growth for all stands. Note that these values represent estimates of the additive MAN parameters, and thus the additional (average) individual tree five year growth in managed stands. Initial exploratory analysis showed that using the stand origin variable produced model projections inconsistent with that expected for managed stands. Also, the common crown class subdataset yielded results similar to the pure stand approach. Thus, these parsing methods were dropped from the final analysis reporting.

Table 4.4. Candidate additive MAN coefficients from four managed stand data parsing methods. Values equal the change in five year growth (in) in managed stand versus all stand projections using the current version of the LS-FVS large tree diameter growth model. Sample sizes are in parentheses and represent number of trees in hundreds (for sample sizes < 1,000 trees, a decimal was included). The species are grouped according to management strategy, and values corresponding to undergrowth are in bold.

Man. Group	Species	Full Stock		Pure		Treatment		Full Stock/ Pure	
M1	Amer. basswood	-0.059	(28)	n/a	(0)	**0.034**	**(8.9)**	n/a	(0)
	Balsam fir	-0.013	(11)	-0.019	(1.9)	**0.068**	**(4.8)**	**0.034**	**(0.4)**
	Black spruce	-0.030	(34)	-0.035	(42)	**0.059**	**(2.2)**	-0.006	(11)
	Eastern white pine	-0.009	(10)	**0.085**	**(2.5)**	**0.101**	**(6.4)**	**0.227**	**(1.0)**
	Jack pine	**0.023**	**(25)**	-0.026	(20)	**0.028**	**(1.5)**	**0.002**	**(4.8)**
	Northern red oak	-0.088	(28)	-0.291	(2.2)	**0.018**	**(7.8)**	-0.262	(1.3)
	Red pine	-0.019	(77)	-0.037	(57)	**0.049**	**(17)**	-0.074	(26)
	Sugar maple	-0.023	(116)	-0.017	(67)	**0.052**	**(42)**	-0.044	(40)
	Tamarack	-0.023	(13)	-0.081	(26)	**0.052**	**(1.4)**	-0.080	(3.1)
	White oak	-0.024	(6.2)	-0.103	(0.8)	**0.035**	**(4.2)**	-0.153	(0.4)
M2	Balsam poplar	**0.032**	**(9.3)**	-0.089	(1.7)	-0.120	(0.7)	**0.113**	**(0.6)**
	Bigtooth aspen	-0.004	(34)	**0.234**	**(2.6)**	-0.028	(2.3)	**0.114**	**(1.4)**
	North. white-cedar	**0.002**	**(164)**	-0.023	(91)	-0.073	(5.4)	**0.002**	**(44)**
	Paper birch	-0.018	(28)	**0.026**	**(3.6)**	-0.012	(4.7)	**0.017**	**(1.7)**
	Quacking aspen	**0.017**	**(122)**	-0.002	(33)	-0.038	(6.0)	**0.063**	**(11)**
	White spruce	**0.055**	**(9.3)**	**0.200**	**(4.0)**	-0.019	(1.9)	**0.309**	**(1.8)**
	Yellow birch	-0.004	(19)	n/a	(0)	-0.012	(4.7)	n/a	(0)

* Northern red oak used the difference in median treatment growth and median all stand growth to compute an estimate of MAN.

Examination of Table 4.4 shows that by themselves, the full stocking and pure stand approaches show no distinct pattern. The full stocking method produced estimates consistent with managed stands for only six species (jack pine, balsam poplar, northern white-cedar, quaking aspen, and white spruce). Only four species showed results consistent with expected managed stand projections when using the pure stand approach (eastern white pine, bigtooth aspen, paper birch, and white spruce). When using the treatment variable approach, the results were mixed, with several species being undergrown by the current LS-FVS growth model (as expected for managed stands). However, several species were overgrown.

4.3.1.1 M1 Species

After initial comparison, no parsing method appeared adequate at separating out the managed stand data from among the aggregate FIA dataset for all species. Species groupings based on shade tolerance or successional stage also failed to suggest a common parsing method for their groups. However, closer examination of species trends for the treatment approach revealed a pattern. For those species actively managed for merchantable sawtimber or other non-pulpwood product (species group M1), the treatment variable method consistently estimated positive MAN coefficients (i.e., model undergrowth). Although this average tree undergrowth is small for some species, the overall trend for M1 is striking. Plausible explanations for this behavior relate to common silvicultural practices. For the M1 species, typical prescriptions require multiple stand entries before final harvest, often in the form of thinnings. Therefore, these stands receive treatments that FIA records (note that the majority (97%) of treatments in the FIA database relate to cuttings). For the remaining species, however, stand entries occur less often, with several species experiencing no intermediate treatments at all (species group M2). This would explain the poor results for the M2 species when using the treatment approach, as the recorded actions likely resulted from non-management activity (e.g., firewood cutting). Thus, the treatment variable parsing methodology will be adopted for defining managed stand data for the M1species.

Note the inclusion of black spruce, jack pine, and tamarack in M1. These species are typically managed for pulpwood, not lumber type products. However, stands of these species may occasionally experience thinnings to promote higher quality yield (e.g., WIDNR 2013). The associated additive MAN coefficients estimated in Table 4.4 pertain to the growth response in these stands.

Also note that the appropriate use of the treatment method depends on the management timeline. Since the FIA treatment variable flags subplots treated within the last five years, the observed increase in growth corresponds to the initial response of the stand to the management action (although this response can vary; see Monserud 1975). Using the MAN variable when growing stands approaching scheduled treatments will likely overgrow those stands, as additional analysis showed that LS-FVS actually overgrew stands scheduled for immediate treatment. Therefore, as expected for stands under thinning regimes, the rapid response to treatment tapers off as the stand matures. Users should employ (or not employ) the managed stand model in a fashion that mimics this time dependent stand response to treatments.

4.3.1.2 M2 Species

Traditionally, the majority of M2 species have seen their greatest commercial utility as pulpwood. Neither the full stocking or pure stand approach adequately represent management of these species, and the treatment method overgrows all of them. Therefore, an additional parsing method was proposed that combines the full stocking and pure stand approaches. By itself, the pure stand method finds plots dominated by one species. However, the identified plot may only have a few trees (i.e., poorly stocked), a condition not consistent with management. In addition, the full stocking approach locates subplots with stocking levels consistent with management. Yet many fully stocked stands have an eclectic species composition, leading to possible confounding between species plurality (i.e., forest type) and species purity. The latter appears more prevalent in management (see Perala 1977). Thus, combining both the full stocking and pure stand approaches separates out those fully stocked stands with relatively pure species composition. In addition, the combined method requires plots with full stocking in both cycles, whereas the original full stocking approach required this in the first cycle only.

Table 4.4 also gives estimates of the additive MAN parameters for the combined approach ("Full Stock/Pure"). These values suggest model projections consistent with managed stands across the included M2 species. Explanations for this behavior again relate to typical silvicultural prescriptions. Pulpwood stands are often clearcut, fostering dense, pure species stand regeneration. As the stand matures, self-thinning will reduce any initial overstocking to fully stocked conditions, but the stand will remain largely one species (e.g., quaking aspen). These conditions are not commonly found in stands reproducing after natural disturbance (except occasionally following a wildfire), and so the combined approach flags FIA subplots that demonstrate this typical managed behavior. Therefore, the combined full stocking and pure stand parsing method was adopted to provide a managed stand subdataset for the M2 species.

Interestingly, the pure/full stocking method failed to identify stands of black spruce, jack pine, and tamarack managed for pulpwood. A potential explanation for this suggests that unmanaged stands of these species may form pure, fully stocked stands more readily than unmanaged stands of the other pulpwood species (e.g., quaking aspen). Thus, the combined approach included unmanaged stands in the managed stand subdataset, leading to the poor results.

In addition, note the inclusion of northern white-cedar and yellow birch in M2. Although typically managed for lumber type products, these species were included in the few to no stand entries group for specific reasons. First, active management of northern white-cedar has declined significantly in the Lake States (Anthony W. D'Amato, personal communication), which significantly lowers the number of thinnings occurring on stands of this species. Second, managed yellow birch rarely exists as pure stands (hence no data), but often as a complimentary species with sugar maple. The poor results using the treatment approach for this species suggests the management actions were intended to promote other species (i.e., sugar maple). With few stand entries specifically targeting yellow birch, this species was included in M2. Note also that this approach does not have the same limiting time dimension as the treatment approach (i.e., only applicable following treatments), since the pure/full stocking conditions will likely exist through the duration of the management scenario.

Even though the combined method yields expected results for M2, the extent of undergrowth is small or unobserved for some species. Paper birch and northern white-cedar showed minimal increased growth under this parsing method, and no FIA subplots contained pure stands of yellow birch. Explanations for some of these results relate to current management objectives described above. In addition, although paper birch shows marginal increased growth under management, relative to mean projected growth this value is reasonable (see Table 4.7). Overall, the combined approach appears to provide the most consistent estimates for the M2 species. Where poor representation or lack of data prevent deriving a realistic MAN coefficient, the estimate for quaking aspen will act as a substitute.

4.3.2 Intensively Managed Stands

Initial investigation revealed that selecting an upper percentile of growth from all stands resulted in subdatasets not fully characterized by management conditions. For example, less than half of the fast growing trees came from fully stocked stands (e.g., 32% for quaking aspen and 30% for red pine). In addition, the all stand data contained larger and more frequent extreme values, unlike the upper percentiles of the managed stand subdataset. Many of these extremes were from trees whose species represented a minor component of the stand (not the forest type). Therefore, candidate upper percentiles were compiled from the managed stand subdatasets selected for each species in order to ensure realistic management conditions. Table 4.5 gives the species specific quantiles and sample sizes associated with each proposed upper percentile alternative.

Table 4.5. Candidate large tree diameter growth quantiles (inches per five years) and sample sizes (number of trees) for defining intensively managed stands for each species, grouped my management strategy.

Man. Group	Species	Quantile			n		
		90th	95th	99th	90th	95th	99th
M1	American basswood	1.1	1.4	1.9	106	45	9
	Balsam fir	1.2	1.5	2.1	63	27	5
	Black spruce	0.7	0.9	1.3	27	13	3
	Eastern white pine	1.9	2.2	3.4	69	39	7
	Jack pine	1.1	1.2	1.5	15	10	2
	Northern red oak	1.3	1.6	2.0	106	42	8
	Red pine	1.2	1.4	1.8	200	103	22
	Sugar maple	1.1	1.3	1.8	434	220	48
	Tamarack	0.7	0.9	1.4	23	10	2
	White oak	0.9	1.1	1.4	58	31	7
M2	Balsam poplar	1.0	1.1	1.4	8	4	1
	Bigtooth aspen	1.2	1.4	1.6	23	8	4
	Northern white-cedar	0.5	0.6	0.8	507	259	71
	Paper birch	0.5	0.6	0.8	21	15	4
	Quaking aspen	1.2	1.4	1.7	131	59	12
	White spruce	0.8	1.0	1.3	21	10	2
	Yellow birch	n/a	n/a	n/a	0	0	0

Clearly, the observed growth increases with increasing quantile. However, the sample sizes decrease rapidly. For the 99th quantile, almost half the species have n < 5, suggesting the extreme upper percentiles do not contain enough information to precisely represent intensive management. Selecting between the remaining two alternatives was less straightforward, as both quantiles do not suffer from chronic lack of data. Ultimately, the 90th quantile was selected in order to obtain the largest sample size, leading to lower standard errors. This quantile appears to provide an efficient balance between isolating high growth rates and obtaining adequate sample sizes.

Note that this approach collects the fasted growing, individual trees from across managed stands. This rapid growth likely results in part from limited local competition for the selected trees. When aggregating the trees together, they may form an under stocked “stand”, a condition not consistent with intensive management. Although current or future silvicultural practices may produce similarly high growth rates, the reduced competition inherent in the upper percentile approach should be considered when using the model.

Table 4.6 gives the additive MAN parameter estimates for species under intensive management. Note that for the M2 species, the estimates may have little utility. These stands typically undergo few to no intermediate stand treatments, whereas the definition of intensive management involves multiple stand entries. Still, the Table 4.6 values represent observed growth that is likely repeatable under certain intensive management scenarios for all species.

Table 4.6. Intensively managed stand additive MAN coefficients. These values were determined from an upper percentile of managed stand subdata based on the 90th quantile of large tree diameter growth. Values represent the change in five year growth (in) in intensively managed stand versus all stand projections using the current version of LS-FVS. The species are grouped according to management strategy.

Man. Type	Species	MAN
M1	American basswood	0.803
	Balsam fir	0.719
	Black spruce	0.396
	Eastern white pine	1.187
	Jack pine	0.496
	Northern red oak	0.651
	Red pine	0.490
	Sugar maple	0.672
	Tamarack	0.469
	White oak	0.501
M2	Balsam poplar	0.455
	Bigtooth aspen	0.313
	Northern white-cedar	0.408
	Paper birch	0.381
	Quaking aspen	0.615
	White spruce	0.696
	Yellow birch	n/a

Figures 4.2 and 4.3 show the distributions of observed minus LS-FVS predicted growth for all, unmanaged, managed, and intensively managed stands of red pine and quaking aspen, respectively (unmanaged stands were defined as those stands not classified as managed). The differences between the centers of the managed stand distributions and the center of the all stands distribution equals the additive MAN parameters. Note that for all density curves, the y-axis has little meaning. The values are chosen so that the area under the curve equals one, and thus the distributions represent probability distributions. Therefore, shorter curves imply larger ranges in the data.

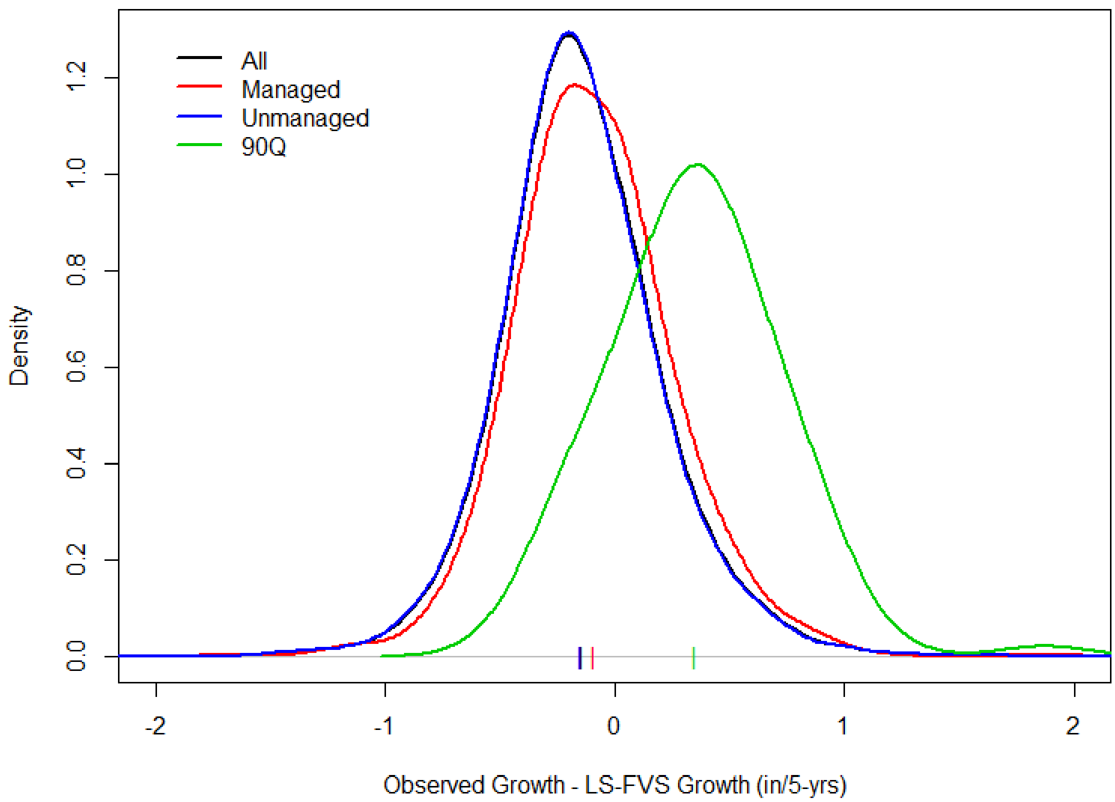

Figure 4.2. Distributions of differences between **red pine** measured large tree diameter growth and LS-FVS predicted growth (five year growth). The center of each distribution (mean) is marked. Distances between the center of the all stands distribution and the centers of the managed distributions equal the additive MAN coefficients. Note that projected annual growth was converted to five year growth through multiplication by five.

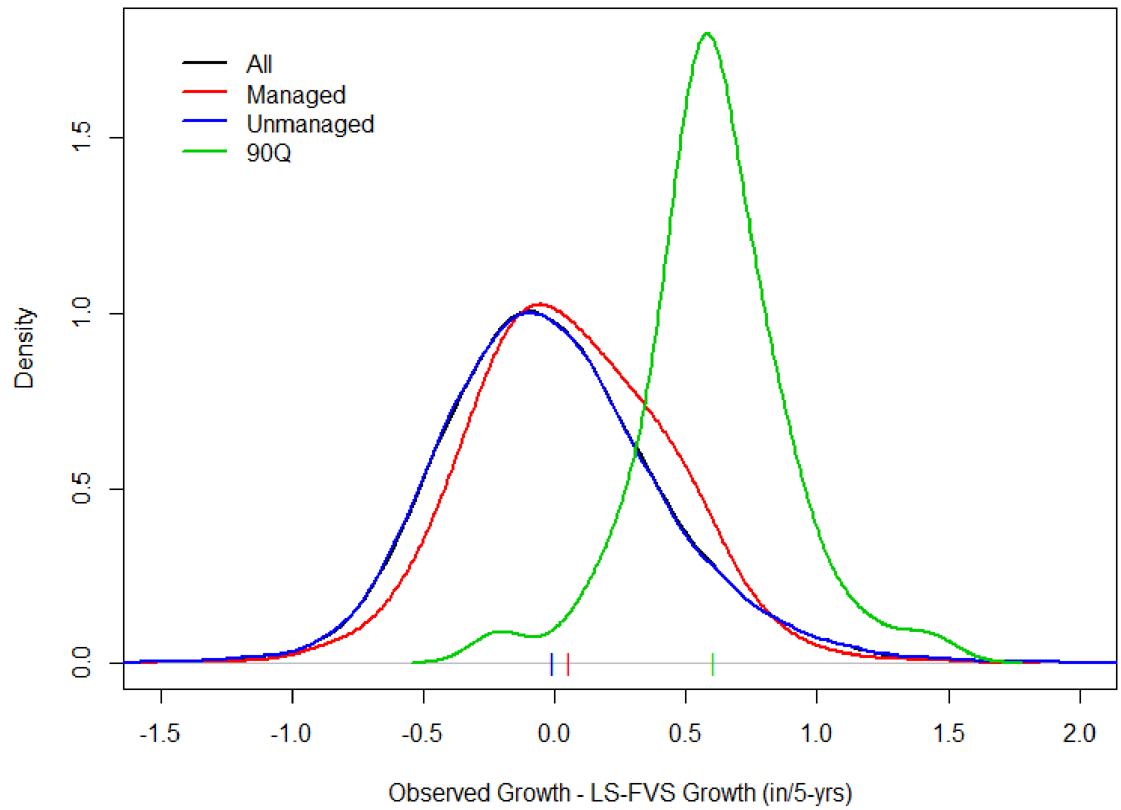

Figure 4.3. Distributions of differences between **aspen** measured large tree diameter growth and LS-FVS predicted growth (five year growth). The center of each distribution (mean) is marked. Distances between the center of the all stands distribution and the centers of the managed distributions equal the additive MAN coefficients. Note that projected annual growth was converted to five year growth through multiplication by five.

4.3.3 Multiplicative MAN Coefficients

Table 4.7 gives the annualized additive MAN coefficients and the multiplicative MAN coefficients, derived from equation 4.9. The table also includes the mean predicted managed stand growth (bias corrected) for each species using the current version of LS-FVS (as used in equation 4.9). The multiplicative MAN coefficients are estimates of the MAN parameter in equation 4.8 and represent the percent increase in diameter growth for managed and intensively managed stands. LS-FVS will use these growth multipliers when growing trees from managed stands.

Table 4.7. Annualized additive and multiplicative MAN parameter estimates for all species (listed by management strategy). Also included are the bias corrected mean diameter growth projections for each species using the current version of LS-FVS. All units are in inches.

Man. Type	Species	Additive MAN		Mean LS-FVS Growth (Bias Corrected)		Multiplicative MAN	
		Man.	Int. Man.	Man.	Int. Man.	Man.	Int. Man.
M1	American basswood	0.007	0.161	0.105	0.127	1.066	2.263
	Balsam fir	0.014	0.144	0.121	0.161	1.113	1.891
	Black spruce	0.011	0.079	0.065	0.111	1.174	1.716
	Eastern white pine	0.022	0.237	0.170	0.252	1.131	1.941
	Jack pine	0.007	0.099	0.103	0.157	1.065	1.634
	Northern red oak*	0.003	0.130	0.137	0.182	1.018	1.715
	Red pine	0.011	0.098	0.134	0.190	1.081	1.516
	Sugar maple	0.008	0.134	0.100	0.138	1.079	1.972
	Tamarack	0.010	0.094	0.060	0.089	1.169	2.054
	White oak	0.006	0.100	0.094	0.126	1.066	1.796
M2	Balsam poplar	0.023	0.091	0.106	0.134	1.214	1.680
	Bigtooth aspen	0.023	0.063	0.151	0.200	1.150	1.313
	Northern white-cedar	0.000	0.082	0.046	0.042	1.008	2.931
	Paper birch	0.004	0.076	0.048	0.049	1.072	2.543
	Quaking aspen	0.013	0.123	0.132	0.152	1.095	1.810
	White spruce	0.062	0.139	0.014	0.055	5.524	3.525
	Yellow birch**	0.013	0.123	0.132	0.152	1.095	1.810

* Northern red oak used the difference in median managed stand growth and median all stand growth to compute an estimate of MAN. Intensive management used the difference in mean growth.

** Yellow birch adopted the values from quaking aspen

In summary, Figures 4.4 and 4.5 provide schematics demonstrating the influence of the MAN coefficients for red pine and quaking aspen, respectively. Figure 4.4 reveals a common trait for the M1 species: the current version of the diameter growth model recognizes the improved growing conditions in managed stands and increases growth accordingly. However, this additional growth only partially represents the increase in observed growth, with the remaining portion accounted for by the MAN coefficient. This relationship between the current model and the MAN coefficient holds for either managed or intensively managed stands.

All M2 species demonstrated similar traits to those found in Figure 4.4. However, the current version actually projected reduced diameter growth in managed stands for some species (e.g., Figure 4.5). The full stocking condition may explain this behavior. LS-FVS reduces growth due to the increased competition in fully stocked stands, but apparently fails to fully capture the improved growing conditions in pure species stands (e.g., Burkhart and Sprinz 1984).

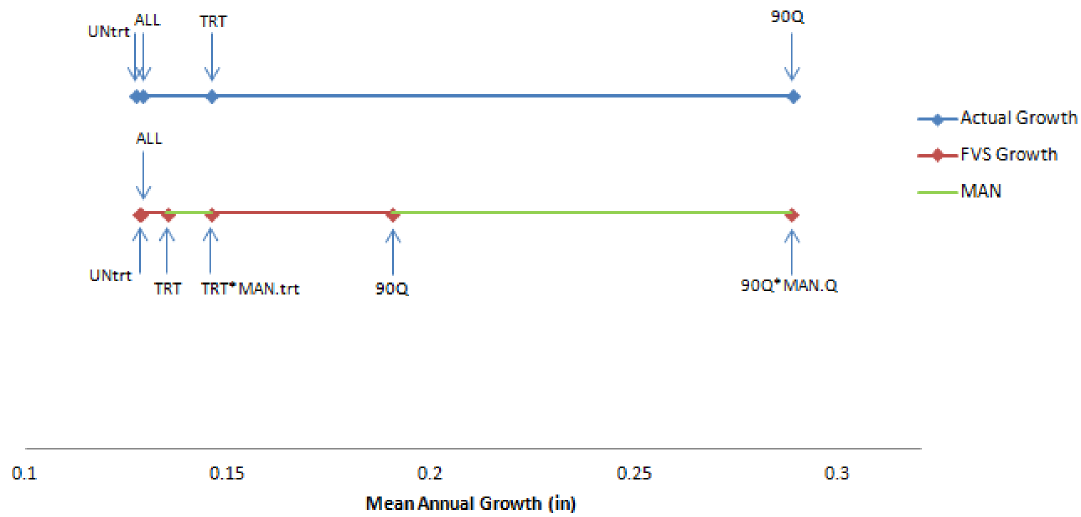

Figure 4.4. Schematic representing the relationship between **red pine** actual growth, LS-FVS predicted growth, and the multiplicative MAN coefficients. The graph shows annual growth, with observed growth divided by five. The FVS projections were shifted to remove observed bias in the model. "90Q" represents intensively managed stands, and MAN.trt and MAN.Q identify the MAN coefficients associated with managed and intensively managed stands, respectively. The points represent mean annual growth for the labeled datasets or labeled projections, with the lines showing the distance between growth values.

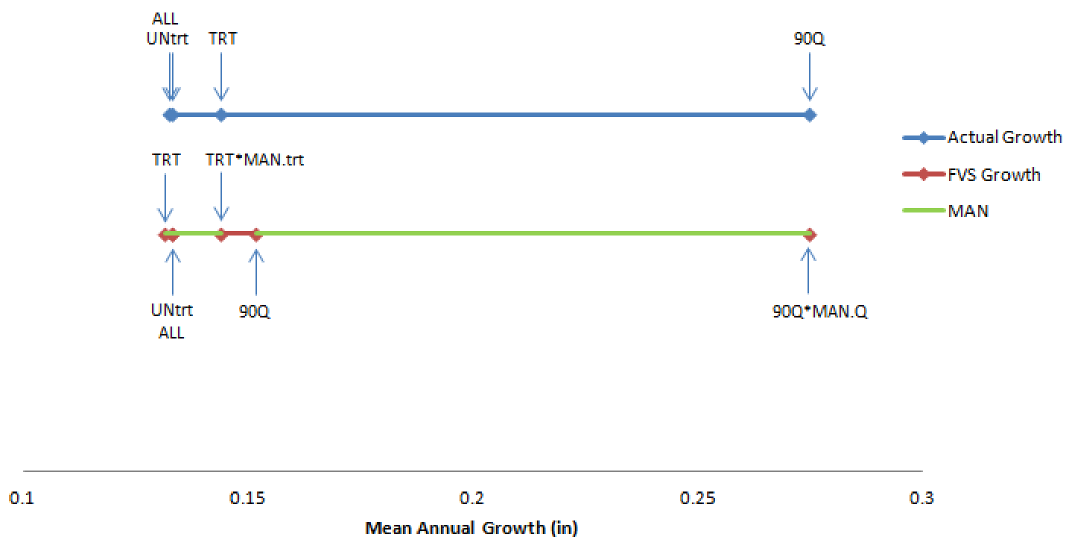

Figure 4.5. Schematic representing the relationship between **aspen** actual growth, LS-FVS predicted growth, and the multiplicative MAN coefficient. The graph shows annual growth, with observed growth divided by five. The FVS projections were shifted to remove observed bias in the model. "90Q" represents intensively managed stands, and MAN.trt and MAN.Q identify the multiplicative MAN coefficients associated with managed and intensively managed stands, respectively. The points represent mean annual growth for the labeled datasets or labeled projections, with the lines showing the distance between growth values.

Note that the large tree diameter growth model represents only one LS-FVS component affected by management. Future work will include (1) updating the small tree diameter and height growth models to better represent the early gains from intensive management and (2) refining the mortality module to obtain estimates consistent with increased management. Finally, the updated LS-FVS components will be programmed into the FVS framework and activated using the existing keyword MANAGED. Users of the new version of LS-FVS will then have the capability to obtain results appropriate across the lifespan of unmanaged to intensively managed stands. Additional work should focus on expanding the limited database of managed and intensively managed stand inventories via directly measuring these stands or including management fields in the FIA surveys. This data will facilitate the evaluation of the assumptions and parsing methods employed in this study and provide for further model refinements.

Chapter 5

Evaluation of the large tree diameter growth model for the managed and intensively managed stand version of the Lake States variant of the Forest Vegetation Simulator

John M. Zobel and Alan R. Ek

Zobel and Ek (2013) proposed a managed and intensively managed stand version of the Lake States (Michigan, Minnesota, and Wisconsin) variant of the Forest Vegetation Simulator (LS-FVS). Their research focused on the large tree diameter (≥ 5.0-in diameter breast height) growth model component. This study seeks to evaluate this model using data from the U.S. Forest Service Forest Inventory and Analysis (FIA) program. Evaluation statistics included mean error, standard deviation of the errors, and mean percent error. Ultimately, the level of acceptable error will depend on the user. Still, evaluation procedures for the new versions of the individual tree growth model showed errors in diameter growth projections that were within ranges found during the validation of the current model. All species/diameter class combinations had reasonable model errors, with the exception of white spruce (*Picea glauca* (Moench) Voss). This species had large errors due to the considerable difference between growth in managed and unmanaged stands. Further work is necessary to stabilize managed stand diameter growth estimates for this species. In addition, diameter dependent height growth appeared reasonable, without any egregious violations of typical height/diameter

relationships. Overall, the proposed model appears to adequately project diameter growth for managed and intensively managed stands in the Lake States.

5.1 Introduction

An essential component of any modeling effort involves comparing model behavior with that observed or expected in the modeled system (i.e., model validation). This often takes the form of comparing measured values with their associated projected values and quantifying the differences. If tests show the model does not adequately mimic the natural system, then the model needs recalibration or re-engineering.

The Lake States variant of the Forest Vegetation Simulator (LS-FVS) large tree diameter growth model (and its previous versions in STEMS (The Stand and Tree Evaluation and Modeling System) and LS-TWIGS (The Woodsman's Ideal Growth System)) has undergone several validation attempts. Leary et al. (1979) and Holdaway and Brand (1983) sought to validate the original STEMS growth model, with modest success. However, the growth model consistently overestimated diameter growth. After including an adjustment factor in the model (Holdaway 1985), Holdaway and Brand (1986) re-evaluated STEMS (known as STEMS85) and found substantial improvements in estimates, including a switch from overgrowth to slight undergrowth for several species.

Since LS-FVS has a wide geographic extent, several studies examined LS-FVS validity for more local conditions and specific species. Guertin and Ramm (1996) and Canavan and Ramm (2000) found that the growth model consistently overestimated growth for upland hardwood stands in Michigan, while Smith-Mateja and Ramm (2002) showed that LS-FVS overgrew red pine plantations in this same region. After subjecting the STEMS model to a battery of tests, Leary (1997) found that the model failed to reproduce several known "laws" of forest stand development in Michigan red pine plantations. More recently, Pokharel and Froese (2008) examined the current version of the LS-FVS large tree diameter growth model using equivalency tests. They were unable to validate the growth model for any of the 30 species explored in Michigan, and they ultimately suggested the growth model needs re-engineering. However, the moderate subjectivity and conservative results of equivalency tests suggest the current model may still have credibility. Overall, although these validation studies indicate improvements are necessary, ultimate model utility depends on user specific accuracy and precision requirements.

Evaluation of the managed stand version of LS-FVS focuses on testing the new model form relative to the current model. As noted during model development, the MAN coefficients were derived after accounting for observed bias in the original model (Zobel and Ek 2013). Comparisons of unadjusted managed stand projections to observed values will reflect the bias in both the current and new model forms. Therefore, evaluation attempts will remove the observed bias in the models before comparing actual and predicted growth values for managed stands.

In addition, the increased diameter growth produced in the managed stand version of LS-FVS could lead to unreasonably large height growth estimates. Obviously, this is an unintended and undesirable consequence. Therefore, model evaluation will include examining height growth estimates from LS-FVS and height/diameter (H/D) relationships for realistic behavior. Results from these comparisons may ultimately serve to constrain diameter growth to appropriate levels.

5.2 Methods

5.2.1 Data

The evaluation dataset comprises measurements from the Forest Inventory and Analysis (FIA) database for the Lake States region (USDA 2010). Since the late 1990s, FIA annually measures 20% of their inventory plots in Michigan, Minnesota, and Wisconsin, with a statewide inventory completed every five years (one FIA cycle). See Zobel and Ek (2013) and Woudenberg et al. (2011) for further details. The calibration dataset for the managed stand diameter growth model came from the last two completed cycles within the region. The current, uncompleted FIA cycles include two (Michigan and Wisconsin) or three (Minnesota) years of additional measurements (through 2011). This most recent sub-cycle data will form the evaluation dataset.

Note that subsequent cycles in FIA do not represent independent inventories, but rather remeasurements. Thus, the evaluation data may not constitute a true independent dataset, with the exception of plots that failed to exist or qualify as managed in the previous cycle, but now fit the management criteria. Table 5.1 gives the number of remeasured and new trees in the evaluation dataset by management strategy. These groups were defined in Zobel and Ek (2013) and essentially described species typically managed using multiple or few stand entries (termed M1 and M2, respectively).

Table 5.1. Number of remeasured and new trees in the evaluation dataset by species and management strategy (as defined in Zobel and Ek (2013)).

Man. Group	Common Name	Scientific Name	Remeas. Trees	New Trees
M1	American basswood	*Tilia americana* L.	0	366
	Balsam fir	*Abies balsamea* (L.) Mill.	0	204
	Black spruce	*Picea mariana* (Mill.) B. S. P.	0	55
	Eastern white pine	*Pinus strobus* L.	0	192
	Jack pine	*Pinus banksiana* Lamb.	0	40
	Northern red oak	*Quercus rubra* L.	0	286
	Red pine	*Pinus resinosa* Ait.	0	691
	Sugar maple	*Acer saccharum* Marsh.	0	1,067
	Tamarack	*Larix laricina (Du Roi)* K. Koch	0	23
	White oak	*Quercus alba* L.	0	113
M2	Balsam poplar	*Populus balsamifera* L.	0	5
	Bigtooth aspen	*Populus grandidentata* Michx.	33	4
	Northern white-cedar	*Thuja occidentalis* L.	1161	640
	Paper birch	*Betula papyrifera* Marsh.	0	0
	Quaking aspen	*Populus tremuloides* Michx.	215	653
	White spruce	*Picea glauca* (Moench) Voss	54	0
	Yellow birch	*Betula alleghaniensis* Britton	0	0

Not surprisingly, the M1 species have only new trees within the dataset. In order to include remeasured trees, a stand would need to undergo treatments during both completed FIA cycles, a stand history excluded during model development. Also as expected, the evaluation data for the M2 species has a substantial component of remeasured trees. In the absence of catastrophic disturbance or stand replacing treatments, managed stands will likely maintain their status as pure/fully stocked for some time. The relatively large number of new trees in quaking aspen and northern white-cedar stands likely resulted from either the establishment of new plots, ingrowth (trees becoming ≥ 5-in dbh), or a forest type change, due to the removal of a previously dominant associate species.

Even with the large component of remeasured trees for three species (bigtooth aspen, northern white-cedar, and white spruce), the evaluation dataset will likely provide adequate data for evaluating the model for these species. The remeasurements represent unique growth observations, with trees likely exhibiting similar, yet not identical growth patterns compared to their previous measurements. In addition, the dearth of managed stand data that necessitated using FIA data for model calibration also necessitated using additional FIA data for model evaluation. This evaluation should continue as more managed stand data becomes available.

Examination of the relationship between estimated diameter and height growth for managed stands will use the original calibration dataset (see Zobel and Ek (2013) for a description of this data). FIA records individual tree heights on a subset of large diameter trees within a subplot and estimates the others using a regionally appropriate height model (Woudenberg et al. 2011). Only actually measured heights from standing trees (no broken tops) were used when calculating observed height growth between the two measurement periods.

5.2.2 Evaluation Statistics

Standard model validation statistics include mean error (observed – fitted), standard deviation of the error, mean absolute error, ratio of observed to predicted values, and/or these statistics reported as percents. The majority of LS-FVS validation studies used mean error to estimate accuracy and its associated standard deviation to estimate precision. This study will use these metrics, in addition to percent mean error (see equations below). Note that nearly all LS-FVS validation studies compute mean error as

$(\hat{y}_i - y_i)$, instead of $(y_i - \hat{y}_i)$ as in most statistical applications. The latter form will be used when reporting errors in this study, and thus positive and negative mean error will represent undergrowth and overgrowth, respectively.

$$\bar{e} = \sum_{i=1}^{n}(y_i - \hat{y}_i)\,/n \tag{5.1}$$

$$s_e = \sqrt{\frac{\sum_{i=1}^{n}(e_i - \bar{e}_i)^2}{n-1}} \tag{5.2}$$

$$\bar{e}^* = \frac{100}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)\,/y_i \tag{5.3}$$

where $\bar{e}$ = mean error, y_i = measured diameter growth for the ith tree, $\hat{y}_i$ = predicted diameter growth for the ith tree, s_e = standard deviation of the errors, and $\bar{e}^*$ = percent mean error.

Validation statistics were computed to evaluate overall model accuracy and precision for a species. In addition, mean errors and their associated standard deviations were computed by diameter class within a species. Only those diameter classes with at least 10 trees and species with at least three qualifying diameter classes were analyzed. In addition, the shapes of the distributions of observed and predicted growth were compared for their similarity, along with the distribution of growth projections from the current version of LS-FVS.

For diameter growth/height growth comparisons, the correspondence (or lack thereof) between observed height growth and estimates using LS-FVS and H/D allometric relationships will reveal any unrealistic patterns in height growth as the result of increased diameter growth. In LS-FVS, the height growth model (Carmean et al.

1989) and algorithm first estimates 10-yr growth before rescaling the estimates to the specified projection length (Dixon and Keyser 2008). H/D height growth is based on either Curtis (1967) and Arney (1985) or Wykoff et al. (1982) (depending on the species) and is the difference between estimated height at the end of the projection and estimated height at the beginning. Note that although these H/D models facilitate comparisons, they only estimate height to replace missing values in LS-FVS (Dixon and Keyser 2008). In addition, all diameter and height projections and calculations were conducted using the R statistical package (R Development Core Team 2011).

5.3 Results and Discussion

Table 5.2 gives the validation statistics and sample sizes for individual species grown under management and intensive management. Several species have limited (<10 trees) to no data available for evaluation, particularly for intensive management. Results for these species should be considered non-conclusive.

Table 5.2. Mean error, standard deviation of errors, percent mean error, and sample size (number of trees) for large tree diameter growth projections using the managed stand version of LS-FVS and the evaluation dataset. No data was available for paper birch and yellow birch. All units are in inches.

Species	Management				Intensive Management			
	ME	SD Error	Mean % Error	n	ME	SD Error	Mean % Error	n
American basswood	-0.02	0.47	-1.43	366	-0.07	0.71	-2.32	51
Balsam fir	0.02	0.45	1.87	204	0.26	0.63	5.68	21
Black spruce	-0.07	0.29	1.01	55	0.01	0.48	2.54	6
Eastern white pine	0.09	0.66	1.43	192	0.21	1.00	3.47	23
Jack pine	0.08	0.30	-0.93	40	0.03	0.12	-2.62	4
Northern red oak*	0.08	n/a	9.94	286	0.51	0.66	7.17	33
Red pine	0.00	0.39	-3.92	691	0.08	0.47	-3.76	86
Sugar maple	-0.02	0.39	-2.97	1,067	-0.06	0.44	-4.02	112
Tamarack	0.29	0.36	4.46	23	0.17	0.59	3.34	5
White oak	0.09	0.38	0.40	113	0.48	0.31	3.57	12
Balsam poplar	-0.30	0.36	-10.21	5	-0.16	n/a	-10.79	1
Bigtooth aspen	0.04	0.24	-0.34	37	0.12	0.17	0.55	7
Northern white-cedar	-0.01	0.26	0.86	1,801	0.04	0.68	2.96	238
Paper birch	n/a	n/a	n/a	0	n/a	n/a	n/a	0
Quaking aspen	0.08	0.36	0.77	868	0.13	0.33	1.39	103
White spruce	0.51	0.75	-44.58	54	0.50	0.43	-26.66	6
Yellow birch	n/a	n/a	n/a	0	n/a	n/a	n/a	0

*ME = median(y) – median($\hat{y}$); thus, standard deviation is unavailable.

For managed stands, Table 5.2 shows that mean error ranges from 0.00-0.51-in during a five year growth period. Only white spruce exceeds 0.5-in, with most species having an error <0.1-in. These errors closely resemble those found by Holdaway and Brand (1986). In particular, red pine behaved remarkably well, with zero mean error to two decimal places. Also, this species had mean percent error of approximately 4% and a reasonable standard deviation (0.39-in). Quaking aspen also showed fairly high accuracy and precision, with a mean error of 0.08-in, mean percent error of 0.77%, and standard deviation of 0.36-in. For all species, precision ranged from 0.24-0.75-in and appears reasonable compared to other validation studies (Guertin and Ramm 1996; Smith-Mateja and Ramm 2002). White spruce and eastern white pine showed the highest variability (0.75-in and 0.66-in, respectively).

Tables 5.3 and 5.4 further divide the results into two-inch diameter classes by species. Due to the limited sample size, only nine and four (out of 17) species had results for managed and intensively managed stands, respectively. These tables show mixed results, with accuracy and precision varying by diameter class. Mean errors ranged from 0.00-0.41-in and standard deviations from 0.11-0.88-in, again reasonable values relative to prior validation attempts. Still, red pine showed a distinct pattern from overgrowth of the smaller diameter classes to undergrowth of the larger classes. Also, two species (eastern white pine and white oak) were undergrown for all diameter classes.

Table 5.3. Mean error and standard deviation of the errors for projected large tree five year diameter growth (in) using the managed stand LS-FVS growth model and the evaluation dataset. Error statistics calculated by two inch diameter class within species.

Diam. Class	American basswood			Balsam fir			Eastern white pine		
	ME	SD	n	ME	SD	n	ME	SD	n
6	0.09	0.50	91	0.06	0.42	136	0.16	0.68	54
8	-0.02	0.53	88	-0.08	0.42	43	0.00	0.55	34
10	-0.12	0.43	70	-0.28	0.51	14	0.08	0.83	36
12	-0.08	0.44	57	n/a	n/a	<10	0.04	0.58	25
14	-0.05	0.32	29	n/a	n/a	<10	0.13	0.56	14
16	-0.19	0.36	14	n/a	n/a	<10	n/a	n/a	<10
Diam. Class	**N. Red oak***			**Red pine**			**Sugar maple**		
	ME	SD	n	ME	SD	n	ME	SD	n
4	n/a	n/a	<10	n/a	n/a	<10	0.10	0.35	13
6	0.03	n/a	116	-0.20	0.40	180	0.01	0.36	364
8	0.02	n/a	120	-0.01	0.39	181	-0.02	0.39	273
10	-0.04	n/a	155	0.08	0.35	152	-0.06	0.40	199
12	-0.04	n/a	150	0.10	0.33	106	-0.05	0.40	120
14	0.03	n/a	105	0.17	0.29	40	0.01	0.41	52
16	0.01	n/a	65	0.29	0.40	15	0.02	0.35	24
18	0.17	n/a	38	n/a	n/a	<10	-0.14	0.53	14
20	0.08	n/a	16	n/a	n/a	<10	n/a	n/a	<10
Diam. Class	**White oak**			**N. White-cedar**			**Quaking aspen**		
	ME	SD	n	ME	SD	n	ME	SD	n
4	n/a	n/a	<10	-0.05	0.11	34	0.07	0.35	55
6	0.13	0.37	25	-0.04	0.22	941	0.10	0.35	543
8	0.01	0.21	19	-0.01	0.24	517	0.08	0.34	167
10	0.01	0.27	18	0.07	0.31	211	0.01	0.37	64
12	0.12	0.43	14	0.11	0.49	65	-0.14	0.33	19
14	0.08	0.43	19	0.21	0.48	23	0.01	0.55	16

* ME = median(y) – median($\hat{y}$); thus, standard deviation is non-informative.

Table 5.4. Mean error and standard deviation of the errors for projected large tree five year diameter growth (in) using the intensive management LS-FVS growth model and the evaluation dataset. Error statistics calculated by two inch diameter class within species.

Diam. Class	Red pine			Quaking aspen		
	ME	SD	n	ME	SD	n
6	-0.14	0.58	14	0.15	0.34	68
8	0.03	0.42	34	0.12	0.35	21
10	0.23	0.50	19	-0.08	0.18	8
12	0.20	0.41	10	n/a	n/a	<10

Diam. Class	N. White-cedar			Sugar maple		
	ME	SD	n	ME	SD	n
6	-0.08	0.57	88	0.18	0.54	24
8	-0.06	0.71	65	-0.05	0.44	26
10	0.13	0.68	50	-0.07	0.39	19
12	0.35	0.88	19	-0.19	0.39	17
14	0.41	0.59	10	-0.15	0.17	11

Overall, most species/diameter class combinations had reasonable model errors, with the exception of white spruce. This species has orders of magnitude increased growth in managed stands versus unmanaged stands, with projection errors increasing accordingly. Also, the white spruce evaluation dataset comprised only remeasured trees. Thus, further work is necessary to stabilize managed stand projections for this species.

In addition to calculating error statistics, the distributions of observed and predicted growth were compared for their similarity. Figure 5.1 graphs the distributions of red pine and quaking aspen managed stand diameter growth using observed growth (D_o), managed/intensively managed stand model growth projections (D_m), and current LS-FVS growth projections (D_{ls}). Since D_{ls}*MAN = D_m, the shapes of the two distributions will be similar, except D_m will have a larger spread (and thus flatter appearance) and have its center shifted toward the center of D_o. In all the graphs, the relationship between D_m and D_o is similar to the relationship between D_{ls} and D_o for all stands. In addition, the shape of D_m more closely matches D_o than D_{ls}, but the spread does not for intensively managed stands. In other words, the new model has higher accuracy than the current model when growing intensively managed stands, but the latter model has higher precision. In this case, accuracy appears clearly preferable, although this will depend on the user.

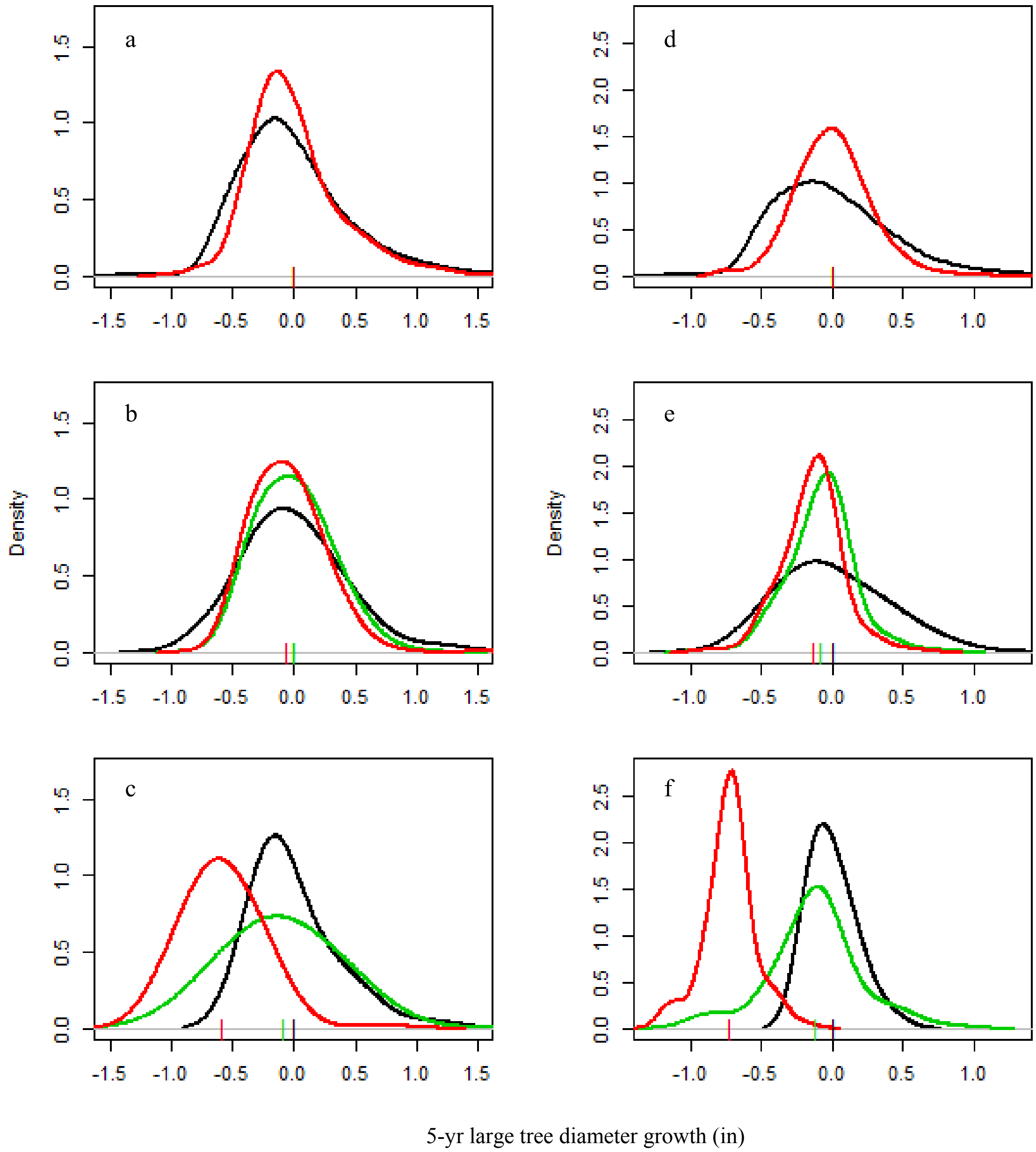

Figure 5.1. Distributions of five year large tree diameter growth using all stand (a,d), managed stand (b,e), and intensively managed stand (c,f) datasets for the red pine (a-c) and quaking aspen (d-f) forest types. Black, red, and green curves represent actual growth, current LS-FVS projected growth, and managed/intensively managed stand model growth projections. For ease of interpretation, the observed growth distributions were centered at zero, with the other distributions shifted accordingly.

Figures 5.2 and 5.3 give schematics showing how actual height growth, FVS height growth, and H/D relationship height growth relate for red pine and quaking aspen, respectively. For red pine, LS-FVS estimated height growth appears reasonable, with the exception of unmanaged stand growth. All conditions, managed, and unmanaged stand H/D height growth estimates resemble those from LS-FVS. However, the estimated growth for intensive management is substantially higher than observed growth (43% higher). This result may indicate a problem with the diameter growth model, or may represent and extrapolation of the H/D equation. The substantial diameter growth in the intensive management subdataset (and thus projected in the model) likely exceeds growth rates inherent in the H/D calibration data. In addition, since LS-FVS uses the height growth model and not H/D relationships for updating tree heights, this large estimated growth should not affect red pine simulations in the managed stand version of LS-FVS. For quaking aspen, the diameter growth estimates appear to produce reasonable height estimates, although the height growth model in LS-FVS seems conservative.

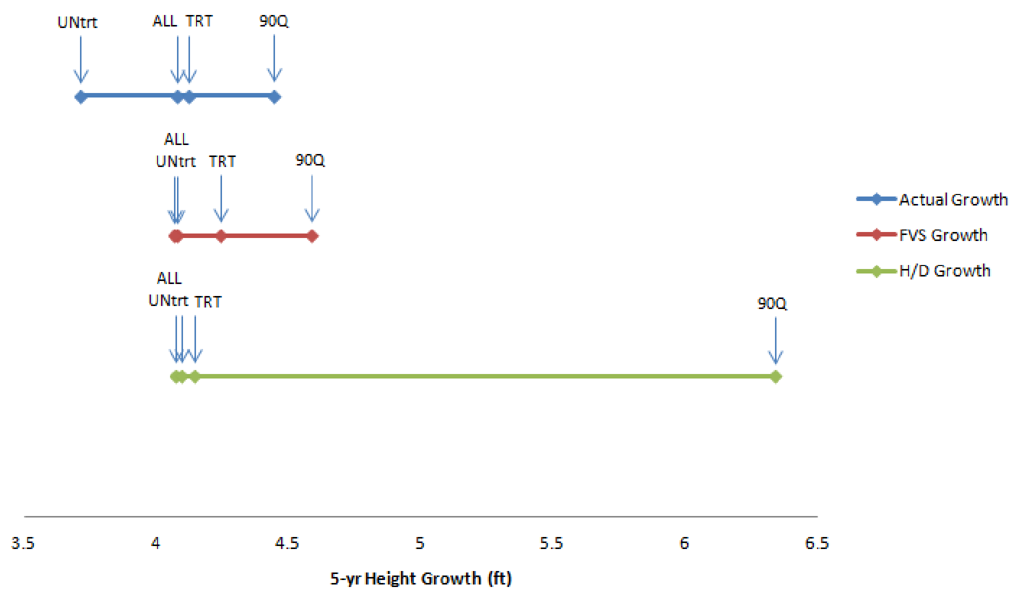

Figure 5.2. Schematic representing the relationship between **red pine** actual height growth, FVS predicted height growth, and H/D estimated height growth for unmanaged, all conditions, managed, and intensively managed stands. Growth represents mean five year growth (ft), with the 10-yr FVS projections divided by two. The FVS projections and H/D estimates were shifted to remove observed bias in their respective models. "90Q" represents intensively managed stands. The points represent mean five year height growth for the labeled datasets or labeled projections, with the lines showing the distance between growth values.

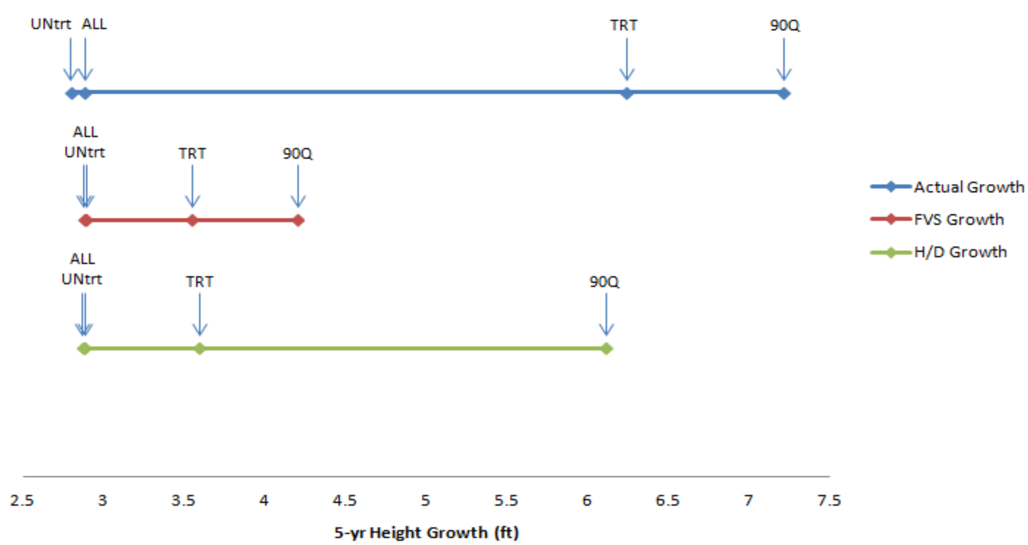

Figure 5.3. Schematic representing the relationship between **aspen** actual height growth, FVS predicted height growth, and H/D estimated height growth for unmanaged, all conditions, managed, and intensively managed stands. Growth represents mean five year growth (ft), with the 10-yr FVS projections divided by two. The FVS projections and H/D estimates were shifted to remove observed bias in their respective models. "90Q" represents intensively managed stands, and "TRT" describes managed stands defined by the full stocking/pure stand approach. The points represent mean five year height growth for the labeled datasets or labeled projections, with the lines showing the distance between growth values.

Note that when using just the managed and intensively managed stand version of the large tree diameter growth model in LS-FVS, users can expect the accuracy and precision discussed previously. However, employing the entire suite of keywords and modules in LS-FVS provides the user with many tools for refining diameter growth estimates (including local calibration). Therefore, skilled application of LS-FVS can further reduce model errors for managed stands.

Chapter 6

A whole stand, lifespan yield model for the red pine and aspen forest types in Minnesota

John M. Zobel, Alan R. Ek, and Tim O'Hara

Recent questions of the habitat quality and ecological benefits provided by older forests have led to the concept of extended rotation forests (ERF). Consideration of this approach has increased in forest planning efforts in Minnesota, with some planning horizons carrying portions of forests well beyond typical rotation ages and thus beyond the calibration data of most local yield models. This study modified an existing volume yield curve for the red pine and aspen forest types (Walters and Ek 1993) to more accurately represent the entire life of a single age cohort (i.e., forest stand). The new model assumed that across the life of the stand, accumulated stand mortality equals accumulated stand growth (i.e., stand mortality eventually reaches 100%). From among several proposed model forms, a symmetric curve based on an underlying basal area model proved superior. The curve first follows the existing yield model until the point of culminating mean annual increment, then departs toward an asymptote (i.e., maximum basal area) at half of maximum stand age. Finally, projections retreat back down the curve to reach zero yield at maximum age. Conversion of basal area yield to volume yield followed the equation found in Walters and Ek (1993). In addition, the study provides a modified version of the model for ease of implementation and proposes a mortality yield model for calculating volume yield loss due to stand aging. Forest

managers and planners tasked with estimating yield (or yield loss) from extended rotations can now obtain more realistic projections for older stands than those given by typical yield models.

6.1 Introduction

For over a century, foresters have produced yield curves to describe the projected amount of product available to generate revenue. In particular, the Lake States region has a considerable history of stand or individual tree yield model development (Brown and Gevorkiantz 1934; Gevorkiantz and Duerr 1938; Gevorkiantz and Olsen 1955; Essex and Hahn 1976; Hahn and Raile 1982; among many others). Typically, these yield curves are expressed as either equations or tables and represent specific species, forest types, or composites of species. Many tree or stand attributes have been modeled, including total volume, merchantable volume, crown ratio, basal area, trees per acre, quadratic mean diameter, and height (e.g., Ek and Brodie 1975; Holdaway et al. 1979; Walters and Ek 1993). Volume yield has dominated the modeling efforts, as this attribute is highly correlated with overall biological productivity and economic interests.

The data available for developing early yield models provided sufficient coverage of stand ages found under typical management regimes (i.e., with harvests at or before the age of maximum mean annual volume increment). Yet these stands were seldom grown and/or infrequently survived far beyond rotation age, leading to a dearth of records on older stands. This limited range of data led to many classic yield curves showing monotonically increasing yield across the observed (and hence unobserved) range of tenable ages (e.g., Gevorkiantz and Duerr 1938; Ek and Brodie 1975; Walters and Ek

1993), with a few more recent exceptions (Dixon 2002; Zobel et al. 2011). But these monotonically increasing curves are unrealistic across the life of a stand, due to biological limits and natural disturbances. Also, succession to another forest type may occur as the number of stems decline, particularly for the short lived aspen species. This may lead to a change in forest type in subsequent inventory data.

In addition, more recent questions regarding the habitat quality and ecological benefits provided by older forests have led to the concept of extended rotation forests (ERF) (MNDNR 2012). Debate continues over the utility of ERF, but consideration of the concept has increased in forest planning efforts. Therefore, planning horizons may carry a portion of the forest well beyond typical rotation ages and thus beyond the calibration of most yield models in the region. However, careful tradeoff analysis in planning will require estimates of yield and/or mortality loss at older ages.

This study seeks to modify an existing volume yield model and associated yield curves (Walters and Ek 1993) to more accurately represent the entire life of a forest stand, with an emphasis on the red pine and aspen forest types. Leading into the study, several assumptions were made regarding model behavior and even-aged stand development: (1) the model represents average stand development and may behave poorly for those stands experiencing disturbance, whether natural or in the form of silvicultural treatment; (2) the model describes one age cohort (i.e., “stand”) through time and does not address associated stands that arise before, during, or after the stand of interest; and (3) across the life of the stand, accumulated stand mortality equals accumulated stand growth (i.e., stand mortality eventually reaches 100%). The resulting refined model will provide improved yield and mortality projections for those tasked with determining volume yields from older stands and/or volume losses as stands age. Also, the curve and its derivatives represent another iteration toward describing stand development and decline across the full lifespan of even-aged stands.

6.2 Methods

6.2.1 Base Model

The Walters and Ek (1993) (hereafter referred to as WE) stand level yield model and implementing equations have seen widespread use in Minnesota, including the Minnesota Department of Natural Resources (MNDNR) (Schwalm 2009). These equations represent a system of linked yield models, including those for gross total volume, merchantable volume, basal area, quadratic mean diameter, and trees per acre. Since the volume equations have stand basal area as an explanatory variable, this study sought to mimic stand development and decline through the basal area model, with results propagated in the volume equations. The WE equations of interest are below:

$$B = a_1 S^{a_2} A^{a_3} \tag{6.1}$$

$$H = b_1 S^{b_2} (1 - \exp(b_3 A))^{b_4 S^{b_5}} \tag{6.2}$$

$$V = d_1 B^{d_2} H^{d_3} \tag{6.3}$$

where B = stand basal area (ft^2/ac) for trees ≥ 0.95-in diameter breast height (dbh), S = site index (ft), A = stand age (years), H = average total height (ft) of dominant/ codominant trees in the stand, V = gross volume (ft^3/ac) of trees ≥ 4.95-in dbh above a 1-ft stump, and a_1-a_3, b_1-b_5, and d_1-d_3 are species specific model coefficients (see Table

6.1). The WE height model came from Ek (1971) and the associated parameters from Hahn (1984). Table 6.1 gives the coefficient estimates for models 6.1-6.3 for the red pine and aspen forest types.

Table 6.1. Coefficient estimates for the basal area, height, and gross volume equations from Walters and Ek (1993) for the red pine and aspen forest types.

Yield Type	Parameter	Forest Type	
		Red Pine	Aspen
B	a_1	2.3990	0.6036
	a_2	0.5913	0.7735
	a_3	0.3469	0.4459
H	g_1	1.8900	11.4804
	g_2	1.0000	0.5039
	g_3	-0.0198	-0.0281
	g_4	1.3892	105.9678
	g_5	0.0000	-1.0590
V	d_1	1.1605	3.1206
	d_2	1.0762	0.9241
	d_3	0.6228	0.5449

6.2.2 Proposed Models

Using equation 6.1 as a base, several lifespan yield models were hypothesized. The initial work emphasized conceptual, realistic curve behavior rather than equation fitting, due to the dearth of data in the older age classes (see Botkin et al. (1972) for a similar approach when encountering the absence of data). These models all incorporated two postulated characteristics associated with stand development and decline. First, the average annual growth of a stand attribute (e.g., gross volume) continues to increase until reaching a maximum. This maximum is often referred to as the point of culminating mean annual increment (CMAI). After this point, the average annual growth declines asymptotically toward zero. Therefore, each proposed model follows equation 6.1 until reaching CMAI, then separates, gradually decreasing toward an asymptote at the point of maximum yield.

Second, each equation uses a maximum stand age to constrain model behavior. Presumably, after reaching maximum age, a stand (i.e., single cohort) has zero yield. Therefore, all the proposed models converge at this age limit. Maximum stand ages were developed from Hardin et al. (2001), Burns and Honkala (1990), and species specific management guides (USDA n.d.a. and USDA n.d.b.). Forest type specific normal yield tables were also examined for the point of maximum basal area (Gevorkiantz and Duerr 1938). These results provided a rough estimate of half maximum age (and thereby maximum age) by indirectly identifying the point of maximum basal area yield. In addition to the above commonalities, the proposed models had similar, yet varied characteristics, as described below.

6.2.2.1 Model 1: Rotation

After CMAI, Model 1 progresses toward a basal area asymptote at half maximum age. The curve continues at this asymptote until the start of a 90 degree clockwise rotation of the WE curve that passes through the point (max age, 0). This curve mimics those stands that remain at maximum basal area for some time before declining rapidly. Conceptually,

$$B = \begin{cases} a_1 S^{a_2} A^{a_3} & if\ A \le A_{MAI} \\ B_0 + \left[\left(B_{WE_1} - B_{WE_0} \right) \left(1 - \left(\frac{B_0}{B_{max}} \right)^S \right) \right] \Big|_A & if\ A_{MAI} < A \le A_{max/2} \\ B_{max} & if\ A_{max/2} < A \le A_{decline} \\ B_{max} - \left[\frac{A - A_{decline}}{a_1 S^{a_2}} \right]^{1/a_3} & if\ A_{decline} < A \le A_{max} \end{cases} \tag{6.4}$$

where B_0 = the previous iterative estimate of B, B_{WE_i}= the basal area estimate from Walters and Ek (1993) for the current (i = 1) and previous (i = 0) stand ages, $B_{max} = a_1 S^{a_2} \left(A_{max/2} - A_{MAI}\right)^{a_3}$ (maximum projected basal area), A_{MAI} = age of culminating MAI, $A_{max/2}$ = half maximum age, A_{max} = maximum age, $A_{decline} = A_{max} - a_1 S^{a_2} B_{max}^{a_3}$ (the point where basal area begins to decline), s = a shape parameter that controls the smoothness of the curve, and a_1-a_3 are from WE.

Note that when $A_{decline} < A_{max/2}$, the equation gives multiple estimates at certain ages. In this situation, the asymptote still occurs at $A_{max/2}$, but the rotated curve is raised to a power < 1 to force the curve to pass through the point (A_{max}, 0). In addition, the shape parameter ensures a smooth curve between A_{MAI} and $A_{max/2}$. In general, s = 3 + 0.2(A_{MAI}), but when A_{MAI} is close to $A_{max/2}$, a larger s may be required to ensure a smooth curve.

6.2.2.2 Model 2: Rotation and Asymptote

After CMAI, Model 2 progresses toward a basal area asymptote at 60% of maximum age and continues at this value until 70% of maximum age. The curve then follows a 90 degree clockwise rotation of equation 6.1 that passes through the point (max age, 0). However, this rotated curve approaches a vertical asymptote at maximum age. This alternative is similar to Model 1, except the maximum basal area attained is higher and obtained later, resulting in more rapid decline. Altering the points of basal area maximum and stand decline may give more realistic behavior for different stands. Conceptually,

$$B = \begin{cases} a_1 S^{a_2} A^{a_3} & if\ A \le A_{MAI} \\ B_0 + \left[\left(B_{WE_1} - B_{WE_0} \right) \left(1 - \left(\frac{B_0}{B_{max}} \right)^S \right) \right] \Big|_A & if\ A_{MAI} < A \le A_{max*0.6} \\ B_{max} & if\ A_{max*0.6} < A \le A_{max*0.7} \\ B_{max} - \left[\left(\frac{A_0 - A_1 - a_1 S^{a_2} {A'_0}^{a_3} + a_1 S^{a_2} {A'_0}^{a_3} \left(\frac{A_0}{A_{max}} \right)^S}{\left(\left(\frac{A_0}{A_{max}} \right)^S - 1 \right) a_1 S^{a_2}} \right) \right]^{1/a_3} & if\ A_{max*0.7} < A \le A_{max} \end{cases} \tag{6.5}$$

where A_i = current (i = 1) and previous (i = 0) stand age, $A'_0 = B_{max} - B_0$, and $A_{max*0.6}$ and $A_{max*0.7}$ = 60% and 70% of maximum age, respectively.

6.2.2.3 Model 3: Symmetric

Model 3 is the same as Model 1, except after reaching the basal area asymptote at half maximum age, the curve retreats back down the curve to the point (max age, 0). Essentially, this alternative represents the approach suggested by Schwalm (2009), but with the addition of a basal area asymptote and zero yield and maximum age. Conceptually,

$$B = \begin{cases} a_1 S^{a_2} A^{a_3} & if\ A \le A_{MAI} \\ B_0 + \left[\left(B_{WE_1} - B_{WE_0} \right) \left(1 - \left(\frac{B_0}{B_{max}} \right)^S \right) \right] \Big|_A & if\ A_{MAI} < A \le A_{max/2} \\ B_0 + \left[\left(B_{WE_1} - B_{WE_0} \right) \left(1 - \left(\frac{B_0}{B_{max}} \right)^S \right) \right] \Big|_{A'} & if\ A_{max/2} < A \le A_{max} - A_{MAI} \\ a_1 S^{a_2} {A'}^{a_3} & if\ A_{max} - A_{MAI} < A \le A_{max} \end{cases} \tag{6.6}$$

where $A' = A_{max} - A$. Note that for Models 1-3, ages were incremented by 0.1-yrs when developing and computing the iterative portions of the models. Using larger (or smaller) increments during conceptual model application will give incorrect results.

6.2.3 Applied Model

Regardless of the final model form, the iterative nature of the asymptotic components in the proposed equations limits their utility for point estimation. Therefore, a fourth model was suggested that uses modeled ratios to substantially increase usability. Ratios were defined as estimates from a proposed model divided by their associated estimates from equation 6.1, and these ratios were modeled as a polynomial function of age. Incorporating the ratios as yield modifiers led to the following applied model:

$$B = a_1 S^{a_2} A^{a_3} w \tag{6.7}$$

where $w = \sum_{i=0}^{n} b_i \tilde{A}^i$, $\tilde{A} = A/100$, a_1-a_3 are from WE, and b_i are species specific coefficients derived from the polynomial fit. The ratios remain constant across site index values, and the appropriate range of the applied model depends on the associated conceptual model.

6.2.4 Empirical Model

In addition to the original and proposed models, data from the U.S. Forest Service Forest Inventory and Analysis (FIA) program was used to calculate mortality rates across observed stand ages for the red pine and aspen forest types. The data came from 35 (red pine) and 480 (aspen) one-acre plots in Minnesota (each comprised of four fixed-radius subplots (1/24th of an acre) and four microplots (1/300th of an acre)). These plots were measured in 1999-2003 (FIA cycle 12) and remeasured in 2004-2008 (FIA cycle 13). For a description of the FIA database, see Woudenberg et al. (2011). The percentage of trees alive in cycle 12, but dead in cycle 13, relative to all live trees in cycle 12, defined the mortality rate. No disturbance or treatment occurred on the plots between cycles 12 and 13. Any plots with cut trees were also excluded, and cycle 13 tree records labeled as cycle 12 inclusion errors or as missing in cycle 13 were deleted. All four subplots had one and the same FIA condition/forest type in both cycles. Each plot had an estimated stand age.

The computed mortality rate had fairly erratic behavior across age classes, especially in the tails. In order to obtain smoothed estimates, percent mortality was modeled as a polynomial function of age. Also, the same polynomial was fit using linear mixed-effects modeling techniques, but with forest type as a random effect. For a discussion of mixed-effects modeling, see Gelman and Hill (2007) and Robinson and Hamann (2011).

Unfortunately, little to no data is available on mortality rates in very young or old age classes. As a result, the polynomial fits gave unrealistic estimates of mortality for these age groups. Therefore, very young mortality rates were held constant at the 2.5 quantile of the mortality data, and the mortality rate for old ages was increased annually at a fixed rate so that mortality equaled 100% at maximum age. Note that the data used to fit the original WE equations inherently incorporated mortality. Thus, using empirical mortality to reduce WE yield may actually double count mortality.

6.2.5 Mortality Yield Model

After establishing a preferred conceptual model, comparisons between WE output and projections using the new model allow for computing losses in volume yield (i.e., mortality yield) due to stand (i.e., cohort) aging. Although the WE models naturally incorporate background mortality, they do not account for aging induced mortality. The new model form includes both. Therefore, the differences between WE estimates and those from the preferred conceptual model represent the loss in volume yield resulting from extended rotations or no management (i.e., stand aging). Formally,

$$V_M = V_{WE} - V_C + r[(V_{WE}/(1-m)) * m] \tag{6.8}$$

where V_M= estimated mortality volume yield (ft^3/ac) due to stand aging, V_{WE} = projected volume yield (ft^3/ac) from Walters and Ek (1993), V_C = projected volume yield (ft^3/ac) from the preferred conceptual model, *r* = a modifier with values between 0-1, and *m* = mean empirical mortality rate (expressed as a decimal).

Since the definition of V_C necessitates $V_{WE} - V_C$ = 0 for ages 0-CMAI, observed mortality yield was added to the model across this age range ($r[(V_{WE}/(1-m)) * m]$). The addition of empirical mortality allows the mortality yield model to provide volume estimates across the entire lifespan of the stand, rather than only where $V_{WE} \neq V_C$. Division by (1 – *m*) removes background mortality from the original WE volume estimates before calculating current mortality volume. Also, *r* reduces the influence of empirical mortality in the computation of overall volume loss. This term equals one (*r* = 1) until CMAI and equals zero (*r* = 0) at half maximum age through maximum age. From CMAI to half maximum age, *r* is calculated from the following equation:

$$r = 1 - \frac{A - A_{MAI}}{A_{max/2} - A_{MAI}} \tag{6.9}$$

This equation incrementally reduces *r* as projection age increases across the applicable range. In addition, estimates of m were calculated from observed mortality in the FIA database (as described in section 6.2.4).

Note that the primary objective of this study was to replace unrealistically high volume estimates (V_{WE}) with realistic estimates (V_C) across the older age classes. Thus, the inclusion of V_{WE} in equation 6.8 could lead to overestimates of volume loss. However, examination of the WE basal area projections used to compute WE volume in this study revealed no violation of species specific biological limits (Dixon and Keyser 2008), and thus V_{WE} remained in the mortality yield model.

The original WE equations, each proposed conceptual model, the applied model, the empirical mortality estimates, and the mortality yield model were generated for the red pine and aspen forest types. All calculations and graphing were completed using the R statistical package (R Development Core Team 2011).

6.3 Results and Discussion

6.3.1 Proposed Model Behavior

Figures 6.1 and 6.2 show the three conceptual model curves for the red pine and aspen forest types, respectively. These figures also give the original WE basal area curve and the WE gross volume estimates using basal area projections from the proposed and original equations. Both figures also include curves for WE model estimates less empirical mortality. As expected, these figures show that equation 6.5 has the highest basal area maximum and most rapid decline among the proposed models. Equations 6.4

and 6.6 have the same asymptote, but equation 6.4 has more consistent decline across the older ages, whereas equation 6.6 decreases gradually before declining rapidly near maximum age. The fixed rate increase in percent mortality led to the empirical mortality curves producing the lowest yield. Also, Figures 6.1 and 6.2 show that the volume curves resemble the basal area curves, but with less symmetry.

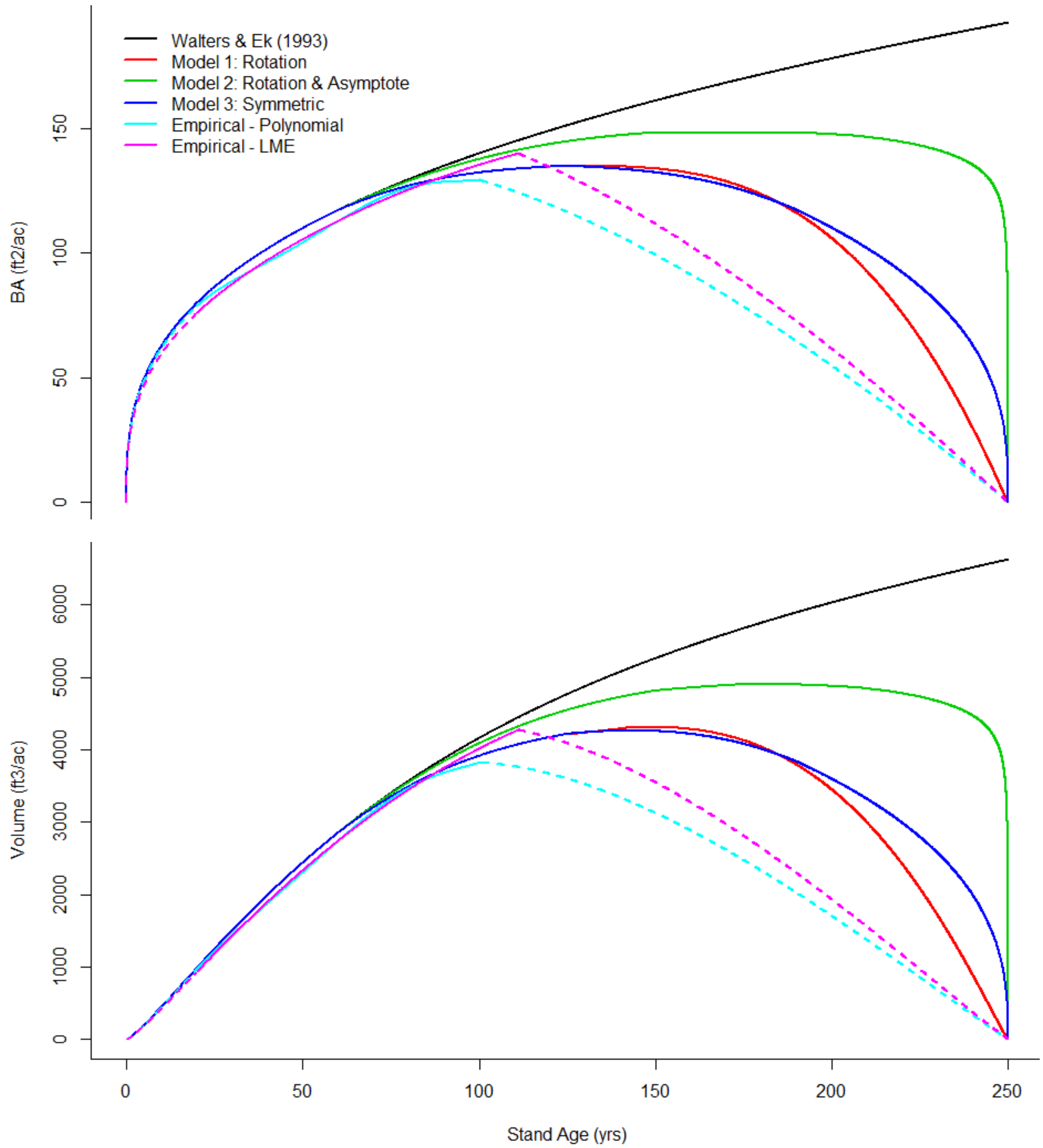

Figure 6.1. Variations of the Walters and Ek (1993) basal area and volume yield curves for **red pine**, including the original model fits, the three proposed conceptual models, and the two empirical mortality methods. Note that the volume curves were derived using the basal area estimates from the various approaches. Dashed lines represent empirical mortality estimates beyond the range of data. Site index = 65 ft, CMAI = 60 years, and maximum age = 250 years.

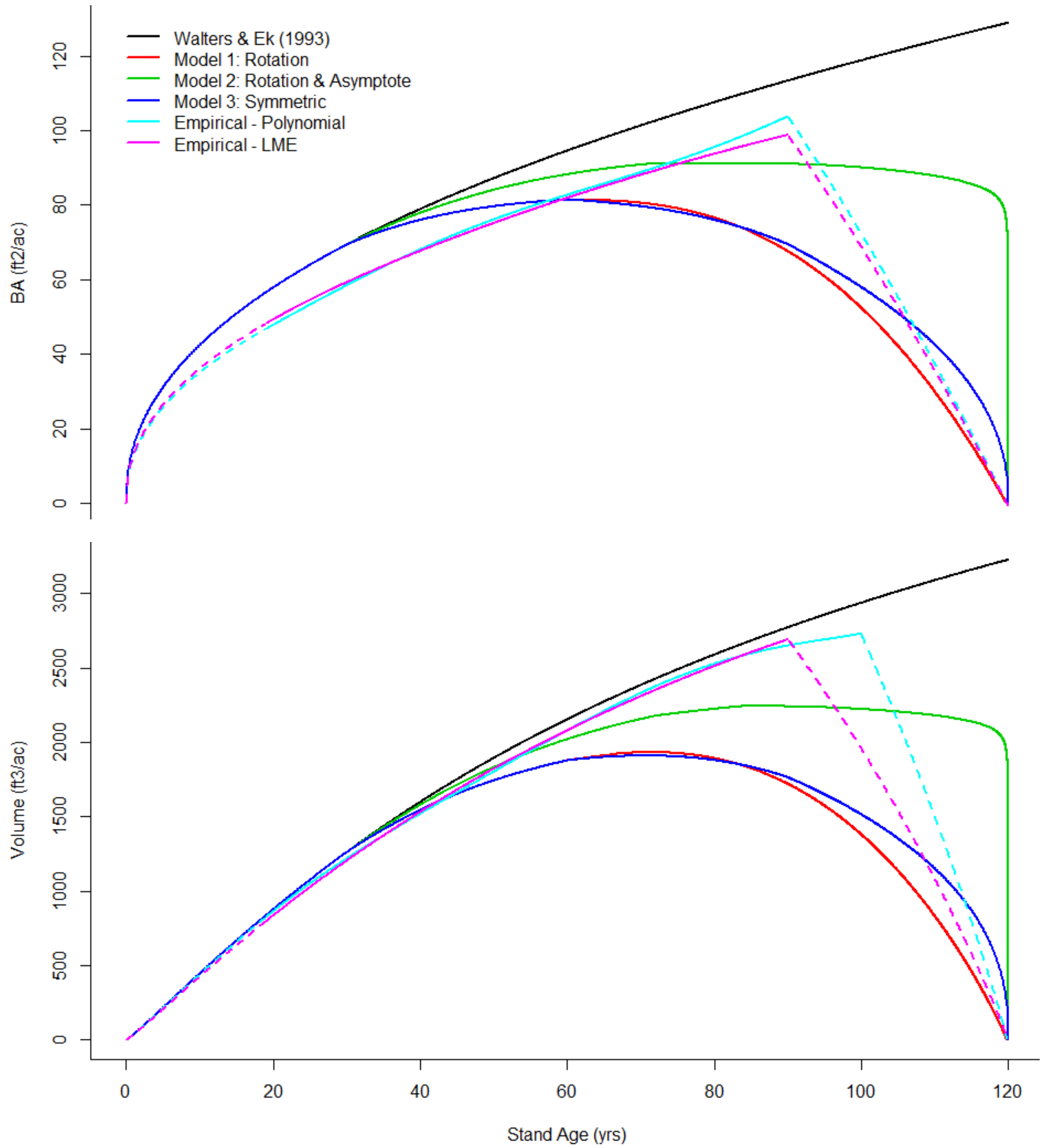

Figure 6.2. Variations of the Walters and Ek (1993) basal area and volume yield curves for **aspen**, including the original model fits, the three proposed conceptual models, and the two empirical mortality methods. Note that the volume curves were derived using the basal area estimates from the various approaches. Dashed lines represent empirical mortality estimates beyond the range of data. Site index = 65 ft, CMAI = 30 years, and maximum age = 120 years.

The choice of preferred model (if any) from among the proposed equations may depend on user needs and/or growth and yield characteristics of a particular stand. Until the addition of data in the older age classes, differentiating between the proposed models will remain challenging. In general, however, the symmetric approach appears superior for several reasons. First, the objective was to describe the lifespan yield for an *average* stand. The symmetric curve represents an "average" curve between the original WE equations and the empirical curves. Second, many older stands may only gradually lose volume over time, but then rapidly increase mortality as they approach maximum age. The mortality increase in equation 6.6 provides a balance between the other two proposed models, with the increase in equations 6.4 and 6.5 appearing too slow and too fast, respectively. Third, the symmetric method coincides with the approach suggested by Schwalm (2009) and used by the MNDNR. Fourth, from an ecological perspective, the symmetric model projects stand development that at least roughly coincides with estimates from modeled successional processes within the region, particularly for pioneer species (Pastor and Post 1986; Host and Pastor 1998). And finally, the symmetric approach represents the most intuitive and easily understandable method for users, in addition to having the most efficient form for implementation.

6.3.2 Applied Model Behavior

After selection of the symmetric model, the applied model was fit to the ratios between estimates from equation 6.6 and equation 6.1, using several candidate powers for the polynomial. Examination of predictions and R^2 values showed that using a third order polynomial gave the best fit while using the fewest parameters ($R^2 = 1.000$). Table

6.2 gives the parameter estimates for the applied model at several values of CMAI and maximum age for the red pine and aspen forest types. Note that for the symmetric approach, the applied model only pertains to the region between CMAI and half maximum age, since the corresponding region after half maximum age uses the same values, but in descending order.

Table 6.2. Parameter estimates, R^2values, and *s* values for the applied model and different values of culminating mean annual increment (CMAI) and maximum age. For the symmetric conceptual model, the applied model only pertains to the region between CMAI and half maximum age.

Forest Type	Max Age	CMAI	a_0	a_1	a_2	a_3	R^2	*s*
Red Pine	250	60	0.876	0.520	-0.633	0.182	1.000	15
		75	0.724	0.906	-0.896	0.237	1.000	21
		90	0.479	1.479	-1.293	0.326	1.000	28
	300	60	0.891	0.401	-0.433	0.106	1.000	15
		75	0.820	0.560	-0.517	0.119	1.000	18
		90	0.725	0.754	-0.622	0.137	1.000	21
Aspen	90	20	0.774	2.395	-7.538	5.869	1.000	15
		30	0.323	5.319	-12.895	8.911	1.000	25
		40	-2.635	23.579	-49.421	32.972	1.000	65
	120	30	0.743	1.940	-4.385	2.519	1.000	15
		40	0.326	3.976	-7.231	3.747	1.000	25
		50	-0.937	9.816	-15.841	7.913	1.000	44

6.3.3 Mortality Yield Model Behavior

Figure 6.3 shows the WE volume yield curves and the mortality yield curves for red pine using output from equation 6.1 and equation 6.6, with an average empirical mortality of 3%. This figure shows that volume loss starts slowly, but increases rapidly as the stand moves into the older ages, with mortality reaching 100% at maximum age. The graph for aspen (not shown) resembles Figure 6.3, but with an estimated average empirical mortality of 10%. Note that although very young stands often experience high mortality rates, the cumulative mortality volume remains relatively low.

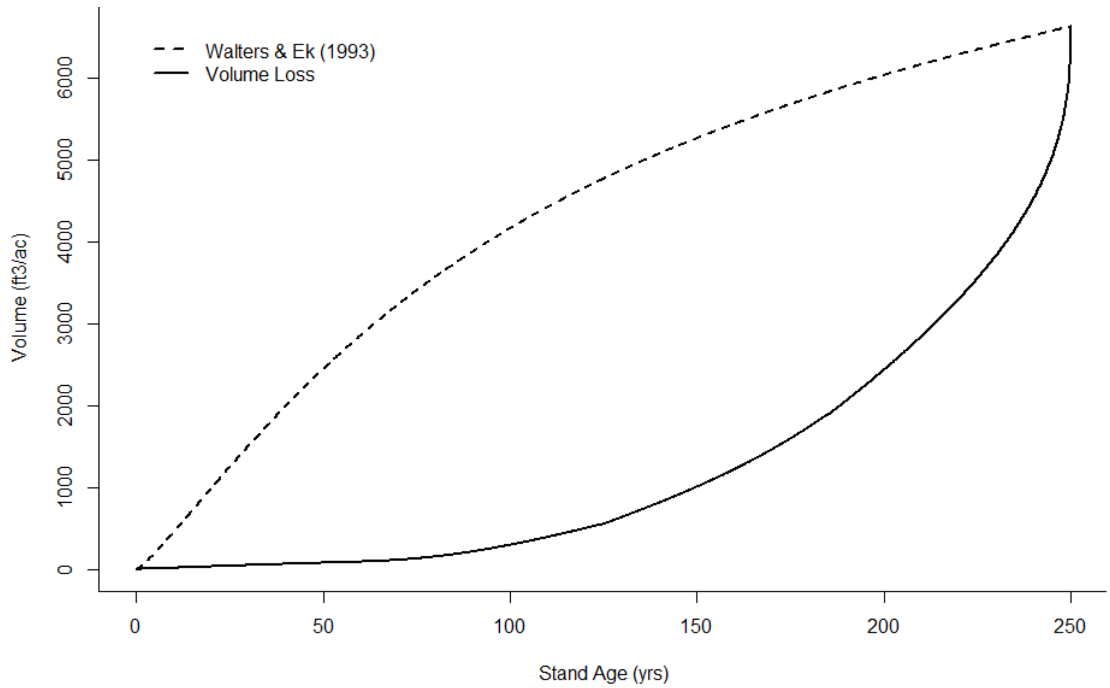

Figure 6.3. Estimated volume and mortality yield (ft^3/ac) for the red pine forest type, based on Walters and Ek (1993) and the newly derived mortality yield model, respectively. Site index = 65 ft, CMAI = 60 years, and maximum age = 250 years.

Ultimately, the mortality yield model will allow forest managers to estimate the impact of extended rotations on volume yield. For example, for an aspen stand with a CMAI of 30 years and a maximum age of 120 years, extending the rotation age from 40 to 70 years increases mortality yield from 7.5 ft^3/ac to 20.1 ft^3/ac. On the contrary, the additional volume yield from delaying harvest 30 years equals only 4.0 ft^3/ac, indicating a considerable loss of volume due to the longer rotation. Although this effect will vary by stand and extended rotation age, like comparisons during forest planning efforts will provide estimates of the economic and ecological effects of extended rotations. Further research efforts that endeavor to measure and observe stand decline may provide data to validate or suggest reengineering the new models. In addition, the simplicity of the final model forms should facilitate the rapid extension of these results to the other forest types in Walters and Ek (1993).

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Appendix 1

Forest type crosswalk

Table A1.1 gives the crosswalk between the GEIS, FIA, and MNDNR forest type definitions (Jaakko Pöyry Consulting, Inc. 1992a; Woudenberg et al. 2011; MNDNR 2012). Those forest types under the last general category "Other" represent forest types encountered in Minnesota FIA data that did not directly correspond to a GEIS forest type. For these non-matching types that reference a specific species, the most closely related forest type (by species) recognized by the GEIS was selected (e.g., Scotch pine mapped to red pine). For those types that referenced broad groups (e.g., other hardwoods), the individual tree data was consulted to determine the most prolific species within that FIA forest type. The associated GEIS forest type then mirrored the dominant tree species.

Table A1.1. Forest type definition crosswalk between the GEIS, FIA, and MNDNR approaches. The forest types are grouped by broad forest type categories. Substantial portions of this table are reproduced from Page and Ek (2005).

General		**GEIS Birds**	**GEIS Mammals**	**FIA Group Code**	**FIA Forest Type Group**	**FIA Code**	**FIA Forest Type**	**CSA Code**	**MNDNR-CSA Cover Types**
Coniferous	Upland	Upland pine	Jack pine	100	White, red, jack pine	101	Jack pine	53	Jack pine
			Red pine			102	Red pine	52	Norway pine
			White pine			103	Eastern white pine	51	White pine
		Upland spruce/fir	Upland spruce/fir	120	Spruce fir	121	Balsam fir	62	Balsam fir
			White spruce			122	White spruce	61	White spruce
	Lowland	Lowland conifer	Black spruce			125	Black spruce	71	Lowland black spruce
			Tamarack			126	Tamarack	72	Tamarack
			Northern white-cedar			127	Northern white-cedar	73	Northern white-cedar

Deciduous	Southern	Northern hardwoods	Oak	500	Oak hickory	503	White oak/red oak/hickory	30	Oak
						504	White oak		
						505	Northern red oak		
						509	Bur oak		
						512	Black walnut	25	Walnut
						516	Cherry/white ash/yellow-poplar	1	Ash
						517	Elm/ash/black locust		
						519	Red maple/oak	40	Central hardwoods
						520	Mixed upland hardwoods		
			Elm-ash-cottonwood	700	Elm, ash, cottonwood	701	Black ash/American elm/red maple	9	Lowland hardwoods
						702	River birch/ sycamore		
						703	Cottonwood	15	Cottonwood
						704	Willow	6	Willow
						706	Sugarberry/hackberry/elm/green ash	9	Lowland hardwoods
						708	Red maple/lowland		
						709	Cottonwood/willow		

	Northern		Maple-basswood	800	Maple, beech, birch	801	Sugar maple/beech/ yellow birch	20	Northern hardwoods
						802	Black cherry		
						805	Hard maple/ basswood		
						809	Red maple/upland		
		Aspen-birch	Aspen	900	Aspen-birch	901	Aspen	12	Aspen
			Paper birch			902	Paper birch	13	Birch
			Balsam poplar			904	Balsam poplar	14	Balm of Gilead
			Aspen-birch			905	Pin cherry		
Other		Upland pine	Red pine	380	Exotic softwoods	381	Scotch pine	54	Scotch pine
			White pine	400	Oak pine	401	White pine/red oak/white ash		
		Northern hardwoods	Elm-ash-cottonwood	990	Exotic hardwoods	995	Other exotic hardwoods		
			Oak	170	Other eastern softwoods	171	Eastern redcedar	81	Red cedar
				400	Oak pine	402	Eastern redcedar/ hardwood		
		Aspen-birch	Aspen-birch	400	Oak pine	409	Other pine/hardwood		
				960	Other hardwoods	962	Other hardwoods		

Appendix 2

Age class to size class map

WHINGS includes an option for generating size class information from age class data. An internal map was created by identifying the age class associated with a change in size class (Figure A2.1; Table A2.1). Small sample sizes and weak relationships prevented determining a reliable map for several forest types, and thus four broad forest type groupings (upland conifer, lowland conifer, northern hardwoods, and aspen-birch) were used to provide the best possible conversion. These groupings roughly coincide with the bird habitat categories.

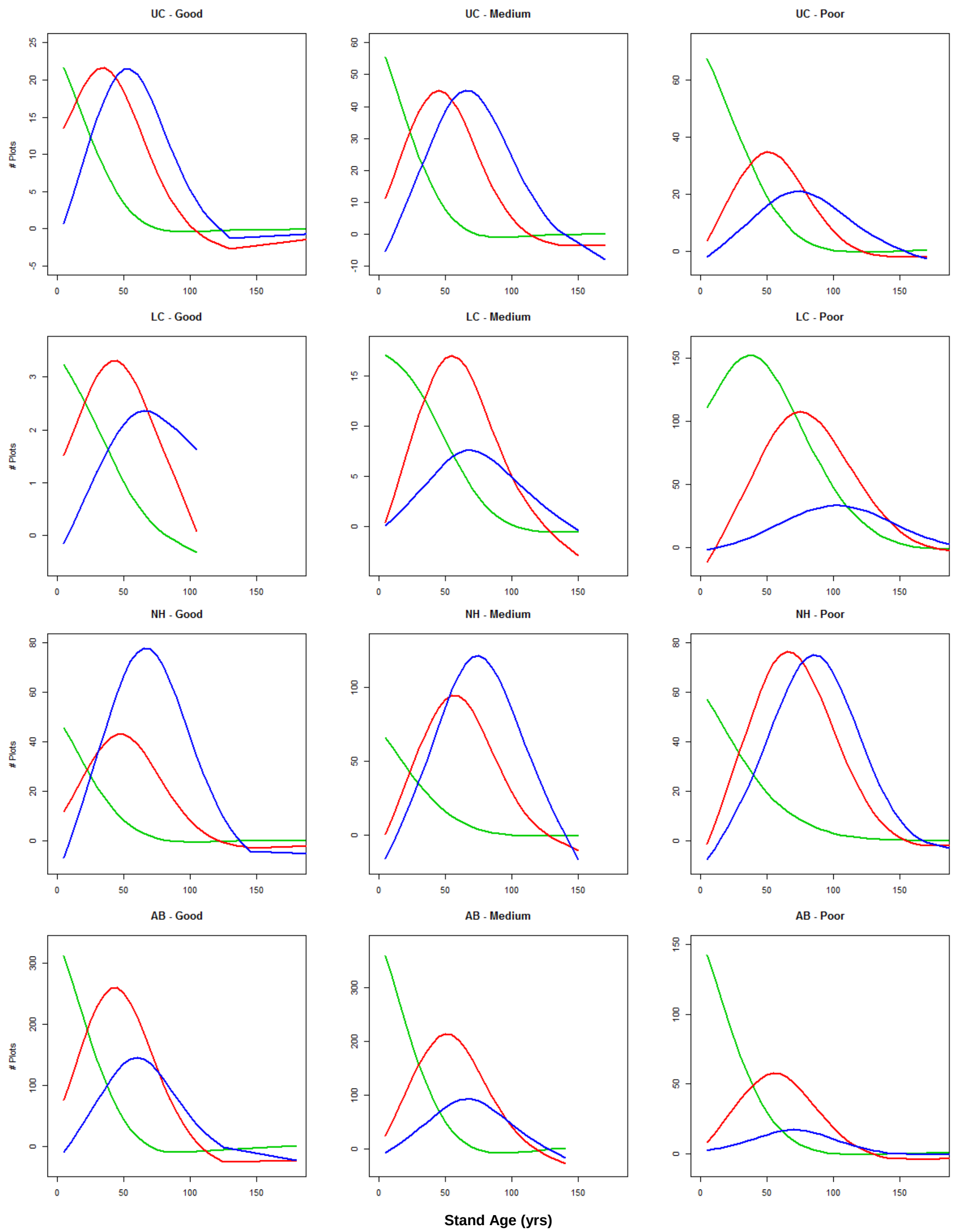

Figure A2.1. The distribution of size classes (seedling/sapling (green), poletimber (red), sawtimber (blue)) by age class for four forest type groups (upland conifer (UC), lowland conifer (LC), northern hardwoods (NH), and aspen-birch (AB)) in Minnesota. The results are grouped by site quality (site index (SI)) (good: SI > 65; medium: 50 < SI ≤ 65; poor: SI ≤ 50). Data came from FIA measurement periods 2004-2008 (USDA 2010). Due to considerable variation in sample size, the y-axis units vary between graphs, but the x-axis units are identical. All curves were fit using a smoothing spline (with smoothing parameter equal to 0.75).

Table A2.1. Age class to size class map for four forest type groups in Minnesota. The results are grouped by site quality (site index (SI)) (good: SI > 65; medium: 50 < SI ≤ 65; poor: SI ≤ 50). Data came from FIA measurement periods 2004-2008 (USDA 2010).

Forest Type	Site Quality	Seedling/ Sapling	Poletimber	Sawtimber
Upland Conifer	Good	≤14	15-44	≥45
	Medium	≤23	24-55	≥56
	Poor	≤43	44-79	≥80
Lowland Conifer	Good	≤21	22-68	≥69
	Medium	≤34	35-101	≥102
	Poor	≤71	72-142	≥143
Northern Hardwood	Good	≤22	23-31	≥32
	Medium	≤23	24-53	≥54
	Poor	≤29	30-77	≥78
Aspen-Birch	Good	≤23	24-77	≥78
	Medium	≤30	31-97	≥98
	Poor	≤39	40-118	≥119

A test involving approximately 31,000 FIA plots (USDA 2010) showed that 67% of all the plots were correctly mapped from age class to size class, and 98% were within one size class (Table A2.2). However, accuracy varied within forest type group and between site qualities (Tables A2.2 and A2.3). Other attempts at increasing the proportion of correct category assignments showed marginal improvement. Thus, WHINGS included the original map. These results suggest that natural resource managers should use caution when applying the map, but if necessary, the map provides a reasonable substitute to using the FIA or other stand size classification methodology.

Table A2.2. Age class to size class map percent mean error for each forest type group. Also included are the error rates across all plots. Errors reported as percentages of the observed total number of plots in the associated category. Data came from FIA measurement periods 2004-2008 (USDA 2010).

Forest Type	Error (Observed - Fitted)				
	-2	-1	0	1	2
Upland Conifer	0.01	0.17	0.70	0.11	0.01
Lowland Conifer	0.02	0.24	0.62	0.11	0.00
Northern Hardwoods	0.01	0.09	0.65	0.23	0.02
Aspen-Birch	0.01	0.24	0.70	0.05	0.00
All	0.01	0.19	0.67	0.11	0.01

Table A2.3. Age class to size class map percent mean error for each forest type group and site quality. Errors reported as percentages of the observed total number of plots in the associated category. Data came from FIA measurement periods 2004-2008 (USDA 2010).

Forest Type	Site Quality	Error (Observed - Fitted)				
		-2	-1	0	1	2
Upland Conifer	Good	0.00	0.11	0.68	0.20	0.01
	Medium	0.01	0.14	0.74	0.11	0.01
	Poor	0.02	0.24	0.67	0.06	0.02
Lowland Conifer	Good	0.00	0.25	0.58	0.17	0.00
	Medium	0.02	0.22	0.65	0.11	0.00
	Poor	0.03	0.24	0.62	0.11	0.00
Northern Hardwoods	Good	0.01	0.03	0.68	0.26	0.02
	Medium	0.01	0.07	0.66	0.25	0.01
	Poor	0.01	0.17	0.63	0.18	0.01
Aspen-Birch	Good	0.01	0.26	0.68	0.05	0.00
	Medium	0.01	0.23	0.72	0.04	0.00
	Poor	0.02	0.18	0.72	0.08	0.00

Appendix 3

Ecoregion crosswalk

Table A3.1 presents a crosswalk between the GEIS, FIA, and MNDNR ecoregion definitions, compiled from Jaakko Pöyry Consulting, Inc. (1992a), Cleland et al. (2007), and MNDNR (2000), respectively. Note that the geographic borders between the FIA and MNDNR ecoregions are essentially identical, and although the GEIS borders do not match the others exactly, they still show close agreement. Any observed differences were considered negligible.

Table A3.1. Ecoregion definition crosswalk between the GEIS, FIA, and MNDNR approaches.

GEIS	FIA	MNDNR	GEIS Name	FIA Name	MNDNR Name
1	212Ma	212Ma	Glacial Lake Plains	Littlefork-Vermillion Uplands	Littlefork-Vermillion Uplands
1	212Mb	212Mb	Glacial Lake Plains	Agassiz Lowlands	Agassiz Lowlands
2	212La	212La	Border Lakes	Border Lakes	Border Lakes
3	212Lb	212Lb	Lake Superior Highlands	North Shore Highlands	North Shore Highlands
4	212Ya	212Ja	Central Pine-Hardwood Forests	Superior-Ashland Clay Plain	Glacial Lake Superior Plain
4	212Qa	212Jd	Central Pine-Hardwood Forests	St. Croix Moraine	St. Croix Moraine
4	212Kb	212Kb	Central Pine-Hardwood Forests	Mille Lacs Uplands	Mille Lacs Uplands
4	212Lc	212Lc	Central Pine-Hardwood Forests	Laurentian Highlands	Nashwauk Uplands
4	212Ld	212Ld	Central Pine-Hardwood Forests	Toimi Uplands	Toimi Uplands
4	212Le	212Le	Central Pine-Hardwood Forests	Laurentian Highlands	Laurentian Uplands
4	212Na	212Na	Central Pine-Hardwood Forests	Chippewa Plains	Chippewa Plains
4	212Nb	212Nb	Central Pine-Hardwood Forests	St. Louis Moraines	St. Louis Moraines
4	212Nc	212Nc	Central Pine-Hardwood Forests	Pine Moraine and Outwash Plains	Pine Moraines and Outwash Plains
4	212Nd	212Nd	Central Pine-Hardwood Forests	Toimi Uplands	Tamarack Lowlands
5	222Ma	222Ma	Western Prairie/Forest Transition Zone	Alexandria Moraine-Hardwood Hills	Hardwood Hills
5	222Mb	222Mb	Western Prairie/Forest Transition Zone	Big Woods Moraines	Big Woods
5	222Mc	222Mc	Western Prairie/Forest Transition Zone	Anoka Sand Plain	Anoka Sand Plain
6	222Lc	222Lc	Eastern Prairie/Forest Transition Zone	Mississippi-Wisconsin River Ravines	Blufflands
6	222Lf	222Lf	Eastern Prairie/Forest Transition Zone	Western Paleozoic Plateau	Rochester Plateau
6	222Md	222Md	Eastern Prairie/Forest Transition Zone	Rosemont Baldwin Plains and Moraines	St. Paul Baldwin Plains and Moraines
6	222Me	222Me	Eastern Prairie/Forest Transition Zone	Oak Savannah Till and Loess Plains	Oak Savanna
6	251Be	222Me	Eastern Prairie/Forest Transition Zone	Southern Des Moines Lobe	Oak Savanna
7	251Ba	251Ba	Western Prairies	Upper Minnesota River-Des Moines Lobe	Minnesota River Prairie
8	251Bb	251Bb	Western Corn Belt Plains	Outer Coteau des Prairies	Coteau Moraines
8	251Bd	251Bc	Western Corn Belt Plains	Northwest Iowa Plains	Inner Coteau
9	222Na	223Na	Red River Valley	Aspen Parklands	Aspen Parklands
9	251Aa	251Aa	Red River Valley	Lake Agassiz Plain	Red River Prairie

Appendix 4

White-tailed deer zones

Table A4.1. Minnesota counties comprising the white-tailed deer zones used in the GEIS and WHINGS. See Frelich et al. (2013) for a description of the deer zones.

Zone 1

FIA County Code	County Name
7	Beltrami
21	Cass
29	Clearwater
31	Cook
57	Hubbard
61	Itasca
69	Kittson
71	Koochiching
75	Lake
77	Lake of the Woods
89	Marshall
113	Pennington
119	Polk
125	Red Lake
135	Roseau
137	St. Louis

Zone 4

FIA County Code	County Name
11	Big Stone
13	Blue Earth
15	Brown
23	Chippewa
27	Clay
33	Cottonwood
43	Faribault
47	Freeborn
51	Grant
63	Jackson
73	Lac qui Parle
81	Lincoln
83	Lyon
85	McLeod
91	Martin
101	Murray

Zone 2 & 3

FIA County Code	County Name
1	Aitkin
3	Anoka
5	Becker
9	Benton
17	Carlton
19	Carver
25	Chisago
35	Crow Wing
37	Dakota
39	Dodge
41	Douglas
45	Fillmore
49	Goodhue
53	Hennepin
55	Houston
59	Isanti
65	Kanabec
67	Kandiyohi
79	Le Sueur
87	Mahnomen
93	Meeker
95	Mille Lacs
97	Morrison
99	Mower
109	Olmsted
111	Otter Tail
115	Pine
123	Ramsey
131	Rice
139	Scott
141	Sherburne
143	Sibley
145	Stearns
147	Steele

103	Nicollet
105	Nobles
107	Norman
117	Pipestone
121	Pope
127	Redwood
129	Renville
133	Rock
149	Stevens
151	Swift
155	Traverse
165	Watonwan
167	Wilkin
173	Yellow Medicine

153	Todd
157	Wabasha
159	Wadena
161	Waseca
163	Washington
169	Winona
171	Wright